ABSTRACT

Predictors of 30-, 60-, and 90-day All-Cause Hospital Readmission in a Socioeconomically Disadvantaged Population: a Retrospective Secondary Data Analysis

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Hospital readmissions are a significant and preventable source of healthcare cost in the United States. The Affordable Care Act (ACA) aims to reduce readmissions by penalizing institutions with excessive 30-day readmission rates. Hospitals serving socioeconomically disadvantaged populations have been shown to be at an increased risk of incurring penalties under these provisions. Early identification of patients at risk of early readmission may help reduce excessive readmission rates. This study examines variables predictive of early readmission in a population of low socioeconomic status. Age, sex, ethnicity, smoking status, blood pressure, body temperature, pulse rate, and days to follow up visit were analyzed in a sample of 2,536 patients at or below 200% of federal poverty guidelines in Central Texas to determine association with risk of readmission at 30, 60, and 90 days. Pulse rate was found to be predictive of 30-, 60-, and 90-day readmission. Increased follow-up time was associated with decreased risk of readmission in all readmission groups, and passive smoking status was associated with decreased risk of 90-day readmission. Results offer tools for at-risk patient identification in a disadvantaged population and suggest further investigation of clinical variables as predictors of readmission risk.

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PREDICTORS OF 30-, 60-, AND 90-DAY ALL-CAUSE READMISSION IN A SOCIOECONOMICALLY DISADVANTAGED POPULATION: A RETROSPECTIVE SECONDARY DATA ANALYSIS

A Thesis Submitted to the Faculty of

Baylor University

In Partial Fulfillment of the Requirements for the

Honors Program

By

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Waco, Texas

May, 2015

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ACKNOWLEDGMENTS

There are numerous people whose guidance and assistance have made this project possible. Dr. Rodney Bowden, the mentor and guide of this work, has been an invaluable source of insight, correction, and wisdom–both academic and otherwise–throughout the duration of this project. Dr. Grant Morgan has graciously provided a good deal of much appreciated support in the analysis and interpretation of the data presented in the following pages. Dr. Ron Wilson, who together with Dr. Bowden and Dr. Morgan served on the thesis defense committee, also very generously offered his time and assistance in the completion of this project. This thesis would not have been possible without the previous work of Stephanie Clendennen, whose initial work on this topic laid much of the foundation for the current work. Gratitude is also due to Dr. Jackson Griggs and the numerous other physicians of the Family Health Center who allowed for the collection of the data that made this project possible. Finally, Dr. Al Beck and the Baylor University Honors College have been unbelievably helpful in their support of the completion of this thesis. To these and the many others who have provided encouragement and friendship throughout this process, thank you.

To my father,

who taught me that education

is far more important than school

CHAPTER ONE

Introduction

The Affordable Care Act

In 2010, the United States faced a healthcare climate characterized by increasing cost of care and extensive insurance coverage gaps. During the 18 year period between 1990 and 2008, national spending on healthcare had increase by an average of 7.2% annually[1]. Additionally, by the year 2010, 18% of United States residents under the age of 65 lacked any form of health insurance[2]. In an effort to lower the cost of care, decrease existing coverage gaps, and increase overall quality of care, members of congress passed the Patient Protection and Affordable Care Act and the Health Care Education and Reconciliation Act, more commonly known together as the Affordable Care Act (ACA). On March 23, 2010, President Barack Obama signed into law the ACA and ushered into the United States a new era of healthcare policy. While there has since been considerably mixed reaction to the legislation within both the fields of Medicine and Politics[3,4], it is impossible to deny the significance of the ACA as it concerns the provision of healthcare in the United States. It is thus necessary for care providers to understand the implications of the ACA and to evaluate current methods of care delivery in order to enhance the efficiency of care in accordance with current legislative policy.

Costliness of Hospital Readmissions

One area that has served as a focus for the aim of the ACA to lower costs and improve the quality of healthcare delivery has been that of unnecessary hospital readmissions. It has long been postulated that hospital readmissions represent a significant source of unnecessary costs in healthcare provision[5]. One report estimates that nearly $17.5 billion are spent annually on hospital readmissions in the United States, with $12 billion of those costs being potentially preventable[6]. Hospital readmissions not only represent a significant financial burden to healthcare institutions, but may also be indicative of decreased quality of care prior to initial hospital discharge. While certain readmissions are unavoidable or even planned, excessive unforeseen hospital readmissions are increasingly coming to be seen as an indicator of the quality of care provided by institutions[7]. Because of the potential of excessive hospital readmissions to serve as a quality metric for healthcare institutions, the ACA provides legislation specifically designed to reduce the level of unnecessary hospital readmissions.

The Hospital Readmissions Reduction Program

Section 3025 of the Affordable Care Act establishes the Hospital Readmissions Reduction Program (HRRP) as a means of decreasing the number of avoidable patient readmissions at institutions and thus improving overall quality of care. Under the initial provisions of the HRRP, which were first applied to the 2013 fiscal year, the Center for Medicare and Medicaid Services (CMS) monitored the 30-day readmission rate for Medicare patients discharged with a diagnosis of acute myocardial infarction (AMI), heart failure (HF), and pneumonia (PN). The number of 30-day all-cause readmissions for each hospital receiving Medicare payments was then entered into an algorithm to compute that hospitals excess readmissions ratio. Hospitals whose readmissions ratios fell above acceptable limits set by the federal government were subject to penalization of up to 1% of Medicare payments from the CMS[8]. For the 2015 fiscal year, the HRRP has been updated to include in readmission counts Medicare patients diagnosed with chronic obstructive pulmonary disease (COPD), total knee arthroplasty (TKA), and total hip arthroplasty (THA), in addition to those patients outlined in the 2013 HRRP guidelines. Furthermore, the penalty cap for hospitals experiencing excessive readmissions was raised for the 2015 fiscal year to 3% of Medicare payments[9,10]. In light of the expanding patient groups counting towards hospital readmission rates and the escalating penalties associated with elevated readmissions, it is becoming increasingly pertinent for healthcare institutions to develop methods of minimizing avoidable hospital readmissions.

At-Risk Patient Identification as a Cost-Efficient Reduction Method

It is important in the development of strategies designed to mitigate excessive hospital readmission costs to pursue cost-efficient methods. As Postel et al. note in their 2014 study, models that decrease readmissions but cost more to implement than the maximum Medicare payment penalty incurred by a hospital will result in a net loss of profit for that institution[11]. While such costly programs might improve overall quality of care before discharge, it would certainly be difficult to encourage healthcare institutions to adopt methods of readmission reduction that would ultimately provide no financial benefit. If the measures instituted by the HRRP are to promote the increased quality of patient care then avenues of cost-efficient reduction of hospital readmission rates must be developed.

