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Primary Payer Status and 30-Day Readmission Rates Among U.S. Diabetes Patients

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Walden University
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Abstract

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MHA, Capella University, 2013

BS, Clayton State University, 2010

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Healthcare Administration

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Abstract

Diabetes is a leading cause of hospitalization and readmission in the United States. The 30-day readmission rate for diabetic patients represents substantial costs to the nation's health care system. The purpose of this quantitative study was to examine the relationship between primary payer status and hospital readmission rates among individuals whose primary or secondary reason for admission was Type 2 diabetes mellitus (T2DM). Secondary data from the Healthcare Cost Utilization Program Nationwide Database of the 2015 National Readmission Database was analyzed. Participants in the data set included 41,068 diabetes patients, 53.8% of whom were female. The average age was 67.26, and the majority had diabetes with complications (62.1%). The Donabedian framework was applied for the analysis. Results of logistic regression analysis showed that possession of Medicare and lack of insurance were significant predictors of being readmitted within 30 days. Women had higher odds of being readmitted within 30 days compared to men. There was no statistically significant relationship between primary payer status and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM. Sociodemographic factors such as age, gender, or income did not moderate the relationship between primary payer status and 30-day hospital readmission rates nationally. The study contributes to positive social change by providing hospital administrators with knowledge they can use to implement protocols prior to discharge that may prevent possible readmissions, potentially reducing costs to facilities and improving patient care.

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Dedication

I dedicate this doctoral study to my family for always encouraging me. My husband, Ronnie, has been my sounding board and listening ear for over 30 years. When I thought the road was too hard to travel and thought about giving up, you were there saying “You can do this; I got you.” Thanks to my daughter, Helena, for her excellent proofreading skills for telling me, “Mom, that’s not flowing,” and to Ronnie Jr., who said, “Mom, we are doing this together. I’m with you every step of the way.” I would be remiss if I did not include a special dedication to my first love, my son, LaShawn, who gained his wings way too early. You were there when I walked across the stage for my master’s degree, and I know you will be there in spirit when I receive my doctorate. I also thank my parents for molding me into the person I am today and always instilling in me the value of education. Thanks, Dad, for bringing me my first *Readers Digest* at age four.

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I thank God who is the head of my life; without my faith in him I could never have completed this journey. I want to thank the staff at Walden University for their instructional leadership. I would especially like to thank Dr. Cheryl Cullen and Dr. Miriam Ross for their guidance and wisdom and for keeping me focused and grounded in my research.

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Section 1: Foundation of the Study and Literature Review

Introduction

Hospital readmission within 30 days of discharge is a significant aspect of health care reform in the United States. The focus of healthcare systems and governmental agencies is to identify ways to improve the quality of healthcare, with a special concentration on reducing 30-day readmission rates (Ostlling et al., 2017). Reducing readmissions gives hospitals a financial incentive to make discharge communication and care coordination efforts seamless for patients and caregivers (VanLare & Conway, 2012).

Thirty-day readmissions have become an important measure of quality care and a target for reducing healthcare costs (Rubin, McDonnell, Golden, & Zhao, 2017). Following implementation of the Patient Protection and Affordable Care Act of 2010, the Centers for Medicare and Medicaid Services (CMS) began the Hospital Readmission Reduction Program (HRRP; Ostlling et al., 2017). The HRRP is composed of five specific measures to determine reimbursement rates for hospital readmissions; these measures include pneumonia, heart failure, chronic obstructive pulmonary disease exacerbation (COPD), acute myocardial infarction, and total hip/knee replacement (Ostlling et al., 2017).

A facility's 30-day readmission rate is based on all unplanned readmissions that occur within 30 days of discharge, regardless of the cause. The risk index includes patients who are readmitted to the same hospital or another acute care hospital for any reason, regardless of their primary diagnosis. The measures do not include planned readmissions. Currently, CMS measures hospital performance in the HRRP by calculating excess readmission ratios (ERRs) for each of the program measures. A hospital's ERR is the ratio of predicted-to-expected readmissions for a given measure (CMS, 2017). Hospitals with high ERRs are subject to a financial penalty; in 2015 alone, more than 2,600 U.S. hospitals received reimbursement reductions from CMS because of high readmission ratios (Chakraborty et al., 2017). Accordingly, 30-day readmission rates have become an important metric for care quality in hospitals in the United States (Chakraborty et al., 2017), as well as a focus of hospital administrators charged with improving the financial viability of acute care facilities.

Diabetes is a leading cause of hospitalization and readmission in the United States (Donze, Lipsitz, Bates, & Schnipper, 2013), and it creates significant burdens to patients, healthcare providers, and the economy (McCoy et al., 2017). This disease affects an estimated 23.6 million Americans and is the seventh leading cause of death in the United States (Kim, Ross, Melkus, Zhao, & Boockvar, 2010). The prevalence of diabetes increases each year (Hicks et al., 2016). An estimated 9.3% of the United States' population was diabetic in 2012 (Centers for Disease Control and Prevention, 2017). Experts estimated that 28% of individuals with diabetes are undiagnosed (Ostlling et al., 2017). The estimated direct costs spent on diabetes in 2012 were $176 billion dollars; healthcare costs for individuals with diabetes were 2.3 times higher than for those without the disease (American Diabetes Association [ADA], 2013; Kim et al., 2010). Hospital care accounts for over half of the healthcare expenditures associated with diabetes (ADA, 2008).

Diabetic patients are susceptible to a host of comorbidities such as congestive heart failure (McCoy et al., 2017), neuropathy, retinopathy, stroke, and nephropathy (Fowler, 2008). The high incidence of comorbidities associated with diabetes contributes to a high 30-day readmission rate among these patients (Ostlling et al., 2017; Raval et al., 2015), which some studies indicate was as high as 22.7% (Burke & Coleman, 2013; Jiang, Stryer, Friedman, & Andrews, 2003; Robbins & Webb, 2006). The costs associated with 30-day readmissions among diabetic patients are substantial; the Medicare Payment Advisory Commission (MedPAC) estimated that 30-day readmissions accounted for annual care spending of $15 billion dollars (Raval et al., 2015). A large portion of those costs may also be preventable. Kim et al. (2010) reported that nearly one fifth of readmissions could have been prevented, which would have resulted in healthcare savings of $72.7 million dollars.

A number of other factors also contribute to high readmission rates among diabetic patients such as longer length of stay (McCoy et al., 2017), male sex (Robbins & Webb, 2006; Rubin et al., 2017; Zapatero et al., 2014), minority race (Basu, Hanchate, & Bierman, 2018; Kim et al., 2010; Robbins & Webb, 2006), and low socioeconomic status (Kim et al., 2010). Another important predictor of 30-day readmission is insurance status, which includes being uninsured or having Medicaid, Medicare, or private insurance (Friedman, Jiang, & Elixhauser, 2008; Robbins & Webb, 2006; Rubin et al., 2017). For example, Rubin et al. (2017) found that diabetic patients with Medicare and Medicaid were significantly more likely to experience a 30-day readmission than were patients with private insurance or those who were uninsured. Similarly, Robbins and Webb (2006) found that the likelihood of readmission among diabetic patients with private insurance or no insurance was 34.5% and 32.2% lower, respectively, than that of diabetic Medicare patients. Kim et al. (2010) also found that patients with Medicare or Medicaid were more likely to experience readmission than patients with private insurance.

A more general study on readmissions conducted by Basu et al. (2018) revealed that uninsured patients had the lowest readmission rates of all payer groups and that publicly insured patients were the most likely to experience readmission. Among the publicly insured, Basu et al. found that Medicare patients were more likely to experience readmission than were patients with Medicaid. Findings from Chakraborty's (2017) study echoed those from Basu et al. regarding the high readmission rates among Medicare patients across all payer groups.

Robbins and Webb (2006) posited that higher rates of readmission among Medicare and Medicaid patients relative to those with private insurance are reflective of socioeconomic factors associated with insurance status. Basu et al. (2018) pointed to research that indicated insurance status is associated with aspects of postacute care, which correlates with readmission rates. For example, those without insurance may lack access to follow-up care, and care decisions for patients with public insurance are often driven by financial incentives (Cai, Miller, Nelson, & Mukamel, 2015). Other researchers have reported similar trends regarding the influence of insurance status on care outcomes (Englum et al., 2016). Basu et al. posited that the phenomenon was the result of the lack of insurance coverage and poor access to care, particularly among minorities. Lower rates of readmission cannot always be assumed to be a positive indicator of care outcomes

(Basu et al., 2018). In addition, the influence of insurance payer status on readmissions among diabetic patients is not quite clear as few researchers have examined this issue across all payer status types.

Applying general interventions across patient populations is cost-prohibitive; thus, it is important to identify patients at the greatest risk of 30-day readmission in order to more efficiently utilize care resources (Rubin et al., 2017). Insurance payer status is likely to be a risk factor, although methodological limitations have made findings from previous research somewhat conflicting. Readmission rates may be the result of differences in patient characteristics (Basu et al., 2018; Carey & Lin, 2015; Singh, Lin, Kuo, Nattinger, & Goodwin, 2014). That is, patients' demographic characteristics may moderate the relationships between insurance payer status and readmission rates.

This study was unique because it involved an examination of the relationship between four insurance payer statuses (Medicare, Medicaid, private insurance, and uninsured) and 30-day readmission rates among individuals whose primary or secondary reason for admission was Type 2 diabetes mellitus (T2DM). A significant proportion of the immense costs associated with diabetes care are attributed to hospitalization and readmissions (ADA, 2008; Raval et al., 2015). Much of the existing research on 30-day readmission of diabetic patients focuses on Medicare (Chakraborty et al., 2017). The findings of this study may inform health care policy makers and healthcare providers regarding the readmission rates grouped by diabetic subpopulations at the greatest risk for readmission. The potential clarification provided by the study is important because interventions aimed at reducing the 30-day readmission rates of diabetic patients are resource intensive (Hansen, Young, Hinami, Leung, & Williams, 2011; Rubin et al., 2017).

In this section, I will provide an introduction to the study along with background information required to conceptualize the research and expose the gap that was addressed in this study. The problem, purpose, research questions and hypotheses, and conceptual framework will be presented, followed by discussion of the study's nature and a review of relevant literature. Key terms, assumptions, and delimitations will also be presented. The section closes with discussion of the study's social significance, a summary and conclusion, and a transition to Section 2.

Problem Statement

Approximately 30.3 million people in the United States have diabetes mellitus (DM), which is a modern epidemic (Centers for Disease Control and Prevention [CDC], 2017). In 2015, diabetes was the seventh leading cause of death in the United States (CDC, 2017). Of all patients who are hospitalized or readmitted, 25% were noted as having diabetes or an associated comorbidity (Zakowski, 2017). Patients with DM have higher acute care hospital readmission rates than non-DM patients (Drincic, Pfeffer, Luo, & Goldner, 2017). Diabetic patients have more underlying comorbidities than patients without the disease including hypertension, renal failure, diabetic neuropathy, and diabetic retinopathy (Moses, Mawby, & Phillips, 2013). These comorbidities may result in increased health care spending, elevated hospital readmission rates, and reduced quality of life (Schram et al., 2014).

