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The Effect of Patient and Hospital-level Factors on 30-Day Readmission After Initial Hospitalization Due to Stroke

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THE EFFECT OF PATIENT AND HOSPITAL-LEVEL FACTORS ON 30-DAY READMISSION AFTER INITIAL HOSPITALIZATION DUE TO STROKE

by

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(Under the Direction of Samuel Opoku)

ABSTRACT

Background: Hospital readmissions account for a large part of health care costs, especially among stroke patients. Readmission is common among disabled stroke survivors because they often suffer some neurological deficits, functional impairment, and other preexisting cardiovascular conditions. Although previous studies have explored the relationship between hospital readmissions after initial hospitalization due to stroke and a set of predictors using various analytical models, it often remains uncertain which predictors are most influential or essential. This study aimed to assess the effect of patient and hospital-levels factors on 30-day readmission after initial hospitalization due to stroke using the Anderson model of healthcare utilization as a guide.

Methods: Data for this study was the 2014 National Readmissions Database. A generalized mixed-effect linear regression using a hierarchical modeling approach was run based on the Andersen model's main block to assess the predictive capabilities of both individual and hospital-level factors on 30-day readmission. Models also assessed geographic differences that may exist among stroke patients.

Results: Overall, the addition of variable blocks corresponding to the Anderson model of health utilization accounted for only a small variance in 30-day readmission. However, the addition of the enabling and need factors resulted in the most significant R^2 change for hospitals in rural areas and urban areas, respectively.

Conclusion: The predictive powers of individual and hospital factors on readmission within 30 days of initial stroke-caused hospitalization is weak. The results of this study suggest a holistic approach should be the goal for policymakers and legislators when developing policies to reduce readmissions.

INDEX WORDS: Hospital readmission, Stroke readmission, 30-day readmission, Andersen behavioral model of healthcare utilization.

THE EFFECT OF PATIENT AND HOSPITAL-LEVEL FACTORS ON 30-DAY READMISSION

AFTER INITIAL HOSPITALIZATION DUE TO STROKE

by

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by

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DEDICATION

I want to dedicate this study to my mom, Mrs. Mary Akowuah, who died in 2015. I thank her for all the support and sacrifices she made to get me to this level of my education. Thank you for believing in me, and I hope you are proud of me. I love you!

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CHAPTER 1

INTRODUCTION

Stroke is a critical health condition to target for efforts to reduce hospital readmission rates because It is the second leading cause of admission among older adults with direct and indirect costs estimated above $73 million annually (Lloyd-Jones et al. 2010). Approximately 795,000 people each year in the United States experience a new or recurrent stroke (Lloyd-Jones et al. 2005; Wang, 2014; Center for Disease Control and Prevention, 2017). Stroke disproportionately affects older adults, with almost 75% of strokes occurring in people over age 65 years (Lloyd-Jones et al. 2010; National Stroke Association, 2016).

Stroke is considered the leading cause of long-term disability, and its effect is overarching (Poston, 2018). Over the past years, the rate of death due to stroke has declined. However, its prevalence is expected to increase in the coming years (Poston, 2018). Recent studies have projected that an additional 3.4 million U.S. adults are likely to suffer a stroke by 2030, which will be a 20.5% increase in the prevalence rate from 2012 (Poston, 2018). The effect of stroke is disproportionate across various racial groups (Poston, 2018). Recent studies report that compared to Whites, Blacks are two times more likely to suffer from a stroke (Poston, 2018). Compared to other racial groups, the death rate of stroke among Hispanics has been rising since 2013 (Poston, 2018).

It is estimated that one person in the United States suffers a stroke every 40 seconds, and on average, one person dies from a stroke every 4 minutes (Benjamin et al., 2017). It is estimated that approximately 60% of stroke deaths occurred outside of an acute care hospital (Benjamin et al., 2017). The risk of death from stroke is high, especially in the initial weeks after the attack (Brønnum-Hansen, Davidsen & Thorvaldsen, 2001). In 2013, there were 6.5 million deaths due to stroke globally, making it the second-leading cause of death behind ischemic heart disease (Benjamin et al., 2017).

The onset of a stroke can be costly and devastating (Lichtman et al., 2015). The cost of stroke treatment is high because stroke survivors tend to rely significantly on the healthcare system due to their long-term disability (Khan, 2017). In most cases, only a small portion (10%) of stroke patients recover fully (Khan, 2017). While twenty-five percent (25%) stroke patients improve with minor impairments, nearly half of them continue to live with severe impairments requiring special care (Khan, 2017).

The estimated annual direct cost of stroke care is about $34 billion (Center for Disease Control and Prevention, 2017; Wang, 2014). This includes medicines, missed work productivity, and healthcare services (Center for Disease Control and Prevention, 2017; Wang, 2014). The cost of a single hospitalization due to stroke is estimated between $18,963–$21,454 (Wang, 2014; Centers for Disease Control and Prevention 2017). This direct cost has been forecasted by the American Heart Associated to increase by 238% by 2030 (Wang, 2014; Centers for Disease Control and Prevention 2017). Experts have projected that the total direct and indirect medical cost for stroke will increase from $71.9 billion to $184 billion between 2012 and 2030 (Ovbiagele et al., 2013). Patients between the ages of 65 and 79 often contribute immensely to the increase in medical costs (Ovbiagele et al., 2013). It has been forecasted that the cost of stroke treatment could hit $2.2 trillion by 2050 if no preventive measures are taken (Brown et al., 2006).

Despite advancements in modern stroke treatment and rehabilitation, stroke survivors are often at risk for several adverse conditions such as recurrent stroke and cardiovascular diseases after the initial stroke onset (White et al. 2014). Studies estimate that nearly half of stroke survivors are discharged from the hospital with some persistent neurological impairments that impact their functional abilities (Verbrugge & Jette, 1994; Andersen et al., 2000). Follow-up studies have reported that in addition to the stroke event, stroke survivors are often faced with several health problems such as falls, depression, deterioration of achieved function, and social inactivity and isolation (Foster & Young, 1995; Kotila, Numminen, Waltimo & Markku, 1998; Pound, Gompertz & Ebrahim, 1998).

The 30-day risk-standardization readmission rates for patients discharged from the hospital is publicly reported by The Center for Medicare & Medicaid Services for most chronic diseases (Horwitz et al., 2011; Poston, 2018). Since the passage of the Affordable Care Act in 2010, CMS has held hospitals accountable for excessive readmissions through financial penalties (Poston, 2018). Nearly three-quarters of hospitals in 2013 were subjected to such penalties in the United States (Rau, 2013). This outcome measure is defined as any hospital readmission within 30 days of initial discharge (Horwitz et al., 2011; Poston, 2018). The 30-day readmission rate is an essential goal for measuring quality and improving services (Poston, 2018). Due to the high risk of readmission among the people who suffer a stroke, the measure of 30-day readmission rate has been prioritized at the national level (Poston, 2018).

The 30-day readmission estimate has been examined by the American Heart Association and American Stroke Association as a measure of quality. It is disruptive to caregivers and patients and places a burden on the healthcare system (Horwitz et al., 2011). It also puts stroke patients at high risk of hospital-acquired infections and complications (Horwitz et al., 2011). Readmission can cause significant stress for patients and their families (Horwitz, 2011). While some readmissions are avoidable, others are inevitable due to the disease's progression or worsening of health conditions and poor quality of care or inadequate transitional care (Horwitz et al., 2015; Poston, 2018).

Several studies have reported a relationship between quality of inpatient or transitional care and early (typically 30-day) readmission rates for a wide range of conditions (Benbassat & Taragin, 2000; Courtney, Ankrett & McCollum, 2003; Halfon et al., 2006; Hernandez, 2010; Horwitz et al., 2011). Some randomized clinical controlled trials also reveal that improving the quality of care, communication with patients, predischarge assessment and coordination of care after discharge can directly reduce readmission rates (Krumholz et al., 2002; Van Walraven et al., 2002; Conley, Kelly, Love & McMahon, 2003; Coleman et al., 2004; Horwitz et al., 2011). Successful randomized trials have reported a reduction in 30-day readmission rates by 20-40% (Horwitz et al., 2011).

Despite the strengths of using 30-day readmission as a measure of quality, it is not without its limitation (Benbassat & Taragin, 2000; Fischer et al., 2014; Poston, 2018). For example, it may not be right to categorize all readmissions as preventable since not all readmissions are (Poston, 2018). This issue can be rectified if elective and planned readmissions are excluded from this measure (Poston, 2018). Also, after the initial hospital discharge, hospitals may have little or no control over the patient's care. So, using readmission as a measure may result in some patients being denied hospital admission (Poston, 2018).

In effect, this could contribute to current healthcare access issues in the United States (Poston, 2018). Combining post-stroke functional status and mortality metrics to readmission may be the best way to use this measure (Poston, 2018). Therefore, identifying predictors of readmission after stroke could play an essential role in preventing them. To better identify stroke patients at risk for hospital readmission, the etiology and risk factors of stroke must be well understood.

Readmission is common among disabled stroke survivors (Hennen, Krumholz, & Radford, 1995; Andersen et al., 1995). Survivors of stroke are at a higher risk of readmission because of neurological deficits, functional impairment, and pre-existing cardiovascular risk factors and comorbidity (Langhorne et al., 2000). Readmission is frequent among stroke patients, especially in the first three months after a stroke (Bravata et al., 2007; Lin, Chang & Tseng, 2011; Fehnel et al., 2015). Although the functional and neurological impairments improve over time, the rate of readmission increases during the chronic phase (Bravata et al., 2007; Lakshminarayan et al., 2011; Rohweder, Salvesen, Ellekjaer & Indredavik, 2017).

Studies have highlighted that compared to patients with other chronic diseases, stroke patients tend to have longer lengths of stay, higher medical expenditure, and readmission rates (Lee, Yau & Wang, 2004; Chuang et al., 2005). Readmissions contribute to increasing healthcare costs and are viewed as an indicator of health care quality and efficiency (Center for Medicare & Medicaid Services, 2007). As a result, reducing stroke readmission has been one of the essential goals of the national healthcare reform since stroke imposes a more significant economic burden on the individual, family, community, and country at large (Taylor et al., 1996; Bernheim et al., 2010; Centers for Medicare & Medicaid Services, 2016).

Several recent studies have shown that older stroke survivors are usually vulnerable to readmission, with at least 40% readmitted in the first year (Kind et al., 2007; Fonarow et al. 2001). Others have also reported that the frequencies for readmission after any type of stroke within 90 days and within one year are 17% and 30%-62%, respectively (Lichtman, 2010). Stroke patients readmitted within 30 days have higher mortality and incur higher healthcare costs than patients who did not (Kind et al., 2008). Current data indicates that 24% of women and 42% of men often experience a recurrent stroke within five years of a stroke incident (National Stroke Association, 2017).

Identifying the causes of stroke readmission could be essential in preventing avoidable readmission (Bjerkreim et al., 2019). The most common causes of stroke are a history of stroke, acute cerebrovascular disease, septicemia, diabetes, coronary artery disease, infection or in-hospital complications, poor functional outcome (Lin, Chang &Tseng, 2011; Bambhroliya et al., 2018; Bohannon & Lee, 2004; Tseng & Lin, 2009; Hsieh, Lin, Hu & Sung, 2017). Financial and social factors are significant contributors to stroke readmission after initial discharge from the hospital (Lewsey et al., 2015).

Also, factors such as a lack of communication among healthcare providers both within and outside the hospital, timely follow-up visit, and inadequate discharge planning are contributing factors to hospital readmission (Goodman, Fisher & Chang, 2013; Calvillo–King et al., 2013). Also, limited socioeconomic resources contributed to stroke readmissions in a high proportion of patients at minority-serving institutions (Prieto-Centurion, Gussin, Rolle & Krishnan, 2013).

Therefore, researchers recommend that follow-up interventions are an effective way of preventing readmission among patients with prolonged inpatient rehabilitation (Andersen et al., 1995).

