Understanding Individual and Contextual Characteristics of Early Readmission in Patients with Heart Failure: A Multilevel Survival Approach and Spatial Analysis

Afnan Hamad Al Swyan

A dissertation

Submitted in partial fulfillment of the

Requirements for the degree of

Doctor of Philosophy

University of Washington

2021

Reading Committee:

Brenda Zierler, Chair

Barbara Cochrane

Min Li

Program Authorized to Offer Degree:

Nursing

University of Washington

Abstract

Understanding Individual and Contextual Characteristics of Early Readmission in Patients with Heart Failure: A Multilevel Survival Approach and Spatial Analysis

Afnan Hamad Al Swyan

Chair of the Supervisory Committee:

Brenda Zierler PhD, RN, FAAN

Department of Biobehavioral Nursing and Health Informatics

Background: Heart failure (HF) is a growing health concern and costly condition. The increasing medical and economic burden of hospitalizations for HF is a significant problem for patients, their families, and the US health care system. Excessive readmission to the hospital imposes a tremendous burden to patients with HF but also on the health care system. During the transition from hospital to home, some patients might be at higher risk of future episodes of decompensation and early (30-day) readmissions. There has been an extensive amount of research focused on understanding individual characteristics and clinical risk factors in predicting 30-day readmissions, such as increasing age, being male, severe illness, and more extended hospital stays. However, additional important factors, such as those at the patients' contextual-level that may contribute to the high risk of readmission have not been included in

risk prediction models. When considering patients' recovery and transitions of care following hospitalization for HF, it is important to identify the role of the post-discharge environment in the readmission of HF patients. The post-discharge environment is defined as the interaction between individual, family, and environmental factors and how these factors relate to each other. **Purpose:** The overall purpose of this dissertation is to address the gap in the literature in understanding how contextual-level factors influence the likelihood of 30-day readmission in patients with HF. This dissertation comprises the following studies: *Study 1* summarizes and critically analyzes the current evidence on risk prediction models that examine individual- and contextual-level risk factors associated with 30-day readmission in patients with HF based on a conceptual framework adapted from the Andersen's Behavioral Model of Health Services Utilization (ABM); *Study 2* categorizes and tests individual- and contextual-level factors associated with the likelihood of 30-day readmission among HF patients and measures the impact of neighborhood socioeconomic disadvantage (a contextual factor) on 30-day readmission for patients previously hospitalized with HF. **Methods:** *Study 1* used a systematic scoping review methodological framework followed by a thematic analysis to assess, summarize, and interpret evidence on risk factors associated with 30-day readmission in patients with HF during the post-discharge vulnerable phase. For the purposes of this paper, the vulnerable phase is defined as the early post-discharge period during which patients with HF are more vulnerable to readmissions within a 30-day period following an HF hospitalization. The review used the ABM as a conceptual framework to select risk factors that may influence the post-discharge vulnerable phase after hospitalization for HF (the health outcome). *Study 2* is a retrospective secondary data analysis of an existing HF dataset. This study was implemented based on the Strengthening Reporting of Observational Studies in Epidemiology criteria to

improve observational research reporting. We used hierarchical linear modeling and a multilevel survival approach to model 30-day HF readmission risk as a function of fixed and random effects that combine individual- and contextual-level factors. In addition, the study used a spatial analysis technique to evaluate the effect of neighborhood socioeconomic disadvantage on? 30-day readmission among patients diagnosed with HF. **Results:** *Study 1* results show that risk prediction models of 30-day readmission used risk factors related to the individual predisposing domain (such as demographics); few risk prediction models used risk factors related to the individual enabling domain (social support); and a majority of risk prediction models examined risk factors related to the individual needs domain (such as the presence of multiple comorbid conditions) to discriminate patients readmitted with HF within 30 days from those not readmitted. At the contextual level, very few risk prediction models included factors related to the health systems and environmental domains (such as patients residing in urban or rural areas or access to care) associated with 30-day readmission during the post-discharge vulnerable phase. *Study 2* results show a variety of individual- and contextual-level risk factors related to 30-day readmission in patients with HF. With regard to individual-level risk factors, longer lengths of hospitalization, being in the surgical unit, and non-cardiac admissions were associated with a significantly shorter time to all-cause readmission (increased risk) during the post-discharge vulnerable phase. With regard to contextual-level risk factors, low household income ($24,999 annually on average) and households with only high school education had a significantly shorter time to all-cause readmission (increased risk) during the post-discharge vulnerable phase. Altogether, these findings indicate that the contribution of both individual-level and contextual-level risk factors simultaneously resulted in a better model fit to assess 30-day readmission risk or patients with HF. Lastly, those who lived in the most disadvantaged