One strategy that holds potential for allowing for a cost-efficient reduction of readmission rates is the early identification of patients with an elevated risk of hospital readmission. Numerous published articles have commented on the potential benefit of using readily available clinical and demographic data to identify at-risk patients and thus decrease the risk of eventual readmission[12–14]. Identification of patients at a high risk for readmission can allow health care providers to work closely with such patients to improve quality of care and discharge strategy and thus reduce the overall cost of care and the likelihood of an unforeseen readmission. Additionally, a number of the clinical and demographic variables that have been examined as predictors of readmission are already routinely measured at the hospital. The use of readily collected variables to identify at-risk patients thus holds significant potential as a low-cost method of reducing avoidable readmissions.

Predictive Value of Certain Variables is Unclear

While the potential of readily collected demographic and clinical data to identify patients at risk for readmission is widely commented upon within the body of scientific literature, there yet exists uncertainty about the exact predictive value of many variables. Of particular interest to past studies have been the demographic variables of low socioeconomic status[13,15,16], race[14,17–23], age[14,17,19–21,24,25], sex[14,17,19–21,26], and smoking status[19,27–30] Clinical variables have also been explored to an extent, and include blood pressure[14,19,31,32], heart rate[14,31,32], body mass index (BMI)[17,33], and body temperature[31]. Additionally, some research has been conducted concerning the effect of decreasing the number of days before a follow up visit on patient readmission rates[34]. While the demographic, clinical, and administrative variables listed here have shown varying levels of potential to serve as markers for elevated risk of hospital readmission, the results presented in published studies for each of these variables have been largely equivocal to date. A detailed examination of these results will be presented in the second chapter of this work. Given the cost efficiency of collecting demographic and clinical variables and the as yet uncertain ability of these variables to identify patients at risk for readmission, further exploration of easily obtained clinical and demographic values as predictors of hospital readmission has become increasingly necessary.

Readmission Rates among Socioeconomically Disadvantaged Populations

Of significant importance to the response by healthcare institutions to the measures instituted by the HRRP is the development of strategies that reduce readmissions within low-income, socioeconomically disadvantaged populations. It has been widely documented that the CMS penalties imposed under the HRRP have greater effects on "safety net" hospitals that provide care to large numbers of low-income, uninsured or underinsured patients[18,22]. An economic analysis by Fuller et al. indicates that the algorithm used by the CMS to calculate payment penalty incurred by hospitals unfairly penalizes hospitals serving disadvantaged populations and calls for restructuring of the current penalty calculation to account for safety net institutions[4]. As payment penalties affect to a greater extent those hospitals providing care to low-income populations it has become of increasing importance to identify predictive variables indicating an elevated risk of hospital readmissions within these patient populations. The need to develop and evaluate models of predicting readmission risk within disadvantaged populations has become even more relevant with the 2015 revisions to the HRRP, as multiple studies have remarked that the inclusion of COPD patients in hospital readmission rates will only further affect safety net institutions[35,36]. As the penalties placed upon institutions serving high numbers of low-income patients increase, methods of identifying patients at an elevated risk for hospital readmission within socioeconomically disadvantaged populations must be developed.

Purpose of Study

The current study was undertaken to explore clinical and demographic variables predictive of 30-day and 60-day all-cause readmission in a low-income, socioeconomically disadvantaged patient population. A retrospective secondary data analysis was performed on 2,536 patients receiving care from the Family Health Center (FHC) of Central Texas. The FHC serves patients living at or below 200% of the federal poverty guidelines. Approximately two-thirds of the patient population of the FHC consists of racial and ethnic minority patients. The sample taken for this study included patients receiving care from the FHC who had experienced a hospitalization within the last 7 years. The study was aimed at providing further elucidation of the effectiveness of the variables of age, sex, race, smoking status, blood pressure, BMI, body temperature, pulse, and days to follow up visit as predictors for all-cause hospital readmissions within 30 or 60 days of discharge. A detailed description of the methodology of the study will be provided in the third chapter of this work.

CHAPTER TWO

Literature Review

Introduction

The introduction of the Affordable Care Act (ACA) and the Hospital Readmissions Reduction Program (HRRP) in 2010 ushered in a renewed focus on avoidable hospital readmissions as an area of potential cost reduction and quality improvement. The HRRP seeks to improve the quality of care by penalizing hospitals whose readmission rates fall above limits set forth for each institution by an algorithm created by the Center for Medicare and Medicaid Services (CMS)[8]. It has long been speculated that excessive hospital readmissions represent an unnecessary and costly area of health care[5]. Furthermore, it is reported that reducing excessive readmissions may serve as a productive target area in the improvement of quality of care[7].

In an effort to address excessive readmission rates, the HRRP established reductions to Medicare payments to institutions with higher than expected readmissions. Patients currently considered in the calculation of institutional readmission rates include those diagnosed with myocardial infarction (MI), pneumonia (PN), heart failure (HF), total knee replacement (TKA), total hip replacement (THA), and chronic obstructive pulmonary disease (COPD) who experience a readmission within 30 days to any institution for any reason. The HRRP Final Rule for the 2015 Fiscal year sets the maximum penalty levied against institutions with excessive readmission rates at 3% of Medicare reimbursements[9]. In light of these recent developments in health care policy, hospitals have encountered an increasing need to discover viable models that can help reduce readmission rates.

One method of reducing avoidable readmissions involves the early identification of patients at an elevated risk of hospital readmission[12]. Recent literature has highlighted the growing need for multi-faceted prediction models that use both demographic and physiologic variables to predict those patients with a higher risk of readmission[37]. Such identification of patients may allow health care workers to more effectively design treatment and discharge plans that can improve quality of patient care and reduce the cost of care for the health care institution. Responding to the need to identify at-risk patients, recent literature has examined a number of variables potentially related to elevated rates of readmission. The following review presents both demographic and clinical variables that have been examined and comments on the potential for further study to expand the models available for reducing excessive readmission rates.

Socioeconomic Status

There exists in the literature equivocal findings for the use of socioeconomic status (SES) as a predictor of hospital readmissions. Although a variety of factors can be used to determine those patients with low socioeconomic status, the most common attributes of low SES patients reported in the literature are low income, limited education, and little or no employment. A number of published studies indicate that low SES has potential as a predictive tool of hospital readmissions. In a recent study of 1557 patients with heart failure, Bikdeli et al. found that hospitalized patients living in socioeconomically disadvantaged neighborhoods were significantly more likely to be readmitted to a hospital within six months than their economically stable peers[13].