Disparities in health care have been well documented, and its elimination remains a major national priority (Institute of Medicine, 2002; U.S. Department of Health and Human Services, 2011). Although the risk of the first-ever stroke is higher for blacks than for whites, it is not entirely clear their relative risk for stroke readmission (Gillum, 1999; Ayala et al., 2001). Stroke disparities are widespread and pervasive throughout the world (Morgenstern & Kissela, 2015).

Data on stroke show that there are significant geographic disparities in stroke onset and mortality in the United States (Benjamin et al., 2017). Higher mortality rates are usually recorded in the southeastern part of the United States, often referred to as "Stroke belt" (Benjamin et al., 2017). This area constitutes the eight (8) southeastern states of North Carolina, South Carolina, Georgia, Tennessee, Mississippi, Alabama, Louisiana, and Arkansas (Benjamin et al., 2017).

Even higher mortality rates are often recorded along the coastal plains of North Carolina, South Carolina, and Georgia, known as the "buckle" region than the other states in the "stroke belt (Benjamin et al., 2017). According to researchers, these geographic differences have been existence since 1940 (Lanska, 1993). It has been estimated that compared to the rest of the nation, the overall average stroke mortality has been 30% higher in the stroke belt and 40% higher in the stroke buckle (Benjamin et al., 2017).

There are limited data on factors associated with readmissions and the geographic disparities of readmissions among patients with stroke. However, studies show that stroke survivors compared to others have a higher risk of readmission 30 days following discharge due to poor health quality and inefficient care (Kind et al. 2008; Medicare Payment Advisory Commission, 2013). Stroke patients are faced with physical and cognitive limitations, complex medication regimens, new diagnoses of chronic conditions, and lack of social support (Bushnell et al., 2009). These barriers challenge independence and stroke recovery and leave patients at high risk for readmissions (Condon, Lycan, Duncan, & Bushnell, 2016). With quality and efficient care, some readmissions that may be due to problems of quality of care could be prevented (Andrews & Freburger, 2015).

Current statistics suggest that disparities exist in health care and remain a growing concern worldwide (Smedley, Stith, & Nelson, 2002). Although the cause of the variation in stroke incidence and mortality is not entirely clear, the distribution of risk factor burden across geographic locations is considered a significant contributor (Cruz-Flores et al., 2011). Identifying people at high risk for stroke is essential in the prevention and reduction of mortality, morbidity, disability, and readmission due to stroke.

Due to the importance of stroke in clinical management and policy formulation, it is essential to identify factors that contribute to readmission risks in stroke patients. This will assist clinicians and healthcare institutions in the care of these patients, but it will also help identify opportunities to reduce avoidable readmissions. It is also anticipated that the result of this study will help providers and other delivery networks estimate risk and plan readmission reduction efforts.

Statement of Problem

Hospital readmissions account for a significant portion of health care costs, especially among stroke patients. Preventing readmissions is now a priority for hospitals and health systems because of the Hospital Readmissions Reduction Program (HRRP) implementation by Centers for Medicaid and Medicare (CMS). This program aims to improve healthcare for Americans by associating payment to the quality of care. Hospitals whose readmissions exceed the national 30-day risk-adjusted all-cause readmission rate will impose some penalties on them (Altarum Institute, 2014; Center for Medicare and Medicaid Services, 2018).

Accurate estimates of the absolute rates of hospital readmission, the associated diagnoses, and temporal patterns are needed to prevent or reduce hospital readmission after initial hospitalization for stroke. This information is required to promote efficient/effective allocation of resources, inform health care management decision making and policy development to improve the care provided to stroke patients in the U.S. Although previous studies have explored the relationship between hospital readmissions due to stroke and a set of predictors using various analytical models, it often remains uncertain to which predictors are most influential or important. This confusion stems from the correlations between the many predictors included in models by researchers.

A predictive tool such as the LACE index has been useful in helping clinicians identify patients at high risk for readmission or death within thirty days of discharge (Besler, 2020). However, upon an exhaustive literature review, there is no stroke-specific risk-standardized model for comparing hospital readmission performance or predicting readmission risk after stroke. The present literature also provides littles guidelines for developing risk-standardized models suitable for the public reporting of hospital-level stroke readmission performance.

Again, upon an exhaustive report of the literature, data on disparities and predictors of readmission within 30-days of initial stroke-caused hospitalization are limited. Empirical evidence on the risk factors and causes of stroke readmission has also been inconsistent. While readmission has been extensively examined, very few studies have examined this issue within the United States to the best of the author's knowledge. Therefore, this study used generalized mixed-effect linear regression to identify demographic and hospital characteristics that have the most significant predictive power on 30-day readmission due to stroke. Andersen's Healthcare Utilization Model guided the predictive models built in this study.

Purpose of the Study

This study aimed:

1. To assess the disparities in 30-day stroke readmissions among hospitals in the urban and rural areas of the United States of America using the 2014 National Readmission Database.
2. To build a predictive model of readmission within 30 days of initial hospitalization due to stroke among hospitals in the urban and rural areas of the United States of America using the Anderson model of healthcare utilization as a framework.

3. Assess the effect of patient and hospital-level factors on 30-day readmission after initial hospitalization due to stroke among hospitals located in the urban and rural areas of the United States of America using the 2014 National Readmission Database.

Significance of the Study

Reducing readmission remains a long-term public health goal since it provides the platform for reducing cost, improving quality, and increasing patient satisfaction. However, the question remains as to the best approach to address this problem. Over the years, most clinicians and healthcare organizations have relied solely on clinical data to inform policies and legislation in addressing community-level issues. This effectiveness of this approach has recently been questioned by some experts in the field of public health.

Factors at the community level do have a significant influence on health. Some experts suggest that improving the quality of care and increasing access to health care require a better understanding of the community in which hospitals are located, the social determinants, and the root cause of the issue at hand. Therefore, there is a push for integrating community-level and hospital-level data in improving access and quality of care in the United States. However, the evidence of the effectiveness of combining non-clinical and clinical data to improve patient health, health equity, and quality of care is limited.

This study uses hospital-level data in assessing the predictive capabilities of the identified predisposing, enabling, need, and health behavior factors on readmission within 30-days after the initial hospitalization due to stroke. The result of this study could inform public health agencies, healthcare systems, and policymakers with regards to the current push for integrating community-level and hospital-level data in addressing the issue of readmission.

Research Questions

1. What are the factors associated with readmissions among stroke patients?
2. How much variance in readmission is explained by the Andersen model of healthcare utilization?

Hypotheses

To determine the predictive capabilities of predisposing factors on readmission within 30 days of initial hospitalization due to stroke

H1: Gender would have a predictive ability on 30-day stroke readmission when controlling for hospital-level factors such as bed size, ownership, and location.

H2: Age would have a predictive ability on 30-day stroke readmission when controlling for hospital-level factors such as bed size, ownership, and location.

To determine the predictive capabilities of enabling factors on readmission within 30 days of initial hospitalization due to stroke.

H3: The type of health insurance would have a predictive ability on 30-day stroke readmission when controlling for hospital-level factors such as bed size, ownership, and location.

H4: Household income would have a predictive ability on 30-day stroke readmission when controlling for hospital-level factors such as bed size, ownership, and location.

To determine the predictive capabilities of need factors on readmission within 30 days of initial hospitalization due to stroke.

H5: The number of comorbidities would have a predictive ability on 30-day stroke readmission when controlling for hospital-level factors such as bed size, ownership, and location.

To determine the predictive capabilities of health behavior on readmission within 30 days of initial hospitalization due to stroke.

H6: The day of admission would have a predictive ability on 30-day stroke readmission when controlling for hospital-level factors such as bed size, ownership, and location.

Outline of the Remaining Chapters

Chapter 2 will include a review of the literature for hospital readmissions and the disparities in stroke readmission. It also describes the conceptual framework for this study and its application. Chapter 3 discusses the research study design and study methodology. It describes the study design, data source, study participants, measures, and statistical analysis. The results of the study are presented in Chapter 4. Finally, Chapter 5 discusses the research findings as well as the strengths and limitations of the study. It also provides recommendations and implications for future public health education, practice, and research.

CHAPTER 2

LITERATURE REVIEW

Hospitalization of stroke patients has been found to represent a large segment of the aggregate healthcare resources in numerous countries (Tseng & Lin, 2009). Therefore, improving patient outcomes and reducing readmission could better utilize the already scarce healthcare resources (Tseng & Lin, 2009; Ness & Kramer, 2013). Stroke care could be improved when the most common reasons behind which patients with stroke are readmitted, and the components that put stroke patients in danger for readmission is better understood (Tseng & Lin, 2009). Although many patients are hospitalized annually for stroke and other cerebrovascular diseases, data on the frequency and factors associated with stroke hospital readmission are limited.

Stroke patients are currently receiving improved stroke care (Royal College of physicians, 2017). People who suffer a stroke in the U.S. often get access to necessary tests and treatments quicker than before and hence have higher improved chances of recovering. (Royal College of physicians, 2017; Parker, Lindsay, Fang, Hill & Swartz, 2016). However, this has resulted in the burden for both patients and the health system because many of these survivors are prone to hospital readmission (Parker et al., 2016). However, coordinated quality stroke care and earlier outpatient follow-up may help prevent most readmissions among stroke patients and other cardiovascular diseases (Nahab et al., 2012).

Some studies suggest that the quality of care and hospital services provided may vary between weekdays and weekends (Bell & Redelmeier, 2001). The quality of care may be higher during the weekdays than on weekends (Khaksari, Kulick, Elkind & Boehme, 2019). This variance in discharge outcomes related to weekend versus weekday admission is known us “Weekend effect.” (Bell & Redelmeier, 2001). Previous studies suggest that weekday’s stroke admission has a lower 30-day case fatality rate than weekend stroke admissions (Saposnik, Baibergenova, Bayer & Hachinski, 2007; Sorita et al., 2014; Sharp, Choi & Hayward, 2013). However, the literature on the “Weekend effect” on 30-day readmission after stroke is limited. One of the recent studies that assessed the discrepancy in 30-day readmission related to weekend versus weekday admission found no association between these variables (Khaksari, Kulick, Elkind & Boehme, 2019).

The length of stay for patients admitted to U.S. hospitals has, over the years, continuously declined at a steady rate (Kominski & Witsberger, 1993; Sgura, Wright, Kopecky, Grill & Reeder, 2001). Though this may reduce admission, some experts have raised concerns that the decline in the length of stay may increase the number of patients discharged before they fully recover (Harrison, Graff, Roos & Brownell, 1995; Epstein, Bogen, Dreyer, & Thorpe, 1991). Therefore, higher mortality and readmission rates are likely to occur If more patients are discharged prematurely because of very short lengths of stay (Baker, Einstadter, Husak, & Cebul, 2004).

Stroke readmission has been studied over the years using different approaches. While some studies focus solely on disparities in readmission rates (Jiang, Andrews, Stryer & Friedman, 2005; Cruz-Flores et al., 2011; Nakagawa et al., 2016) or reasons for stroke readmission (Lichtman et al., 2010) others have studied both while considering patient demographics, hospital and societal factors (Sun et al., 2013; Bravata, Ho, Meehan, Brass & Concato, 2007; Nahab et al., 2012; Rohweder, Salvesen, Ellekjær & Indredavik, 2017). Typically, studies that have focused on stroke readmission have evaluated readmission rates for stroke survivors at one month, six months, and one year after the initial hospital discharge (Tseng & Lin, 2009; Li, Yang, & Chung, 2010; Nahab et al., 2012; Vivo et al., 2014). Most of these readmission rates were assessed using either hospital or national-level data.

Studies assessing stroke readmission have reported that readmission rates for stroke patients increase with time (Tseng & Lin 2009; Li, Yang & Chung, 2010). Previous studies have reported stroke readmission rates of 21% and 55% within 30 days and one year, respectively (Fehnel et al., 2015). This was evident in the study conducted by Li, Yang, and Chung (2010), where they reported stroke readmission rates of 9.9%, 23.0%, and 30.7% for survivors of a stroke at one month, six months, and one year after the index discharge respectively. Other studies have also reported a stroke readmission rate of 50% for study participants within one year after the initial hospitalization (Tseng & Lin, 2009). Only a small portion of stroke patients are not readmitted over a year after the initial hospital hospitalization (Bravata, Ho, Meehan, Brass, & Concato, 2007).

