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External Validation and Modification of a 30-day Readmission Risk Prediction Model for Heart Failure Patients

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Abstract

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MPH, New York Medical College, 2008

BS, Stony Brook University, 2004

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Abstract

The development and validation of 30-day readmission risk prediction models, such as the LACE index, have been of interest to researchers and healthcare organizations, especially since the Centers for Medicare and Medicaid Services began to impose monetary penalties on hospitals with higher than expected 30-day readmission rates. However, there is a lack of consensus concerning the efficacy of the LACE index in the heart failure population. The purpose of the study was to examine the discriminative accuracy of the LACE index to predict all-cause 30-day readmission for heart failure patients and to build a modified 30-day readmission risk prediction model based on variables known to influence the risk of readmission. Andersen's behavioral model of health services was used to understand how the patient level variables of interest contributed to readmission risk as predisposing, enabling, and need factors. Using a correlational study design, quantitative data were retrospectively collected from the electronic medical records (n=655) of heart failure patients. The Receiver Operating Characteristic curve and simple binary logistic regression were used to answer the research questions. The results of the analyses revealed that both the LACE index and the modified risk prediction model had poor discriminatory accuracy for predicting the risk of 30-day readmission for the sample population. The results of the simple binary logistic regression indicated several of the independent variables were statistically significantly associated with all-cause 30-day readmission. Healthcare facilities operate with limited resources, and the identification of patients at a higher risk for 30-day readmission would allow healthcare professionals to initiate preventive measures before and after discharge.

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Chapter 1: Introduction to the Study

Reducing readmissions has become a key component of quality improvement efforts for acute care hospitals due to the subsequent financial and human costs (Upadhyay et al., 2019). Annually in the United States, approximately $41.3 billion in hospital costs are associated with all-cause 30-day hospital readmissions (Hines et al., 2014). For the patient, readmission to an acute care hospital is associated with a higher risk of all-cause mortality at 1 year, a longer cumulative length of stay, and higher cumulative costs (Arundel et al., 2016; Guerrero et al., 2016). When national data are examined by diagnosis, the heart failure population has one of the highest all-cause 30-day readmission rates (Fingar et al., 2017).

With the implementation of the electronic medical record (EMR), 30-day readmission risk prediction models are increasingly being used by acute care hospitals to identify heart failure patients at risk for readmission (Goldstein et al., 2017; Zhou et al., 2016). Risk prediction models can advise the healthcare provider on the patient's probability of experiencing the health outcome of interest and help guide the associated clinical decision-making process (Flaks-Manov et al., 2019; Lee et al., 2016). The accurate prediction of 30-day readmission risk for heart failure patients can help inform the implementation of appropriate patient-specific interventions during hospitalization and post-discharge, as well as alleviate the patient and hospital costs associated with readmission.

This chapter will provide a background for the research and support for the research's necessity. The chapter will also include the research questions and hypotheses, nature of the study, assumptions, limitations, and scope of the research.

Background

According to the American Heart Association (2017), heart failure is a "chronic, progressive condition in which the heart muscle is unable to pump enough blood to meet the body's needs for blood and oxygen." Risk factors for heart failure include medical conditions such as diabetes, high blood pressure, obesity, and lifestyle behaviors, including smoking tobacco, excessive alcohol intake, and a diet high in fat, cholesterol, and sodium (Centers for Disease Control and Prevention, 2020). Heart failure is characterized by typical signs and symptoms, including shortness of breath, ankle swelling, fatigue, pulmonary crackles, and peripheral edema (Ponikowski et al., 2016). The American College of Cardiology and the American Heart Association place patients into four stages of heart failure: Stage A (at high risk of heart failure but without symptoms and structural heart disease), Stage B (structural heart disease but without signs and symptoms), Stage C (structural heart disease with prior or current heart failure symptoms), and Stage D (refractory heart failure requiring specialized interventions; Inamdar & Inamdar, 2016). The medical evaluation of patients with suspected heart failure should involve an assessment of the patient's medical history and performance of a physical examination, laboratory testing, chest radiography, and electrocardiography (Inamdar & Inamdar, 2016). Treatment options include heart-healthy lifestyle changes, medications, and surgical procedures that help improve the functioning of the heart muscles. The early diagnosis and treatment of heart failure patients can help them live longer and more active lives.

In the United States, heart failure affects approximately 6.2 million adults and annually accounts for more than $30 billion in health care expenditures (Reddy & Borlaug, 2019). Though the 5-year survival rate after a diagnosis of heart failure increased 7.2% from 2000 to 2012, the 2012 survival rate at 5 years was still only 48.2% (Taylor et al., 2019). In addition, high rates of all-cause 30-day readmission have been found for the heart failure population. According to the latest publicly reported data by the Centers for Medicare and Medicaid Services (CMS, 2017), the national risk-standardized 30-day readmission rate for heart failure patients was 21.4%, the highest 30-day readmission rate of the primary diagnoses measured.

In response to high readmission rates, all-cause and diagnosis-specific, in hospitals across the United States, the Affordable Care Act established the Hospital Readmission Reduction Program, and 30-day readmissions became thought of as a measure of hospital quality. According to CMS, a 30-day readmission occurs when a patient experiences an unplanned readmission to the same hospital or another acute care hospital within 30 days of discharge from the initial admission, regardless of the reason (CMS, 2020). The selection of a 30-day time frame by CMS was based on Horwitz et al.'s (2011) review of the time-to-event curves for readmission. Horwitz et al. found that, for all discharge conditions examined, the time-to-event curves revealed a rapid early accrual of readmission and stabilization, typically within 30 days of discharge. Readmission within 30 days is more likely to be related to the quality of care received and the transition to the outpatient setting; therefore, it is a reasonable quality measure (Horwitz et al., 2011).

The use of readmission as a quality measure and the utilization of the EMR has led to the creation of readmission risk prediction models that calculate a risk score within the patient's EMR during hospitalization. Such models can be used to predict future events and are based on statistical analyses that incorporate multiple parameters that influence the outcome of interest. van Walraven et al. (2010) developed the LACE index (length of stay, acuity of the admission, comorbidity of the patient, emergency department use) to predict the risk of death or unplanned readmission within 30 days of discharge from a hospital and identify patients who may benefit from more intensive post-discharge care. The LACE index was derived from a sample population from Ontario, Canada, and for the original research both an internal and an external validation were performed (van Walraven et al., 2010). Although the original researchers found the model to be discriminative and accurate for predicting the outcomes of interest, subsequent research has been inconsistent, and there is a lack of research focused on heart failure patients.

Researchers have supported the practice of externally validating a risk prediction model before its adoption into clinical practice (Grant et al., 2018). The lower performance of a prediction model may be observed when the model is applied to a different population other than the population from which it was derived (Stessel et al., 2017). It is believed that the poor performance of a risk prediction model is the result of patient populations with different distributions of the measured characteristics or the observed frequency of the health outcome (Myers et al., 2020). Therefore, the aim of this study was to increase the knowledge regarding the discriminative accuracy of the LACE index in heart failure patients and to examine whether the inclusion of additional demographic and clinical variables increased the model's ability to predict the risk of all-cause 30-day readmission.

Problem Statement

Risk prediction models are frequently used as a tool to assist with 30-day readmission reduction efforts within acute care hospitals. Prediction models should be both relatively simple and accurate, as an inaccurate prediction of future outcomes can lead to poor management of patients or resources (Lee et al., 2016). The LACE index is a simple risk prediction tool commonly used by acute care hospitals to predict readmission risk for hospitalized patients. The literature focusing on the LACE index's ability to predict readmission in heart failure patients has been conflicting, and there is limited research focused on the heart failure population (Calderon et al., 2018; Yazdan-Ashoori et al., 2016). Whereas Calderon et al. (2018) found no significant difference in readmission rates when comparing the LACE index score of high-risk patients versus low-moderate risk patients, research by Yazdan-Ashoori et al. (2016) demonstrated moderate discrimination of the LACE index in predicting readmission in heart failure patients. The intent of this study was to address the insufficient scientific evidence regarding the discriminative accuracy of the LACE index for heart failure patients and to create a version of the model that better predicted readmission in the heart failure patient population seen in New York.

Purpose of the Study

The purpose of this quantitative study was to explore the ability of the LACE index to predict the risk of all-cause 30-day readmission in heart failure patients and investigate whether there were additional independent risk factors predictive of readmission that improved the performance of the LACE index. The dependent variable was readmission within 30 days of discharge, regardless of the diagnosis at the time of readmission. The independent variables were the LACE index, length of stay, acuity of the admission, comorbidity score, emergency department visits in the previous 6 months, age, serum albumin and blood urea nitrogen (BUN) levels, number of prescription medications, prescriptions for heart medications, number of inpatient hospitalizations in the previous 12 months, and access to a primary care physician. The patient's race was explored as a covariate.

Research Questions and Hypotheses

Research Question 1: What is the discriminative accuracy of the LACE index to predict all-cause 30-day readmissions in heart failure patients?

$H_0$1: The LACE index does not have statistically significant discriminative accuracy.

$H_1$1: The LACE index does have statistically significant discriminative accuracy.

Research Question 2: Do length of stay, acuity of the admission, comorbidity score, emergency department utilization, age, serum albumin and BUN levels, number of prescription medications, prescriptions for heart medications, number of inpatient hospitalizations in the previous 12 months, and access to a primary care physician statistically significantly predict all-cause 30-day readmissions in heart failure patients?

$H_0$2: Length of stay, acuity of the admission, comorbidity score, emergency department utilization, age, serum albumin and BUN levels, number of prescription medications, prescriptions for heart medications, number of inpatient hospitalizations in the previous 12 months, and access to a primary care physician do not predict all-cause 30-day readmission in heart failure patients.

$H_1$2: Length of stay, acuity of the admission, comorbidity score, emergency department utilization, age, serum albumin and BUN levels, number of prescription medications, prescriptions for heart medications, number of inpatient hospitalizations in the previous 12 months, and access to a primary care physician do predict all-cause 30-day readmission in heart failure patients.

Research Question 3: Is there a combination of potential predictors (length of stay, acuity of the admission, comorbidity score, emergency department utilization, age, serum albumin and BUN levels, number of prescription medications, prescriptions for heart medications, number of inpatient hospitalizations in the previous 12 months, and access to a primary care physician) that results in a higher predictive value (*c* statistic) than LACE index to predict all-cause 30-day readmission in heart failure patients?

$H_0$3: There is no difference in the *c* statistic between the modified 30-day readmission risk prediction model and the LACE index.

$H_1$3: There is a difference in the *c* statistic between the modified 30-day readmission risk prediction model and the LACE index.

Theoretical Framework

Andersen's behavioral model of health services use was first developed in 1968 to assist in understanding the differences in medical services utilization between families (Andersen, 1968). The model, described in more detail in Chapter 2, considers the individual and contextual level factors that influence healthcare utilization. The model has three types of influencing factors:

> (1) existing conditions that predispose people to use or not use services even though these conditions are not directly responsible for use, (2) enabling conditions that facilitate or impede use of services, and (3) need or conditions that laypeople or health care providers recognize as requiring medical treatment. (Andersen, 1968, p. 36)

Over time, the three-stage model has evolved to recognize the influences of the healthcare system, external environment, personal health practices, and health status outcomes on healthcare utilization, and the unit of analysis shifted to the individual rather than the family (Andersen, 1995).

Within this research, predisposing, enabling, and need factors were discussed in relation to the risk of all-cause 30-day readmission to an acute care hospital for heart failure patients. Andersen's behavioral model of health services served as the theoretical framework for the research by providing an understanding of how the components of the LACE index contribute to readmission risk as predisposing, enabling, and need factors. The model also offered context for the selection of the variables included within the modified 30-day readmission risk prediction model.

Nature of the Study

The study design was correlational using quantitative retrospective data. The quantitative method suited the needs of this study, as numerical data were extracted from the EMR. A correlational study design is considered a nonexperimental method where the researcher studies the relationship between the variables of interest with no manipulation of the variables (Curtis et al., 2016). The focus of the research was to examine the relationship between the risk prediction models and all-cause 30-day readmission in heart failure patients; consequently, there was no attempt to influence the dependent or independent variables, which made a correlational, nonexperimental study design an appropriate selection.

This research has two parts: an evaluation of the discriminative accuracy of the LACE index to predict all-cause 30-day readmissions in heart failure patients and the development of a modified version of the LACE index. A secondary dataset was used for this study. The secondary data source was de-identified medical records provided by a multihospital healthcare system in New York State. The healthcare system allowed access to a limited dataset containing administrative and clinical data routinely collected during hospitalization. The data collected included age, race, gender, readmission status, and the independent variables of interest. Simple logistic regression was used to examine the relationship between the independent variables and all-cause 30-day readmission to determine which variables were included within the modified 30-day readmission risk prediction model. The Receiver Operating Characteristic (ROC) curve (reported as a concordance statistic) was examined to establish the discriminative accuracy of the

LACE index and the modified risk prediction model to predict all-cause 30-day readmission when applied to the study population. A stratified analysis was conducted to determine whether race influenced the performance of the models. Chapter 3 contains a further discussion of the data analysis plan.

Definitions

Acuity of the admission: The acuity of the admission represents whether the patient is admitted to the hospital through the emergency department or as an elective admission (van Walraven et al., 2010)

Acute care hospital: An acute care hospital provides inpatient medical care or other related services, usually for short-term illness or conditions (CMS, n.d.).

All-cause 30-day r*eadmission*: This study uses the term 30-day readmission as defined by CMS for the Hospital Readmissions Reduction Program (HRRP). Under the HRRP program, a 30-day readmission occurs when a patient is readmitted to the same or another acute care hospital for any reason within 30 days of discharge from the initial hospital admission (CMS, 2020).

Centers for Medicare and Medicaid Services: CMS is a federal agency that provides health coverage through Medicare, Medicaid, the Children's Health Insurance Program, and the Health Insurance Marketplace (U.S. Department of Health and Human Services, n.d.).