neighborhoods, as measured by the Area Deprivation Index (ADI), had a higher risk of all-cause readmission than their counterparts who lived in less disadvantaged neighborhoods. **Conclusions:** This dissertation adds to the growing literature on the contribution of both individual- and contextual-level risk factors on 30-day HF readmission. Living in a disadvantaged neighborhood brought a higher risk for 30-day readmission following hospitalization for HF. Thus, the findings of the scoping review and the testing of individual- and contextual-level risk factors associated with 30-day readmission highlighted the need to develop patient-centered health care interventions based on the patient's social context to target the individual- (patient) and contextual-level (neighborhood) risk factors to reduce 30-day readmissions among patients with HF.

TABLE OF CONTENTS

LIST OF TABLES

CHAPTER 1: The Individual and Contextual Risk Factors Associated with 30-Day Readmission in Patients with Heart Failure During the Vulnerable Phase: A Systematic Scoping Review

CHAPTER 2: Contextual Risk Factors in Heart Failure Readmission: A Multilevel and Geospatial Analysis

LIST OF FIGURES

CHAPTER 1: The Individual and Contextual Risk Factors Associated with 30-Day Readmission in Patients with Heart Failure During the Vulnerable Phase: A Systematic Scoping Review

CHAPTER 2: Contextual Risk Factors in Heart Failure Readmission: A Multilevel and Geospatial Analysis

ACKNOWLEDGEMENTS

I thank God for providing me with perseverance during the many difficult moments that presented themselves throughout the course of this doctoral process.

I dedicate this dissertation to my extraordinary committee members; without their support, I would not have accomplished this personal milestone. I am eternally indebted to my advisor, *Dr. Brenda Zierler*, Director of Research, Training, and Faculty Development at UW Center for Health Sciences Interprofessional Education, Research, and Practice. I appreciate Dr. Zierler's willingness to serve on my Ph.D. dissertation committee. It has been an honor to work with an expert like Dr. Zierler. I am very grateful for all the support she has extended to me during my time here at the UW. She has always pushed me forward, regardless of the very challenging years I have experienced since 2018. She has been a great mentor in advising me, connecting me with the resources that I need, being available, and responding to my emails and questions. She provided an enabling and supportive environment for me to succeed in my Ph.D. study. I am thankful for her time, guidance, and support throughout my development as a scholar and a researcher. She is not only my supervisor but also my mentor and a role model! I would not be completing my dissertation if she had not been so willing to continue along the path of achieving my long-awaited goal with me. I look forward to having an opportunity to collaborate with her in the future.

This study would not have been successful without the dedication and commitment of *Dr. Barbara Cochrane*. Her feedback always made it easy for me to understand my own work with more depth and clarity. I sincerely appreciate the supportive environment that she created for me in order to succeed at UW. I have been blessed by *Dr. Cochrane*'s kindness and especially by her care about my overall progress and personal well-being, not just my dissertation. I have

benefited immensely from her support, advice, and critical feedback in the development and completion of this dissertation.

I would also like to extend my deepest gratitude to *Dr. Min Li* for her unique wisdom and her advanced ability to translate the most complex modeling into easy explanations. I am extremely thankful for her excellent teaching and for guiding me into the fascinating world of statistics. She always offered help, advice, and support throughout my doctoral training. Her doors have always been open to me, and she has been extremely generous with her time and her advice. She is not only a committee member but also my mentor and role model. I have grown so much under her expert supervision.

Many thanks to *Dr. Erin Blakeney* for serving on my dissertation committee and providing me with valuable insights into the world of healthcare services. Her scholarly knowledge never ceases to amaze me. Also, I would also like to acknowledge the invaluable assistance of *Dr. Todd Dardas* for his guidance during my early dissertation process in the operationalization of my cohort, data development, and analysis. Also, I would like to express my gratitude towards my GSR, *Dr. Noel Weiss* for all of his constant support to achieve this academic milestone. I am truly grateful for his gifts of knowledge and unwavering support.