Several multifaced risk factors and etiologies affect stroke readmissions. These predictive factors can be categorized into five main areas: patient characteristics, social circumstances, clinical processes of care, health outcomes, and health system determinants, including hospital location (Kilkenny et al., 2013). Although the risk factors associated with stroke readmission varies in current studies, the most common causes of stroke readmission are stroke recurrence and infection (Bravata, Ho, Meehan, Brass & Concato, 2007; Tseng and Lin, 2009; Sun et al., 2013; Rohweder, Salvesen, Ellekjær & Indredavik, 2017). Other causes identified also include vascular conditions, falls, hemorrhagic events, acute myocardial infarction, pneumonia, or respiratory illnesses (Rohweder, Salvesen, Ellekjær, and Indredavik, 2017; Bravata, Ho, Meehan, Brass, and Concato (2007) Sun et al., (2013).

Nouh et al., (2017) in their retrospective study evaluating the etiologies and predictors of 30-day readmissions using data from Hartford Hospital Stroke Center Registry reported that the most common reason for readmission was infection (30%), mostly urinary (47.5%) or respiratory (42.5%). This is due to due to recumbence, indwelling urinary catheters, and aspiration risk. Other reasons for readmission identified were recurrent stroke or TIA (20%), and cardiac complications (14%). Another 6% accounted for frequent symptoms of the initial stroke. Finally, other etiologies such as seizures fall, and non-infectious respiratory, gastrointestinal, renal, hematologic, and orthopedic complications accounted for the remaining 30%.

A similar study conducted by Poston (2018) using the 2013 Nationwide Readmission Database found recurrent stroke, urinary tract, and respiratory infections as the most common reasons for stroke readmission. Risk factors associated with stroke readmission identified in this study included Medicare coverage, lower household income, increased age, a high number of individual comorbidities. Living in a facility before the stroke, admission to non-neurology service, and poor medication adherence. The study also found that the lower odds of readmission were associated with lower comorbidity scores on formalized comorbidity indexes and higher levels of social engagement in nursing homes after hospital discharge.

Lee et al., in 2018, also used claim data to investigate patient and hospital factors associated with 30-day readmission in patients with stroke in South Korea. Patient characteristics such as medical aid and longer hospital stay were associated with 30-day readmission rate. They also reported that hospital factors such as hospital type and quality of care were associated with readmission. Thus, patients admitted to a low-grade hospital or a non-capital area hospital were more likely to be readmitted within 30 days of discharge.

Smajlović, Kojić, and Sinanović in 2006 analyzed 5-year survival for 836 patients who suffered a first-ever stroke first-ever stroke between 1997 and 1998 in Tuzla, Herzegovina, and Bosnia. After the first month, 36% of the patients died. The study found that participants who were 50 years or younger had a higher survival rate (57%) compared to those 70 or older (9%). The survival rate for those who suffered an ischemic stroke and intracerebral hemorrhage was 60% and 38%, respectively, after the first year, compared to 31% and 24% after the five years.

Compliance with treatment remains an essential key that links the medical care process and outcome (Urquhart, 1996). Lower compliance with treatments and interventions presents a complex problem, especially for patients with chronic conditions such as stroke (Vermeire, Hearnshaw, Royen & Denekens, 2001). Patients' risk factors such as alcohol use following stroke are significantly associated with stroke readmission (Parikh et al., 2017). Compared to whites, minority groups have poorer control of risk factors for stroke, partly due to lower compliance with treatment recommendations (Cruz-Flores et al. 2005). Therefore, interventions addressing such patient behaviors after the initial hospital admission could reduce hospital readmissions due to stroke within 30 days (Parikh et al., 2017).

Understanding why disparities exist in stroke readmission has a significant effect on efforts in reducing readmission. Such information could help design interventions that target the most vulnerable patients, community, and hospitals (Joynt, Orav & Jha, 2011). Like a stroke, some studies have found considerable racial/ethnic differences in the prevalence and management of other health conditions (Curry, Carter & Baker, 2010; Nahab et al., 2012; Vivo et al., 2014). Several recent studies with a focus on hospital readmission in other health conditions have shown that ethnic minorities have higher rates of readmission in conditions such as heart failure (Vivo et al., 2014), cerebrovascular disease (Nahab et al., 2012) and cancer (Curry, Carter & Baker, 2010). These studies also looked at payer type and geographic location (Urban/Rural) and found some relationship between these variables and readmission rates.

To explain the ethnic differences in readmission among patients with stroke and other health conditions, some researchers have highlighted that the difference in stroke awareness, attitude, beliefs, and compliance, in part, may explain the existence of disparities in stroke care (Cruz-Flores et al. 2005). Knowledge of stroke warning signs is poor, with most people (30% to 60%) not knowing or recognizing at least one warning sign of stroke (Nicol &Thrift, 2005). Racial-ethnic disparities exist in the awareness and understanding of the nature of the stroke, its signs and symptoms, the need for urgent care, and risk factors (Cruz-Flores et al. 2005).

A study conducted by Wiley, Williams, and Boden-Albala in 2009 revealed that compared to whites, blacks, or African Americans and Hispanics have lower knowledge about stroke. Another study by Ellis and Egede in 2008 also reported that even among people with a prior history of stroke, whites were more likely than non-Hispanic blacks or African Americans and Hispanic/other group members to seek emergency medical services. Others have also found that compared to whites, African Americans have a lower level of knowledge of risk factors for stroke and other cardiovascular events even after controlling for level of education (Reeves, Hogan & Rafferty, 2002; Lynch, Liu, Kiefe & Greenland, 2006).

Several recent studies have shown that gender disparities exist in the outcome, treatment, and readmission of stroke (Caso et al., 2010; Seshadri et al., 2006; Turtzo & McCullough, 2008; Reeves et al., 2008; Caso et al. 2010). Although the incidence of stroke is higher in men compared to women, the effect of stroke is more significant in women when matched for age (Caso et al., 2010). This is because of women's longer life expectancy and the fact that their stroke incidence rates increase substantially at older ages (Seshadri et al., 2006; Turtzo & McCullough, 2008; Reeves et al., 2008; Caso et al. 2010).

Besides, the societal impact of stroke on women is greater because older women are more likely to be isolated or live alone (Reeves et al., 2008). Some empirical studies have shown that compared to men, women tend to have poorer outcomes and quality of life and greater disability before and after stroke (Di Carlo et al. 2003). Although other studies focusing on other health conditions such as myocardial infarction have found women to have a higher risk for readmission after controlling for potential confounders, information on the gender difference in stroke readmission is inconsistent and limited (Dreyer et al., 2015). On the other hand, some studies have reported that gender was not significantly associated with the risk of mortality or stroke recurrence (Sun et al., 2013).

Another cause of disparity identified by researchers in the incidence, treatment, and readmission of stroke is socioeconomic status. Empirical evidence shows that the incidence of stroke is not evenly distributed across all population because individuals in low socioeconomic groups tend to have a higher incidence of stroke compared to those in other groups (Avendano et al., 2006; Cox, McKevitt, Rudd &Wolfe, 2006; Kuper, Adami, Theorell & Weiderpass, 2007). Like other health conditions, researchers suggest that the association between socioeconomic status and stroke incidence could be explained by the differential distribution of behavioral or clinical risk factors and access to health services (Cox et al., 2006).

Despite these findings, the association between socioeconomic status and stroke readmission has not been thoroughly studied. The available evidence of their association is inconsistent. While some studies have found a strong association (Gillum & Mussolino, 2003; Arrich, Lalouschek & Müllner; 2005; Zhou et al. 2006) between these two variables, others have found little to no association between socioeconomic status and stroke survival or readmission (Cox et al., 2006; Cesaroni, Agabiti, Forastiere &Perucci, 2009). However, some studies have highlighted that although there is evidence of socioeconomic disparities in stroke incidence, socioeconomic status may not substantially impact the outcome of treatment after first hospital admission and readmission (Cesaroni et al., 2009).

Individuals who have suffered a stroke are often at risk of stroke recurrence and death (Sun, Lee, Heng & Chin, 2013). As a result of that most families, providers, and healthcare planners are interested in finding information that will help them make rational decisions to ensure proper patient’s long-term post-stroke outcomes (Mackenzie et al., 2007; Cadilhac, Carter, Thrift & Dewey, 2007; Kolominsky-Rabas, 2006). Although the relationship between patients’ demographics and long-term survival and recurrence after stroke have been well studied, the results have been inconsistent (Van Staten et al., 2001; Olsen, Dehlendorff & Andersen, 2007; Andersen, Andersen, Kammersgaard & Olsen, 2005; Cushman et al., 2008; Xian, Holloway, Noyes, Shah & Friedman, 2011).

Disparities in readmission after stroke, though not thoroughly studied, do exist. Addressing this issue remains a major concern for most hospitals and families looking at the major implications of this disease. Understanding the predictive factors that influence readmission is imperative in reducing 30-day readmission after stroke (Nouh et al., 2017). Readmission rates may be reduced if hospitals and physicians fully implement proven interventions in response to public reporting and benchmarking (Ross et al., 2010). Therefore, there is a need for more research in this area to help protect vulnerable and minority populations from most preventable stroke readmissions.

Conceptual Framework

Some researchers have defined healthcare utilization as the point in health systems where patients' needs meet the professional system (Babitsch, Gohl & von Lengerke, 2012). Other than need-related factors, the use of health care is supply-incited and hence strongly reliant on the structures of the health care system (Babitsch, Gohl & von Lengerke, 2012). The level of utilization differs within populations and among various social groups (López-Cevallos, & Chi, 2009; Louvison et al., 2008 Reyes-Ortiz et al., 2007). For example, findings of some studies report that women have higher medical care service utilization and higher associated charges than men (Bertakis, Azari, Helms, Callahan & Robbins, 2000).

Other findings suggest that the use of acute care services, including hospitalizations, inpatient physician visits, and emergency services, increase with age, while the use of primary care providers decreases with age (Murphy & Hepworth, 1996). Like the number of studies describing the differences in the use of health care services in different health care settings, many researchers have developed and adopted several models capable of identifying the predictors of health care utilization (Babitsch, Gohl & von Lengerke, 2012).

One of the most widely used theoretical frameworks for predicting and analyzing health services utilization is the Andersen Behavioral Model of Health Service Utilization, developed in 1968 by Ronald M. Andersen (Andersen, 2008; Andersen & Newman, 1973; Aday & Andersen, 1974; Andersen, 1995; Andersen, Rice & Kominski, 2011; von Lengerke, Gohl & Babitsch, 2014). The goal of developing this framework was to develop a behavioral model that provided measures of access to health care (Andersen, 1995). The initial design of the model was to assist in understanding why families use health services and to define, measure, and promote equitable health access to health care through policy development (Andersen, 1995). Thus, this model was developed to discover conditions that facilitated or impeded health care utilization (Andersen, 1995).

Andersen's BM of health service utilization is a multilevel model that posits that health service use is dependent on social, service system, and individual factors (Bradley et al., 2002; Anderson, 2008). Andersen's conceptual framework has gone through several modifications over the years since its first design. The initial model focused on the family as the unit of analysis because an individual's health care use is a function of the family's demographic, social, and economic characteristics as a unit (Andersen, 1995). However, due to the difficulty in developing family-level measures that factored the potential heterogeneity of family members, Andersen shifted to using the individual as the unit of analysis in his subsequent work (Andersen, 1995). Several researchers have adopted this model to predict and analyze health service use (Andersen & Newman, 1973; von Lengerke, Gohl & Babitsch, 2014).

The second design of this model was developed by Aday and Andersen in the 1970s to construct an integrated theoretical framework for the study of healthcare access and to identify indicators derived from this framework (Andersen & Newman, 1973; Aday & Andersen, 1974). Healthcare concepts, such as resources, organization, and policy, were included in this model's new design (Aday & Andersen, 1974). The initial outcome of utilization was extended to include consumer satisfaction (Aday & Andersen, 1974). Other researchers also built on this framework and added health status (perceived and evaluated) to patient satisfaction as an essential outcome of this model (Evans & Stoddart, 1990).