Charlson comorbidity index: The Charlson comorbidity index is a weighted index used to predict the risk of death within one year of hospitalization for patients with specific comorbid conditions based on the international classification of diseases (ICD) diagnosis codes found in administrative data (Charlson et al., 1987).

Comorbidity: Comorbidity, as defined by Valderas et al. (2009), is the presence of more than one distinct medical condition in an individual.

Electronic medical record: The EMR is a digital patient chart that contains patient-centered information collected and used by personnel in the healthcare organization, including medical history, medical notes, diagnosis, medications, treatment plans, immunization history, allergies, radiological images, and laboratory and test results (Office of the National Coordinator for Health Information Technology, 2019).

Emergency department: A hospital emergency department is responsible for providing immediate care (CMS, n.d.). A patient's medical visit is considered an emergency department visit when they are discharged from the emergency department without an inpatient stay.

Heart failure: A chronic, progressive condition where the heart muscles are unable to supply a sufficient amount of blood to meet the body's need for blood and oxygen (American Heart Association, 2017).

Hospital Readmission Reduction Program (HRRP): The HRRP is a Medicare value-based purchasing program. The program monitors six conditions and procedure-specific 30-risk-standardized unplanned readmission measures and reduces payments to hospitals with excess readmissions (CMS, 2020).

Inpatient hospitalization: A patient is considered an inpatient when a doctor places an order for inpatient care based on medical necessity, typically when 2 or more days of hospital care are required (CMS, n.d.).

LACE index: The LACE index is a predictive tool developed by van Walraven et al. (2010) to identify patients at risk for readmission or death within 30 days of discharge from the hospital. The LACE index considers the length of stay, acuity of the admission, comorbidity of the patient, and emergency department use (van Walraven et al., 2010).

Length of stay: The length of stay is the number of days a patient stays in a healthcare facility and is calculated by subtracting the admission date from the discharge date (Healthcare Cost and Utilization Project, n.d.).

Laboratory results: Laboratory results provide clinicians with quantitative information that may be used to confirm a diagnosis or compare how a patient's condition is progressing or responding to treatment (Dasgupta & Sepulveda, 2019).

Primary care physician: A primary care physician is a specialist in family medicine, internal medicine, or pediatrics who provides comprehensive care and assists the patient in accessing a wider range of specialty healthcare services (Venes, 2013).

Risk prediction model: Risk prediction models are used in healthcare to guide decision-making processes to improve health outcomes, predict the risk of future events, or reduce healthcare costs through the efficient allocation of healthcare resources (Lee et al., 2016).

Assumptions

Due to the use of secondary data, one assumption of this research was that the data extracted from the EMR were accurate. It was also assumed that examining data from hospitals within a single healthcare system would capture all or most occurrences of all-cause 30-day readmission. However, it must be acknowledged that patients may have sought care at a healthcare facility outside of the system that served as the study site; therefore, the readmission event would not be counted within the dataset.

Scope and Delimitations

The focus of this study was on the ability of two risk prediction models to predict all-cause 30-day readmissions in adults with heart failure. Patients younger than 18 years of age were excluded from the study. The study dataset consisted of data collected from six acute care hospitals located in Long Island, New York, and was limited to information from the medical records of patients with a billing diagnosis of heart failure. All six facilities are located in a suburban area, thereby, limiting the generalizability of the results to rural or city areas.

Limitations

A limitation of this study was the use of secondary data, which constrains the researcher’s control over the quality of the data collection process and threatens the study’s internal validity. Variable documentation in the EMR could have resulted in missing data and the possibility of systematic differences between the complete patient records and those that are not, leading to nonresponse bias (see Cheung et al., 2017). Another limitation of this study was the use of convenience sampling, a form of nonprobability sampling that threatens the external validity of the study and limits the generalizability of the results (Jager et al., 2017). According to Panacek (2007), strict adherence to guidelines for proper chart review, including specific inclusion and exclusion criteria and well-defined research questions and variable definitions, could help minimize the effect of the biases inherent in retrospective chart reviews.

Significance of the Study

This research provides information regarding the effectiveness of the LACE index in predicting the risk of all-cause 30-day readmission in the study population and for similar populations. The insights provided from this study can help advise hospitals whether the implementation of the LACE index would be an appropriate measure to help avoid CMS's financial penalties associated with a higher than expected risk-standardized 30-day readmission rate. Further, this study has the potential to lead to positive social change by developing a model that more accurately identifies heart failure patients at risk for readmission who would benefit from the implementation of appropriate patient-specific interventions. The prevention of readmission can help heart failure patients avoid the negative medical and financial consequences known to be associated with readmission to the hospital within 30 days of discharge.

Summary

Regulatory agencies, such as CMS, regard 30-day readmission rates as a quality metric for healthcare providers. Consequently, hospitals across the United States have implemented targeted performance improvement efforts to reduce 30-day readmission rates to avoid the associated economic costs and decrease unnecessary patient suffering.

A review of the current literature has shown that even though the LACE index is a commonly used risk prediction tool, and one that has been externally validated, the efficacy of the tool in predicting the risk of readmission is variable between different sample populations and when applied to patients with specific diagnoses. To address the issue of possible lower performance and, therefore, ineffectiveness in clinical practice, the aim of this study was to evaluate the discriminative accuracy of the LACE index for predicting all-cause 30-day readmission within the selected sample population of heart failure patients. Further, the secondary purpose of the study was to develop and analyze a modified version of the LACE index that includes additional variables. Chapter 2 consists of a more detailed explanation of the study’s theoretical framework and an overview of the current literature related to 30-day readmission to an acute care hospital for heart failure patients.

Chapter 2: Literature Review

Heart failure is one of the leading causes of hospitalizations and readmission in the United States. Jackson et al. (2018) used national data to examine the burden of heart failure and found that in 2014, there were 978,135 hospitalizations, 1,068,412 emergency department (ED) visits, and 83,705 deaths associated with a primary diagnosis of heart failure. Among the patients hospitalized for heart failure, many meet the definition of readmission set by CMS. Patil et al. (2019) analyzed data on heart failure patients supplied by the Healthcare Cost and Utilization Project National Readmission Database and found that 20.14% of patients were readmitted within 30 days, with a median readmission time of 12 days from initial discharge.

Though the extent of the current literature focusing specifically on the heart failure population is limited, researchers have shown that the high rates of readmission experienced by heart failure patients are associated with substantial healthcare costs and poor patient outcomes. Kwok et al. (2021) found that the estimated total mean cost for heart failure patients with a 30-day readmission was $15,618 ± 25,264, compared to $11,845 ± 22,710 for heart failure patients without a 30-day readmission. Similarly, Fingar and Washington (2015) examined the annual aggregate cost of readmission and attributed $2.7 billion in healthcare spending to readmission for heart failure patients. Along with financial costs, the adverse patient outcomes associated with 30-day readmissions have also been documented. Arundel et al. (2016) researched the long-term outcomes of readmission for Medicare beneficiaries with heart failure using a propensity-based matched cohort of heart failure patients with and without a 30-day all-cause readmission. Over the 8.7-year follow-up period, those with an all-cause 30-day readmission experienced a longer cumulative length of stay (51 days vs. 43 days) and higher cumulative costs ($38,972 vs. $34,025). The researchers also found that all-cause mortality within 1 year occurred in 41% of the patients with a 30-day all-cause readmission compared to 27% in those without a 30-day all-cause readmission (Arundel et al., 2016). The unnecessary financial costs and adverse patient outcomes associated with 30-day readmissions highlight the necessity to accurately identify high-risk patients while hospitalized who would benefit from targeted 30-day readmission reduction efforts.

In this nonexperimental, quantitative study, I explored the ability of the LACE index to predict the risk of all-cause 30-day readmission in heart failure patients and investigated the relationship between 30-day readmission and additional clinical and demographic factors. Previous studies have validated the use of the LACE index in various populations; however, the results have been conflicting, and the heart failure population has been understudied (Calderon et al., 2018; Yazdan-Ashoori et al., 2016). This chapter contains a synthesis of findings from the current literature relating to 30-day readmission in heart failure patients, the LACE index, and the associated risk factors and outcomes. This chapter will also include background information on the relevance of the research problem and evidence to support the Andersen behavioral model of health services use as the theoretical basis for the study.

Literature Search Strategy

I used the Walden University Library to conduct a review of the literature related to 30-day readmission in the heart failure population, risk factors, and the LACE index using the CINAHL & MEDLINE Combined Search and SocINDEX with Full-Text databases, along with the Thoreau multidatabase search. The key search terms used were *heart failure*, *30-day readmission*, *30-day rehospitalization*, *LACE index*, *length of stay*, *acuity*, *Charlson comorbidity index*, *emergency department*, *age*, *medication*, *laboratory results*, *healthcare utilization*, *risk of readmission*, and *Andersen behavioral model of health services use.* Articles were included in the review if they were peer-reviewed, written in English, published after 2015, and excluded if focused on a pediatric study population. Under certain circumstances, older or seminal articles were included to supplement the breadth of the relevant knowledge contained in the current literature. For nationally representative statistics, data from U.S. government websites were used.

Theoretical Framework

Andersen's (1968) behavioral model of health services use, hereafter referred to as the Andersen model, served as the theoretical basis for this study. The Andersen model was first developed in 1968 to "assist the understanding of why families use health services, to define and measure equitable access to healthcare, and to assist in developing policies to promote equitable access" (Andersen, 1995, p. 1). The Andersen model provides a framework for exploring the contextual (circumstances and environment related to access to care) and individual factors that influence healthcare utilization (Andersen et al., 2013). Though the framework examines both the contextual and individual influences, this research focused only on individual factors. In the following section, I describe the Andersen model and review the existing literature in which the model is applied as the theoretical framework in a way similar to the current study.

The Andersen Behavioral Model of Health Services Use

Since it was first published, the Andersen model has evolved in response to criticisms and the advancing concepts of the discipline (Andersen, 1995; Andersen et al., 2013). The original model concentrated on the family as the unit of analysis, but the focus shifted to the individual due to the difficulty of developing measures that consider the heterogeneity of the family unit (Andersen, 1995). The Andersen model identifies three influencing factors: predisposing, enabling, and need (Andersen, 1968). Predisposing factors influence an individual's predisposition to access healthcare and include gender, race, genetic susceptibility, health belief attitudes, and social factors, such as education and occupation, that determine a person's status in the community (Andersen et al., 2013). According to the Andersen model, enabling factors facilitate or impede the use of health services (Andersen, 1968). This category of influencing factors considers the individual's support network and financial resources, as finances influence an individual's ability to pay for services (Andersen et al., 2013). Finally, need factors include the individual's emotional response to the illness, and their perception of their health status and the magnitude of the health problem (Andersen et al., 2013). The Andersen model categorizes a healthcare provider's professional judgment of the need for care based on objective measurement as a need factor (Andersen et al., 2013).

Prior Research Using the Andersen Model

The Andersen model has often served as a theoretical framework in research focused on readmission to a healthcare facility. Smith et al. (2017) conducted a prospective cohort study to examine the influence of patient-level sociodemographic characteristics on readmission risk in medical patients. The researchers used the Andersen model to guide the conceptualization of the independent variables into predisposing, enabling, and needs factors. The researchers found that while predisposing and enabling factors were not significantly associated with unplanned readmission within 30 days, needs factors, such as the frequency of emergency department visits, were significantly associated. Smith et al.'s study is particularly relevant to this research because the authors analyzed the individual components of the LACE index and classified them as need factors.

Similar to Smith et al. (2017), Kaya et al. (2019) examined the predictors of readmission in internal medicine patients and used the Andersen model to divide the chosen independent variables into four groups: predisposing, enabling, need, and utilization. The researchers concluded that need factors, such as higher comorbidity, length of stay, and weaker coping ability, were the most powerful predictors of readmission (Kaya et al., 2019). However, Hamilton et al. (2016) used the Andersen model to explore the predictors of psychiatric readmissions and found that both enabling (housing instability/insurance coverage) and need factors were strong predictors of readmission.

According to Chan et al. (2019), when the focus of research is solely on well-established risk factors, the prediction of readmission risk is hindered. Therefore, Chan et al. used the Andersen model to justify the idea that perceived social support is an enabling resource for healthcare utilization. In alignment with the Andersen model, the authors argued that social support buffers the patient against the medical, financial, and emotional stresses associated with hospitalization and protects against 30-day readmission. Chan et al. found that those with low social support were more likely to be readmitted than those with high social support. This study further establishes the Andersen model's flexibility when exploring the factors that influence health care utilization as predisposing, enabling, and need factors.

Application of the Andersen Model

As described above, the Andersen model has been widely used to investigate the utilization of healthcare services in relation to readmission risk. The model assumes that healthcare utilization depends on the person's predisposition to use health services, their ability to access services, and their illness level (Andersen & Newman, 2005). The framework allows for the development of a risk model that considers the individual characteristics of healthcare utilization and guides the selection of relevant variables (see Andersen & Newman, 2005). In alignment with the Andersen model, the following literature review examines the LACE index and provides evidence of the relevant predisposing, enabling, and need factors that are thought to contribute to the risk of readmission for heart failure patients.

Literature Review Related to Key Variables

The next section of the literature review will include the key variables used in the study and how each variable relates to the risk of 30-day readmission.