According to MedPac, approximately 20% of Medicare patients who are discharged from hospitals are readmitted within 30 days (Mcllvennan, Eapen, & Allen, 2015). Hospital readmissions have become a dangerous and regular occurrence, placing an enormous monetary burden on the United States' health care system (Stefan et al., 2012.). Reducing preventable readmissions by just 10% could reduce Medicare expenditures by $1 billion dollars annually (Raval et al., 2015). More than half of hospital readmissions are preventable (Miller & Washington, 2012), including those for diabetic patients. In order to prevent readmissions among diabetic patients most employ targeted interventions must be employed among patient subpopulations at the greatest risk for readmission. A known predictor of readmission is insurance status (Rubin, McDonnell, Golden, & Zhoa, 2017); however, a gap in the literature exists regarding differences in 30-day readmission rates across different insurance payer groups for individuals whose primary or secondary cause for remission is T2DM. According to my research, little is known regarding whether and how sociodemographic factors, such as race, education level, or marital status, moderate the relationship between insurance primary payer status and readmission rates among individuals whose primary or secondary reason for readmission is T2DM.

More research is needed to better understand the factors that place diabetic patients at the greatest risk for readmission. Insurance status may affect rates of 30-day readmission, for diabetic patients (Friedman et al., 2008; Robbins & Webb, 2006; Rubin et al., 2017), yet much of the existing literature focused on Medicare recipients or includes all payer groups together (Chakraborty et al., 2017). Jiang et al. (2005) argued that examining 30-day readmission rates across individual payer groups may be useful for identifying and targeting interventions for the diabetic subpopulations at the greatest risk for readmission.

Purpose of the Study

The purpose of this quantitative, correlational study was to use secondary data to examine the relationship between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and hospital readmission rates among individuals whose primary or secondary reason for admission was T2DM. In addition, I analyzed whether sociodemographic factors (age, gender, and income) moderate the relationship between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and hospital readmission rates among individuals whose primary or secondary reason for admission was T2DM. Four independent variables (Medicare, Medicaid, uninsured, or private insurance) were included in the primary payer status. The dependent variable was hospital readmission rate. Three additional variables (age, gender, and income) were tested for moderation. I gathered data from the 2015 Healthcare Cost and Utilization Project (HCUP) Nationwide Readmission Database (NRD). The scope of the study was the United States as a nation, where 9.4% of the population has diabetes, and several hundred thousand others are prediabetic (Centers for Disease Control and Prevention, 2017). Findings from the study may inform health care providers about a possible correlation between DM patients' rate of readmission and insurance payer status.

Research Question and Hypotheses

Following are the research questions (RQs) and hypotheses for the study. The RQs are also illustrated in Figures 1 and 2.

RQ1. What is the relationship, if any, between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally? Figure 1 illustrates RQ1.

$H_0$1. No statistically significant relationship exists between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally.

H_A1. A statistically significant relationship exists between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally.

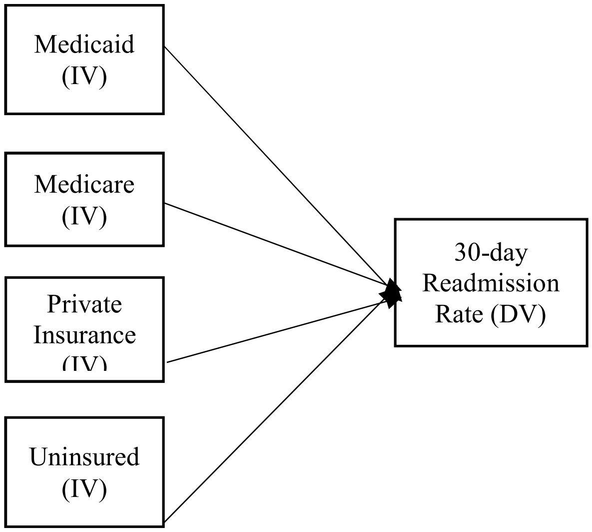

Figure 1. Model for Research Question 1.

RQ2. Do sociodemographic factors like age, gender, and income moderate the relationship between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally? Figure 2 illustrates RQ2.

$H_0$2. Sociodemographic factors like age, gender, and income do not moderate the relationship between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and hospital 30-day rates among individuals whose primary or secondary reason for admission was T2DM nationally.

H_A2. Sociodemographic factors like age, gender, and income moderate the relationship between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally.

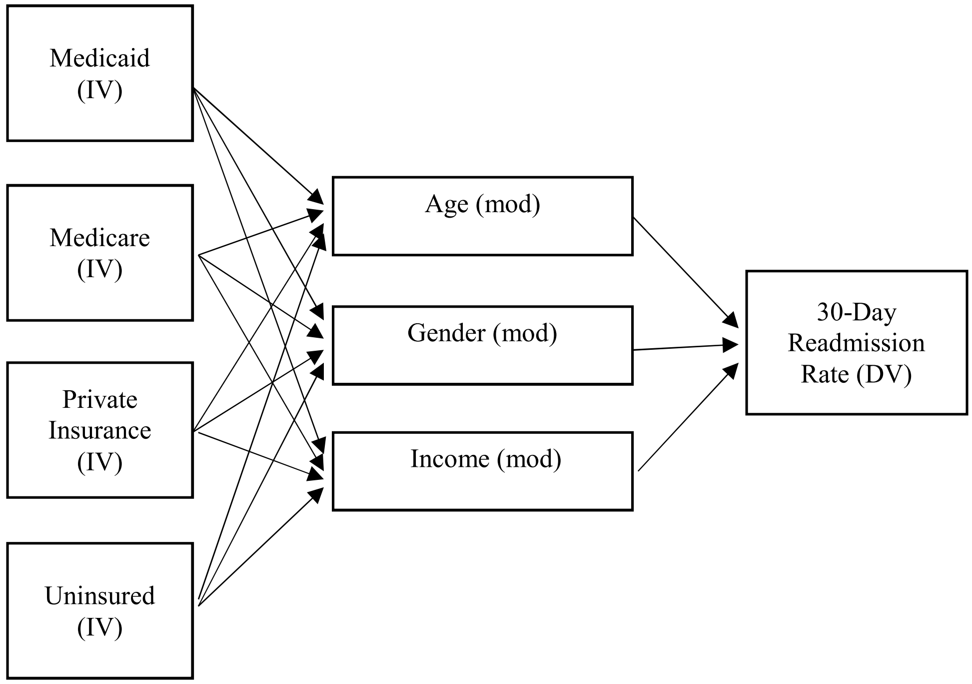

Figure 2. Model for Research Question 2.

Conceptual Framework

The conceptual framework of the study was the Donabedian framework, which is a conceptual model for examining health services and evaluating the quality of healthcare (Sund, Iwarsson, & Brandt, 2015). This framework was developed by Avedis Donabedian, a professor at the University of Michigan School of Public Health and one of the leaders commissioned to review the quality of public health following enactment of the Medicare and Medicaid programs in 1965 (Ayanian & Markel, 2016). The Donabedian framework uses information from three categories to determine the quality of care including structure, process, and outcome. *Structure* refers to the method by which care is delivered. Structural factors may include, but are not limited to, the hospital's facility, qualifications of care providers, human resources, accounting, and material resources (Sund et al., 2015). *Process* entails the transactions between patients and providers during the delivery of healthcare, and it includes the components of care delivered to patients (Ayanian & Markel, 2016). *Outcome* describes the effect of healthcare on the health status of patients and populations such as recovery, survival, and restoration of health (Ayanian & Markel, 2016; Sund et al., 2015).

The Donabedian framework provided an important foundation for examining the relationships between insurance primary payer's status, demographic characteristics, and 30-day readmission rates among patients with T2DM. In the context of this investigation, factors related to Donabedian's definitions of structure and outcomes were examined. Insurance coverage and payer status are structural factors, while 30-day readmission rates are outcomes. Hyder et al. (2013) used the framework to discuss hospital, physician, and patient-level factors that influenced 30-day readmissions among pancreatoduodenectomy patients. Moore, Lavoie, Bourgeois, and Lapointe (2015) employed the framework to examine trauma care outcomes including readmissions. McHugh and Ma (2013) used Donabedian's framework to explore 30-day readmissions among Medicare patients with pneumonia, heart failure, and acute myocardial infarction. In diabetes research, Miles (2019) used the framework to assess diabetics' knowledge of care management as a strategy to improve care transition and reduce readmissions.

Nature of the Study

The nature of the study was quantitative, and it followed a cross-sectional, correlational design. The population of focus consisted of patients who experienced 30-

day readmissions to hospitals nationally in 2013 to 2015 for a primary or secondary reason of T2DM. The researcher conducted multiple linear regression to assess for a correlation between the independent variables of primary payer status (Medicare, Medicaid, uninsured, or private insurance) and the dependent variable of hospital readmission rate.

Although some researchers combine Medicaid and Medicare recipients, or Medicaid and uninsured patients, Robbins and Webb (2006) cautioned that this exercise ought to be evaded except if the two groups are found to have comparative dangers in the data. The majority of literature on hospital readmission rates is based on Medicare data; much less is known about differences in readmission risks across insurance payer groups (Chakraborty et al., 2017). Accordingly, the study involved an examination of each of these groups separately. Payer status is an indicator of a patient's socioeconomic status and an impression of the extraordinary segment and clinical attributes of every subpopulation (Jiang et al., 2005). In addition, each payer has unique financing mechanisms, provider networks, and models of delivery (Jiang et al., 2005), so it is important to examine payer status, separately. By examining 30-day readmission rates associated with each payer status, and understanding how demographic characteristics may moderate these relationships, policymakers and healthcare providers may use findings to more efficiently target subpopulations at risk for readmission (Jiang et al., 2005).

For the second RQ, demographic characteristics, age, gender, and income were examined as potential moderators in the relationships between primary insurance payer status and hospital readmission rates. A multivariable analysis allowed the researcher to examine the relationships between the dependent and independent variables. Findings may shed light on differences in readmission rates among T2DM patients based on primary payer status, and how patient characteristics may moderate those relationships.

Literature Review

This section includes a review of the existing research on diabetes, hospital readmissions, and the influence of insurance coverage on care outcomes such as readmission rates. Topics in this review include 30-day readmission rates in United States' hospitals, Medicare history, incidence of diabetes in the United States, costs of diabetes, diabetes and 30-day readmission rates, Medicare spending on diabetes, readmission risk index for diabetic patients, socioeconomic status and readmission, insurance coverage and 30-day readmission rates, and care discrepancies by insurance status.

Literature Search Strategy

The intention of the research study was to examine the relationship between insurance primary payer status (Medicare, Medicaid, uninsured, or private insurance) and hospital readmission rates among individuals whose primary or secondary reason for admission was T2DM. In addition, the researcher examined if sociodemographic factors (age, gender, income) moderate the relationship between insurance primary payer status and hospital readmission rates among these patients. In order to contextualize the study and provide adequate background information, an exhaustive review of the literature was performed. Relevant peer-reviewed sources were gathered from a number of online databases, including Medline, EBSCOhost, government reports, Cochrane, PubMed, BioMed Central, Google Scholar, and Cumulative Index to Nursing and Allied Health Literature (CINAHL). Additional relevant resources included databases provided by the Centers for Medicare & Medicaid (CMS) and the National Institute of Health (NIH). The researcher endeavored to include recent scholarship published within the last 5 years. Older studies that were relevant or seminal were included as appropriate. Table 1 provides a summary of search terms employed, the number of corresponding results, and the total resources used for each.