The current version of the Andersen model uses the individual as the unit of analysis and extends the endpoint of interest from health care utilization to health outcomes (Andersen, Davidson & Baumeister, 2014). This version postulates that needs and health beliefs may be affected by health outcomes and hence, provides feedback loops to illustrate this in its design (Andersen, Davidson & Baumeister, 2014). Andersen's B.M. incorporates concepts such as genetic susceptibility and quality of life as predisposing factors and outcomes, respectively (Andersen, Davidson & Baumeister, 2014). One of the newer versions' strengths is that it conceptualizes the predisposing, enabling, and need factors on both the individual and contextual levels as determinants of an individual's use of health services in a similar manner (von Lengerke, Gohl & Babitsch, 2014).

The Andersen's model defines health service use as a function of three major components: predisposing, enabling and need factors (Andersen & Davidson, 2001; Andersen & Newman, 1973;

Jahangir, Irazola, & Rubinstein, 2012 Andersen, 1995; Babitsch, Gohl & von Lengerke, 2012; von Lengerke, Gohl & Babitsch, 2014; Kim & Liu, 2016). Predisposing factors are considered as the socio-cultural characteristics of the individual that exist before the onset of their illness (Andersen, 1995). These include social structure (ethnicity, occupation, education, social networks, culture, and social network), health beliefs (attitudes, values, and knowledge people have about and towards health care) and demographic (age and gender) (Andersen, 1995).

Enabling factors deal with the logistical aspects of seeking care (Andersen, 1995). These include personal/family (the how and where to access health services, health insurance, regular source of care, income and extent and quality of social relationships), community (available health personnel and facilities, and waiting time), genetics and psychological characteristics (Andersen, 1995). Finally, the need factors lead to the immediate use of health services and reflect disease characteristics (Andersen, 1995; Van Doorslaer, 2002). The Andersen BM model differentiates between perceived (individuals view about their disease and how they experience the pain and symptoms of the disease) and evaluated (objective or professional assessment of patient health status and need for health care) needs for health services (Andersen, 1995).

Andersen's Behavioral Model of health service utilization suggests individuals' use of health services is influenced by their predisposition to use services, factors that enable or impede use, and their need for care (Andersen, 1995). It further explains that where the predisposing factors are exogenous (demographic and social structures), some form of enabling factors must be present though not required and a need defined for actual use to take place (Andersen, 1995). Before its development, most existing healthcare utilization theories and empirical studies had focused more on the individual characteristics with less attention given the societal impact (Jahangir, Irazola, & Rubinstein, 2012).

Empirical evidence shows that this B.M. has frequently been adopted by studies conducted in the United Kingdom and the United States (Babitsch, Gohl & von Lengerke, 2012). Andersen's B.M. has been used as the theoretical framework to guide many systematic reviews that have focused on health services utilization (Hulka & Wheat, 1985; de Boer Wijker & de Haes, 1997; Kadushin, 2004). In other countries such as Germany, this model has been adopted by the Federal Health Reporting System since 2001 for analyzing health service utilization (von Lengerke, Gohl & Babitsch, 2014).

One of the major strengths of this framework is its ability to establish disparities in access to health services by setting out the differences in its three major components (von Lengerke, Gohl & Babitsch, 2014). In addition to disease factors, health services utilization is influenced by an individual's demographic, economic, and socio-structural factors (Aday, 1973; Hurd & McGarry, 1997). The Andersen BM of health services utilization has been used by some studies to analyze health service utilization by examining individuals' socioeconomic and community characteristics (Kim & Lee, 2016). Most of these studies reported that the use of health services is inspired by individual illness or the presence of a disease, however, its quantity and quality varies significantly based on health insurance status and income (Andersen, Lewis, Giachello, Aday & Chiu, 1981; Gilberg, Andersen & Leake, 2000).

Recent studies have also used this model to examine the predictors of readmission among patients with various diseases, disabilities, and disorders (Hamilton et al., 2015; DePalma et al., 2012; O'Connor et al., 2016). For example, Hamilton et al. in 2015 adapted the Andersen's Behavioral Model to examine predictors of psychiatric readmission within 30days, 90days and one year of discharge among patients 2443 adult patients admitted consecutively to a psychiatric hospital in the United States due to bipolar disorder.

Their study highlighted that being uninsured, having more than three psychiatric hospitalizations, and patient economic status was significantly associated with an increased risk of readmission across all times examined. Patient race/ethnicity was not found to be a strong predictor of readmission. However, they found that compared to females, males were more likely to be admitted within one year. Therefore, this suggests that compared to predisposing factors, enabling and need factors are the strongest predictors of psychiatric readmission.

Other studies by DePalma et al., (2012) and O'Connor et al., (2016) also found need factors as the strongest predictors of readmission. Therefore, their findings highlight the fact that identifying the right predictors of readmission will help develop and implement innovative interventions or transitional care initiatives that will be effective in preventing readmission for patients with various health conditions. Some researchers suggest that interventions may need to be general in design with the specific intervention depending on each patient's unique clinical profile (O'Connor et al., 2016).

Conceptualization of constructs of the Andersen's Behavioral Model of Healthcare Utilization

Predisposing factors

Although not directly responsible for utilization, predisposing factors can influence an individual's likelihood to need or use health services (Andersen, Rice & Kominski, 2001). These conditions include demographic characteristics, social structures, and health beliefs (Andersen, 1995). Among these factors, demographic characteristics such as gender and age represent biological imperatives (Andersen, 1995). Social structures constitute individuals' status in the community, and this is often measured using variables such as education, occupation, and ethnicity (Andersen, 1995). Health beliefs, on the other hand, are individuals' attitudes, values, and knowledge that may influence their perception of need and health service utilization (Andersen, 1995).

Several studies using the Andersen's model to examine utilization among the elderly (Evashwick, Rowe, Diehr & Branch, 1984; Babitch, Gohl, & von Lengerke, 2012), all reported predisposing factors were strong predictors of health services utilization. The predisposing factors measured in both studies included age, sex, race, education, household compositions, and marital status. Other studies using the Andersen's model (Jahangir, Irazola & Rubinstein, 2012; Kim & Lee, 2016; Azfredrick, 2016) also examined predisposing factors using variables such as sex, age, marital status, civil state, household situation, and education level. The results of these studies all showed that predisposing factors were associated with the use of health services.

Existing literature also highlights that although age-specific stroke is higher in men, women tend to have more stroke events overall because women have higher life expectancy and incidence of stroke at older ages (Caso et al., 2010).

Therefore, all things being equal, it was hypothesized that:

Hypothesis 1

H1a: Gender would have a predictive ability on 30-day stroke readmission when controlling for hospital-level factors such as bed size, ownership, and location.

H1b: Age would have a predictive ability on 30-day stroke readmission when controlling for hospital-level factors such as bed size, ownership, and location.

Enabling factors

The enabling factors are the resources that influence an individual's decision to utilize health services. The most common enabling factors examined in several studies have included the household income, economic activity, parental support, and communication, type of health facility and type of access to health insurance (Andersen, 1995; Jahangir, Irazola & Rubinstein, 2012; Kim & Lee, 2016; Azfredrick, 2016).

Several studies have also used the Andersen's model to study the influences of enabling factors such as household income and type of insurance on the utilization of medical services (Weller, Minkovitz, & Anderson, 2003; Evashwick, Rowe, Diehr & Branch, 1984; Jahangir, Irazola & Rubinstein, 2012). For example, Weller, Minkovitz, and Andersen (2003) examined the influence of the type of health insurance on the use of medical and health-related services, which showed that enabling factors had a significant influence on medical services utilization, especially among patients who used public insurance.

Differences in the scope of benefits covered by public insurance and private insurance may give rise to differences in medical utilization (Weller, Minkovitz, & Anderson, 2003; Sohn & Jung, 2016). Current studies also highlight the association between poor health and income levels and hence has a potential effect on health services utilization (Pollack et al., 2013; Cooper, Cooper, McGinley, Fan & Rosenthal, 2012). Studies show that individuals at all income levels are less healthy than those with incomes higher their own (Braveman et al., 2010). Cooper et al. (2013) showed that lower household income was associated with the aggregate use of health services.

Therefore, all things being equal, it was hypothesized that:

Hypothesis 2

H2a: The type of health insurance would have a predictive ability on 30-day stroke readmission when controlling for hospital-level factors such as bed size, ownership, and location.

H2b: Household income would have a predictive ability on 30-day stroke readmission when controlling for hospital-level factors such as bed size, ownership, and location.

Need factors

The need constructs assess the health and functional status of an individual and its effect on the use of health care resources (McManus, 2016). Health and functional status can both be measured as perceived and evaluated need (Andersen, 1995). The most common need factors examined in several studies have included disease, symptoms, health, and disability status (Jahangir, Irazola & Rubinstein, 2012; Oladipo, 2014; Kim & Lee, 2016; Azfredrick, 2016). The intensity of illness and the number of comorbidities significantly affect the utilization of healthcare services (Girma, Jira & Girma, 2011). The higher the severity or number of comorbidities, the higher the degree of utilization of health services (Pathak, Ketkar, & Majumdar, 1981; Sauerborn, Nougtara & Diesfeld, 1989).

Therefore, all things being equal, it was hypothesized that:

Hypothesis 3

H3: The number of comorbidities would have a predictive ability on 30-day stroke readmission when controlling for hospital-level factors such as bed size, ownership, and location.

Health Behavior

Various researchers have applied several factors to expand Andersen's Healthcare Utilization Model. These expansions have included health behavioral characteristics, psychosocial factors, and effectiveness variables (Guilcher et al., 2012; Bradley et al., 2004; Fu et al., 2017; Alders, Deeg & Schut, 2019). Therefore, the present study includes the day of admission as a health behavior characteristic to expand the Andersen's model being used. This will help understand the predictive power of health behavior on 30-day readmission due to stroke.