The LACE Index

van Walraven et al. (2010) conducted a prospective cohort study with the intent of developing an easy-to-use model that would predict the risk of death or unplanned readmission within 30 days after discharge from a hospital. The study sample consisted of 4,812 medical and surgical patients discharged from 11 community hospitals located in Ontario, Canada (van Walraven et al., 2010). Multivariable logistic regression was used to measure the independent relationship between 48 patient-level variables and early death or readmission. Four variables were found to be independently associated with the outcomes: length of stay in days (*OR* = 1.47; 95% CI [1.25, 1.73]), acuity of the admission (*OR* = 1.84; 95% CI [1.29, 2.63]), Charlson comorbidity index score (*OR* = 1.21; 95% CI [1.10, 1.33]), and emergency department visits during the previous 6 months (*OR* = 1.56; 95% CI [1.27, 1.92]). The LACE index score is calculated by adding the numeric values assigned to the variables relevant to the patient. The score ranges from 1 to 19, with 0–4 indicating low risk, 5–9 indicating moderate risk, and a score of greater than 10 indicating a high risk of readmission.

The LACE Index and the Prediction of Heart Failure Readmission

Although a review of the current literature revealed research that analyzed the ability of the LACE index to predict the risk of unplanned readmission within 30 days after hospital discharge, the findings were conflicting, particularly when applied to specific patient subgroups (Damery & Combes, 2017). The following section focuses on a review of the current published literature related to the heart failure population.

Calderon et al. (2018) studied the ability of the LACE index to predict 30-day readmission in patients with acute decompensated heart failure. The researchers found slightly elevated LACE index scores in patients who were readmitted within 30-days compared to those who were not readmitted (12.53 vs. 11.41). Despite this, Calderon et al. found no significant difference in readmission risk when comparing patients classified as high-risk based on the LACE index score to those categorized as low-moderate risk (*OR* = 5.37; 95% CI [0.82, 35.0]; $p = .07$). Wang et al. (2014) performed an external validation of the LACE index using a population of congestive heart failure patients. Similar to Calderon et al., while the calculated LACE index score was slightly higher in those readmitted, Wang et al. found no significant difference in the rates of readmission between those with a high LACE index score and those with a low LACE index score (24.34% vs. 25.93%, respectively; $p = .856$). The findings of Calderon et al. and Wang et al. support the view that the LACE index may not accurately predict unplanned 30-day readmission in the heart failure population.

In comparison, Yazdan-Ashoori et al. (2016) found that the odds of 30-day readmission increased with higher LACE scores (*OR* = 1.13; 95% CI [1.02, 1.24]). Yazdan-Ashoori et al. conducted a prospective cohort study as part of the Patient-Centered Care Transitions in Heart Failure (PACT-HF) pilot study to assess whether the LACE index could predict readmission risk in hospitalized heart failure patients. However, Yazdan-Ashoori et al. noted that the PACT-HF pilot study delivered evidence-informed transitional care services to all patients hospitalized for heart failure, and 42% of the study population received additional post-discharge nursing services. As a result, the researchers acknowledged that readmission rates might have been lower in the study population than the rates typically calculated for standard heart failure patients (Yazdan-Ashoori et al., 2016).

Similarly, research results by Regmi et al. (2020) supported the clinical application of the LACE index. Although the primary purpose of the research performed by Regmi et al. was to examine whether the type of heart failure affected readmission rates, the authors found that the mean LACE index score of patients readmitted was 12.59 compared to a mean score of 11.31 in the non-readmitted group ($p < .001$). The findings of Yazdan-Ashoori et al. and Regmi et al. suggest that the LACE index could be a valuable tool for predicting the risk of 30-day readmission in patients with heart failure. When limited resources are available, acute care facilities need to utilize a model that discriminates patients at a high risk for readmission from patients with a low risk for optimal resource use.

A common theme found in the literature was to compare the LACE index to other readmission risk models. The results of research by Au et al. (2012) found the LACE index to have poor discriminative accuracy for predicting readmission with a *c* statistic of 0.59 (95% CI [0.58, 0.60]), but the LACE index showed superior performance when compared to other models. The researchers explored the net reclassification index, an estimate that attempts to measure how well a new model reclassifies participants compared to an older model (Au et al., 2012). The LACE index showed a 12.6% reclassification improvement for predicting 30-day readmission over the Charlson score and a 15% net reclassification improvement over the Keenan prediction model (Au et al., 2012).

Van Spall et al. (2018) compared the performance of the LACE index to an abbreviated version, LE (length of stay and ER visits). The ROC curve analysis associated with the LACE index produced a *c* statistic of 0.617 (95% CI [0.586, 0.648]), and the LE showed slightly improved discrimination with a *c* statistic of 0.629 (95% CI [0.593, 0.655]). Likewise, Zheng et al. (2015) compared the accuracy, specificity, and sensitivity of the LACE index to data mining approaches in a population of heart failure patients. The LACE index was found to be inferior compared to data mining models with an accuracy of 43.5%, specificity of 21.8%, and sensitivity of 51.8% (Zheng et al., 2015). The comparison of the LACE index to other models and the findings of inferior performance is relevant to this study because it shows that it may be possible to develop an alternative model that better predicts the risk of 30-day readmission in the study population.

LACE Index Variables as Independent Risk Factors for Readmission

Although the effectiveness of the LACE index for predicting the risk of 30-day readmission in the heart failure population is understudied, considerable research efforts have focused on the risk factors predictive of readmission for heart failure patients. The relationship between the individual variables of the LACE index (length of stay, acuity of the admission, comorbidity score, and emergency department use) and 30-day readmission have been covered in the current literature. In the following section, I discuss the variables of the LACE index as independent risk factors of 30-day readmission for heart failure patients.

Length of Stay

Of the variables included in the LACE index, length of stay (LOS) was the most extensively covered in the literature. A patient’s LOS in an acute care facility is measured from the admission date to the discharge date. While a longer LOS is associated with an increased risk of hospital-acquired infections and deconditioning, a shorter LOS may not allow for symptom resolution and the proper identification of patients requiring post-discharge services (Sud et al., 2017). The patient outcomes associated with both a longer and shorter LOS may lead to an increased risk of 30-day readmission.

The research regarding the relationship between LOS and 30-day readmission for heart failure patients is inconsistent. A review of the literature revealed studies that 1) have linked both a longer LOS and a shorter LOS with an increased risk of readmission, and 2) studies that have found no association between LOS and the risk of 30-day readmission. After controlling for age, gender, and comorbidities, Whittaker et al. (2015) found that while the mean LOS was higher in heart failure patients who experienced a 30-day readmission (12.8 +/- 22.2 days vs. 8.9 +/- 12.2 days), LOS was not significantly associated with readmission ($p = .77$). Research by Carlson et al. (2019) found similar results. However, the researchers acknowledged that the average LOS of the study population was 3.4 days, compared to 5.7 to 7.8 days reported in other studies, which may have affected the study results. In contrast, research by Sud et al. (2017) found a U-shaped relationship between LOS and cardiovascular ($p < .001$) and heart failure ($p = .005$) readmissions with increased rates of readmission associated with the shortest and longest LOS. Noncardiovascular readmissions increased linearly as the length of stay increased in the study population (Sud et al., 2017).

Different definitions for the LOS variable were used throughout the literature, making it difficult to compare the researcher's findings. Mirkin et al. (2017) used a oneweek LOS as the reference and found that having a LOS of 1 to 2 weeks (*AOR* = 1.26; $p < .001$) or ≥ 2 weeks (*AOR* = 1.62; $p < .001$) was associated with an increased risk of readmission in patients with congestive heart failure. Research by Arora et al. (2017) and Miñana et al. (2017) differed from Mirkin et al. by evaluating the relationship between LOS and 30-day readmission using shorter timeframes. Arora et al. divided LOS into ≤ 2 days, 3–4 days, 5–8 days, and >8 days and found that an index admission with a LOS of ≥ 3 days was a significant predictor of an increase in 30-day readmission for heart failure patients ($p < .001$). Similarly, Miñana et al. divided LOS into four categories: ≤ 4 days, 5–7 days, 8–10 days, and >10 days. The researchers found that a LOS of ≤ 4 days was not related to an increased risk of readmission, and a LOS of 8–10 days and >10 days were associated with a marginal increase in the risk of 30-day readmission when compared to 5–7 days (Miñana et al., 2017). Bradford et al. (2017) and Roshanghalb et al. (2019) found that a LOS longer than 5 days was associated with an increased risk for 30-day readmission (*OR* = 1.58; 95% CI [1.15, 2.15]; *OR* = 1.12, 95% CI [1.10, 1.14], respectively). Further research is needed to clarify whether a longer LOS or shorter LOS is a stronger predictor of readmission. Standardization of the LOS variable definition would make it easier to compare research findings and assist with the identification of patients who would benefit from enhanced discharge planning.

Acuity of the Admission

Acuity of the admission refers to the type of admission to the acute care facility: through the emergency department versus an elective admission (van Walraven et al., 2010). Using a population of patients with acute decompensated heart failure, Patil et al.

(2019) found an elective admission was independently associated with a lower risk of 30-day readmission (*OR* = 0.91; $p < .01$). Approaching the variable from the other direction, Mirkin et al. (2017) found that emergent admissions were significantly associated with 30-day readmission in patients diagnosed with congestive heart failure who were discharged home or to a skilled nursing facility following their index admission ($p < .001$). Chung et al. (2017) also found an emergency department admission increased the risk of 30-day readmission in heart failure patients when compared to those admitted electively (*AOR* = 1.20; 95% CI [1.12, 1.29]). The association between an emergent admission and an increased risk of 30-day readmission validates the inclusion of the variable in the LACE index and the development of the modified risk prediction model.

Comorbidity Score

The medical community acknowledges that patients with heart failure have a high burden of noncardiovascular comorbidities (Ponikowski et al., 2016). Using data from the American Heart Association's Get with the Guidelines registry, Sharma et al. (2018) found that the prevalence of 0, 1, 2 and >3 noncardiovascular comorbidities in heart failure patients was 18%, 30%, 27%, and 25%, respectively. The LACE index evaluates a patient's comorbidities through the Charlson comorbidity index score (CCI). The CCI was first developed by Charlson et al. (1987) to be a weighted index used to predict the risk of death within one year of hospitalization for patients with specific comorbid conditions. The CCI is considered a summary comorbidity measure; this type of measure is commonly used as a substitute for individual comorbidity variables in health services research and application (Austin et al., 2015).

The relationship between a higher CCI score and the risk of 30-day readmission for heart failure patients has been documented in the literature. Arora et al. (2017) selected a heart failure study cohort from the National Readmission Database and used the Deyo et al. (1992) modification of the CCI to examine the relationship between comorbidities and 30-day readmission. The researchers found that a higher burden of comorbidities, CCI ≥ 3, was a statistically significant predictor of 30-day readmission ($OR = 1.09$; $p < .001$) (Arora et al., 2017). Likewise, research by Patil et al. (2019) showed that a higher CCI score in patients with decompensated heart failure was independently associated with a higher rate of 30-day readmission ($OR = 1.11$; $p < .01$). Research by Chung et al. (2017) found a mean CCI score of 5.2 +/- 2.9 for the study participants in the readmission group and 4.3 +/- 2.5 for those in the non-readmission group. Multiple comorbidities complicate recovery and increase hospitalization rates; therefore, a link between 30-day readmission and comorbidities is not unexpected.

Emergency Department Use

Nationally, in 2014, there was an estimated 1,068,412 emergency department visits for patients with heart failure (Jackson et al., 2018). Although it is known that heart failure patients have a high incidence of emergency department use, few researchers have focused specifically on the relationship between previous emergency department visits and 30-day readmission risk for heart failure patients. Research by Bradford et al. (2017) found that 24.87% of the patients who were readmitted in the study sample visited the emergency department 1 or more times in the 90 days preceding the index admission, and there was a statistically significant relationship between emergency department utilization and the risk of 30-day readmission (*OR* = 1.58; 95% CI [1.15, 2.15]). Using logistic regression, Carlson et al. (2019) found the number of emergency department visits in the previous 6 months was an independent predictor of 30-day readmission for heart failure patients (*OR* = 1.5; *p* = .009). The authors suggested that the higher incidence of emergency department visits in patients who are readmitted within 30 days of discharge may indicate a lack of access to non-emergency care within the study population (Carlson et al., 2019).

Demographic and Clinical Factors Associated with Readmission

Age

In the literature, age is commonly considered a covariate in statistical analyses; however, some researchers have examined age as an independent predictor of 30-day readmission risk in the heart failure population. Although research by Arora et al. (2017) found that age was not an independent predictor of readmission for heart failure patients, other studies have found a statistically significant association between the variables. For example, the purpose of research by Chamberlain et al. (2018) was to develop a predictive readmission model for patients with congestive heart failure, the Readmission After Heart Failure (RAHF) scale. In the derivation cohort, the researchers found that age less than 65 years was independently associated with higher readmission risk after hospitalization (*OR* = 1.14; 95% CI [1.11, 1.18]; Chamberlain et al., 2018). Mirkin et al. (2017) found similar results when they explored the relationship between age and 30-day readmission based on discharge disposition of the index admission. Compared to patients without a 30-day readmission, patients who were discharged home from their index admission and were readmitted within 30 days were more likely to be less than 65 years of age, $p = .007$ (Mirkin et al., 2017). Likewise, for patients discharged home with home nursing care, those readmitted were more likely to be between 18 and 65 years old, $p = .013$ (Mirkin et al., 2017). Among patients admitted to a skilled nursing facility, patients less than 76 years old were more likely to be readmitted, $p < .001$ (Mirkin et al., 2017). Although Mirkin et al. and Chamberlain et al. acknowledged the higher risk of readmission experienced by those less than 65 years of age, they did not hypothesize explanations for why.

Research by Whellan et al. (2016) found a dichotomous relationship when examining the association between age and 30-day readmission in heart failure patients. The statistical analyses performed by the researchers showed that for patients under 55 years of age, there was a significantly lower likelihood of all-cause 30-day readmission for each 10-year increase in age ($OR = 0.81$; 95% CI [0.70, 0.93]), while for patients older than 55 years of age there was a significantly higher likelihood of all-cause readmission for each 10-year increase in age ($OR = 1.23$; 95% CI [1.14, 1.32]; Whellan et al., 2016). The increased risk of readmission identified in the older population may be the result of a greater number of comorbidities; however, there is an opportunity for further research to better explore the increased risk of 30-day readmission identified for heart failure patients less than 55 years of age.