Table 1

Summary of Literature Review Keywords/ Boolean Phrase Search Terms

Keyword/Boolean phrase	Google Scholar search engine results	Resources
Affordable Care Act and 30 readmission rate	18,000	4
Medicare spending on diabetes	17,000	12
Medicare spending in the state of Georgia on diabetes	14,100	7
30-day readmission rate for Medicare diabetic patients	16,100	12
30-day readmission rate and Medicare spending for diabetic patients	17,800	12
ICD 10 code for diabetes	19,200	3
How is Medicare funded	24,500	4
CMS and diabetes	21,800	2
Studies on diabetes and hospital 30-day readmission rates	17,700	6

A matrix of the selected literature is provided in Appendix. This matrix highlights the following characteristics of each study: authors, population, variables, study type, and outcomes. Overall, findings from the matrix revealed the gap in research regarding the ways primary payer status and sociodemographic factors may influence readmission rates among individuals with T2DM. This literature review expands on the information included in the matrix by revealing the research gap and contextualizing the study.

30-Day Readmission Rates in United States' Hospitals

Thirty-day readmissions have become an important measure of care quality and target for reducing healthcare costs (Rubin et al., 2017). Following implementation of the Affordable Care Act, the Center for Medicare and Medicaid Services (CMS) began utilizing a Hospital Readmission Reduction Program (HRRP), which was part of the Patient Protection and Affordable Care Act (Ostlling et al., 2017). The HRRP is composed of five specific measures to determine reimbursement rates for hospital readmissions which include pneumonia, heart failure, chronic obstructive pulmonary disease exacerbation (COPD), acute myocardial infarction, and total hip/knee replacement (Ostlling et al., 2017).

The 30-day readmission measures include all unplanned readmissions that occur within 30 days of discharge, regardless of the cause. The risk index includes patients who are readmitted to the same hospital or another acute care hospital for any reason, regardless of their primary diagnosis. The measures do not include planned readmissions. Currently, CMS measures hospital performance in the HRRP by calculating excess readmission ratios (ERR) for each of the program measures. A hospital's ERR is the ratio of predicted-to-expected readmissions for a given measure (Centers for Medicare and Medicaid Services, 2017). Hospitals with high ERRs are subject to financial penalty; in 2015, more than 2,600 hospitals received reimbursement reductions from CMS because of high readmission ratios (Chakraborty et al., 2017). Accordingly, 30-day readmission rates have become an important metric for care quality in United States' hospitals (Chakraborty et al., 2017), as well as a focus of leaders charged with improving the financial viability of acute care facilities. Many local, state, and national campaigns have emerged to help reduce readmission rates (Bradley et al., 2013).

Despite increase attention to the issues of readmission, evidence regarding the best strategies for reducing readmissions is still limited (Bradley et al., 2013). In controlled trials, readmission interventions focus on follow-up and nurse staffing demonstrated success (Coleman, Parry, Chalmers, & Min, 2006). Bradley et al. (2013) pointed out less is known about the effectiveness of such interventions outside of controlled trials. Large variation exists in the strategies used by hospitals to reduce readmission (Bradley et al., 2012; House, Stephens, Whiteman, Biearman, & Printz, 2016).

Medicare History

The topic of 30-day readmission has received growing attention since CMS began to penalize acute care facilities that demonstrate high rates of readmission among Medicare and Medicaid patients by reducing reimbursements. Medicare is a federal health insurance program that was formed in 1965 by President Lyndon B. Johnson (Tierney, 2013). The Medicare Program is the second-largest social insurance program in the United States (CMS, 2013). The initial purpose of the Medicare program was to provide medical insurance to individuals who were 65 years of age or older (Oberlander, 2019). In 1972, President Nixon expanded the Medicare program to include individuals with end-stage renal disease and acute disabilities (Tierney, 2013). Medicare spending is mainly controlled and regulated by the federal government (McHugh & Ma, 2013). Medicare is paid through the Hospital Insurance Trust Fund (HI) and the Supplemental Insurance Trust (Tierney, 2013).

The HI trust is funded through payroll taxes, income taxes, and Medicare Part A premiums (Tierney, 2013). These HI funds are managed by a board of trustees that provides annual reports to Congress on the financial status of the plan. The soundness of the HI trust fund is one of the measurements of Medicare's financial status (Davis et al., 2017). Since the sole concentration of the HI trust fund is the status of Medicare Part A, it does not portray a thorough analysis of the program expenditures (Davis et al., 2017). During years when annual income to the trust fund exceeds benefits spending, the asset level increases; when yearly spending exceeds revenues, the asset level decreases (Davis, et al., 2017). Although the HI trust fund was expected to become insolvent, government regulations and changes have sustained it. The latest legislative changes suggest the HI trust fund will become bankrupt by the year 2026, barring any further governmental regulations (Davis et al., 2017).

The Supplemental Insurance Trust Fund, which includes Medicare Part B and Part D, is funded through premiums of Medicare recipients (Davis et al., 2017). Part B covers outpatient services, home health, and preventive care services (Davis et al., 2017). Part D offers voluntary Medicare prescription drug benefits for recipients through private insurance plans (Shrank & Polinski, 2015). When Medicare Part D was implemented in

2006, it was the most significant expansion to Medicare since its inception in 1965 (Shrank & Polinski, 2015).

The number of individuals enrolled in Medicare is substantial. It was reported that in 2013, there were over 40 million beneficiaries in the United States and by 2030 this number will increase to about 84 million (MedPAC, 2017). As the baby boomer generation ages out of the workforce, the burden to support Medicare will rise as contributors decrease. According to MedPAC (MedPAC, 2017), "the number of taxpaying workers per Medicare beneficiary has declined form 4.6 during the early years of the program to 3; by 2029, this number is projected by the Medicare Trustees to be 2.4" (p. 16). These figures help to illustrate how increasingly burdened the Medicare program will continue to become, and why the costs of hospital readmissions receive growing attention from leaders and policymakers.

Prevalence of Diabetes in the United States

A major contributor to the readmission rate among individuals with Medicare and Medicaid is diabetes (Rubin et al., 2017). Diabetes affects an estimated 23.6 million Americans, and it is the seventh leading cause of death (Kim et al., 2010). The prevalence of the disease is steadily rising (Hicks et al., 2016). Ostlling et al. (2017), and it has been estimated that 9.3% of the United States' population is diabetic, 28% of which is undiagnosed. A comprehensive estimate of the prevalence of diabetes in the United States conducted by Menke, Casagrande, Geiss, and Cowie, (2015) revealed the prevalence rate was even higher. Using cross-sectional survey data, Menke et al. (2015) reported that the unadjusted prevalence of diabetes was 14.3% with over 25% of those cases undiagnosed. The rate of the disease is higher among non-Hispanic Blacks (21.8%), non-Hispanic Asians (20.6%), and Hispanics (22.6%) (Menke et al., 2015).

The increasing prevalence of diabetes aligns well with the increasing prevalence of obesity among the United States' population (Menke et al., 2014). As explained by the NCD Risk Factor Collaboration (2015), the incidences of diabetes and diabetes-related mortality have increased throughout the world, largely fueled by global increases in being overweight and obese. The upward trend in diabetes created significant consequences for individuals and health care systems (Zimmet, Magliano, Herman, & Shaw, 2014). The prevalence of T2DM is highest among the elderly, minorities (non-Hispanic American Indian, non-Hispanic Blacks, and Hispanics), and slightly more common in men than women (Bullard et al., 2018).

Cost of Diabetes

The costs of the increasing prevalence of diabetes in the United States are substantial. The estimated direct costs spent on diabetes in 2012 were $176 billion dollars (ADA, 2013); healthcare costs for individuals with diabetes are 2.3 times higher than for those without the disease (Kim et al., 2010). Hospital care accounts for over half of the healthcare expenditures associated with diabetes (ADA, 2008), which are not just related to enormous healthcare expenses, but also the loss of productivity among those sick with the disease. Menke et al. (2015) estimated the total costs in care and lost productivity associated with diabetes to be $245 billion dollars annually, while Bullard et al. (2018) estimated total costs of diabetes to be $327 billion dollars.

Diabetes and 30-Day Readmission Rates

A large proportion of the healthcare costs associated with diabetes is attributed to hospital readmissions. Diabetic patients are susceptible to a host of comorbidities such as congestive heart failure (McCoy et al., 2017), neuropathy, retinopathy, stroke, and nephropathy (Fowler, 2011). Co-morbidities associated with diabetes correlate to the 22.7% 30-day readmission rate among these patients at a substantial cost (Burke & Coleman, 2013; Ostlling et al., 2017; Raval et al., 2015). The 30-day all-cause readmission rate is 13.9% (Fingar, Barrett, & Jiang, 2017), indicating that readmission rates specific to diabetes are significantly higher. Robbins and Webb (2006), in a germinal study, found that when diabetes was a primary diagnosis, the 30-day readmission rate was 9.4% but if a diabetic patient was admitted for another reason and diabetes was not listed as a secondary diagnosis, the 30-day readmission rate was 30.6%. For example, Medpac estimated that all-cause 30-day readmissions accounted for annual care spending of $15 billion dollars (Raval et al., 2015). Kim et al. (2010) estimated that nearly one-fifth of readmissions may have been prevented, which would have resulted in healthcare savings of $72.7 million dollars. The potential for reducing readmissions is of interest to policymakers and healthcare leaders and is a target of the study.

Insurance Coverage and 30-Day Readmission Rates

In addition to high rates of comorbidities, several research studies indicate that a number of other factors contribute the high readmission risk among diabetic patients. These factors include hospital length of stay, male gender, minority race, and low socioeconomic status (Basu et al., 2018; Kim et al., 2010; McCoy et al., 2017; Rubin et al., 2017; Zapatero et al., 2014). An important predictor of 30-day readmissions may be insurance status and type, Medicaid, Medicare, private insurance, or uninsured (Friedman et al., 2008; Robbins & Webb, 2006; Rubin et al., 2017). Rubin et al. (2017) found that diabetic patients with Medicare and Medicaid were more likely to experience a 30-day readmission than patients with private insurance or those who were uninsured. Rubin et al. reported 30-day readmission rates for Medicare and Medicaid recipients were 45.6% and 11.6%, respectively. Everett and Mathioudakis (2019) found that insurance status was the strongest predictor of readmission among diabetic ketoacidosis patients.

In a study of socioeconomic, clinical, and demographic factors associated with readmissions among diabetic patients, Kim et al. (2010) found that patients with Medicare or Medicaid were more likely to experience readmission than patients with private insurance. Hicks et al.'s (2016) study on the costs of foot ulcers among diabetic patients revealed that over three-quarters of hospitalized patients had Medicare or Medicaid. A more general study on readmissions conducted by Basu et al. (2018) revealed that uninsured patients had the lowest readmission rates of all payer groups, and publicly insured patients were the most likely to experience readmission. Among the publicly insured, Basu et al. found that Medicare patients were more likely to experience readmission than patients with Medicaid. Findings from Chakraborty's (2017) study echoed those from Basu et al. regarding the highest readmission rates among Medicare patients across all payer groups.

Robbins and Webb (2006) posited that higher rates of rehospitalization among Medicare and Medicaid patients relative to those with private insurance is likely to reflect socioeconomic factors associated with insurance status. Basu et al. (2018) indicated insurance status is associated with aspects of post-acute care which correlates with readmission rates. For example, those without insurance may lack access to follow-up care, and care decisions for patients with public insurance are often driven by financial incentives (Cai et al., 2015). Other researchers have reported similar trends regarding the influence of insurance status on care outcomes (Chakraborty, et al., 2017; Englum, et al., 2016). For example, Englum et al. (2016) examined the relationship between hospital status and length of stay among trauma patients and found that uninsured patients had a significantly shorter length of stay than patients with private insurance. Publicly insured patients in Englum et al.'s study had the longest length of stay; however, this does not necessarily indicate that publicly insured patients received the best care. In fact, researchers reported that longer lengths of stay are associated with higher risks for 30-day readmission (Chakraborty et al., 2017).