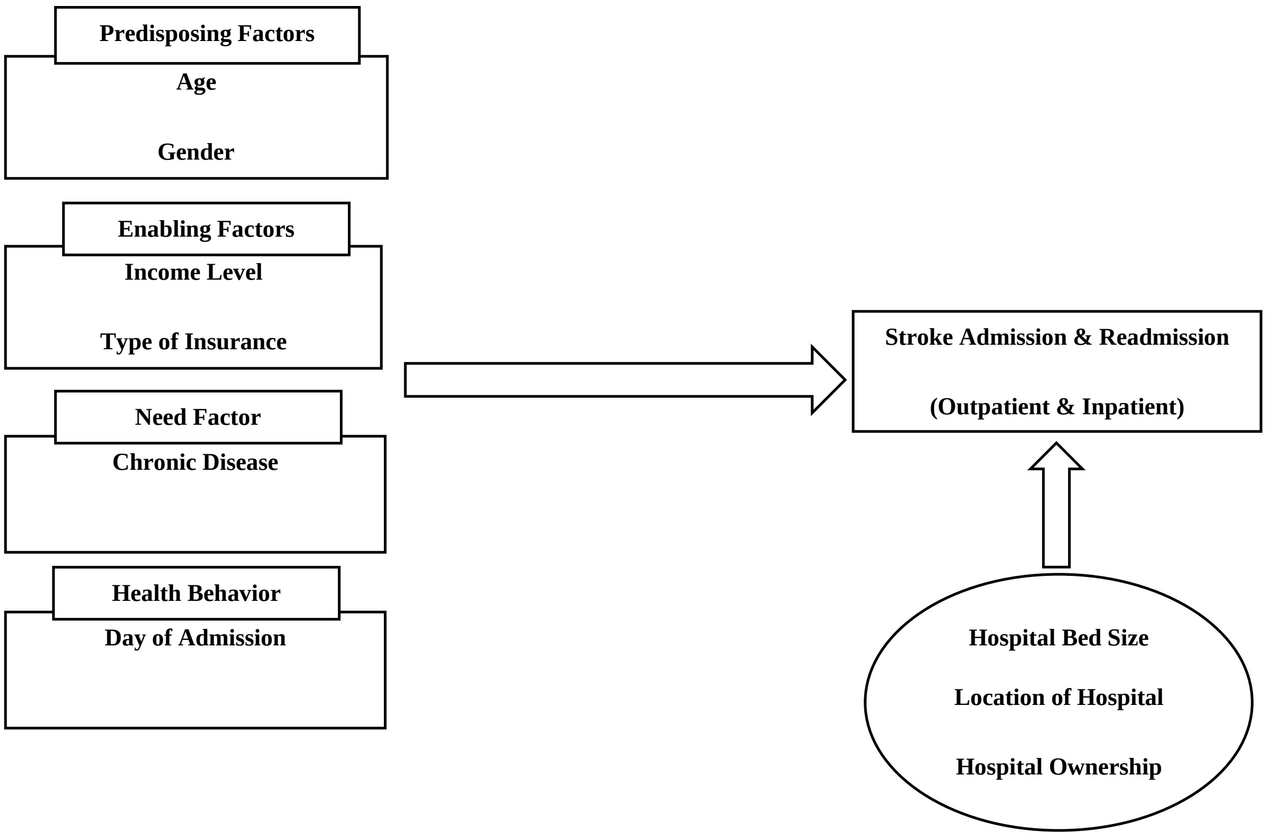
Studies of the stroke "weekend effect" has been widely studied across countries such as Canada, Japan, Taiwan and the United States of America (Saposnik, Baibergenova, Bayer & Hachinski, 2007; Janszky Ahnve & Ljung, 2007; Hasegawa et al., 2005; Tung, Chang & Chen, 2009; Reeves et al., 2009). The results of these studies have been varied and inconsistent. Some of these studies have shown a strong association (Rudd et al., 2007; Lees et al., 2008). Others have reported little to no association between day of admission and stroke treatment, admission, and mortality (Albright et al., 2009).

Therefore, referring to previous literature, it was hypothesized that:

Hypothesis 4

H4: The day of admission would have a predictive ability on 30-day stroke readmission when controlling for hospital-level factors such as bed size, ownership, and location.

Figure 2.1: Adopted Research Model



Chapter Summary

In summary, this chapter presented an overview of the existing literature on stroke readmission, the conceptual framework used in the study, and its application in developing the hypotheses of the current study. Chapter 3 describes the study methodology and research study design. It describes in detail the study designs, data source, study population, measures, and analysis.

CHAPTER 3

METHODOLOGY

Introduction

This study utilized a quantitative approach to analyze secondary data to answer the stated research questions and test the stated hypothesis. This chapter will discuss the study design, data source, study population, measures, and analytical approach employed

Study Design

This study was a population-based retrospective cohort study of a sample of eligible stroke patients in the United States, followed up for 30-day hospital readmission during 2014. An observational study allows researchers to observe subjects or measure variables of interest without assigning treatment or intervention to subjects. A retrospective study design also allows researchers to look to the past to examine medical events or outcomes, as well as developing ideas and assessing possible associations or relationships between study variables (Song & Chung, 2010).

Data Source

The study used secondary data. The data source was the 2014 Healthcare Care Utilization Project's (HCUP), Nationwide Readmissions Database (NRD), which forms part of the family of databases and software developed through a Federal-State-Industry partnership, sponsored by the Agency for Healthcare Research and Quality. The NRD was developed to aid the analyses of national readmission rates for all payers and the uninsured. Before the design of the NRD, there was a lack of nationally representative hospital readmission information for all ages and hence, has addressed a significant gap in health care data (Healthcare Cost and Utilization Project, 2017).

The NRD is drawn from State Inpatient Databases and contains reliable, verified patient linkage numbers that can be used to track a patient across hospitals within a state while adhering to strict privacy guidelines. This database includes approximately 17 million unweighted and 36 million weighted discharge records of patients treated in U.S. short-term or community hospitals excluding rehabilitation and long-term acute care facilities. It is a nationally representative database that, until 2015, covered about 22 geographically dispersed states representing 49% of the U.S.

The NRD contains more than 100 clinical and non-clinical variables that aid in analyzing hospital readmissions while protecting the privacy of patients, physicians, and hospitals. The NRD includes variables essential to readmission analysis (e.g., verified patient linkage numbers, the timing between admissions for patients and length of inpatient stay in days) and calculating national estimates (e.g., discharge weight for generating national estimates, Stratum used for weighting), patient demographics (e.g., sex, age, median household income quartile, and urban/rural location of the patient's residence), expected payment source (e.g., Medicare, Medicaid, private insurance, uninsured, and other insurance types), and total charges and hospital cost (Calculated using the Cost-to-Charge Ratio file).

This database has been used over the years to inform decisions at the community, state, and national levels (Healthcare Cost and Utilization Project, 2017). Areas of research associated with this database include but are not limited to readmissions by special populations, reasons for readmission, the cost associated with readmission, national readmission rates by diagnosis, procedure, patient demographics, or insurance type and impact of health policy changes (Healthcare Cost and Utilization Project, 2017). These data were provided after completing the required training and conforming to the "Data Use Agreement" with the HCUP. To avoid inferential error or other potential problems, it is essential first to ensure the variable names are consistent across datasets.

Study Population

Adults 18 years of age and over with an index admission for stroke between January 1, 2014, and November 30, 2014, were identified using the International Classification of Diseases, Ninth Revision (ICD-9) codes. (43301, 43310, 43311, 43321, 43331, 43381, 43391 43400, 43401, 43411, 43491, 436, 430, 431). The end date of November 30, 2014, was chosen to allow for a full 30-day readmission window for all index admissions. The first (index) hospital admission for eligible patients was included for further analyses. Data for patients transferred to another acute hospital, mortality, or left against medical advice were excluded.

Measures

Index Admissions

Stroke index readmissions were assessed across all patients' age group. Patients index readmission and reasons for readmission were assessed using the Clinical Classification Software-based diagnostic categories by the Agency for Healthcare Research and Quality (AHRQ).

Main Outcome Measure

Hospital readmission was defined as any admission within 30 days after initial hospitalization discharge. Readmissions, classified as planned or unplanned, and potentially preventable readmissions due to ambulatory care sensitive conditions, were identified using Centers for Medicare and Medicaid Services (CMS) algorithms. Readmission to any hospital during the study period was referred to as any-hospital readmission. Same-hospital and different hospital readmissions were defined as readmission to the same or different hospital from which the patient was discharged during the initial admission.

Patient Demographic Characteristics

The patient-level demographic characteristics included in this study were sex, age, payer, household income, and the location of the patient home. The HCUP data element for sex or gender is FEMALE. Male and Female variables were coded as 0 and 1, respectively. To ensure the accuracy, age was imputed for other records with the same patient linkage number of missing. Missing sex was imputed using other records with the same patient linkage number.

The HCUP data element for age was AGE. The age variable in years was coded between 0 to 90 years. Any age greater than 89 years was set at 90. The age in years (AGE) variable was calculated from the birth date (DOB) and the admission date (ADATE) in the HCUP State databases. Supplied age was used where age was missing or could not be calculated (i.e. ADATE and/or DOB was missing or invalid). However, the supplied age is not used when it is the age at discharge instead of the age at admission. AGE was considered invalid when it was outside the range (AGE NE 0-124), could not be calculated, or the supplied age was not numeric.

PAY1 represents the HCUP data element for the expected primary payer for a patient's care. These variables were coded as Medicare (1), Medicaid (2), Private Insurance (3), Self-Pay (4), No Charge (5), and Other (6). The HCUP data element for the median household quartiles for the patient's ZIP Code was ZIPINC_QRTL. This variable was defined as (1) $1 - $37,999; (2) $38,000 - $47,999; (3) $48,000 - $63,999; and (4) $64,000 or more.

The HCUP data element for the patient location was PL_NCHS. The coding of this variable was based on the National Center for Health Statistics (NCHS) urban-rural classification scheme for U.S. counties. These were defined as (1) "Central" counties of metro areas of >=1 million population,(2) "Fringe" counties of metro areas of >=1 million population,(3) Counties in metro areas of 250,000–999,999 population,(4) Counties in metro areas of 50,000–249,999 population,(5) Micropolitan counties,(6) Not metropolitan or micropolitan counties.

Patient Clinical Characteristics

The patient clinical characteristics included in this study were the type and number of chronic conditions. The severity of the illness was also included. The AHRQ's Chronic Condition Indicator (CCI) was used to identify chronic conditions in the NRD, and counting was used to assess the number of chronic conditions per patient (0,1,2-3 or ≥4). The HCUP data element for the number of chronic conditions was NCHRONIC. Chronic conditions are medical conditions expected to last for at least 12 months that are severe enough to warrant the involvement of multiple subspecialists and/or have a high probability of hospitalization (Healthcare Cost and Utilization Project, 2016).

Hospital Characteristics

The hospital characteristics included hospital ownership, location, teaching status, bed size, and admission day. The control or hospital ownership was coded as H_CONTRL in the HCUP data. This variable was defined as: (1) government, nonfederal [public]; (2) private, not-for-profit [voluntary]; (3) private, investor-owned [proprietary]. The HCUP data element for hospital location was HOSP_URCAT4. Hospital urban-rural location was defined as (1) large metropolitan areas with at least 1 million residents, (2) small metropolitan areas with less than 1 million residents, (3) micropolitan areas, (4) not metropolitan or micropolitan, (8) metropolitan, collapsed category of large and small metropolitan, (9) non-metropolitan, collapsed category of micropolitan and rural. The size of the hospital-based on the number of beds was coded as HOSP_BEDSIZE. Hospital bed size was defined as (1) small, (2) medium, (3) large. These categories were defined using the region of the U.S., the urban-rural designation of the hospital, in addition to the teaching status

Statistical Analysis

The predisposing, enabling, need, and health behavior factors were identified from previous literature reviews and results of the univariate analysis. The data were inspected to detect inconsistency and ensure accuracy. A summary statistic about the data was conducted to give a general idea about its quality. Statistical methods such as mean, standard deviation, range, or quantiles were conducted to detect unexpected and erroneous data values. The data was then cleaned to remove or fix the inconsistencies and anomalies discovered in the database.

Data for patients who were less than 18 years, had a same-day event, died in the hospital, had unknown discharge, and were transferred to another acute hospital or left against medical advice were dropped. Index events were then created using HCUP's events documentation. The study variables were then coded to aid data analysis. The final data set was split into rural/urban variables. The rural/urban variables were created using the United States Department of Agriculture's rural/urban codes.

Descriptive Analysis

A descriptive analysis was conducted to assess the contents of key variables, as well as determining the demographical characteristics of stroke patients. Weights were used to achieve national estimates of index admissions and readmissions, and continuous variables were summarized using medians and interquartile ranges (IQRs) and categorical variables using frequencies and percentages.

Bivariate Analysis

A generalized mixed-effect linear regression using a hierarchical linear approach was used to assess the predictive power of the predisposing, enabling, and need factors as well as the health behavior characteristics on stroke readmission based on Andersen's model healthcare utilization. Each model was adjusted for the following fixed effects: hospital bed size, hospital ownership type, and hospital location.

A generalized mixed-effect linear regression is often used in evaluating the contributions of predictors above and beyond previously entered predictors, as a means of statistical control, and for examining incremental validity (Lewis, 2007). By using this type of analysis, one can show how the variables of interest explain statistically significant variance in the dependent variable after controlling for all other variables. In a generalized mixed-effect linear regression, predictor variables are sequentially entered into the analysis after controlling for other variables (Lewis, 2007).

This "control" is achieved by calculating the change in the adjusted R^2 at each step of the analysis, thus accounting for the increment in variance after each variable (or group of variables) is entered into the regression model (Pedhazur, 1997). Often, the order in which these predictor variables are entered into the analysis is based on theory and past research (Lewis, 20017). Generalized mixed-effects linear regression has been used in several studies that have focused on reading comprehension, adolescent development, reading disability, school counselor burnout, college student alcohol use and children with movement difficulties in physical education

(Megherbi, Seigneuric, & Ehrlich, 2006; Moller, Fouladi, McCarthy, & Hatch,2003; Badian, 2005; Wilkerson & Bellini, 2006; Yanovitky, 2006; Dunn & Dunn, 2006).