Medication

The literature discusses the influence of a medication regimen on the risk of 30-day readmission through two different mechanisms: medication regimen complexity and the use of medication responsible for risk reduction. Research conducted by Picker et al. (2015) found a statistically significant association between an increasing number of medications prescribed at discharge and the prevalence of 30-day readmission ($p < .001$). The prescribing of more than six discharge medications was found to be an independent predictor of 30-day readmission (*OR* = 1.26; 95% CI [1.17, 1.36]; $p = .003$; Picker et al., 2015). Picker et al. suggested that the complexity of the medication regimen serves as a suitable proxy for the complicated disease process in heart failure patients offering foundational support for the variables influence on 30-day readmission risk.

Conversely, Colavecchia et al. (2017) postulated that a complex medication regimen is an indicator of medication burden, which may negatively impact patient medication adherence leading to adverse drug events, such as hospital readmission. Colavecchia et al. researched the medication regimen complexity index (MCRI) and its use at discharge as a means for identifying heart failure patients at risk for hospital readmission. The MCRI is a weighted calculation based on drug route, frequency of administration, and additional directions of the patient's prescribed medications (Colavecchia et al., 2017). The researchers performed multivariate logistic regression and found that heart failure patients with an MCRI greater or equal to 15 were more likely to be readmitted within 30-days than those with an MCRI less than 15 (*OR* = 1.65; 95% CI [1.01, 2.56]). Although the mechanisms responsible for the association between complex medication regimen and an increased risk of 30-day readmission in the heart failure population is unclear, the association has been documented.

A review of the literature by Ziaeian and Fonarow (2016) found that evidence-based medical therapies recommended by the American College of Cardiology and the American Heart Association (i.e., beta blockers [BB], angiotensin-converting enzyme [ACE] inhibitors, and angiotensin receptor blockers [ARB]) have been shown to reduce readmissions and improve outcomes for heart failure patients. Primary research by Lim et al. (2019) showed that the use of BB, ACE inhibitors, and ARB medications at discharge were lower in those who experienced a 30-day heart failure readmission than those who were not readmitted ($p < .0001$). With a research purpose similar to Lim et al., Loop et al. (2020) used prescription fill claims as a proxy for BB use and found that filling a prescription for a BB was associated with an approximately 20% lower risk of a heart failure readmission 30 days after discharge.

With a focus specifically on ACE/ARB usage, Sanam et al. (2016) analyzed readmission rates for Medicare beneficiaries with heart failure. The statistical analyses showed that the use of an ACE/ARB was associated with a significantly lower risk of 30-day all-cause readmission ($HR = 0.74$; 95% CI [0.56, 0.97]; $p = .030$; Sanam et al., 2016). The positive association between the adherence to the evidence-based medical therapy guidelines and a reduced risk of 30-day readmission supports the consideration of pharmaceutical use within the modified 30-day risk prediction model.

Laboratory Results

Laboratory results of heart failure patients may reflect renal dysfunction or the interaction of decongestive therapy and provide insight on the occurrence of readmission (Vader et al., 2016). Bradford et al. (2017) abstracted the last value before discharge for several laboratory tests and found that BUN over 45 mg/dL was the only laboratory value associated with an increased risk of 30-day readmission (*OR* = 1.80; 95% CI [1.15, 2.82]). Using Cox proportional hazards models, Vader et al. (2016) showed that a higher BUN, higher bicarbonate (total CO2), and lower sodium at baseline predicted a greater risk of readmission within the study population ($p = <.001$).

The enhancement of administrative 30-day readmission risk models with the inclusion of a patient's laboratory results has shown modest improvements in discrimination over more basic models for heart failure patients (Huynh et al., 2016). Research by Huynh et al. (2016) sought to develop a score for the likelihood of readmission due to heart failure and included several laboratory measurements. BUN and albumin were determined to be significant predictors and were added to the multivariate model (Huynh et al., 2016). The overall model was found to have adequate discriminatory power for predicting readmission within 30 days of discharge (*c* statistic = .77; 95% CI [0.74, 0.81]; Huynh et al., 2016). However, it is important to note that the model also considered mental health variables.

Use of Health Care Services

Within the current literature, researchers have explored the influence a patient's use of healthcare services may have on 30-day readmission rates, including access to a physician and previous inpatient hospitalizations. Research by Dupre et al. (2018) focused on a population of patients with cardiovascular disease and found that after controlling for several covariates, patients who reported difficulty accessing care had a higher risk of 30-day readmission than patients who did not report difficulty accessing care (adjusted *OR* = 2.17; 95% CI [1.29, 3.66]). These findings support the statistical results of research conducted by Tung et al. (2017). Tung et al. observed that early physician follow-up (within seven days of discharge) in patients with heart failure was associated with a lower hazard ratio of 30-day readmission when compared to patients who did not receive early physician follow-up (*HR* = 0.54; 95% CI [0.48, 0.60]). According to Tung et al., adequate access to a physician following discharge can reduce the risk of 30-day readmission by facilitating the transition from hospital to home, providing medical interventions in response to disease instability, and offering clinical guidance on medical therapies.

A lack of access to a physician may cause heart failure patients to seek care at an acute care facility leading to the possibility of a patient meeting the CMS definition of 30-day readmission. McLaren et al. (2016) found that patients with one prior admission had a 50% higher risk (95% CI [1.10, 2.05]; p = .011) for 30-day readmission, while those with two or more prior admissions had more than a 3-fold increased risk for 30-day readmission (95% CI [2.27, 4.09]; p < .001). However, in conflict with the results of McLaren et al., Bradford et al. (2017) found that one or more inpatient admissions within the past 90 days was not significantly associated with 30-day readmission (*OR* = 1.28; 95% CI [0.95, 1.73]; p = .106). The inconsistent evidence regarding previous inpatient hospitalizations supports the need for more research exploring the variable as a significant predictor of 30-day readmission before its inclusion into risk prediction models.

Race

There is evidence of an association between a heart failure patient's race and the risk of 30-day readmission within the current literature. Results of research by Mirkin et al. (2017) showed that congestive heart failure patients who were readmitted were more likely to be black (p = .001). Similarly, after adjusting for patient characteristics, hospital characteristics, and socioeconomic status, Ziaeian et al. (2017) found that when compared to white patients, black patients had a higher risk of 30-day readmission (*HR* = 1.09; 95% CI [0.66, 0.88]; p = .012). The researchers found that black patients in the study population had a higher prevalence of preventable comorbidities, such as diabetes, hypertension, and renal insufficiency, which may explain the higher risk of 30-day readmission (Ziaeian et al., 2017).

Methodological Considerations

The following section summarizes the research that supported the chosen methodology of the current study. The findings of the research studies were discussed in detail earlier in this chapter; therefore, in this section I will only refer to the methodology. Out of the seven studies reviewed regarding the ability of the LACE index to predict readmission in the heart failure population, all were conducted using retrospective chart reviews and secondary data. The most commonly used statistical test to research the ability of the LACE index to predict readmission in the heart failure population was the Receiver Operating Characteristic (ROC) curve (reported as a concordance (c) statistic). The ROC estimates the probability that a risk prediction model can correctly discriminate between randomly selected individuals with and without the event of interest (Verbakel et al., 2020). Based on the current literature, there was foundational support for calculating the ROC curve for this research study. Reporting the *c* statistic also allowed the results of the research to be compared to the original derivation of the LACE index by van Walraven et al. (2010). Logistic regression was used to evaluate if the variables discussed in the literature review are independently associated with the risk of all-cause 30-day readmission for the creation of the modified risk prediction model. The use of logistic regression aligned with the methodology of the literature reviewed and allowed the research results to be compared to similar research. Chapter 3 will present further details of the data analysis plan.

Literature Review Summary

Healthcare facilities face financial penalties for higher than expected 30-day readmission rates for heart failure patients. In response, healthcare systems have turned to risk predictive models, built into the EMR, to reduce readmission rates. The predictive model can alert providers of patients at a greater risk of readmission and those who would benefit from interventions. The ability of the LACE index to predict readmission in the heart failure population is understudied, and the results contained within the existing literature have been conflicting (Calderon et al., 2018; Wang et al., 2014; Yazdan-Ashoori et al., 2016).

Further, heart failure readmission risk is a complex phenomenon. The LACE index accounts only for the patient’s length of stay, the acuity of the admission, existing comorbidities, and the number of times the patient has visited the emergency department in the last 6 months. This literature review discussed the influence of age, medication, laboratory results, and healthcare utilization on 30-day readmission risk providing foundational support for further research of the variables and the possible inclusion of the variables into a modified risk prediction model. Chapter 3 consists of a more detailed explanation of the study's methodology and contains the study design and rationale, population, sampling and data collection procedures, data analysis plan, and ethical considerations.

Chapter 3: Research Method

The purpose of this study was to evaluate the discriminative accuracy of the LACE index to predict the risk of 30-day readmission for heart failure patients and explore whether the addition of demographic and clinical variables improved the performance of the model. This chapter contains a discussion of the methodology of the study, including the research design, study population, sampling procedures, data collection process, and the data analysis plan. This chapter also includes threats to the validity of the study, ethical concerns, and data protection measures taken.

Research Design and Rationale

For this study, I used a quantitative, correlational study design using retrospective data to compare an established readmission risk prediction model to a modified version. Correlational research explores the relationship between variables and assesses the statistical relationship without manipulation (Lau, 2017). The selected study methodology was appropriate because I extracted quantitative data through a retrospective review of the EMR system, and the manipulation of the variables of interest was not required to address the research questions. The choice of methodology was consistent with previous studies (e.g., Calderon et al., 2018; Regmi et al., 2020; Wang et al., 2014), in which researchers assessed the ability of the LACE index to predict the risk of 30-day readmission in patients with heart failure and examined additional predictors of 30-day readmission.

The dependent variable was readmission to an acute care hospital within 30 days of discharge from the initial hospital admission, regardless of the diagnosis at the time of readmission. The independent variables included the patient’s length of stay, acuity of the admission, comorbidity score, number of emergency department visits in the previous 6 months, age, number of medications prescribed to the patient, a prescription for a BB, ACE, or ARB, serum albumin and BUN levels, access to a primary care physician, and number of inpatient admissions in the previous 12 months. Race was examined as a covariate.

Methodology

Population, Sample, and Sampling Procedures

The intended target population for this research was adults aged 18 and older hospitalized for heart failure at an acute care hospital. A convenience sampling technique was used to select a study sample that included adults with an inpatient hospital stay and a billing diagnosis of heart failure during the specified time frame. Convenience sampling is a nonprobability sampling method widely used in clinical research where participants are selected based on their availability and accessibility (Elfil & Negida, 2017). I chose this sampling method because convenience sampling is inexpensive and allowed for the extraction of readily available information from the EMR system based on inclusion and exclusion criteria. However, it should be acknowledged that convenience sampling is vulnerable to selection bias and lacks clear generalizability, which may yield biased estimates of the target population (Jager et al., 2017).

The study setting was a healthcare system located in New York, consisting of six acute care hospitals. The inclusion criteria for the study’s participants were set as adults aged 18 and older with an ICD-10 billing diagnosis of heart failure during the index admission and hospitalization in one of the six hospitals from January 2019 to December 2019. Patients younger than 18 years old and those without an active billing diagnosis of heart failure were excluded.

G*Power 3.1 software was used to calculate the sample size required to have sufficient power to detect a meaningful effect. The G*Power program is commonly used in social, behavioral, and biomedical research as a stand-alone tool to conduct power analysis for statistical tests (Faul et al., 2007). For this research, an a priori analysis based on logistic regression was performed to determine the sample size. Based on standard social science practices, sample size analysis was conducted using an alpha level of .05, an odds ratio of 1.3 (representative of effect size), and 80% power (Chinn, 2000; Cohen, 1988).

Data Collection

Patient-level characteristics and readmission data were extracted from the EMR system once I received Institutional Review Board (IRB) approval from Walden University (Approval no. 07-08-21-0726119) and an IRB exemption letter from the study site. The extraction of data from patient medical records allowed me to overcome the inherent limitations of administrative datasets, including a lack of clinical specificity for conditions and laboratory results (see Mahmoudi et al., 2020). The secondary data collected comprised information available during a routine hospitalization, and there was no personal contact with study participants.

The healthcare system's EMRs are maintained and supported by EPIC software. To extract the data for patients that meet the inclusion criteria, a report was created with the variables of interest with the assistance of the information technology team that services the healthcare system. Only information necessary to answer the research question was collected from the EMRs. Data for the study sample were uploaded into a Microsoft Excel spreadsheet where the patients were assigned a random number to help protect their identity.

Operationalization of Constructs

LACE Index

The LACE index was derived from a Canadian population of medical and surgical patients by van Walraven et al. (2010) to predict the risk of death or unplanned readmission within 30 days after discharge from the hospital. The researchers examined 48 patient-level variables and found that length of stay, acuity of the admission (admission through the emergency department), comorbidity of the patient (measured by the Charlson comorbidity index score), and emergency department use in the previous 6 months were independently associated with the outcomes of interest. To build the risk prediction model, van Walraven et al. created categories within each of the four significant variables and assigned points to each categorical level. A patient's LACE index score is the sum of the categories applicable to the patient, with scores ranging from 1 to 19. The readmission risk classification is as follows: 0–4 low risk, 5–9 moderate risk, ≥ 10 high risk. Appendix A contains details on the composition and weighted values of the LACE index variables.

van Walraven et al. (2010) internally validated the LACE index using data collected from 4,812 patients and used administrative data on a random sample of

1,000,000 patients discharged from Ontario hospitals to perform an external validation. To measure the ability of the LACE index to discriminate between patients who experienced the outcomes of interest and those who did not experience the outcomes of interest, the researchers published the concordance (*c*) statistic with the corresponding 95% confidence intervals. The model's overall calibration was summarized using a Hosmer–Lemeshow goodness-of-fit test. The *c* statistics for all cohorts revealed moderate discrimination: derivation cohort 0.7114 (95% CI [0.6736, 0.7491]), internal validation cohort 0.6935 (95% CI [0.6548, 0.7321]), and external validation cohort 0.684 (95% CI [0.679, 0.691]). The results of the Hosmer–Lemeshow statistic demonstrated a well-calibrated model and were as follows: derivation cohort 18.7 (p = .42) and the validation cohort 14.1 (p = .59). van Walraven et al. concluded that the LACE index was appropriate to use to quantify the risk of death or unplanned readmission within 30 days of discharge and demonstrated that the LACE index could be used with primary and administrative data.

