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Relationship Between Rurality, Home Telehealth, and Bed Days of Care for Military Veterans Readmitted for Heart Failure

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This is to certify that the doctoral study by

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has been found to be complete and satisfactory in all respects,
and that any and all revisions required by
the review committee have been made.

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Walden University
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Abstract

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MBA, Brenau University, 2003

BSN, Excelsior College, 2000

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Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Business Administration

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Abstract

Heart failure (HF), the leading hospital admission diagnosis for military veteran patients discharged from a Department of Veterans Affairs (VA) hospital, is more common in patients residing in rural than urban areas. Primary care managers prioritize reducing readmissions for HF as up to 80% of health care costs for HF, projected to increase to $69.7 billion annually by 2030, incur during hospitalizations. Underpinned in Andersen's behavioral model of health services use, the purpose of this quantitative ex post facto correlational study was to examine the relationship between residence rurality, home telehealth enrollment, and bed days of care for military veteran patients readmitted for HF. The data comprised archival routinely collected health data files (N = 1081) from the VA corporate data warehouse of military veteran patients readmitted for HF at any VA hospital in the United States during the 2017 calendar year. The results of the multiple linear regression model were statistically non-significant. A key recommendation is for VA healthcare leaders to avoid routinely referring rural and urban military veteran patients to home telehealth for HF care without a compelling clinical reason. The implications for positive social change include the potential to improve the health of military veteran patients with HF and enhance health care value, decreasing the financial burden of HF care on individuals and VA hospitals by home telehealth optimization.

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Dedication

I dedicate this doctoral study to my family including my loving husband, Arthur, whose unwavering support and endless patience made this endeavor possible. My children provided continuous encouragement and a source of motivation while I strived to show that anything is possible when an individual perseveres to reach high goals. Finally, I dedicate this doctoral study to the military service members, veterans, and other people who defend freedom.

Acknowledgments

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Table of Contents

List of Tables

List of Figures

Section 1: Foundation of the Study

Healthcare leaders seek strategies to improve hospitals' financial performance by decreasing readmissions for heart failure (HF) care (Mihailoff et al., 2017). HF was the leading hospital admission diagnosis for patients 65 years of age and older in the United States and a common cause of readmissions within 30 days of discharge (Ensign & Hawkins, 2017). Considerations for identifying cost reduction strategies for HF care included understanding the cost drivers of health care (Buttigieg et al., 2018; Lesyuk et al., 2018) and the influences of health care reform (Warner et al., 2020).

Background of the Problem

Priorities in the United States included reducing readmissions for HF to curtail high health care costs (O'Connor et al., 2016; Sud et al., 2017). As the incidence of HF increases with the aging population (Nguyen et al., 2020), projections show annual costs for HF care will increase by 127% to $69.7 million by 2030 (Benjamin et al., 2017) and up to 80% of health care costs for HF incur during hospitalizations (Fitch et al., 2016). HF was the most common diagnosis for military veterans discharged from a U.S. Department of Veterans Affairs (VA) hospital (Garvin et al., 2018), with HF admissions exceeding 17,000 per year (Wray et al., 2021). A diagnosis of HF and preventable admissions were more common in patients residing in rural than urban areas (Johnston et al., 2019). Messina (2016) identified home telehealth as an effective HF management strategy to reduce readmissions and costs for HF in VA. Promoting enhanced HF management by using home telehealth for select patients provides opportunities to decrease readmissions, bed days of care, and health care costs for military veterans with HF (Messina, 2016).

Problem Statement

An increased number of bed days of care during hospital readmissions for HF reduced hospitals' bottom line (Mihailoff et al., 2017). Hospital costs, averaging $3,172 per day for HF care, decreased by over 5% when military veteran patients using home telehealth experienced fewer readmissions (Messina, 2016). The general business problem was healthcare organizations incur escalating inpatient costs and lower revenue as bed days of care increase during readmissions for HF. The specific business problem was some VA primary care managers do not understand the relationship between residence rurality, home telehealth enrollment, and bed days of care for military veteran patients readmitted for HF.

Purpose Statement

The purpose of this quantitative ex post facto correlational study was to examine the relationship between residence rurality, home telehealth enrollment, and bed days of care for military veteran patients readmitted for HF. Residence rurality and home telehealth enrollment were the predictor variables. The criterion variable was the bed days of care for military veteran patients readmitted for HF. To include pertinent data and an adequate sample size of the predictor variables, the targeted population comprised archival routinely collected health data files of military veteran patients with admission for HF at any VA hospital in the United States during the 2017 calendar year. The implications for positive social change from this study included the potential to improve patient satisfaction and lower the financial burden of high HF costs on individual patients, populations, and healthcare organizations. Patient satisfaction and the health of the military veteran patient population with HF may improve as VA primary care managers expand the appropriate use of home telehealth. The financial burden on patients and families and the stability of hospitals may improve as the cost to deliver HF care decreases with fewer bed days of care.

Nature of the Study

The quantitative method was the most appropriate method for this study. Researchers can empirically examine relationships between variables by applying the quantitative method, collecting and statistically analyzing numerical data (Rutberg & Bouikidis, 2018). The current study's objective was to empirically examine the relationship between two predictor variables and one criterion variable; therefore, a quantitative method was appropriate. Researchers use the qualitative method to explore a phenomenon and collect data in text or spoken words, typically from open-ended interview questions (Basias & Pollalis, 2018). The qualitative method was not appropriate for the current study because analyzing statistical data from archival routinely collected health data files was not possible using the qualitative method. A mixed methods approach comprising qualitative and quantitative methods (Caffery et al., 2017) was not appropriate because only a quantitative method aligned with the study objective to analyze statistical data about HF care from a large, geographically diverse population of military veteran patients.

The ex post facto correlational design as a form of nonexperimental research (Giuffre, 1997) without manipulating the variables (Fagbenro et al., 2018; Johan et al., 2017) was appropriate for this study to include archival data from HF care of military veteran patients. Researchers use the ex post facto design to examine the relationship between the variables occurring in the past and analyze and interpret the results in the present (Johan et al., 2017). It was impossible to manipulate the variables in this study because care delivery for military veteran patients with HF occurred before conducting the study. Experimental and quasi-experimental designs were not appropriate for this study. In the experimental design, researchers may manipulate variables and observe the effects of the manipulation on other variables (Rutberg & Bouikidis, 2018), which was not feasible in this study because manipulating variables in real time was not possible when using archival data for care delivery in 2017. Researchers manipulate an intervention without randomization in the quasi-experimental design (Rutberg & Bouikidis, 2018). The manipulation of an intervention without randomization was not possible in this study because manipulating an intervention in real-time cannot occur when using archival data from hospital records for care delivered in the past.

Research Question

What is the relationship between residence rurality, home telehealth enrollment, and the bed days of care for military veteran patients readmitted for HF?

Hypotheses

H_0: There is no statistically significant relationship between residence rurality, home telehealth enrollment, and the bed days of care for military veteran patients readmitted for HF.

H_1: There is a statistically significant relationship between residence rurality, home telehealth enrollment, and the bed days of care for military veteran patients readmitted for HF.

Theoretical Framework

Andersen (1968, 1995) developed the behavioral model of families' use of health services in 1968, renamed the behavioral model of health services use (known as the behavioral model). Advancing the behavioral model (1968) by Andersen (1995) and Andersen and Newman (1973/2005) explained the individual's use of health services with influences from (a) predisposing factors, (b) enabling factors, and (c) need factors. Andersen (1995) suggested health services are a function of the perceived need for care, predisposing or existing factors, and the variables that enable patients to use health care.

Predisposing factors existed before the onset of illness, and enabling factors affected the ability of individuals to secure health services (Hirshfield et al., 2018). Of the factor types, need factors and demographic characteristics exerted the most influence on individuals to seek and receive health care for serious health concerns requiring hospitalization (Andersen, 1995). Friedman et al. (2015) applied the behavioral model to examine the relationship between distance barriers and attrition of rural or urban military veteran patients to seek health services at the VA, noting the potential benefit of using telehealth to mitigate distance challenges. The variables of rural or urban military veteran patients (Friedman et al., 2015) and telehealth (Friedman et al., 2015; Guzman-Clark et al., 2020) aligned with the predictor variables of residence rurality and home telehealth enrollment in the current study. O'Connor et al. (2016) applied the behavioral model to explain the relationship between patient factors and health services use in measuring readmissions for HF, aligning with the criterion variable in the current study of bed days of care during readmissions for HF.

Application of the Behavioral Model

In this study, potential access in the inpatient area was bed availability for hospital admissions for HF, and the measurement for realized access was bed days of care, representing the duration of hospital bed occupancy during readmissions for HF. The structure of the healthcare organization pertained to the features of the health care system (Andersen & Newman, 1973/2005). The structure included the characteristics of outpatient clinics, inpatient units, and medical practices; the steps in the admission and discharge process; and the referral process to other health care services (Andersen & Newman, 1973/2005). Further, interrelated influences exist between access and structure, where structure influences access and is dependent on resources (Andersen & Newman, 1973/2005).

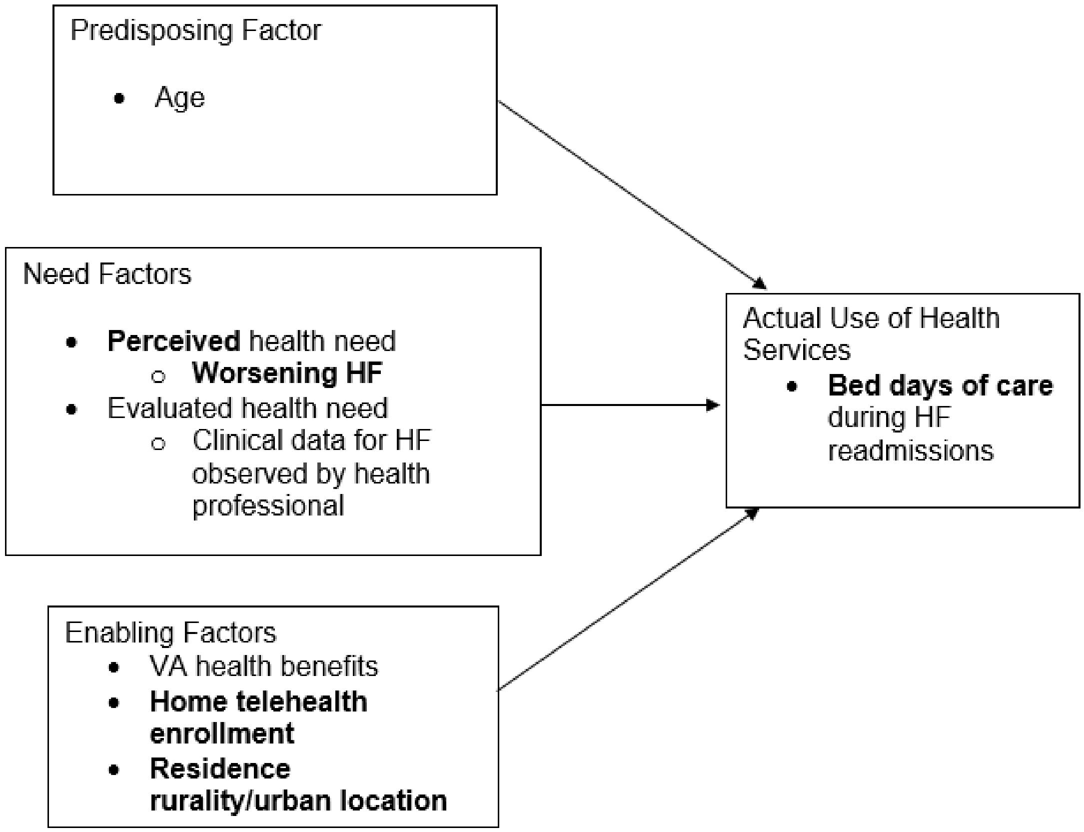
Organizational Structure in the Department of Veterans Affairs

The structure of the VA healthcare organization in this study pertained to military veteran patients' health care services, the predictor variables of residence rurality and home telehealth enrollment, and the criterion variable of bed days of care. The VA organizational structure includes the necessary infrastructure of informatics and telecommunications technology for home telehealth (Wakefield & Vaughan-Sarrazin, 2017). Supplementing usual HF care with home telehealth is an effective strategy for improving HF care for military veteran patients (Darkins et al., 2015), including for patients in underserved areas (Andrès et al. (2018). As recognition and interventions for worsening HF symptoms occur earlier, bed days of care for readmissions may decrease (Messina, 2016).

Figure 1 is a graphical depiction of the behavioral model as it applies to examining bed days of care for military veteran patients with HF. Appendix A includes the email correspondence with the original theorist acknowledging permission to adapt the behavioral model to this study. Predisposing, enabling, and need factors influence the use of health care services in the inpatient setting in the form of bed days of care. The purpose of bold words in Figure 1 was to emphasize the pertinence of the military veteran patient’s perception of worsening HF symptoms as an influence to seek health care. Other bold words depict the content related to the predictor and criterion variables in the study.

Figure 1

Adapted Behavioral Model of Health Services Use



Note. Graphical representation of a behavioral model of health services use to examine bed days of care for military veteran patients readmitted for HF. Adapted with permission from "*A Behavioral Model of Families' Use of Health Services*, by R. M. Andersen, 1968, ProQuest Dissertations Publishing (Order No. 6902884), p. 71.

Age is a predisposing factor in Figure 1 because the targeted population comprised adult military veteran patients readmitted for HF. An enabling factor in Figure 1 is VA health benefits, consistent with the targeted population comprising archival hospital records of military veteran patients with readmission for HF at any VA hospital in the United States during 2017. The bold enabling factors of home telehealth enrollment and residence rurality reflect the predictor variables in the study. The larger box for the need factors in Figure 1 shows the more significant influence of need factors over predisposing or enabling factors for HF care. The purpose of bold words within the need factors box was to emphasize the importance of the perceived health need category as the primary influence for individuals to seek health care. Health professionals observe the clinical data for worsening HF in the evaluated need factor category. Bed days of care during readmissions for HF, the criterion variable in this study, depicted the actual use of health services.

Operational Definitions

The operational definitions were intended to improve the clarity of the meaning of the terms included in the study. Providing definitions may enhance the readers' understanding of my intended meaning. The following operational definitions pertain to the predictor variables of residence rurality or home telehealth enrollment, the criterion variable of bed days of care, and the HF diagnosis or coding classification.

Bed days of care: A bed day of care, used to measure workload, is the unit of analysis of an individual's overnight stay in a VA bed within an assigned treating specialty bed section (Veterans Health Administration [VHA], 2013).

Highly rural area: A highly rural area is a sparsely populated census tract including rural-urban commuting area codes 10.0, where less than 10% of the working population commutes to any community larger than an urbanized cluster as defined by the Bureau of the Census (Cowper Ripley et al., 2017).

Home telehealth: Home telehealth is a system of care delivery using information and communication technology, including the transmission of patient data about a health condition to provide health care services at a distance (Wade & Stocks, 2017).

Index admission: An index admission is a hospital stay in which the patient was not discharged within the previous 30 days (Carey & Stefos, 2016).

International statistical classification of diseases and related health problems (ICD-10): The ICD-10 is a system of categories to which morbid entities are assigned according to established criteria and used to translate diagnoses of diseases and other health problems from words into an alphanumeric code, permitting easy storage, retrieval, and analysis of data (World Health Organization, 2016).

Readmission: A readmission occurs when a patient is rehospitalized to any acute care hospital for an unplanned condition within 30 days of discharge from an admission (Centers for Medicare & Medicaid Services [CMS], 2021b).

Rural area: A rural area is a census tract not defined as urban or highly rural, including rural-urban commuting area codes 2.0, 2.1, 3.0, 4.0, 4.1, 5.0, 5.1, 6.0, 7.0, 7.1, 7.2, 8.0, 8.1, 8.2, 9.0, 10.1, 10.2, 10.3 (Cowper Ripley et al., 2017).

Urban area: An urban area is a census tract including rural-urban commuting area codes 1.0 or 1.1, with at least 30% of the population residing in an urbanized area as defined by the Census Bureau (Cowper Ripley et al., 2017).

Assumptions, Limitations, and Delimitations

Research investigations include potential unproven ideas, weaknesses, and boundaries described as assumptions, limitations, and delimitations (Theofanidis & Fountouki, 2018). Strengthening the quality and interpretation of the study findings occurs when researchers describe assumptions, limitations, and delimitations to expose potential uncertainties and explain study planning and design decisions (Theofanidis & Fountouki, 2018). Aggarwal and Ranganathan (2019) emphasized how understanding the benefits and limitations of correlational studies impacts effective resource planning, supporting the need to conduct this ex post facto correlational study to examine the use of home telehealth and inpatient bed resources for HF care by rural and urban military veteran patients readmitted for HF.

Assumptions

Assumptions are issues, ideas, or positions widely accepted as probable without proof (Theofanidis & Fountouki, 2018). The first assumption in the current study was bed days of care, also known as length of stay (see Davis et al., 2017) during readmissions for HF was a valid and reliable measure of inpatient health care use. Carey and Stefos (2016) explained the VA process used to track and report military veteran patients’ readmissions to a VA hospital for HF includes measuring the number of hospitalization days. The second assumption was archival routinely collected health data included accurate coding used to identify patients with a primary diagnosis of HF. Presley et al. (2018) verified coding accuracy for HF in VA by comparing consistency between routinely collected health data and diagnosis codes for HF. Groeneveld et al. (2019) described few financial incentives to upcode or overcode the care and standardization by using an electronic health record and a national system for administrative coding as reasons there were minimal variations in coding at the VA.

Third, I assumed VA archival routinely collected data accurately represented the residence rurality and home telehealth enrollment history of each patient with HF. The VA accounting system reviews revealed accurate and detailed data available at the patient level and redundancies between clinical and administrative files for HF care of military veteran patients (Carey & Stefos, 2016). Last, I assumed the patients enrolled in the home telehealth program met all VA eligibility criteria. Consistent with the eligibility criteria to participate in home telehealth applied by Guzman-Clark et al. (2020), I assumed the patient resided in a home setting within the service area and voluntarily engaged in the program.

Limitations

Limitations are potential weaknesses of a study beyond the researcher's control (Astroth & Chung, 2018b; Theofanidis & Fountouki, 2018) or bias (Astroth & Chung, 2018a). Potential limitation areas in studies are research design, statistical model, funding constraints, or other factors (Theofanidis & Fountouki, 2018). A limitation of the current study was consistent with assertions by Aggarwal and Ranganathan (2019) and Tobías et al. (2019) that correlational studies include the inability to imply causation or conclude findings pertinent to an individual from population-level data.

Using archival routinely collected health data from VA databases was a limitation because those available data may not have addressed all the desired factors or included an optimal level of detail (see Carey & Stefos, 2016). Edmondson and Reimer (2020) explained the rigor of data in the electronic health record is lower when collected by different people for clinical rather than research purposes. The vast amount of VA data collected in the electronic health record for clinical care may be difficult to access (Velarde et al., 2018), and secondary data may not align with the research study (Harron et al., 2017). Mitigation strategies applied to ensure adequate data to answer the research question included reviewing findings from a VA feasibility report (see Appendix B), identifying the relevant data sources, and collecting archival data aligned with the variables in this study.

Data needed for the study may not have been available, and coding inaccuracies may have lowered the ability to identify and compare data when using administrative databases (Y. Wang et al., 2018). Recommendations by Hughes et al. (2019) to address missing data included determining the reasons, patterns, and pertinence of missing data; evaluating additional data sources; and selecting a method to address missing data. Using substitute VA archival data sources was an alternate planned strategy to replace missing data in this study. However, there were minimal missing data in this study.

An additional limitation of this study was the variable of home telehealth enrollment rather than home telehealth use. Patients may enroll in home telehealth, but the actual use of home telehealth after enrollment was unknown in the study and could have varied widely. However, limiting the variable to home telehealth enrollment improved the feasibility of conducting the study.

Delimitations

Delimitations are the boundaries or limitations the researcher decides to adopt to improve the feasibility of achieving the aims and objectives of the study by narrowing the focus of the study (Theofanidis & Fountouki, 2018). The current study included archival routinely collected health data from VA databases comprising records of patients readmitted to a VA hospital with a primary discharge diagnosis of HF during 2017. Health care data collection for the study also included (a) residence rurality categories, (b) home telehealth enrollment, (c) bed days of care during readmissions for HF to a VA hospital within 30 days after discharge from an index hospitalization for HF, and (d) demographic data to promote an understanding of transferability of findings to different populations. Narrowing the home telehealth data to the enrollment information improved the study's feasibility by reducing the resources required to collect home telehealth use data.

Exclusions were records with missing data required for the predictor and criterion variable measurements such as residence rurality category, home telehealth enrollment, HF diagnosis, admission, readmission, and discharge dates for HF. Other exclusions encompassed records of patients admitted for a non-HF primary diagnosis, those transferred to or from a non-VA hospital for HF, those admitted or readmitted to a non-VA hospital for HF, those discharged to a location other than home, or those who died within the 30-day readmission window or during the readmission. Excluding records for these reasons was necessary because it was impossible to calculate the bed days of care for readmissions when data for the admission, readmission, or discharge dates were inaccessible or incomplete. Calculating the bed days of care was also not possible when the patient received inpatient care for HF at a non-VA hospital or died because the frequency or duration of actual or potential readmissions was unknown. Excluding records of patients discharged to locations other than home, such as prisoners, was appropriate to narrow the population to patients eligible to receive home telehealth services. There was alignment with the predictor variable of home telehealth enrollment by meeting the eligibility criteria. Additional exclusions pertained to children’s records because these individuals did not meet the minimum requirement of 18 years old and adults’ long-term stay readmissions. Records for readmissions with a duration of 25 days or fewer met the acute hospital stay criteria rather than a long-term stay (Carey & Stefos, 2016).

Significance of the Study

Added value, contributions to the improvement of business practice, and the implications for social change comprised the significance of the study. Groenewoud et al. (2019) stipulated value achieves the best outcomes at a reasonable cost. Y. Wang et al. (2018) recommended to compare the cost of applying a health strategy or intervention to alternate treatment options when determining the value. K. H. K. Lee et al. (2016) described value as quality, known as patient outcomes, divided by cost. Health care cost measurements include care delivery by an episode of care, diagnosis, per capita (K. H. K.

Lee et al., 2016), or population (Groenewoud et al., 2019). Justification for the current study included the priority to increase value in health care by identifying variables influencing bed days of care for military veterans readmitted for HF.

Daub et al. (2020) asserted health care quality is reliably achieving goals for clinical care, operations, finances, and patient and provider satisfaction rather than prioritizing the volume of care delivered. Value in health care is consistent with activities and responsible allocation of resources to optimize the health and well-being of patients by providing effective, economical, and equitable clinical care that is medically necessary and desired by patients (Elshaug et al., 2017). High-value health care provides patients a benefit or likelihood of a benefit that exceeds the risk of harm from the intervention (Elshaug et al., 2017). In contrast, Chalmers et al. (2017) stated low-value care occurs when services are inappropriate for a specific clinical indication, a population, or the frequency of care. Reduced hospital readmission days for HF was one measure of higher quality in health care achieved at lower costs (Oh, 2017), consistent with improving health care value. Expanding geographical reach, as described by van der Nat (2021) as one strategy for improving value in health care, aligned with the current study because using home telehealth for military veteran patients with limited access to health care in rural communities may enhance health care value if patients experience fewer bed days of care during readmissions for HF.

Contribution to Business Practice

This study may be significant to applied business practice if informed primary care managers identify and promote the appropriate use of home telehealth to lower costs for military veteran patients' HF care, measured as decreased bed days of care during readmissions. The specific business problem was some VA primary care managers do not understand the relationship between residence rurality, home telehealth enrollment, and bed days of care for military veteran patients readmitted for HF. The effective use of home telehealth in primary care services is necessary to promote optimal HF care and resource use in VA (Brainerd & Hawkins, 2016; Messina, 2016). Most outpatient HF management occurs in general clinics rather than in specialized cardiology clinics (Kapelios et al., 2021); therefore, informed primary care managers promoting the effective use of home telehealth for HF care is appropriate. Through analysis of residence rurality, home telehealth enrollment, and bed days of care during readmissions for HF, primary care managers may identify variances in care by geographical areas and plan the optimal use of home telehealth to enhance value in HF care.

HF was the leading diagnosis for hospital admission of patients 65 years of age and older in the United States (Ensign & Hawkins, 2017) and the most common diagnosis for military veteran patients discharged from a VA hospital (Garvin et al., 2018). Hospitalization costs comprised up to 80% of the total health care costs for HF care (Ensign & Hawkins, 2017). In 2017, admissions for HF totaled 20,320 among the 114,798 military veteran patients treated for HF at any VA healthcare facility in the United States (see Figure B1, Table B1). Lowering escalating costs of care for the population of military veteran patients with HF occurred by reducing readmissions and bed days of care (Carey & Stefos, 2016), promoting the need to conduct the current study to expand knowledge about home telehealth enrollment for HF management.

Krishnamurthi et al. (2018) used the VA electronic health record data to examine the relationship between demographic factors and hospitalization rates of military veteran patients with cardiovascular conditions, including HF. Krishnamurthi et al. identified geographical differences in health care patterns and emphasized the importance of considering the uniqueness of the VA and the military veteran patient population when planning resource allocation. Holder (2017) suggested telehealth may mitigate the distance barrier for rural military veteran patients to receive health care. Aggarwal and Ranganathan (2019) recognized the benefit of using reliable secondary data in correlational studies to identify resources needed to provide care for populations, consistent with using archival routinely collected health data in the current study to examine the relationship between residence rurality, home telehealth enrollment, and bed days of care for the military veteran population readmitted for HF.

Song et al. (2017) argued reducing costs, primarily through cost avoidance in the inpatient setting, improves the financial performance of healthcare organizations. Lowering costs by decreasing readmissions for HF (Messina, 2016; Yoon et al., 2016) and managing internal resources are valuable ways to improve hospital financial performance (Chahal et al., 2018). Revenue in the VA annual budget does not increase from readmissions for HF; therefore, cost avoidance through reduced readmission rates, such as for HF, is a primary way to improve financial performance (Carey & Stefos, 2016). Understanding the costs and cost drivers is a prerequisite to identifying the high economic burden on healthcare organizations from readmissions for HF care (Carey & Stefos, 2016; Lesyuk et al., 2018). Cost control strategies in hospitals include reducing variation in practice patterns (Yoon et al., 2016) by increasing evidence-based care (Song et al., 2017). Brainerd and Hawkins (2016) and Messina (2016) described home telehealth in VA for HF management as meeting evidence-based criteria to standardize the care and reducing readmissions and costs for HF care, supporting the need for the current study.

Military veteran patients receiving home telehealth as an adjunct to usual HF care experienced reduced costs and bed days of care (Brainerd & Hawkins, 2016). Messina (2016) described reducing bed days of care by over 5% and decreasing costs for patients receiving home telehealth as an additional service to the usual care of military veteran patients with HF. Earlier recognition and treatment of HF occurred through home telehealth monitoring, creating opportunities to avoid or delay the need for readmissions for HF (Messina, 2016). The use of telehealth mitigates the shortages of healthcare providers, long distances to access care, and limited transportation in rural communities where a large portion of the military veteran patient population resides (Lum et al., 2020). The large population of military veteran patients with HF and the experience and infrastructure in VA to provide home telehealth (Brainerd & Hawkins, 2016) contributed to the significance of the applied business problem and the justification for the current study.

Hospital financial performance may improve when the variable and fixed direct costs decrease from fewer readmissions for military veteran patients with HF (Carey & Stefos, 2016). In a study conducted to examine methods of calculating VA health care costs, Carey and Stefos (2016) described the importance of improving healthcare management to reduce readmissions and costs of HF care for military veteran patients. Page et al. (2017) recognized hospital bed value by the costs needed to operate the bed and the opportunity cost. Carey and Stefos stated the potential short-term cost savings from decreasing bed days of care might include lowering variable direct costs for labor and supplies. Labor comprised over 50% of hospital costs in medical-surgical units and 80% of costs for care in an intensive care unit (Song et al., 2017). Opportunity costs include using a released bed to meet a higher hospital priority, such as admitting another patient or reduce admission waitlists (Page et al., 2017). After 1 year or longer following decreased readmissions, long-term cost savings realized may reduce fixed direct costs (Carey & Stefos, 2016). Like the appropriate use of home telehealth for military veteran patients with HF increases, bed days of care and the overall cost per day may decrease while health care value improves (Messina, 2016), justifying the need for the current study.

Implications for Social Change

The implications for positive social change include the potential to improve patient satisfaction and decrease the financial burden on individuals, populations, and healthcare organizations by improving the value of HF care. Patient satisfaction may improve with home telehealth use, and the financial burden may decrease as the individual requires fewer inpatient health care services during readmissions (Messina, 2016). The financial burden from admissions for HF impacts patients, families or caregivers, healthcare organizations, and society (Okumura et al., 2016). Patients and informal caregivers lose wages (Wakefield & Vaughan-Sarrazin, 2017) and productivity from HF care demands (Lesyuk et al., 2018). Greater than 17,000 military veteran patients are admitted for HF annually (Wray et al., 2021), affecting over 80% of patients diagnosed with HF (Benjamin et al., 2017). Fifty percent of people die within 5 years of receiving a HF diagnosis (Benjamin et al., 2017; L. G. Park et al., 2019), negatively impacting the life expectancy and quality of life.

Availability of scarce health care resources may increase as HF management improves and admissions and costs for HF care decrease (Parissis et al., 2015). The health of individuals and groups of patients with HF may improve, and the economic burden on patients and society may decrease if healthcare leaders optimize health care services (Okumura et al., 2016). Health outcomes of people with barriers to care for chronic conditions, including distance, limited transportation, and scarce health care resources, may improve with the use of telehealth (Lum et al., 2020). In the current study, positive social change may occur if HF care improves by using home telehealth for military veteran patients with geographical or transportation barriers to receiving health care, decreasing the need for hospital admissions.

A Review of the Professional and Academic Literature

The literature review reflects a critical examination of published research to clarify known information on the research topic and verify a gap exists to support the study (Astroth & Chung, 2018b). Including the findings from recent, relevant studies promotes a comprehensive understanding of the research topic and research design selected in studies with similar topics (Abutabenjeh & Jaradat, 2018). Informed researchers consider the gaps in knowledge, the strength of evidence, and potential application to health care when identifying the pertinence of published literature to the study (Astroth & Chung, 2018b).

Literature Review Organization and Strategy

The multiple sources in the literature review included journal articles, publications, and websites of government agencies and professional organizations representing the views of healthcare leaders, researchers, professional organizations, and patients. Priorities included a systematic approach identifying peer-reviewed, full-text literature published in English within 5 years of completing the current study. Walden University’s Library databases of articles, books, and dissertations and Google Scholar were the main sources of the literature search. The primary subjects included business and management, health sciences, nursing, and psychology. The leading search engines used were Business Source Complete, Cumulative Index to Nursing and Allied Health Literature (CINAHL), MEDLINE, ProQuest, PubMed, and Cochrane Library. The broad categories covered were theoretical frameworks, HF and readmission, telehealth, residence rurality, veterans, and routinely collected health data.

The keywords comprising the theoretical framework’s category were *Andersen’s behavioral model of health services use*, *consolidated framework for implementation research*, *resource dependency theory*, *complex adaptive systems*, and *systems theory*. The research method and design categories included keywords of *quantitative*, *qualitative*, *correlation*, *ex post facto*, *multiple regression*, *reliability*, and *validity*. The HF and readmission categories contained keywords of *heart failure*, *bed days of care*, *length of stay*, *rehospitalization*, *readmission*, *index admission*, *health care use*, *value*, *quality*, *costs*, *ambulatory care sensitive conditions*, and *Hospital Readmission Reduction Program*. The telehealth category included home telehealth and telemedicine. The keywords of *veteran*, *rural*, *distance*, *travel*, *geographical information systems*, and *telehealth legislation* composed the residence rurality category. The category of the routinely collected health data included *administrative data*, *secondary data*, and *reuse data*.