Medicare Spending on Patients with Diabetes Mellitus

Medicare spending is estimated to grow to about $171 billion dollars by the year 2034 (Raval, et al., 2015). Diabetic patients are hospitalized frequently (Raval et al., 2015). The program currently spends about 32% of its budget on diabetes and associated comorbidities (Silveira et al., 2018). According to Erkan Erdem (2014), the average annual Medicare spending on diabetes patients with Part A and Part B Medicare is $5,741 to $5,991 dollars.

Hospital readmissions are linked to poor patient outcomes and increased monetary expenditures (McIlvennan et al., 2015). Approximately 25% of all hospitalized patients have DM (Ostlling, et al., 2017) The direct medical costs of DM were $176 billion dollars in 2012, 43% of which was spent on direct inpatient care (Ostlling et al., 2017). Many factors contribute to hospital readmission within 30-days of discharge. For example, diabetes care increases the use of health care services, medications, and medical supplies (Mcllvennan et al., 2015). Medicare patients comprise almost 20% of 30-day hospital readmissions (Mcllvennan et al., 2015).

Over 21 million medical doctor office visits annually are scheduled for diabetes. An estimated one-third of Medicare expenditures are related to diabetes (Dugan & Shubrook, 2017). Coding for diabetes must be accurate to ensure that the providers and institutions receive the proper reimbursement rate. In accordance with ICD-10 guidelines, coding for diabetes requires four or five digits, for accuracy. The coding identifies the type of diabetes, patient's current diabetic status (i.e. Type 1, Type 2, or gestational diabetes), and comorbidities of the disease (Dugan & Shubrook, 2017).

In 2010, under the Affordable Care Act, the federal government instituted two programs aimed at reducing 30-day hospital readmissions. These programs included the Hospital Readmissions Reduction Program (HRRP) and the Bundled Payments for Care Improvement Initiative (BPCI) (Carey & Stefos, 2016). The HRRP is the most developed mandatory incentive of the CMS program and has the largest monetary impact on hospitals across the country (Ryan, Adler-Milstein, Damberg, Maurer, & Hollingsworth, 2017). Under the HRRP, CMS reduces payments to inpatient prospective payment systems (IPPS) hospitals with excessive readmission rates (Carey & Stefos, 2016). The first penalties affecting the payments were for discharges beginning in October, 2012.

During the 2013 fiscal year, CMS began imposing a payment reduction of up to 1% to hospitals that exceeded expected readmission rates for acute myocardial infarction (AMI), heart failure, and pneumonia (Ryan et al., 2017). By the 2015 fiscal year, the payment reduction increased to 3% (Ryan et al., 2017).

The BPCI was an initiative developed by CMS to improve care by bundling payments for beneficiaries of multiple services for single care episodes (Andrawis, Koenig, & Bozic, 2016). Under the BPCI, healthcare facilities enter payment agreements that stipulate financial and performance accountability for care episodes. The goal of the BPCI is to improve care quality and coordination while lowering Medicare costs (Andrawis, Koenig, & Bozic, 2016).

Medicare's prospective payment system (PPS) was introduced in 1983. Under this system, hospitals are paid a fixed rate per admission diagnosis (Krinsky, Ryan, Mijanovich, & Blustein, 2017). A primary component of PPS is the diagnosis-related groups (DRGs), which consist of medical and surgical services (Bowman, 2016). The World Health Organization adopted the International Classification of Disease, ICD-10 revision in 2004, which is the international standard (Bowman, 2016). The ICD-10 replaced the ICD-9, which lacked detail expected to precisely reflect current clinical phrasing and methods and can't be extended further to remember new revelations and methodology for medication (Coutasse & Paul, 2013). The United States did not officially mandate the implementation of the ICD-10 until October 2015 (Bowman, 2016). Although the CMS originally mandated the transition to ICD-10 codes by 2011, the transition was twice delayed due to financial and administrative concerns expressed by care providers regarding their ability to comply with the transition deadlines. The DRGs categorize all human ailments according to the body part that is affected by the illness, the sex of the patient, and morbidity (Bowman, 2016). Eight diagnoses are accounted for in the classification and up to six procedures during the hospital stay (Bowman, 2016).

Readmission Rate for Medicare Patients with Diabetes

A systematic review by Raval et al. (2015) utilized a nationwide database of Medicare recipients to estimate the frequency of 30-day readmission rates among elderly Medicare beneficiaries with T2DM. The study followed a retrospective longitudinal cohort design. The timeframe of the study was between January 2007 and August 2011. The study population consisted of 12 million Humana Medicare Advantage part D recipients who (a) had a primary or secondary diagnosis of T2DM; (b) were 65 years of age and older; and (c) were enrolled in the plan between January 2007 and April 2012. Participants were enrolled in the plan six months before admission and 30 days after hospital discharge. The dependent variable of the study was readmission rate. Recipients were categorized into two groups: (a) recipients who were re-admitted within 30 days; and (b) recipients with no readmission with 30 days.

The independent variables in Raval et al.'s (2015) study included length of stay, sex, age, secondary diagnosis diabetes, and primary diagnosis diabetes. The results of the study were consistent with similar studies on patient 30-day readmission rates for T2DM, in which patient-level stressors of overall poor health conditions that are specifically related to the elderly population (such as cognitive impairment, falls, and fall risks) were the most commonly identified risk factors for readmission. These findings may have implications for reducing the 30-day hospital readmission rate through effective post-care planning before discharge.

Sonmez, Kambo, Avtanksi, Lutsky, and Poretsky (2017) conducted a retrospective cohort study of 102,694 patients who were admitted to an urban teaching hospital between January 1, 2013 and September 30, 2015. The primary or secondary admitting diagnosis had to be diabetes in order for the patient to be included in the study. The number of patients with a primary or secondary admitting diagnosis of diabetes was 16,266. The researchers compared 30-day hospital readmission rates for patients with diabetes to those without the disease. The researchers also examined the connections between the length of stay (LOS) for patients with diabetes and the length of stay for patients without diabetes. The data source was the hospital billing system. The dependent variables were readmission rate with or without diabetes. The independent variables were length of stay, gender, age, secondary diabetes, and primary diabetes.

The results of Somez et al.'s (2017) study revealed that diabetic patients were 2.47 times more likely to be readmitted than patients without diabetes. Patients 65 years of age and older were more likely to be readmitted within 30 days than patients between the ages of 18 and 64. The researchers also found that male diabetic patients were more likely to be readmitted than female patients. A major limitation of this study is that it was conducted at a single urban hospital, and other area hospitals were not included in the study. As a result of the study being retrospective, there may have been bias in the patient selection process, data accuracy, and patient follow-up. The data from the hospital billing system did not include clinical information about patients' medical conditions which may have impacted the LOS or readmission rates.

A cross sectional study conducted by Alavi, Baharlooei, and AdelMehraban (2017) revealed that despite the advances in diabetic care and treatment, elderly patients still had high rates of hospital readmissions. The primary goal of the study was to examine the psychosocial factors that may contribute to the readmission rate of elderly diabetic patients. The researchers concluded that developing social support services may help in the reduction of readmission rate for this population while also improving the mental health status of the elderly. However, the researchers recommended further research on ways to decrease depression, anxiety, and stress among the elderly.

Readmission Risk Index for Diabetic Patients

The Diabetes Early Readmission Risk Index (DERRI^{TM}) is a multivariable logistic regression model tool that predicts all-cause 30-day readmission risks for patients who are hospitalized with diabetes (Rubin, 2018). Persons with diabetes account for about 20% of hospitalizations annually (Rubin et al., 2017). Diabetic patients with cardiovascular disease (CVD) comprise 25% to 30% of the hospital admissions for this subgroup (Rubin et al., 2017). Rubin et al. (2017) simulated the tool and added cardiovascular disease to the tool in a retrospective cohort study. The tool was called the Diabetes Early Readmission Risk Indicator for cardiovascular disease (DERRI-CVD^{TM}). The aim of the study was to compare the performance of the DERRI^{TM} to the DERRI-CVD^{TM}. The study consisted of 8,189 discharges between January 1, 2004, and December 31, 2012, which were selected from the electronic medical records system of

Boston Medical center. The cohort was the same one that was used for the DERRI ™. However, the DERRI ™ did not have the stipulation of having a primary diagnosis of CVD. The primary purpose of the study was to invent a functional tool that would predict the 30-day readmission risk for diabetic patients with CVD (Rubin et al., 2017).

To be included in Rubin et al.'s (2017) study, the patient's primary discharge diagnosis had to be CVD, which included heart attack, heart disease, stroke, peripheral vascular disease, and diabetes. The researchers believed that if the readmission risk of this population could be predicted, the patients identified as high risk could be singled out which would enable resources to be used more efficiently and effectively. The results of the study revealed vast similarities in the predictors of the DERRI™ and the DERRI-CVD™.

The most common shared 30-day readmission predictors in Rubin et al.'s (2017) study were diabetes, heart failure, shortness of breath, chest pain, peripheral arterial disease, and acute kidney failure. The results of the DERRI-CVD™ were similar to the DERRI™; therefore, either model may be useful for identifying diabetic patients admitted with CVD who are at an elevated risk for a 30-day readmission. All these predictors are easily gathered at the time of patient admission, health administrators may utilize the tool to implement protocols focused on diabetic CVD patients with high risks for 30-day readmissions. This tool may help to lower the financial burdens to healthcare facilities while improving patient outcomes (Rubin et al., 2017).

Socioeconomic Status and Hospital Readmission Rates

Socioeconomic status is a significant determinant of health among patients with diabetes (Assari, Moghani Lankarani, Piette, & Aikens, 2017). Researchers around the world have reported that social characteristics, such as low education, low income, marital status, and race, are associated with increased risks for diabetes. Likewise, comparative trends have been documented for readmission frequency and rate among diabetic patients (Assari et al., 2017).

Assari et al. (2017) conducted a cross-sectional study using a consective sampling strategy. The purpose of the study was to evaluate the differences between socioeconomic status (SES) and Hemoglobin A1c (HbA1c) levels among Black and White patients with T2DM. The researchers found that SES had a greater impact on the HbA1c levels of Black males than any other subgroup in the study. Findings also revealed that Black males and females developed diabetes at a younger age than White males and females. The results of the study may contribute to governmental policy reform, but more research is needed among a larger sample (Assari et al., 2017).

Diabetic ketoacidosis (DKA) is one of many acute complications of Type 1 diabetes mellitus (T1DM) and a leading cause of death in children and young adults with the disease (Everett & Mathioudakis, 2019). Everett and Mathioudakis (2019) conducted a cross-sectional study using the National Readmission Database (NRD) to identify 181,284 T1DM patients admitted for DKA between 2010 and 2015. The purpose of the study was to examine patient- and hospital-level predictors of T1DM patients with recurrent DKA who were admitted or readmitted with a special focus on patient socioeconomic status. To be included in the study, the admission had to be the first admission for the patient within the specific calendar year and the primary diagnosis had to be recurrent DKA. Results revealed that participants from the lowest socioeconomic income quartile had a 50% chance of four or more hospital readmissions with DKA within a single calendar year. The researchers also reported that patients with government insurance (i.e., Medicare or Medicaid) were at an increased risk of hospital readmissions with DKA, as well as those who went home against the advice of medical professionals. The researchers concluded that further investigation was needed to examine the relationship between DKA and hospital readmissions among this high-risk subgroup. Such research may reveal which types of interventions such as patient education or community outreach will help this population (Everett & Mathioudakis, 2019) .