The LACE index was used in this study as a tool to predict the risk of 30-day readmission in a population of heart failure patients and served as the gold standard to which the *c* statistic of the modified 30-day readmission risk prediction model was compared. Dr. Carl van Walraven granted permission to use the LACE index (see Appendix B). The previous use of the LACE index in the heart failure population was discussed in depth in Chapter 2 and will not be reexamined.

Variable Descriptions

The measurements of the variables were based on recommendations and standard practices found in the literature. However, the way the variables were recorded in the EMRs also had to be considered. The next section will describe the operationalization of the variables of interest. If the individual independent variable was found to be a significant predictor of readmission ($p < .05$), the measurement of the variable may have been adjusted to create the modified 30-day readmission risk prediction model.

Dependent Variable

The dependent variable for the study was all-cause 30-day readmission, as defined by CMS. The study site's EMR system maintains patient-level data on the occurrence of a 30-day readmission to any of the six facilities. The dependent variable was measured as dichotomous and defined as 1 = readmitted within 30 days and 0 = not readmitted.

Independent Variables

LACE Index. The operationalization of the LACE index score was previously described in detail. Additionally, the individual variables of the LACE index were investigated as independent predictors of 30-day readmission and were defined and measured similarly to the research by van Walraven et al. (2010).

Age. Age was measured as a ratio variable. For the modified 30-day readmission risk model, the age categories corresponded to the values used by Chamberlain et al. (2018) to develop the Readmission After Heart Failure (RAHF) scale (18–64, 65–84, and > 85).

Prescription Medication. Data were extracted related to the overall number of medications prescribed to the patient (inpatient and outpatient) and the prescription of BB, ACE inhibitors, and ARB. The data was taken from the list of active medications within the patient's EMR, with the exception of over-the-counter medicine. The process of medication reconciliation, the comparison of a patient's medication orders to the medicines the patient verbalizes they are taking, occurs at hospital admission and discharge with the intent to create a complete and accurate list. For the simple logistic regression calculations, the number of prescriptions was considered a ratio variable, and the prescription of the specific medications was nominal. To create the modified risk prediction model, the number of prescriptions (i.e., 1–3, 4–6, > 7) was based on research by Picker et al. (2015).

Laboratory Results. For laboratory data, the serum albumin and BUN levels before discharge were extracted. Due to restrictions in the dataset, the variable was measured as dichotomous and defined as 0 = normal or 1 = abnormal.

Access to a Primary Care Physician. At the time of hospital admission, patients are asked to provide the name of their primary care physician as part of the required documentation. Access to a primary care physician was a dichotomous variable and defined as 1 = primary care physician listed in the EMR and 0 = primary care physician not listed in the EMR.

Inpatient Admissions in the Previous 12 Months. The selection of the 1-year timeframe and measurement as a continuous variable was based on research by McLaren et al. (2016). The variable was divided into categories for the modified risk prediction model (0, 1, 2, 3, >3; McLaren et al., 2016).

Race. Race was examined as a covariate. Based on conventional definitions, the variable was categorized as White, Black, Hispanic, and Asian.

Table 1 contains the measurement definitions for the dependent and independent variables, and Table 2 contains the categories used for the modified risk prediction model.

Table 1

Variable Measurement for Simple Logistic Regression Analyses

Variable name	Measurement
30-day all-cause readmission	0 = No readmission within 30 days 1 = Readmission within 30 days
LACE index	LACE index score
Length of stay	Length of stay in days
Acuity of the admission	0 = Emergent admission 1 = Elective admission
Comorbidity score	Charlson comorbidity index score
Emergency department (ED) use	Number of ED visits in past 6 months
Age	Age in years
Number of prescriptions	Number of inpatient and outpatient prescriptions
Prescribed beta blocker (BB)	0 = BB not prescribed 1 = BB prescribed
Prescribed angiotensin converting enzyme inhibitors (ACE)	0 = ACE not prescribed 1 = ACE prescribed
Prescribed angiotensin receptor blockers (ARB)	0 = ARB not prescribed 1 = ARB prescribed
Serum blood urea nitrogen (BUN) level	0 = Normal 1 = Abnormal
Serum albumin level	0 = Normal 1 = Abnormal
Primary care physician (PCP)	0 = PCP not listed in the EMR 1 = PCP listed in the EMR
Number of inpatient admissions	Number of inpatient admissions in the previous 12 months
Race	0 = White 1 = Black 2 = Hispanic 3 = Asian

Table 2

Variable Measurement for Modified Risk Prediction Model

Variable name	Measurement
Length of stay	< 1
	1
	2
	3
	4–6
	7–13
	≥ 14
Acuity of admission	Emergent admission
	Elective admission
Charlson comorbidity index	0
	1
	2
	3
	≥ 4
Emergency department (ED) visits	0
	1
	2
	3
	≥ 4
Age	18-64
	65-84
	> 85
Number of prescriptions	1-3
	4-6
	> 7
Prescription for BB, ACE, or ARB	Not prescribed
	Prescribed
Serum ALB and BUN level	Normal
	Abnormal
Primary care physician	Primary care physician not listed in the EMR
	Primary care physician listed in EMR
Inpatient admissions	0
	1
	2
	3
	> 3

Data Analysis Plan

Data Cleaning Procedures

The secondary dataset was subjected to data cleaning procedures before the statistical analyses were performed in SPSS to improve the quality of the data. The data cleaning methods used in this research study were based on the data cleaning framework proposed by Van den Broeck et al. (2005). First, formatting errors were addressed, and duplicate entries were deleted. Medical records missing data for any of the variables of interest were excluded from the analysis, as all independent variables were required to calculate the LACE index and the modified 30-day readmission risk prediction model score. The dataset was screened for outliers and lack of/excess data through graphical presentations of distributions, frequency distributions, summary statistics, and statistical outlier detection. According to Van den Broeck et al., outliers are diagnosed as erroneous, true extreme, true normal, or idiopathic (suspect but not explained), and suspicious points should be investigated for possible measurement or transcription errors. No outliers or data issues were detected within the dataset.

Research Questions and Hypotheses

Research Question 1: What is the discriminative accuracy of the LACE index to predict all-cause 30-day readmissions in heart failure patients?

$H_0$1: The LACE index does not have statistically significant discriminative accuracy.

$H_1$1: The LACE index does have statistically significant discriminative accuracy.

Research Question 2: Do length of stay, acuity of the admission, comorbidity score, emergency department utilization, age, serum albumin and BUN levels, number of prescription medications, prescriptions for heart medications, number of inpatient hospitalizations in the previous 12 months, and access to a primary care physician statistically significantly predict all-cause 30-day readmissions in heart failure patients?

$H_0 2$: Length of stay, acuity of the admission, comorbidity score, emergency department utilization, age, serum albumin and BUN levels, number of prescription medications, prescriptions for heart medications, number of inpatient hospitalizations in the previous 12 months, and access to a primary care physician do not predict all-cause 30-day readmission in heart failure patients.

$H_1 2$: Length of stay, acuity of the admission, comorbidity score, emergency department utilization, age, serum albumin and BUN levels, number of prescription medications, prescriptions for heart medications, number of inpatient hospitalizations in the previous 12 months, and access to a primary care physician do predict all-cause 30-day readmission in heart failure patients.

Research Question 3: Is there a combination of potential predictors (length of stay, acuity of the admission, comorbidity score, emergency department utilization, age, serum albumin and BUN levels, number of prescription medications, prescriptions for heart medications, number of inpatient hospitalizations in the previous 12 months, and access to a primary care physician) that results in a higher predictive value (*c* statistic) than LACE index to predict all-cause 30-day readmission in heart failure patients?

$H_0$3: There is no difference in the *c* statistic between the modified 30-day readmission risk prediction model and the LACE index.

$H_1$3: There is a difference in the *c* statistic between the modified 30-day readmission risk prediction model and the LACE index.

Statistical Analysis Plan

SPSS (Version 27) was used to analyze the data collected for this study. Pertinent characteristics of the study sample were expressed as descriptive statistics. Descriptive statistics allowed for a comparison between the current study population and the study samples used in the literature.

To investigate the first research question, the LACE index score was calculated at the patient level. The discriminative accuracy of the LACE index to predict the risk of 30-day readmission was assessed using the Receiver Operating Characteristic curve (ROC). The result of the analysis was reported as a concordance (*c*) statistic with the accompanying 95% confidence interval. The ROC curve is a measure of discrimination, the ability of a model to distinguish between patients who experienced the event of interest from those who did not (Caetano et al., 2018). The interpretation of the ROC curve is as follows: a value of 0.5 signifies the model is no better than random chance, values of 0.60 to 0.70 indicate poor discrimination, values of 0.70 to 0.80 represent adequate power of discrimination, and values of 0.80 to 0.90 indicate excellent discrimination (Grant et al., 2018). Additionally, the sensitivity and specificity of the LACE index at different cutoff points was explored.

SPSS uses a nonparametric method to calculate the ROC curve and produce the *c* statistic (IBM Knowledge Center, n.d.). Although nonparametric tests are not subject to assumptions of probability distribution, the assumption of independence should not be violated; therefore, the groups must be mutually exclusive. For this study, this assumption was supported because study participants were either admitted to an acute care facility within 30 days of discharge or not readmitted within 30 days of discharge.

Logistic regression was used to address the second research question. Multivariable logistic regression can be used to determine whether specific variables are associated with a binary outcome (Grant et al., 2019). The purpose of this question was to explore if length of stay, acuity of the admission, comorbidity score, emergency department utilization, age, serum albumin and BUN levels, number of prescription medications, prescriptions for heart medications, number of inpatient hospitalizations in the previous 12 months, and access to a primary care physician independently predict 30-day readmission in the heart failure population. The assumptions of binary logistic regression include a dichotomous dependent variable, one or more continuous or categorical independent variables, independent observations, linearity in the logit of continuous independent variables, and a lack of strongly influential outliers. The assumptions concerning the coding of the study variables and the independence of observations were supported by the study's design, and influential outliers were addressed during the data cleaning process. The linearity in the logit of continuous independent variables was tested in SPSS using the Box-Tidwell test. Independent variables that violated the assumption of linearity and the logs odd were recoded into categorical variables. The odds ratio, 95% confidence interval, and *p* value were reported for each variable.

To address the third research question, the variables found to be independent predictors of readmission ($p < .05$) were included in a modified 30-day readmission risk prediction model. A method proposed by Sullivan et al. (2004) and applied by van Walraven et al. to create the LACE index was used to modify the logistic regression model into a risk score. The ROC curve was calculated for the modified risk prediction model so that the *c* statistics of the LACE index and the modified model could be compared. A stratified analysis was conducted to determine if a patient's race affected the discriminative accuracy of the models for predicting the risk of readmission.

Potential Covariate

The ROC curve of a risk prediction model is a pooled analysis of the average performance in the study population, and the possibility exists that the predictive model performs differently in subgroup analysis. A method initially recommended by Pepe (1997) was applied to address potential covariates. According to Janes and Pepe (2008), covariates that affect the ROC curve are equivalent to effect modifiers, and the authors suggest that separate ROC curves should be estimated for each subgroup. In this research, race was considered a possible covariate because researchers have consistently found that race is a significant predictor of 30-day readmission rates in heart failure patients (Downing et al., 2018; Lloren et al., 2019; Mirkin et al., 2017). Further, the association has been found to persist after adjusting for patient characteristics, socioeconomic status, and hospital factors (Pandey et al., 2019; Ziaeian et al., 2017). Race was not included in the LACE index or the modified version; therefore, there was a possibility that the variable could influence the performance of the 30-day readmission risk prediction models.

Validity

Aspects of the study design may threaten the internal and external validity of the study. Internal validity is the degree of confidence that the relationships established by the researcher signify a true finding, whereas external validity evaluates the generalizability of the results (Patino & Ferreira, 2018). The use of EMRs as the data source threatened the internal validity of this study. The EMRs may not have contained all the required information to sufficiently address the relationship between the variables, or the recorded data may not have been accurate, possibly leading to unmeasured and inadequately measured confounders (Andrade, 2021). The external validity of this study was threatened by the use of convenience sampling. The use of convenience sampling only allows the research results to be generalized to the population used to select the study participants or populations with similar characteristics (Andrade, 2021). The effects of the mentioned threats to the internal and external validity of this study will be discussed in further detail in Chapter 4.

Ethical Procedures and Data Protections

IRB approval was granted from Walden University before the research was begun to ensure that the research followed Walden University's ethical standards and U.S. federal regulations. It was also necessary to obtain a separate IRB approval and a data user agreement from the healthcare system that served as the data source. After review, the IRB at the healthcare system determined the research to be exempt and the Chief Information Officer granted permission to conduct data collection. Before beginning the research, I completed the Collaborative Institutional Training Initiative (CITI) course for Doctoral Student Researchers (Completion Record ID: 39762547).