Most researchers prefer this type of regression because it does not have the same drawbacks of stepwise regression in terms of replicability, degree of freedom, and the identification of the best predictor (Thompson, 1995: Lewis, 2007). Although this approach may sound appealing, it contains an inherent problem, such as sampling error (Lewis, 2007). However, this issue can be addressed through techniques such as cross-validation. This type of error will not be an issue with a larger sample and effect sizes (Lewis, 2007). However, it is necessary to exercise greater caution to be sure a larger sample size does not lead to significant inferential errors (Kaplan, Chambers & Glasgow, 2014).

The models entered for this present study were:

Model 1: 30-day readmission = Intercepts (Hospital Location, Hospital Bed Size, and Hospital Ownership) + Predisposing Factors (Gender + Age).

Model 2: 30-day readmission = Intercepts (Hospital Location, Hospital Bed Size and Hospital Ownership) + Predisposing Factors (Gender + Age) + Enabling Factor (Insurance Type + Household Income).

Model 3: 30-day readmission = Intercepts (Hospital Location, Hospital Bed Size, and Hospital Ownership) + Predisposing Factors (Gender + Age) + Enabling Factors (Insurance Type + Household Income) + Need Factor (Number of Chronic Diseases).

Model 4: 30-day readmission = Intercepts (Hospital Location, Hospital Bed Size, and Hospital Ownership) + Predisposing Factors (Gender + Age) + Enabling Factors (Insurance Type + Household Income) + Need Factor (Number of Chronic Diseases) + Health Behavior (Day of Admission).

Ethical Consideration and IRB

The Institutional Review Board at Georgia Southern University deemed this study exempt from institutional board review.

Chapter Summary

This chapter described the study design, data source, study population, measures, and analytical approach used. In the next chapter, Chapter 4, the results of the study are presented

CHAPTER 4

RESULTS

This chapter, therefore, presents the findings of all the statistical analysis and testing of the hypothesis. The participants' descriptive demographic characteristics are first presented, followed by results for the generalized mixed-effect linear regression using the hierarchical modeling approach.

Demographic Characteristics of Participants

The study included 1,940,570 index admissions and 127,184 thirty-day, stroke readmission for an overall readmission rate of 6.6% (Table 4.1). The mean age for index admission was 71.5 years; 54.17% of index admissions were for male patients; 81.1% were associated with public insurance (Medicare & Medicaid), and 95.2% were for patients residing in a non-metropolitan area. The mean number of chronic disease for participants was 7.7 ($p<0.001$).

Approximately 73% of index admissions were at private, not-for-profit hospitals, with 90.3% of hospitals located in the urban areas and 56.7% of them being hospitals with large bed size. The number of stroke patients admitted during the weekdays (77.1%) was higher than those during the weekends. Approximately 96% of stroke patients did not die, with 42.7% of them experiencing a moderate loss of function. The number of patients in the household income of $1 – 37,999 was higher (29.8%) than patients in other household income ranges.

Patient and Hospital Characteristics Associated with 30-day Hospital Readmission.

The average age for stroke patients readmitted was 71.2 years. Compared to females, males accounted for the largest percentages of index admission (54.1%) and total 30-day readmission (53.5) (Table 1). There were differences in 30-day readmission by the other subcategories of insurance type, the severity of illness, location of patients’ home residence, number of chronic diseases, and disposition of discharge. Amongst the patients that were readmitted, 84.8% were associated with government insurance (Medicare & Medicaid), and 96.4% were for patients residing in a non-metropolitan area. The mean number of chronic diseases patients had was 7.9.

Approximately 74% of readmissions occurred at private, not-for-profit hospitals and in hospitals urban areas (90.3%). Compared to other hospitals, large bed size hospitals (58.2%) recorded the highest percentage of 30-day readmission due to stroke. More patients were readmitted during the week (76.1%) than the weekend (Table 1). Most stroke patients readmitted did not die (96.5%), and 41.9% of them suffered a major loss of function. All the measured variables of age, gender, patient's residence location, household income, insurance type, hospital bed size, hospital ownership, the day of admission number of chronic diseases, the severity of illness and hospital discharge status were significantly associated with 30-day readmission due to stroke ($p<0.001$).

Table 4.1: Characteristics of the Study Population

	Index Admissions, [a] *N (%)*	Index Admissions without a Readmission, [a] *N (%)*	Index Admissions with a Readmission, [a] *N (%)*
Index Admissions	1,940,570 (100)	1,813,386 (93.4)	127,184 (6.6)
Demographic Characteristics			
Age***	71.5	71.5	71.2
Gender			
Female	891,388 (45.9)	832,210 (45.9)	59,178 (46.5)
Male	1,049,182 (54.1)	981,177 (54.1)	68,005 (53.5)
Location of Patient's Home Residence			
Urban (Metropolitan)	92,982 (4.8)	88,349 (4.9)	4,633 (3.6)
Rural (Non-Metropolitan)	1,847,589 (95.2)	1,725,038 (95.1)	122,551 (96.4)
Household Income			
$1 – 37,999	570,409 (29.8)	531,807 (29.8)	38,602 (30.8)
$38,000 – 47,999	517,243 (27.1)	483,864 (27.1)	33,379 (26.6)
$48,000 – 63,999	433,180 (22.7)	405,265 (22.7)	27,915 (22.3)
≥$64,000	390,783 (20.4)	365,295 (20.5)	25,488 (20.3)
Insurance Type			
Government	1,441,147 (81.1)	1,343,839 (80.8)	97,308 (84.8)
Private	289,365 (16.3)	274,526 (16.5)	14,839 (12.9)
Other	46,388(2.6)	43,811 (2.6)	2,577 (2.2)
Hospital Factors			
Hospital Bed Size			
Small	296,359 (15.3)	278,490 (15.4)	17,869 (14.0)
Medium	544,366 (28.1)	509,082 (28.1)	35,284 (27.7)
Large	1,099,845 (56.7)	1,025,814 (56.6)	74,031 (58.2)
Hospital Ownership			
Government, Nonfederal (Public)	213,390 (11.0)	199,843 (11.0)	13,547 (10.7)

Private, Not-for-profit (Voluntary)	1,423,581 (73.4)	1,329,961 (73.3)	93,620 (73.6)
Private, Investor-owned (Proprietary)	303,600 (15.6)	283,583 (15.6)	20,017 (15.7)
Hospital Location			
Urban	1,753,227 (90.3)	1,636,695 (90.3)	116,532 (91.6)
Rural	187,343 (9.7)	176,691 (9.7)	10,652 (8.4)
Day of Admission			
Weekday	1,495,596 (77.1)	1,398,841 (77.1)	96,755 (76.1)
Weekend	444,971 (22.9)	414,542 (22.9)	30,429 (23.9)
Comorbidity and Disease Severity			
Number of Chronic Diseases***	7.7	7.4	7.9
Severity of Illness (Loss of Function)			
Minor	267,437 (13.8)	255,866 (14.1)	11,570 (9.1)
Moderate	827,894 (42.7)	778,931 (43.0)	48,963 (38.5)
Major	654,059 (33.7)	600,761 (33.1)	53,298 (41.9)
Extreme	191,035 (9.8)	177,686 (9.8)	13,349 (10.5)
Died During Hospitalization			
Did not Die	1,864,677 (96.1)	1,741,932 (96.1)	122,745 (96.5)
Died	75,140 (3.9)	70,750 (3.9)	4,390 (3.5)

***$P < .001$
[a] Individual categories of data may not add to the total number of index admissions because of the presence of missing or incomplete data
Age of patients' data is presented as mean.
Number of chronic disease data presented as mean.

Patient and Hospital Characteristics Associated with 30-day Hospital Readmission (Urban Vs Rural)

A total number of 127,184 (6.6) stroke readmissions were recorded in 2014. From this number, 84.5% of the readmissions occurred in hospitals located in urban areas. Compared to females, males accounted for the highest percentage of total readmissions (45.2%) in both hospitals located in the urban and rural areas. The average ages for patients readmitted into hospitals in urban and rural areas were approximately 71 years and 72 years. Most patients readmitted into hospitals located in urban (27.0%) and rural (51.3%) areas were in the household income range of $1- $37,999. Also, patients with government insurance (Medicare & Medicaid) accounted for the highest percentage of 30-day readmissions among hospitals in both urban (84.6%) and rural (86.4%) areas.

Considering bed size, hospitals with large bed size had the highest percentage of 30-day readmissions in urban (56.6%) and rural (67.2%) areas. Private, Not-for-profit (Voluntary) hospitals recorded the highest percentages of 30-day readmissions among the hospitals in both urban (74.5%) and rural (69.1%) areas. The majority of the readmissions among hospitals in urban (75.9) and rural (76.7%) areas were done during the weekday. Most stroke patients readmitted into hospitals in urban (96.7) and rural (96.0) areas did not die with 42.1% and 41.0% of them suffering a major loss of function, respectively.

For hospitals in rural areas, all the measured independent variables except for age and gender were significantly associated with 30-day readmission due to stroke ($p<0.001$). However, for hospitals in the urban areas, all the measured variables but hospital ownerships, were significantly associated with 30-day stroke readmission ($p<0.001$).

Table 4.2: Characteristics of the Study Population by Hospital location (Rural)

	Index Admissions, [a] *N (%)*	Index Admissions without a Readmission, [a] *N (%)*	Index Admissions with a Readmission, [a] *N (%)*
Demographic Characteristics			
Age***	71.5	71.5	71.6
Gender			
Female	154,043 (46.6)	145,108 (46.6)	8,935 (46.2)
Male	176,668 (53.4)	166,261 (53.4)	10,407 (53.8)
Location of Patient's Home Residence			
Urban (Metropolitan)	30,719 (9.3)	29,350 (9.4)	1,369 (7.1)
Rural (Non-Metropolitan)	299,992 (90.7)	282,019 (90.6)	17,973 (92.9)
Household Income			
$1 – 37,999	159,565 (49.2)	149,817 (49.1)	9,748 (51.3)
$38,000 – 47,999	116,389 (35.9)	109,718 (36.0)	6,671 (35.1)
$48,000 – 63,999	42,909 (13.2)	40,644 (13.3)	2,265 (11.9)
≥$64,000	5,255 (1.6)	4,937 (1.6)	318 (1.7)
Insurance Type			
Government	256,601 (82.9)	240,988 (82.6)	15,613 (86.4)
Private	44,026 (14.2)	42,057 (14.4)	1,969 (10.9)
Other	9,066 (2.9)	8,584 (2.9)	482 (2.7)
Hospital Factors			
Hospital Bed Size			
Small	46,618 (14.1)	44,191 (14.2)	2,427 (12.5)
Medium	68,547 (20.7)	64,622 (20.8)	3,925 (20.3)
Large	215,546 (65.2)	202,556 (65.1)	12,990 (67.2)
Hospital Ownership			
Government, Nonfederal (Public)	59,787 (18.1)	56,536 (18.2)	3,251 (16.8)
Private, Not-for-profit (Voluntary)	225,391 (68.2)	212,019 (68.1)	13,372 (69.1)

Private, Investor-owned (Proprietary)	45,532 (13.8)	42,813 (13.7)	2,719 (14.1)
Day of Admission			
Weekday	256,852 (77.7)	242,013 (77.7)	14,839 (76.7)
Weekend	73,858 (22.3)	69,356 (22.3)	4,502 (23.3)
Comorbidity and Disease Severity			
Number of Chronic Diseases***	7.5	7.2	7.7
Severity of Illness (Loss of Function)			
Minor	46,689 (14.1)	44,831 (14.4)	1,858 (9.6)
Moderate	146,864 (44.4)	139,200 (44.7)	7,664 (39.6)
Major	106,942 (32.3)	99,006 (31.8)	7,936 (41.0)
Extreme	30,197 (9.1)	28,314 (9.1)	1,883 (9.7)
Died During Hospitalization			
Did not Die	315,915 (95.6)	297,357 (95.5)	18,558 (96.0)
Died	14,700 (4.4)	13,917 (4.5)	783 (4.0)

***$P < .001$

[a] Individual categories of data may not add to the total number of index admissions because of the presence of missing or incomplete data

Age of patients' data is presented as mean.