Across the globe, it is estimated that one person dies from diabetes-related complications, every six seconds (Bird, Lemstra, Rogers, & Moraros, 2015). In 2011, the Public Health Agency of Canada (PHAC) published a report on diabetes that determined the primary adjustable risk factors for diabetes were obesity, lack of physical activity, smoking, and unhealthy eating habits. The non-adjustable risks factors included race and recent immigration status, but the report did not mention correlations with socioecomonic status or income.

A cross-sectional population-based study conducted by Bird et al., (2015) was conducted to determine if a correlation existed between T2DM and socioecomonic/ income status in the Canadian province of Saskatchewan. Data collected from the Canadian Community Health Survery (CCHS) between 2000 and 2008 were analyzed.

The CCHS is a self reporting survey. The sample included 27,090 residents. Four distinct and separate models were built, which examined the effect of income on T2DM in correlation wih the conditions of hypertension, obesity, and physical activity. Study results revealed that socioeconmic status was closely associated with T2DM and its underlying comorbidites, such as hypertension and obesity. Internationally, findings from this study provide evidence that socioeconomic and income status may relate to increased morbidity and mortality (Bird et al., 2015).

Care Discrepancies by Insurance Status

Readmission among diabetic patients may also relate to insurance status. Basu et al. (2018) indicated insurance status is associated with aspects of post-acute care, which correlates with readmission rates. Those without insurance may lack access to follow-up care, and care decisions for patients with public insurance are often driven by financial incentives (Cai et al., 2015). Other researchers have reported similar trends regarding the influence of insurance status on care outcomes. Englum et al. (2016) examined the relationship between hospital status and length of stay among trauma patients and found that uninsured patients had significantly shorter lengths of stay than patients with private insurance. Publicly insured patients in Englum et al.'s study had the longest lengths of stay; however, this does not necessarily indicate that publicly insured patients received the best care. In fact, many researchers have reported that longer lengths of stay are associated with higher risks for 30-day readmission (Chakraborty et al., 2017).

Discrepancies in resource use among underinsured patients may reflect the shorter lengths of stay (Englum et al., 2016), but do not explain the lower rates of readmission among this group. Basu et al. (2018), who also found readmission rates to be lower among the underinsured, posited that the phenomenon was the result of the lack of insurance coverage and poor access to care – particularly among minorities. Accordingly, the researchers cautioned that lower readmission rates may not generally be interpreted as a decent result (Basu et al., 2018).

A substantial body of literature indicates that uninsured patients receive inefficient and lower quality care than insured patients; however, less is known about differences in the quality of care provided to privately-insured versus publicly-insured patients (Englum et al., 2016). Some researchers have reported publicly insured patients undergo fewer procedures (Haas & Goldman, 1994; Wenneker, 1990) and have worse morbidity (Ayanian et al., 1993; Braveman et al., 1994) than the privately-insured. Other researchers have reported incongruence in findings comparing mortality rates among publicly and privately insured patients (Englum et al., 2016).

To date, interventions aimed at reducing 30-day readmissions among diabetes patients have demonstrated inconsistent outcomes (Hansen et al., 2011; Rubin et al., 2017). Such interventions have focused on improving discharge planning and transactional care and providing patients with timely follow-up (Drincic et al., 2017). As Rubin et al. (2017) explained, applying general interventions, especially when they only demonstrate modest effects, across patient populations is cost-prohibitive. Thus, it is important to identify patients at the greatest risk of 30-day readmission in order to more efficiently utilize resources. Similarly, Dugan and Shubrook, (2017) suggested that targeting interventions to high-risk groups could improve cost-to-benefit ratios.

Structured and individualized discharge plans may help reduce 30-day readmission among patients at the highest risk (ADA, 2019). As Basu et al. (2018) urged, the role of insurance should be examined in order to evaluate efforts to reduce readmissions. In addition, because readmission rates may be the result of differences in patient characteristics (Basu et al., 2018; Carey & Lin, 2015; Singh et al., 2014), it is also important to understand how patients' demographic characteristics may moderate the relationships between insurance payer status and readmission rates.

Definitions

Following are definitions of key terms that will be used throughout this study:

30-day readmission: Rehospitalization that occurs within 30 days of discharge from the initial hospitalization (Rubin et al., 2017).

Centers for Medicaid and Medicare (CMS): A unit within of the Department of Health and Human Services (CMS, 2017).

Diabetes mellitus (DM): A chronic disease caused by an inherited or acquired deficiency in production of insulin by the pancreas. Symptoms of the disease include excessive urination, elevated blood sugar, and insulin resistance (CMS, 2017).

Diabetic ketoacidosis (DKA): A serious acute complication of Type 1 diabetes caused by a build-up of acid in the blood (Everett & Mathioudakis, 2019).

Diagnosis-related group (DRG): A statistical method of classifying inpatient stays into groups, which assists with insurance compensation (CMS, 2017).

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

Healthcare Cost and Utilization Project (HCUP): A family of health care databases and related software tools and products developed through a federal and state industry partnership and sponsored by the Agency for Healthcare Research and Quality (CMS, 2017). The HCUP databases bring together the data collection efforts of state data organizations, hospital associations, private data organizations, and the federal government to create a national information resource of encounter-level health care data (CMS, 2017).

Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS): The first national, standardized, and publicly reported survey of patients' views of the care they receive in hospitals (CMS, 2017). The survey is also known as the CAHPS hospital survey. The survey consists of 27 question about patients' hospital stays, 18 of which are related to critical elements of the patient hospital experience (CMS, 2017).

Hospital Readmissions Reduction Program (HRRP): A pay-for-performance program that lowers payments to Inpatient Prospective Payment System (IPPS) hospitals that have too many readmissions (Centers for Medicare and Medicaid Services, 2017).

Medicaid: A state and federally funded program that provides health coverage to eligible low-income adults, children, pregnant women, older adults, and people with disabilities (CDC, 2017). The program is state-administered in compliance with federal requirements (CDC, 2017).

Medicare: A single-payer, national social insurance provider governed by the United States government (CMS, 2017).

National Inpatient Sample (NIS): One of the HCUP databases that is the most extensive and publicly available all-payer inpatient health care database in the United States, yielding national estimates of hospital inpatient stays (CMS, 2017).

Primary payer status: An indicator of insurance type, categorized by the party responsible for payment (Xu et al., 2017). In this study, primary payer status was categorized into the following four groups: Medicare, Medicaid, uninsured, and private insurance.

Private insurance: Any type of health insurance that is purchased by an individual or obtained through an employer (Delaware Assistive Technology Initiative, n.d.). Unlike Medicare and Medicaid, private insurance is not federally funded.

Race: Groups of people who have differences and similarities in biological traits deemed by society to be socially significant (CMS, 2017).

Readmission: The return of a patient to a healthcare facility after being previously discharged for the same illness (CMS, 2017).

Type 2 diabetes mellitus (T2DM): A form of diabetes in which the pancreas produces too little insulin, or the body rejects the insulin that it produces. T2DM can usually be controlled with medication, diet, and exercise (Georgia Department of Public Health, 2018). T2DM is the form of diabetes that was focused on in this study.

Assumptions

The first assumption of this study was that the HCUP NRD database would contain all the necessary variables for the study for T2DM. Variations may be shown depending on the geographical location in which data is derived to demonstrate differences in readmission rates and insurance status. It was also assumed that all utilized data have been accurately entered into the HCUP NRD database.

Scope and Delimitations

The scope of the study was based on the Healthcare Cost and Utilization Project (HCUP) Nationwide Readmission Database (NRD), 2015. This investigation only included readmission data for patients who were admitted to hospitals nationally between Jan 1, 2015 and Dec 31, 2015. Nationally was selected as the focus of this investigation because 9.4% of the population has diabetes (American Health Rankings, 2019).

This study was also limited by the payer status categories selected. For example, a status of private insurance included any type of insurance plan purchased by an individual or provided by an employer. Differences across types of private insurance were not included. The researcher also selected to examine Medicare and Medicaid separately rather than combining them under the category of public insurance, as many previous researchers have. Findings may differ if the definition and organization of payer status was different.

Other delimiting factors included the researcher's selection of conceptual framework and study method and design. The demographic factors selected for examination as moderators also represented a delimitation. The use of other demographic factors, such as household income, may have resulted in different findings.

Significance, Summary, and Conclusions

Findings from the study may have an impact for positive social change by informing health care providers and administrators regarding a correlation, if any, between health insurance payers and readmission rates. Healthcare providers and leaders can create programs to ensure all patients with a primary or secondary diagnosis of diabetes, receive appropriate care and education to reduce readmissions, improve health outcomes, and improve quality of life for this patient population, and result in significant financial savings.

The study may also inform government policymakers with analytical data needed to amend the guidelines for the Hospital Readmissions Reduction Program (HRRP) (Krinsky et al., 2017). The study may inform hospital administrators regarding readmissions and diabetics to align their organization with healthcare reform guidelines associated Medicare spending and the HRRP. The impact of this alignment may improve care transitions between patients and healthcare organizations. The study results may also lead to improved outcomes for patients to further social good, by relieving the patient of the burden of returning to the hospital, which can also result in a burden relief to the taxpayers because of the high costs of readmissions.

Summary

A review of the literature on hospital readmission among patients with diabetes has revealed the lack of distinction between planned and unplanned readmissions

(Drincic et al., 2017) and mixed findings regarding the influence of insurance payer status on readmissions among patients with T2DM. The researcher of this study sought to provide evidence to fill a gap in the literature regarding the correlation, if any, between readmission rates and insurance payer status among patients with T2DM. A review of existing research on readmission rates revealed that patients with diabetes have higher readmission rates than those without diabetes; yet limited information exists on efforts to reduce readmissions among these patients (Drincic et al., 2017). Lawmakers have suggested that healthcare organizations implement strategies to reduce readmissions to lower cost (Drincic et al., 2017). The strategies focus on identifying risk factors that may be associated with readmissions such as underlying comorbidities, age, the severity of illness, previous hospitalization and low socioeconomic status (Drincic et al., 2017). Applying general interventions across patient populations is cost-prohibitive. It is important to identify patients at the greatest risk of 30-day readmission in order to more efficiently utilize resources.

An examination of the relationship between insurance payer status and 30-day readmission rates among T2DM patients may provide leaders with information needed to target appropriate interventions and reduce readmission rates. In addition, because readmission rates may be the result of differences in patient characteristics (Basu et al., 2018; Carey & Lin, 2015; Singh et al., 2014), it is also important to understand how patients' demographic characteristics may moderate the relationships between insurance payer status and readmission rates. The study addressed these important gaps in the existing literature with the aim of developing findings that may be used to reduce readmission among patients with T2DM

In Section 1, I presented an introduction to the investigation and an overview of the literature associated with readmission rates among patients with T2DM. The next section presents methodological details of the study. Discussions about the study design, population, sample, data analysis plan, data cleaning, and RQs are provided in Section 2.