Bernheim et al. likewise studied the effects of low SES on the readmission of patients diagnosed with acute myocardial infarction (AMI), reporting that low SES was indeed predictive of hospital readmission within one year[15]. Interestingly, while Bernheim et al. were able to explain increased mortality rates for low SES AMI patients on poor baseline clinical characteristics, they could offer no such correlation between baseline clinical characteristics and hospital readmission for low SES patients. The authors suggest that poor follow-up behavior by low SES patients may be responsible for the increased rate of readmission and indicate the need for further investigation into the connection between socioeconomic status and readmission risk.

In spite of the wide range of authors suggesting the importance of socioeconomic status in predicting hospital readmissions, there exists some published findings of the ineffectiveness of socioeconomic status as a predictor of elevated risk for readmission. A 2013 study by van Walraven et al. of over 40,000 patients found no significant relationship between low SES and all-cause readmissions within 30 days of discharge[38]. It should be noted of van Walraven's study that it occurred in Ontario, Canada, under a public health system. The authors indicate that this may very well affect the role played by socioeconomic status in health outcomes such as 30-day readmission, and highlight the importance of further study in health systems that are not publicly funded. In spite of the van Walraven study, a good deal of the research within the United States indicates that socioeconomically disadvantaged populations are at an increased risk of readmission to the hospital. This has become especially relevant with the recent addition of COPD to the list of diagnoses qualifying a patient to be counted in institutional readmission statistics. Shah et al. and Feemster et al. both indicate that the inclusion of COPD in readmission statistics will further increase the economic penalties experienced by hospitals serving primarily disadvantaged patients, as these patients are more likely to smoke and be affected by COPD[35,36]. The evidence in support of socioeconomic status as a predictor of increased readmissions and the recent inclusion of COPD patients in readmission rates underscores the increasing need to examine variables predictive of readmission in low socioeconomic status populations.

Race

A number of study authors have examined the relationship between race and risk of hospital readmission. Many of the findings suggest that race is an important predictor of elevated readmissions, with Black and Hispanic patients facing a higher risk of early readmission than their white counterparts[20,23]. A particularly important finding of previous studies is the effort of hospitals to reduce readmission rates reporting a connection between elevated readmissions and hospitals serving higher numbers of ethnic minority patients. Both McHugh et al. in 2010 and Tsai et al. in 2014 have reported that hospitals that primarily serve minority patients are at an increased risk for elevated readmission rates[18,22]. The authors of both studies express the need to examine further the potential of using race as a predictor of elevated risk of readmission.

While many study authors have reported a predictive relationship between race and hospital readmissions, there exists equivocal findings with previous studies in which race has not significantly predicted readmission rates[14,17,19,21]. Iloabuchi et al. specifically note that the inability of race to predict elevated readmission risk runs contrary to a good deal of previous literature. Examination of the study population of the Iloabuchi article, however, reveals that the percentage of ethnic minority patients is significantly higher than in other studies examining race. Because a large majority of patients involved in the Iloabuchi study were a racial minority, it may have been difficult to detect a statistical difference in minority and non-minority patients that yielded an odds ratio indicative of elevated readmission risk. Equivocal findings highlight the need for further investigation to ascertain the relationship between race and hospital readmission rates.

Age

The literature reports mixed findings on the relationship between patient age and risk of readmission. Multiple studies in the literature report finding that an analysis of age provided no ability to predict readmission rates[14,17,19,21,25]. As with their findings on race, Iloabuchi et al. expressed surprise at the inability of age to predict readmissions, and suggest further study to clarify the predictive ability of age.

Other studies have reported age as a viable predictor of hospital readmission. Navarro et al. reported in 2012 that higher age serves as a predictor of increased all-cause 30-day readmission[20]. Likewise, Fuller et al. in 2013 noted increased readmission rates with increasing age past the age of 65, with patients having a 10 percent greater risk of readmission at the age of 75, and a 20 percent greater risk at 85 years old[24]. As patients age, the number of health complications experienced tends to increase, leading to an increased risk of readmission. These findings contradict the results obtained by Iloabuchi, possibly again as a result of the patient population used in the Iloabuchi trial. The Iloabuchi study consisted of primarily minority patients living in socioeconomically disadvantaged conditions. Both of these factors predispose patients to experience elevated readmission risk, meaning that age could have been seen as a relatively less important predictor of readmission in Iloabuchi's analysis. Further investigation could prove very helpful in elucidating the as yet uncertain relationship between age and the risk of hospital readmission.

Sex

Findings regarding the use of sex in determining patient risk of early readmission have to this point been fairly equivocal. In their 2013 study of patients undergoing lower limb bypass surgery, McPhee et al. report that female gender is associated with adverse healing outcomes, including increased hospital readmission rates[19]. Conversely, Navarro et al. have reported in their 2012 study finding that male gender is predictive of all-cause readmission in Medicare-aged patients[20]. Neither McPhee nor Navarro offer any explanation as to the reasoning underlying the association of sex to increased readmission ratios. Krumholz et al. and Iloabuchi et al. yet present further studies that show no association between sex and increased readmission ratios[14,21]. Again, no venture is made within these studies to offer an explanation for the discrepancies between findings in the literature. Further study could prove helpful in elucidating the true relationship between sex and risk of early hospital readmission, especially within a disadvantaged patient population.

Smoking Status

Past studies have provided mixed evidence regarding the effects of smoking on hospital readmission, as well. In the study by McPhee et al. on patients undergoing lower limb bypass surgery, current smoking status was found to be predictive of elevated rates of hospital readmission[19]. Likewise, a 2013 study by Mlodinow et al. of patients experiencing breast reconstruction found that current smokers experienced elevated risk of hospital readmission within 30 days of discharge[27]. Conversely, Beaulieu et al., Rambachan et al., and Sales et al. have all reported no relationship between smoking status and risk of early readmission[28–30]. Studies presenting evidence for smoking status as a predictor of readmission cite the well-known complications that smoking provides to wound healing. It is also well accepted that smoking is related with elevated morbidity[39]. Complications arising from delayed wound healing and smoking-related comorbidities could very likely put a patient at increased risk of readmission to the hospital after discharge. Studies that did not find an association between smoking status and readmission did not report potential reasons for these findings, but each of the studies indicated that smoking status was self-reported. It has been reported that patients tend to underreport smoking status[40,41], thus falsely low frequencies of current smokers within the studies could have possibly led to the conclusion that smoking was not associated with readmission. Continued study on the effects of smoking on readmission must be conducted to further understand the relationship between smoking status and all-cause readmission.