Number of chronic disease data presented as mean.

Table 4.3: Characteristics of the Study Population by Hospital location (Urban)

	Index Admissions, [a] *N (%)*	Index Admissions without a Readmission, [a] *N (%)*	Index Admissions with a Readmission, [a] *N (%)*
Demographic Characteristics			
Age***	71.3	71.5	71.1
Gender			
Female	734,388 (45.8)	684,371 (45.7)	50,017 (46.5)
Male	870,111 (54.2)	812,680 (54.3)	57,431 (53.5)
Location of Patient's Home Residence			
Urban (Metropolitan)	58,685 (3.7)	55,653 (3.7)	3,032 (2.8)
Rural (Non-Metropolitan)	1,545,814 (96.3)	1,441,398 (96.3)	17,973 (97.2)
Household Income			
$1 – 37,999	409,403 (25.8)	380,697 (25.7)	28,706 (27.0)
$38,000 – 47,999	400,854 (25.3)	374,146 (25.3)	26,708 (25.1)
$48,000 – 63,999	390,271 (24.6)	364,621 (24.6)	25,650 (24.1)
≥$64,000	385,528 (24.3)	360,358 (24.4)	25,170 (23.7)
Insurance Type			
Government	1,181,782 (80.8)	1,100,271 (80.5)	81,511 (84.6)
Private	244,070 (16.7)	231,262 (16.9)	12,808 (13.3)
Other	37,051 (2.6)	34,987 (2.6)	2,064 (2.1)
Hospital Factors			
Hospital Bed Size			
Small	249,038 (15.5)	233,632 (15.6)	15,406 (14.3)
Medium	474,120 (29.5)	442,905 (29.6)	31,215 (29.1)
Large	881,342 (54.9)	820,515 (54.8)	60,827 (56.6)
Hospital Ownership			
Government, Nonfederal (Public)	153,191 (9.5)	142,918 (9.5)	10,273 (9.6)
Private, Not-for-profit (Voluntary)	1,195,156 (74.5)	1,115,131 (74.5)	80,025 (74.5)

Private, Investor-owned (Proprietary)	256,152 (16.0)	239,002 (16.0)	17,150 (16.0)
Day of Admission			
Weekday	1,234,626 (76.9)	1,153,021 (77.0)	81,605 (75.9)
Weekend	369,870 (23.1)	344,027 (23.0)	25,843 (24.1)
Comorbidity and Disease Severity			
Number of Chronic Diseases***	7.7	7.4	7.9
Severity of Illness (Loss of Function)			
Minor	219,917 (13.7)	210,246 (14.0)	9,671 (9.0)
Moderate	678,687 (42.3)	637,554 (42.6)	41,133 (38.3)
Major	545,570 (34.0)	500,356 (33.4)	45,214 (42.1)
Extreme	160,198 (10.0)	148,773 (9.9)	11,425 (10.6)
Died During Hospitalization			
Did not Die	1,543,643 (96.2)	1,439,837 (96.2)	103,806 (96.7)
Died	60,199 (3.8)	56,606 (3.8)	3,593 (3.3)

***$P < .001$
[a] Individual categories of data may not add to the total number of index admissions because of the presence of missing or incomplete data
Age of patients' data is presented as mean.
Number of chronic disease data presented as mean.

Predicting 30-day Readmission from Predisposing, Enabling, Need, and Health Behavior Factors (Rural)

The hierarchical regression for hospitals located in the rural areas revealed that at step one, the predisposing factors, age, and gender did not significantly contribute to the regression model. However, they accounted for 0.30% of the variation in 30-day readmission due to stroke. Introducing the enabling factors, household income, and insurance type explained an additional 0.50% of the variation in 30-day readmission due to stroke, and the change in R^2 was significant. Adding the need variable, the number of chronic diseases, to the regression model explained an additional 0.34% of the variation in 30-day readmission due to stroke, and this change in R^2 was significant.

Finally, the addition of the day admission to the regression model explained an additional 0.01% of the variation in 30-day readmission due to stroke, and this change in R^2 was also significant. When all six independent predictors were added in step four of the regression model, gender was not a significant predictor of 30-day stroke readmission. The significant predictors of the 30-day readmission due to stroke were age, household income, insurance type, number of chronic diseases, and the day of admission. The most important predictor of 30-day readmission due to stroke in the final model was the admission day, which uniquely accounted for 0.01% of the variation in readmission. Together, all six independent variables accounted for 1.15% of the variance in 30-day readmission due to stroke.

Predicting 30-day Readmission from Predisposing, Enabling, Need, and Health behavior Factors (Urban)

The hierarchical regression for hospitals located in the urban areas revealed that at step one, the predisposing factors, age, and gender significantly contributed to the regression model. However, they accounted for 0.11% of the variation in 30-day readmission due to stroke. For hospitals located in the urban areas, introducing the enabling factors, household income, and insurance type, explained an additional 0.46% of the variation in 30-day readmission due to stroke, and the change in R^2 was significant. Adding the need variable, the number of chronic diseases, to the regression model explained an additional 0.64% of the variation in 30-day readmission due to stroke, and this change in R^2 was significant.

Finally, the addition of the day of admission to the regression model explained an additional 0.02% of the variation in 30-day readmission due to stroke, and this change in R^2 was also significant. When all six independent predictors were added in step four of the regression model, all variables were significant predictors of 30-day readmission due to stroke. The most important predictor of 30-day readmission due to stroke in the final step was the day of admission, which uniquely accounted for 0.02% of the variation in readmission. Together, all six independent variables accounted for 1.23% of the variance in 30-day readmission due to stroke.

TABLE 4.4: Summary of the Generalized Mixed-effect Linear Regression for Variables Predicting Stroke Readmission (Rural)

	Regression 1		Regression 2		Regression 3		Regression 4	
	B	***z***	***B***	***z***	***B***	***z***	***B***	***z***
Hospital Bed Size								
Small (ref)								
Medium	1.21	3.20***	1.20	3.10***	1.19	2.94***	1.18	2.85***
Large	1.29	4.78***	1.29	4.74***	1.25	4.26***	1.25	4.18***
Hospital Ownership								
Government, nonfederal (Public) (ref)								
Private, not-for-profit (Voluntary)	1.10	1.70	1.09	1.47	1.06	1.01	1.06	0.99
Private, investor-owned (Proprietary)	1.06	0.74	1.03	0.39	1.02	0.31	1.02	0.29
Hospital Location	0.92	-1.92	0.90	-2.30*	0.93	-1.75	0.92	-1.82
Sex								
Male (ref)								
female	1.02	1.18	1.02	1.28	1.03	1.63	1.03	1.56
Age	1.00	1.17	1.00	-4.40***	1.00	-4.48***	1.00	-4.58***
Household Income								
\$1 - \$39,999 (ref)								
\$40,000 - \$50,999			0.94	-2.97***	0.94	-2.84***	0.94	-2.94***
\$51,000 - \$65,999			0.87	-4.52***	0.87	-4.33***	0.87	-4.37***
\$66,000 or more			0.99	-0.17	1.00	0.04	1.00	-0.08
Insurance Type								
Government (ref)								
Private			0.69	-13.42***	0.73	-11.58***	0.73	-11.58***
Other			0.81	-4.11***	0.83	-3.59***	0.83	-3.71***
Number of Chronic Diseases					1.04	15.38***	1.20	15.26***
Day of Admission								
Weekday (ref)								
Weekend							1.07	3.56***
R^2		***0.30***		***0.80***		***1.14***		***1.15***
R^2 **Change**		***0.30***		***0.50***		***0.34***		***0.01***

***p<0.05; **p<0.01; ***p<0.001**

TABLE 4.5: Summary of Generalized Mixed-effect Linear Regression for Variables Predicting Stroke Readmission (Urban)

	Regression 1		Regression 2		Regression 3		Regression 4	
	B	***z***	***B***	***z***	***B***	***z***	***B***	***z***
Hospital Bed Size								
Small (ref)								
Medium	1.08	2.98***	1.07	2.59*	1.06	2.32*	1.06	2.29*
Large	1.16	5.77***	1.15	5.36***	1.13	4.82***	1.13	4.80***
Hospital Ownership								
Government, nonfederal (Public) (ref)								
Private, not-for-profit (Voluntary)	1.04	1.19	1.08	2.22*	1.03	1.04	1.03	1.07
Private, investor-owned (Proprietary)	1.03	0.77	1.04	1.15	1.03	0.93	1.04	0.97
Hospital Location	0.81	-3.99***	0.82	-3.65***	0.85	-3.07**	0.85	-3.09**
Sex								
Male (ref)								
Female	0.97	-4.66***	0.97	-5.27***	0.98	-3.73***	0.98	-3.75***
Age	1.00	-6.41***	1.00	-14.28***	1.00	-15.84***	1.00	-15.97***
Household Income								
$1 - $39,999 (ref)								
$40,000 - $50,999			0.98	-2.49*	0.98	-2.25*	0.98	-2.23*
$51,000 - $65,999			0.96	-3.86***	0.97	-3.32**	0.97	-3.32**
$66,000 or more			0.93	-5.82***	0.94	-4.81***	0.94	-4.77***
Insurance Type								
Government (ref)								
Private			0.70	-32.47***	0.74	-26.74***	0.74	-26.74***
Other			0.74	-12.81***	0.76	-11.20***	0.76	-11.23***
Number of Chronic Diseases					1.05	44.86***	1.05	44.86***
Day of Admission								
Weekday (ref)								
Weekend							1.06	7.60***
R^2		***0.11***		***0.57***		***1.21***		***1.23***
***R^2* Change**		***0.11***		***0.46***		***0.64***		***0.02***

***p*<0.05; ***p*<0.01; ****p*<0.001**

CHAPTER 5

DISCUSSION AND CONCLUSIONS

Introduction

This study investigated the predictive effects of predisposing, enabling, need, and the health behavioral factor associated with readmissions within 30-days of initial stroke-caused hospitalization. The data used was the 2014 National Readmission Database from HCUP. Descriptive and bivariate correlation was used to assess the relationship between independent variables (predisposing, enabling, need and health behavioral factors, and 30-day readmission due to stroke. (Tables 4.1, 4.2 & 4.3). A mixed effect generalized linear regression was used to assess the predictive power of the independent factors on 30-day stroke readmission

Stroke is a costly and detrimental disease (Nouh et al., 2017). The annual direct and indirect cost of stroke is estimated at around $65 billion, with the mean lifetime cost of ischemic stroke around $140,0458 (Demaerschalk, Hwang & Leung, 2010; Johnson, Bonafede & Watson, 2016). Therefore, this places a stroke among the top 10 Medicare beneficiaries' most costly conditions (Johnson et al., 2016). The burden of stroke can be doubled due to the costs of initial hospital admission and ensuing readmissions due to stroke and other related factors. It is estimated clinically that approximately 70% of acute stroke results in hospital admission (Lee et al., 2004).

Hospital readmissions within 30 days of initial discharge frequently occur (Garrison, Mansukhani & Bohn, 2013). Compared to patients with other conditions, stroke patients tend to have higher readmission rates (Lee et al., 2004; Chaung et al., 2005) Some studies have reported stroke readmission rates of 21% and 55% within 30 days and one year respectively (Fehnel et al., 2015). Previous studies have highlighted the association of readmission socioeconomic status, disease burden, patient characteristics, poor quality inpatient care and unresolved problems at discharge (Balla, Malnick & Schattner, 2008; Halfon et al., 2006; Balaban, Weissman, Samuel &

Woolhandler, 2008; Coleman, Parry, Chalmers & Min, 2006; Garrison et al., 2013; Chuang et al., 2005).