The data for this research study were de-identified, private, and confidential. The dataset was password protected and opened only on computers protected by anti-virus software. Due to the use of medical information, the research also needed to comply with Health Insurance Portability and Accountability Act (HIPAA) regulations, which protects sensitive patient health information from being disclosed without the patient's consent or knowledge. Measures, such as de-identifying the dataset and proof of IRB approval, complied with the HIPAA Privacy Rule. The data collected for this study will be destroyed seven years after submission to ProQuest.

Summary

For this study, a quantitative, correlational study design was utilized to explore the utility of two risk prediction models, the LACE index and a modified version, in predicting the risk of readmission in a population of heart failure patients. The chosen methodology also allowed for the examination of length of stay, acuity of the admission, comorbidity score, emergency department utilization, age, serum albumin and BUN levels, number of prescription medications, prescriptions for heart medications, number of inpatient hospitalizations in the previous 12 months, and access to a primary care physician as independent predictors of readmission. Chapter 3 contained the research design and rationale, sampling procedures, data collection methods, and the data analysis plan. Chapter 4 consists of an in-depth description of the sample population characteristics and the results of the research.

Chapter 4: Results

The purpose of this quantitative study was to explore the use of the LACE index for predicting all-cause 30-day readmission among heart failure patients, to examine additional variables that have been recognized in the literature as influencing the risk of readmission, and to build a modified risk model based on the statistically significant variables. In Chapter 4, I describe the data collection process and the statistical findings related to the descriptive characteristics of the study sample and the data analysis.

Data Collection

I collected data from the EMRs of patients from a heart failure registry maintained by a healthcare system located in Long Island, New York. I intended to extract data from January 2019 to December 2019, but due to the size of the dataset, the timeframe was reduced to January 2019 to June 2019. The dataset did not differentiate between an inpatient hospitalization and a surgical encounter; therefore, data on the number of inpatient hospitalizations in the past year were not collected, and the variable could not be examined as an independent predictor of all-cause 30-day readmission. Additionally, the structure of the dataset required the laboratory values to be measured as dichotomous, normal versus abnormal.

Sample Characteristics

The study sample consisted of 655 patients admitted with a diagnosis of heart failure to one of the six acute care facilities managed by the study site. The prevalence of readmission within 30 days of discharge was 11.3%. The study sample included 331 (50.5%) males and 324 (49.5%) females. The average age of the study participant was 77 years old, and an overwhelming majority (83.5%) of the study sample identified as White. The baseline demographic characteristics of the sample are reported in Table 3.

Table 3

Baseline Demographic Characteristics

Variable	Frequency	Percent
Readmission		
Not readmitted	581	88.7
Readmitted	74	11.3
Gender		
Male	331	50.5
Female	324	49.5
Race		
White	547	83.5
Black	74	11.3
Hispanic	21	3.2
Asian	13	2.0
Age		
18 to 64	139	21.2
65 to 84	252	38.5
85 and older	264	40.3

Due to the use of a nonprobability sampling frame, the representativeness of the sample to the population of interest was important to consider. According to Weiss and Jiang (2021), the national 30-day readmission rate for heart failure patients is 22.9%, higher than the readmission rate found in the present study. Additionally, although the sample population is comparable to the current literature based on gender and age, the categorization of the sample by race is not representative of the national heart failure population.

Despite the homogeneity of the sample, univariate analysis was performed to justify the inclusion of race as a covariate in the model. I examined the relationship between race and all-cause 30-day readmission using simple binary logistic regression, and the result of the analysis was not statistically significant. However, the relationship between race and the discriminative accuracy of the LACE index in predicting the risk of 30-day readmission in heart failure patients was still explored for the third research question based on evidence found in the current literature.

Descriptive Statistics

The characteristics of the sample population were analyzed based on the independent variables of interest. The average length of stay was found to be 6 days, with patients most frequently staying in the hospital for 3 days. The patient's comorbidity score was calculated using the modified Charlson comorbidity score used in the LACE index. The diseases and conditions considered included cerebrovascular disease, peripheral vascular disease, diabetes, congestive heart failure, chronic pulmonary disease, kidney disease, connective tissue disease, AIDS, dementia, cancer, liver disease, and a history of myocardial infarction. The comorbidity scores ranged from 0 to 16, with an average score of 6. The most common comorbidity seen was kidney disease (48.9%), followed by diabetes (43.7%). Patients in the study sample were prescribed an average of 13 medications, with patients more frequently prescribed a BB medication (86.1%) when compared to an ACE (32.7%) or an ARB (32.5%). Abnormal serum albumin laboratory levels were found in 49.2% of the study sample, whereas 47.5% of the patients had abnormal serum BUN levels.

The acuity of the admission was defined as being admitted to the hospital through the ER. In the study sample, 99.5% of the patients were considered an acute admit. The disproportionate percentage observed can be explained by the infrequent practice by the study site of directly admitting patients to the hospital without first receiving care in the hospital ER. Having a primary care physician listed in the EMR was examined as a measure of access to care, and 99.5% of patients in the study sample had a doctor on record. Despite having access to a primary care physician, in the 6 months before the index admission, the patients visited the ER seven times on average, with the majority of patients having four ER visits. Further information regarding the descriptive statistics of the study sample can be found in Table 4.

Table 4

Descriptive Statistics

Variable	Frequency	Percent
Length of stay		
1–3	248	37.9
4–6	196	29.9
7–13	162	24.7
≥ 14	49	7.5
Acuity of the admission		
Emergent	652	99.5
Elective	3	.5
Charlson comorbidity index		
1 to 4	179	27.3
5 to 8	316	48.2
9 to 12	145	22.1
13 to 16	14	2.1
≥ 17	1	.2
Number of ED visits		
0–4	202	30.8
≥ 5	453	69.2
Age		
18-64	139	21.2
65-84	252	38.5
> 85	264	40.3
Number of prescriptions		
1–3	5	.8
4–6	46	7
≥ 7	604	92.2
Beta Blocker		
Prescribed	564	86.1
Not Prescribed	91	13.9
Prescription of ACE		
Prescribed	214	32.7
Not Prescribed	441	67.3
Prescription of ARB		
Prescribed	213	32.5
Not Prescribed	442	67.5
BUN		
Normal	344	52.5
Abnormal	311	47.5
ALB		
Normal	333	50.8
Abnormal	322	49.2
Primary Care Physician		
PCP listed in EMR	652	99.5
No PCP listed in EMR	3	.5

Statistical Assumptions

To explore the discriminative accuracy of the 30-day readmission risk models to predict all-cause 30-day readmission, I used the ROC curve, a nonparametric test not subjected to the assumptions of probability distribution. Binary logistic regression was performed to examine the independent predictors of all-cause 30-day readmission for the heart failure patient. The assumption of the linearity in the logit of continuous independent variables was tested in SPSS using the Box-Tidwell test, and the Cook's D was used to detect strongly influential outliers. The SPPS Box Tidwell results showed that the number of ER visits violated the assumption of linearity in the logit, and the variable was transformed into a categorical variable for the binary logistic analysis. Based on research by Locker et al. (2007) that established the definition of frequent use of an emergency room commonly found in the literature, I defined the variable as dichotomous (0–4, >4). The results of the Cook's D analysis did not indicate the presence of strongly influential outliers in the dataset.

Statistical Analyses Results

Research Question 1

Research Question 1: What is the discriminative accuracy of the LACE index to predict all-cause 30-day readmissions in heart failure patients?

$H_0$1: The LACE index does not have statistically significant discriminative accuracy.

$H_1$1: The LACE index does have statistically significant discriminative accuracy.

For this research question, I calculated the individual LACE index scores for the patients in the study population and assigned them to a risk category (see Table 5). The ROC curve was calculated in SPSS, and sensitivity and specificity were examined. A patient with a LACE index score of 10 or greater is considered at a high risk for readmission according to van Walraven et al. (2010); therefore, sensitivity and specificity were examined at the value closest to 10. For a cut-point value of 9.5, the LACE index had high sensitivity (1.0) and a high false-positive rate (.991). Next, I examined the area under the curve value (*c* statistic) to investigate the model's discriminative accuracy to predict all-cause 30-day readmission in heart failure patients. The calculated *p* value was statistically significant, and the *c* statistic was .616 ($p = .001$; 95% CI [0.550, 0.681]; see Table 6). The null hypothesis was rejected.

Table 5

Frequency of the LACE Index Risk Classification

LACE index risk classification	Number	Percent
Low risk (0–4)	0	0
Moderate risk (5–9)	5	0.8
High risk (>10)	650	99.2

Table 6

LACE Index ROC Curve Analysis

			Asymptotic 95% CI	
Area	Std. Error	Asymptotic Sig	Lower Bound	Upper Bound
.616	.033	.001	.550	.681

Note. CI = confidence interval.

Research Question 2

Research Question 2: Do length of stay, acuity of the admission, comorbidity score, emergency department utilization, age, serum albumin and BUN levels, number of prescription medications, prescriptions for heart medications, and access to a primary care physician statistically significantly predict all-cause 30-day readmissions in heart failure patients?

$H_0$2: Length of stay, acuity of the admission, comorbidity score, emergency department utilization, age, serum albumin and BUN levels, number of prescription medications, prescriptions for heart medications, and access to a primary care physician do not predict all-cause 30-day readmission in heart failure patients.

$H_1$2: Length of stay, acuity of the admission, comorbidity score, emergency department utilization, age, serum albumin and BUN levels, number of prescription medications, prescriptions for heart medications, and access to a primary care physician do predict all-cause 30-day readmission in heart failure patients.

I performed binary logistic regression and examined each variable as an independent predictor of all-cause 30-day readmission for heart failure patients. The dependent variable was all-cause 30-day readmission (0 = no readmission within 30 days of the index admission; 1 = readmitted within 30-days of the index admission). The independent variables examined were length of stay, acuity of the admission, comorbidities, emergency department visits in the previous 6 months, age, laboratory results for BUN and ALB, number of medications prescribed to the patient, a prescription for a BB, ACE, or ARB, and having a primary care physician listed in the EMR. Table 7 presents a summary of the binary logistic regression results. The following section will review the independent variables as predictors of all-cause 30-day readmission.

Table 7

Summary of Simple Binary Logistic Regression

Variable	*B*	Sig.	*OR*	95% CI	
				Lower	Upper
Length of stay	.041	.024	1.042	1.005	1.079
Acuity of the admission	-1.378	.263	.252	.023	2.815
Comorbidity score	.132	.002	1.141	1.051	1.239
ED utilization	-2.202	.000	.111	.040	.307
Age	.002	.785	1.002	.985	1.020
BUN result	.053	.831	1.054	.650	1.711
ALB result	-.532	.035	.587	.358	.963
BB use	.318	.334	1.374	.721	2.618
ARB use	.075	.779	1.078	.639	1.816
ACE use	.227	.404	1.255	.736	2.141
Number of medicines	.061	.006	1.063	1.017	1.111
Primary care physician	1.378	.263	3.966	.355	44.277

Note. CI = confidence interval.

Length of Stay

LOS was a statistically significant predictor of all-cause 30-day readmission for heart failure patients (p = .024). Given that the p value was significant, the odds ratio can be interpreted. This finding suggests that a one day increase in the length of stay leads to a 4% increase in the odds of readmission within 30 days of the index admission (OR = 1.042; β = .041; 95% CI [1.005, 1.079]). The null hypothesis was rejected.

Acuity of the Admission

The variable, acuity of the admission, which determines if the patient was emergently or electively admitted, was not statistically significant (p = .26). There is no association between the route of admission and all-cause 30-day readmission. The null hypothesis was retained.

Comorbidity Score

A statistically significant association was detected between a patient's comorbidity score and all-cause 30-day readmission (p = .002). The positive odds ratio indicates that a 1 point increase in comorbidity score leads to a 13% increase in the odds of readmission (OR = 1.141; β = .132; 95% CI [1.051, 1.239]). The null hypothesis was rejected.

Emergency Department Visits in the Previous 6 Months

As a continuous variable, emergency department visits violated the assumption of linearity in the logit; consequently, the variable was recoded as a categorical variable. The result of the binary logistic regression calculation was statistically significant (p = .000). A negative beta coefficient and an odds ratio of less than 1 suggests that as the number of ED visits increases, the patient's odds of readmission within 30-days decreases (OR = .111; β = -2.202; 95% CI [0.040, 0.307]). The null hypothesis was rejected.

Age

The p value for age was not statistically significant (p = .785); therefore, the values within the model could not be considered. The null hypothesis was retained.

Laboratory Results

Serum BUN and ALB were examined individually as pertinent laboratory values for predicting all-cause 30-day readmission in the heart failure population. ALB was analyzed as a dichotomized variable with an abnormal result defined as less than 3.0 g/dl or greater than 4.8 g/dl, and a BUN greater than 45 mg/dL was considered abnormal. While the *p* value for BUN was not statistically significant ($p = .831$), a statistically significant *p* value was detected for ALB ($p = .035$). These findings indicate that although there is no association between BUN results and all-cause 30-day readmission, those with a normal ALB result are .587 times less likely to be readmitted within 30-day than those with an abnormal ALB result ($OR = .587$; $\beta = -.532$; 95% CI [0.358, 0.963]). The null hypothesis was retained with regards to BUN but rejected for ALB results.

Medication Usage

The individual binary logistic regression models for a prescription for a BB, ARB, or ACE medication were not statistically significant ($p = .334$, $p = .779$, $p = .404$, respectively). The null hypothesis was retained. The odds ratio and confidence intervals were not examined. In contrast, the number of medications prescribed to the patient was significantly associated with all-cause 30-day readmission ($p = .006$). These results suggest that as the number of medications prescribed to the patient increases, the patient's odds of being readmitted within 30 days of the index admission increases ($OR = 1.063$; $\beta = .061$; 95% CI [1.017, 1.111]). The null hypothesis was rejected.

Primary Care Physician

The association between the patient having a primary care physician listed in the EMR and all-cause 30-day readmission was determined to be not statistically significant ($p = .263$). The null hypothesis was retained.