Blood Pressure

The use of blood pressure as an indicator for elevated risk of readmission may hold some promise. In a 2012 study of patients who had spent time in the ICU, Fialho et al. found that elevated blood pressure served as one of a number of physiological variables predicting elevated ICU readmission rates[31]. Eapen et al. likewise found a relationship between blood pressure and readmission rate in their 2012 investigation; yet, the authors report that patients readmitted to the hospital were more likely to have lower blood pressure[32]. Both the Fialho and Eapen studies consider blood pressure alongside a number of other variables, and neither study comments extensively on reasons for the association of blood pressure with readmissions. It has been shown, however, that both hypertension and hypotension are associated with disease progression and elevated morbidity in patients [42,43]. Complications related to blood pressure abnormalities may work to increase the likelihood of patient readmission, especially in low SES patients who, as mentioned above, tend to display worse follow-up compliance than their non-disadvantaged peers.

At the same time, other study authors have reported no relationship between blood pressure and the rate of hospital readmission[14,19]. As with studies reporting a relationship between blood pressure and readmission, little reason is given by researchers for the lack of such association in articles that fail to find this relationship. The Fialho study reporting predictive value was conducted among ICU patients, thus the population likely had generally poorer health than that in studies conducted among all patients reporting no association. It is possible that the effects of abnormal blood pressure were experienced to a greater extent in the more diseased population, and that blood pressure is simply a less important factor in influencing disease progression among non-ICU hospital patients. Further study is certainly needed to determine the exact relationship between blood pressure and elevated risk of hospital readmission.

Heart Rate

Though studies examining the physiological variables that may be predictive of elevated hospital readmissions have been increasing since the passage of the ACA, few have examined the role of heart rate as a predictor. Krumholz et al.[14] examined a number of physiological and demographic variables influencing the readmission of heart failure patients above the age of 65 and found no relationship between heart rate and readmission risk. Similarly, Eapen et al. discovered no ability for heart rate to serve as a predictor of readmissions in their multi-national study[32]. Fialho et al., however, have reported the ability of heart rate to predict adverse outcomes[31]. In their study of ICU patients at four different institutions, they found that elevated heart rate indicated an elevated risk of readmission to the ICU within 72 hours of discharge. In fact, the authors note that mean heart rate over the last 24 hours of the ICU stay was the most predictive factor in indicating high risk for readmission. The authors suggest that this predictive capacity may be attributable to the fact that elevated heart rate potentially signifies other cardiorespiratory conditions that could eventually lead to readmission. It should be noted that Fialho et al. focused specifically on 72-hour ICU readmissions, while other studies were in patients that were not admitted to the ICU. These results suggest that critical care patients may be more likely to have heart rate as a predictor of readmissions. Yes, nascent literature on the subject suggests the need for further investigation into the predictive capacity of heart rate in preventing excessive all-cause readmissions.

Body Mass Index

Very little has been reported in the literature concerning the explicit relationship between body mass index (BMI) and hospital readmission risk. In their 2011 analysis of outcomes of 1,065 gastric bypass patients, Dallal and Trang found that BMI was unrelated to the risk of hospital readmission[17]. Conversely, Tayne et al. report that a BMI of greater than 60 kg/m^2 was associated with elevated 30-day readmission risk in the 358 gastric bypass patients included in their study[33]. Literature is lacking in the role that BMI might play in readmission risk among non-surgical patients.

One factor relating patient outcomes to body mass index that has been of increasing interest in recent years has been the phenomenon known as the obesity paradox. A 2006 study by Nigam et al. of 894 patients below the age of 80 diagnosed with acute myocardial infarction (AMI) found that those patients who were obese actually experienced lower 6-month and overall mortality relative to normal weight patients[44]. A number of studies have since confirmed the apparent protective benefit of obesity in certain chronic conditions such as AMI and end stage renal disease (ERSD) with little explanation for the phenomenon currently available[45–48]. The majority of the studies of the paradoxical relationship between high BMI and patient outcomes have focused primarily on morbidity. Literature examining the connection between BMI and hospital readmissions is more novel, and investigation in this area holds potential for increasing the understanding of both the obesity paradox and the factors that may be identifiable in reducing hospital readmissions.

Some authors have suggested that in order to make sense of the obesity paradox, it is necessary to move beyond BMI to a more complete picture of patient nutrition as BMI may simply be a proxy measure for nurtional status[49,50]. A 2012 study by Lee, Rucinski & Bernstein examining the effects of malnutrition and the adherence to a diet order on patient outcome found no significant relationship between patient nutrition and readmission risk[51]. Tappenden et al., however, report that patient malnutrition is indeed a predictor of elevated readmission risk, and call for a stricter monitoring of patient nutrition to improve hospital outcomes[52]. Certainly, there exists a need for further investigation of the role that patient nutrition, and especially easily measurable variables such as BMI, might play in the prediction of elevated readmission risk.

Body Temperature

There exists very little literature regarding the effect of body temperature in predicting the risk of hospital readmission. In their 2012 study of patients readmitted to the ICU within 72 hours of discharge, Fiahlo et al. report no significant relationship between body temperature and readmission risk. As with the other clinical variables presented in their study, the authors offer very little in the way of reasoning for the lack of association. It has been shown in previous studies that elevated body temperature is associated with higher mortality rates, especially in patients experiencing ischemic and hemorrhagic strokes[53,54]. Researchers often site as a reason for this phenomenon the slowing of neurodegenerative processes that occurs with lower body temperatures. Conversely, mortality has been shown to decrease with increased temperature in patients experiencing respiratory disease and hip fracture[55,56]. Theories as to why hypothermia may be tied to mortality in these cases discuss the fact that fever is often a biomarker for the body's acute phase response to illness and that low body temperature can adversely affect enzymatic and organ processes. Given the ease of obtaining body temperature as a clinical variable and the dearth of literature discussing its effects on 30-day readmission rates for patients with chronic conditions, there exists potential for the exploration of body temperature as a viable predictor of elevated risk of avoidable hospital readmission.

Days to Follow-Up

Limited literature explores the effects of follow-up time on the rate of patient readmissions, but what has been published suggests that patient follow up is an important factor in decreasing the risk of avoidable readmissions. In a 2010 study of 30,136 patients over the age of 65, Hernandez et al. report that patients who are discharged from hospitals that have earlier follow-up times are at a significantly lower risk of being readmitted within 30 days. The authors of the study comment that early follow up visits allow patients to work with physicians to coordinate the often multiple aspects of care being offered by different health professionals. Additionally, follow-up visits allow for physicians to ensure that patients understand any changes or updates that are being made to their care plans. While follow-up time is obviously not a factor that can be assessed in the hospital to identify at-risk patients, further research on the effect of follow-up time as it relates to avoidable readmissions time may provide evidence that allows for the development of more effective discharge strategies and improved patient outcomes.