Section 2: Research Design and Data Collection

Introduction

The purpose of this quantitative, correlational study was to use secondary data to examine the relationship between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and hospital readmission rates among individuals whose primary or secondary reason for admission was T2DM. In addition, I analyzed whether sociodemographic factors (age, gender, and income) moderate the relationship between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and hospital readmission rates among individuals whose primary or secondary reason for admission was T2DM. In Section 2, I will detail the research design and rationale and methodology. In the section, I will discuss the target population, sampling design, instrumentation, and data analysis plan. I also discuss issues of validity and the ethical procedures used in working with study data.

Research Design and Rationale

The research method applied to assess the hypotheses was a quantitative multivariate analysis and the Donabedian framework. Logistic regression analysis testing helped to determine if there was a direct relationship between the readmission rate and insurance payer status for patients with T2DM as a primary or secondary diagnosis and 30- day readmission rates. It was also helpful in determining whether a relationship existed when controlling for age, gender, and income. I performed a quantitative analysis to verify the data in the Statistical Package for the Social Sciences (SPSS). I reviewed multiple studies that had similar and consistent data when controlling for covariates similar to the ones used in the study. The research design allowed me to measure data from the target population and quantified the prevalence of multiple characteristics within the sample population. I used the quantitative research method to determine patterns in payer status and 30-day readmission rates for patients nationally with T2DM.

Methodology

I analyzed the 2015 NRD of the HCUP using logistic regression to establish a relationship between the variables. To verify the data, I conducted a quantitative analysis using SPSS. To obtain secondary data from HCUP NRD, I completed a mandatory data use agreement course that included discussion of the key elements of using secondary data from the HCUP website. A certificate code was then issued to access the secondary data set electronically; the code provided authorization to use the data for research concentrated in the United States.

Population

The focus of this research was on individuals who are medically diagnosed with T2DM nationally. The inclusion of all patients with T2DM nationally was a requirement to assess the hypothesis and determine if there was a correlation between 30-day readmission rates and insurance payer status and between 30-day readmission rates and sociodemographic variables for patients with T2DM. I excluded patients who were not medically diagnosed with T2DM from the research study. I did not exclude participants based on their gender, ethnicity/ race, age, physical disability, or preexisting comorbidities; rather, I used the covariates to further determine additional factors that may show disparities.

Sampling Design

I used a quantitative correlational design to examine the relationship between insurance primary payer status (Medicare, Medicaid, uninsured, or private insurance) and hospital readmission rates among individuals whose primary or secondary reason for admission was T2DM. I also examined sociodemographic variables, insurance payer status, and 30-day readmission rate for patients with T2DM. A correlational research design allows for the measurement of a relationship between two variables without the researcher controlling either of them (Creswell, 2009). A correlational design was the most appropriate method to examine the relationship between insurance payer status and 30-day readmission rates for patients with T2DM.

I used a secondary data set in the research study acquired from the HCUP NRD for the time period of 2013 to 2015. HCUP-NRD is the Nationwide Readmission Database and software tools developed for the HCUP (HCUP, 2015). The NRD includes inpatient discharge records form community hospitals in the United States. I used the HCUP-NRD to look at the 30-day readmission rate for patients nationally whose primary or secondary reason for admission was T2DM. I used insurance payer type while simultaneously controlling for covariates categorized from the secondary data set.

Data analysis. I analyzed the secondary data by using IBM SPSS Statistics v. 23.0 (2016). The statistical analysis consisted of conducting a descriptive analysis, a two-way test of association, followed by multivariate logistic regression to address RQ1 and logistic regression to address RQ2. Categorical variables were investigated to determine the percentage of male and female subjects and to define by race/ethnicity in each category. Additional analysis assisted with categorizing the number of subjects by medical condition and year. The mean, mode, and standard deviation were calculated per category to exhibit variations per year. The research analyses assisted in establishing a pattern of 30-day readmission rates for patients nationally with T2DM and determining insurance payer status and 30-day readmission rates for patients with T2DM nationally. The covariates were analyzed to determine if there was a pattern associated with 30-day readmission rates, sociodemographic variables, and insurance payer status for T2DM patients nationally.

Power analysis. I completed a power analysis using IBM SPSS Statistics v. 23.0 (2016) with .80 power and alpha of < .05 to determine the sample size needed for each RQ. The power analysis calculation sample size revealed a minimum sample size of 398 for RQ1 with power .80 and alpha < .05. This sample size needed to be significant to determine if there was a correlation between insurance primary payer status (Medicare, Medicaid, uninsured, or private insurance) and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally.

The power analysis for RQ2 for .80 power and an alpha < .0 also revealed a minimum required sample size of 398. This sample size needed to be significant to determine whether sociodemographic factors such as age, gender, and income moderate the relationship between insurance primary payer status (Medicare, Medicaid, uninsured, or private insurance) and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally.

Data Analysis Plan

I used the HCUP NRD for 2013 to 2015 for the study. To analyze the data, I performed logistic regression using SPSS. Logistic regression is the multivariate extension of a bivariate chi-square analysis (Sperandei, 2014). Logistic regression allows the researcher to control for various demographic, analytical, clinical, and potentially confounding factors that affect the relationship between a primary predictor variable and a dichotomous categorical outcome variable (Sperandei, 2014). Logistic regression generates adjusted odds ratios with 95% confidence intervals (Sperandei, 2014). Once the calculations have been received, the logistic regression analysis will assist in determining a null or alternative hypothesis.

The dependent variable was the 30-day hospital readmission rate and was analyzed in conjunction will the independent variables of insurance payer status (Medicare, Medicaid, uninsured or private insurance). The covariates within the research were comprised of age, gender, income, and timeframe in which services rendered ethnicity/race, and comorbidities. The location of the research was nationally, and the ethnicity consisted of Non-Hispanic/White, Asian/Pacific Islander, Black/African-American, Hispanic, and Native American/Alaska Native. The timeframe for the research included three consecutive years of data to exhibit a current study aimed at exploring the gap in literature and current and past findings pertaining to the dependent and independent variables. The secondary data set was analyzed to address the following research study questions and corresponding hypotheses:

RQ1. What is the relationship, if any, between primary payer status Medicare, Medicaid, uninsured, or private insurance and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally?

$H_0$1. No statistically significant relationship exists between primary payer status Medicare, Medicaid, uninsured, or private insurance and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally.

H_A1. A statistically significant relationship exists between primary payer status Medicare, Medicaid, uninsured, or private insurance and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally.

RQ2. Do sociodemographic factors like age, gender, income moderate the relationship between primary payer status like Medicare, Medicaid, uninsured, or private insurance and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally?

$H_0$2. Sociodemographic factors like age, gender, income do not moderate the relationship between primary payer status like Medicare, Medicaid, uninsured, or private insurance and hospital 30-day rates among individuals whose primary or secondary reason for admission was T2DM nationally.

H_A2. Sociodemographic factors like age, gender, income moderate the relationship between primary payer status like Medicare, Medicaid, uninsured, or private insurance and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally.

Threats to Validity

In this quantitative study, the research identified, if there was the possibility of external and internal threats to validity. Internal and external validity are perceptions that replicate if the results of a study are trustworthy and meaningful (Anrade, 2018). Internal validity relates to how well a study is conducted external validity relates to how applicable the findings are to the real world (Anrade, 2018).

Internal Validity

Internal validity examines whether the manner in which a study was designed, conducted, and analyzed allows trustworthy answers to the RQs in the study (Anrade, 2018). There could be numerous threats to internal validity such as, improper randomization, inadvertent unblinding of patients or raters, missing data. Internal validity is based on judgment and is not a computed statistic (Anrade, 2018). Internal validity examines the extent to which bias is present.

External Validity

External validity of the study may be affected if the study population is not a true representation of the target population that is eligible for the study (Anrade, 2018). External validity pertains to appropriate inferences or generalizations of research results to other populations (Rooney et al., 2016). Random sampling was chosen to assure the validity of the study.

Data Protection and Privacy

Treatment of Data

The research study underwent the approval process from Walden University Institutional Review Board (IRB) to utilize an external secondary dataset. The Data Protection Act 2018 (DPA) (updated to the 1998 DPA) protects individuals from being exploited and their personal information from unwanted distribution (Spencer & Patel, 2019). This update to the DPA was necessary due to the ongoing technological advances of social media. The data protection act ensures that Protected Health Information (PHI) is safeguarded. PHI includes an individual's demographic information, such as age, date of birth, Social Security number, address, and telephone number (Craig, 2017). The Health Insurance Portability and Accountability Act (HIPAA) privacy rule requires healthcare providers to maintain the confidentiality of a patient's protected health (Craig, 2017).

Permissions

For this doctoral research, before data collection could begin, the IRB had to review and approve the methods and procedures that the researcher planned to use. To obtain secondary data from HCUP, a mandatory data use agreement course was completed that discussed the key elements of utilizing secondary from the HCUP website (Agency for Healthcare Research and Quality, 2019). A certificate code was then issued to access the secondary dataset electronically and provide authorization for utilizing data to conduct testing for the research.

Ethical Concerns

The protection of human subjects during research requires permission for academic institutions and clinical trials. All patient specific information was protected and underwent re-coding where necessary to uphold patient privacy during the duration of the research study. Approval from Walden IRB and HCUP privacy agreement use were obtained. The research does not present any ethical issues for the university, researcher, or the participants to further determine gaps in previous related literature.

Ethical Procedures

In meeting the requirements of Walden's standards, this was a Walden doctoral study which required the approval of the Institutional Review Board (IRB) to fulfill all the requirements of Walden University. As a researcher, the ethics of confidentiality and data security are important. To alleviate research bias, only data gathered from a public database was used for this study.

Permission

The 2015 HCUP NRD is a public database; therefore, there was not direct contact with participants in this study. Permission to obtain and use this data was obtained after completion of the HCUP Data Use Agreement Training Course. Before data collection can begin on a project, the IRB must review and approve the methods and procedures that will be used. Prior to implementation of this practice change, appropriate knowledge and training regarding human research subject matter protections, ethical conduct of research, applicable regulations.

Summary

This section presented the methodology of the quantitative study. The description about population, sampling, design, and rationale for data collection and analysis were described. Section 3 will provide the interpretation of the results of the data, results, and findings, and summarize answers to the RQs.

Section 3: Presentation of the Results and Findings

Introduction

In Section 3, I will review the data collection and statistical analysis of the secondary data discussed in Section 2. The objective of the research study was to determine whether there was a correlation between 30-day readmission rates among patients whose primary or secondary reason for admission was T2DM, while controlling for multiple covariates. I calculated and analyzed a number of descriptive and inferential statistics, including the frequency, standard deviation, average, percentage, mean, mode, sum, and differences of the participants.

I retrieved participants from the HCUP nationwide readmissions database of the 2015 NRD, which is an extensive, publicly available inpatient database containing data on over 7,000,000 hospital stays in the United States (HCUP, 2015). Logistic regression was the primary analysis employed for this research. The RQs and hypotheses for this study were,

RQ1. What is the relationship, if any, between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally?

$H_0 1$. No statistically significant relationship exists between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally.

H_A2. A statistically significant relationship exists between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally.

RQ2. Do sociodemographic factors like age, gender, and income moderate the relationship between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally?

H_02. Sociodemographic factors like age, gender, and income do not moderate the relationship between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and hospital 30-day rates among individuals whose primary or secondary reason for admission was T2DM nationally.

H_A2. Sociodemographic factors like age, gender, and income moderate the relationship between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally.