Expanding the literature search included a review of the U.S. government and professional organization websites. The main websites comprising the review were the VA; Centers for Disease Control and Prevention (CDC); CMS; American Heart Association; Agency for Healthcare Research and Quality, Office of Research & Development (ORD), and the World Health Organization. Table 1 displays the number and percentage of current, peer-reviewed references included in the literature review.

Table 1

Summary of Literature Review References

Reference	Number	%
Peer-reviewed	135	98.5
Government websites	7	
Published on or after 2017	115	84
Total	137	

Application to the Business Problem

The purpose of this quantitative ex post facto correlational study was to examine the relationship between the predictor variables of residence rurality and home telehealth enrollment and the criterion variable of bed days of care for military veteran patients with HF. The null hypothesis was there is no statistically significant relationship between residence rurality, home telehealth enrollment, and the bed days of care for military veteran patients with HF. The alternative hypothesis was there is a statistically significant relationship between residence rurality, home telehealth enrollment, and the bed days of care for military veteran patients with HF.

Andersen's Behavioral Model of Health Services Use

Using theoretical models helps explain relationships among the variables (Astroth & Chung, 2018b) and enhances study interpretation (Handley et al., 2018). Applying the behavioral model promotes understanding the relationships between variables and factors influencing health services use for HF care before, during, and after hospital admissions (O'Connor et al., 2016). The term bed days of care reflects the number of overnight hospital days in VA (VHA, 2013), like the alternate phrase of the length of stay (Davis et al., 2017). The rationale for applying the behavioral model in the current study was the application of this theoretical framework in other studies to examine admissions for HF.

Application of the Behavioral Model

Researchers commonly applied the behavioral model to explain health care use, including inpatient care (Babitsch et al., 2012; O'Connor et al., 2016; Zhang et al., 2019). A gap existed in applying the behavioral model and inpatient health care use during readmissions for HF. Justification for this study existed because using the behavioral model to explain the relationship between residence rurality, home telehealth enrollment, and bed days of care for military veteran patients readmitted for HF may add to the body of knowledge.

Descriptions of the behavioral model comprise aspects of health care use for HF, including during hospital admissions (O'Connor et al., 2016). However, the routine measurement for HF care included the readmission rate (Wu, 2018) rather than bed days of care for admissions and readmissions. Zuckerman et al. (2017) reported the mean number of index hospital stays rather than the bed days of care. A description of an index admission included a hospitalization when the patient was not discharged within the previous 30 days (Carey & Stefos, 2016). Understanding improves by analyzing data from HF hospitalizations at different times, supporting the reason to conduct the current study to examine the relationship between home telehealth enrollment, residence rurality, and bed days of care for military veteran patients readmitted for HF.

Andersen's (1968, 1995) behavioral model evolved over several decades with revisions, empirical testing, and refinement of the model by various theorists, including Andersen, Newman, Aday, and Awe (Andersen, 1995; Babitsch et al., 2012). The early behavioral model predicted health care use by applying psycho-socio-economic factors to understand why and how individuals within the family unit accessed health care services (Andersen, 1995). Influences of the community, environment, and healthcare organization impacted patients' use of health services in varied health care sectors (Andersen, 1995; Babitsch et al., 2012). Researchers adapted and expanded the application of the behavioral model from individuals' use of general health services to explain health services use and outcomes for specific populations and health conditions, including military veteran patients with HF (Guzman-Clark et al., 2020; O'Connor et al., 2016). Support for the current study included adding to the body of knowledge by applying the behavioral model to explain bed days of care for military veteran patients readmitted for HF.

An advantage of underpinning studies with the behavioral model is the versatility to align factors with the predictor variables, population, and health care setting specific to the study (see Babitsch et al., 2012). Applying the behavioral model promotes an understanding of health service use for HF care in outpatient and inpatient settings for populations of non-military veteran patients (O'Connor et al., 2016) and military veteran patients (Guzman-Clark et al., 2020). Hirshfield et al. (2018) adapted the behavioral model to examine risk factors for populations with heart conditions in the United States. Studies underpinned in the behavioral model included patients with or at risk of developing heart conditions (Hirshfield et al., 2018) and HF (Guzman-Clark et al., 2020; O'Connor et al., 2016), aligning with the current study comprising military veteran patients with HF, a type of heart condition. Applying the behavioral model to studies involving readmissions for HF (Guzman-Clark et al., 2020; O'Connor et al., 2016) was consistent with the criterion variable in the current study of bed days of care during readmissions for HF.

Predisposing, Enabling, and Need Factors

In the behavioral model, categorizing and applying predisposing, enabling, and need factors facilitated understanding of the influences on patients seeking health care services (Graham et al., 2017). Promoting effective health service use involves anticipating health-seeking patterns of patient populations; identifying facilitators or inhibitors; and considering predisposing, enabling, and need factors (Graham et al., 2017). In a systematic review of 16 studies underpinned in the behavioral model, Babitsch et al. (2012) concluded there was a consistent classification of most variables. In many examples in which classification differed, variables were applied to both predisposing and enabling factor categories (Babitsch et al., 2012). Justification for the current study included contributing to the body of knowledge about applying the behavioral model to examine the enabling factors of home telehealth enrollment and residence rurality and the need factor of bed days of care for HF readmissions.

Predisposing factors. Predisposing factors are characteristics of the individual existing before the decline in health (Hirshfield et al., 2018; Parkman et al., 2017). Common predisposing factors were unchanging and increased an individual’s likelihood to use a specific type of health care (A. P. Costa et al., 2014). Predisposing factors comprise demographics of age, gender, health condition history, social structure, and health beliefs (Parkman et al., 2017). Social structure elements include education, occupation, ethnicity, and coping (Andersen, 1995). Health beliefs consisting of attitudes, values, and knowledge influence an individual’s perception of the need for and use of health services (Andersen, 1995). Understanding the predisposing factors was important to understanding the bed days of care and supported the need for the current study.

In this study, age was a predisposing factor because HF is the most common cause of hospital admissions for patients 65 years of age or older (see Ensign and Hawkins, 2017). The mean age for patients readmitted for HF was 75.8 years old (Castillo et al., 2017), and more than 50% of patients treated for HF in VA were 70 years of age or older (Yoon et al., 2016). In a systematic review of 34 studies underpinned in the behavioral model, O'Connor et al. (2016) identified adult age as a common predisposing factor, with a mean age ranging between 55 and 81 years old for patients with HF. Further, identifying adult age as a predisposing factor is consistent with a HF study underpinned in the behavioral model by Guzman-Clark et al. (2020), as the mean age of patients with HF in the VA using home telehealth was 71 years old.

Gaps exist in applying the behavioral model to understand the influences of age as a predisposing factor for readmission for HF (O'Connor et al., 2016). Babitsch et al. (2012) noted most articles reviewed in a systematic review included secondary data analysis and cited the lack of using multivariate models as a reason for inconsistencies in the correlation of age to other variables in studies underpinned in the behavioral model. O'Connor et al. (2016) found inconsistencies in the ages of targeted populations with HF and the impact of age on readmissions. Potential reasons cited for the inability to assess correlations between variables were understudied predisposing factors, limited inclusion of younger ages, and the varied selection of continuous or categorical age variables

(O'Connor et al., 2016), promoting the need to conduct the current study to add to the body of knowledge about factors impacting the HF outcome of bed days of care.

Enabling factors. Enabling factors are environmental characteristics that may facilitate individuals to obtain health services (A. P. Costa et al., 2014). An adequate type and amount of the enabling factor external to the individual facilitated seeking needed health services, whereas an absent or insufficient factor impeded receiving health services (Babitsch et al., 2012). Eligibility for VA health benefits, residence rurality, and home telehealth enrollment were enabling factors pertinent to the current study.

Babitsch et al. (2012) described organizational factors as conditions in the health care system enabling the use of health services. Examples of organizational health care conditions included the type, amount, and locations of health services; hours of operation; personnel; and policies (Babitsch et al., 2012). In a systematic review of 34 studies grounded in the behavioral model, O'Connor et al. (2016) identified the supply of services and provider characteristics as organizational factors enabling health service use for HF care during readmissions. Andersen (1995) recognized knowledge about the types and availability of health services within healthcare organizations and the individual's community as a potential facilitator for individuals to seek health services. Management of the HF condition improved when the military veteran patient received health care through an established relationship with a healthcare provider and early recognition and treatment of worsening symptoms occurred (Messina, 2016). The organizational factors and services established at the VA supported the justification to conduct the current study to examine the relationship between home telehealth enrollment, residence rurality, and bed days of care for military veteran patients readmitted to the VA for HF care.

Organizational conditions in the VA include resources to provide HF care in outpatient and inpatient settings (Patel & Dickerson, 2018; Yoon et al., 2016) and home telehealth (Lum et al., 2020). The VA developed an infrastructure comprising a shared electronic health record, telehealth capacity at all VA hospitals and community-based outpatient clinics, and a system of information technology and analytics to support the organizational strategy to expand the effective use of technology throughout VA (Abbott et al., 2018). Optimizing the use of VA services includes developing targeted health care strategies and considering the use of home telehealth for HF care of individual patients (Messina, 2016), strengthening the rationale for conducting the current study at the VA.

O’Connor et al. (2016) identified income, health insurance, and access to health services as enabling factors when applying the behavioral model to HF care. Johnson et al. (2015) listed income and health insurance as enabling factors in a study to evaluate health services use by residence rurality of military veteran patients with mental health conditions. Enabling factors included service connection for VA health service benefits eligibility (Friedman et al., 2015; Guzman-Clark et al., 2020). Determining eligibility for VA health benefits includes considering income, disability status, and military history (Zelaya & Nugent, 2018). Individuals without health benefits reported a lower quality of health (Boudreaux et al., 2019), consistent with improved chronic disease management when patients are insured and receive health care from a usual source (Nothelle et al., 2018). Admon et al. (2019) associated higher insurance coverage with the increased use of primary care, seeking health services earlier for worsening symptoms, and less frequent episodes of severe illness. Conducting the current study at the VA was supported because military veteran patients had access to primary care services and the ability to seek health care services for HF.

Home telehealth enrollment. The VA enabled the use of home telehealth for HF care through an organizational commitment to improving access to care by expanding the use of technology and care by virtual care modalities (Wakefield & Vaughan-Sarrazin, 2017). In a study to evaluate home telehealth use by VA patients with HF, Guzman-Clark et al. (2020) identified patients’ familiarity with health technologies as an enabling factor influencing adherence to using home telehealth. Andersen (1995) clarified how coordinated health care services are an attribute of the early behavioral model (1968), and improved care coordination is a component of the home telehealth program in VA (Messina, 2016). Therefore, home telehealth enrollment was an appropriate enabling factor in the behavioral model. Although the literature includes examples of the application of the behavioral model and the use of health services in the form of telehealth, a gap existed to explain home telehealth as an enabling factor for HF care when the predictor variable is bed days of care for readmissions for HF. This gap was consistent with the findings by O’Connor et al. (2016) of understudying and underreporting the enabling factors when applying the behavioral model to studies for HF care. Support for conducting this study included increasing knowledge about home telehealth for HF as an enabling factor with the behavioral model.

Residence rurality. There are diverse examples in the literature of enabling factors about geography (Babitsch et al., 2012; A. P. Costa et al., 2014) or distance (Fleming et al., 2016; Friedman et al., 2015). Hirshfield et al. (2018) applied enabling factors of geographic region and community size in a study to evaluate the characteristics and health conditions of adult males diagnosed with hypertension. Babitsch et al. (2012) identified the region of residence as an enabling factor and found residing in a rural location impeded receiving health care when specialized health services were scarce. Justification for this study included the benefit of expanding information about the influence of geography on patients receiving care for HF, consistent with this study to examine the relationship between home telehealth enrollment, residence rurality, and bed days of care during readmission for HF.

Friedman et al. (2015) noted greater distance and time to travel are barriers to seeking health care. The influences of rural military veterans seeking health care identified in studies grounded in the behavioral model included perceived distance barriers to care (Fleming et al., 2016; Friedman et al., 2015; Johnson et al., 2015), preferences of how to receive health care information (Fleming et al., 2016), and higher attrition rates for female military veteran patients newly enrolled in VA health care (Friedman et al., 2015). A deterrent to increased travel time is the cost of travel (Friedman et al., 2015). The distance between the patient’s residence and the nearest VA facility was an enabling factor (Fleming et al., 2016). Friedman et al. also calculated the distance between the patient’s residence and the VA health care services but did not specify the distance element as an enabling factor. Findings from the studies by Fleming et al. (2016), Friedman et al., and Johnson et al. (2015) show the common application of the behavioral model to examine the influence of distance and time on veterans' seeking health care. Rural patients travel longer distances over increased time to access health care services, consistent with selecting the predictor variable of residence rurality of military veteran patients with HF in the current study.

In a systematic review of 16 studies grounded in the behavioral model, Babitsch et al. (2012) identified six studies with a region of residence comprising rural, urban, or community variables as a predisposing rather than an enabling factor. Babitsch et al. concluded the varied application of the geographic region as a predisposing factor existed to explain the impact of the residential location on health services use. In contrast, Johnson et al. (2015) grounded a study in the behavioral model and combined the presence or absence of VA or other health insurance coverage with rural or urban residency in predisposing variable categories.

Although Babitsch et al. (2012) found the residence rurality categories varied by predisposing or enabling factors in different studies, rurality impacted patients' health care seeking behaviors. The findings of Babitsch et al. demonstrate the broad application of the behavioral model to explain health care delivery and the influence rurality may exert on patients' health care decisions. Therefore, the findings supported the inclusion of residence rurality as an enabling factor and predictor variable in this study because patients residing in rural areas may experience altered health care access for HF than patients residing in urban areas.

A. P. Costa et al. (2014) identified the predisposing factor of rurality as exerting a significant impact on health services use in at least two of 18 studies in a systematic review. However, A. P. Costa et al. (2014) listed the impact of rural residence in the enabling factor section of the outcomes table, making comparisons with other articles difficult because of categorization inconsistencies. In a systematic review of 34 articles on patients with HF and readmissions, O'Connor et al. (2016) noted statistically insignificant results from analyzing travel time and transportation sources as enabling factors, and health services use. O'Connor et al. suggested researchers understudied and underreported some factors in the studies because of the belief there was a limited impact of patient characteristics on readmissions for HF. In contrast, Rodriguez and Dobalian (2017) explained the lack of collecting data about transportation in their study, suggesting transportation did not emerge as a topic of concern during data extraction; therefore, transportation may be an unknown factor. Selecting various enabling factors allows flexibility to apply the behavioral model to different scenarios (Andersen, 1995). Including residence rurality as an enabling factor and predictor variable in the current study was appropriate because health care for HF may improve with enhanced understanding of the influences impacting health care decisions of rural patients.

Need factors. Many elderly, chronically ill patients focused on the need factor and placed less importance on the predisposing and enabling factors (Hajek et al., 2017). Fleming et al. (2016) identified similar motivations in Vietnam military veteran patients to prioritize need factors rather than predisposing factors or enabling factors for mental and physical conditions. In contrast, the elements included in the predisposing or enabling factors influenced patients in good health who sought primary care services for health screenings or minor illnesses (Andersen & Newman, 1973/2005). In the current study, the adapted behavioral model (see Figure 1) emphasized a more significant influence of the need factor than the predisposing and enabling factors because HF is a chronic condition requiring frequent admissions.

Categories of the need factor in the behavioral model were perceived and evaluated (Andersen, 1995; Hajek et al., 2017). The perceived need was the individual's subjective view of their health and functional condition level, response to symptoms, and the level of importance to seek health services (Andersen, 1995; Parkman et al., 2017). The severity and progression of HF symptoms were the main influences for the patient to seek and use health services for HF (O'Connor et al., 2016). Individuals sought health care services when their perception of the need for health care rose high enough to act (Graham et al., 2017; Johnson et al., 2015). Guzman-Clark et al. (2020) described HF severity level, other health conditions, and risk of hospitalization or death within 90 days as contributing to the need factor. After patients seek health care for a perceived need (Parkman et al., 2017), health professionals evaluate the need factor by observing clinical data and applying professional judgment to determine the individual's clinical indication for health services (Andersen, 1995). Health professionals assess changes in HF symptoms to evaluate the need and adjust the medical plan of care (Messina, 2016). Reasoning to conduct the current study included the importance of identifying ways to decrease bed days of care during readmissions for HF.

National Health Care Systems

In the behavioral model, the resources and organization of national health care systems affected the health care use by individuals and populations (Andersen & Newman, 1973/2005). Labor and capital necessary for providing health care comprised the resources, whereas organization referred to how the health care system used the resources (Andersen & Newman, 1973/2005). The volume of resources included the number and type of healthcare personnel providing care to the targeted populations (Andersen & Newman, 1973/2005). The geographical distribution of resources pertained to the location of healthcare personnel, hospitals, and clinics within the country available to provide services (Andersen & Newman, 1973/2005). Johnston et al. (2019) emphasized the need to improve access to the supply of healthcare provider resources for specialized health care services in rural areas to lower preventable hospitalizations for chronic conditions, including HF. Justification for the current study included the priority to identify effective HF care in rural areas where access to health care may be limited.

Access and Structure

Andersen and Newman (1973/2005) described the categories of organization in the behavioral model as access and structure. Access pertains to the way patients receive initial and ongoing treatment, the requirements for delivering the care, and any constraints to health care (Andersen & Newman, 1973/2005). Andersen (1995) identified four categories of access including (a) potential access, (b) realized access, (c) equitable access, and (d) inequitable access. Creating potential access requires enabling resources to assure the availability of health services (Andersen, 1995), whereas realized access is the actual use of health services (Andersen, 1995; O'Connor et al., 2016). In the current study, home telehealth enrollment and urban rurality were enabling factors consistent with creating potential access.

Factors enabling access include eligibility for VA health care (Friedman et al., 2015; Guzman-Clark et al., 2020), ability to access services (Parkman et al., 2017), and readiness of inpatient beds for admissions (Page et al., 2017). The health care system structure includes services to support team-based care, including in hospitals (Andersen & Newman, 1973/2005). O'Connor et al. (2016) noted a regular source of care and a transportation method to receive the care are organizational and enabling factors. In the current study, potential access in the inpatient area was bed availability for patients with worsening HF symptoms, and the measurement for realized access included bed days of care for military veteran patients readmitted for HF.

Behavioral Model and Archival Routinely Collected Health Data

An advantage of underpinning studies in the behavioral model involved comparing common data elements from archival routinely collected health databases (Babitsch et al., 2012). Archival databases contained a limited number of common variables collected for a different purpose than the original study (Babitsch et al., 2012). In a systematic review, Babitsch et al. (2012) noted 14 of 16 studies grounded in the behavioral model included archival routinely collected health data with a limited choice of variables, allowing comparisons of core study findings. Goode et al. (2017) applied the behavioral model and used secondary data in large data sets to examine quality outcomes and patient safety practices. Goode et al. recognized the benefit of using secondary data in large data sets and emphasized the importance of the sample, purpose, and method during data analysis because small associations between variables in large data sets may be statistically significant. Selecting the behavioral model as the foundation for the current study was supported by the examples of studies underpinned in the same theoretical framework and using archival routinely collected health data from large databases as the data source.

In a systematic review grounded in the behavioral model, O’Connor et al. (2016) noted the use of archival data in 29 of 34 studies where the most common data sources were hospital records or national administrative databases for patients hospitalized with HF. Two of the 34 articles involved 100,957 military veteran hospital records or VA patient treatment files (O’Connor et al., 2016). The common use of archival administrative and clinical data in studies grounded in the behavioral model (Babitsch et al., 2012; O’Connor et al., 2016) aligned with the design of the current study to use VA archival routinely collected health data to examine the relationship between the variables.

In contrast, the disadvantages of including secondary data in studies underpinned in the behavioral model were the limited data selection choices to conduct studies, narrowing the ability to select optimal variables or compare variables from published studies (Babitsch et al., 2012). The omission of specific data elements and the inclusion of data elements in more than one study category contributed to further inconsistencies (Babitsch et al., 2012). O’Connor et al. (2016) noted a lack of standardized measures, including organizational factors, in studies grounded in the behavioral model to examine the risk for HF readmissions. Babitsch et al. (2012) posited variables in more than one category indicated different influences on health care use. Based on findings by Babitsch et al. and O’Connor et al., gaps existed in applying the behavioral model, supporting the need for the current study.

Rival Theoretical Frameworks

Researchers apply theoretical frameworks in correlational studies to explain the relationship between variables (Curtis et al., 2016). Applying frameworks may benefit different types of studies by improving the interpretation of validity (Handley et al., 2018). Theoretical frameworks used to underpin studies in health care include the consolidated framework for implementation research (CFIR; Birken, Powell et al., 2017), resource dependency theory (RDT; Ellis Hilts et al., 2018), and complex adaptive systems (CAS; Nurjono et al., 2018).

CFIR

The focus of the CFIR is implementation theory development and verification of how and why actions work across multiple contexts (Birken, Powell et al., 2017; Hill et al., 2018; Low et al., 2019). Thirty-nine constructs consisted of five domains including (a) intervention characteristics, (b) outer setting, (c) inner setting, (d) characteristics of the individuals involved, and (e) the process of implementation (Birken, Powell et al., 2017; Hill et al., 2018; Low et al., 2019). The CFIR is helpful when planning or implementing an intervention in health care (Birken, Powell et al., 2017; Low et al., 2019). However, five domains and 39 constructs (Birken, Powell et al., 2017; Hill et al., 2018; Low et al., 2019) exceed the framework necessary to address my research question.

Birken, Powell et al. (2017) advised against using a framework that includes complexity without clear value to address the research question.

In a study to examine readiness for hospital discharge, four study investigators identified the appropriateness of including 20 of the 39 CFIR potential constructs (L. L. Costa et al., 2020), reflecting the elevated level of resources needed to apply the complex CFIR model. Hill et al. (2018) evaluated the effectiveness of applying the CFIR model when implementing multiple interventions to achieve cultural transformation at the VA. Hill et al. noted the value of using a comprehensive but flexible framework to evaluate the implementation of interventions. Wakefield et al. (2019) applied the CFIR framework to examine barriers and facilitators to implementing a home-based cardiac rehabilitation program at the VA. Qualitative data were collected to analyze the implementation processes (Wakefield et al., 2019). It was inappropriate to apply the CFIR framework to this study to examine the relationship between variables because the CFIR framework aims to systematically evaluate the implementation of interventions and factors influencing change adoption (Keith et al., 2017).

RDT

Applying the RDT promotes an understanding of the organization’s external environment and the impact of influences on organizational behavior and resource procurement decisions (Birken, Bunger et al., 2017; Ellis Hilts et al., 2018). Organizations experience dependencies on other entities to provide some necessary resources (Ellis Hilts et al., 2018). Leaders within organizations decrease uncertainty and increase control by developing external alliances to attain essential resources (Birken, Bunger et al., 2017; Ellis Hilts et al., 2018). The focus on the external environment was not consistent with the research question in the current study.

Applying the RDT to healthcare organizations is appropriate because dynamic environments with regulatory requirements promote alliances to decrease high levels of uncertainty (Spaulding et al., 2018). Controlled or lowered costs through improved contracting or group purchasing may occur through effective alliances (Song et al., 2017), such as when vendors provide home telehealth equipment for patients receiving VA home telehealth for HF care (M. M. Murphy, 2018a). However, it was inappropriate to select the RDT as the theoretical foundation of the current study because alliances between VA and the private sector or other government entities were inconsistent with the research question.

CAS

A CAS comprises diverse, semi-autonomous actors; self-organizing capacity; uncomplicated rules; and nonlinearity (Nurjono et al., 2018). Actors include internal and external stakeholders such as patients, families, healthcare providers, and healthcare organizations or systems (Nurjono et al., 2018). Interdependencies by connected actors impact the behavior of the central system (Nurjono et al., 2018; Pype et al., 2018). A CAS can change or learn from experience (Flieger, 2017). Emerging behaviors from feedback loops may affect all system levels (Nurjono et al., 2018; Pype et al., 2018). The impact of emerging behaviors is unpredictable and intended or unintended, ranging from minor to significant effects and under different circumstances (Barasa et al., 2017). The characteristics of CAS apply to healthcare organizations but were not specific to understanding the relationships between the variables in this study.

Pype et al. (2018) examined the factors influencing workplace learning as an emergent behavior when healthcare teams applied CAS principles to interactions. Pype et al. identified all CAS principles during individual interviews, suggesting there may be value in conducting training for teams and individuals. Barasa et al. (2017) applied the CAS framework to examine factors affecting priority setting and resource allocation at hospitals in Kenya. Barasa et al. emphasized the value of recognizing the hospital as a CAS when planning interventions and policies. A CAS was a potential framework to underpin the current study, but the focus was not specific to health care use or bed days of care in the inpatient setting. Similar to the CFIR, the CAS framework included more constructs than were needed to answer the research question in this study. The CAS framework was too general to optimally explain the phenomena in the research question, justifying the rationale for underpinning the current study with the behavioral model.

Health Care as a Business

Maintaining a competitive advantage and achieving solid organizational performance in health care requires leaders to consider the impact of the dynamic environment, new regulations, and the introduction of technologies and new competition (Rouyendegh et al., 2019). Chahal et al. (2018) argued responding to the uncertainties in health care to gain a sustainable competitive advantage requires operational flexibility. Chahal further asserted financial performance, market performance, and customer satisfaction contribute to hospital performance. However, Zanotto et al. (2021)

emphasized a lack of methodological rigor when measuring financial outcomes, and underemphasis on patient-centered outcomes limits accurate organizational assessments, comparisons, and outcome measurements that matter to patients. By measuring the relationship between bed days of care for military veteran patients readmitted for HF and home telehealth enrollment of rural and urban patients in the current study, primary care managers may contribute to improved organizational performance by promoting optimal home telehealth use.

Optimal hospital capacity and staff efficiency, objectively identifying organizational strengths and weaknesses, evaluating performance as compared to rivals, and acting on the findings are criteria for reaching competitive advantage (Rouyendegh et al., 2019). Choi et al. (2017) stated hospitals might have limited ability to improve the cost efficiency for HF care without decreasing the quality of care. Alternately, Miller et al. (2018) argued reducing wasteful spending and expanding opportunities for innovation in health care requires eliminating inefficient, low-value care. Messina (2016) found VA financial performance and patient satisfaction improved with home telehealth use when readmissions decreased for military veteran patients with HF. Expanding knowledge about how to improve value in health care, including the use of home telehealth for military veterans readmitted for HF, supported the need for the current study.

In the behavioral model, the organization of formal health care occurs within the healthcare organization and comprises goods and services (Andersen & Newman, 1973/2005). Hospitals, insurers, and medical organizations prioritize lowering readmissions for HF because the highest costs for HF care incur during hospitalization

(Palazzuoli et al., 2019). The use of telehealth and related health care value may improve by building alliances with major companies, state agencies, telecommunication service providers, equipment manufacturers, and software service providers, expanding the traditional list of telehealth stakeholders beyond providers, insurers, and patients (Pereira, 2017). Enhanced understanding of home telehealth enrollment for HF management by military veterans in rural and urban locations supported the need for the current study.

Resources

Providing value in a dynamic and regulated healthcare environment (Rouyendegh et al., 2019) by addressing the influences of rising health care costs, such as the increasing life span of the population, greater disease detection, and shortages of medical professionals (Pereira, 2017) requires physical resources, such as beds; people; space; and information flow and technology (Chahal et al., 2018). Optimizing resource use and process efficiencies entails aligning the supply of resources with patient demand to provide planned and unplanned health care (Chahal et al., 2018). Zsilinszka et al. (2017) emphasized effective management of HF and avoiding hospitalizations requires a collaborative team approach from multiple services and providers within the healthcare organization. By examining the relationship between residence rurality, home telehealth enrollment, and bed days of care for military veteran patients readmitted for HF in the current study, primary care managers may improve resource use for HF management.

Physical assets comprise staffed beds in the inpatient setting (Winasti et al., 2018), available clinic appointments in the outpatient setting (Zsilinszka et al., 2017), and telehealth (Pereira, 2017). Identifying the optimal use of staffed beds in the inpatient setting is complex and includes accounting cost and opportunity cost considerations to achieve efficiency and effectiveness (Page et al., 2017). Winasti et al. (2018) affirmed the importance of aligning the supply of staffed inpatient beds with patient demand but emphasized how ongoing staffing deficits or surpluses, suboptimal bed utilization, and staff dissatisfaction may impede staffed bed balance. Understanding health care costs and cost drivers during hospitalizations promotes decision-making to maximize value in health care, concepts central to justifying the need for the current study.

Labor. Song et al. (2017) grouped resources into high-tech, high-touch, and other cost categories to enhance understanding of potential cost reduction opportunities. The resources for high tech care for HF included heart monitoring and other technology-intensive services, whereas high touch HF care included labor-intensive services (Song et al., 2017). Labor costs rose from 50%-80% of total hospital costs when clinical needs increased to require care in an intensive medical unit with higher nurse staffing ratios (Song et al., 2017). Yoon et al. (2016) noted the costs during hospitalization are greater than 50% of the annual health care costs for military veteran patients with HF, with most of those costs for care in medical/surgical units. Conducting this study was important to understanding health care cost containment for veterans with HF.

Effective cost reduction strategies include standardization to improve productivity in clinical areas, considering the rate of price increases of resource inputs, and reducing the variation of costs between conditions and hospitals (Song et al., 2017). Ziaeian and Fonarow (2016) recognized readmission rates for patients with HF decreased when care included higher nurse staffing ratios and specialized cardiac services. Stock et al. (2014)

suggested an association exists between paying higher average hospital salaries, reduced bed days of care, and improved customer satisfaction, without an elevated cost per patient. Stock et al. speculated higher-paid employees might exhibit greater skill or motivation than lower-paid employees, suggesting why the cost per patient did not increase with higher salaries. Flexibility in adding capacity allowed hospital managers to balance supply and demand (Chahal et al., 2018) and minimize staffing shortages and surpluses (Winasti et al., 2018). Priorities included identifying effective and efficient ways to provide care, including using home telehealth for selective patients, supporting the need for the current study.

Telehealth. Using telehealth is a strategy to mitigate the increasing shortages of physician and nurse resources and reduce transportation and geographical barriers to accessing health care (Pereira, 2017). Haun et al. (2017) recognized telehealth as a high-volume health information technology resource used by military veteran patients receiving VA health care. Resources for telehealth services include a health information technology infrastructure with personnel for data collection, data monitoring, and patient management to shift care for HF from the hospital or clinic to the home (Fraiche et al., 2017). The health information technology infrastructure and established telehealth services justified conducting the current study at the VA.

The impact on health care costs may vary by telehealth use (Licurse & Mehrotra, 2018). Health care costs may diminish when telehealth is a substitute rather than an addition to usual in-person care encounters (Licurse & Mehrotra, 2018). Measurements of cost savings include the cost difference between telehealth and in-person care (Licurse

& Mehrotra, 2018). There may be cost avoidance from fewer emergency department visits, treatment by specialty providers, or inpatient admissions if selection criteria for telehealth include populations with high health care use (Licurse & Mehrotra, 2018). Of 119 military veteran patients with HF enrolled in home telehealth, Messina (2016) identified 20 readmissions within 30 days, or a 17% readmission rate, compared to 28 readmissions or a 23% readmission rate within the same period for 99 military veteran patients receiving usual care for HF without home telehealth. Messina noted a net positive cash flow of $1,164 correlated with reducing bed days of care from 3.8 to 3.3 days during readmissions. In contrast, Greenhalgh et al. (2017) recognized inconsistencies in samples and study variables contributed to differences in telehealth cost estimates for HF care. Identifying the relationship between the military veteran patients' residence rurality status, home telehealth enrollment, and bed days of care for military veteran patients with HF may inform primary care leaders about optimal conditions to use home telehealth, supporting the need for the current study.