Conclusion

Demographic, clinical, and administrative variables have yielded largely equivocal results in determining what variables might prove useful for the identification of patients at an elevated risk of early hospital readmission. Sparse within the scientific community is literature reporting on the use of these variables in socioeconomically disadvantaged populations, in spite of the fact that hospitals serving these populations are at an increased risk of experiencing elevated readmissions rates. In order to further understand the potential for the use of these variables to identify at-risk patients, studies should be conducted specifically examining variables predictive of all-cause 30-day readmission within a socioeconomically disadvantaged population. Furthermore, as the future of healthcare policy is uncertain, it would be prudent to examine the capacity of demographic and clinical variables to predict 60- and 90-day readmission risk as well. The following chapter details the current study, which was aimed at addressing the need for study of readmission predictors in a low SES population as highlighted by the above literature review.

CHAPTER THREE

Methodology

Population Overview and Setting of Study

Data collected for the study were obtained from patients (≥13 years old) at 12 federally qualified acute primary care facilities throughout Central Texas. These primary care facilities serve patients whose annual income lies at or below 200% of the federal poverty guidelines. The study examined 2,536 patients from the acute primary care facilities who were hospitalized for any reason between 2006 and October 1, 2013. The total sample included 1803 (71.1%) females and 733 (28.9%) males, and the majority of patients belonged to an ethnic minority group (815 [32.1%] Black/African American, 654 [25.8%] Hispanic or Latino, 1067 [42.1%] White/Not Hispanic). The average age of participants in the study was 44.81 years (σ = 18.06 years). Of the total sample, 1271 (50.1%) patients did not experience a readmission within 180 days, 635 (25.0%) patients experienced a readmission within 30 days, 368 (14.5%) patients experienced a readmission between 31 and 60 days, and 262 (10.3%) patients experienced a readmission between 61 and 90 days. A complete set of descriptive statistics for the sample will be presented in Chapter 4 of this work.

Data Collection

The acute care facilities at which this study was conducted store patient data using the Epic Systems database management system. For the current study, a retrospective secondary data analysis was performed using patient data taken from the electronic health records system of these facilities. Data obtained for the analysis included age, sex, ethnicity, BMI, systolic blood pressure, diastolic blood pressure, temperature, pulse rate, smoking status, and the number of days between hospital encounter and follow up visit. The original search query included all patients from the care facilities who had experienced a hospitalization from 2006 to October 13, 2013. Patients were then divided into those experiencing a readmission to the hospital for any cause within 30, 60, and 90 days of original discharge, as well as those who experienced no readmission within 180 days of discharge. Clinical data was obtained by the merging of the Epic Systems "Clarity" database management system and the Crystal Reports business intelligence application. Data was imported into a spreadsheet devoid of patient names or other identifying information, pursuant to the IRB approval of the regional host university (IRB approval #523332-1).

Statistical Analysis

An analysis was conducted to determine the relationship between the variables under study and hospital readmission. Patients who did not experience a readmission within 180 days of their initial hospital encounter served as the control group against which patients experiencing a readmission within 30, 60, and 90 days were compared. Descriptive analysis of the data was performed to yield frequency distributions for the categorical variables under study, and means and standard deviations for the quantitative variables examined. A multinomial analysis was then performed to compare the 30-, 60-, and 90-day readmission groups to the group experiencing no readmission within 180 days. The odds ratios resulting from this multinomial analysis were used to determine the ability of each of the variables of interest to serve as predictors of readmission. SAS statistical software was used for the analysis of the data.

CHAPTER FOUR

Manuscript

The following is the document that is to be submitted for publication to a peer-reviewed journal. It includes information from the first three chapters of this work as well as the results obtained from this study and a discussion of those findings.

Abstract

Hospital readmissions are significant and potentially preventable sources of healthcare cost in the United States. The Affordable Care Act (ACA) establishes the Hospital Readmissions Reduction Program (HRRP) in an attempt to reduce readmissions by penalizing institutions whose 30-day readmission rates are above the national average. Hospitals serving socioeconomically disadvantaged populations are at an increased risk of incurring penalties under the HRRP. Recent research has focused on methods of identifying patients at risk of early hospital readmission in an effort to diminish readmission rates. The current study examines demographic and clinical variables predictive of early hospital readmission in a low socioeconomic status, underserved population. Age, sex, ethnicity, smoking status, systolic blood pressure, diastolic blood pressure, body temperature, pulse rate, and days to follow up visit were analyzed in a sample of 2,536 hospitalized patients at or below 200% of federal poverty guidelines in Central Texas to determine association with risk of 30-, 60-, and 90-day all-cause readmission. Multinomial statistical analysis found pulse rate was predictive of 30-, 60-, and 90-day readmission as compared to a control group. Days to follow-up were associated with decreased risk of readmission in all groups, and passive smoking status was associated with decreased risk of 90-day readmission as compared to a control group. Results offer healthcare providers with tools for potentially identifying patients at elevated risk for readmission in a disadvantaged population and suggest further investigation of other clinical and laboratory variables as predictors of readmission risk.

Introduction

In the year 2010 the United States faced what many considered to be a healthcare crisis characterized by escalating costs and expanding coverage gaps. Between 1990 and 2008, national healthcare spending had risen by an average of 7.2% annually[1], and by 2010 18% of U.S. residents under the age of 18 lacked any form of health insurance coverage[2]. The Patient Protection and Affordable Care Act (ACA) was passed by Congress in 2010 as an effort to address the inflation of costs and coverage gaps and to attempt to increase the overall quality of care through a number of regulatory measures. One area of focus for the ACA in improving healthcare delivery has been the reduction of excessive hospital readmissions. It has long been postulated that hospital readmissions represent an unnecessarily costly burden to national healthcare delivery[5]. One report estimates that nearly $12 billion of the $17.5 billion spent annually on readmissions in the United States are related to potentially preventable readmissions[6]. In addition to representing a significant cost burden, unnecessary readmissions have also come to be seen in recent years as a possible indicator of poor quality of care during a patient's initial hospital encounter[7].