Data Collection of Secondary Data Sets

I filtered the available raw data of the NRD database to review the study variables for the doctoral study. The initial sample size for the secondary data set comprised over 500,000 cases for 2013, 2014, and 2015. All three years were reviewed. I focused on the most current year of the 2015 NRD dataset, which resulted in a sample size of 41,068. The data set was filtered to include age, gender, income, diagnosis, and insurance payer status. Participants in the data set included 41,068 patients with T2DM. The age range of the participants was 20 to 90 years old.

Results

A binary logistic regression was the analysis to test the contributions of primary payer status (i.e., Medicare, Medicaid, uninsured, or private insurance) in predicting the likelihood that respondents, with diabetes without complications, would be readmitted within 30 days. With the dependent variable being dichotomous, logistic regression was the appropriate statistical analysis because it permitted the examination of the odds of membership in one of the two outcome groups (i.e., under 30 days, more than 31 days). The $\chi 2$ omnibus test of model coefficients was used to assess whether adding the independent variables significantly increased the ability to predict hours per week worked. Additionally, I used the Nagelkerke R2 to assess the percentage of variance accounted for by the independent variables. Finally, the predicted probabilities of an event occurring were determined by examining the odds ratio. Preliminary analyses of the data set were conducted to observe whether the assumptions of logistic regression were met.

Participants

Participants in the data set included 41,856 diabetes patients. The largest income bracket was those in the $1-$41,999 range (34.1%). A majority (53.7%) were female, and the largest age group was those who were 60 years of age and older (N = 30,309). Most participants used Medicare (68.4%). For the additional analysis, the majority of the sample identified had diabetes with complications (61.7%). The frequencies are presented in Table 2.

Table 2

Demographic Frequencies

Variables	Categories	*N*	%
Income	$1-41,999	14,288	34.1
	42,000-51,999	10,382	24.8
	52,000-67,999	9,499	22.7
	68,000 and higher	7,072	16.9
Payment status	Medicare	27,906	68.4
	Medicaid	5,419	13.3
	Private Insurance	6,593	16.2
	No Insurance	843	2.07
Gender	Male	19,397	46.3
	Female	22,517	53.7
Age brackets	20-29	741	1.77
	30-39	1,513	3.61
	40-49	2,986	7.12
	50-59	6,365	15.19
	60 and older	30,309	72.31

RQ1 and its corresponding hypotheses were as follows:

RQ1. What is the relationship, if any, between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally?

$H_0$1. No statistically significant relationship exists between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally.

H_A1. A statistically significant relationship exists between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally.

First, I examined the assumptions. The multicollinearity tolerance values for the independent values ranged from 1.73 to 8.90, which lies between the 1-10 range; therefore, multicollinearity was not present (see Hair, Anderson, Tatham, & Black, 1995). Next, an inspection of the data (see Table 1) confirmed that the ratio of cases to variables was adequate. Finally, the Hosmer and Lemeshow Goodness-of-Fit test was conducted to test the null hypothesis that the data fit the specified model, $\chi 2(3) = 0.001$, $p = 1.00$, and the test was not statistically significant; therefore, a non-statistical result indicated that the data indeed fit the specified model. As a result, the null hypothesis was retained.

Medicare and those without insurance were significant predictors of being readmitted within 30 days. Those with Medicaid (95% CI: 0.76 – 0.92; p = .001) had a 45.76% probability of being re-admitted within 30 days while those with no insurance (95% CI: 0.76 – 0.94; $p = .002$) also had a 45.76% probability of being re-admitted within 30 days. The overall model was statistically significant $\chi 2(4) = 40.95$, $p = 0.001$. Additionally, the four independent variables explained only 1% (Nagelkerke R2) of the variance for the probability of being re-admitted and correctly classified 71.8% of the cases. As a result, for $H_0 1$, the null hypothesis was rejected, and the alternative hypothesis was accepted. The results are presented in Table 3.

Table 3

Logistic Regression Analysis of Hospital Readmission with OR, 95% CI, Wald and P Values (N = 41,856)

	OR	95% CI		Wald	*P*
Variables		Lower	Upper		
Medicare	1.25	1.10	1.43	11.63	0.001
Medicaid	1.16	1.01	1.33	4.22	0.040
Private Insurance	1.05	0.92	1.21	0.51	0.474
No Insurance	1.22	1.00	1.48	3.77	0.052
Constant	2.22			135.90	0.001

Research Question 1

For the first RQ, a binary logistic regression was the statistical analysis to examine which independent variables were significant in predicting 30-day readmission. Readmission analyses often consider the time between the end of one admission and the start on the next admission, where the number of days between the beginning of each entry was coded '0' for readmission within 30 days or less and '1' for re-entry over 31 days. To calculate this date, the verified patient linkage (i.e., NRD-visitLink) variable was used.

The NRD-visitLink variable is a data element created for the Nationwide Readmissions Database to track patients across hospitals in a year. For this dataset, if a patient had more than two rows of data, then they were readmitted. Data were transposed on the patient linkage variable, and the number of days between each admission was calculated. The frequency of those being admitted within 30 days was 28.1% (N = 11,884) compared to those who were not (N = 30,344). For RQ2, a hierarchal logistic regression was the statistical procedure to examine which demographic variables were significant in moderating the 30-day readmission rate.

Research Question 2

RQ2. Do sociodemographic factors like age, gender, and income moderate the relationship between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally?

$H_0$2. Sociodemographic factors like age, gender, and income do not moderate the relationship between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and hospital 30-day rates among individuals whose primary or secondary reason for admission was T2DM nationally.

$H_1$2. Sociodemographic factors like age, gender, and income moderate the relationship between primary payer status (Medicare, Medicaid, uninsured, or private insurance) and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally.

A hierarchal binary logistic regression was the statistical analysis to test the contributions of primary payer status (i.e., Medicare, Medicaid, uninsured, private insurance) along with the moderating variables of age, gender, income in predicting the likelihood that respondents, with diabetes without complications, would be readmitted within 30 days. Age was treated as a continuous variable, while gender and income were dummy coded. First, the assumptions were examined. The multicollinearity tolerance values for the independent values ranged from 1.01 to 9.35, which lies between the 1-10 range; therefore, multicollinearity is not present (Hair et al., 1995).

Next, an inspection of the data (See Table 1), confirmed that the ratio of cases to variables was adequate. The Hosmer and Lemeshow Goodness-of-Fit test was conducted to test the null hypothesis that the data fit the specified models for model 1, $\chi 2(8) = 12.681$, $p = .123$, and for model 2 $\chi 2(8) = 6.573$, $p = .583$. Both tests for models 1 and 2 were not statistically significant; therefore, a non-statistical result indicated that the data does indeed fit the specified model. As a result, the null hypothesis was retained.

The first model (i.e., step one), which only considered the socioeconomic variables, was significant $\chi 2(5) = 33.18$, $p = .001$. Both gender and age were significant predictors of being readmitted within 30 days. Females had a .91 (95% CI: 0.87 – 0.95) times higher odds of being readmitted within 30 days, compared to males. Additionally, as age increased by one unit, the odds increased by 1.00 (95% CI: 1.00 – 1.00). Overall, model one correctly classified 71.9% of the cases. The second model, which took the socioeconomic variables and the payment methods, was also significant $\chi 2(9) = 64.26$ $p = .001$.

In this model, gender was the only socioeconomic variable to moderate readmission status. Females had a .91 (95% CI: 0.87 – 0.95) times higher odds of being readmitted within 30 days, compared to males. Additionally, Medicare was a significant predictor of being readmitted where those with Medicare were .80 (95%

CI: 0.87 – 0.95) times higher odds of being readmitted. Model two correctly classified 71.9% of the cases and explained less than 2% of the variance. As a result, for H02, the null hypothesis was rejected, and the alternative hypothesis was accepted. The results are presented in Table 4.

Table 4

Hierarchical Logistic Regression Analysis of Hospital Readmission with OR, 95% CI, Wald, and P Values (N = 41,856)

	OR	95% CI		Wald	*P*
Variable		Lower	Upper		
		Model 1			
Female	1.11	1.07	1.16	23.72	0.001
Ages 20-29	0.91	0.77	1.07	1.32	0.250
Ages 30-39	0.74	0.67	0.83	27.36	0.001
Ages 40-49	0.99	0.91	1.08	0.06	0.813
Ages 50-59	1.00	0.94	1.06	0.03	0.868
Income 1 - 41,999	1.04	0.98	1.11	1.71	0.191
Income 42,000 - 51,999	1.04	0.97	1.11	1.26	0.261
Income 52,000 - 67,999	0.97	0.90	1.03	0.99	0.320
Constant*	2.41			907.71	0.001
		Model 2			
Female	1.11	1.06	1.16	20.72	0.001
Ages 20-29	1.00	0.84	1.18	0.00	0.967
Ages 30-39	0.81	0.72	0.91	12.45	0.001
Ages 40-49	1.07	0.98	1.17	2.00	0.157
Ages 50-59	1.08	1.01	1.15	4.37	0.037
Income 1 - 41,999	1.04	0.97	1.10	1.14	0.287
Income 42,000 - 51,999	1.04	0.97	1.11	0.98	0.323
Income 52,000 - 67,999	0.97	0.90	1.04	0.93	0.336
Medicare	1.25	1.09	1.43	10.57	0.001
Medicaid	1.13	0.98	1.30	2.59	0.107
Private Insurance	1.05	0.91	1.20	0.40	0.528
No Insurance	1.19	0.98	1.46	3.02	0.083
Constant*	1.99			91.50	0.001

The reference group contains male participants in the 60 and over age range and those with an income of $68,000 more.

Additional Analysis

For both RQs, I only analyzed patients who had diabetes without complications; however, I was interested in whether there was a significant difference between those with (*N* = 62,627) and without complications (*N* = 41,184) regarding readmitted status. Those who had diabetes with without complications were coded as '0' and those with diabetes with complications were coded as '1.' The logistic regression results revealed a significant relationship $\chi 2(1) = 200.07$, $p = 0.001$ and correctly identified 74.2% of the cases. Those with complications (95% *CI*: 1.19 – 1.26; $p = .001$) had a 75.7% predicted probability of being re-admitted within 30 days while those who did not have complications had only a 71.83% probability of being admitted within 30 days. This model explained approximately 1% of the variance. The results are presented in Table 5.

Table 5

Logistic Regression Analysis of Hospital Readmission with OR, 95% CI, Wald, and P values (N = 103,811)

	OR	95% CI		Wald	*p*
Variable		Lower	Upper		
With Complications	1.22	1.19	1.26	201.14	0.001
Constant	2.55			7431.22	0.001

Summary

In this section I used a descriptive analysis to summarize the variables and measurements within the research study, utilizing a quantitative analysis. The Hosmer and Lemeshow Goodness-of-Fit test was conducted to test the null hypothesis to ensure that the data fit the specified models for both RQs. The objective of the binary logistic regression was to establish which variables correlated to the 30-day readmission rate for patients with diabetes and determine the odds ratio, 95% confidence interval, and the statistical significance of each variable.

Participants in the data set included 41,068 diabetes patients. The largest income bracket was those in the \$1 - \$41,999 range (34.1%). A majority (53.8%) were female, and the age range of all participants was grouped between 20-29, 30-39, 40-49, 50-59, and 60- 90 years old (M = 67.26, SD = 15.68). Most participants used Medicare (67.9%). For the additional analysis, the majority of the sample identified had diabetes with complications (62.1%).

The null hypothesis for RQ1 was retained. No statistically significant relationship existed between insurance primary payer status (Medicare, Medicaid, uninsured, or private insurance) and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally. It was observed that possession of Medicare and lack of insurance was significant predictors of being readmitted within 30 days.