Veterans Health Administration as an Organization

The VHA is the healthcare organization within the VA, the largest integrated health care system in the United States, providing health care for 9 million enrolled military veteran patients at 171 hospitals and 1,113 outpatient sites throughout the United States (U.S. Department of Veterans Affairs, 2022). Geographically dispersed VA hospitals and outpatient clinics provide HF care at multiple locations (Yoon et al., 2016). Roles of the VA include payer and provider of health care services (Lewinski et al., 2021) for enrolled military veterans (Zelaya & Nugent, 2018). Categories of health care services used by enrolled military veteran patients were VA-only, dual care (Pope, Davis, Wine, Nemeth, Haddock et al., 2018), and the third category of using non-VA care one time for emergency treatment of worsening HF symptoms (Pope, Davis, Wine, Nemeth, & Axon, 2018). Dual care use refers to an enrolled military veteran patient receiving health care from VA and non-VA providers or facilities (Pope, Davis, Wine, Nemeth, & Axon, 2018). Military veterans using dual care for HF contrasted with VA-only health care experienced a greater risk of safety concerns and inefficient care, potential inconsistencies in treatment plans, duplication of care (Pope, Davis, Wine, Nemeth, Haddock et al., 2018), 40% higher admissions, and 46% higher all-cause readmissions (Pope, Davis, Wine, Nemeth, & Axon, 2018). Justification for conducting the current study in the VA included the integrated health care system and the ability to study a large population from rural and urban areas, which was appropriate for examining the relationship between residence rurality, home telehealth enrollment, and bed days of days for readmissions of military veteran patients with HF.

The funding source of the VA fixed, global budget for VA hospitals and affiliated clinics is through an annual appropriation from the U.S. Congress (Groeneveld et al., 2019). The VA uses a national patient-level cost accounting system, allowing the separation of fixed and variable costs at the patient level (Carey & Stefos, 2016). There are nationally established costs for pharmaceuticals and wage scales, but VA hospital leaders affect other costs at the hospital level through resource allocation decisions (Groeneveld et al., 2019). The lack of financial incentives by VA managers and salaried physicians minimizes medically unnecessary readmissions of military veteran patients

(Carey & Stefos, 2016) or upcoding of diagnoses (Groeneveld et al., 2019). Using scarce health care resources efficiently is important because raising revenues by increasing the number of profitable care episodes is inconsistent with the VA funding structure (Groeneveld et al., 2019). The justification for conducting the current study at the VA included the need to expand knowledge about optimal home telehealth use as a possible strategy to reduce bed days of care for military veteran patients readmitted for HF.

The VA multihospital and clinic system provides an infrastructure of informatics technologies and connectivity, the electronic health record, and home telehealth across the health care system (Abbott et al., 2018). The VA is the largest telehealth provider in the United States (Lum et al., 2020) and was an early adopter of technology with telehealth as a primary method to mitigate military veteran patients' geographical or transportation barriers to accessing health care (Zulman et al., 2019). Conflicting financial incentives between hospitals and physicians impede the adoption of modern technologies, organizational changes, and detailed documentation by physicians to support maximizing eligible coding and revenue (Sacarny, 2018). Rather than the fee-for-service payments for care billed to Medicare (Sacarny, 2018), the VA pays physicians under a salaried structure, eliminating financial incentive conflicts between hospitals and physicians (Carey & Stefos, 2016). Physicians and hospital managers in the VA do not have incentives to unnecessarily admit or readmit patients, making the VA an optimal environment to examine admission and readmission data (Carey & Stefos, 2016). The technology infrastructure and financial design supported the appropriateness of conducting the current study in the VA to examine the relationship between residence rurality, home telehealth enrollment, and bed days of care for veterans readmitted for HF.

Reducing variations in the quality of HF care includes collecting, monitoring, and reporting VA HF quality measures data for inpatient and outpatient care (Garvin et al., 2018). Sacarny (2018) analyzed HF coding data from administrative files for Medicare billing to examine factors influencing the adoption of new technologies and practices. Sacarny correlated improved data extraction of detailed documentation in hospitals following established standards of care and demonstrating high treatment performance. Healthcare organizations use performance measures to decrease the bed days of care by monitoring, evaluating, improving performance, and setting goals for future improvements (Horvat & Filipovic, 2020). Krishnamurthi et al. (2018) described using the VA corporate data warehouse (CDW) to standardize patient-level data collection from VA facilities and outpatient clinics, providing the ability to evaluate population-level hospitalization rates, including for HF by residence rurality status and across regions. Further, Krishnamurthi et al. emphasized the value of using national data to identify geographic variations in health care to inform resource decisions, supporting the need to conduct the current study. The VA integrated and adopted the telehealth program throughout the health care system, providing an optimal environment to examine the use of home telehealth and supporting the need to conduct this study at the VA.

HF Condition

HF is a chronic, progressive condition (Wu, 2018) in which the heart does not pump an adequate supply of blood to meet the needs of the body’s organs (CDC, n.d.).

Projections show the total annual cost of HF in the United States will rise to $69.7 billion by 2030 (Benjamin et al., 2017) as the demand for HF care increases with the aging population and improved survival rates after cardiac events (Yun et al., 2018). HF was a contributing cause of death in 13.4% of deaths in the United States in 2018, but the incidence of HF varied by geographical area (CDC, n.d.). Patient factors and variation in treatment patterns by medical providers, rather than the VA hospitals, impacted the range in HF costs (Yoon et al., 2016) and the complexity of HF management (Zsilinszka et al., 2017). HF is prevalent in the military veteran patient population and a frequent cause of admission and unplanned readmission (Pope, Davis, Wine, Nemeth, Haddock et al., 2018), justifying the need to conduct the current study at the VA.

Krishnamurthi et al. (2018) examined electronic health records of military veteran patients hospitalized at a VA facility or non-VA healthcare facility reimbursed by the VA between 2010 and 2014, noting HF was the second most common diagnosis for cardiovascular hospitalization. Sacarny (2018) recognized the frequent incidence of hospitalization for HF and the perception of HF treatment impacting quality and outcomes. Garvin et al. (2018) emphasized the importance of following evidence-based care standards to decrease worsening symptoms, mortality, and readmissions for HF. However, Iorio et al. (2019) argued there is a need to improve risk stratification, targeted interventions, and resource allocation to better align with the underlying HF condition and prognosis. Home telehealth for military veteran patients with HF is an effective technology tool to reduce readmissions for HF (Messina, 2016), consistent with justification to conduct the current study.

According to the behavioral model, individuals seek health services when the level of importance is high enough to access care (Graham et al., 2017). Improving HF management includes considering a history of admission within one year when the risk for readmission is high (Ziaeian & Fonarow, 2016). In addition to the admission history, Iorio et al. (2019) emphasized the importance of understanding the rate and risk of HF progression in stable patients with HF to improve HF management and resource allocation. Differences between the patient's and healthcare provider's recognition of the severity and urgency of HF symptoms contributed to inconsistencies in timeliness and approaches to care (Jurgens et al., 2017). Further, patients with HF exhibiting early and minor symptoms, such as fatigue, experienced twice the risk of an adverse clinical event (Jurgens et al., 2017). Interviews of 20 VA and 11 non-VA healthcare providers revealed the providers' perception of military veteran patients frequently not recognizing worsening HF symptoms (Pope, Davis, Wine, Nemeth, Haddock et al., 2018). Patients have experienced confusion in accurately interpreting HF symptoms or the level of severity until the condition required emergency intervention (Pope, Davis, Wine, Nemeth, & Axon, 2018). Enhancing knowledge about factors influencing readmissions of patients with HF may promote lower costs, improved patient care planning, and better health care resource allocation (Castillo et al., 2017), supporting the need to conduct the current study.

Admissions for HF

HF was the most prevalent diagnosis requiring hospital admission for patients 65 years of age or older in the United States (Ensign & Hawkins, 2017). Greater than 17,000 patient admissions for HF occur annually (Wray et al., 2021), the most common discharge diagnosis for military veteran patients admitted to a VA hospital (Garvin et al., 2018). HF patients comprised 41.5% of the total Medicare fee-for-service hospitalizations (Fitch et al., 2016). Vader et al. (2016) reported hospital admissions for adult patients with HF under the age of 65 years increased from 23% to 29% over 10 years ending in 2010. During the last 6 months of life, up to 80% of patients with HF receive inpatient care (Fitch et al., 2016). Of the patients evaluated for HF in the emergency department, 18.2% required hospitalizations ranging from 1 to 38 days (M. M. Murphy, 2018b). The common HF diagnosis, frequent admissions, and high HF costs for military veterans supported the need to conduct this study.

Classifications of admissions are index admissions or readmissions (Carey & Stefos, 2016). Measuring resource use in the inpatient setting comprised the number of hospitalization days, also known as bed days of care (VHA, 2013) or length of stay (Davis et al., 2017). Estimates included up to 80% of total costs for HF care incurred during a hospitalization (Fitch et al., 2016). In a systematic review of 16 cost-of-illness studies for HF, Lesyuk et al. (2018) found most expenses were during hospitalization. During HF admissions, room and board charges totaled 43% of the overall health care costs, followed by costs for medications, procedures, imaging, and laboratory testing (Lesyuk et al., 2018). Only three studies included indirect costs, showing the limited indirect cost data for HF care (Lesyuk et al., 2018). The lack of a standardized method for data collection and comparing studies from different health care systems in various countries contributed to the significant variations in cost reports (Lesyuk et al., 2018).

Increasing information about the influences on bed days of care for military veteran patients readmitted for HF supported the need to conduct the current study.

Palazzuoli et al. (2019) described associations between reducing avoidable admissions for HF, high quality of care, and costs. Sacarny (2018) emphasized differences in coding practices at hospitals affected the ability to compare quality and revenue capture. However, Groeneveld et al. (2019) explained coding variations were minimal in VA because there were few financial incentives to upcode or overcode the care. Using the electronic health record and a national system for administrative coding promoted standardization (Groeneveld et al., 2019). Garvin et al. (2018) estimated 55% of hospitalizations for HF may be avoidable, and Ware et al. (2018) stated half of the readmissions for HF are preventable. Messina (2016) identified the average cost per bed day to provide inpatient care for HF at a VA hospital in Florida as $3328. Decreasing the average bed days of care from 3.8 to 3.3 days during an episode of care improved a $501 loss to a positive cash flow of $1,164 (Messina, 2016). Military veteran patients with chronic conditions, such as HF, and ineffective management in the home setting were at greater risk for admission (Darkins et al., 2015). Admissions decreased by enhancing HF management in the home, including home telehealth (Messina, 2016). Carbo et al. (2018) recognized the ability to lower health care costs by reducing admissions when HF management improved in patients using remote monitoring, supporting the need to conduct the current study and enhance understanding of the effectiveness of home telehealth use by rural or urban populations.

Readmissions for HF

As health care costs rise for HF care—especially in the hospital setting—healthcare organizations seek to understand costs and cost drivers for HF care (Lesyuk et al., 2018). Pugh et al. (2021) explained measuring the readmissions within 30 days for HF reflects the quality of care. Garnier et al. (2018) suggested measuring the length of stay was more valuable than the readmission rate because costs are higher during more prolonged admissions and may reflect complications. Incentives for the VA to decrease readmissions for HF included lowering costs (Carey & Stefos, 2016; Wray et al., 2021) and increasing transparency through public reporting (CMS, 2021a; CMS, 2021b), justifying the need for the current study.

Castillo et al. (2017) noted influential factors for readmissions within 30 days include (a) disease severity, (b) other health conditions, (c) disease management, (d) adherence to prescribed medication and treatment regimen, (e) follow-up frequency and timing, (f) hospital characteristics, and (g) distance to healthcare providers. Additional factors for readmissions of patients diagnosed with HF were advanced age, prior admission, increased length of stay (Patel & Dickerson, 2018), gender, and hospital quality (Pope, Davis, Wine, Nemeth, & Axon, 2018). There is an association between medication communication before discharge from the hospital and high readmissions for HF (Tabisula, 2021). Readmissions also occurred after an expected progression of the HF condition (Iorio et al., 2019). Influential need factors for hospital readmission included a prior HF diagnosis and the number of recent hospital admissions (O’Connor et al., 2016).

The importance of understanding the impact of variables related to readmissions for HF explained the need to conduct the current study.

Messina (2016) stated HF was the most common diagnosis for readmission of elderly patients within 30 days. The readmission rate of 22%-25% at a VA hospital in Florida was consistent with the national readmission rate of 20-25% for VA patients with HF (Messina, 2016). Davis et al. (2017) reported a HF readmission rate of 21.4% and Castillo et al. (2017) noted readmissions occurred in a minimum of 20% of the patients discharged for HF. Palazzuoli et al. (2019) described the 20%-30% readmission rate for HF within 30 days as reflecting the most vulnerable period for readmission, followed by readmissions escalating after 60 days post-discharge. Increased risk for readmission also exists in the expanding population of patients with HF under the age of 65 years (Vader et al., 2016). Guzman-Clark et al. (2021) stated readmission of patients with HF was highest on day four post-discharge, but the primary diagnosis for the readmission was frequently for non-HF causes and may have been preventable. Understanding the rurality category of readmitted patients with HF and the timeframes of readmissions may lead to developing strategies to reduce readmissions, justifying the value of conducting the current study.

Topaz et al. (2017) used data from administrative claims and electronic health records from a multihospital health care system to identify an association between ineffective self-management behaviors in patients with HF and preventable hospital readmissions. Self-management domains comprised adherence to (a) diet, (b) medication, (c) exercise and physical activity, (d) attending medical appointments, and (e) nonspecific HF management. In a sample of 8,901 admitted patients with a history of HF, documentation reflected ineffective self-management behaviors in 14.4% (*n* = 1,282) of the patients (Topaz et al., 2017). The 30-day readmission rate for patients with HF and ineffective self-management practices was 37.4% compared to 21.5% ($p < .001$) for patients effectively managing HF (Topaz et al., 2017). Wakefield and Vaughan-Sarrazin (2017) recognized the correlation between effective management of HF in the home setting and positive patient outcomes. Messina (2016) correlated medication nonadherence with 60% of military veteran patients' readmissions for HF, suggesting the benefit of involving pharmacists in HF home care. Messina (2016) suggested using home telehealth for HF management promotes effective self-management behaviors and decreases readmissions. In contrast, Stevenson and Payne (2017) only identified nonadherence in four out of 217 health records of military veteran patients' readmissions for HF. There was a need for the current study to examine whether a relationship existed between home telehealth enrollment and readmissions for HF because patient self-management behaviors may improve, and readmissions may decrease with home telehealth use.

Cotter et al. (2016) conducted a post hoc data analysis from 1,347 patients enrolled in the double-blind, randomized clinical trial to examine the association between length of stay and risk of readmission for HF. A longer length of stay during admissions correlated with a higher risk of readmission but did not correlate with greater HF severity (Cotter et al., 2016). In an observational study using secondary data comprising 178,905 patients' medical records from the Canadian Institute for Health Information Discharge

Abstract Database, Sud et al. (2017) examined associations between length of stay for patients admitted for HF and readmissions. Sud et al. found readmission rates for HF and other cardiovascular conditions were higher but lower for other conditions when the length of stay was 1-2 days. After long admissions of 9-14 days, Sud et al. recognized readmissions for any cause were higher than when the length of stay did not exceed the mean of 5-7 days. Increasing the understanding of variables affecting bed days of care justified conducting the current study.

Cotter et al. (2016) identified influences from geography, local medical practices, and different healthcare organizations' operations impacted the variability in practice and readmission rates for patients with HF. Cotter et al. speculated that hospital bed availability contributed to differences in length of stay. Fonarow and Ziaeian (2017) suggested other causes of a short length of stay for HF included (a) lower patient complexity or symptom burden, (b) a patient failing to describe the severity of symptoms accurately, and (c) providers influenced to discharge patients early and admit patients with a higher clinical need. A justification for conducting the current study was the need to expand understanding of influences associated with readmissions for HF.

Davis et al. (2017) conducted a retrospective all-payer cohort study comprising 547,068 health records of patients in California, New York, and Florida with a primary discharge diagnosis of HF. Findings included readmissions within 30 days occurred in 21.4% of discharges (Davis et al., 2017). The median time to readmission was 12 days, but only 30.3% of the health records listed HF as the primary diagnosis for readmission (Davis et al., 2017). Recommendations included improving care for common conditions to reduce all-cause readmissions of patients with HF because 69.7% of the readmissions were for non-HF diagnoses, such as other cardiovascular conditions (14.9%), pulmonary disease excluding pneumonia (8.5%), and infections (7.7%; Davis et al., 2017). Alternately, Palazzuoli et al. (2019) found the reasons for readmissions of patients with HF within 30 days were equal between worsening HF, other cardiac symptoms, and other health conditions. Reducing readmissions for HF requires enhanced knowledge about effective HF care, reinforcing the need for the current study.

Influences of readmissions of patients with HF included national factors, geographical location, comorbidities, the background of the healthcare provider, and effectiveness of care coordination (Palazzuoli et al., 2019). Effective management after discharge may minimize the readmission risks from social factors, limited family support, and insufficient follow-up care (Palazzuoli et al., 2019). In a retrospective, descriptive study with Medicare patients 65 years and older, Oh (2017) found that 19% of discharges occur on the weekend. Effective care coordination and monitoring after discharge to mitigate the increased risk of readmission increases for patients experiencing weekend discharges (Oh, 2017). Improving coordination of care and monitoring may reduce avoidable readmissions while also increasing necessary readmissions for HF (Heidenreich et al., 2016), supporting the need to conduct this study to improve understanding of optimal home telehealth enrollment for patients with HF.

Public Reporting for Readmissions

Through collaboration with the CMS, voluntary public reporting provides a forum for disclosing VA quality and safety data, including readmission rates for specified common conditions (CMS, 2021b). The VA External Peer Review Program reviews patient data in electronic health records (Garvin et al., 2018). Quality evaluation occurs through performance measures and quality indicators by comparing actual VA care for HF to established evidence-based care standards (Garvin et al., 2018). The VA follows criteria for ambulatory care sensitive indicators for HF by the Agency for Healthcare Research and Quality to measure the effectiveness of primary care services to prevent hospitalizations for HF as another way to monitor the quality of HF care (Helmer et al., 2020). Providing feedback about quality at the provider, local, regional, and organizational levels and public reporting promoted accountability of HF care in VA (Garvin et al., 2018). The transparency about care delivery and reporting at the VA promoted justification to conduct the current study at the VA.

The Hospital Readmission Reduction Program by the CMS incentivized healthcare organizations in the United States to control costs by avoiding excessive readmissions for specific conditions, including HF (Carey & Stefos, 2016; Chen & Grabowski, 2019; Zuckerman et al., 2017). The 30-day readmission rate for HF care is a primary indicator used to evaluate and compare hospital performance (CMS, 2021a). Carbo et al. (2018) stated public reporting of quality measures, including 30-day readmission rates, improves transparency about hospital care, informs consumers, and may be used for quality improvement. Zuckerman et al. (2017) recognized the progress in reducing readmissions since hospitals receiving Medicare funds incur financial penalties for excessive readmissions. However, some hospitals do not qualify for penalties because the sample size for eligible conditions is too small (Zuckerman et al., 2017). Expanding knowledge about the relationship between bed days of care during readmissions and home telehealth enrollment for rural and urban military veteran patients with HF may inform primary care managers about reducing readmissions, justifying the need for the current study.

Okumura et al. (2016) argued that readmissions for HF do not accurately reflect treatment for worsening HF symptoms when patients receive an escalated level of care in an emergency room or a community clinical setting. In addition to the emergency room, Zsilinszka et al. (2017) identified outpatient clinics and observation units as alternate clinical locations where patients receive treatment for worsening HF symptoms that is not reported in the HF readmission data. Heidenreich et al. (2016) also emphasized the limited applicability of measuring the readmission rate because up to 75% of readmissions may be unavoidable. Many VA hospitals have prioritized reducing readmissions for several years since quality outcome reports on the CMS Hospital Compare website improved transparency (Heidenreich et al., 2016). However, it is challenging to reduce readmission rates further without applying new interventions (Heidenreich et al., 2016). Readmissions for HF may decrease as primary care managers enhance their understanding of effective interventions for HF care to reduce readmissions, including to use home telehealth for select patients, supporting the need for the current study.

Residence Rurality

Residence rurality is an enabling factor in the behavioral model (Babitsch et al., 2012). Geographical accessibility enables securing health services (Andersen, 1968), and travel is a component of the means to reach health services (Andersen, 1995). Fleming et al. (2016) identified the distance to the VA as an enabling factor, whereas Guzman-Clark et al. (2020) named the rurality of the VA facility as an organizational variable. Babitsch et al. (2012) listed the urban or rural region of residence as an enabling factor in a systematic review. Alternately, Johnson et al. (2015) applied VA and non-VA rural and urban care locations as predisposing variables. Residing in an urban location facilitates when patients can readily access health care services (Babitsch et al., 2012). In contrast, rural areas impede patients from seeking care if health care services and transportation resources are unavailable (Weeks, 2018). Underpinning the current study in the behavioral model enhanced understanding of the influences of residence rurality on military veteran patients receiving health care for HF, supporting the justification for the current study.

Vader et al. (2016) suggested an association between increased bed days of care and differences in health care practice patterns in varied geographical areas. Sacarny (2018) concluded the health care outcomes, including HF outcomes and overall quality of care, are lower in rural versus urban hospitals. The assertion by van der Nat (2021) for expanding the geographical reach to achieve value in health care supported the need to conduct the current study to enhance the understanding of effective resource utilization for HF care.

Rural Designations

Defining the term rural frequently followed boundaries established to meet the interests of different organizations and agencies, including geographic boundaries of counties, ZIP Code Tabulation Areas, and census tracts (Bennett et al., 2019). Geographic criteria identified in studies varied by distance (Fleming et al., 2016), travel time as a correlate of distance (Friedman et al., 2015), and location by geographical area (Sacarny, 2018). Routinely collected data in VA includes the residence rurality status of each military veteran patient, categorized as urban; rural; highly rural; and insular island, comprising designated U.S. territories (Cowper Ripley et al., 2017). The need for the current study included enhancing awareness about the varied definitions of residence rurality in the literature, limiting the ability to compare studies and make informed decisions about resource planning for HF management.

Goode et al. (2017) used secondary data to describe urban or rural locations of hospitals based on metropolitan statistical area population standards. Alternately, Krishnamurthi et al. (2018) used the CDW at the VA to obtain demographic information and determine the rural or urban status based on zip codes for all military veteran patients receiving care for a cardiovascular diagnosis at a VA facility or paid for by VA between 2010 and 2014, and then coded the data to designate patients' residence in five U.S. regions. Applying varied definitions of rurality creates measurement bias, inaccurate interpretation of research outcomes, inconsistencies during comparisons, and alters eligibility for research grants and other funding (Bennett et al., 2019). Aligning rural definitions with existing boundaries may cause the loss of cohesion and recognition of cultural diversity, demographics, resources, and needs within communities (Bennett et al., 2019). The justification for conducting the current study included a lack of standardization in the literature when collecting and measuring rurality data.

Rural Military Veteran Population

Lum et al. (2020) stated 24% of all military veterans reside in rural areas where the military veteran population is older, more medically complex, and heart condition diagnoses are more common than for urban military veterans. Enrollment to receive VA health care includes 58% of military veterans residing in rural areas, compared to the 38% enrollment rate of military veterans residing in urban areas (Office of Rural Health, 2022). Military veteran enrollees comprise 2.7 million of the 4.7 million military veterans residing in rural and highly rural areas (Office of Rural Health, 2022). Constraints to accessing health care by military veterans residing in rural compared to urban areas include (a) larger geographic and distance barriers; (b) fewer transportation options; (c) scarcity of physicians, hospitals, and other health care resources; (d); a higher number of hospital closures; and (e) limited broadband internet services where internet is not available in 26% of homes (Office of Rural Health, 2022). Chu et al. (2021) acknowledged other challenges impact rural patients' access to health care, such as long times for travel, limited options for public transportation and associated costs, and time required away from work. The health care demands and constraints to care for military veteran patients with HF residing in rural areas supported the need to conduct the current study to enhance understanding of the relationship between residence rurality and bed days of care for HF.

The lack of public and private transportation minimizes the ability to receive health care services in person (Weeks, 2018). Results from a survey of 42,351 enrolled military veterans revealed barriers to accessing the closest primary care services included

(a) cost (16.5%), (b) distance or travel time (9.9%), and (c) availability of medical services (6.1%; Z. J. Wang et al., 2021). There are limited physician resources in rural areas where 20% of the U.S. population resides, but only 10% of the physicians provide medical services (Weeks, 2018). Gawron et al. (2017) underscored the impact female military veteran patients in rural areas experience from distance barriers when seeking specialty health care services. Challenges in accessing health care experienced by patients residing in rural locations supported the justification to include residence rurality as a predictor variable in the current study.

In a retrospective cohort study to examine adherence and associated characteristics of military veteran patients' use of home telehealth for HF, Guzman-Clark et al. (2020) identified 91.4% (*n* = 3,151) of the patients received health care in a VA hospital designated as urban, compared to 8.6% (*n* = 298) of the patients in the cohort receiving health care in a rural VA hospital. Findings by Zulman et al. (2019) reinforced the challenges military veteran patients residing in rural areas experience when seeking health care access. Zulman et al. found 33% of veterans receiving VA health care resided in rural, highly rural, or insular islands. However, more than 50% of the rural patients received primary care in urban VA facilities, suggesting transportation challenges increase the difficulty of rural veterans to access needed and timely health care in their rural communities. The transportation challenges reported by veterans residing in rural areas supported the justification to conduct the current study to expand knowledge about the relationship between residence rurality, home telehealth enrollment, and bed days of care for military veteran patients with HF.

Home Telehealth

Brainerd and Hawkins (2016) described VA as an industry leader in designing and using home telehealth for patients with chronic conditions, including HF. Organizational strengths for promoting telehealth in VA include (a) mature technology infrastructure, (b) policies and a commitment to expand telehealth, (c) a shared electronic health record promoting integration throughout the healthcare organization, and (d) telehealth capability at every VA hospital and community-based outpatient clinic (Abbott et al., 2018). Policies and an organizational commitment to telehealth expand access to care for military veteran patients 65 years and older and those residing in rural areas (Lum et al., 2020), supporting the need for the current study to enhance knowledge about the optimal use of home telehealth for military veteran patients with HF.

A goal of the VA Home Telehealth Program is to promote military veteran patients' ability to remain in their homes with the support of home telehealth, care coordination, and oversight by healthcare personnel for a specified health condition, including HF (Darkins et al., 2015). Penney et al. (2018) emphasized the importance of intersections, coordination, and collaboration between various parts of the VA's integrated health care system to reduce readmissions within 30 days. Control of factors by the patient and caregiver to manage care at home reduced the risk of readmissions (Penney et al., 2018), consistent with recommendations by the CDC (n.d.) for patients with HF to monitor and report HF symptoms to their health care provider. Examining the relationship between residence rurality, home telehealth enrollment, and bed days of care for veterans readmitted for HF at an integrated health care system with an established home telehealth program supported the need to conduct the current study at the VA.

Home Telehealth Benefits and Constraints

Wade and Stocks (2017) examined studies using telehealth for patients with HF and found mixed outcomes. However, findings frequently showed improved mortality and hospitalization rates in patients post-discharge for acute HF symptoms (Wade & Stocks, 2017). Andrès et al. (2018) explained the reasons for widely varied and inconclusive findings of readmission rates in early home telemonitoring studies were (a) inappropriate selection of patient groups, including a lack of control groups, small samples, and short periods for follow up; (b) lack of well-structured organizations specifying the role responding to alarms, no association with medical providers, nor optimal processes for guided medical management; (c) delays or inadequate responses to alarms; (d) no educational programs; and (e) no interaction between the patient or clinical staff. Early studies emphasized weight monitoring without reporting related symptoms or parameters to guide responses to weight changes (Andrès et al., 2018). Ware et al. (2018) noted limited discussions in the literature about the quality and sensitivity of algorithms and guidelines used to provide self-management directions to patients in response to clinical symptoms. The variability of patient samples and characteristics of telehealth programs and the minimal discussion about the quality of algorithms used to guide the care of patients receiving home telehealth weaken the ability to compare programs accurately and support the justification for the current study.

In contrast, the VA Home Telehealth Program included nurses using evidence-based questions and interventions to monitor patients' HF condition, prompt medical provider notifications of worsening HF symptoms, serve as the basis of patient education, and promote self-management behaviors (Messina, 2016). Further, Bashi et al. (2017) asserted patients may experience reduced HF symptoms and admissions with effective HF self-management. Ware et al. (2018) emphasized HF outcomes may improve when patients receive interventions earlier and benefit from self-management support between scheduled clinic visits. The evidence-based VA Care Coordination Telehealth Program demonstrated appropriate conditions to conduct the current study at the VA.

Telehealth may help lower admissions for patients diagnosed with HF if patients assume greater responsibility for their care, receive appropriate education, and monitoring by the home telehealth staff is effective (Andrès et al., 2018). Guzman-Clark et al. (2021) described reductions in admissions by 31% and length of stay by 59% for 150,000 military veteran patients using home telehealth for chronic disease management. Conversely, evidence from randomized controlled trials to support remote monitoring was mixed, ranging from no change to reduced length of stay for patients using remote telemonitoring compared to usual care (Brahmbhatt & Cowie, 2019). T. M. Murphy et al. (2017) explained that reducing readmissions for HF requires flexibility in the disease management program because the workload and associated costs for HF management were higher in the first 3 months after discharge for patients with more advanced HF. Alternately, admissions for non-HF conditions were more common in patients with less advanced HF over 12 months after HF discharge (T. M. Murphy et al., 2017). Reducing readmission days for HF may require healthcare leaders to consider multiple variables, supporting the need to conduct the current study.

Using telehealth reduced barriers to care from limited access, time, and travel (Abbott et al., 2018), improving readmissions and costs for military veteran patients' HF care (Messina, 2016). Applying telehealth mitigated transportation barriers (Lum et al., 2020), described as distance, travel costs (Z. J. Wang et al., 2021) and the lack of public and private transportation impeding the ability to receive health care services in person (Weeks, 2018). A newer phase of telehealth adoption promoted accessing care anyplace and anytime to promote access, convenience, and effectiveness (Botrugno, 2019).

Compared to urban veterans, rural veterans comprised 4.7 million (24%) of the veterans in the United States, are older, more medically complex, and experience a higher incidence of heart conditions (Lum et al., 2020). Achieving optimal clinical outcomes and return on investment for HF care involves using home telehealth for the populations best served by that modality (Darkins et al., 2015; Messina, 2016). Although telehealth use may improve HF care for patients in any geographical area, VA continued to emphasize the benefits of telehealth for rural military veteran patients (Lum et al., 2020). Evidence in the literature about telehealth's convenience, effectiveness, and acceptability was minimal (Botrugno, 2019), supporting the justification to conduct the current study to examine if a relationship existed between home telehealth enrollment and bed days of care during readmissions for HF.

Carbo et al. (2018) noted total costs for HF care included the initial setup and installation of mobile monitoring. Lack of motivation and technical problems, such as internet connectivity, were the main reasons patients withdrew from mobile monitoring, but some never started the program (Carbo et al., 2018). While studying patient barriers to using home telehealth, Hawley et al. (2020) found 34 of 50 patients (68%) expressed interest, 32 (64%) had access to the technology, and 21 (42%) were confident in their ability to participate. After providing individualized training, all 32 patients completed a home telehealth visit (Hawley et al., 2020). Expanding knowledge about the use of home telehealth and outcomes supported the need for this study.