In an effort to curb unnecessary and costly readmissions the ACA establishes the Hospital Readmissions Reduction Program (HRRP). Under the initial provisions of the HRRP, which took effect in 2013, the Center for Medicare and Medicaid Services (CMS) monitored the 30-day all cause hospital readmission rate for Medicare patients receiving an initial diagnosis of acute myocardial infarction (AMI), heart failure (HF), or pneumonia (PN). Institutions whose readmission rates fell above the national average were subject to reductions in Medicare and Medicaid payments of up to 1%[8]. For the

2015 fiscal year the provisions of the HRRP were updated to include patients diagnosed with chronic obstructive pulmonary disease (COPD) or undergoing total knee or total hip arthroplasty (THA/TKA). Additionally, the HRRP penalty cap was raised to 3% of CMS payments[9].

The expanding regulatory measures and penalties of the HRRP have created within healthcare institutions an increased focus on finding measures of reducing readmissions that are both effective and cost efficient[11]. One strategy that has shown promise as such a measure is the use of readily collected clinical and demographic variables to identify patients at an elevated risk to experience early readmission[12–14]. Most variables that have been proposed as viable risk predictors are already readily collected in the course of patient care, and are thus relatively cost efficient. Furthermore, the identification of at-risk patients could allow care providers to work closely with such patients to improve quality of care and discharge strategy and thus minimize the likelihood of an unforeseen readmission.

While the potential benefit of using readily collected clinical variables to identify patients at risk of early readmission has been highly commented upon within the literature, there exists some uncertainty as to which variables might serve as useful predictors of readmission risk. Many studies have examined commonly collected demographic variables. It has been reported that increasing age could potentially serve as a predictor of all-cause hospital readmissions, especially in patients over the age of 65[20,24]. Race has also been reported to be a potential predictor of readmission risk, with Black and Hispanic patients facing a higher risk of early readmission than their white counterparts[20,23], and hospitals serving primarily minority patient groups experience elevated readmission rates[18,22]. Mixed results have been procured for sex as a variable predictive of readmissions, with some studies finding elevated risk of 30-day readmission in females[19,26], and others finding the same risk elevation in males[20]. Studies have also been conducted which show no ability to predict early readmissions associated with age[14,17,19,21,25], race[14,17,19,21], or sex[14,17,20].

Clinical variables have also received attention as potential identifiers of patients at an elevated risk of readmission, albeit to a much lesser extent than demographic predictors. Certain study authors have reported elevated blood pressure to be predictive of readmission in patients who had spent time in the ICU[31], whereas other studies have found that readmitted patients are more likely to have low blood pressure upon admission[32]. Pulse rate has been examined to a very limited extent, with results from a study of ICU patients suggesting that elevated pulse rate is highly associated with readmission to the ICU within 72 hours of discharge[31]. Body mass index (BMI) has also been examined briefly, with a BMI above 60 kg/m^2 found to be predictive of 30-day readmissions in a 2014 study of gastric bypass patients[33]. Smoking status has also been linked to readmission in patients undergoing breast reconstruction[27] and lower limb bypass surgery[19]. In limited study, body temperature has not been reported to be predictive of early readmission[31]. Likewise, studies exist that report no significant relationship between early readmission and blood pressure, pulse rate[14,32], smoking status[28–30] or BMI[17].

Days between hospital encounter and follow-up visit may also play a significant role in early patient readmission. A 2010 study by Hernandez et al.[33] of over 30,000

Medicare-aged patients found that earlier follow-up times were significantly associated with lower rates of 30-day all-cause readmission.

While multiple studies have examined the relationship of clinical/demographic variables, follow-up time and early readmission, few have reported on a socioeconomically disadvantaged population. There exists a good deal of evidence that low socioeconomic status (SES) patients are at an increased risk of experiencing early readmission[13,15], and that safety net institutions experience greater penalties under the HRRP than hospitals serving primarily non-disadvantaged populations[18,22,24]. Recent studies have suggested that the addition of COPD to the diagnoses included in the calculation of readmission penalties will only further harm hospitals serving large numbers of low SES patients[35,36]. Given the increasing penalties levied on institutions serving socioeconomically disadvantaged populations and the potential for readily collected patient variables to identify patients at risk of early readmission, the evaluation of clinical and demographic variables as viable predictors of readmission risk within low SES populations has become exceedingly necessary. The purpose of the current study was to examine risk factors predictive of 30-, 60-, and 90-day all-cause hospital readmission within an underserved, socioeconomically disadvantaged patient population.

Methods

Population Overview and Setting of Study

Data collected for the study were obtained from patients at 12 federally qualified acute primary care facilities throughout Central Texas that serve patients whose annual income is 200% or below federal poverty guidelines. The study examined 2,536 patients from the acute primary care facilities who were hospitalized for any reason between 2006 and October 1, 2013. The total sample included 1803 (71.1%) females and 733 (28.9%) males, and the majority of patients belonged to an ethnic minority group (32.1% Black/African American, 25.8% Hispanic or Latino, 42.1% White/Not Hispanic). The average age of participants in the study was 44.81 years (σ = 18.06 years).

Data Collection

Patient data was obtained from the Epic electronic health records system of the primary care facilities under study. The demographic variables collected included age, sex, ethnicity, and smoking status. Ethnicity was self-reported by patients using preselected options based on federal government classification standards. Smoking was also self-reported, allowing for choice between the options of current smoker, former smoker who has quit, non-smoker who lives with smoker, never smoked, or choose not to answer. BMI, systolic blood pressure, diastolic blood pressure, temperature, and pulse rate were recorded by healthcare professionals during the initial hospital encounter, and the follow-up time was recorded at the patient's follow-up visit to a primary care facility. Data was encrypted and made devoid of patient names or other identifying information, pursuant to the IRB approval of the host university.

Statistical Analysis

Descriptive analysis of the data was performed to yield frequency distributions for the categorical variables under study and means and standard deviations for the quantitative variables examined. Patients were then divided into groups based on their readmission status of 30, 60, 90 day readmission or control (no admission within 180 days). A multinomial analysis was performed to compare the 30-, 60-, and 90-day readmission groups to the group experiencing no readmission within 180 days. Odds ratios and confidence intervals were calculated to determine the risk of readmission associated with each variable under study. Data analysis was conducted using the SAS statistical software program.

Results

Patients in the study were primarily female (71.1%) belonging to an ethnic minority group (32.1% Black/African American, 25.8% Hispanic or Latino, 42.1% White/Not Hispanic). The average age of the study participants was 44.81 years (σ = 18.06 years). Frequency distributions of sex, ethnicity, and smoking status are presented for each of the readmission groups in Table 1. Minimum, maximum, mean, and standard deviation of age, days to follow up visit, BMI, diastolic and systolic blood pressure, body temperature, and pulse rate for the sample are presented in Table 2.