I would also like to extend my deepest gratitude to *Dr. William Brown* from the Center for Statistics and the Social Sciences (CSSS) for his statistical guidance throughout my dissertation journey. Words are inadequate to describe my gratitude to *Dr. Brown*. He helped me to understand the statistical concepts that underpinned my study. I appreciate all his shared knowledge and expertise, which have enabled me to reach this milestone. He helped me to understand how to write a code, a skill for which I am forever grateful. Many thanks to *Dr.*

Kevin Cain from the Office of Nursing Research for the analytic support he provided to my analysis plan.

I owe a debt of gratitude to *Dr. Annette Fitzpatrick* from the Schools of Medicine and Public Health. She has been a constant inspiration to me. I am forever grateful that I had the opportunity to work with her; and for allowing me to grow as a research scientist.

I would like to give special thanks to all the incredible mentors in the UW COE Measurement & Statistics (M&S) graduate program for giving me the opportunity to complete my second master's degree that contributed to my development as a data analyst. I would like to give special thanks to *Dr. Elizabeth Sanders* who gave me continuous support, guidance, encouragement, and provided wonderful insight and helped to make my research stronger and more meaningful. Thank you for the analytic support you provided throughout the process of pursuing my master's degree.

I also acknowledge the support I received from *Dr. Frances Marcuse Lewis* for all of her encouragement throughout my journey. She always inspired me with an appreciation for the value of research, the profession, and patient care. She has always pushed me forward despite some very challenging years. *Dr.* Lewis is the greatest nurse, professor, scientist, and mentor I've ever known, and her healing presence will continue to inspire and frame the work I do in the future. She always encouraged me and instilled me with confidence when I was lacking it.

I would like to express my love and gratitude towards *Betsy Mau*, who has been my mentor since my enrollment in the program. My PhD journey would have been much more difficult without her continuous support. I could not have completed such a challenging journey without her guidance. Also, I send my deep thanks to *Elisabeth Mitchell* who was always there for me when I needed her. She has been there for me when the challenges of graduate school

seemed too great to overcome. I would not have been able to balance my mental health as a graduate student without the help of *TeResa Regan.* She kept me focused and helped me to keep going when things got tough and was there to help me find a way to relax when I needed it.

I would like to take this opportunity to say a warm thanks to all my beloved friends who have been so supportive along the way while I was doing my dissertation. Words fail when I want to thank my best friend, *Heba Al Mulla* and her daughter (my daughter too), *Fai*, for all the fun, support and happy moments we shared during the tough times throughout my PhD. I thank her for her unwavering belief in me, for loving me as a sister, and for always celebrating with me when even the littlest things went right. This journey would not have been possible without her support through long phone calls, daily texts, and funny Snapchat pictures. *Fai*, thank you for always being my biggest cheerleader. I am also grateful to my beautiful lawyer, *Njood Bafarat* (future doctor soon) who was always there to give me support. I do not think she knows how much her friendship helped to guide me to the end of this process. I thank her for the little things she has done, like brining me dinner when I worked late nights. Also, I owe profound gratitude to my aunt *Amal* for the support I received from her in the U.S. She has always been there to talk if ever something was bothering me about my research or in life. She has always loved me unconditionally.

Above all, however, this work is dedicated to the foundation of my life, my siblings, *my brothers and sisters*, for the generous support they provided me throughout my entire life. Thanks for listening to my problems, keep up my spirits, and keep things in perspective. I must also thank my beautiful niece and nephew, *Hoor and Sultan*. To them, I promise that I will make up the lost time. Also, I would like to give special thanks to my *brother-in-law* who has been a constant source of support during the challenges of graduate school and life. And most of all for

my loving, supportive, encouraging *uncle* whose warm support during the final stages of this Ph.D. is so appreciated. I feel grateful for having him in my life. I could not have gone through this journey successfully without his constant support.

Also, I would like to thank all individuals I have met at UW. Thank you all for the time and expertise you have shared with me. I have gained so much by having the opportunity to get to know you and work with you as I went through this journey.

Finally, I gratefully acknowledge the funding sources that made my Ph.D. work possible. I was very grateful that I was among those receiving the Magnuson award from the "Warren G. Magnuson Institute for Biomedical Research and Health Professions Training" to help me succeed in my education. I am very honored to be the recipients of this award.