Guzman-Clark et al. (2021) examined the use of home telehealth by military veteran patients with HF and identified drop out of the VA Home Telehealth Program was higher for older, sicker, White, patients and those with at least one readmission during the study period. Older and sicker patients may drop out more frequently because of the high mortality rate associated with advanced HF (Guzman-Clark et al., 2021). White veterans dropped out of the VA Home Telehealth Program for HF 41% more frequently than Black veterans and the drop out risk for readmitted patients was 39% higher than for patients with no readmissions (Guzman-Clark et al., 2021). However, dropout rates were 10% lower for patients enrolled in the VA electronic patient health portal (Guzman-Clark et al., 2021). Of the patients remaining enrolled in VA home telehealth for HF, adherence to the program requirements was higher for older, White, military veteran patients without depression, and those with a longer duration in the program (Guzman-Clark et al., 2020). There were gaps in the literature about why veterans dropped out of the HF home telehealth programs and the racial differences in drop out (Guzman-Clark et al., 2021) and enrollment (Guzman-Clark et al., 2020), providing a rationale for the current study to expand knowledge about military veteran patients’ home telehealth enrollment for HF.

Inconsistencies in broadband connectivity, particularly in rural areas, limit the option to use home telehealth in some locations (Weeks, 2018). Constraints to using home telehealth in the United States include reimbursement limitations and inconsistent state licensure regulations (Weeks, 2018). A constraint to telehealth expansion is the need to improve reimbursement rates, so medical providers can receive adequate payment for using telehealth to monitor, manage, and address patients’ health care needs (Raj et al., 2021). Policies in VA allow healthcare providers to cross state lines to deliver care to military veteran patients, removing state licensure restrictions for care (Lum et al., 2020). Guzman-Clark et al. (2020) emphasized the benefit of clinical staff providing telehealth without constraints of state restrictions. The benefits of home telehealth as an intervention for HF care without state licensure restrictions supported the need to conduct the current study at the VA.

Coronavirus Disease-2019

Telehealth is an effective strategy to decrease community transmission rates of infectious diseases, especially during the coronavirus disease-19 (COVID-19) pandemic (CDC, 2022; Qureshi et al., 2020). Home telehealth growth included care for military veteran patients with positive COVID-19 screens or tests to reduce exposure in the community (Guzman-Clark et al., 2020). Telehealth expansion during the COVID-19 pandemic offered an opportunity to provide care while maintaining social isolation and improving access to chronic disease management at a lower cost (Bowman et al., 2021).

Shura et al. (2021) affirmed telehealth had become an alternate and safe way to deliver care that may benefit rural patients beyond the COVID-19 pandemic. Justification for the current study included the broader benefits of home telehealth for rural and urban patients with HF. Optimizing patient selection for home telehealth may promote the availability of home telehealth resources for the highest priority patients.

Application of Home Telehealth

Pekmezaris et al. (2018) emphasized choosing home telehealth for the right patient, conditions, and duration. Using home telehealth as a supplemental strategy to usual care in VA promoted early recognition and intervention of worsening HF symptoms (Messina, 2016). Ware et al. (2018) suggested home telehealth comprises several components rather than one intervention. The VA Home Telehealth Program provides symptom management, telephone care, and case management, promoting patient self-management behaviors for HF (Messina, 2016), consistent with more than one intervention within the home telehealth program. Puckett (2017) described the lack of coordination and communication within the health care system as a factor in readmissions. Communication, coordination, teaching, and support for HF self-management behaviors improve with home telehealth (Messina, 2016). Self-care improved when patients received feedback after transmitting health data, but healthcare personnel only provided feedback in five studies and documented responses to treatment changes in one study (Carbo et al., 2018). Readmissions and bed days of care decreased with improvements in patients' self-care, coordination of care by the healthcare team, and case management through the VA Home Telehealth Program (Messina, 2016), supporting the reason to conduct the current study to enhance understanding of home telehealth enrollment.

Wade and Stocks (2017) noted the recommendation to incorporate home telehealth into HF care was inconsistent in the literature. Most studies involved monitoring vital signs, weights, and symptoms with automated, daily questionnaires for patients with HF in the community or recently discharged from the hospital (Wade & Stocks, 2017). However, studies with descriptions of nurse case management and the military veteran patient population were minimal. Darkins et al. (2015) acknowledged the variance in results between studies to evaluate home telehealth in non-VA facilities compared to the effective home telehealth program in VA, citing the biopsychosocial approach with a self-management focus as a strength of the VA home telehealth program. Outcomes may improve when patients receive interventions earlier and benefit from self-management support between scheduled clinic visits (Ware et al., 2018), supporting the need for the current study to examine whether relationships exist between residence rurality, home telehealth enrollment, and bed days of care for military veteran patients readmitted for HF.

Ziaeian and Fonarow (2016) noted readmission rates did not decrease based on one common intervention. However, clarifying instructions about medication administration and transitions in care between the hospital and home may lower the risk of readmission. Monitoring and early interventions lowered readmissions from the frequent and avoidable factors of incomplete discharge orders, suboptimal continuity of care, medication administration errors or omissions, and poor transitions to home

(Messina, 2016). In a disease management program for HF to reduce readmissions and improve long-term outcomes, nurses contacted patients through regular outbound telephone calls to clinically observe and educate patients about self-care and medication management (T. M. Murphy et al., 2017). Fifteen percent of the total volume of calls were inbound calls from patients with worsening clinical symptoms, 30% of the patients in the study required same-day interventions for advancing symptoms, and 10% of the patients needed same-day interventions more than once. The highest risk period was during the first-week post-discharge (T. M. Murphy et al., 2017). Increasing effective monitoring may lower the avoidable factors associated with readmission, supporting the justification to conduct the current study to expand information about home telehealth enrollment for patients with HF.

Military veteran patients used telehealth technology to transmit daily reports of vital signs, HF symptoms, and self-care adherence to the VA healthcare team. Nurses contacted patients by telephone to respond to reports, clarify symptoms, provide education, and reinforce medical orders (Messina, 2016). Nurses used evidence-based disease management protocols in the VA Home Telehealth Program to standardize high-quality care delivery by following guidelines for health education, care delivery, and HF symptom assessment (Messina, 2016). Boscolo et al. (2020) noted clinical decision-support tools promoted health care value by clarifying the most appropriate clinical pathway, reducing excessive discretion, and supporting personalized care. As the effectiveness of medical management in the home setting improved with home telehealth, the frequency of readmissions for HF care decreased (Messina, 2016). The success of using the home telehealth modality for HF care supported the justification for the current study to expand knowledge about the relationship between home telehealth, residence rurality, and bed days of care during readmissions for HF.

In a meta-analysis of 37 studies, Yun et al. (2018) noted 70% of the home telehealth transmissions were asynchronous for relaying HF symptoms and medication management. The transmission frequency of patient data varied from daily in 28 studies, weekly in three studies, monthly in one study, and unreported in two studies (Yun et al., 2018), making accurate data comparisons difficult. Fewer hospitalizations for HF occurred among the group participating in telehealth, but the data were inadequate to evaluate the bed days of care (Yun et al., 2018). In a retrospective matched cohort study of 4,999 military veteran patients in VA, Darkins et al. (2015) found the bed days of care decreased by 60% for patients using home telehealth. Darkins et al. stated contrasts between these positive findings and earlier randomized controlled trials conducted in VA might be explained by the different (a) study populations without the inclusion of concurrent Medicare usage, (b) care models, (c) evaluation methodologies, (d) electronic health record usage, and (e) influences from the health care system. Using a large, national sample of archival health records from military veteran patients readmitted for HF provided an opportunity to examine data collected with minimal variation, supporting the need to conduct the current study.

A study including 218 military veteran patients with HF, Messina (2016) found readmissions decreased by over 5% with improved financial performance over 4 months for military veteran patients using home telehealth compared to usual care. Financial performance improved after reductions in readmissions and bed days of care (Messina, 2016). Alternately, Carbo et al. (2018) conducted a meta-analysis of 10 randomized clinical trials and one quasi-experimental study published between 2009 and 2015 to examine the impact of mobile monitoring on HF care outcomes. Standard daily monitoring with internet transmission included heart rate, blood pressure, and weight (Carbo et al., 2018). Less than 50% of the studies reported admission frequencies, and 30% of the studies addressed costs (Carbo et al., 2018). Admissions decreased 46% for HF, and emergency room visits decreased 65%. In comparison, clinic visits increased by 51% in three studies with available clinic data, reflecting improved health care utilization and lower costs when patients used mobile monitoring (Carbo et al., 2018). Inconsistently reporting measures limited analyzing all outcomes (Carbo et al., 2018). Examining the relationship between home telehealth enrollment and bed days of care during readmissions for HF for military veteran patients contributed to the literature, supporting the need to conduct the current study.

Topaz et al. (2017) associated ineffective self-management behaviors by patients with HF with 30% higher readmission rates. Strategies to decrease readmissions and health care costs included promoting patient self-care (Ensign & Hawkins, 2017) and closely monitoring, detecting, and intervening when HF symptoms worsened (Zsilinszka et al., 2017). Messina (2016) noted admissions for HF followed ineffective transitions of care from the inpatient to the outpatient setting and inadequate ongoing care. Worsening HF symptoms followed nonadherence to medication or dietary orders or failure to recognize changes in health condition (Messina, 2016; M. M. Murphy, 2018b). Howie-

Esquivel et al. (2019) emphasized the benefit of self-management practices with patients recording and notifying their medical provider of worsening HF symptoms. Howie-Esquivel et al. suggested clinic visits increased without admissions when patients recognized and reported the early HF symptom of increased shortness of breath. Potentially improving transitions in care and self-management by effectively using home telehealth supported the need for the current study.

Reasons cited for the effectiveness of the VA home telehealth program include mature technology infrastructure, use of a shared electronic health record (Abbott et al., 2018), organizational policies, a commitment to expand telehealth (Lum et al., 2020), and an emphasis on self-management practices and care coordination (Darkins et al., 2015). Comparisons between home telehealth programs varied when small sample sizes limited the data (Long et al., 2017). Differences existed in the interventions and naming conventions for the services (Yun et al., 2018). Findings from studies designed to examine the effectiveness of home telehealth for patients with HF are mixed (Wade & Stocks, 2017). However, Darkins et al. (2015) found an association between the emphasis on self-management and the effectiveness of telehealth in VA. Gaps and inconsistent findings in the literature provided a rationale for conducting the current study to increase knowledge about the relationship between residence rurality, home telehealth enrollment, and bed days of care for military veteran patients readmitted for HF.

Transition

Section I covered the main introductory aspects of the study. The foundation comprised the background, problem statement, purpose statement, nature of the study, research question, and hypotheses. The theoretical framework section discussed the relationship between the predictor variables and criterion variable as underpinned in the behavioral model. Next, there was a list of operational definitions, assumptions, limitations, delimitations, and significance of the study, highlighting ways the findings from the study may contribute to advancing HF care for military veteran patients. The final topics described were a review of the professional and academic literature, including detailed explanations of how the behavioral model underpinned the study to examine residence rurality, home telehealth enrollment, and bed days of care for military veteran patients with HF.

The topics in Section 2 involve the design and plan for the study. Descriptions include the purpose statement, followed by the role of the researcher, participants, and an expansion of the research method and research design from Section I. Explanations follow to justify the population and sampling method and describe ethical considerations, data collection, data analysis, and study validity. Section 3 includes an introduction, presentation of the findings, applications to professional practice, implications for social change, recommendations for action, and recommendations for further research. The final sections include reflections and a conclusion.

Section 2: The Project

Section 2 includes a description of the research strategy for the study. The content comprises a restatement of the purpose of the study and a discussion of the role of the researcher, study participants, and expanded content of the research methods and design. Next, the discussion includes population and sampling, ethical research, data collection, data analysis, study validity, and a transition and summary.

Purpose Statement

The purpose of this quantitative ex post facto correlational study was to examine the relationship between residence rurality, home telehealth enrollment, and bed days of care for military veteran patients readmitted for HF. Residence rurality and home telehealth enrollment were the predictor variables. The criterion variable was the bed days of care for military veteran patients readmitted for HF. To include pertinent data and an adequate sample size of the predictor variables, the targeted population comprised archival routinely collected health data files of military veteran patients with admission for HF at any VA hospital in the United States during the 2017 calendar year. The implications for positive social change from this study included the potential to improve patient satisfaction and lower the financial burden of high HF costs on individual patients, populations, and healthcare organizations. Patient satisfaction and the health of the military veteran patient population with HF may improve as VA primary care managers expand the appropriate use of home telehealth. The financial burden on patients and families and the stability of hospitals may improve as the cost to deliver HF care decreases with fewer bed days of care.

Role of the Researcher

The ex post facto correlational design used in this study allowed the quantitative analysis of archival routinely collected health data as the data source. There were no surveys, interviews, or participants used in the study. The role of the researcher in a quantitative study using routinely collected health data includes (a) upholding ethical standards; (b) answering the research question; (c) correctly describing the population, database, and linkages; (d) explaining data collection and statistical analysis; and (e) controlling for bias (Benchimol et al., 2015). Maximizing the quality of results when using routinely collected health data from electronic health records requires the researcher to understand the database structure, data retrieval process, and clinical pertinence of the value ranges assigned for the variables (Byon et al., 2022). Successful researchers effectively communicate with members of the research team and individuals knowledgeable about factors impacting the variables (Byon et al., 2022). Researchers understand data collection and interface navigation tracks, including when using large data sets (Byon et al., 2022). The attributes of an effective researcher, as identified by Benchimol et al. (2015) and Byon et al. (2022), included clarifying the data collection steps with a VA Informatics and Computing Infrastructure (VINCI) expert (see Appendix C) prior to developing and following a series of preparation and data collection steps (see Appendix D.).

Role of the Researcher in Data Collection

The VINCI virtual workspace provides VA researchers with a secure data-processing environment designed to protect patient privacy and data security during data analysis and reporting (Office of Health Sciences Research & Development [ORD], 2022b) of data transferred from large VA databases (ORD, 2022c). The VA Computerized Patient Record System is the standardized electronic health record used to document clinical care provided at any hospital or clinic across the VA and the interface to the CDW for data storage (Velarde et al., 2018). Standardized data collection with consistent terminology and domains representing clinical care improves the completeness and accuracy of large data sets (H. Kim et al., 2017), consistent with using a standardized electronic health record across the VA. To facilitate safe and accurate data transfers from the CDW, VINCI staff approved authorized VA researchers to access data needed for the study (see Appendix D; Velarde et al., 2018). My role in the data collection and analysis for this study was to (a) complete the required training; (b) obtain the proper approvals from the VA and Walden University institutional review boards (IRB) and VA Research and Development Committee; (c) retrieve, clean, and merge the data; (d) remove unique identifiers prior to data analysis (see Appendix D); and (e) analyze the data.

Relationship Between the Researcher and Research Topic

As an insider to the VA organization, I avoided a conflict of interest between my roles as researcher and VA employee because there was no direct interaction with patients, cardiology services, or home telehealth services. Furthermore, there was no pressure to reach a predetermined study result to support VA telehealth services or a motivation to reach a specific conclusion for professional benefit. The relationship risks were low because interaction with healthcare personnel at the VA hospital was unnecessary when using data from archival routinely collected health databases rather than collecting primary data from patients. Research activities occurred outside of official duty hours, avoiding a financial conflict of interest.

Researcher's Role and Ethics

Effective researchers understand the ethical obligations and protect patients when researching topics in health care (National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, 1979). Completing the training from the Collaborative Institutional Training Initiative (see Appendix E) aligned with ethics topics in the *Belmont Report*, including human subject protections. The main ethical principles in the *Belmont Report* are respect for persons, beneficence, and justice (Miracle, 2016).

Respect for persons includes the topic of informed consent and autonomy for shared decision-making (Friesen et al., 2017; Miracle, 2016). Obtaining informed consent and promoting autonomy for shared decision-making was not possible when using archival routinely collected health records because the care occurred before the current study. Beneficence means to promote the greatest good and minimize risks, and justice refers to respecting and treating each patient equally (Friesen et al., 2017; Miracle, 2016). Minimizing privacy risks to patients when using archival routinely collected health data to learn ways to improve HF care for military veteran patients supported beneficence. Actions supporting justice included maintaining data security by applying consistent processes and conducting all research behind the VA firewall.

This study comprised a secondary data analysis using patient data collected as part of routine clinical care, and there were no physical risks to participants. Protecting patient privacy included adhering to IRB requirements, such as completing training and obtaining permission to access unique identifiers through data use agreements. Using the VINCI workspace for data computing and storage behind the secure VA firewall, VA policy disallowing the transfer of patient-level data away from the secure VINCI workspace without special permission, and file transfer utility processes for all data transfers reduced the risk of a breach in patient privacy (ORD, 2022d). Data computation, analysis, and storage occurred in the VINCI workspace to ensure data security. Avoiding the export of any personally identifiable information or protected health information from the VINCI workspace provided additional data security and privacy protection. Obtaining approval from Walden University IRB, the VA IRB, and the VA Research and Development Committee occurred before collecting data for the study.

Performing research under the supervision of a VA principal investigator met the stringent VA research requirements (ORD, 2022a). Qualifications to fulfill the principal investigator role in VA research include experience and a requirement to conduct research during work hours (ORD, 2022a). Students may participate in VA research but are not eligible to serve in the VA principal investigator role (ORD, 2022a). The principal investigator's responsibilities are to ensure the study's security, amend the data access request when study personnel no longer participate, verify adherence to all VA information security and privacy policy training requirements (ORD, 2022a), and oversee students' research activities. The processes followed during the current study were consistent with all VA privacy policies. No breaches in privacy occurred.

Participants

Researchers apply predetermined inclusion and exclusion criteria from primary data collection to select participants when using routinely collected health data in a study (Benchimol et al., 2015; Hemkens et al., 2016). Strategies to access or establish a relationship with participants were not required in the current study because no individual patients or hospitals participated. The data source for the study was archival routinely collected health data from non-publicly available VA national databases initially used for administrative or clinical purposes. Researchers collate primary data directly from participants, whereas gathering and storing routinely collected health data from individual patients occurs for a purpose other than the study (Benchimol et al., 2015).

Routinely collected health data files comprise individual-level data generated for health care services rendered (Harron et al., 2018), costs, payments, and payer information for billing and business operations (Harbaugh & Cooper, 2018). Individual-level data in administrative files, financial files, and electronic health records combined to form data files for populations of patients used in research (Harron et al., 2018). Selections of routinely collected health data include alignment with the research question, diagnosis codes or other descriptors of data elements consistent with the patient population, and linkages between databases (Benchimol et al., 2015).

Advantages of using archival routinely collected health data include accessing clinical data from large numbers of patient records, eliminating patient recruitment and outcome monitoring needs, decreasing costs, and minimizing time to conduct the study (Hemkens et al., 2016). Yoon et al. (2016) used archival routinely collected data from

VA databases to evaluate the type and costs of military veteran patients' care for HF. The collection of VA archival routinely collected health data was consistent with the current research question and aligned with the military veteran patient's HF diagnosis, predictor and criterion variables, and inclusion and exclusion criteria (see Appendix F). Seeking access to data in the VA databases occurred during the VA IRB and data access request process, following Walden University IRB approval. Researchers may query large, system-wide files of routinely collected administrative and clinical data (ORD, 2022c) by accessing data in the VINCI workspace.

Research Method and Design

The research methodology is the blueprint of the study (Astroth & Chung, 2018b), and the design is a set of procedures used to collect and analyze data to answer the research question (Ranganathan & Aggarwal, 2018). Choosing the current research method and design included considering the researcher's worldview (Ryan, 2018), ensuring a gap in research findings for the topics, and confirming more information from the study may advance health care (see Rutberg & Bouikidis, 2018). Various research designs align with each research method (Astroth & Chung, 2018a; Rutberg & Bouikidis, 2018).

Research Method

The two broad categories of research methods are quantitative and qualitative (Basias & Pollalis, 2018; Gibson, 2017; Rutberg & Bouikidis, 2018). Mixed methods research combines quantitative and qualitative data collection and analysis to examine the research questions in one study (Baškarada & Koronios, 2018; Caffery et al., 2017;

Rutberg & Bouikidis, 2018). The quantitative method is consistent with the positivist worldview (Basias & Pollalis, 2018; Baškarada & Koronios, 2018; Ryan, 2018) and was the research method used to examine the research question in the current study. Analyzing objective numerical data (Astroth & Chung, 2018b; Zyphur & Pierides, 2020), determining truth without human perception or considering contextual factors (Baškarada & Koronios, 2018), and a simplified process for comparing a large amount of data (Basias & Pollalis, 2018) were key features of the quantitative method that aligned with the current study.

Researchers apply the quantitative method to answer research questions, test hypotheses, examine causal and noncausal relationships between variables (Rutberg & Bouikidis, 2018), and statistically analyze data from large samples (Mir, 2018). The quantitative method aligns with replicating methods (Ludwig & Johnston, 2016), testing theories (Basias & Pollalis, 2018), and independence between the researcher and the research (J. Park & Park, 2016). Bed days of care during readmissions for HF were the standard measurement monitored and publicly reported in the healthcare industry (Carey & Stefos, 2016). In the current study, the numeric data for collection and statistical analysis related to the predictor variables of residence rurality and home telehealth enrollment and the criterion variable of bed days of care.

The quantitative method is appropriate when studying a large population (J. Park & Park, 2016), processing and analyzing large volumes of data (Basias & Pollalis, 2018), or extending the population over a broad geographical area (Harbaugh & Cooper, 2018). Collecting and analyzing statistical data, including from archival VA databases, aligned with understanding phenomena in HF care of military veteran patients (see Patel & Dickerson, 2018; Yoon et al., 2016). The targeted population in the current study was large and comprised archival hospital records of military veteran patients with admission for HF at any VA hospital in the United States during 2017. The geographical area comprised rural and urban regions throughout the United States where military veteran patients with HF reside.

The qualitative method was not appropriate for the study because only a quantitative method aligned with the study objective to analyze statistical data using large VA databases of archival routinely collected health data to examine the relationship between predictor and criterion variables. In contrast to the quantitative model, qualitative research does not involve examining the relationship between variables, analyzing numerical data representing a population (Curtis et al., 2016), or accepting or rejecting hypotheses (McCusker & Gunaydin, 2015). Qualitative researchers use open-ended questions to collect narrative data from a small number of participants to explore and understand the phenomenon highlighting human experiences and attitudes, practices, and behaviors in a culture (Rutberg & Bouikidis, 2018). Researchers do not use qualitative methodology to statistically analyze data representing a large population residing across broad geographical areas. A mixed-methods approach comprising both quantitative and qualitative methods (Baškarada & Koronios, 2018; Caffery et al., 2017; Gibson, 2017) was not appropriate for the current study because a qualitative method did not align with collecting numeric data and analyzing statistical data to answer the research question.

Research Design

The research design selected for this study was the ex post facto correlational design. The correlational design is nonexperimental research applied to answer the research question by examining noncausal relationships between variables (Curtis et al., 2016). Omair (2015) described correlational research as a noninterventional design in which the researcher uses secondary data from government sources. Aggarwal and Ranganathan (2019) emphasized researchers in correlational studies seek associations between independent and dependent variables affecting populations rather than individuals. The current ex post facto correlational study included examining the relationship between residence rurality, home telehealth enrollment, and bed days of care during readmissions of military veteran patients with HF. Aggregating the results from individual patients applied to the population of veterans readmitted for HF.

In contrast to experimental research, nonexperimental researchers do not manipulate variables or randomly assign participants to the study (Reio, 2016; Rutberg & Bouikidis, 2018). Lower costs, less time required for the study (Aggarwal & Ranganathan, 2019), and greater organizational interest to participate in research are benefits of nonexperimental versus experimental research (Reio, 2016). Researchers apply an intervention without a control group in the quasi-experimental design (Rutberg & Bouikidis, 2018). Selecting an experimental or quasi-experimental design in the current study was inappropriate because it is impossible to manipulate the predictor variables in real time when using archival data from hospital records for care delivered in 2017.

Correlational studies frequently use data collected before the study (Aggarwal & Ranganathan, 2019; Omair, 2015). The correlational design was appropriate for the current study when using archival routinely collected health data from VA databases. Harbaugh and Cooper (2018) emphasized data representing clinical conditions, health care use, and costs are prevalent in archival routinely collected health data. Ex post facto correlational designs include data representing independent variables occurring in the past and the dependent variable observed in the present (Johan et al., 2017). In the ex post correlational design, researchers observe and collect pertinent data for the study and draw inferences later (Fagbenro et al., 2018). Applying the ex post facto correlational design was appropriate for the current study because the original data collection occurred during routine care of HF patients in the past.

Harbaugh and Cooper (2018) recognized using administrative databases includes the potential for data to represent large numbers of participants from diverse geographic areas. In the current study, the data represented the dichotomous and categorical predictor variables of residence rurality and home telehealth enrollment and the ratio criterion variable of bed days of care. The data sources included archival VA routinely collected health data records of military veteran patients with an index admission for HF at any VA hospital in the United States during 2017. The focus on population outcomes and administrative and clinical data in the correlational design (Omair, 2015) was consistent with abundant archival VA routinely collected health data and the emphasis on the military veteran patient population in the current study.

Other nonexperimental designs considered but not selected for the study were case reports, case series, case studies, and cross-sectional studies. Case reports and case series examine the care of a small number of patients (Aggarwal & Ranganathan, 2019), which was inconsistent with the current study to use data from a large population of military veteran patients with HF to examine the relationship between variables. Cook and Cook (2016) explained researchers use case studies to describe the variables in the study rather than examine relationships between the variables. Cross-sectional studies are also inappropriate because collecting data at a specific time reveals disease prevalence and risk factors (Aggarwal & Ranganathan, 2019), which is inconsistent with the current study to measure the number of hospital days during readmissions for HF. Using routinely collected health data from VA databases to examine the relationship between residence rurality, home telehealth enrollment, and bed days of care for military veteran patients with HF was only possible by applying the ex post facto design.

Population and Sampling

Researchers identify and select the population and the sampling method consistent with the purpose of the study (Curtis et al., 2016). Clarity about the researcher's rationale and steps followed for selecting and identifying the population and sampling method may inform readers about the strength of the evidence in the research study (see Astroth & Chung, 2018b). Further, generalizability may occur when the sample represents the population (Bowring et al., 2017; Cook & Cook, 2017; Thygesen, 2017). Generalizing the observations from the sample to the larger population is not relevant in the current study because the sample comprises the entire population of military veteran patients admitted to a VA with HF in 2017. However, transferability of research findings increases as the participants' characteristics in the study match a different population (see Cook & Cook, 2017).

Population

A population refers to a collection of individuals (Campbell, 2016), items, cases of interest (Etikan et al., 2016), or other elements with similar characteristics or attributes from which the researcher may derive conclusions about the data (van Rijnsoever, 2017). The population in the current study included archival routinely collected health records of military veteran patients to align with the research question by clarifying the relationship between residence rurality, home telehealth enrollment, and the bed days of care for military veteran patients readmitted for HF. The criterion variable comprised bed days of care for military veteran patients readmitted for HF. The data source included archival hospital records of military veteran patients admitted at any VA hospital with a diagnosis of HF on or after January 1, 2017, through December 31, 2017.

The geographical area comprising military veteran patients residing within the United States ensured the representation from different regions and practice patterns affecting home telehealth use. Patients may have experienced more than one hospitalization for HF within a specific period. Estimating the population size for the study included using data compiled for a feasibility report by a VINCI analyst. According to the feasibility report (see Appendix B), the data collected during the study showed 21,078 military veteran patient admissions with at least one admission for HF in 2017, and 9,751 admissions met the criteria of two or more admissions for HF during the same time (see Appendix G). The population in the study comprised the number of admissions for HF rather than the number of admitted patients during 2017 to reflect accurate admission data.

Sampling

The sampling for this study included a nonprobabilistic sampling method and the total population sampling technique to minimize risks to sampling bias and population validity. Purposive sampling is a subset of nonprobabilistic sampling (Cook & Cook, 2017), and total population sampling is a type of purposive sampling (Etikan et al., 2016). Researchers use a nonprobabilistic sampling method to select participants based on alignment with the purpose of a study, rather than random sampling (Cook & Cook, 2017; Etikan et al., 2016).

Minimal bias occurred with probabilistic or random sampling as every individual, object, or case of interest representing the targeted population had an equal chance of selection (Etikan et al., 2016). Applying nonprobabilistic sampling methods to studies includes fewer challenges in recruiting participants (Barros et al., 2015), lower costs, and less time required than probability sampling methods (Etikan et al., 2016). In contrast, weaknesses of nonprobabilistic sampling include a lack of randomization (Barros et al., 2015), the inability to accurately make inferences to a broader population (Cook & Cook, 2017), researcher bias, and sample selection bias (Etikan et al., 2016). Astroth and Chung (2018b) emphasized researchers may minimize selection bias by ensuring consistency of characteristics between the sample and the population.

Total population sampling is purposive sampling used to examine an entire population of interest (Kang, 2021) with similar characteristics or attributes (Etikan et al., 2016). Research studies' findings are more accurate when using total population than other sampling techniques (Kang, 2021), and the relevance of findings to a broader population may improve (Bowring et al., 2017). Researchers commonly applied total population sampling methods with small samples in qualitative studies (Etikan & Bala, 2017), but examples also exist with large routinely collected health data sets used in quantitative studies (Thygesen, 2017). The source for the current quantitative study was large data sets of archival data collected during routine clinical care for HF.

Total population sampling is feasible when the sampling method aligns with the purpose of the study, the identified population is accessible (Etikan et al., 2016; Thygesen & Ersboll, 2014), and the resources are available (Barros et al., 2015). Deterrents of total population sampling are increased time, cost, effort, and resource requirements that may make this sampling technique impractical and inefficient. There were no feasibility or high-cost concerns for using total population sampling in the current study.

The risk of sampling bias diminished when researchers used total population sampling, a large data set comprising routinely collected health data, and inclusion and exclusion criteria to identify the sample (Thygesen & Ersboll, 2014). Bowring et al. (2017) applied total population sampling to reduce biases, stating examples of over or underreporting attributes when healthcare samples represented geographical regions or limited referral sources. Using a large data set of routinely collected health data representing the VA care of military veteran patients with HF by different providers, hospitals, and geographical regions reduced the risk of sampling bias in the current study from inaccurately reporting attributes with regional or organizational differences.

Traditionally, researchers apply information from the power analysis, comprising power, effect size, and significance, to calculate the sample size (Cohen, 1992; Fetzer, 2017) and make informed decisions in health care (Thygesen & Ersboll, 2014). Statistical power refers to the probability of test results accurately reflecting significant differences and relationships studied within a population (Malone et al., 2016). Altman and Krzywinski (2017) explained researchers use proper sampling design and computing to analyze p values to assess consistency with a null hypothesis. A sample is a portion of a population (Etikan et al., 2016) and total population sampling includes the entire population (Kang, 2021). The sampling technique for the current study was total population sampling using a large data set of observations representing military veteran patients' readmissions for HF.

During study planning, the feasibility report revealed there were 20,320 admissions for military veteran patients with HF at any VA hospital in 2017 (see Figure B1, Table B1), revealing a large sample of hospitalized patients that could meet the criteria for readmission within 30 days and other inclusion criteria. I conducted an a priori power analysis using G*Power version 3 statistical software (Faul et al., 2009), assuming a medium effect size ($F = 0.15$), $\alpha = 0.05$ (Cohen, 1992; Malone et al., 2016), and two predictor variables (see Appendix H). The sample size in the current study exceeded the minimum sample size of 107 readmissions required to achieve a power of 0.95.