Table 1. Frequency Distributions of Categorical Variables for Readmission Groups

Readmission Group		Frequency	Percent
	Sex		
	Female	451	71.0
	Male	184	29.0
	Total	635	100.0
	Ethnicity		
	Black/African American	180	28.3
	Hispanic or Latino	194	30.6
0-30 days (N=635)	White, Not Hispanic	261	41.1
	Total	635	100.0
	Smoking Status		
	Never Smoked	295	46.5
	Passive Smoker	19	3.0
	Quit Smoking	123	19.4
	Current Smoker	149	23.5
	No Response	49	7.7
	Total	635	100.0

	Sex		
	Female	270	73.4
	Male	98	26.6
	Total	368	100.0
	Ethnicity		
	Black/African American	116	31.5
31-60 days (N=368)	Hispanic or Latino	94	25.5
	White, Not Hispanic	158	42.9
	Total	368	100.0
	Smoking Status		
	Never Smoked	162	44.0
	Passive Smoker	14	3.8
	Quit Smoking	64	17.4
	Current Smoker	99	26.9
	No Response	29	7.9
	Total	368	100.0
	Sex		
	Female	201	76.7
	Male	61	23.3
	Total	262	100.0
	Ethnicity		
	Black/African American	94	35.9
61-90 days (N=262)	Hispanic or Latino	54	20.6
	White, Not Hispanic	114	43.5
	Total	262	100.0
	Smoking Status		
	Never Smoked	131	50.0
	Passive Smoker	2	0.8
	Quit Smoking	40	15.3
	Current Smoker	69	26.3
	No Response	20	7.6
	Total	262	100.0
	Sex		
	Female	881	69.3
	Male	390	30.7
	Total	1271	100.0
	Ethnicity		
	Black/African American	425	33.4
Control (>180 days)	Hispanic or Latino	312	24.5
(N=1271)	White, Not Hispanic	534	42.0
	Total	1271	100.0
	Smoking Status		
	Never Smoked	533	41.9
	Passive Smoker	46	3.6
	Quit Smoking	243	19.1
	Current Smoker	394	31.0
	No Response	55	4.3
	Total	1271	100.0

Table 2. Descriptive Statistics for Variables Collected from Total Sample

Variable	Minimum	Maximum	Mean	Std. Deviation
Age	13	101	44.81	18.06
Days to Follow Up	1	336	21.99	31.436
BMI	3	91	31.41	9.39
Diastolic Blood Pressure	24	135	76.39	12.341
Systolic Blood Pressure	72	250	128.2	20.421
Temperature	95.2	103	98.0	0.693
Pulse Rate	32	160	84.14	15.637

Of the 2,536 patients included in the study, 635 (25.0% of the total sample) experienced a readmission within 30 days of initial hospital encounter, 368 (14.5% of the total sample) experienced a readmission between 31 and 60 days, and 262 (10.3%) experienced a readmission between 61 and 90 days. There were 1271 patients (50.1% of the total sample) who did not experience a readmission within 180 days of their initial hospital encounter. A multinomial analysis was employed to compare the 30-, 60-, and 90-day readmission groups to the group that experienced no readmission within 180 days using odds ratios with 95% confidence intervals. The results of this analysis are presented in Table 3.

Table 3. Readmission Risk Associated with Variables of Study

			95% Confidence Interval	
Readmission Group	Variable	Odds Ratio	Lower Bound	Upper Bound
	Age	0.995	0.989	1.001
	BMI	0.994	0.983	1.006
	Diastolic Blood Pressure	0.991	0.979	1.003
	Systolic Blood Pressure	0.999	0.991	1.006
	Temperature	0.951	0.818	1.105
0-30 days (N = 635)	Pulse Rate	1.008	1.001	1.015
	Black/African American Ethnicity	0.880	0.688	1.126
	Hispanic/Latino Ethnicity	1.134	0.875	1.469
	Days to Follow Up	0.939	0.930	0.949
	Female Sex	1.064	0.852	1.345
	Passive Smoking	0.778	0.433	1.398
	Quit Smoking	0.966	0.728	1.282
	Current Smoker	0.775	0.597	1.011

	Age	0.999	0.992	1.006
	BMI	0.997	0.983	1.011
	Diastolic Blood Pressure	0.991	0.977	1.005
	Systolic Blood Pressure	0.999	0.990	1.008
	Temperature	0.893	0.749	1.065
	Pulse Rate	1.012	1.004	1.020
31-60 days (N=368)	Black/African American Ethnicity	0.971	0.732	1.289
	Hispanic/Latino Ethnicity	0.989	0.725	1.350
	Days to Follow Up	0.970	0.962	0.978
	Female Sex	0.903	0.683	1.194
	Passive Smoking	1.037	0.546	1.969
	Quit Smoking	0.888	0.630	1.251
	Current Smoker	0.873	0.643	1.186
	Age	0.997	0.989	1.005
	BMI	1.000	0.986	1.016
	Diastolic Blood Pressure	0.988	0.972	1.003
	Systolic Blood Pressure	1.006	0.996	1.016
	Temperature	0.830	0.680	1.014
61-90 days (N=262)	Pulse Rate	1.013	1.004	1.022
	Black/African American Ethnicity	1.058	0.775	1.444
	Hispanic/Latino Ethnicity	0.766	0.529	1.109
	Days to Follow Up	0.986	0.980	0.992
	Female Sex	0.791	0.570	1.097
	Passive Smoking	0.179	0.043	0.751
	Quit Smoking	0.675	0.453	1.005
	Current Smoker	0.725	0.515	1.019

Discussion

It has long been estimated that excessive hospital readmission represents a significant cost burden to healthcare delivery in the United States, with a sizable majority of the nearly $17.5 spent annually on readmissions being potentially preventable[6]. In an effort to reduce these costs and improve quality of care, the Affordable Care Act, under the provisions of the Hospital Readmissions Reduction Program, penalizes hospitals that have excessive 30-day readmissions in Medicare-aged patients with certain diagnoses. In light of escalating penalty caps and expanding patient diagnoses included in penalty calculations, there has emerged a heightened need to develop methods of reducing readmission rates. This is especially true for institutions serving primarily socioeconomically disadvantaged patients, as this patient population is at an increased likelihood of early readmission[18,22,24]. One method that has shown potential for the reduction of readmission is the identification of patients with elevated readmission risk using routinely collected clinical and demographic variables[12–14]. Therefore, the purpose of the current study was to examine risk factors predictive of 30-, 60-, and 90-day all-cause hospital readmission within an underserved, socioeconomically disadvantaged patient population. Results from our study discovered pulse rate was associated with increased risk of 30-, 60-, and 90-day all-cause readmission, while days to follow up were associated with decreased readmission risk at 30, 60, and 90 days, and passive smoking was associated with decreased risk in only the 90-day readmission group. All other variables were not significant predictors of elevated readmission risk.