DEDICATION

*This dissertation is dedicated to **my parents**, without whom I would not be here today. They gave me a love for knowledge and provided me with the fundamental traits that made the completion of this pursuit possible.*

*To my **father**, who transitioned from this life in 2018 just weeks before my general examination. His love for me, which did not transition, has been a sustaining force over the years it has taken to complete my journey.*

*To my **mother**, without whom I would not be here today, for all the sacrifices she made for my education and success. Her prayer for me was what sustained me thus far.*

*Also, this dissertation is dedicated to **Mr. John Lewis**, who is no longer with us but his support to me during my difficult times left an indelible imprint on my memories.*

CHAPTER 1: The Individual and Contextual Risk Factors Associated with 30-Day Readmission in Patients with Heart Failure During the Vulnerable Phase: A Systematic Scoping Review

Target Journal: Health Services Research

The Individual and Contextual Risk Factors Associated with 30-Day Readmission in Patients with Heart Failure During the Vulnerable Phase: A Systematic Scoping Review

Afnan Hamad Al Swyan,[1] MEd, MSN, CCRN, Barbara Cochrane,[2] PhD, RN, FAAN, FGSA, Brenda Zierler,[1] PhD, RN, FAAN

Affiliations

[1]Department of Biobehavioral Nursing and Health Informatics, University of Washington, Seattle, Washington, [2]Child, Family, and Population Health Nursing, University of Washington, Seattle, Washington

Corresponding author:
Afnan Hamad Al Swyan MEd, MSN, CCRN
University of Washington
Department of Biobehavioral Nursing and Health Informatics
1959 NE Pacific St.
Seattle, WA, 98195
afswyan@uw.edu

Alternative corresponding author:
Brenda Zierler PhD, RN, FAAN
University of Washington
Department of Biobehavioral Nursing and Health Informatics
1959 NE Pacific St.
Seattle, WA, 98195
brendaz@uw.edu

Running title: *Individual and Contextual Factors Associated with Vulnerability*

Citation: (to be Submitted to Health Services Research)

ABSTRACT

Background: Heart failure (HF) is a major public health concern. Patients with HF are more vulnerable to readmissions in the early post-discharge period. Readmission immediately after hospital discharge and for 2 to 3 months following a HF hospitalization occur during the high-risk period that has been called the "vulnerable phase." To better predict readmission risk, the Andersen's Behavioral Model of Health Services Utilization (ABM) was used as a framework for understanding individual-level and contextual-level risk factors associated with 30-day readmission during the post-discharge vulnerable phase in patients with HF. **Purpose:** To summarize and critically analyze the current evidence on risk prediction models that examine individual- and contextual-level risk factors associated with 30-day readmission in patients with HF based on a conceptual framework adapted from the ABM. **Methods:** A systematic scoping search of the literature was conducted. A two-step selection process with prespecified inclusion/exclusion criteria for identified studies. A thematic analysis guided by the ABM as a conceptual framework was used to identify individual- and contextual-level risk factors of 30-day readmission in patients with HF. Studies were appraised and findings summarized and categorized. **Results:** This scoping review showed that very few risk prediction models in the current HF literature were developed using contextual-level factors (health systems and environmental) factors (such as the type of residence). **Conclusion:** The results from the scoping review showed that individual-level factors were more likely to be reported than contextual-level factors. The findings of this review also demonstrated that contextual-level factors that have the potential to influence readmission have received very little attention compared to individual-level risk factors. The ABM might be a useful framework for understanding different risk factors and their association with HF readmission.

Keywords: Readmission, vulnerable, individual, contextual, heart failure

What is already known on this topic?

- The early transition period from inpatient hospitalization to home or other settings, termed the vulnerable phase, is a period of heightened vulnerability to readmission.
- Most risk prediction models have focused primarily on clinical factors and demographic factors (such as age and marital status), with poor performance in predicting or preventing HF readmission.

What does this study add?

- This scoping review of the literature showed that individual-level factors were more likely to be reported than contextual-level factors.
- The adapted framework based on the Andersen's Behavioral Model (ABM) could be used for future research to explain factors associated with vulnerability to 30-day readmission during the post-discharge vulnerable phase.