Previous works of literature have identified some variables such as age, gender, social-economic status, insurance type, the number of comorbidities, and the day of admission as predictors of stroke readmissions (Gillum & Mussolino, 2003; Arrich, Lalouschek & Müllner; 2005; Zhou et al. 2006; Hoh et al., 2010; Prieto-Centurion, Gussin, Rolle & Krishnan, 2013; Fehnel et al., 2015). While some of these studies have reported significant associations between these independent variables and 30-day readmission due to stroke, others have highlighted little to no significant association between them (Cox et al., 2006; Cesaroni, Agabiti, Forastiere &Perucci, 2009; Litchman et al., 2010). Similar associations between some of these identified independent variables and 30-day readmissions due to other chronic diseases have also been reported (Casalini et al., 2017; Kaya et al., 2019).

Predictive models for readmission within 30 days of stroke-caused hospitalization have an array of applicability across healthcare organizations. Retrospectively testing the association of patient-level factors with 30-day readmission may help determine the suitability of these factors for prediction. An accurate selection of these predictors could help create effective and efficient interventions at various levels of care during a stroke patient's initial hospitalization. Currently, there are no risk-standardized models for predicting patients' risk after stroke (Litchman et al., 2010).

Summary and Interpretation of Findings

This study had three main objectives. The first objective was to assess the disparities in 30-day stroke readmissions among hospitals in the urban and rural areas of the United States of America. From the results, there exit some disparities between hospitals located in the urban areas versus those in the rural areas in terms of age, gender, insurance type, household income, number of comorbidities, and the day of admission. Almost all the variables were strongly associated with 30-day stroke readmission.

The second objective was to build a predictive model of readmission within 30 days of an initial stroke-caused hospitalization among hospitals in the urban and rural areas of the United States of America using the 2014 National Readmission Database. Andersen's Healthcare Utilization Model was used to guide the building of these models. The predictors included in this model were grouped under predisposing (age and gender), enabling (insurance type and household income), need (number of comorbidities), and health behavior (day of admission). Hospital characteristics, such as hospital location, bed size, and ownership, were controlled.

The final objective was to apply the generalized mixed-effect linear regression in assessing the effect of the identified predictors on readmission within 30 days of initial stroke-caused hospitalization. The study results show the independent variables had some relationship or predictive abilities on 30-day readmission after the initial stroke-caused admission.

The present study first hypothesized that the predisposing factors of gender and age would have predictive abilities on 30-day stroke readmission among hospitals in urban and rural areas. The result of the generalized mixed-effect linear regression supported this hypothesis. From the results, approximately 0.11% and 0.30% of the change in 30-day stroke readmission can be explained by the predisposing factors (age and gender) for hospitals in the urban and rural areas, respectively. Although R^2 values of the first models for hospitals in the urban (0.11%) and rural areas (0.30%) were small, the model was significant. The present findings support other studies that have reported age and gender as factors associated with hospital readmission (Rao et al., 2016; Hirayama et al., 2018; Li et al., 2018; Jain, Mortensen & Weissler, 2018; Patel et al., 2019; Lam et al., 2019).

The study further hypothesized that household income and insurance type would have predictive abilities on 30-day stroke readmission among hospitals in both urban and rural areas. Household income and insurance type were considered as the enabling factors under Andersen's Healthcare Utilization Model. The results of the study once again supported this hypothesis. The second model's addition of the enabling factors explained an added 0.46% and 0.50% of the change in 30-day stroke readmission among hospitals in urban and rural areas, respectively. Although the R^2 change is smaller, the second model was also significant. This shows a positive relationship between these enabling factors and 30-day stroke readmission. The relationship between these enabling factors and 30-day readmission may differ sometimes. Lower readmission rates may not always be considered a good health outcome because this could be an indication of a lack of health insurance and lower household income (Basu, Hanchate & Bierman, 2018).

This study hypothesized the number of comorbidities would have a predictive ability on 30-day stroke readmission when controlling for hospital-level factors such as bed size, ownership, and location. The results of the study also supported this hypothesis. The number of comorbidities was selected as a need factor using the Andersen's healthcare utilization Model. Several studies that have focused on hospital readmission among patients who suffer a stroke and other chronic diseases have reported an association between the number of comorbidities and 30-day readmission (Hohansen et al., 2006; Ramsey, Burnett & Cowperthwaite, 2012; Zhang, Hayashida & Peterl, 2016; Kwok et al., 2018; Wen et al., 2018; Buhr et al., 2019). Though the model was still significant ($p<0.001$) after the addition of the need factor, the number of comorbidities had a lower predictive power among hospitals in urban and rural areas. However, this was higher among hospitals in the urban areas (0.64%) than those located in rural areas (0.34%).

Finally, this present study hypothesized the day of admission would have a positive predictive ability for 30-day stroke readmission when controlling for hospital-level factors such as bed size, ownership, and location. The day of admission was considered as the health behavior characteristic under Andersen's Healthcare Utilization Model. The result of this study also supported this hypothesis. The R^2 change was slightly higher among hospitals located in the urban areas (0.02%) than those found in rural areas (0.01%). Both models were significant. This result supports previous studies that have reported an association between the day of admission and 30-day readmissions (Khaksari et al., 2019; Martin et al., 2019).

The study generated four models to assess the predictive powers of the predisposing, enabling, need and health behavior characteristics on 30-day readmission due to stroke. The research sought to answer the question, "Does the addition of one predictive variable change the relationship of another predictive variable with 30-day stroke readmission in the United States?" From the results of the study, the inclusion of the predictive factors in each model resulted in an additional explanation of the variance in the 30-day readmission due to stroke. However, the R^2 change differed for each model among hospitals located in both urban and rural areas.

While the addition of the enabling factors resulted in the highest R^2 change (0.50%) for hospitals in rural areas, the addition of the need factor instead resulted in the most significant R^2 change for the hospitals in the urban areas. The total R^2 change was higher for hospitals in the urban area (1.23%) than in rural areas (1.15%) when all the independent variables were entered into the model. The result of the study, therefore, shows that the addition of any predictive variable resulted in an improved relationship or predictive ability of the previous variable added in the model on the 30-day readmission due to stroke.

Deciding and implementing strategies in the health care system has been marked with additional complexity concerning the relevance of the predictors of a clinical outcome. The use of generalized mixed-effect linear regression provides a means to test the strength and identify the important predictors of stroke readmission. Accurately identifying these significant predictors using this type of analysis may be essential in developing interventions aimed at preventing and reducing readmission. From the study results, all the predictors demonstrated some predictability among hospitals in urban and rural areas. Although their predictive abilities were quite lower, all the models built were significant.

This study's results highlight that the predictive powers of demographic factors on readmission within 30 days of initial stroke-caused hospitalization are weak. These predictors can provide small benefits for predicting which stroke patients are more likely or at risk of being readmitted after the initial hospital admission. However, it is recommended to use other credible big data sources to validate this finding. This will help provide enough evidence in improving the quality of care for stroke patients. Studies have shown that combining predictive analysis to preventive measures is effective in proactively engaging physicians, patients, and payers to participate in improving health (Shameer et al., 2017).

In the wake of continuous pressure on hospitals in reducing readmission, many of them are adopting prediction models aimed at identifying patients at risk of various chronic diseases (Gallegos, 2014). Prediction models for readmission could vary in terms of risk criteria, complexity, and implementation (Gallegos, 2014). It is, therefore, important for hospitals to develop targeted models that best fit their facility. Little information exists for interventions that have been successful in reducing stroke readmission. Among the known transitional care model for stroke, only a few have demonstrated some level of effectiveness (Kansagara et al., 2011; Poston, 2018). Continuous evaluation of these transitional models is warranted since multicomponent interventions could effectively reduce readmission and healthcare costs and provide efficient patient-centered stroke care (Poston, 2018).

Prediction models should be individualized. Thus, taking into consideration the setting and population under study. A successful predictive model in a setting or among a particular population does not warrant success in all other settings or populations. This shows that demographic or patient-levels predictors associated with readmission may differ depending on the setting or population being studied. The results of this study supported this argument. The factors that had the highest predictive power for the models built in this study were different among hospitals in urban and rural areas. While enabling factors had the highest predictor ability in the models for hospitals in rural areas, need factors had the highest predictive power for those in the urban areas.

While patient-level factors may be important in building models to reduce readmission, it is worth exploring other social or environmental factors that may influence the association between these variables. Since the result of this study showed a lower predictive power of patient-level factors on readmission within 30-day of initial stroke-caused hospitalization, it will be necessary to incorporate other variables beyond this level. The review of current literature indicated that only a few models had included these types of variables (Kansagara et al., 2011).

Readmission after stroke is an important health issue, and currently, no models for modeling the risk of readmission for an individual stroke patient exist. This study's results suggest that patient predictors for readmission after the initial hospitalization due to stroke do exist and therefore call for further studies. Further study using a more current dataset may have a greater impact on current policies focused on stroke readmission reduction, pattern, and practice. More studies are also needed to identify reliable and consistent predictors of stroke readmission to create a more standardized risk assessment for hospital readmission after stroke.

The predictors for models could be identified using reliable datasets and appropriate statistical analysis, such as a hierarchical analytical method. From a public health and policy perspective, since the Centers for Medicare & Medicaid Services uses readmission rates to profile hospitals or to access their quality and performance, risk-standardized models created should adjust for the patient or demographic -level predictors for readmission. This level of predictors often has the less predictive ability for readmission among hospitals in urban and rural areas.

Limitations and Strengths

The study was a population retrospective cohort study, so the effect of the different predictive variables on 30-day readmissions was assessed among the study population. Also, the study's result adds to the limited knowledge of integrating clinical and non-clinical data in addressing health issues. Although hospital readmissions have been extensively studied, only a few studies have assessed this issue among stroke patients in the United States of America.

This study has several limitations. First, conclusions are limited to the 2014 National Readmission Database. It is, therefore, important to be cautious in generalizing the study results. Second, racial/ethnic variables that have been important demographic characteristics across several studies were not available in the database for inclusion in the models. Third, for this study design, only the initial stroke-related hospitalization and the subsequent 30 days after index discharge for each patient were used, even if a patient had numerous "index" hospitalizations before or after the study year. Fourth, the National Readmission Database relies on data from the reporting hospitals across the United States, so common data limitations such as inaccurate coding of diagnoses or procedures may exist.

Public Health Practice Implications and Recommendations

Reducing readmission remains an important health policy goal since it could improve access to healthcare in the United States. Therefore, efforts to reduce readmissions that stem from poor stroke outpatient and inpatient care will have greater implications for public health. Reducing readmission could present the chance for healthcare organizations and other stakeholders to lower healthcare costs and improve patient satisfaction and quality. Also, the healthcare industry is full of uncertainties; therefore, implementing predictive models could help public health agencies and other health organizations identify at-risk individuals and prepare well for the future.

Again, most clinicians and some public health agencies have, over the years, relied solely on clinical data to inform policies and legislations in addressing community-level issues. The results of this study clearly show that focusing on patient and hospital-level data alone is not enough to address hospital readmission. Therefore, it is recommended that integrating community-level and hospital-level data might help better understand hospital readmissions. Several factors, such as societal, environmental factors, may have a significant effect on hospital readmission. Therefore, approaches in addressing readmissions should focus on understanding the community in which hospitals are located, the social determinants, and the root cause of the issue.

Conclusion and Next Steps

This study found a 6.6% readmission rate within 30 days for all-cause events following an initial stroke hospitalization among patients in the United States using the National Readmission Database for 2014. The significant predictors for readmission using the Andersen's Utilization Model among hospitals in the urban and rural areas of the United States were need (the number of comorbidities) and enabling (insurance type and household) characteristics. From this study, demographic characteristics have lower predictive powers on 30-day readmission after initial stroke hospitalization. However, it is still worth considering when implementing strategies to reduce readmission since all the models built were significant. For health care organizations or payers targeting cause-specific stroke readmissions, demographic and hospital characteristics remain important, but increasing attention should be paid to other characteristics beyond these levels

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