Elevated pulse rate was a predictor of increased readmission risk in all three readmission groups examined in our study (0-30 days: odds ratio =1.008, 95% confidence interval = [1.001, 1.015]; 31-60 days: OR=1.012, 95% CI = [1.004, 1.020]; 61-90 days: OR=1.013, 95% CI = [1.004, 1.022]). Examination of the relationship between pulse rate and readmission risk within the scientific community has to this point been sparse. In their 2012 study of ICU patients at four different institutions, Fialho et al.[22] reported elevated pulse rate to be associated with increased likelihood of readmission to the ICU within 72 hours of discharge[31]. The study authors note that elevated pulse rate may be indicative of other cardiopulmonary conditions that may lead to eventual readmission. Examination of pulse rate as a readmission predictor in patient populations beyond the ICU has until this point shown little association with readmission risk. Both Krumholz et al. and Eapen et al. found no association between pulse rate and early hospital readmission[14,32]. Our study finding suggesting that pulse rate is a predictor of 30, 60, and 90 day readmission is a novel finding that partially agrees with the literature. Our finding may be due to the study being conducted in a socioeconomically disadvantaged population. As Fialho et al.[22] note, elevated pulse rate may accompany cardiovascular and respiratory diseases. It is generally well understood that patients from poverty and the underserved experience worse health outcomes from cardiorespiratory disease than their economically stable peers[57]. Any disease associated with elevated pulse rate in a disadvantaged population, then, may be more likely to result in an adverse health outcome (such as early readmission) than if that disease were encountered in the patient populations examined in previous studies of the effects of pulse rate.

Increased days between initial hospital encounter and follow-up visit at a primary care facility were found to be predictive of lower risk of readmission within 30, 60, and 90 days when compared to patients who were not readmitted within 180 days (0-30 days: OR =0.939, 95% CI = [0.930, 0.949]; 31-60 days: OR=0.970, 95% CI = [0.962, 0.978]; 61-90 days: OR=0.986, 95% CI = [0.980, 0.992]). This result runs contrary to the small amount of research that has previously investigated the effects of follow-up time on early all-cause readmission. In their 2010 study of patients with heart failure above the age of 65, Hernandez et al.[34] report an association between early follow-up visit (within 7 days of discharge) and decreased risk of readmission. As has been previously stated, our study is novel in that it was conducted in a socioeconomically disadvantaged patient population. This low-income patient population may contribute to the divergence of our results from those of Hernandez et al.[34]. Study authors have reported that socioeconomically disadvantaged patients have an increased propensity for missing scheduled primary care appointments and often do not visit their physician unless their disease has progressed significantly[58]. Low SES patients in this study who did indeed follow up with their physician promptly after hospitalization, then, may have done so because their illness had worsened rapidly. Such disease progression would predispose these patients to hospitalization, leading to the association between early follow-up and increased readmission observed in our analysis. It is likely that the benefits reported by Hernandez et al.[34] of patient education and care coordination that accompany early follow up are still applicable to low-income patient populations. Our findings suggest that in order for these benefits to result in readmission reduction in these populations, methods must be found to ensure early follow-up times in all patients regardless of patient perception of disease progression.

Status as a passive smoker was also found to be associated with lower readmission risk between 60 and 90 days when compared to patients who did not experience readmission within 180 days (OR=0.179, 95% CI = 0.073, 0.751). Past research on the association between smoking status and readmission rates has produced equivocal results.[17,25-28] Certain studies have found smoking to be predictive of readmission in patients experiencing breast reconstruction[27] and lower limb bypass surgery[19], while others have reported no significant relation between smoking and early readmission[28–30]. Our study findings of an association between passive smoking and lower readmission in the 90-day readmission group, with no association between those variables in 30- and 60-day groups and no association between current or past smoking status and readmission risk are difficult to explain. The most likely explanation for these results is the small number of patients within the study who self-identified as passive smokers. Of the 2,536 patients included in the study, only 86 (3.4%) were categorized as passive smokers. The small number of patients reporting as passive smokers makes analysis of the risk associated with passive smoking fairly variable and could have led to the anomalous results of this study. It should also be noted that smoking status was self-reported by patients to healthcare providers collecting data. Studies have suggested that smoking status often tends to be underreported in trials, especially in ethnic minority populations[40,41]. It is thus possible that the true prevalence of smoking in the readmission groups is higher than was reported in the data. Such an elevation might lend itself to the possibility that smoking is indeed a more predictive factor of readmission than is indicated in the current study. Further study should examine the relationship between smoking and early readmission with an eye towards the potential use of serum and salivary cotinine as more accurate indicators of smoking status.

Several variables showed no association with an increased risk of 30-, 60-, or 90-day all-cause readmission, consistent in part with the equivocal findings of the literature. Contrary to a previous study[31], body temperature was not a predictor of early hospital readmission. The demographic variables of age and female sex were also not found to be significant predictors of 30-, 60-, or 90-day readmission, in partial agreement with past equivocal findings[14,17,19–21,24–26]. The inability of the clinical variables of BMI, systolic blood pressure, and diastolic blood pressure to predict early readmission also supported in part the indeterminate findings of past studies[14,17,19,31–33].

There did exist some limitations to the design of this study. Smoking status was measured as a self-identified variable, lending to the potential for self-reporting bias. Additionally, the calculation of days to follow up visit only included the time between the initial hospital encounter and the follow-up visit with the physician, and did not report the time between hospital discharge and follow up. Because of this limitation, the reported days to follow up serve only as a proxy measure for the actual time between hospital discharge and patient visit to a primary care facility, though the variable remains an important measure to ascertain.

In spite of these limitations, the results of the current study still provide evidence of the usefulness of certain variables in identifying patients at risk of early hospital readmission within a socioeconomically disadvantaged population. The identification of patients with elevated heart rate may allow healthcare providers to develop more effective treatment plans and discharge strategies to reduce the likelihood of unforeseen readmission. Among these strategies should be an increased focus on ensuring that patients adhere to scheduled follow-up visits with their physician to mitigate the risk of experiencing early hospital readmission. These findings are novel and provide healthcare providers with further tools to identify at-risk patients in a socioeconomically disadvantaged population. Further study should examine the potential use of other readily collected clinical variables and laboratory tests to identify readmission risk in underserved patient populations. The continued evaluation of such methods of readmission reduction will allow health institutions to reduce costs and increase the overall quality of care provided to patients.

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