Using routinely collected data from large VA databases minimized the resource feasibility concerns for conducting the study and was a factor when selecting high power inputs consistent with large sample sizes. Cohen (1992) recommended using a medium effect size ($F = 0.15$) for correlational studies. The use of a medium effect size ($F = 0.15$), $\alpha = 0.05$ to achieve a power level of 0.95, and total population sampling was appropriate for the current ex post facto correlational study using a large database comprised of national data representing residence rurality, home telehealth enrollment, and bed days of care for military veteran patients readmitted for HF.

Ethical Research

Walden University and the VA require researchers to adhere to all ethical obligations. The IRB protects the rights of persons and safeguards them from harm by ensuring adherence to laws, regulations, and established standards (Miracle, 2016). The current study requirements did not include an informed consent process, procedures for participants withdrawing from the study, or incentives to participate in the study because the data source was VA archival routinely collected data, rather than involving individual VA hospitals or humans as participants. Identity disclosure of individual VA hospitals was unnecessary because data collection did not include information about hospitals. Collecting data from archival data files included aligning with a predictor variable designating each military veteran patient’s rural or urban residence category. By limiting the reports from the study to aggregated data protected patient privacy from disclosed data for rurality or unique identifiers. Using archival databases of routinely collected health data eliminated the need to contact individual patients or access patients’ electronic health records. Obtaining a waiver of consent and authorization as part of the research project approval process protected military veteran patients' privacy and confidentiality since consent by individual patients was not feasible. For example, obtaining consent would not have been possible if patients died or were unable to be contacted.

The target population identified in the current study was military veteran patients 18 years of age and older with readmissions for HF. Though not the target of this study, military veterans may have also been VA employees, students, individuals with impaired decision-making capacity, pregnant women, economically or educationally disadvantaged persons, illiterate, those with limited or no English proficiency, or terminally ill patients. The data collection process did not include identifying or searching for vulnerable designations, thereby avoiding harm to these individuals from this study.

Rutherford-Hemming and Feliciano (2015) described the requirement to defer collecting data until after IRB approval. Preparatory to research, but after seeking permission from Walden University (see Appendix I), the VA developed a feasibility report (see Appendix B) to identify the number of military veteran patients admitted with a primary HF diagnosis during 2017 and to pull population-level data for the predictor variables associated with those patients. Velarde et al. (2018) explained a function of VINCI is to fulfill preparatory to research data requests by accessing population pools and providing feasibility data for planning VA research studies. Reviewing the feasibility report (see Appendix B) did not risk patient privacy because the report comprised aggregate data without unique identifiers. Data analysis from the feasibility report occurred after receiving VA and Walden University IRB approval.

Accessing all extracted patient-level data and data analysis tools behind the VA firewall protects patient privacy and data security (ORD, 2022b). Using the secure VINCI workspace with a dedicated project site for data analysis and storage provided further patient privacy and data security protections, such as restricting unauthorized researchers from inappropriately accessing data for the study (ORD, 2022b). Special permission and the required use of a VINCI-controlled data transfer process to remove patient-level data from the VINCI workspace safeguards data security (ORD, 2022d), protecting patient confidentiality from accidental or inappropriate data release of unique identifiers in the study. Maintaining data files in a secure and protected environment on the VINCI workspace during the study shielded breaches in patient privacy. When the study was closed, VA archived the data on tape and storage for 6 years, intent to write over the tape after 6 years to destroy the data (see Appendix J).

Verification of the completed human research training requirements included training from the Collaborative Institutional Training Initiative (see Appendix E). No separate VA IRB number was issued, but the project approval number was 1631225-2. The VA Research and Development Committee issued the final approval to conduct the study on September 27, 2021. The Walden University IRB approval number was 11-19-21-0308910.

Data Collection Instruments

I did not collect any primary data for this study. The data source for the current study was archival data collected during routine clinical care for HF and stored in a secure VA database. The centralized VA data sources for the study were in the CDW. Analyzing available, accurate, and pertinent archival routinely collected health data, including information from demographic and health care services use files,* promoted understanding of whether a relationship existed between residence rurality, home telehealth enrollment, and bed days of care during readmissions for HF. All data transfers for the study occurred behind the VA firewall, between the CDW and VINCI.

Data collection dates for admissions for HF included January 1, 2017, through December 31, 2017. Because readmissions included in the study could occur within 30 days after discharge, the data collection dates for readmissions extended through January 30, 2018, and counts for bed days of care extended through February 26, 2018, allowing a complete count of the bed days of care during the readmission without including extended stays lasting longer than 25 days. See Appendix F for a list of data elements and data sources for the study.

Corporate Data Warehouse

The CDW is a national repository comprising data from multiple VHA systems and designed to standardize patient-level data collected at the VA hospitals and community-based outpatient clinics throughout the VA enterprise (Krishnamurthi et al., 2018). Stored data in the CDW includes information about dates of service, demographics, diagnosis, and procedure codes for inpatient and outpatient care in VA

(Axon et al., 2018). The early development of the VA electronic health record began in the 1970s with computerized applications at the VA hospitals in the 1980s (Brown et al., 2003). The VA electronic health record is comprised or supported by (a) Veterans Health Information Systems and Technology Architecture (VistA) for database support of patient-specific clinical transactions, (b) Computerized Patient Record System as an interface to VistA, (c) VA CDW as a database used to receive national patient data from VistA and store data for analysis and reporting, and (d) VINCI as a secure research virtual workspace for authorized researchers to access VA data (Rajeevan et al., 2017). Researchers use VINCI to analyze electronic health record patient data from the CDW for VA inpatients with HF (see Garvin et al., 2018), consistent with the population of military veteran patients readmitted for HF in the current study.

Using the CDW was to facilitate standardized data at the patient level (Krishnamurthi et al., 2018) while reporting and analyzing data at an enterprise level by linking information from multiple data sets throughout VHA into one database structure (Rajeevan et al., 2017). The CDW is a large-scale data warehouse with built-in repeatability; designed to support business practices, research, and innovations in health care (Health Services Research & Development, 2022). Using large databases, such as these, to conduct research comprised broad archived data collected directly from patients during routine clinical encounters (Hemkens et al., 2016).

Description of the Data

Heart Failure

The diagnosis of HF corresponded with ICD-10 codes (Virani et al., 2020) throughout the VA clinical and administrative files. The data source was the CDW. Table B2 includes a list of ICD-10 codes for the HF diagnoses in this study. Appendix F includes the data sources within the CDW to locate ICD-10 codes for HF.

Residence Rurality

Residence rurality was an enabling factor and a predictor variable in the current study. The rurality level designations for each patient were urban, rural, or highly rural based on the population density where the patient resided. Combining the rural and highly rural data into the larger rural data set prevented too few highly rural values for accurate analysis. The designated rurality levels categorized by VA match the zip code of the residence to the corresponding Rural-Urban Commuting Area code. There were no missing residence rurality data. The data source was CDW. Appendix F includes the data sources within the CDW to locate residence rurality levels.

Home Telehealth Enrollment

Home telehealth enrollment was an enabling factor and a predictor variable in the current study. Criteria to enroll in the home telehealth program required the patients' agreement to use a system of care delivery comprising information and telecommunication technologies to deliver health care from a distant location to patients in their homes (see Wade & Stocks, 2017). Using home telehealth enabled patients for early detection and interventions when HF symptoms worsened. The data source was the

CDW. Table B3 includes the stop code information used in the feasibility report. The stop codes and the data sources used to locate home telehealth encounter data within CDW are listed in Appendix F.

Bed Days of Care

Bed days of care was a measurement of the need factor and the criterion variable in this study. A bed day of care is an overnight stay of an individual in a VA bed within an assigned treating specialty bed section (VHA, 2013). The bed days of care are the unit of analysis used by the VA to determine inpatient, residential, and extended care workload at a given point of service (VHA, 2013). The data source was CDW. To calculate the bed days of care required using admission and discharge data. This study excluded admission and discharge on the same date and an admission exceeding 25 days. Measuring the bed days of care began the day after hospital discharge for HF when a patient's readmission occurred within 30 days. Appendix F includes the data sources within the CDW to locate admission and discharge dates for HF.

Age, Gender, Race, and Ethnicity

Aggregated age, gender, race, and ethnicity data were collected to describe demographic characteristics to inform readers about the potential transferability of the research findings to alternate populations (see Díaz Rios et al., 2022). The data source was CDW. Appendix F includes the description of categories of the data elements and data sources within the CDW to locate information about the age, gender, race, and ethnicity. The classification type for age was continuous but bounded to begin at 18 years of age to meet veteran eligibility criteria. Gender was dichotomous and categorical (female = 1, male = 2). The classifications for race and ethnicity were categorical. Race categories included (a) American Indian or Alaskan Native, Black or African American, Native Hawaiian or Pacific Islander, White, more than one race, declined to answer, unknown by patient, and missing. Ethnicity categories included (a) Hispanic or Latino, (b) not Hispanic or Latino, (c) declined to answer, and (d) declined to answer.

Validity of the Database

Feder (2018) recognized validating databases is an essential part of conducting research when using data from an electronic health record. Ensuring accountability for providing quality HF care in VA as documented in the electronic health record includes independent monitoring of care through the VA External Peer Review Program and public reporting of the audit findings (Garvin et al., 2018). Reporting adherence to effective inpatient patient care measures for HF and readmissions within 30 days in the Hospital Compare public reporting site promotes transparency about the quality of care provided in hospitals (CMS, 2021a).

Applying positive predictive values from validation studies estimates the accuracy of HF events documented in the electronic health record for a cohort of patients with HF (Floyd et al., 2016). Thygesen and Ersboll (2014) described the validity of patient registers of health data as measured by completeness or inclusion of all eligible patients in the database and validity of the variables as accurate data collection and recording of all applicable information in the database. Floyd et al. (2016) noted missed events occur when enrolled military veteran patients receive care at a private sector hospital, potentially contributing to lower sensitivity values while high positive predictive values.

However, this study did not include private sector hospital admissions data. Validation of the data in the CDW pertains to military veteran patients' HF care provided at a VA hospital.

In a validation study conducted by Floyd et al. (2016), electronic health record reviews for 180 randomly selected VA patients revealed a high level of accuracy of coding over 12 months for cardiovascular conditions, including HF. Using 95% CIs, Floyd et al. found the positive predictive value for HF was 72% [47%, 86%], negative predictive value of 99% [91%, 100%], sensitivity of 90% [57%, 98%] and specificity of 95% [88%, 98%], respectively. Presley et al. (2018) conducted a validation study to review a random sample of 500 hospital records of 10,766 hospitalizations in VA for HF between 2001 and 2012. Using an algorithm comprising ICD codes, the diagnosis-related group code for HF, and 95% CIs, Presley et al. noted a positive predictive value of 89.7% [86.8%, 92.7%], a negative predictive value of 93.9% [89.1%, 98.6%], sensitivity of 45.1% [25.1%, 65.1%] and specificity of 99.4% [99.2, 99.6], respectively. Presley et al. postulated the low sensitivity occurred from limiting the measurement to the principal diagnosis of HF, whereas the sensitivity and risk of diagnosis misclassification increased when including HF as a secondary diagnosis. Findings from the study suggested a high level of coding accuracy for HF in VA electronic health records (Presley et al., 2018).

Mahajan et al. (2017) used the VA electronic health record data to study 59 predictor variables and build a risk model for readmissions 30 days after discharge for HF. Topics included demographics, clinical factors, and psychosocial determinants of health as consistent with specific values required in the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009 (Mahajan et al., 2017). Data for the dependent variable of HF were present for all the 1,210 admissions, and the readmission rate within 30 days was 21.74% and 28.54% for repeat readmissions (Mahajan et al., 2017). Testing of variables revealed up to 5% of missing predictor variables and no patterns (Mahajan et al., 2017). According to Mahajan et al. (2017), the highest concordance statistic was in the model with combined predictors from all domains (0.84, CI: 0.83, 0.85), whereas the lowest concordance statistic comprised the psychosocial domain (0.50, CI: 0.49, 0.51). Using data from multiple domains in the VA electronic health record effectively identified patients with a diagnosis of HF (Mahajan et al., 2017). Goode et al. (2017) emphasized the value of using archival data from ICD-10 codes to collect information about diagnoses for research. In the current study, the data source to identify the population of patients with HF and the bed days of care for readmissions was archival data from ICD-10 codes.

Electronic health record data is a common data source in VA research, and using validated databases is essential to verify the data accuracy of cardiovascular conditions (Floyd et al., 2016). Reviews of VA hospital costs reflected the accuracy of VA archival data encompassing broad variables used to examine fixed and variable costs for HF admissions and readmissions for HF (Carey & Stefos, 2016). Validation studies of data in VA databases for the care of military veteran patients with HF revealed high positive predictive values (Floyd et al., 2016; Mahajan et al., 2017; Presley et al., 2018), high negative predictive values (Floyd et al., 2016; Presley et al., 2018), high specificity (Floyd et al., 2016; Presley et al., 2018) and high sensitivity (Floyd et al., 2016).

Previously collected health information is frequently the data source for correlational studies (Aggarwal & Ranganathan, 2019), like the archival routinely collected health data used in the current study. Therefore, it was appropriate to use VA databases with data from the CDW in the current study to examine the relationship between residence rurality, home telehealth enrollment, and bed days of care for military veteran patients readmitted for HF.

Data Collection Technique

This study examined the following research question: What is the relationship between residence rurality, home telehealth enrollment, and the bed days of care for military veteran patients readmitted for HF? I did not collect any primary data for this study. The data source was archival routinely collected health data recorded in the electronic health record during clinical care at VA hospitals and stored in the CDW. Researchers use data in large archival routinely collected health data files as technology and costs improve (see Friesen et al., 2017). The availability of archival health data expanded as electronic health records became a common way to plan and document clinical care (Feder, 2018). Hughes-Cromwick and Coronado (2019) described data from federal sources as comprehensive, encompassing the entire United States, and valuable for benchmarking. Routinely collected health data may be analyzed to inform the design of quality improvement projects, service redesign, policy changes, and regional and national benchmarking (Todd et al., 2020). There were no physical risks to research subjects in the current study. There were potential risks associated with the loss of privacy when using secondary health data from archival databases, but no loss of data or privacy breaches occurred.

Data Collection

Data collection for the current study included preparation, followed by detailed data collection processes (see Appendix D). Preparation activities included completing the required training before accessing the VINCI workspace to retrieve VA data behind the secure, password-protected VA firewall. Safeguards were in place to protect patient privacy and ensure the appropriate data were collected to answer the research question. The data use agreement requirements included submitting a list of the data elements and the data sources needed to access those data in the CDW (see Appendix F). The requested data aligned with the cohort based on inclusion and exclusion criteria in the study (see Appendix F).

Appendix D lists the steps followed to prepare for the data collection and retrieval from the CDW. Data access was through views in Microsoft SQL Server Management Studio v18.9.1 (SQL) software, available on the VINCI workspace for use by approved VA researchers for data collection from the CDW. Saving the retrieved data in two identical Microsoft Excel 2016 (Excel) tables preserved historical data in one table and provided the second table for data sorting, cleaning, and merging. Storing an unaltered master file ensured fidelity of the data sets, avoided data loss, and maintained data security (see Watson, 2015).

Advantages and Disadvantages

Advantages of using large archival, routinely collected health data files are the low cost, the limited time needed to conduct the study (see Edmondson & Reimer, 2020), and the ability to examine population-level research questions (Y. Wang et al., 2018). Thygesen and Ersboll (2014) stated selection bias decreases when archival data is the data source in studies. Using archival records to study a large population of military veteran patients with HF in the current study was possible because access to robust data was readily available for approved researchers, and research costs were low.

Advantages of the data collection technique included the safeguards in place to protect patient privacy and ensure data access was limited to the data needed to answer the research question (see Appendix D). Performing data retrieval activities behind the VA firewall protects patient privacy and data security (see ORD, 2022b). All the resources, such as SQL and other tools needed for data collection and analysis, were available in the workspace. Following organizational policies prevented individual-level patient data, including unique identifiers, from being removed from the VINCI workspace. Using the secure VINCI workspace with a dedicated project site for data analysis and storage security protections (see ORD, 2022b) limited access to data for the current study to authorized individuals with written approval.

Disadvantages of using archival routinely collected health data sets included misalignment between the purpose of the original data collection and the research study, missing or low-quality data, as well as difficulty obtaining permission to access data (see Benchimol et al., 2015; Harron et al., 2017; Y. Wang et al., 2018). Information about the quality and comprehensiveness of discharge planning was missing in reviews of archival routinely collected health data (see Carey & Stefos, 2016). However, the purpose of this study was not to make the determinations about care quality but instead to provide data to VA primary care managers about whether there was a relationship between residence rurality, home telehealth enrollment, and bed days of care for military veteran patients with HF.

A primary disadvantage of using archival routinely collected health data sets was the expertise required to use SQL to retrieve data. There were limited resources available to assist with SQL in non-funded studies, and viewing the data was restricted to individuals identified by the IRB approval. Second, the data collection technique included time delays for permissions to access data. The lack of clarity by some personnel caused procedural delays when working with researchers employed outside of the VA medical center. Last, data collection delays occurred during scheduled maintenance and gaps in connectivity.

Consideration to Conduct a Pilot Study

Planning for the study did not include conducting a pilot study. Evaluating the instrument's effectiveness and determining whether the findings from the original research study are transferable to a different study setting are benefits of conducting a pilot study (Malmqvist et al., 2019). Holding pilot studies helps identify concerns about implementing the study protocol before the study, affecting the data collection process, data quality, inclusion and exclusion criteria, and recruitment (see K. C. Lee & Wessol, 2021). In the current study, data collection occurred by transferring data from the CDW to a research workspace rather than by using an instrument. The current study did not include validating findings from another study. Findings from the VA feasibility report (see Appendix B) revealed an adequate sample size, minimal missing data, and effective processes to pull the data needed to answer the research question. Therefore, conducting a pilot study would add little value while increasing the time and resources required to conduct the current study.

Data Analysis

This study examined the following research question: What is the relationship between residence rurality, home telehealth enrollment, and the bed days of care for military veteran patients readmitted for HF? Finding answers to the research question included testing the hypotheses.

H_0: There is no statistically significant relationship between residence rurality, home telehealth enrollment, and the bed days of care for military veteran patients readmitted for HF.

H_1: There is a statistically significant relationship between residence rurality, home telehealth enrollment, and the bed days of care for military veteran patients readmitted for HF.

Nature of the Scale for Variables

Residence Rurality

Residence rurality was a predictor variable in the current study. The rurality level designations for each patient were the combined category of rural and highly rural and a second category of urban. The classification type was dichotomous and categorical (rural or highly rural = 1, urban = 2).

Home Telehealth Enrollment

Home telehealth enrollment was a predictor variable in the current study. The measurement was dichotomous and categorical (1 = enrolled in home telehealth, 2 = not enrolled in home telehealth). Home telehealth enrollment counted after two home telehealth encounters.

Bed Days of Care

Bed days of care was the criterion variable in this study. To calculate the bed days of care required using admission and discharge data for patients readmitted with HF. The measurement type was continuous but bounded by 25 days to meet the requirement of acute care readmission.

Statistical Tests

I used multiple linear regression as the data analysis technique in this study. Considerations when selecting statistical tests include the study design, research question, number of comparison groups, sample size, and the type and characteristics of data comprising the predictor and criterion variables (Sullivan et al., 2016). Descriptive statistics are mathematical tools used to summarize a description of a study sample (Campbell, 2016; Curtis et al., 2016; Simpson, 2015). Selecting statistical tests may include more than one appropriate option and decisions may change based on assumption violations (Campbell, 2016; Sullivan et al., 2016). Sebastião and St. Peter (2018) recognized influences to choosing a different statistical method include the purpose of the research and whether the dependent variable is continuous or categorical.

Nominal categorical variables are descriptive values without order (Sebastião & St. Peter, 2018). Nominal subcategories comprised two variables, known as dichotomous (Simpson, 2015) or binary, or more than two variables identified as multinomial (Sebastião & St. Peter, 2018). Dichotomous classifications included sorting data about individuals or events into one of two groups without ordering (Campbell, 2016; Sullivan et al., 2016), aligning with two-tailed tests (Bettany-Saltikov & Whittaker, 2014). When the variables comprise dichotomous categories, descriptive statistics are limited to frequencies expressed as counts or proportions, and there is no justification to compute the mean and standard deviation (Simpson, 2015; Sullivan et al., 2016). Data analysis of the dichotomous predictor variables in the current study included the number and percentage of patients in the population residing in rural versus urban areas and the number of patients enrolled versus not enrolled in home telehealth.

Descriptive statistics include the frequency and summary measures used to determine whether the study findings are transferable to other situations (Sebastião & St. Peter, 2018). Applying parametric statistics of the mean to measure central tendency and standard deviation to measure the dispersion of ratio data is appropriate when there is a normal distribution of values (Simpson, 2015). Bettany-Saltikov and Whittaker (2014) described the consistency between similar mean, median, and mode results and a normal distribution and central tendency, meeting partial criteria for parametric tests. Alternately, reporting the median to measure central tendency and the range to measure dispersion aligned with statistical testing for a continuous variable without normal distribution (Bettany-Saltikov & Whittaker, 2014; Simpson, 2015).

Researchers apply inferential statistical techniques to examine and draw conclusions from a population sample (Sebastião & St. Peter, 2018; Simpson, 2015). Statistical significance is the probability of a relationship between two or more variables rather than a chance occurrence (Simpson, 2015). The current study used descriptive statistics to summarize the numeric data for the entire population of military veteran patients readmitted to a VA hospital for HF in 2017. Inferential statistics were used to show the relationships between the dichotomous predictor variables of residence rurality and home telehealth enrollment and the ratio continuous criterion variable of bed days of care for military veteran patients readmitted for HF.

Correlational research involves statistically measuring the strength and direction of a relationship between two or more variables in a population (Curtis et al., 2016). Aggarwal and Ranganathan (2019) recognized researchers in correlational studies seek associations between independent and dependent variables affecting populations, and the findings may not be pertinent to individuals. Correlation does not suggest causation, irrespective of the correlation strength between variables (Curtis et al., 2016). Whereas independent and dependent variables may be correlated, there is no implication in correlational studies of a change in one variable causing a change in the other variable (Aggarwal & Ranganathan, 2019; Curtis et al., 2016; Tobías et al., 2019). The current study included the use of VA archival routinely collected health data to conduct statistical testing to examine the relationship between home telehealth enrollment, residence rurality, and bed days of care for veterans readmitted for HF.

Regression analysis is a statistical technique researchers apply to estimate the correlations or relationships among variables (Sebastião & St. Peter, 2018). Researchers use multiple regression to examine the association between more than one explanatory variable and one continuous dependent variable (Malone & Coyne, 2019). Linear regression is an appropriate statistical method for examining the relationship between one or more predictor variables and a continuous criterion variable when meeting the assumptions for linear regression (Schmidt & Finan, 2018; Sebastião & St. Peter, 2018). Researchers apply multiple regression to answer a research question about whether there are any associations between an independent variable and one or more continuous dependent variables, the power of the association, and make predictions about the dependent variable (Sebastião & St. Peter, 2018). A linear regression model with main effects of residence rurality and telehealth enrollment along with their interaction effect was appropriate for this study.

Alternate Statistical Analyses

Other regression analysis methods considered for the study included simple linear regression, logistic regression, and Poisson distribution. There is one predictor variable and one criterion variable in simple linear regression (Aggarwal & Ranganathan, 2017; Jan & Shieh, 2019), an inappropriate design for the current study comprised of two predictor variables and one criterion variable. Researchers use logistic regression to predict a dichotomous categorical dependent variable (Curtis et al., 2016), inconsistent with a continuous criterion variable of bed days of care in the current study.

Considerations included a count model, such as the Poisson distribution (see Baghaei & Doebler, 2019), if assumption violations for multiple regression altered the fit or swayed the appropriateness draw conclusions, and the characteristics of the data met the count model criteria. Researchers apply the Poisson model when the independent variables and whole numbers comprise the data set (Baghaei & Doebler, 2019; Coupé, 2018). The Poisson model was not relevant to the current study because the assumptions for multiple linear regression were met after transforming the data. Second, some bed days of care for patients readmitted and discharged on consecutive days did not meet the whole number requirement for the Poisson distribution model. Thus, it was inappropriate to apply the Poisson distribution for this study.

Statistical Software

I used Microsoft SQL Server Management Studio, v18.9.1 (SQL) software to access and retrieve data from the CDW, Microsoft Excel 2016 (Excel) for data cleaning, and uploaded those data to Stata 17.0-MP-Parallel Edition (Stata; see ORD, 2022b) software for statistical analysis. The data extraction and analysis software were available on the VINCI workspace for VA researchers (see ORD, 2022b). The current study included VA archival routinely collected data and statistical software housed on the VINCI research platform to securely examine the relationship between residence rurality, home telehealth enrollment, and bed days of care for military veteran patients readmitted for HF.

Missing Data

Bias of conclusions may occur if missing data reduces the sample to the extent that the sample no longer represents the population (Abulela & Harwell, 2020; Hughes et al., 2019). The bias occurs by reducing the accuracy of means and variances estimations, as well as the power of statistical tests used to analyze those data (Abulela & Harwell, 2020). Missing data that was pertinent for conducting statistical analysis of this study included the admission and discharge dates used to calculate the criterion variable, bed days of care. The residence rurality designation and dates of home telehealth enrollment and use were also needed for the predictor variable data. Missing or inconsistent data were addressed during a visual data inspection of the Excel tables throughout the data cleaning and merging process. I considered using the listwise feature in Stata to exclude admissions with missing data but performing the visual inspection improved data accuracy by allowing me to identify and address inconsistent dates or overlapping entries.

I considered reviewing alternate data sources within the CDW to locate missing data, but minimal data were missing, and removing the missing data entries did not impact the accuracy of answering the research question. There were no missing data for the predictor variables of home telehealth enrollment and residence rurality. Less than 1% (n = 4) of the original 9,751 admission data entries was inconsistent or missing the admission or discharge date. I removed the data entries with missing essential data.

Identifying and Testing Assumptions

Reliable and valid results of the study require satisfaction of assumptions of the statistical model to be used (see Coupé, 2018). The current study used a multiple linear regression model to test the hypotheses. A linear regression model produces the best (unbiased, consistent, and efficient) model effects when the following assumptions are satisfied: (a) error terms are normally distributed, (b) error terms are not serially correlated, (c) error term distribution has constant variance (homoscedasticity), and (d) there is a linear relationship between the independent variables and dependent variable (Gujarati, 2003). I addressed each of these assumptions in the current study except linearity because it is not possible to test the linearity assumption with categorical independent variables (see Harris, 2021). Multicollinearity was not relevant in the current study because it is not feasible to assess this assumption unless there is more than one continuous predictor in the study (see Harris, 2021). Both predictor variables, home telehealth enrollment and rurality, are categorical variables in the current study. Age is the only continuous variable used to measure a demographic characteristic. Therefore, in the current study there was only one continuous predictor variable used in the regression model, and the question of multicollinearity was not relevant.

The central limit theorem suggests there is an assumption of normality of the outcome in the population when using a large sample (Altman & Krzywinski, 2018; Malone & Coyne, 2019; Sullivan et al., 2016). Schmidt and Finan (2018) demonstrated how linear regression models used with large samples were robust to violations of a normal distribution, emphasizing the importance to address high priority assumption areas of nonlinearity, outlying values, heteroscedasticity, and correlated errors. However, Altman and Krzywinski (2018) stated normal distribution is necessary to calculate accurate prediction and tolerance intervals, even though the normality of those data is less important for confidence intervals of the mean when the sample is large. Therefore, the first assumption I tested was the normality assumption.

Assessing the normal distribution assumption included visualizing graphical histograms of residuals and a normal Q-Q plot of standardized residuals (see H.-Y. Kim, 2019; see Malone & Coyne, 2019). Human population data are frequently positively skewed in studies (see Malone & Coyne, 2019). Therefore, I anticipated the data in the current study may be positively skewed because the criterion variable, bed days of care, was derived from human population data. The Q-Q plot shows the quantiles of a variable against the quantiles of a normal distribution (Los Angeles Advanced Research Computing, n.d.), supplementing information about normality from visually inspecting the histogram (H.-Y. Kim, 2019). The Q-Q plot is sensitive to non-normality near the tails compared to the P-P plot that is sensitive to non-normality at the center range of data (see UCLA Advanced Research Computing, n.d.). Using the Q-Q plot was appropriate in the current study with a positively skewed distribution.

Powell et al. (2020) noted care received during short hospital stays, frequently for a duration of one day, is sometimes classified as an observation stay, rather than a traditional hospitalization or rehospitalization. The information revealed from the hospital admission and discharge dates in the current study reflects the duration of time the patient received HF care in the inpatient setting but does not specify an observation versus a readmission. It may be appropriate to remove short hospital stays of less than one day in the current study to avoid analyzing observation stay data and partially address a positively skewed distribution.

Transforming the data to yield a normal distribution for statistical analysis is an alternate way to address a non-normal distribution issue (Coupé, 2018; Sullivan et al., 2016). Logarithm (log) can be used to transform skewed nonnegative data to a more normal distribution (Altman & Krzywinski, 2018). Count data may be transformed to address nonnormality of the residuals (Coupé, 2018), consistent with the current study because the criterion variable, bed days of care, is count data. For that reason, log transformation was an appropriate method to satisfy the normality assumption (Malone & Coyne, 2019; Sebastião & St. Peter, 2018). A regression model was constructed and tested using log bed days of care. Log transformation is monotonic and results in a reduction in skewness of data while retaining the same character for the interpretations of the results compared with the original scale (see Hair et al., 2010). Bootstrapping was not necessary after performing log transformation because the distribution of the estimator was clear, and the underlying assumptions were met.

Violations of serial correlation, known as autocorrelation, may result when data are influenced by past values (Flatt & Jacobs, 2019). Serial correlation violations may reflect the need to improve the model or that the model underpredicted or overpredicted the coefficient estimates (Nau, 2020). I assessed the assumption of no serial correlation of error terms by using the alternate Durbin-Watson test for autocorrelation and the assumption of constant error variance (homoscedasticity) by using the modified Breusch-Pagan test (Hair et al., 2010). The Breusch-Pagan test is used to test the null hypothesis that the variance of residuals is homogenous (UCLA Advanced Research Computing, n.d.). If the results of the Breusch-Pagan test for heteroskedasticity indicated an issue of non-constant error variance (heteroscedasticity), robust, heteroscedastic consistent standard errors would be used in place of the standard ordinary least squares (OLS) standard errors (Hair et al., 2010). The assumption of independence of error terms may be satisfied based on the results in the Durbin-Watson test showing the residuals not being serially correlated. Assessing the range of the standardized residuals included verifying there were no outliers or influential observations adversely affecting the results of the regression analysis. Therefore, the assumptions identified for multiple linear regression may be satisfied based on the results of the residual analysis from the histogram of standardized residuals, normal Q-Q plot, Breusch-Pagan test, and Durbin-Watson test.

Study Validity

Accurate research is important because decisions about health care practices arise from research study findings (Cor, 2016; Sebastião & St. Peter, 2018; Sullivan et al., 2016). Methods used to improve rigor minimize threats to reliability and validity (Ellis & Levy, 2009) and increase accurate study analysis and reporting (J. Park & Park, 2016). Decreasing bias in quantitative studies improves objectivity and comprehension of facts, cases, and phenomena (J. Park & Park, 2016).

Internal Validity

Internal validity refers to the researcher's ability to establish causal relationships from a justified conclusion in a research study (Handley et al., 2018). Determining causation also requires ruling out rival hypotheses (Cor, 2016; Straub, 1989). Researchers apply nonexperimental correlational designs to statistically answer whether a relationship exists between variables rather than determine causality (Curtis et al., 2016; Reio, 2016).