Introduction

Heart failure (HF) is a major public health concern. By 2030, HF will affect more than 8 million Americans, accounting for an increase in prevalence by 46%.[1] Roughly 20% of HF patients are readmitted within 30 days, and 5% may die after discharge from the hospital.[2-7] The increasing number HF patients being readmitted within 30-days imposes a tremendous burden on the patients, their caregivers, and the health care system.[8-10] The total costs for HF care in the US are projected to increase by 127% to $69.8 billion by 2030.[1] Given the national goal to "Improve Healthcare for Americans," set in 2012, the Center for Medicare and Medicaid Services (CMS) began using financial penalties to reduce reimbursement payments to hospitals with high readmission rates based on the 30-day readmission rate following an index HF admission.[11] The rate of readmissions that occur within 30 days of an initial hospital discharge has also been used as a quality standard measure in health care and a metric that health care systems use as a benchmark when comparing similar institutions.[11]

Patients with HF are more vulnerable to readmissions in the early post-discharge period.[12] Readmission immediately after hospital discharge and for 2 to 3 months following a HF hospitalization occur during what has been called the "vulnerable phase."[8,12-18] This critical period represents a time of heightened vulnerability for adverse outcomes, including repeated readmissions to the hospital.[12,18-21] However, the duration of the vulnerable phase remains an unsettled matter. In addition to the first 2 to 3 months following hospital discharge, the 30-day post-discharge period is referred to as the vulnerable phase.[22] Given the absence of clarity regarding the duration of the vulnerable phase (the duration after discharge when patients are at highest risk), a timeframe of 30-days has been established based on health care metrics set forward by the CMS as a target of quality of care. In this context, a close follow-up of patients at

high risk for readmission during the 30-day post-discharge period is considered an opportunity to prevent readmission.[17,23]

With high numbers of HF readmissions and associated financial penalties to hospitals with excessive 30-day readmission rates, greater attention has been paid by hospitals, policymakers, and researchers to reduce 30-day readmission rates. The increasing concern about the need to reduce hospital 30-day readmissions has led to a growing number of risk prediction models that have been purposefully developed to identify risk factors associated with 30-day hospital readmission for patients with HF.[24-26] Most risk prediction models have focused primarily on clinical factors of risk (such as the worsening of hemodynamics)[27] and demographic factors (such as age and marital status),[28] but they have shown relatively poor performance in predicting or preventing HF readmission.[29-31] Therefore, there is a need to assess other risk factors that might contribute to the likelihood of 30-day readmission. The variability in 30-day readmission has a complex multifactorial cause across a broad range of individual, clinical, and health care system risk factors that may potentially affect 30-day readmission.[32]

Theoretical models have the potential to add new insight to the understanding of the multidimensional aspects of HF 30-day readmission. To better predict 30-day readmission risk, the ABM may be a useful framework for understanding individual- and contextual-level risk factors associated with 30-day HF readmission during the post-discharge vulnerable phase.[33] According to the ABM (see Figure 1), multiple aspects of individual, behavioral, and contextual factors may contribute to our understanding of post-discharge outcomes, allowing us to understand the range of risk factors that increase the risk for 30-day readmission.[33]

This current review expands on prior studies describing risk prediction models for hospital readmission following HF care. Several systematic reviews of risk prediction models for

hospital readmission in patients with HF have already been conducted.[28,34,35] However, the existing systematic reviews synthesized risks at different follow-up times (not specific to 30-day readmission) and did not use a framework to address the process of synthesizing results on the individual contextual risk factors of 30-day readmission among patients with HF. To address the research gap, this up-to-date review build upon previous systematic reviews of all readmission models to better understand risk factors of 30-day readmission among patients with HF.

The objective of this systematic scoping review was to identify individual- and contextual-level risk factors contributing to variation in 30-day readmission among patients with HF. The research question was defined as follows: Which individual- and contextual-level risk factors were associated with 30-day readmission during the post-discharge vulnerable phase in patients with HF using a conceptual model adapted from the ABM?

By structuring the findings using the ABM, individual- and contextual-level risk factors for 30-day HF readmission were categorized using the ABM domains to delineate where research is currently focused and where it is lacking in order to make suggestions for future research directions.

Methods

A scoping review methodological framework was used followed by a thematic analysis [36] to assess, summarize, and interpret evidence on individual-and contextual-level risk factors associated with 30-day readmission during the vulnerable phase in patients with HF. A protocol was developed based on the guidelines from the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) extension checklist for scoping reviews[37] as well as the recommendations from other studies.[36, 38-41]

Scoping review

The 5-step scoping methodology framework, developed by Arksey and O'Malley,[38] was adopted as outlined below.