I did not consider an inclusive model with all the variables because the purpose of the research question was to determine which variables independently predicted all-cause 30-day readmissions in heart failure patients so that a modified risk model could be developed.

Research Question 3

Research Question 3: Is there a combination of potential predictors (length of stay, acuity of the admission, comorbidity score, emergency department utilization, age, serum albumin and BUN levels, number of prescription medications, prescriptions for heart medications, and access to a primary care physician) that results in a higher predictive value (*c* statistic) than LACE index to predict all-cause 30-day readmission in heart failure patients?

$H_0$3: There is no difference in the *c* statistic between the modified 30-day readmission risk prediction model and the LACE index.

$H_1$3: There is a difference in the *c* statistic between the modified 30-day readmission risk prediction model and the LACE index.

The creation of the modified 30-day readmission risk prediction model was based on the method developed by Sullivan et al. (2004) to create a points system that allowed the complex statistical models in the Framingham Heart study to be useful for practitioners. van Walraven et al. (2010) applied this method to develop the LACE index. Table 8 displays the assigned points for the statistically significant variables established by the binary logistic regression calculations. The number of ER visits was omitted because an increase in the number of visits decreased the odds of 30-day readmission suggesting a protective relationship. ALB results were also excluded due to the negative beta coefficient. The level of risk assigned to the number of points was based on the categories established by van Walraven et al. (2010) to facilitate the comparison between the two models; 0–4 (low risk), 5–9 (moderate risk), ≥ 10 (high risk). Table 9 contains the number of patients classified by risk category.

Table 8

Modified 30-day Readmission Risk Prediction Model Point System

Variable	Categories	Points
Number of comorbidities	1–4	0
	5–8	2
	9–12	4
	≥ 13	5
LOS	1–3	0
	4–6	0
	7–13	1
	≥ 14	3
Number of medications	1–3	0
	4–6	1
	≥ 7	3

Note. A constant of 0.2875 used based on Sullivan et al. (2004).

Table 9

Frequency of the Modified Risk Model Classification

Modified risk model category	Frequency	Percent
Low risk (0–4)	194	29.6
Moderate risk (5–9)	447	68.2
High risk (≥ 10)	14	2.1

The ROC curve for the modified 30-day readmission risk prediction model was calculated in SPSS to answer the third research question. The *p* value associated with the ROC curve for the modified risk prediction model was found to be statistically significant

(p = .001), and the c statistic was .618 (95% CI [0.555, 0.681]). A comparison of the c statistics revealed a slight difference between the modified 30-day readmission risk prediction model and the LACE index. The null hypothesis was rejected.

Race was examined as a covariate based on evidence identified in the literature. The categories of race were defined as White, Black, Hispanic, and Asian. The ROC curves were calculated individually to compare the performance of the models based on race (see Table 10). When only those who identified as white were considered, the discriminative accuracy (c statistic) of the LACE index improved and was higher than the discriminative accuracy of the modified 30-day readmission risk prediction model (c = .648 vs. c = .635). The ROC curves for both the LACE index and the modified risk prediction model were not statistically significant for the Black, Hispanic, and Asian categories.

Table 10

ROC Curve by Race

Race	LACE index ROC curve			Modified model ROC curve		
	c	*p*	95% CI	*c*	*p*	95% CI
White	.648	.000	[0.581, 0.715]	.635	.000	[0.566, 0.704]
Black	.348	.314	[0.190, 0.578]	.473	.817	[0.296, 0.651]
Hispanic	.775	.364	[0.546, 1.000]	.725	.457	[0.486, 0.964]
Asian	.295	.183	[0.000, 0.655]	.477	.921	[0.133, 0.821]

Note. ROC = Receiver Operating Characteristic; c = concordance statistic; CI = confidence interval.

Summary

Three research questions were examined using SPSS to better understand the topic of all-cause 30-day readmission. The first research question used the ROC curve to assess the discriminative accuracy of the LACE index to predict all-cause 30-day readmission in the heart failure population. The result of the analysis was statistically significant, and the model had poor discriminative accuracy to predict all-cause 30-day readmission. The second research question examined several independent predictors of all-cause 30-day readmission discussed within the current literature. When examined individually, the independent variables (age, primary care physician, a prescription for BB, ARB, or ACE, BUN result, and the acuity of the admission) were not statistically significantly associated with all-cause 30-day readmission. The number of ER visits, comorbidity score, length of stay, ALB result, and the number of medications prescribed were determined to be statistically significantly associated with all-cause 30-day readmission. The intent of the third research question was to develop a modified risk model based on the statistically significant variables that would be compared to the discriminative accuracy of the LACE index. Though the modified 30-day readmission risk prediction model also demonstrated poor discrimination, it was a slight improvement over the performance of the LACE index. Lastly, the models' performances were compared across race. The results of the ROC curve analyses were statistically significant only for those heart failure patients who identified as white. Statistical significance was not detected for the other race categories.

The findings of the study will be explained further in Chapter 5. Chapter 5 will discuss the results of the study in the context of what is known on the subject matter. Additionally, the limitations of the study, recommendations for further research, and implications for social change will be provided.

Chapter 5: Discussion, Conclusions, and Recommendations

The intent of this study was to provide a further understanding of all-cause 30-day readmission in the heart failure population. In this quantitative study, I used secondary data from the EMRs of 655 heart failure patients. The purpose of the study was to examine the use of the LACE index in the sample population and develop a modified 30-day readmission risk prediction model using additional variables found to be statistically significant predictors of all-cause 30-day readmission.

Using SPSS (Version 27), I explored three research questions. The first and third research questions used the ROC curve analysis as the statistical test, and the second research question used simple binary logistic regression. In this chapter, I summarize the study findings, the limitations of the research, recommendations for further research, and the implications for social change.

Interpretation of Findings

Research Question 1

For Research Question 1, the ROC curve analysis was used to evaluate the performance of the LACE index. The *c* statistic in the SPSS ROC curve analysis was used to determine whether the model could accurately distinguish between heart failure patients who were readmitted within 30 days of discharge from heart failure patients who were not readmitted. A *c* statistic value of 0.5 suggests the model is no better than random chance for classifying the outcome, and a value of 1 indicates the model perfectly classifies the outcome. Based on the *c* statistic, I found the LACE index to have poor discriminative accuracy to predict all-cause 30-day readmission in the sample of heart failure patients (c = .616, 95% CI [.550, .681], p = .001).

The plotting of the ROC curve provides information on the sensitivity and specificity of the risk prediction model and allows for the discussion of an optimal cut-point value, which is where most individuals are classified correctly (Perkins & Schisterman, 2006). van Walraven et al. (2010) defined a high risk of readmission within 30 days as a LACE index score of 10 or greater. At a cut-point value of 9.5, the LACE index had a high true positive rate (sensitivity) and a very low true negative rate (specificity) when the ROC plot was examined. The low specificity of the LACE index suggests that the model may not be appropriate for clinical use in the study population.

The Index of Union method proposed by Unal (2017) suggests that the optimal cut-point value is one where the sensitivity and specificity are closest to the value of the area under the ROC curve. Using this method, the optimal cut-point value for the LACE index for predicting all-cause 30-day readmission for the study population was 15.5. However, with the cut-point value of 15.5, the probability that the LACE index would predict readmission when the patient was indeed readmitted (sensitivity) was only .662, indicating the LACE index incorrectly classified many of the patients in the study population.

Different statistical analyses have been applied within the literature focused on the performance of the LACE index, and the results demonstrate varying degrees of effectiveness of the LACE index for the heart failure population. The results of the current study are comparable to the ROC curve analysis performed by Ibrahim et al.

(2020), who similarly examined the *c* statistic and concluded that the LACE index was not an effective predictor of 30-day readmission for patients with heart failure. The poor performance of the LACE index in the current study population could be the result of a difference in the predictor case-mix or the outcome variable when compared to the population used to derive the model (see Myers et al., 2020; Ramspek, et al., 2020). The original derivation of the LACE index by van Walraven et al. (2010) was completed on a population of medical-surgical patients in Canada with different sample demographics and a younger sample population. For example, in the LACE index derivation sample, 58.1% were emergent admissions, 75% of the patients had a comorbidity score of 0, and the average age was 61 years old. The patients included in the current study were predominantly White, emergent admissions, older than 75 years old, and had high comorbidity scores.

Additionally, to avoid bias created by censoring deaths, van Walraven et al. (2010) combined unplanned 30-day readmissions with death within 30-days as the outcome variable. I only examined 30-day readmission as the dependent or state variable for the ROC curve analysis. In van Walraven et al.'s study, 8% of the population experienced death or readmission within 30 days compared to 11.7% in the current study, with only 30-day readmissions measured. It is possible that the difference in sample characteristics and the outcome variable could account for the conflicting performances of the LACE index between the original research and this study.

A 30-day readmission risk prediction model that demonstrates moderate or excellent discrimination when applied to a specific population would be a valuable tool to integrate into the EMR to identify patients at a higher risk of experiencing a 30-day readmission. The poor discrimination, as evidenced by the *c* statistic, and the low sensitivity and specificity of the LACE index at different cut-point values suggest the LACE index would not accurately identify heart failure patients in the study population who are at risk for readmission. The results of this study do not support the integration of the LACE index into the EMR system at the study site for heart failure patients.

Research Question 2

The Andersen model (1968) provided the framework for exploring the independent variables as influencing factors on all-cause 30-day readmission. The Andersen model assumes that healthcare utilization depends on predisposing, enabling, and need factors (Andersen & Newman, 2005). The independent variables chosen based on a review of the literature were length of stay, acuity of the admission, comorbidity score, emergency room utilization, age, serum albumin and BUN levels, number of prescription medications, prescriptions for heart medications, and access to a primary care physician. With the exception of age and access to a primary care physician, the previous literature established these variables as need factors (Kaya et al., 2019; Smith et al., 2017). Age and the covariate, race, have been categorized as predisposing factors, and access to a primary care physician has been viewed as an enabling factor (Hirshfield et al., 2018; Lederle et al., 2021; Li et al., 2016). Similar to Smith et al. (2017) and Kaya et al. (2019), the current study found that the statistically significant predictors of all-cause 30-day readmission were need factors.

Simple logistic regression analyses were conducted to determine the relationship between the independent variables and all-cause 30-day readmission. Having a primary care physician listed in the EMR, acuity of the admission, age, serum BUN level, and a prescription for BB, ARB, or ACE inhibitors were not statistically significantly associated with all-cause 30-day readmission. The number of ER visits, length of stay, comorbidity score, serum albumin level, and the number of medications prescribed to the patient were determined to be statistically significantly associated with all-cause 30-day readmission. The results of the logistic regression were examined in the context of the current literature for each independent variable.

The finding of nonsignificant results for the variables primary care physician and acuity of the admission contradicts the previous literature that suggests these variables influence all-cause 30-day readmission in the heart failure population (Carlson et al., 2019; Tung et al., 2017). It is possible that the logistic regression calculations could not detect a significant difference with regards to the variables, access to a primary care physician and acuity of the admission, because of the baseline characteristics of the sample, 99.5% of the sample were acute admissions and 99.5% had a primary care physician listed in the EMR. It is possible that statistically significant relationships would have been detected if the study population had more variation in these two variables.

The literature examining age as an independent predictor of readmission in the heart failure population has been inconsistent. Though Chamberlain et al. (2018) found that age less than 65 years was independently associated with higher readmission risk after hospitalization, Whellan et al. (2016) found a dichotomous relationship. The nonsignificant result found in the current study was consistent with research by Arora et al. (2017), in which the sample population had a narrow age range and were predominately older (73.3% older than 65 years), like in the current study. Mirkin et al. (2017) found the relationship between age and 30-day readmission was influenced by the discharge disposition, the setting to which the patient was discharged. I did not account for discharge location, and it is possible that this variable influenced the relationship between age and 30-day readmission.

A prescription for a BB, ARB, or ACE medication is recommended by the American College of Cardiology and the American Heart Association for heart failure patients. Researchers have supported the use of evidence-based medical therapy guidelines to improve health outcomes in the heart failure population (Lim et al., 2019; Loop et al., 2020; Sanam et al., 2016). However, the results of the logistic regression analyses in my study do not support the hypothesis that a prescription for a BB, ARB, or ACE medication reduced the likelihood of readmission. The discrepant results may partly be because I focused on all-cause 30-day readmission as the outcome of interest rather than a cardiovascular-related readmission. For instance, while Loop et al. (2020) found that a prescription for a BB was associated with a lower risk of heart failure readmission (HR = 0.79; 95% CI [0.76, 0.82]), a prescription for a BB was not significantly associated with all-cause readmission (HR = 1.02; 95% CI [0.97, 1.07]). All-cause 30-day readmission does not account for the diagnosis at the time of readmission. Research has shown that 51% of heart failure patients are readmitted within 30 days for a noncardiovascular diagnosis (Vader et al., 2016). Therefore, although previous research has shown a prescription for heart medications may reduce the risk of heart disease-related outcomes, the variable may not influence all-cause 30-day readmission for the sample population. Additionally, the recommendation by the American College of Cardiology and American Heart Association is for patients to be prescribed a BB along with either an ARB or ACE medication, however, I examined the medication individually.

Serum BUN level was not statistically significantly associated with all-cause 30-day readmission. This finding differs from previous research that linked elevated serum BUN levels to an increased risk of death and all-cause readmission (Bradford et al., 2017; Vader et al., 2016). Restrictions in the dataset I was provided required serum BUN levels to be examined as a dichotomous variable, normal versus abnormal. The dichotomizing of a continuous variable may lead to the loss of information, reducing the statistical power to detect a relationship between the variables of interest and creating the question of an optimal cutoff point (Altman & Royston, 2006). Based on research by Bradford et al. (2017), which had a purpose similar to my study, I defined an abnormal serum BUN level as greater than 45 mg/dL. When examining the literature related to serum BUN levels and cardiovascular disease, a lower cutoff point was frequently set, typically between 20 and 24 mg/dL (Ghrair et al., 2017; Jujo et al., 2017). The dichotomizing of the variable and the high cutoff point that defined an abnormal serum BUN could explain why the result of the logistic regression analysis was not statistically significant.