Internal validity pertains to studies designed for examining cause and effect (Handley et al., 2018), and correlational studies cannot establish causality (Ellis & Levy, 2009). Therefore, threats to internal validity did not apply to the current study because an ex post facto correlational design was used.

Statistical Conclusion Validity

Statistical conclusion validity refers to assessing the accuracy of inferences about the relationship between variables and determining whether conclusions are true or by chance (Cor, 2016; Ellis & Levy, 2009). Achieving valid research outcomes includes minimizing bias by avoiding errors in conducting, analyzing, or interpreting results (Sullivan et al., 2016). Additional strategies to attain validity include meeting assumptions, using appropriate statistical techniques, such as parametric or nonparametric tests, and recording the rationale for making decisions to minimize Type I errors (Cor, 2016).

Violations of statistical conclusion validity occur when the mathematical associations between the variables in the study are inaccurate because of covariation influences (Straub, 1989). Selecting the appropriate statistical tests decreased the risk of a Type I error (Bettany-Saltikov & Whittaker, 2014). The risk of a Type II error or false-negative result occurs when test results do not detect a true effect (Malone et al., 2016; Sullivan et al., 2016). The threats to statistical conclusion validity increase when researchers do not address Type I and Type II errors (Straub, 1989). The validity of the current study improved by addressing statistical testing violations before conducting statistical analysis.

Reliability of the Instrument

Reliability in quantitative studies refers to the consistent accuracy of data measurement (Straub, 1989; Watson, 2015). Instrument reliability was not pertinent to the current study because I did not use a formal instrument for data collection. Alternately, data collection occurred by transferring data from the CDW to a research workspace. The CDW is a large-scale data warehouse that links information from multiple data sets and uses built-in repeatability designed to support business practices, research, and innovations in health care (Health Services Research & Development, 2022). It is not possible to verify internal consistency of an instrument in the current study because I did not use a formal instrument for data collection.

Data Assumptions

Model checking of valid inferences involves the plausibility of assumptions underlying the statistical techniques, implying the appropriateness of treating the estimated effects and statistical results as accurate (Abulela & Harwell, 2020). Increasing the statistical power above a level needed to detect an effect, higher than .80 power, reduces the risk of a Type I error and occurs when the sample is large (see Sullivan et al., 2016). However, if assumption violations are not addressed, the actual probability of rejecting a true statistical hypothesis (Type I error) may be higher and the statistical power may be lower than the probability and power settings (Abulela & Harwell, 2020). The key parameters in the current study included two predictor variables, a moderate effect size (F = .15) and α = .05, to achieve a power of .95. I addressed the assumption violations to minimize the risk of committing Type I or Type II errors.

The data assumptions pertaining to the current study using multiple linear regression with categorical predictor variables and a continuous criterion variable were (a) error terms are normally distributed, (b) error terms are not serially correlated, and (c) error term distribution has constant variance (homoscedasticity; see Gujarati, 2003). The correct assumption is that the error terms are normally distributed rather than the common belief that the normal distribution pertains to the variables **(**Flatt & Jacobs, 2019). Validity of the *p* values of the *t* tests and *F* test, used for hypothesis testing, is dependent on meeting the assumption of normality (UCLA Advanced Research Computing, n.d.). Normality does not impact obtaining unbiased estimates of regression coefficients and does not pertain to the predictor variables. Addressing a normal distribution violation in the current study was consistent with accurate statistical results and interpretation.

Violations of the no serial correlation assumption may include the need to improve the model or consider that the coefficient estimates are underpredicted or overpredicted in the model (Nau, 2020). Minor violations may include adding lagged independent or dependent variables (Flatt & Jacobs, 2019). Using an alternate model may be appropriate in extreme assumption serial correlation violations to avoid committing a Type I error (Flatt & Jacobs, 2019). Heteroscedasticity is frequently the result of another assumption violation (Flatt & Jacobs, 2019); therefore, I considered other assumption violations before testing for heteroscedasticity. Violations of homoscedasticity affect the validity of the standard deviation of the forecast errors, confidence intervals that are too wide or narrow, or the effect giving too much weigh to a small subset of the data when estimating coefficients (Nau, 2020).

Tests for the model assumptions included using graphical (histogram and normal Q-Q plot of standardized residuals) to test normal distribution of error terms as well as formal statistical tests (Breusch-Pagan test for heteroscedasticity and Durbin-Watson test for independence of error terms). Results from a statistical model satisfying all the assumptions will produce unbiased, consistent, and efficient estimators of the effect of the predictor variables on the criterion variable (Gujarati, 2003). Satisfying all the assumptions in the current study will result in valid estimators of the effect of residence rurality and home telehealth enrollment on bed days of care.

Sample Size

The current study included the entire VA population of military veteran patient readmissions with HF (N = 1,081). This sample size exceeded the minimum sample size of 107 readmissions, identified during an a priori power analysis using G*Power version 3 statistical software (Faul et al., 2009), assuming a medium effect size (F = 0.15), α = 0.05 to achieve a power level of 0.95 (see Cohen, 1992; Malone et al., 2016), and 2 predictor variables (see Appendix H). Increasing the statistical power above a level needed to detect an effect, higher than .80 power, reduces the risk of a Type I error and occurs when the sample is large (Sullivan et al., 2016).

Total population sampling minimizes the risk of sampling bias or selecting a nonrepresentative population sample (Bowring et al., 2017; Thygesen & Ersboll, 2014). Using a large sample decreased the risk of a type II error (see Sullivan et al., 2016).

Further, using total population sampling and a power of .95 reduced the risk of a Type I error (see Kang, 2021). Applying total population sampling and using a large sample minimized sampling bias and risks to population validity in the current study.

External Validity

External validity includes the ability and extent to generalize findings from the study to individuals and populations and across settings, times, and situations (see Cor, 2016; Ellis & Levy, 2009). Reducing bias included minimizing risks to external validity in the categories of ecological, temporal, treatment variation, and outcome validity (Cor, 2016). In the correlational design, findings may suggest there is a relationship between variables, but it is not always possible to infer those findings from the sample to the target population (Curtis et al., 2016). However, generalizing the observations from the sample to the targeted population is not relevant in the current study because the sample comprised the entire population of military veteran patients readmitted for HF.

Harbaugh and Cooper (2018) explained generalizability is limited when researchers use administrative databases because the sensitivity and specificity of diagnosis coding is unique to the database rather than collected for a study. Collecting data over the same months and year may minimize differences from factors outside of the study related to time. In the current study, data collection for admissions and predictor variables occurred from January 1, 2017, through December 31, 2017, readmissions extended an additional 30 days through January 30, 2018, and bed days of care extended through February 25, 2018, to meet the requirement of acute care readmissions (see CMS, 2021b). Collecting data over 12 months may promote external validity related to changes in time by minimizing the impact of seasonal variances in hospital admission rates.

Findings from this study are not generalizable to military veteran and non-veteran patient populations hospitalized at a VA hospital for diagnoses other than HF, or for HF or other diagnoses in the private sector or government hospitals outside of VA. Thygesen and Ersboll (2014) emphasized study findings are limited to the specific data set comprising register-based healthcare records; therefore, the findings from the current study do not extend to alternate time frames beyond the population of patients readmitted for HF 2017. However, researchers informed by the study may deem entire or partial findings appropriate to transfer to alternate populations, environments, or situations (Thygesen, 2017).

Transition and Summary

Section 2 begins with the study's intent, the researcher's role, and the participants of military veteran populations with HF. The research method and study design were quantitative ex post facto correlational using VA archival routinely collected health data. This study examined the relationship between residence rurality, home telehealth enrollment, and bed days of care for military veteran patients readmitted for HF. The predictor variables included dichotomous categorical measurements of residence rurality (rural or urban) and home telehealth enrollment (yes or no). Bed days of care for military veteran patients readmitted for HF was a ratio continuous criterion variable. Section 2 continued with a discussion about the population, sampling, and research ethics. Using total population sampling minimized the risk of sampling error and sampling bias. Next, there was an explanation about data instruments and collection. The data source for analysis included archival VA routinely collected data for HF care, rather than employing data instruments or collecting data directly from participants. Finally, Section 2 included considerations for data analysis and validity.

Section 3 includes the results of the statistical analysis with interpretive findings. The analysis includes the application of findings on HF care in the VA, especially the impact of home telehealth enrollment in rural locations. Discussions comprise the impact of findings from the study on the healthcare industry and social change. Final discussions close with recommendations for future actions and research, followed by the study summary and conclusions.

Section 3: Application to Professional Practice and Implications for Change

Introduction

The purpose of this quantitative correlational ex post facto study was to examine the relationship between residence rurality, home telehealth enrollment, and bed days of care for military veteran patients readmitted for HF. Residence rurality and home telehealth enrollment were the predictor variables. The criterion variable was the bed days of care for military veteran patients readmitted for HF. I failed to reject the null hypothesis. This may imply that the main effects of residence rurality and home telehealth enrollment and their interaction do not have significant association with bed days of care. Findings from descriptive and inferential statistics with a 95% confidence interval formed the basis of considerations and recommendations for professional practice, social change, action, and further research.

Presentation of the Findings

In this section, I will discuss testing of the assumption, present descriptive statistics and inferential statistics results, provide a theoretical discussion pertaining to the findings, and conclude with a concise summary. I employed log transformation, using 1,081 samples to address the possible influence of assumption violations. Thus, log transformation with 95% confidence intervals is presented where appropriate.

Tests of Assumptions

Assumptions are important to evaluate because biased results may occur if there are unaddressed assumption violations for the statistical model (Coupé, 2018). The assumptions of (a) error terms are normally distributed, (b) error terms are not serially correlated, and (c) error term distribution has constant variance (homoscedasticity) were evaluated. Log transformation, using 1,081 samples, enabled addressing the influence of assumption violations.

Normal Distribution of Error Terms

The histogram of the standardized residuals (see Figure 2) indicated a reasonably symmetric and bell-shaped distribution. Furthermore, the standardized residuals ranged from -2.15 to 2.5. This range agrees with the typical range of a standardized normal distribution and indicates that there are no outliers or influential observations adversely affecting the results of the regression analysis. The normal Q-Q plot of standardized residuals (see Figure 3) indicated strong matching of observed qualities of standardized residuals with theoretical quintiles of a standard normal distribution. The assumption of normality of the error term was therefore considered to be satisfied.

Figure 2

Histogram of the Standardized Residuals

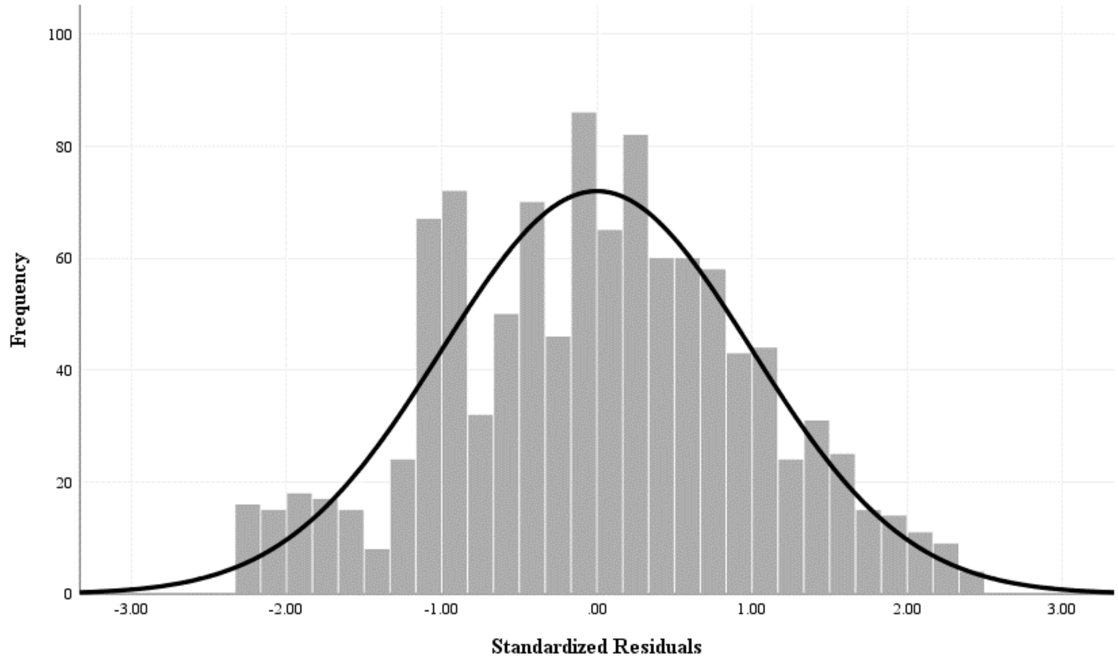
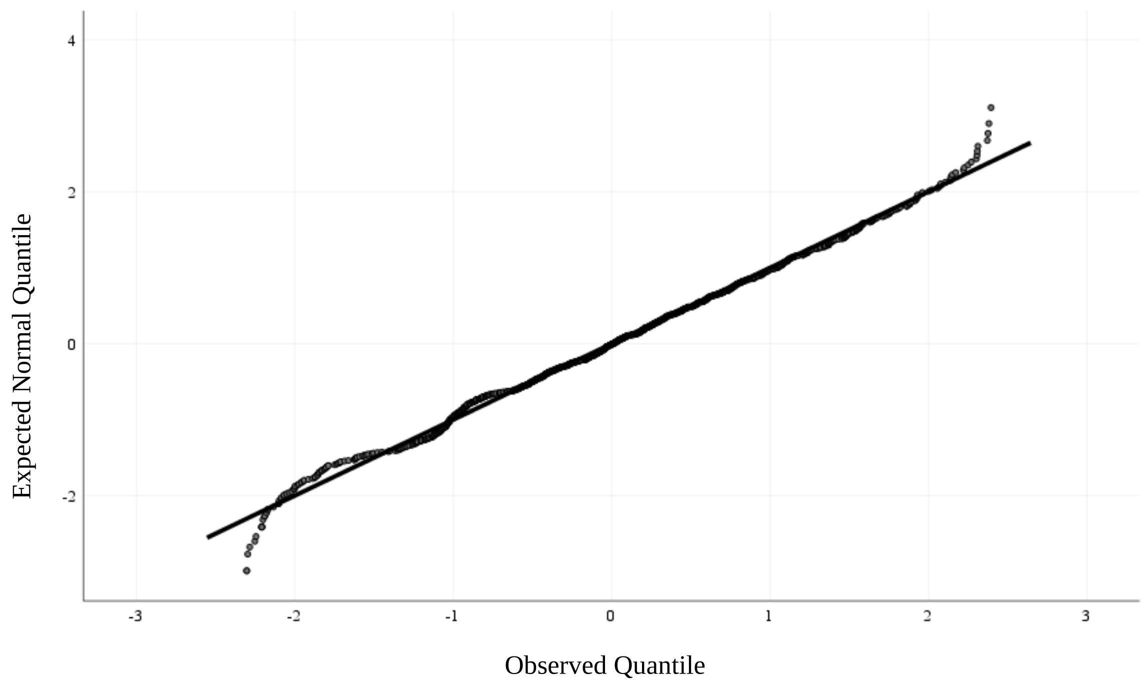


Figure 3

Normal Q-Q Plot of the Standardized Residual



No Serial Correlation of Error Terms

The results of the Durbin-Watson's test indicated that residuals are not serially correlated (χ^2 (1) = 0.41, p = .520).

Constant Variance of Error Terms

The results of the modified Brusch-Pagon test indicated that the assumption of constant error variance (homoscedasticity) was satisfied (χ^2 (1) = .001, p = .981). Therefore, the assumption of independence of error terms may be satisfied.

The results of the residual analysis based on the histogram of standardized residuals (see Figure 2), normal Q-Q plot (see Figure 3), Brusch-Pagon test, and Durbin-Watson test indicated that all the assumptions of the linear regression model were satisfied.

Descriptive Statistics

The first predictor variable was residence rurality comprising combined rural and highly rural versus urban categories. Home telehealth enrollment as the second predictor variable included categories of enrolled or not enrolled in home telehealth for HF management. The criterion variable was bed days of care for military veteran patients readmitted for HF within 30 days of the hospital discharge. The population consisted of archival routinely collected health data files of military veteran patients readmitted for HF to any VA hospital across the United States within 30 days of hospital discharge for HF from January 1, 2017, through December 31, 2017.

The original data set of admissions for HF comprised 9,742 patient files. I removed records with (a) single admissions, (b) duplicate entries, (c) admission and discharge on the same day, (d) readmissions more than 30 days after discharge, (e) deaths within 30 days of discharge from the index admission or during rehospitalization, (f) readmissions exceeding 25 days, and (g) discharges other than regular discharges to home, leaving 1,081 records in the analysis (see Appendix G). I calculated the number and percentage of categorical data entries for the gender, ethnicity, and race, followed by the measures of central tendency and dispersion for the bounded continuous age. As shown in Table 2, most military veteran patients were male (*n* = 1,063; 98.33%), not Hispanic or Latino (*n* = 1,003; 92.78%), and White (*n* = 708, 65.49%). The age varied from 32 to 103 years (range = 71 years) with the mean age of 73.4 years, median age of 73, and mode of 70 years, showing a wide range of ages, but most patients were in the 70-year-old range.

Table 2

Descriptive Statistics for Demographics

Characteristic		*n*	%	Cumulative
Gender				
	Female	18	1.67	1.67
	Male	1.063	98.33	100.00
Ethnicity				
	Hispanic or Latino	44	4.07	4.07
	Not Hispanic or Latino	1.003	92.78	96.85
	Declined to answer	23	2.13	98.98
	Unknown by patient	11	1.02	100.00
Race				
	American Indian or Alaskan Native	7	0.65	0.65
	Black or African American	304	28.12	28.77
	Native Hawaiian or Pacific Islander	5	0.46	29.23
	White	708	65.49	94.73
	More than one race selected	4	0.37	95.10
	Declined to answer	41	3.79	98.89
	Unknown by patient	7	0.65	99.54
	Missing	5	0.46	100.00
Total		1,081		
Age		*M* = 73.4	*Mdn* = 73	

Table 3 displays descriptive statistics for the continuous criterion variable of bed days of care. The positively skewed distribution of the data set (see Figure 4) indicated short hospital stays during readmissions for HF occurred more frequently than extended hospital stays (see Table 3). The average number of bed days of care was 5.28 days, with a median of 3.95. The range in bed days of care was 24.13 days with a maximum of

24.79, consistent with meeting acute care criteria not to exceed 25 days, and a minimum of 0.66, less than one bed day of care reflecting an admission and discharge on consecutive days. As shown in Table 4, of the 10 diagnoses for HF included in the study, 75% of the patients' readmission diagnoses were for acute on chronic systolic HF (*n* = 504, 46.62%) or acute on chronic diastolic HF (*n* = 308, 28.49%). The histogram of the log-transformed bed days care is presented in Figure 5. No observations were removed during the log transformation process. The distribution of the log-transformed bed days indicated an approximate symmetric distribution.

Table 3

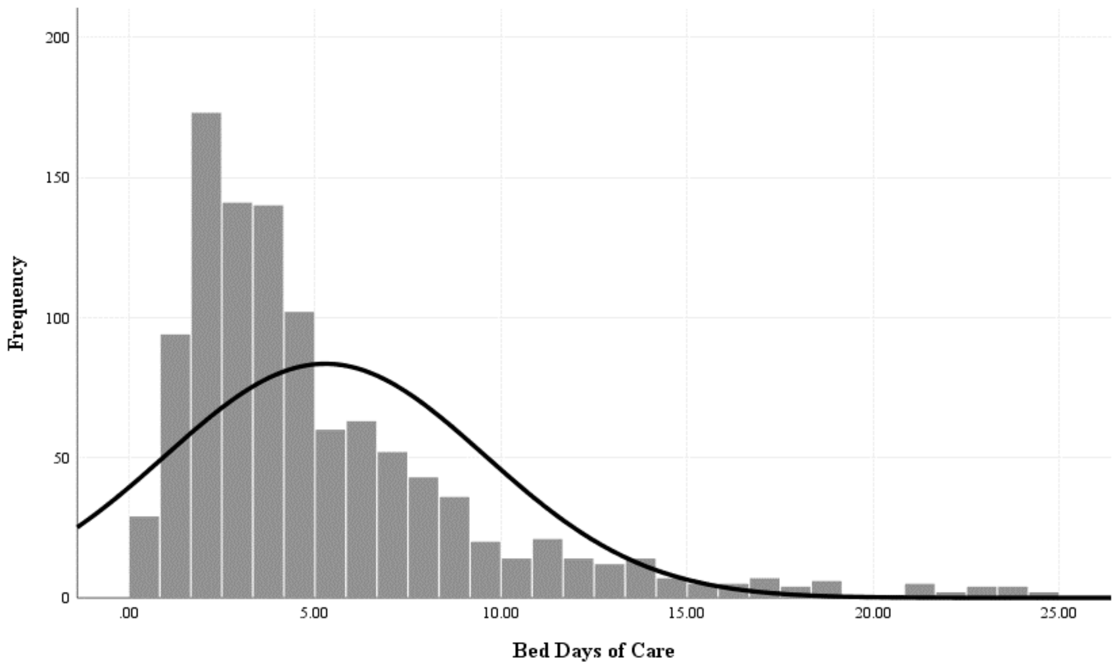
Descriptive Statistics for Demographics

Criterion variable	*N*	*Mdn*	*M*	*SE*	*SD*	95 % CI		Skew	Kurt	Min	Max	Range
						LL	*UL*					
BDOC	1081	3.95	5.28	0.13	4.38	5.02	5.53	1.85	6.91	0.66	24.79	24.13

Note. *N* = total number of 30-day readmissions for HF between January 1, 2017, through December 31, 2017, in the sample. BDOC = bed days of care, counted as the number of hospitalization days during 30-day readmissions for HF. Skew = skewness, Kurt = kurtosis, Min = minimum, Max = maximum.

Figure 4

Histogram of Bed Days of Care



Note. The histogram of bed days of care shows a positively skewed distribution.

Table 4

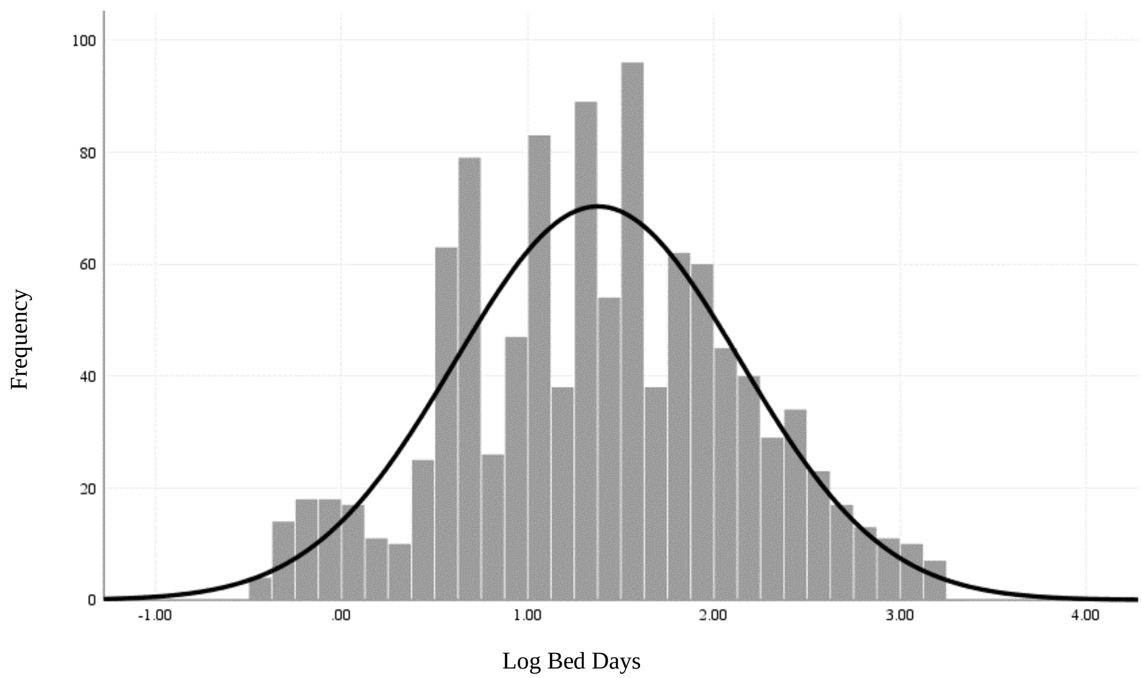
ICD-10 Diagnosis Codes During Readmissions

ICD-10 Code	Description	*n*	%
I50.1	Left ventricular failure	1	0.09
150.21	Acute systolic (congestive) HF	66	6.11
150.22	Chronic systolic (congestive) HF	34	3.15
I50.23	Acute on chronic systolic (congestive) HF	504	46.62
I50.30	Unspecified diastolic (congestive) HF	13	1.20
I50.31	Acute diastolic (congestive) HF	44	4.07
I50.32	Chronic diastolic (congestive) HF	14	1.30
I50.33	Acute on chronic diastolic (congestive) HF	308	28.49
I50.40	Unspecified combined systolic (congestive) and diastolic (congestive) HF	6	0.56
I50.41	Acute combined systolic (congestive) and diastolic (congestive) HF	12	1.11
I50.42	Chronic combined systolic (congestive) and diastolic (congestive) HF	12	1.11
I50.9	HF NOS (Not otherwise specified)	67	6.20
Total		1081	100

Note. Coding for some readmissions included both a primary and secondary diagnosis of HF.

Figure 5

Histogram of Log Bed Days of Care



As shown in Table 5, more military veteran patients resided in urban areas (*n* = 792, 73.3%) than in combined rural (*n* = 289, 27%) and highly rural (*n* = 10, 0.9%) areas. Of the 202 patients enrolled in home telehealth, approximately one-third of the patients (*n* = 65, 32%) resided in rural areas compared to two-thirds of the patients residing in an urban location (*n* = 137, 68%).

Table 5

Descriptive Statistics for Predictor Variables

Predictor variable	*N*	*Mdn*	*M*	*SE*	*SD*	95% CI *LL*	95% CI *UL*	Skew	Kurt	Min	Max	Range
HT enrolled												
Rural	63	3.87	4.73	0.41	3.28	3.91	5.56	1.10	3.29	0.68	14.10	13.42
HR	2	7.30	7.30	5.33	7.54	-60.42	75.02	-0.00	1.00	1.97	12.63	10.66
Urban	137	4.04	5.74	0.41	4.82	4.92	6.55	1.74	5.89	0.73	24.79	24.06
Total	202	3.96	5.44	0.31	4.42	4.83	6.05	1.76	6.31	0.68	24.79	24.11
HT not enrolled												
Rural	216	4.17	5.37	0.30	4.38	4.79	5.96	1.85	6.82	0.74	23.70	22.96
HR	8	7.90	8.32	1.20	3.40	5.48	11.16	0.32	1.61	4.88	13.79	8.91
Urban	655	3.86	5.16	0.17	4.24	4.83	5.48	1.92	7.28	0.66	24.20	23.54
Total	879	3.95	5.24	0.14	4.28	4.95	5.52	1.88	7.06	0.66	24.20	23.54
Rurality												
Rural	279	4.00	5.23	0.25	4.16	4.74	5.72	1.83	6.94	0.68	23.70	23.02
HR	10	7.90	8.11	1.24	3.94	5.30	10.93	-0.01	1.67	1.97	13.79	11.82
Urban	792	3.92	5.26	0.15	4.35	4.95	5.56	1.89	7.02	0.66	24.79	24.13
Total	1,081	3.95	5.28	0.13	4.30	5.02	5.53	1.85	6.91	0.66	24.79	24.13

Note. Med = median, Skew = skewness, Kurt = kurtosis, Min = minimum, Max = maximum.

Inferential Statistics

The overall model was statistically not significant, $F(3, 1077) = 0.995$, $p = .394$ as shown in Table 6. This may imply that the main effects of residence rurality and home telehealth enrollment and their interaction do not have significant association with bed days of care. The results of the *t*-test associated with the main effects and the interaction effect in the model confirmed the non-significant effect on bed days of care ($p > .05$, see Table 6). Figure 6 and Table 7 present the estimated marginal mean log bed days for combinations of categories of residence rurality and home telehealth enrollment. Results of the overall significance (from ANOVA *F* test) and individual factor (main and interaction effects) based on t-test results indicated no significant group differences in log bed days of care. Therefore, based on the data and analysis, it is not possible to reject the null hypothesis stating there is no statistically significant relationship between residence rurality, home telehealth enrollment, and the bed days of care for military veteran patients readmitted for HF.

Table 6

Linear Model Based Effect of Rurality and Telehealth Enrollment on Bed Days of Care

Bed days of care		β (SE)	T	*P*	95% CI
Telehealth	Not enrolled	0[a]			
	Enrolled	0.096 (.072)	1.327	.185	[-.05, .24]
Rurality	Urban	0[a]			
	Rural	0.075 (.059)	1.263	.207	[-.04, .19]
Combined telehealth and rurality	Enrolled and rural	-0.186 (.130)	-1.433	.152	[-.44, .07]
Constant		1.350 (.030)	45.054	<.001	[1.29, 1.41]
$R^2 = .003$, $F(3, 1077) = 0.995$, $p = .394$					

Note. The *df* reflects the 2 predictor variables of telehealth enrollment and rurality and the combined effect of the predictor variables on the criterion variable of bed days of care.

SE = standard error, 0[a] = reference category used in the estimation of the regression coefficient for a categorical variable.

Figure 6

Marginal Predicted Means of Bed Days of Care by Predictor Variables

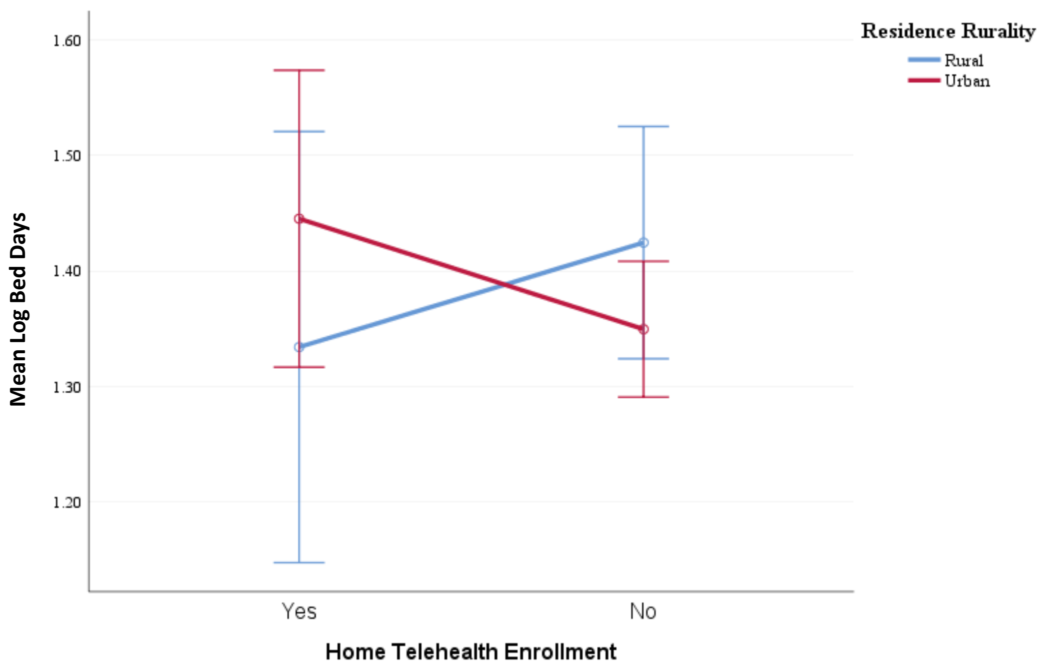


Table 7

Marginal Predicted Means of Log Bed Days of Care

Variable	Margin	SE	95% CI	
			LL	*UL*
Home telehealth enrollment by residence rurality				
Enrolled by rural/highly rural	1.334	0.095	1.147	1.521
Enrolled by urban	1.445	0.065	1.317	1.574
Not enrolled by rural/highly rural	1.424	0.051	1.324	1.525
Not enrolled by urban	1.350	0.030	1.291	1.408

Analysis Summary

This study examined the relationship between the predictor variables of home telehealth enrollment and residence rurality and the criterion variable of bed days of care for military veteran patients readmitted for HF. The results of the regression model main effects and interaction effect of residence rurality and home telehealth enrollment indicated non-significant results implying that the individual variables of residence rurality and home telehealth enrollment and the combined interaction between those predictor variables are not significantly associated with bed days of care. For that reason, it is not possible to reject the null hypothesis stating there is no statistically significant relationship between residence rurality, home telehealth enrollment, and the bed days of care for military veteran patients readmitted for HF.