1. Identifying the research question

The research question was defined as follows: Which individual- and contextual-level risk factors were associated with 30-day readmission in patients with HF during the post-discharge vulnerable phase? To the researcher's knowledge, no studies have determined that individual and contextual-level risk factors as a system of multiple pathways contributed to 30-day readmission in patients with HF.

2. Identifying relevant studies

The search strategy for this systematic scoping review was developed based on the population–concept–context framework recommended for scoping reviews.[42] The primary author and expert librarian developed the final search strategy to ensure all related papers in electronic databases were included. The literature search was initially performed in 2018 and then updated in 2020 using 5 bibliographic databases: PubMed, Proquest, Ovid Medline, PsycINFO, and Cochrane. A list of MeSH terms was generated with the help of experienced methodologists to construct a comprehensive set of search terms (see Table 1).

3. Study selection

The primary author independently screened all identified references by title and abstract. Reference lists of all included articles were reviewed to obtain further relevant studies for this review. For the study selection for the scoping review, the primary author followed a screening process to reduce the number of studies that would require a full-text review. The primary author conducted an initial title, abstract, and keyword screen for inclusion then

extracted information from the article's full text, based on the ABM, after assessing relevancy for final inclusion/exclusion criteria. The inclusion criteria were defined a priori; they were applied to identify publications as follows:

- Type of publication: All types of studies published in the English language with full-text access and studies on risk prediction models for 30-day readmission were considered.
- Participants: Only studies including subjects older than 18 years with HF were considered for evaluation.
- Outcomes: Retrieved papers were assessed targeting only the outcome of 30-day readmission.

Publications of studies in which there were no 30-day readmission outcomes, those with abstract-only access, reviews or methodological publications, and descriptive studies were excluded. In addition, pediatric or psychiatric risk prediction model publications were also excluded.

4. Charting the data

For each study included in the review, the primary author extracted and synthesized data associated with the defined research question. The data extraction form was based on the methodological guidelines and recommendations of Peters et al[40] and Arksey and O'Malley[36] for conducting systematic scoping reviews.[36] A data extraction form was designed to extract the following data consistently from the articles: study characteristics, purpose of study, study design, participants, risk factors, type of study, methodology, outcomes, key findings, implications, and conclusion. The primary author piloted the data extraction form by reviewing 5 articles, resulting in appropriate data extraction and synthesis. After completion of the pilot process, the primary author completed the data extraction for each paper.

5. Collating, summarizing, and reporting the results

The primary author assessed, summarized, and interpreted evidence guided by the ABM for more effective post-discharge interventions to prevent 30-day readmission. The findings included basic descriptive numerical analysis of the studies' nature and distribution and thematic grouping of risk factors according to the ABM. The ABM specifies relationships among the individual level (e.g., predisposing, enabling, and needs domains) and the contextual level (e.g., external environmental and health care system domains) as well as the category of health behavior [33] (see Figure 1).

Framework

This scoping review utilized the ABM as the conceptual framework (see Figure 1) to describe risk factors associated with 30-day readmission during the post-discharge vulnerable phase. To structure this review, extract the evidence, and analyze the aims, all risk factors included in the selected risk prediction models were listed and then sorted into levels and domains according to ABM. Furthermore, the ABM guided the categorization and interpretation of the results as to whether the risk factors fell into the individual level (e.g., predisposing, enabling, and needs domains), the contextual level (e.g., environmental and health system), or the category of health behavior.[33] At the individual level, the ABM shows that the predisposing domain influences the enabling domain, which in turn influences the perceived and evaluated need domain. Specifically, health service utilization, indicated here by 30-day readmission, depends on individuals' predisposition to using services, their ability to secure those services, and their need-related factors (see Table 2). At the contextual level, the ABM includes two subsequent categories assumed to affect the individual's use of health services: health care system and environmental domain (see Table 2). This model helped to describe the interplay

between the individual- and contextual-level risk factors associated with 30-day readmission during the post-discharge vulnerable phase in patients with HF (see Figure 1).

Results

Study identification

The initial electronic database search yielded 1325 citations. After the removal of duplicates, 624 citations remained for further screening. Articles that were deemed irrelevant based on titles and abstracts were then excluded, and the remaining 280 citations were screened, resulting in 56 relevant publications for full-text review. An additional 35 publications were excluded because they did not meet the selection criteria. Consequently, a total of 21 unique articles describing risk prediction models across a variety of settings met all inclusion criteria. The flow chart in Figure 2 depicts how articles using the screening process of database search results described by the PRISMA were included.