The null hypothesis was also retained for RQ2. Sociodemographic factors like age, gender, and income did not moderate the relationship between insurance primary payer status like Medicare, Medicaid, uninsured, or private insurance) and 30-day hospital readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally. When controlling for gender, females had a .91 (95% CI: 0.87 – 0.95) times higher odds of being readmitted within 30 days, compared to males.

The evidence collected and the data analyzed during this quality improvement project added benefit to the advancement of research in this area. In the next section I will expand on the findings, implications, and recommendations relating to the objective of the research study were to determine whether there was a correlation between 30-day readmission rates among patients whose primary or secondary reason for admission was T2DM (i.e., diabetes) while controlling for multiple covariates as listed in the RQs.

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

Introduction

In this chapter, I will further discuss the study findings and present recommendations formulated as an outcome of the research study. Hospital readmission within 30 days of discharge is a significant topic of health care reform in the United States. Reforms can include implementing protocols prior to discharge that may prevent possible readmissions and possibly reduce the cost to both the facility and the patient. A facility's 30-day readmission rate encompasses all unplanned readmissions that occur within 30 days of discharge regardless of the cause (CMS, 2013). The risk index includes patients who are readmitted to the same hospital or another acute care hospital for any reason regardless of their primary diagnosis (CMS, 2013). The measures do not include planned readmissions. Currently, CMS measures hospital performance in the HRRP by calculating ERRs for each of the program measures.

The quantitative cross-sectional study looked at patients who experienced 30-day readmissions to hospitals nationally in 2015 for a primary or secondary reason of T2DM. Logistic regression was used to analyze data to find a correlation between the independent variables of primary payer status (Medicare, Medicaid, uninsured, or private insurance) and the dependent variable of hospital readmission rate. Results of logistic regression analysis showed that possession of Medicare and lack of insurance were significant predictors of being readmitted within 30 days. Women had higher odds of being readmitted within 30 days compared to men.

Interpretation of the Findings

Findings from this quantitative research study revealed that the largest income bracket was \$1-\$41,999 range (34.1%), that majority of the participants (53.8%) were female, and that the age range of all participants was between 20-90 years old (M = 67.26, SD = 15.68). Most participants had Medicare (67.9%). An additional analysis revealed that much of the sample identified had diabetes with complications (62.1%). The data analysis showed there was no statistically significant relationship between primary payer status and 30-day readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally. Participants with Medicare and those without insurance were significant predictors of being readmitted within 30 days. Sociodemographic factors like age, gender, and income do not moderate the relationship between primary payer status and 30-day hospital readmission rates among individuals whose primary or secondary reason for admission was T2DM nationally. Women had higher odds of being readmitted within 30 days compared to men. These findings implied that the control health systems have achieved substantial improvements in readmission rates among patients with T2DM is limited. More work is needed to distinguish the expected impact of intrinsic hospital traits versus quality improvement strategy implementation particularly when considering how costly implementation of strategies can be in a resource-limited environment (Bennett, et al., 2020).

Limitations of the Study

This doctoral research study was subject to some limitations. One very significant limitation was the use of the HCUP NRD (2015), which is a very large public data set.

When using large data sets, researchers often face issues with accuracy (Smith, et al., 2011). The source of the data input for the NRD came from a host of state-level affiliates. Even though the NRD strives for consistency of its affiliates, the consistency of the submission often comes with challenges such lack of control over variables and data. Large sample sizes may introduce bias, like errors in measurements, errors in sampling, and systematic omission of essential information (Kaplan, Chambers, & Glasgow, 2014). Current literature also identifies the limits of administrative data (Harron, et al., 2017). It is important that the data collection and the data analysis are consistent and/or in alignment when using large data sets. This is not always the case. The difficulty in the coding process and the expertise of the coders can also adversely affect the results of the study. The impacts cannot be regulated or measured by the researcher, which is also a limitation. Regardless of these limitations, I believe that this research should be deemed original and indicative of the need for more meaningful research to be performed.

Recommendations

Patient education and care transitions are important in the reduction rate of 30-day readmission rate for patients with T2DM. The present study's time frame (FY2015) was 3 years after implementation of the HRRP in (2012), so the present results should be at least somewhat indicative and representative of projected outcomes of the HRRP, after adequate implementations have taken place. A mixed-methods study on comorbidities should also be conducted to see what role or if any percentage of underlying health conditions are involved in the 30-day readmission rate of patients with T2DM. Hospital administrators should conduct both internal and external surveys. The survey results may help connect hospital performance measures with the 30-day readmission rate. The prime objective of administrators and personnel within hospitals is to provide impeccable service to patients (Loria, 2018). Findings suggest that administrators and personnel should continue their efforts to improve services. Internal surveying could also help shape the climate and effectiveness of the working environment.

Implications for Professional Practice and Social Change

Methodological, Theoretical, and Empirical Implications

I used a quantitative design as this was the most appropriate research design for studying the 30-day readmission rate for patients with T2DM and insurance payer status and sociodemographic status of patients with T2DM. A statistical analysis was performed for the HCUP NRD (2015). Income, insurance payer status, age, and gender were the variables used to collect data. These variables were properly used for testing as they met the qualifications and conditions for statistical analysis as it related to the research (see Section 3). I did not find a significant predictor model. The results may therefore offer limited applications for professional practice.

The conceptual framework used in this quantitative research study was the Donabedian framework (Ayanian & Markel, 2016). Healthcare facilities may use the model to exam health services and evaluate the quality of healthcare (Ayanian & Markel, 2016). A hospital administrator can utilize the concepts of the Donabedian model to develop strategies and programs that may help the organization and the community reduce the rate of 30-day readmissions for patients with T2DM.

Positive Social Change

Evidence from this research may create positive changes by informing administrators, healthcare professionals, and hospital leaders regarding the importance of providing resources for patients with T2DM. Findings from the study may specifically lead to positive social change by informing health care providers and administrators regarding whether there is a correlation between health insurance payers and readmission rates of patients with T2DM. Healthcare providers and leaders can create programs to ensure that all patients with a primary or secondary diagnosis of diabetes receive appropriate care and education to reduce readmissions, improve health outcomes, and improve quality of life for this patient population, which may result in significant financial savings for patients and healthcare facilities.

Administrators can potentially use the findings of the study to decrease hospital readmission rates of patients with T2DM by providing thorough after-care instruction for the lay person. According to experts, providers should encourage follow-up care with primary care physician at least a week after discharge for T2DM treatment (Loria, 2018). The hospital and the patient must work as a team to reduce hospital readmissions and costs to both the hospital and the patient (Loria, 2018).

Conclusion

Thirty-day hospital readmission rates are an important performance indicator for hospitals in the United States (Gerhardt et al., 2012). The government put policies such as HRRP in place to encourage hospitals to find strategies to reduce excessive readmission rates. At the time of this study, these policies have been somewhat effective in achieving their specified goal (Ferro, et al., 2019). Current regulations indicate that the hospital is the primary stakeholder in the healthcare equation in decreasing 30-day readmission rates. However, this study showed that hospitals can affect only a small proportion of readmission rates. The current policy does not take into consideration many of the readmission-driving factors that are not modifiable by the hospital in its readmission rate calculations despite recognition of these factors by key policy makers study.

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Appendix: Literature Review Matrix

Literature Matrix

Study Authors	Sample	Variables	Type of study	Outcomes
Alavi, Baharlooei, & AdelMehraban, 2017	150	DV- Readmission Rate IV-gender, marital status, education, income, age, depression, anxiety, stress, and social support	Cross-sectional analysis	Programs to improve mental health of the elderly and development of social support network are suggested to help reduce the risk of readmission among diabetic elderly patients. More studies are needed to facilitate this change
Assari, Moghani Lankarani, Piette, & Aikens, 2017 Looked at socioeconomic status (SES) and HbA1c levels of black and white, male and female participants, to attempt to find a correlation between SES status and HbA1c.	112	DV-SES IV- HbA1c, sex, race	Cross-sectional analysis	SES has a greater effect on black males with diabetes. Due to the small sample population of the study, more research is needed

Bird, Lemstra, Rogers, & Moraros, 2015 Analyzed data from four cycles of the Canadian Community Health Survey to determine the adjusted and unadjusted effects on income of patient with Type 2 diabetes	27,090		Cross-sectional population based study	Income was closely and independently associated with Type 2 diabetes
Busby et al., 2015 A systematic review of the scale and reason of geographical differences in unplanned hospital admission rates & length of stay for ambulatory care	43,819	DV – LOS IV – Admission rates	Cross-sectional analysis	Differences in admission rate fewer admission causing shorter LOS
Comino et al., 2015 Looked at individual patient characteristics and hospital-level factors affecting the length of stay and total cost of hospitalization	162 Counties 6 states	DV-Inpatient cost IV- Geographical location	Multivariate analysis Linear regression	Prices are significantly higher for private vs. Medicare. Payment policies from Medicare affect private payers. Public policy that takes into consideration the market-based approach or payment reform to reduce price variation

Everett & Mathioudakis, 2019 Looked at the readmission rate of patients with Diabetic Ketoacidosis (DKA) while primarily focusing on the socioeconomic indicator of the patients	181 284 DKA admissions	DV- Socioeconomic status IV- Readmission rate DKA	Cross- sectional analysis	Lower socioeconomic status and government insurance are strong predictors of DKA readmissions in adults with type 1 diabetes in the USA.
Qureshi, Adil, Zacharatos & Suri 2013 Identified the factors of prolonged hospitalization while concurrently trying to determine the effect of hospital charges	385	DV- Length of stay IV-Hospital charges	Multivariate analysis	More studies are needed to determine what can lead to the reduction of length of stay
Raval, et al., 2015) Looked at the 30-Day Readmission Among Elderly Medicare Beneficiaries with Type 2 Diabetes	202,496 elderly Medicare recipients with Type 2 DM	DV-Readmission days IV-Demographics, insurance, hospitalization index, clinical characteristics elderly specific complexities, i.e. fall risk cognitive impairments, urinary incontinence	Multivariable logistic regression	Intervention programs to reduce the risk of readmissions among elderly patients with T2DM might need to be tailored to suit the needs of elderly patients

Rubin, Sherita, McDonnell, & Zhoa, 2017 Looked at medical records of the patients from Boston Medical Center that were discharged been January 2004 and December 2012 to develop a tool Diabetes Early Readmission Risk Indicator CVA (DEERI™-CVD) that predicts 30-d readmission risk for diabetic patient's hospitalized for cardiovascular disease	8189 electronic medical records	DV-CVA patients IV-Education level, employment, pre- admission diabetes, diabetes complications, creatinine and bun levels at admissions, recent hospital discharge	Multivariable logistic regression analysis	The DEERI™-CVD may be a useful tool in predicting the cause of 30-d readmission patients with diabetes hospitalized for CVD. This tool can help with lowering healthcare cause by identifying patients that are high risk and targeting those patients for better healthcare outcomes
Sonmez, Kambo, Avtanksi, Lutsky, & Poretsky, 2017 Compared the readmission rate for patients with the secondary diagnosis of diabetes, while also looking at the association between the length of stay and readmission rates in patients with diabetes and those without	102,694 16,266 with diabetes	DV- Readmission rate with/without diabetes IV- Length of stay, sex, age, secondary diagnosis diabetes, primary diagnosis diabetes	Logistic regression analysis	30-day readmission rates are higher in patients with DM compared to patients without DM regardless of age and gender; readmission rates are significantly higher in male patients and patients greater than 65 years old.