Theoretical Conversations on Findings

The behavioral model has been used to explain the influences of the predisposing, enabling, and need factors linked with using health services (Hirshfield et al., 2018). The behavioral model underpinned studies by Guzman-Clark et al. (2020, 2021) to explain the use of home telehealth for military veteran patients with HF receiving health care at rural and urban VA facilities. The studies revealed gaps in the literature about optimal patient selection and use of home telehealth for HF (Guzman-Clark et al. (2020, 2021). Identifying cost reduction strategies requires understanding the drivers of health care use (Buttigieg et al., 2018; Lesyuk et al., 2018). Conducting the study extended the application of the behavioral model to explain the relationship between residence rurality, home telehealth enrollment, and bed days for care for military veteran patients with HF. Underpinning the study with the behavioral model explained the influences on decision-making about health care use for HF, including home telehealth.

Applications to Professional Practice

The purpose of this quantitative study was to examine the relationship between home telehealth enrollment, residence rurality, and bed days of care for military veteran patients readmitted for HF. Reducing readmissions for HF is a priority because annual costs for HF care are projected to increase to $69.7 billion by 2030 (Benjamin et al., 2017) and up to 80% of health care costs for HF incur during hospitalizations (Fitch et al., 2016). Oh (2017) described consistency between lowering readmission days for HF and achieving high-quality health care at lower costs. An inappropriate type or frequency of services for a clinical condition or population contributes to low-value health care (Chalmers et al., 2017).

Providing the needed health services without geographical barriers is a strategy for improving health care value (van der Nat, 2021). Goldstein et al. (2018) recognized telehealth to connect patients to health care resources across long distances. Ware et al. (2018) suggested further defining the population, the home telehealth system, and the services provided will enhance understanding of the varied significance and magnitude of the effects of home telehealth use. Guzman-Clark et al. (2020) and Ware et al. identified broad factors influenced the benefits of home telehealth. The results of the regression model main effects and interaction effect in the current study implied that residence rurality and home telehealth enrollment were not significantly associated with bed days of care for military veteran patients readmitted for HF. Most outpatient HF management occurs in general clinics rather than in specialized cardiology clinics (Kapelios et al., 2021). Therefore, informed primary care managers might apply the findings from the current study to identify and influence appropriate resource use, including the avoidance of routinely recommending home telehealth for HF care, unless there is a compelling clinical reason to do so. Identifying the influences of predisposing, enabling, and need factors may guide decision-making to optimally align home telehealth resources for individual patients.

Implications for Social Change

The implications for positive social change included the potential to improve the effectiveness and efficiency of HF care and management for military veteran patients. The health of patients with HF may improve as healthcare leaders select the most beneficial health care services (Okumura et al., 2016), address limitations to transportation (Weeks, 2018), and improve access to specialty health services (Johnston et al., 2019). Military veteran patients with HF may experience improved health and quality of life when the use of home telehealth is limited to patients with a compelling clinical reason to use that resource. The financial performance of VA hospitals may strengthen if home telehealth resources are used for the military veteran patients that will experience the greatest benefit. Findings from the current study may be applied to improve decision-making about resources, including home telehealth for HF care and management.

Recommendations for Action

Healthcare leaders may apply recommendations from this study when considering strategies and resource allocation for HF care. Recommendations for action align with the findings from this study that there is no statistically significant relationship between residence rurality, home telehealth enrollment, and the bed days of care for military veteran patients readmitted for HF. The results and recommendations from this study will benefit individuals, clinicians, primary care managers, other healthcare leaders, and academia. Disseminating information from this study will include presenting the study findings at a Southern Arizona VA Health Care System research meeting and, upon request, to the VA community of practice or other interested healthcare groups involved in the care or oversight of military veteran patients with HF. Sharing study results with VA healthcare leaders may influence policy and resource recommendations for HF care. Informing VA primary care managers and providers about the study results may influence HF care planning decisions for individual patients.

Recommendations for Further Research

Healthcare leaders may extend the research from this study to examine the effective use of home telehealth to lower HF costs by reducing bed days of care. Future research may affect the population, limitations, delimitations, predictor variables of residence rurality and home telehealth enrollment, and the criterion variable of bed days of care for military veteran patients readmitted for HF. First, studying the population of military veteran patients diagnosed with HF that were admitted or not admitted would increase data about hospital avoidance, possibly reflecting less advanced HF or improved HF management. Second, including HF as a primary or secondary diagnosis would expand information about HF costs because patients are frequently readmitted for common comorbidities with HF as a secondary diagnosis (Castillo et al., 2017; Davis et al., 2017).

Third, expanding the predictor variable of home telehealth enrollment to home telehealth use by race, age, comorbidities, and HF severity might provide information about the frequency and duration of time subpopulations of patients used home telehealth. Guzman-Clark et al. (2020) recommended future strategies to improve HF management, including to expand knowledge about the variables of race, age, and adherence to HT use. Including a severity classification of the patient's HF condition (Guzman et al., 2021) may improve understanding of the benefit of home telehealth for patients identified with a specific stage of HF progression. Therefore, collecting data about home telehealth use, race, age, and severity of HF would inform future studies.

Fourth, calculating the distance from the patient's residence to the healthcare facility or clinic may provide more information about access to HF care than applying the rural or urban residence rurality classification. Measuring the distance to the VA clinic is an improved reflection of access to care because some VA healthcare facilities and clinics are in rural areas. Implementing these recommendations for future research would expand healthcare leaders' understanding of the impact of home telehealth on readmissions for HF, providing a framework to develop effective strategies to decrease HF readmissions and costs.

Reflections

The Walden University College of Management and Technology Doctor of Business Administration program has been challenging but rewarding. A difficult part of the doctoral study journey involved selecting a research question to address an applied business problem. In the concentration of health care management, several topics of recent innovations lacked adequate studies to conduct a literature review. Other topics interpreted as public health issues did not meet applied business problem criteria. Working in the healthcare industry provides daily insight into business principles for health care services in a dynamic and regulated environment with scarce resources.

Limiting interpretations to objective findings during the doctoral study process avoided biases from broad clinical and organizational experience.

Applied business problems in health care provide the impetus to address and partially mitigate some public health concerns by using technology. During the COVID-19 pandemic, the benefits of using home telehealth for HF care and management evolved to include minimizing infectious disease exposures in the community, supporting COVID-19 screening and testing (Guzman-Clark et al., 2020), and improving access to in-person care for chronic care management (Bowman et al., 2021). As health care advances, there is potential to further expand the use of home telehealth to improve health care access and quality of care for the right patient populations and circumstances.

The availability and abundance of large data sets hold promise as a data source for research (Goode et al., 2017; Harbaugh & Cooper, 2018). Experience gained by using a large national sample of routinely collected health data files to conduct an ex post facto correlational study included using SQL coding and Stata software for data analysis. Learning how to use these types of software required significant independent study and consultation with data analysts and statistical analysis experts. Decreasing biases in the current study included understanding the strengths and limitations of the data sets, using SQL and Stata software properly to ensure data validity, and objectively analyzing and interpreting those data. Delays during reviews, approvals, and technology disruptions required flexibility and persistence. Increasingly, select patient populations with HF may benefit from remote monitoring to reduce admissions and health care costs (Carbo et al., 2018; Guzman-Clark et al., 2020). The findings from the current study reinforced the need to increase awareness of the factors leading to effective home telehealth use for military veteran patients with HF.

Conclusion

The high costs of HF care during readmissions underscores the need to understand the variables related to bed days of care during readmissions. This quantitative ex post facto correlational study examined the relationship between residence rurality, home telehealth enrollment, and bed days of care for military veteran patients readmitted for HF. Underpinned in the behavioral model, this study involved total population sampling in collecting data from archival data files representing routinely collected health care of 1,081 military veteran patients readmitted for HF to any VA hospital across the United States.

Conducting the study extended the application of the behavioral model to explain the relationship between residence rurality, home telehealth enrollment, and bed days for care for military veteran patients with HF. The findings from this study provided an answer to the research question. The implications for positive social change include the potential to improve the health of military veteran patients with HF and enhance health care value, while decreasing the financial burden of HF care on VA hospitals by optimizing the use of home telehealth. Topics recommended for future research included expanding the population to military veteran patients with a diagnosis of HF, rather than only readmitted patients with HF, and examining the influence of race, age, comorbidities, and HF disease severity. Expanding the predictor variables to home telehealth use and mileage between the residence and the healthcare facility are additional topics recommended for future research.

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Appendix A: Permission From Theorist to Adapt Theoretical Model

From: Storm Morgan
Sent: Saturday, March 10, 2018 11:27 AM
To: randerse@ucla.edu <randerse@ucla.edu>
Cc: Storm Morgan <storm.morgan@waldenu.edu>
Subject: Seeking Permission to Adapt Behavioral Model for Doctoral Study

Ronald M. Andersen, PhD
Wasserman Professor Emeritus
UCLA Center for Health Policy Research
Professor of Health Services and Sociology
UCLA Fielding School of Public Health

Dear Dr. Andersen,
I am a doctoral student at Walden University pursuing a doctor of business administration degree with a specialization in healthcare management. I am contacting you to seek permission to adapt the behavioral model for health services use to underpin my study. The figure of the adapted theoretical model is attached and emphasizes the predictor and criterion variables in my study. My research question is: What is the relationship between residence rurality, home telehealth (HT) enrollment, and the bed days of care (BDOC) for veterans with heart failure (HF)? Should I receive written approval from you to underpin my study with the adapted behavioral model for health services use, I plan to acknowledge the approval in my study. Thank you for your consideration.

Sincerely,
Storm Morgan, MSN, RN, MBA
Evans, GA
Walden University
Doctor of Business Administration in Healthcare Management Candidate
storm.morgan@waldenu.edu

Note: The continued email correspondence with the theorist is on the following page.

Ron Andersen <randerse@ucla.edu>

Tue 3/13/2018 2:39 AM

Storm Morgan

Dear Storm,

You have my permission to adapt the Behavioral Model for your doctoral study. Best wishes for the successful completion of your study.

Ron Andersen

...

Storm Morgan

Tue 3/13/2018 8:18 AM

Ron Andersen <randerse@ucla.edu>

Dr. Andersen,

Thank you!

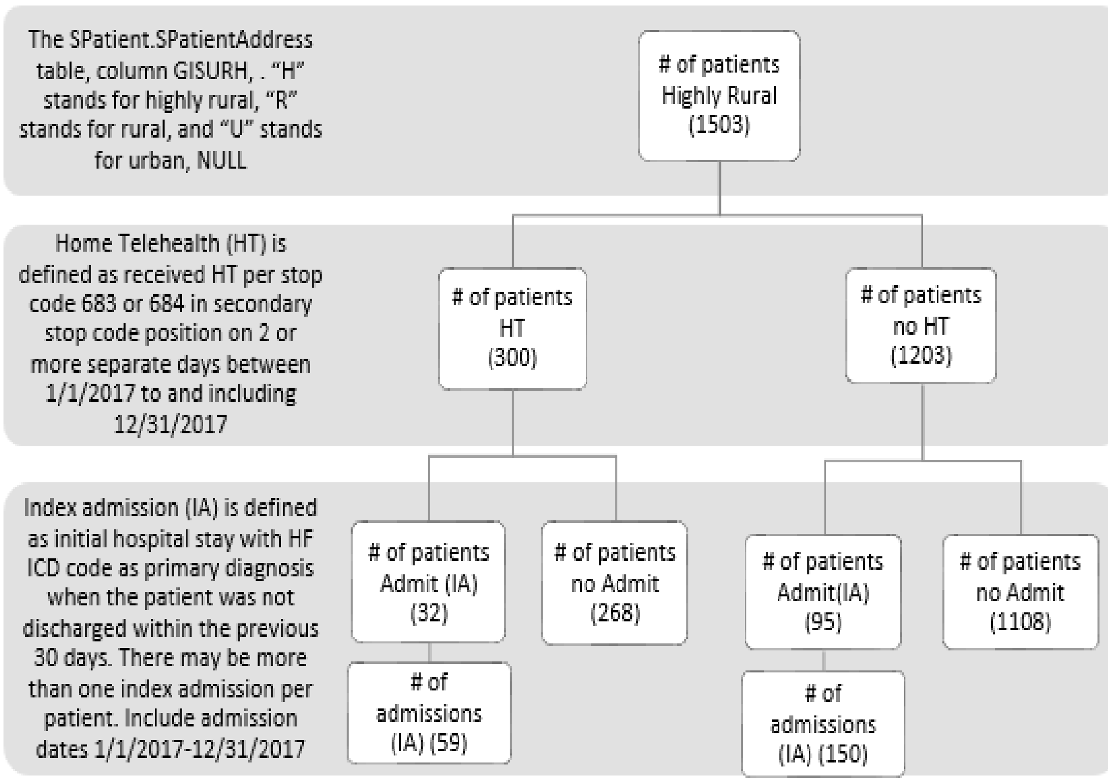
Storm Morgan

Note: The screen shots of email communications show permission granted by the original theorist to adapt the behavioral model for health services use to the study.

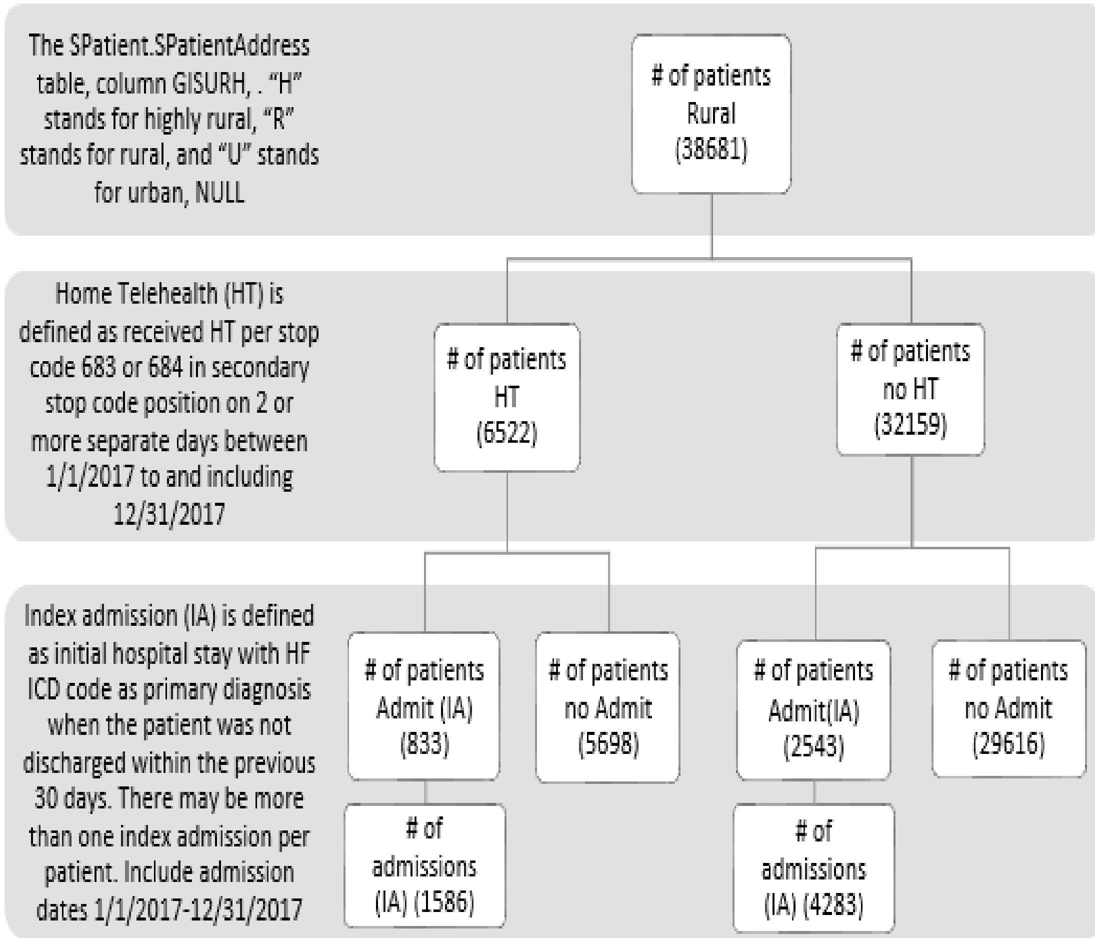
Appendix B: Department of Veterans Affairs Feasibility Report

Figure B1

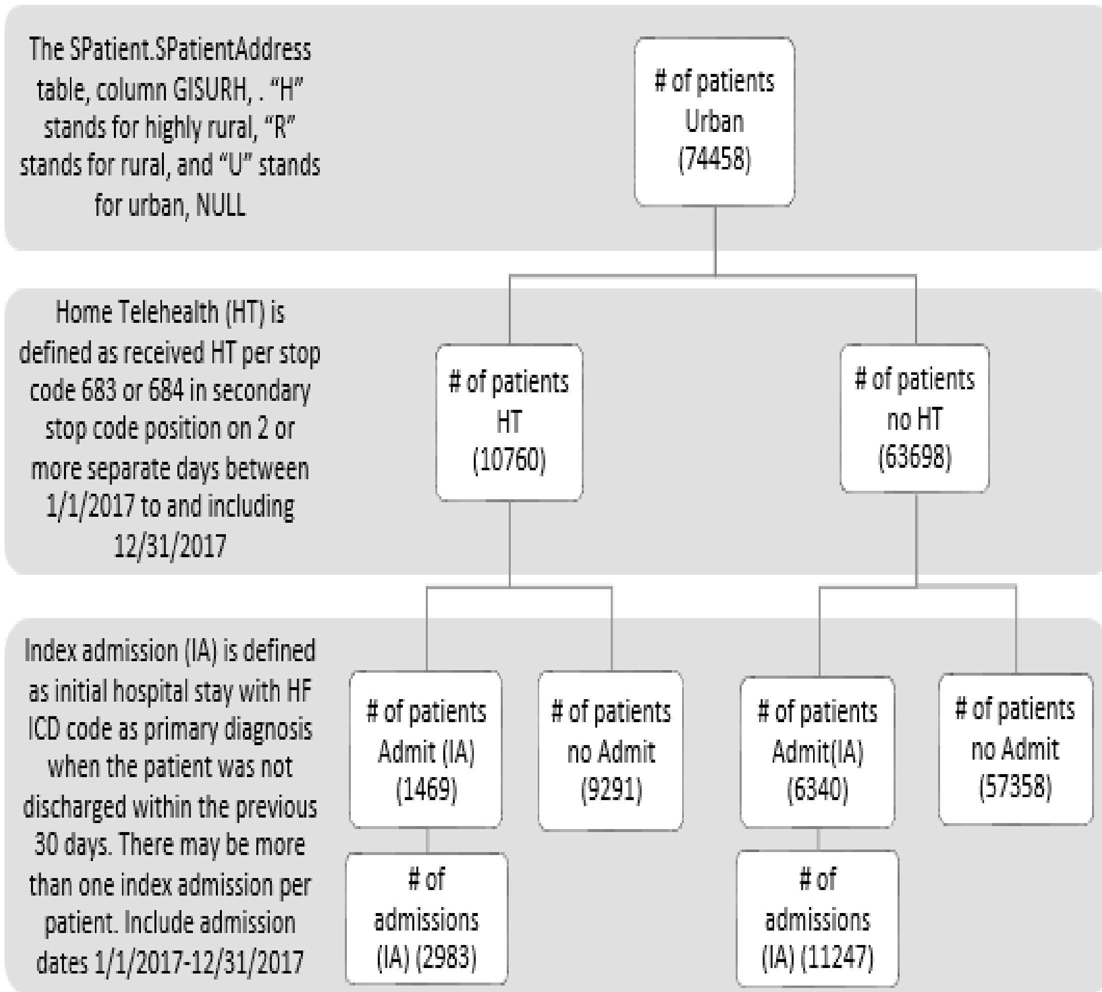
Funnel Analysis Diagram



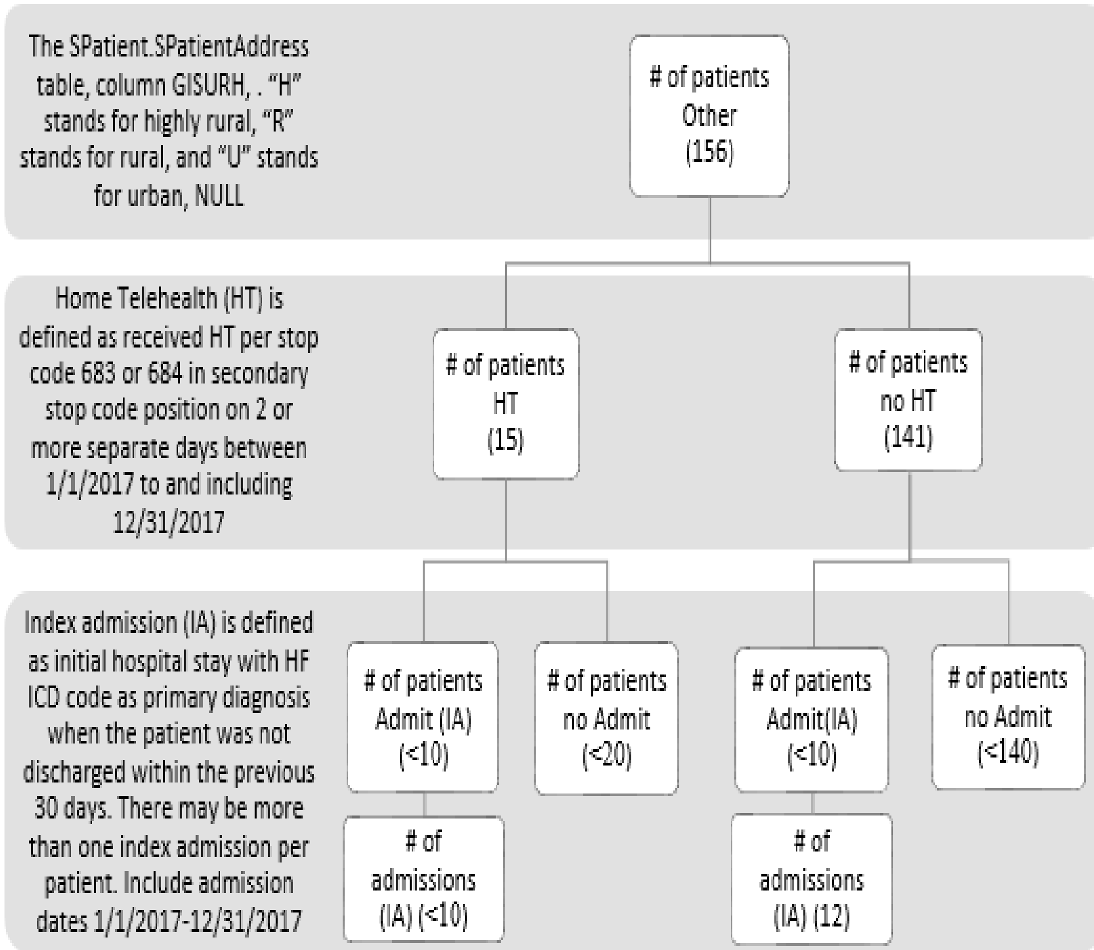
Note: The data source is the diagram section of the feasibility report developed by data experts at the VA Informatics and Computing Infrastructure. The data include the number of highly rural military veterans that received care for HF at a VA medical facility on or after January 1, 2017, through December 31, 2017, categorized by receiving or not receiving home telehealth, admitted or not admitted, and the number of admissions for HF. The continued funnel analysis diagram of the feasibility report is on the following page.



Note: The data source is the funnel analysis diagram section of the feasibility report developed by VA Informatics and Computing Infrastructure. The data include the number of rural military veterans that received care for HF at a VA medical facility on or after January 1 through December 31, 2017, categorized by receiving or not receiving home telehealth, admitted or not admitted, and the number of admissions for HF. The continued funnel analysis diagram of the feasibility report is on the following page.



Note: The data source is the funnel analysis diagram section of the feasibility report developed by VA Informatics and Computing Infrastructure. The data include the number of urban military veterans that received care for HF at a VA medical facility on or after January 1, 2017, through December 31, 2017, categorized by receiving or not receiving home telehealth, admitted or not admitted, and the number of admissions for HF. The continued funnel analysis diagram of the feasibility report is on the following page.



Note: The data source is the funnel analysis diagram section of the feasibility report developed by VA Informatics and Computing Infrastructure. The data include the number of military veterans not classified as highly rural, rural, or urban that received care for HF at a VA medical facility on or after January 1, 2017, through December 31, 2017, categorized by receiving or not receiving home telehealth, admitted or not admitted, and the number of admissions for HF. The feasibility report continues the following page.

Table B1

Funnel Analysis

	A	B	C	D
1		FEAS_Mogran_180702		
2		1. This is a funnel analysis. Numbers presented in column D are based on the number in the row above. For example, Row 6 will be less than or equal to the number in Row 5.		
3		**Criteria Definition**	**Query Definition**	**Number of distinct patients remaining**
4		**Inclusion criteria**		
5		Number of patients nationwide seen for Heart Failure at period of time 01.01.2017-12.31.2017 (ICD code used 2 or more times)	Number of patients had Outpatient and Inpantient visits between 01.01.2017-12.31.2017 with HF ICDcode used for more than 2 times. The test patients are not included.	114,798
6		**1. Patients from highly rural area**	Use GISURH from [CDWWork].[Spatient].[SPatientAddress] to identified the patient rural area. The value = H is "Highly Rural".	1,503
7		1.1. Had Home Telehealth (HT) (per stop code 683 or 684 in secondary stop code position) 2 or more separate days between 1/1/2017 to and including 12/31/2017	Patients had 2 or more outpatient visits with 683 or 684 stop codes during 01.01.2017 to 12.31.2017.	300
8		1.1.1. Had hospital stay with HF ICD code as primary diagnosis when the patient was not discharged within the previous 30 days. There may be more than one index admission per patient. Include admission dates	The patients from previous line had HF as primary diagnosis code (ordinal number is 0 or the first number in the same stays) for the inpatient visits and the previous discharged date is not within 30 days from the admitted date.	32
9		1.1.1.1. Number of admissions	Use count of the admitted date during 01.01.2017-12.31.2017 with the previous discharged date not within 30 days for each patients from previous line.	59
10		1.1.2. Did not admit to the hospital for HF	The patients from previous line had never had HF as primary diagnosis code for inpatient visits during 01.01.2017 - 12.31.2017	268

Note: This section of the funnel analysis report, developed by data experts in the VA Informatics and Computing Infrastructure, includes admission data for HF at any VA hospital by highly rural residence and home telehealth enrollment on or after January 1, 2017, through December 31, 2017. The continued funnel analysis of the feasibility report for preresearch is on the following page.

11	1.2. Did not have HT at period of time 1/1/2017 to and including 12/31/2017	Patietns had less than 2 outpatient visits with 683 or 684 stop codes during 01.01.2017 to 12.31.2017	1,203
12	1.2.1. Had hospital stay with HF ICD code as primary diagnosis when the patient was not discharged within the previous 30 days. There may be more than one index admission per patient. Include admission dates	The patients from previous line had HF as primary diagnosis code (ordinal number is 0 or the first number in the same stays) for the inpatient visits and the previous discharged date is not within 30 days from the admitted date.	95
13	1.2.1.1. Number of admissions	Use count of the admitted date during 01.01.2017-12.31.2017 with the previous discharged date not within 30 days for each patients from previous line.	150
14	1.2.2. Did not admit to the hospital for HF	The patients from previous line had never had HF as primary diagnosis code for inpatient visits during 01.01.2017 - 12.31.2017	1,108
15	**2. Patients from rural area**	Use GISURH from [CDWWork].[Spatient].[SPatientAddress] to identified the patient rural area. The value = R is "Rural".	38,681
16	2.1. Had Home Telehealth (HT) (per stop code 683 or 684 in secondary stop code position) 2 or more separate days between 1/1/2017 to and including 12/31/2017	Patients had 2 or more outpatient visits with 683 or 684 stop codes during 01.01.2017 to 12.31.2017.	6,522
17	2.1.1. Had hospital stay with HF ICD code as primary diagnosis when the patient was not discharged within the previous 30 days. There may be more than one index admission per patient. Include admission dates	The patients from previous line had HF as primary diagnosis code (ordinal number is 0 or the first number in the same stays) for the inpatient visits and the previous discharged date is not within 30 days from the admitted date.	833
18	2.1.1.1. Number of admissions	Use count of the admitted date during 01.01.2017-12.31.2017 with the previous discharged date not within 30 days for each patients from previous line.	1,586
19	2.1.2. Did not admit to the hospital for HF	The patients from previous line had never had HF as primary diagnosis code for inpatient visits during 01.01.2017 - 12.31.2017	5,689
20	2.2. Did not have HT at period of time 1/1/2017 to and including 12/31/2017	Patietns had less than 2 outpatient visits with 683 or 684 stop codes during 01.01.2017 to 12.31.2017	32,159
21	2.2.1. Had hospital stay with HF ICD code as primary diagnosis when the patient was not discharged within the previous 30 days. There may be more than one index admission per patient. Include admission dates	The patients from previous line had HF as primary diagnosis code (ordinal number is 0 or the first number in the same stays) for the inpatient visits and the previous discharged date is not within 30 days from the admitted date.	2,543

Note: This section of the funnel analysis report, developed by data experts in the VA Informatics and Computing Infrastructure, includes admission data for HF at any VA hospital by highly rural or rural residence and home telehealth enrollment on or after January 1, 2017, through December 31, 2017. The continued funnel analysis of the feasibility report for preresearch is on the following page.