Risk prediction model outcomes and HF readmission

Table 3 summarizes the characteristics of the final risk prediction models included in this updated scoping review. Among the 21 unique HF prediction models described, all but 3 of these studies used retrospective data.[44-47] Twelve studies were conducted in the US, 2 in Australia, 2 in Canada, and 1 each in Switzerland, Korea, the UK, Spain, and Italy. All studies included healthcare data from adult HF patients ranging in age from 56 to 80 years. All studies used discrimination methods to assess the HF prediction models' prognostic utility, such as the area under the curve-receiver operating characteristic (AUC-ROC) and C-statistic (n = 6).[33,48-52] The majority of studies (n = 13) assessed composite outcomes,[29, 44,47,53-61] whereas the remaining eight studies assessed 30-day readmission for patients hospitalized for HF as an outcome.[48,50,52,62-65,67] The overall observed rate of 30-day readmission ranged from 1.1% to 38%.

Mapping factors that influenced 30-day readmission utilizing the ABM

Table 4 shows the number and type of risk factors associated with 30-day readmission by the ABM domains.[33] The risk factors from each article were categorized the relevant levels and domains of the ABM:

1. Individual level: This level includes the predisposing, enabling, and needs domains.
    a. Health behavior: These behaviors include the personal health practices and use of personal health services domains.
2. Contextual level: This level includes the external environmental and health care systems domains.

In the scoping review, 30-day readmission was considered as the outcome measure (endpoint of interest) because CMS uses 30-day readmission as a quality measure of care.[11]

Individual Level Risk-Factors by Domain

An overall synthesis of findings on ABM's three individual-level risk factors (the predisposing, enabling, and needs domains) will be described below by domain.

Predisposing domain. As shown in Table 4, 14 risk prediction models initially included demographic risk factors, but in many cases, these variables were less likely to be included in the final model. Factors that were examined to predict 30-day readmissions included patients' gender,[29,30,61,62,65,68] foreign-born status/language,[65] race/ethnicity,[62,69] and marital status.[53,65]

Enabling domain. Of the risk prediction models reviewed, 7 unique risk prediction models included the individual enabling domain, considering factors such as economic burden, health insurance, and social support (i.e., living alone).[29,60,62,65,69,70] The most frequent individual enabling domain predictor included in the models was having health insurance (n = 6).[29,60, 62,65,69,70] Living alone and having support were also risk factors for 30-day readmission.[61,62] Three

studies examined economic burden and the risk of 30-day HF readmission.[29,62,69] Krumholz et al[62] reported socioeconomic status (SES) did not predict a 30-day readmission risk and did not improve model discrimination (see Table 4).

Individual needs domain. The majority of risk prediction models (n = 18) examined the presence of factors related to multiple comorbid conditions.[30,44-46,48,53,55-57,60-62,64,65,68-70] Specifically, 20 of 21 studies included comorbid conditions, and diabetes mellitus[30,46,62,68] was the most commonly included risk factor within the needs domain (see Table 4).

An overall synthesis of findings on ABM's contextual-level factors. Few risk prediction models (n = 2) included contextual-level environmental factors, such as the type of residence (i.e., rural, metropolitan) (n = 2),[29,70] discharge to long-term care (n=1),[69] the distance from the patient's residence to the hospital (n = 1),[69] hour of discharge (n = 2),[55] service declined (n = 1),[65] challenges to getting care (n = 1),[62] or having an established physician for health care (n=1).[62] Thus, the results of this systematic scoping review showed that, at the individual level of the model, most risk prediction models used risk factors related to the predisposing domain (such as age). At the contextual level, very few of the risk prediction models included factors in the external environmental and health care systems domains (such as the type of residence) associated with 30-day readmission during the post-discharge vulnerable phase (see Table 4).