The number of times the patient visited the ER in the past 6 months before the index admission was a statistically significant predictor of all-cause 30-day readmissions in heart failure patients (*p* = .00). The negative β associated with the logistic regression analysis for ER visits suggests the variable is a protective factor against all-cause 30-day readmission (*B* = -2.202). Though there is a lack of research in the area, this result was not consistent with the results of other studies. For example, Carlson et al. (2019) found that patients with a greater number of ER visits in the 6 months before the index admission were 50% more likely to be readmitted than those with a lower number of ER visits. The relationship I observed between ER visits and all-cause 30-day readmission may differ from what is found in the literature because the study site has a strong focus on preventing avoidable readmissions due to the monetary penalties imposed by CMS. The study site often utilizes observation status, when appropriate, to avoid an inpatient admission for patients unable to be directly discharged from the ER and has many homecare resources available to ensure safe patient discharge without an inpatient admission.

The result of the simple binary logistic regression analysis showed a statistically significant relationship between length of stay and all-cause 30-day readmission (*p* = .024). Patients readmitted within 30-days of the index admission had a statistically significantly longer length of stay (7.41 ± 6.4) compared to patients who were not readmitted (5.84 ± 5.3, *p* = .03). This finding was similar to Whittaker et al. (2015), who also examined the length of stay as a continuous variable and found a mean difference in length of stay of 3.4 days between patients who were readmitted and patients without a readmission. Other studies have also shown a longer length of stay is associated with an increased risk of readmission; however, length of stay was typically examined as a categorical variable. For example, Roshanghalb et al. (2019) found that patients with a LOS over 5 days were at an increased risk for 30-day readmission when compared with those with a length of stay less than 5 days (*OR* = 1.58; 95% CI [1.15, 2.15]). A meta-analysis of the literature performed by Rojas-Garcia et al. (2018) found prolonged lengths of stay were associated with an increased risk of inpatient complications (i.e., hospital-acquired infections), increased costs, and negatively impacted the patient's mobility and daily living activities. It is possible that a decline in the patient's functionality and in-hospital complications could lead to future hospitalizations, increasing the likelihood of 30-day readmission.

The relationship between serum albumin levels and all-cause 30-day readmission was statistically significant, and patients with normal serum albumin levels were less likely to be readmitted within 30-days of the index admission. This finding was consistent with previous studies that have shown an abnormal serum albumin is associated with an increased odds of readmission (Huynh et al., 2016). Serum albumin is thought to have anti-inflammatory, antioxidant, and antiplatelet activity, suggesting that a normal serum albumin level is a protective factor for patients with heart failure (Arques, 2018).

The term *comorbidity* is used to communicate the patient's burden of illness or the total burden of physiological dysfunction (Valderas et al., 2009). The comorbidity score was measured using a modified Charlson comorbidity index, a summary measure that assigns cumulative points based on specific comorbidities or illnesses. The summary measure was used by van Walraven et al. (2010) to develop the LACE index. Previous research has linked comorbidity burden to a greater risk of 30-day readmission for heart failure patients. For example, Patil et al. (2019) found a higher comorbidity burden in patients with decompensated heart failure was independently associated with a higher rate of 30-day readmission (*OR* = 1.11; $p < .01$). Similarly, I found that comorbidities statistically significantly predict all-cause 30-day readmissions in heart failure patients (*OR* = 1.14; $p = .002$). A higher comorbidity score could drive 30-day readmission rates by complicating recovery or increasing the patient’s risk for noncardiovascular inpatient admissions.

The number of medications prescribed to the patient was statistically significantly associated with all-cause 30-day readmission for the study population ($p = .006$). The patients within the study population most commonly had 11 prescription medications listed in their EMR as current medications. Picker et al. (2015) found the prescribing of more than six medications at discharge was an independent predictor of 30-day readmission (*OR* = 1.26; 95% CI [1.17, 1.36]; $p = .003$). The results of research by Al-Tamimi et al. (2021) recognized compliance with medication regime as the most significant predictor of readmission for a population of heart failure patients (*OR* = 3.6; 95% CI [1.57, 8.28]; $p = .002$). Poor medication adherence is frequently found among heart failure patients leading to increased occurrence of heart failure exacerbations and subsequent readmission to the hospital (Akkineni et al., 2020).

Research Question 3

The final modified 30-day readmission risk prediction model included the statistically significant predictors of all-cause 30-day readmission: comorbidity score, length of stay, and the number of medications prescribed to the patient. The number of emergency room visits in the past 6 months and serum albumin level were excluded because the results of the logistic regression calculations suggest the variables lower the risk of all-cause 30-day readmission. Grounded by the Andersen model (1968) and based on the existing literature, the three variables included in the modified risk prediction model correspond to need factors. According to Andersen et al. (2013), need factors include how the patient perceives their health status and how the healthcare provider evaluates the patient's health status. Smith et al. (2017) proposed that need factors indicate illness level. Therefore, those with a higher level of illness are at a greater risk of readmission within 30 days of the index admission.

The ROC curve analysis of the modified model produced a *c* statistic of .618 (95% CI [0.555, 0.681]; $p = .001$) and the optimal cut-point value was 5.5 (sensitivity = .554; specificity = .63). The poor performance of the modified 30-day readmission risk model does not support the integration of the model into the EMR system at the study site.

The modification of the LACE index for different target populations is a common theme in the literature. For example, Van Spall et al. (2018) studied a population of heart failure patients and found a higher *c* statistic was produced when only length of stay and emergency room visits were included in the LACE index. Similar results were published by Makam et al. (2017), who developed a modified LACE index for patients with pneumonia and found a higher predictive value for the modified model. Makam et al. included the patient's Pneumonia Severity Index score, platelet laboratory results, discharge location, income, and vital signs. Significant clinical and demographic predictors of 30-day readmission vary between disease conditions, and it is possible that disease-focused readmission models would better predict 30-day readmission.

Based on a comparison of the *c* statistics between the LACE index and the modified risk model, there was a minimal change in the discriminative accuracy to predict 30-day readmission. The combination of independent variables within the modified 30-day readmission model had a slightly higher predictive value (*c* statistic) than the LACE index (c = .618 vs. c = .616). However, both risk prediction models demonstrated poor discriminative accuracy to predict all-cause 30-day readmission in heart failure patients, and with the selection of an optimal cut-point value for high risk, both models demonstrated low sensitivity and low specificity.

I analyzed race as a covariate for the performance of the LACE index and the modified 30-day readmission risk prediction model. For both models, the ROC curve results were statistically significant only for those who identified as White when the analyses were stratified based on race. Additionally, when only considering patients in the White race category, the discriminative accuracy (*c* statistic) of the LACE index to predict all-cause 30-day readmission was higher than the modified risk prediction model. The *p* values associated with the ROC curves were not statistically significant for the Black, Hispanic, and Asian categories. The finding of nonsignificant results could be because 83.5% of the sample population identified as White, not allowing for the diversity necessary to accurately identify those at risk of 30-day readmission in the other race categories.

Limitations of the Study

The current study was subject to several limitations. Secondary data was collected from a single healthcare system and did not account for patients who may have been readmitted within 30 days to a different healthcare system. The study sample was selected using convenience sampling from six acute care facilities located in a suburban area in New York and may not reflect the experiences of heart failure patients in other locations. In addition, the study sample disproportionately identified as White, further limiting the generalizability of the study results.

The use of secondary data limited the control over the quality of the data, how the variables were defined, and restricted what variables were included in the data analyses. This could lead to the possible loss of information and unidentified covariates. Lastly, the logistic regression calculations were done individually to determine the statistically significant predictors of readmission. Therefore, confounding variables that may influence the relationship between the individual independent variables and 30-day readmission were not considered.

Recommendations

The results of the study showed the LACE index and the modified 30-day readmission risk prediction model have poor discriminative accuracy for predicting all-cause 30-day readmission for heart failure patients. However, this study was limited in generalizability because of the baseline sample characteristics. I recommend that subsequent studies use a more diverse sample of heart failure patients to examine the discriminative accuracy of the LACE index and the relationship between the independent variables and all-cause 30-day readmission.

Future studies may also consider modifying certain variable definitions. For example, while access to a primary care physician was examined in the current study, it may be more appropriate to study the influence of access to a cardiologist for follow-up care in the heart failure population. Subsequent studies may also consider applying a modified version of the comorbidity score when examining the discriminative accuracy of the LACE index. According to Quan et al. (2011), improvements in treatment and chronic disease management, and advances in technology necessitate the revision of the Charlson comorbidity index score. The purpose of research by Quan et al. was to update the weights assigned to the diseases incorporated into the Charlson comorbidity index score using the current one-year mortality rates for each specific disease condition. The researchers found that out of the 16 diseases examined, the weights of 12 of the diseases were modified; three diseases decreased in point value, four increased in point value, and five diseases were reduced to have a weight of zero points. Finally, future studies may choose to examine the outcome variable as 30-day heart failure readmission rather than all-cause 30-day readmission.

Social Change Implications

The positive social change implications of the current study include providing an improved understanding of the risk factors related to 30-day readmission in the heart failure population. The results of the study found a statistically significant relationship between the number of ER visits, length of stay, comorbidity score, serum albumin levels, and medication regimen on the occurrence of readmission within 30-days of the index admission. The existence of modifiable patient-level factors can guide healthcare professionals to identify patients at a higher risk of being readmitted within 30-days of discharge. For example, the results of this study suggest the importance of achieving normal albumin levels and an easy-to-understand medication regimen post-discharge. Identifying at-risk patients is a first step to implementing targeted interventions to reduce 30-day readmission rates.

The occurrence of 30-day readmission has been linked to adverse patient outcomes, including higher mortality rates and increased medical costs (Arundel et al., 2016; Kwok et al., 2021). From a healthcare facility perspective, 30-day readmission rates impact financial performance due to penalties imposed by CMS for higher-than-expected rates (Upadhyay et al., 2019). Research published by Auerbach et al. (2016) suggested 26% of 30-day readmissions in the study population were potentially preventable through better communication, greater attention to the patient's readiness for discharge and needed support for self-management, and enhanced disease monitoring. Risk prediction scores built within the EMR help provide healthcare professionals with actionable data to identify individuals needing proactive and preventative care (Goldstein et al., 2017). However, although statistically significant, both risk models tested demonstrated poor discrimination for identifying patients readmitted within 30-days suggesting a lack of clinical significance for the study results. Before instituting the LACE index in the EMR system at a healthcare facility, I would recommend that the

LACE index be further validated using a sample of patients seen at the facility before allocating scarce financial resources to support the use of the LACE index.

Conclusion

The conclusions of this study offer further understanding of the patient-level factors that influence all-cause 30-day readmission for heart failure patients. Furthermore, it contributes to the limited literature on the use of the LACE index to predict all-cause 30-day readmission in the heart failure population. The LACE index and the modified 30-day readmission risk prediction model did not demonstrate sufficient discriminative accuracy to justify the clinical use of the prediction models for heart failure patients. However, this research supported the importance of considering the patient’s length of stay, comorbidity burden, serum albumin level, tendency to visit the emergency room, and the number of medications prescribed to the patient when assessing the risk of all-cause 30-day readmission. Identifying patients with an increased risk of all-cause 30-day readmission can help inform the development of targeted interventions designed to lower readmission rates and decrease the adverse medical and financial outcomes associated with 30-day readmission.

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Appendix A: LACE Index

Variable	Value	Points
L: Length of stay (days)		
	1	1
	2	2
	3	3
	4 – 6	4
	7 -13	5
	14 or more	7
A: Acute (emergent) admission		
	Yes	3
C: Comorbidity * (Charlson comorbidity index score)		
	History of myocardial infarction	1
	Peripheral vascular disease	1
	Cerebrovascular disease	1
	Diabetes without complications	1
	Congestive heart failure	2
	Chronic obstructive pulmonary disease	2
	Mild liver disease	2
	Cancer	2
	Dementia	3
	Connective tissue disease	3
	HIV infection	4
	Moderate or severe liver disease	4
	Metastatic solid tumor	6
E: Emergency department visits during the previous six months		
	1	1
	2	2
	3	3
	≥4	4

*Comorbidity score: If the total score is between 0 and 3 add that number to the total count. If the score is 4 or higher, add 5 to the total count

Appendix B: Permission to Use LACE Index

From: Carl Vanwalraven <cvanwalraven@toh.ca>
Sent: Wednesday, January 13, 2021 1:55 PM
To: Debra Kelly <debra.kelly2@waldenu.edu>
Subject: Re: Permission to use LACE Index for Readmission

Hi Debra. You may use it. Carl

Get Outlook for iOS

From: Debra Kelly <debra.kelly2@waldenu.edu>
Sent: Wednesday, January 13, 2021 4:26:02 PM
To: Carl Vanwalraven <cvanwalraven@toh.ca>
Subject: Permission to use LACE Index for Readmission

CAUTION: External Mail. Do not click on links or open attachments you do not trust.
ATTENTION: Courriel externe. Ne cliquez pas sur des liens et n'ouvrez pas de pièces jointes auxquels vous ne faites pas confiance.

Dr. Carl van Walraven,

I am a doctoral student at Walden University, completing a dissertation in Public Health. I am writing to ask written permission to use the LACE Index for Readmission in my research study. The purpose of my research is to explore its use in a population of heart failure patients admitted to a six-facility healthcare system in New York. I will be evaluating the current model used by the healthcare system as well. The dissertation will be published in the Walden University ScholarWorks and deposited in the ProQuest Dissertations & Theses database. I would be happy to provide any additional information you would like.