22	2.2.1.1. Number of admissions	Use count of the admitted date during 01.01.2017-12.31.2017 with the previous discharged date not within 30 days for each patients from previous line.	4,283
23	2.2.2. Did not admit to the hospital for HF	The patients from previous line had never had HF as primary diagnosis code for inpatient visits during 01.01.2017 - 12.31.2017	29,616
24	**3. Patients from urban area**	Use GISURH from [CDWWork].[Spatient].[SPatientAddress] to identified the patient rural area. The value = U is "Urban".	74,458
25	3.1. Had Home Telehealth (HT) (per stop code 683 or 684 in secondary stop code position) 2 or more separate days between 1/1/2017 to and including 12/31/2017	Patients had 2 or more outpatient visits with 683 or 684 stop codes during 01.01.2017 to 12.31.2017.	10,760
26	3.1.1. Had hospital stay with HF ICD code as primary diagnosis when the patient was not discharged within the previous 30 days. There may be more than one index admission per patient. Include admission dates	The patients from previous line had HF as primary diagnosis code (ordinal number is 0 or the first number in the same stays) for the inpatient visits and the previous discharged date is not within 30 days from the admitted date.	1,469
27	3.1.1.1. Number of admissions	Use count of the admitted date during 01.01.2017-12.31.2017 with the previous discharged date not within 30 days for each patients from previous line.	2,983
28	3.1.2. Did not admit to the hospital for HF	The patients from previous line had never had HF as primary diagnosis code for inpatient visits during 01.01.2017 - 12.31.2017	9,291
29	3.2. Did not have HT at period of time 1/1/2017 to and including 12/31/2017	Patietns had less than 2 outpatient visits with 683 or 684 stop codes during 01.01.2017 to 12.31.2017	63,698
30	3.2.1. Had hospital stay with HF ICD code as primary diagnosis when the patient was not discharged within the previous 30 days. There may be more than one index admission per patient. Include admission dates	The patients from previous line had HF as primary diagnosis code (ordinal number is 0 or the first number in the same stays) for the inpatient visits and the previous discharged date is not within 30 days from the admitted date.	6,340
31	3.2.1.1. Number of admissions	Use count of the admitted date during 01.01.2017-12.31.2017 with the previous discharged date not within 30 days for each patients from previous line.	11,247
32	3.2.2. Did not admit to the hospital for HF	The patients from previous line had never had HF as primary diagnosis code for inpatient visits during 01.01.2017 - 12.31.2017	57,358

Note: This section of the funnel analysis report, developed by data experts in the VA Informatics and Computing Infrastructure, includes admission data for HF at any VA hospital by rural or urban residence and home telehealth enrollment on or after January 1, 2017, through December 31, 2017. The continued funnel analysis of the feasibility report for preresearch is on the following page.

33	**4. Patients from other (unknown) area**	Use GISURH from [CDWWork].[Spatient].[SPatientAddress] to identified the patient rural area. There is no value (NULL). (Set the value to N for easier query	156
34	4.1. Had Home Telehealth (HT) (per stop code 683 or 684 in secondary stop code position) 2 or more separate days between 1/1/2017 to and including 12/31/2017	Patients had 2 or more outpatient visits with 683 or 684 stop codes during 01.01.2017 to 12.31.2017.	15
35	4.1.1. Had hospital stay with HF ICD code as primary diagnosis when the patient was not discharged within the previous 30 days. There may be more than one index admission per patient. Include admission dates	The patients from previous line had HF as primary diagnosis code (ordinal number is 0 or the first number in the same stays) for the inpatient visits and the previous discharged date is not within 30 days from the admitted date.	<10
36	4.1.1.1. Number of admissions	Use count of the admitted date during 01.01.2017-12.31.2017 with the previous discharged date not within 30 days for each patients from previous line.	<10
37	4.1.2. Did not admit to the hospital for HF	The patients from previous line had never had HF as primary diagnosis code for inpatient visits during 01.01.2017 - 12.31.2017	<20
38	4.2. Did not have HT at period of time 1/1/2017 to and including 12/31/2017	Patietns had less than 2 outpatient visits with 683 or 684 stop codes during 01.01.2017 to 12.31.2017	141
39	4.2.1. Had hospital stay with HF ICD code as primary diagnosis when the patient was not discharged within the previous 30 days. There may be more than one index admission per patient. Include admission dates	The patients from previous line had HF as primary diagnosis code (ordinal number is 0 or the first number in the same stays) for the inpatient visits and the previous discharged date is not within 30 days from the admitted date.	<10
40	4.2.1.1. Number of admissions	Use count of the admitted date during 01.01.2017-12.31.2017 with the previous discharged date not within 30 days for each patients from previous line.	12
41	4.2.2. Did not admit to the hospital for HF	The patients from previous line had never had HF as primary diagnosis code for inpatient visits during 01.01.2017 - 12.31.2017	<140

Note: This section of the funnel analysis report, developed by data experts in the VA Informatics and Computing Infrastructure, includes admission data for HF at any VA hospital by urban or unknown residence and home telehealth enrollment on or after January 1, 2017, through December 31, 2017. The funnel analysis diagram of the feasibility report is on the following page.

Table B2

ICD-10 Codes for Heart Failure

ICD-10 Code Number	ICD-10 Code Description
I50.1	Left ventricular failure, unspecified
I50.2x	Systolic (congestive) HF
I50.3x	Diastolic (congestive) HF
I50.4x	Combined systolic (congestive) and diastolic (congestive) HF
I50.9	HF, unspecified

Note: The data source is the International Classification of Disease (ICD)-10 section of the feasibility report developed by data experts at the VA Informatics and Computing Infrastructure. The data include the ICD-10 code number with the associated diagnosis for HF.

Table B3

Stop Codes for Home Telehealth

Stop Code Number	Stop Code Description
683	Home telehealth monitor only/nonvideo (non-count)
684	Home telehealth intervention/nonvideo

Note: The data source for VA home telehealth stop codes is the Stop Codes section of the feasibility report developed by data experts at the VA Informatics and Computing Infrastructure. The data include the VA stop code numbers with stop code descriptions for home telehealth.

Appendix C: Communication With VINCI Researcher About Data Collection

From: Efimova, Olga V. <Olga.Efimova@va.gov>
Sent: Tuesday, September 15, 2020 5:01 PM
To: Morgan, Storm L. <Storm.Morgan@va.gov>
Cc: VINCI Services <VINCIServices@va.gov>
Subject: RE: Ticket 36293 Open --> Questions about Unique Identifiers in Data Pull...

Hello Storm,

Following our phone conversation.

1. You should be part of DART application to get access to the data
2. Data base will contain table for the cohort with identifiers (SID – site specific, ICN – VA specific, can be real SSN or/and scrambled SSN) and views for the domains/data sources selected in you DART application and related to the cohort
3. Research folder will be created at P share drive for your project that you can use to store you data, code, etc.
4. You can select patients with heart failure by ICD codes and check for the telehealth visits by using stop codes for the telehealth. This information is available in outpatient domain. If you will have additional information from other external data sources, you can incorporate it to your data base

I am sending you links to the DART web site
http://vaww.vhadataportal.med.va.gov/DataAccess/DARTRequestProcess.aspx#Resources
VINCI central web site (to check application, information about data sources, etc.)
https://vaww.vinci.med.va.gov/vincicentral/

Let me know, if you have question or need assistance

Regards,
VINCI Services,
Olga

Olga Efimova, MD, PhD
Research Health Science Specialist
VA Informatics and Computing Infrastructure
500 Foothill Drive
Salt Lake City, UT 84108
(801)-582-1565 ext. 3937
(801) 703-7311 cell
olga.efimova@va.gov

Note: The screenshot shows email communications with a VA research expert to clarify data collection steps. The continued email correspondence about the data collection process is on the following page.

From: VINCI Program <VINCI@va.gov>
Sent: Tuesday, September 15, 2020 8:57 AM
To: Efimova, Olga V. <Olga.Efimova@va.gov>
Subject: Ticket 36293 Open --> Questions about Unique Identifiers in Data Pull...

Client

Name	Storm Morgan <storm.morgan@va.gov>
Phone	706-993-8915
Address	

Ticket Info

Ticket No.	36293
Report Date	9/15/20 9:54 am
Due Date	
Reporter	Joe Cleland <joseph.cleland@va.gov>
Tech	Olga Efimova <olga.efimova@va.gov>
Priority	Low
Status	Open
Request Type	Data Services > Feasibility
Subject	Questions about Unique Identifiers in Data Pulled for Doctoral Study

Request Detail

From: Morgan, Storm L.
Sent: Monday, September 14, 2020 4:06 PM
To: VINCI Program <VINCI@va.gov>
Subject: FW: Questions about Unique Identifiers in Data Pulled for Doctoral Study

I am a VA employee at VACO and planning to conduct my doctoral study at VA. I plan to examine the relationship between residence rurality, home telehealth enrollment, and bed days of care for veterans readmitted within 30 days for heart failure during the calendar year 2017. I plan to use national data. I attached the feasibility report prepared for me that I used to consider the adequacy of the sample size. I listed several questions below:
• How will the data look that is set up for me to use in the VINCI workspace? I understand there will be an original folder retained that includes all unique identifiers and a second folder for me to access.
• How will the data be presented in the second folder? Will that data include unique identifiers?
• Will I likely need a data use agreement with the Office of Connected Care/Telehealth Services (after IRB approval) to match home telehealth enrollment during the timeframe the patient is readmitted for heart failure?
• Do you recommend I consider other questions?

I appreciate assistance you provide to clarify the process as I need this information to finalize my proposal, and then apply for IRB approval.

Regards,
Storm

Storm L. Morgan, MSN, RN, MBA

Note: The screenshots depict email and telephone communications with a VA Informatics and Computing Infrastructure (VINCI) expert to clarify data collection steps.

Appendix D: Preparation and Data Collection Process

As this ex post facto correlational study includes the use of health data collected as part of routine clinical care, there are no potential physical risks to research subjects but there may be risks associated with a loss of privacy. The following steps describe the data collection process and the safeguards for protecting patient privacy during the study at the VA.

Preparatory to Research

- Complete Collaborative Institutional Training Institute Program Course.
- Complete additional training required for VA researchers.
- Review the use of structured query language (SQL) and Stata software, the programs used on the VINCI workspace for data sorting, cleaning, and statistical analysis.
- After approval of the proposal by Walden University, include data from VA preresearch feasibility report to complete and submit VA Form F309: Determination of Proposal Oversight used by VA to categorize the proposal as research, human subject research, quality assurance, or quality improvement.
- Submit Walden University Form A: First Step of Ethics Review (2019). Include the category of research as determined by VA.
- Submit the additional IRB application forms per instructions from Walden University and VA.

Note: The continued data collection process steps are on the following page.

Data Collection Steps After IRB Approval

- Submit a data use agreement application through the Data Access Request Tracker (DART) to the National Data System to request assistance from a VINCI manager and access to real social security numbers and other data from the corporate data warehouse (CDW). The CDW is in the VA Austin Information Technology Center (AITC). Select views in SQL for the domains and data sources that are consistent with the cohort, based on inclusion and exclusion criteria in the study.
- The VINCI manager will create a research folder on the shared P drive on the secure VA research workspace and set up views that are specific to the research project. Data in views is determined by selections approved in the DART application. Access to the research folder is limited to the VINCI staff and researchers identified in the approved IRB and DART applications.
- Use SQL to retrieve authorized CDW data via views. Copy and paste extracted data to two identical Microsoft Excel 2016 (Excel) tables. Save the tables to the research project folder on the shared P drive, leaving one table unchanged for historical reference and one table to use for sorting and cleaning data. Each row in Excel includes one patient's name and data from corresponding columns that are specific to variables in the study for that patient. Columns include the real social security number; other VA identifiers; dates of admissions and discharges for HF,

Note: The continued data collection process steps are on the following page.

home telehealth use, birth, and death, if applicable; HF diagnosis and ICD-10 code; home telehealth stop code; discharge location and type; rurality category; age; gender; race; and ethnicity. Unique identifiers include the patient's name; real social security number; zip code; and dates of birth, and death, if applicable.

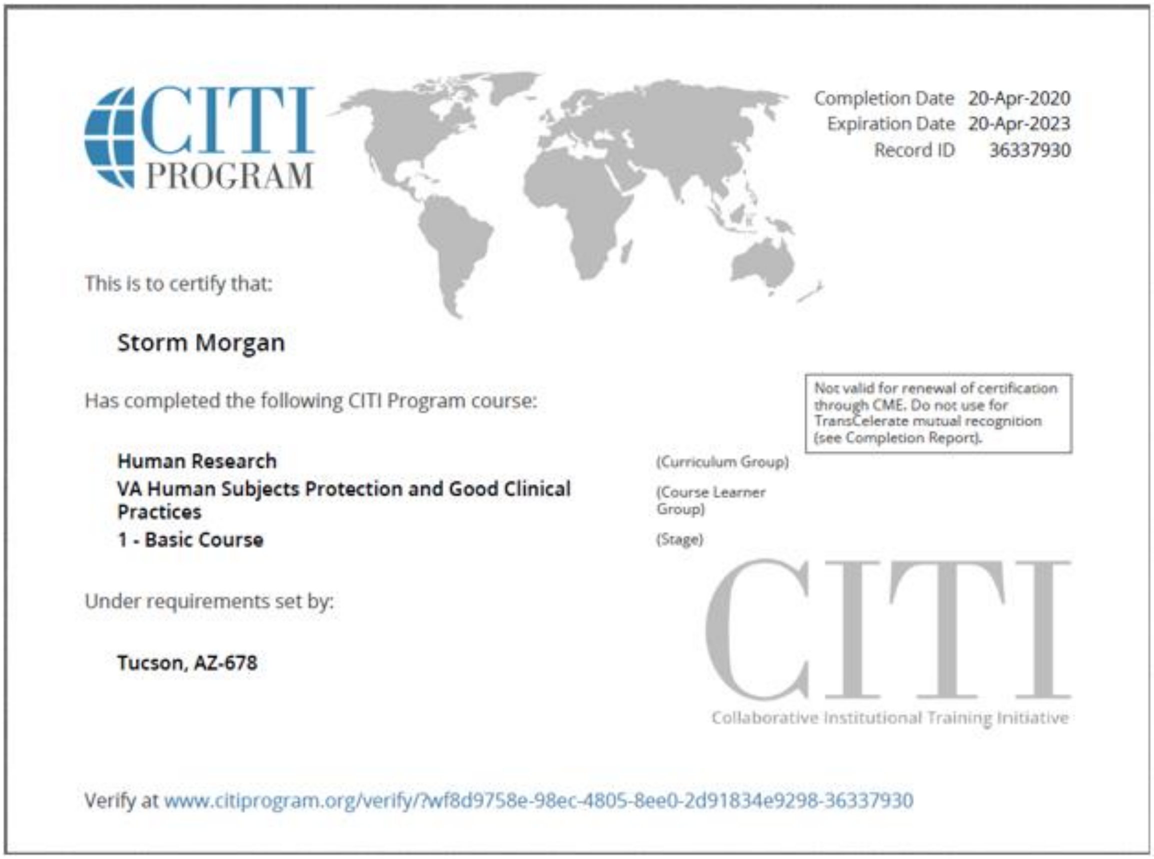
- Consult the VINCI manager for questions about the data retrieval process, data accuracy, or concerns about missing data as alternate data sources may be available.
- Perform data sorting, cleaning, and merging. Use the unique identifiers of patient name and real social security number to match data in data sets during the sorting and merging processes.
- In the final data set before data analysis, begin the process to de-identify the data set by adding a column with a new identifier that includes a letter corresponding with the first letter of the patient's last name, followed by a sequential number listed according to alphabetical order of the patient's last name. For example, C-3 depicts the third patient listed alphabetically with a last name beginning with the letter C. Save one table with the patient's name, prior columns of data, and the new identifier for historical reference.
- De-identify the second table by removing the unique identifiers, leaving the new patient identifier. Use the de-identified table for data analysis.

Note: The continued data collection process steps are on the following page.

Data Analysis

- Use Stata software to statistically analyze the de-identified data on the VINCI workspace
- Data will remain on the VINCI project servers and only aggregate data without unique identifiers or protected health information may be transferred from VINCI for purposes of manuscript preparation.

Appendix E: Collaborative Institutional Training Institute Program Course



CITI PROGRAM

Completion Date 20-Apr-2020
Expiration Date 20-Apr-2023
Record ID 36337930

This is to certify that:

Storm Morgan

Has completed the following CITI Program course:

Not valid for renewal of certification through CME. Do not use for TransCelerate mutual recognition (see Completion Report).

Human Research	(Curriculum Group)
VA Human Subjects Protection and Good Clinical Practices	(Course Learner Group)
1 - Basic Course	(Stage)

Under requirements set by:

Tucson, AZ-678

CITI
Collaborative Institutional Training Initiative

Verify at www.citiprogram.org/verify/?wf8d9758e-98ec-4805-8ee0-2d91834e9298-36337930

Appendix F: Data Elements and Data Sources

	Unique Identifier		Inclusion Criteria			
	Name	Social Security Number	ICD-10 codes 150.1, 150.2x, 150.3x, 150.4x, 150.9 to identify patients with a HF diagnosis	Dates of admission/ readmission for HF between 1/1/2017, and 1/31/2018	Dates of discharge for HF hospitalization from 1/1/17, to 2/25/18	Admission and discharge dates for HF to calculate readmission within 30 days from index admission. Patients may have several admissions.
Data Source	MVI, Patient, Spatient domain, Enroll-ment (ADR)	MVI, Patient, Spatient domain, Enroll-ment (ADR)	IP, OP	IP	IP	IP (determined from admission data and whether another admission [readmission] took place within 30 days of discharge)

	Exclusion Criteria			Variables			
	Dates of death within 30 days from discharge from index admission or during readmission, if applicable	Dates of discharge after readmission exceeding 25 days (becomes long term stay after 25 days)	Discharge location (exclude patients not discharged home)	Bed days of care (length of stay) for readmissions (based on dates of readmission and discharge from that readmission)	Zip code (for rurality if category is missing)	Rurality (missing, rural, highly rural, urban)	Clinic stop codes 683 & 684 for Home Tele-health
Data Source	MVI, Patient, Spatient domain, Enrollment (ADR)	IP (from readmission data and whether duration of readmission exceeded 25 days)	IP	IP (from readmission data. Counted BDOC from 1-25 days and whether duration of readmission exceeded 25 days)	MVI, Patient, Spatient domain, Enroll-ment (ADR)	GISURH field in [CDWWork]. [Spatient]. [SPatient Address]	OP

Note: The table shows data elements for collection and analysis identified in the study and the data sources within the VA corporate data warehouse. The continued data table is on the following page. HF= heart failure, IP = inpatient, OP = outpatient.

	Demographics			
	Race (Black or African American, Native Hawaiian or Pacific Islander, White, more than one race, declined to answer, unknown by patient	Ethnicity (Hispanic or Latino, not-Hispanic or Latino; White)	Gender (female, male)	Date of birth (for age)
Data Source	MVI, Patient, Spatient domain, Enrollment (ADR)	MVI, Patient, Spatient domain, Enrollment (ADR)	MVI, Patient, Spatient domain, Enrollment (ADR)	MVI, Patient, Spatient domain, Enrollment (ADR)

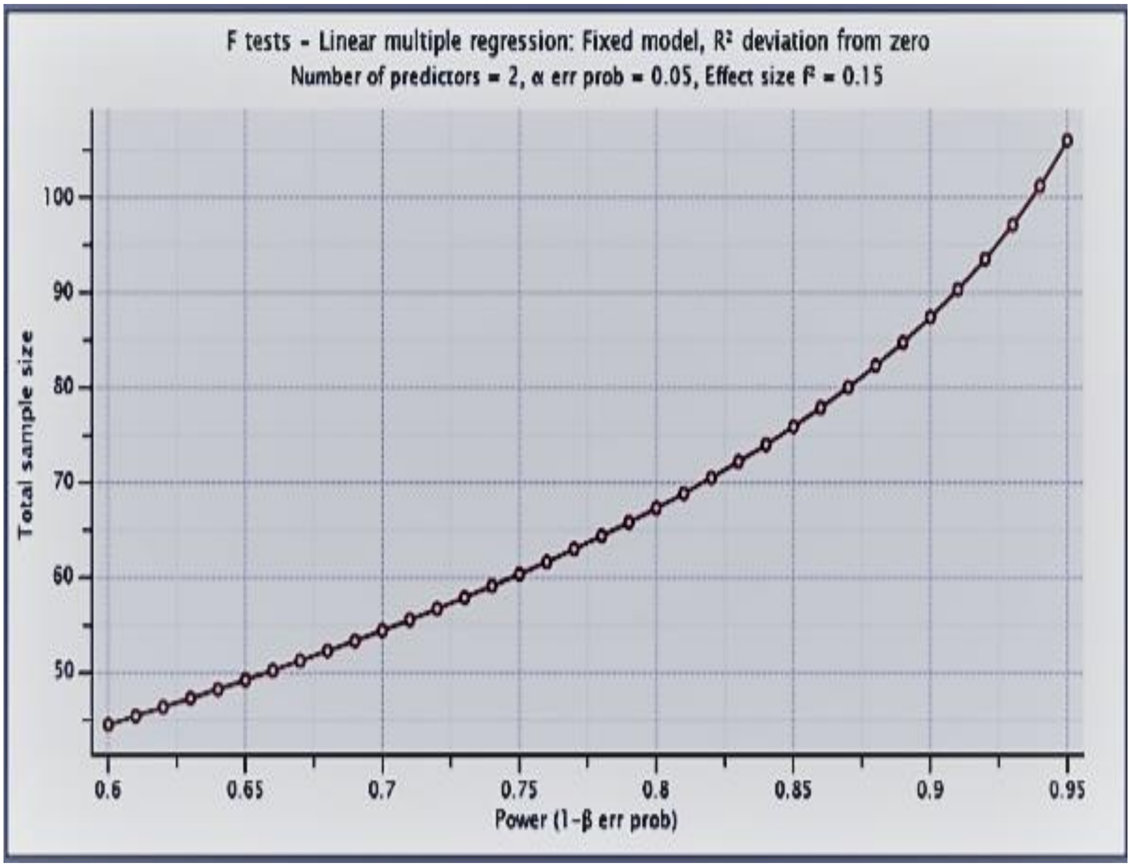
Appendix G: Data Cleaning Procedure

1.	Start with first data pull of patients admitted for HF to any VA hospital in the United States from 01012017-12312017 (see MultiAdmitsNOTcleaned data set)	***n***
	Total: Row label- count of patient name	21,078
2.	Remove single admissions (see SingleAdmissions =0, 2 or more admissions = 1). 0 = number of patients with single admissions for principal diagnosis of HF	11,327
	1 = number of patients with 2 or more admissions for principal diagnosis of HF (see Raw Original Data)	9,751
	Total, number of readmissions within 30 days of index admission- after exclusions removed (see FinalCleanedCopy)	**1,081**
	Data Cleaning Details	
3.	See MultiAdmitsNOTcleaned data set to identify readmissions within 30 days. Data cleaning shown in DataCleanedV1, readmissions within 30 days highlighted in blue.	
4.	Remove rows with missing or inconsistent data admission or discharge data	4
5.	Merge rows when there is more than one row for the same patient and the discharge date on one row is within 1 hour of the admission date on a separate row. This will avoid counting intrafacility transfers as separate admissions.	73
6.	Highlight and remove rows when discharge disposition is other than regular discharge to home (Disposition 1) because other dispositions may affect the bed days of care (BDOC). Note: Disposition list description published by The Joint Commission (TJC) is at https://manual.jointcommission.org/releases/TJC2018B1/DataElem0537. Disposition 8 on TJC site is not on the VA list	
	Disposition type: 1. Home, 2. Hospice-home, 3. Hospice-healthcare facility, 4. Acute care facility, 5. Other healthcare facility, 6. Expired, 7. Left AMA, 8. Null. Note: some rows excluded for other reasons.	
7.	Remove rows with deceased patients that expired during readmission because that would skew the BDOC data. Note: separate list from dispositions.	2

Note: The continued table is on the following page.

8.	Calculate BDOC. Length of stay = date of discharge - date of admission. Exclude admissions and readmissions that do not meet acute stay criteria and highlight in red, comprising rows with same admission and discharge date (*n* = 16) or BDOC exceeding 25 days (*n* = 19).	35
9.	Sort patients by residence rurality as 1= rural (R, *n* = 279) + highly rural (H, *n* = 10), and 2 = urban (U, *n* = 803). Rural and highly rural are merged for the predictor variable because the highly rural count is too small to be statistically significant.	
10.	Add home telehealth enrollment. Yes if 2 HT encounters within 90 days prior to readmission; No if there were not 2 HT encounters or if HT is not within 90 days prior to readmission (see separate table for home telehealth). Add final list of home telehealth enrollment to main table.	
11.	Sort by gender, race, ethnicity, and ICD-10 code for descriptive statistics. Gender 1= female (*n* = 18), 2 = male (*n* = 1063). Race: 1 = American Indian or Alaskan Native (*n* = 7), 2 = Black or African American (*n* = 304), 3 = Native Hawaiian or Pacific Islander (*n* = 5), 4 = White (*n* = 708), 5 = More than one race selected (*n* = 4), 6 = Declined to answer (*n* = 41), 7 = Unknown by patient (*n* = 7) 8 = Missing (*n* = 5). Ethnicity. There are 2 separate data pulls for ethnicity to include broad categories and Hispanic/Latino versus not Hispanic/Latino. Ethnicity column- 1 = Declined to answer (*n* = 23), 2 = Hispanic or Latino (*n* = 45), 3 = Not Hispanic or Latino (*n* = 1003), 4 = Unknown by patient (*n* = 11)	
12.	Add a new column to identify patients without disclosing unique identifying information and then remove unique identifiers (see Appendix D). The table without unique identifiers was used for data analysis.	

Appendix H: Power Analysis



Note: Graphical depiction of power analysis with sample size requirements of 3.1: Tests readmissions for HF. Adapted from "Statistical Power Analysis Using G*Power 3.1: Tests for Correlation and Regression Analyses" by F. Faul, E. Erdfelder, A. Buchner, & A.-G., Lang, 2009, *Behavior Research Methods, 41*, p. 1159.

Appendix I: Permission to Conduct Prerequest Steps

Storm Morgan
Fri 1/12/2018 4:34 PM
IRB

Veterans Health Administrati...
15 KB

Dear IRB Representative,
I plan to conduct a quantitative ex post facto study at the Veterans Health Administration (VHA). My research question is: RQ1: What is the relationship between residence rurality, home telehealth enrollment, and the bed days of care for veterans with heart failure? I understand I will apply for IRB approval at VHA after I receive IRB approval at Walden University. The VHA has a "Preparatory to Research" process (description is attached), allowed by a provision of the HIPAA Privacy Rule for the researcher to determine feasibility and practicality of conducting the research. In my case, I would request a VHA analyst to pull data regarding the number of heart failure patients admitted during a specified time frame, the number of patients readmitted within 30 days from the hospital discharge, the number of patients with a rural versus urban residence status, and the number of patients enrolled in home telehealth for heart failure. I do not plan to review individual patient's electronic health records, but the"Preparatory to Research" approval allows viewing of individual health records if it is necessary during the preresearch phase. Also, the VHA does not guarantee the deidentification of any records, even when the key identifies, such as name, social security number, and date of birth are removed. Without conducting the preresearch through the VHA, I will not have access to accurate data needed to determine the sample size, since the data is not available to the public. My question is whether requesting VHA to pull data as outlined in the VHA "Preparatory to Research" process is an acceptable, according to Walden University's IRB requirements. I will not proceed with the preresearch inquiry until I receive your response. Thank you for your consideration.

Sincerely,
Storm Morgan
DBA Candidate
A00308910

Note: The continued email correspondence is on the following page.

IRB <irb@mail.waldenu.edu>
Tue 1/16/2018 7:29 PM
Storm Morgan

Hi Storm,

Yes, it is acceptable to do any 'pre-request' steps prior to Walden IRB approval. If the VHA determines you are not far enough along in your program to begin that process, that would be up to them. You may not analyze any data until after you have received Walden IRB approval though.

Sincerely,
Libby Munson
Research Ethics Support Specialist
Office of Research Ethics and Compliance
Walden University
100 Washington Avenue South, Suite 900
Minneapolis, MN 55401
Email: irb@mail.waldenu.edu
Phone: (612) 312-1283
Fax: (626) 605-0472

Information about the Walden University Institutional Review Board, including instructions for application, may be found at this link: http://academicguides.waldenu.edu/researchcenter/orec

Storm Morgan
Wed 1/17/2018 5:23 PM
IRB; Robert J. Hockin

I understand I am not to analyze data received from the VA for pre-research until after Walden IRB approval. Thank you.

Storm Morgan

...

Note: The screenshots of email communications with a representative of the Walden University Office of Research Ethics and Compliance show the request and approval to contact the VA to conduct pre-research for the purpose of gaining information needed to determine the sample size for the doctoral study.

Appendix J: Data Retention and Destruction Process

FW: Ticket 39497 Open --> language for destruction of research data in VI...

FW: Ticket 39497 Open --> language for destruction of research data in VI...

Morgan, Storm L <storm.morgan@va.gov> 5:24 PM

To storm.morgan@comcast.net

Reply Forward Delete

ML

From: Guzman, Jenice Ria S. <JeniceRia.Guzman@va.gov>
Sent: Tuesday, April 27, 2021 11:52 AM
To: Trautman, Timothy N. <Timothy.Trautman@va.gov>
Cc: Morgan, Storm L. <Storm.Morgan@va.gov>
Subject: RE: Ticket 39497 Open --> language for destruction of research data in VI...

Thanks - hope you are feeling better!.... Is this data destruction plan in any of the VINCI documentation? (in case IRB asks - otherwise, I will just reference this email. 😊)

From: Trautman, Timothy N. <Timothy.Trautman@va.gov>
Sent: Tuesday, April 27, 2021 8:49 AM
To: Guzman, Jenice Ria S. <JeniceRia.Guzman@va.gov>
Subject: FW: Ticket 39497 Open --> language for destruction of research data in VI...

Hi Jenice,
Sorry for that late reply as I was out sick. As for data retention and destruction, when a study is closed, we archive their data to tape and store for 6 years. When 6 years have elapsed, the tape is written over thus destroying the data. Let me know if you have questions.
My best,
Tim N. Trautman
Research Health Science Specialist & DART Program Manager
VA Informatics and Computing Infrastructure (VINCI)
VA Salt Lake City Health Care System/Salt Lake OI&T Field Office
550 Foothill Drive, Suite 400, Salt Lake City, UT 84113
timothy.trautman@va.gov

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Note: The continued email correspondence is on the following page.

FW: Ticket 39497 Open --> language for destruction of research data in VI...

From: VINCI Program <VINCI@va.gov>
Sent: Monday, April 26, 2021 10:25 AM
To: Trautman, Timothy N. <Timothy.Trautman@va.gov>
Subject: Ticket 39497 Open --> language for destruction of research data in VI...

Client

Name	Jenice Ria Guzman <JeniceRia.Guzman@va.gov>
Phone	VA Cell 520-269-1576
Address	
Domain	VHA18

Ticket Info

Ticket No.	39497
Report Date	4/26/21 11:23 am
Due Date	
Reporter	Joe Cleland <joseph.cleland@va.gov>
Tech	
Priority	Low
Status	Open
Request Type	Concierge > DART
Subject	language for destruction of research data in VINCI workspace/server
Request Detail	

From: Guzman, Jenice Ria S. <JeniceRia.Guzman@va.gov>
Sent: Friday, April 23, 2021 4:37 PM
To: VINCI Program <VINCI@va.gov>
Subject: language for destruction of research data in VINCI workspace/server

Hello - I'm trying to complete an IRB application. I plan on using VINCI workspace to store/analyze my data. Per the Jan 2020 VA Records Control Schedule, all research data is destroyed after 6 years of the completion of the study. How is the electronic files in the VINCI server destroyed?

Thank you in advance. I've been looking through the VA Data Portal website but unable to find the information....J

Jenice Guzman-Clark, PhD, GNP-BC, FAMIA
Gerontological Nurse Practitioner, Home Telehealth, PCCCS; Nurse Scientist, SAVAHCS
Clinical Nurse Advisor for Geriatrics/Gerontological Nursing, Office of Nursing Services
GEC Council Member, Office of Electronic Health Record Modernization
3601 S. 6th Avenue, Tucson AZ 85723
520-269-1576

Office of Nursing Service (ONS):
Intranet Site: http://vaww.va.gov/nursing/cpp.asp
Internet Site: https://www.va.gov/NURSING/practice/cpp.asp

https://vaww.va.gov/nursing/2020yon.asp

Notes

Date	Name	Note Text

Note: The screenshots of email communications with a representative of VINCI describe the VA record retention and destruction process after completion of the study.