Discussion

Our purpose in this review was to address a gap in the research literature by identifying individual- and contextual-level risk factors contributing to variation in 30-day readmission among patients with HF as guided by the ABM. Our review adds to the findings of several other reviews that found that HF readmission is the result of a complex interplay between an individual

and the context of their lives.[35] Hersh et al's[35] study was relevant for understanding the complexity of HF readmission; their approach integrated the patient, the provider, the health system, and environmental factors. Because of the burden of HF and the heightened rate of readmission, it is important to examine the influence of risk factors within and across all levels of the model at the same time. This scoping review showed that other possible risk factors, such as enabling, needs, contextual, and behavioral factors, can affect the association between a predisposing factor and readmission. More precisely, high readmission rates among older adults (predisposing) may be attributable to longer lengths of stay (needs), lack of supports (enabling), concerns about privacy (behavioral), and reduced mobility (needs) factors.[44,45] Only three models from this scoping review included individual-level factors for all of the ABM model domains (needs, predisposing, and enabling domains).[7,9,12] These three models showed that C-indices were 0.80, 0.62, and 0.62, respectively. Specifically, the model with the highest C-statistic (0.80)[7] was characterized by a practical methodology for predicting the risk of short-term readmission for HF, including being older, living alone, having a sedentary lifestyle, and having multiple comorbid conditions. In contrast, Krumholz et al[12] included individual-level domains (needs, predisposing, and enabling domains) as well as to contextual and health behavior factors, but with modest model discrimination (C-statistic = 0.65).

For the individual-level predisposing domain, the results showed inconsistencies in the associations between age and readmission in the existing risk prediction models. Huynh et al's[55] model reported strong discriminatory power, including several variables that predicted 30-day readmissions, such as individual -level factors including age (C-statistic = 0.77). Meanwhile, Krumholz et al[62] reported that age did not provide sufficient predictive power because it was assessed with other patient-reported outcomes in predicting readmission. For

instance, a systematic review by Damiani et al. found that race/ethnicity and marital status (predisposing) showed a positive association with readmission.[25] While some studies have reported increased readmission risk in people from racial and ethnic minorities,[62,69] differences in readmission rates among racial and ethnic groups were often confounded by other predisposing factors, such as limited education, or contextual-level factors, such as residing in lower-income neighborhoods or having limited access to high-quality care; thus, further discussion is warranted.[78-80]

The lack of incorporation of patient reported outcomes, such as patient values, into risk prediction models may be overlooked; for instance, patients' cultural beliefs (including the meaning ascribed to HF) may influence patients' health behaviors and perceptions of care.[72,73] A systematic qualitative study reported that factors associated with 30-day readmission are multifactorial and include the following themes: "distressing symptoms, the unavoidable progression of the illness, influence of psychosocial factors, good but imperfect self-care adherence, and health system failures."[74 (p171)] Taken together, these findings suggest a need for more consistent assessment of patients' beliefs or conceptions regarding HF readmission to reduce patient vulnerability to 30-day readmission. Among the individual-level domains, the results showed that the enabling domain was not described or reported as often as the other two domains in these studies. This could be because they may not have had robust enough data to examine enabling domain factors since most of these studies involved secondary data analysis of clinical or administrative data where many social risk factors are not captured.

Identifying enabling domain factors is particularly important because they can be modified in several ways. For example, "social support" was identified as an enabling factor in this review. Chun[14] showed that assessing and addressing perceived social support and structural

measures, such as living alone among older hospitalized adults, may prevent 30-day readmission. Conceptually, identifying patients with inadequate social supports may help target high-risk patients.

The present study also found that contextual-level factors, which include the environmental domain, as they interact with individual characteristics to influence readmission, have not been largely reported. Amarasingham et al[29] found that patients with a lack of continuous housing, were at increased risk of readmission. Environmental domain factors have also been less frequently examined; these include information related to geographic variables (e.g., residence and urban or rural location). Nevertheless, these factors can affect the supply of services or care access.[5,10,13]

Based on the ABM and the literature reviewed in this systematic scoping review, a potential framework was hypothesized that uses the outcome of 30-day readmission with risk factors at both the individual and contextual levels (Figure 3).[33] In the examination of the assumptions underlying the framework, there is no single risk factor that predicts 30-day readmission. The hypothesized framework, which builds on the ABM, revealed several gaps in the existing literature that present future research opportunities. There is a need to include patient-reported measures to increase the likelihood of identifying a patient's vulnerability to readmission. This would help identify patients with multiple health needs for whom an intervention that targets various risk factors may be beneficial. To mitigate vulnerability to readmission following hospitalization for HF, it is important include factors that extend beyond the boundaries of traditional, individual-level risk with multiple contextual-level factors. These investigations are essential to determine how to prevent 30-day readmission.

Limitations

There were several limitations of this scoping review, including (a) generalizability of current results, because the review was conducted of the risk prediction model literature but not all study designs; (b) generalizability to other time frames, because the review included a risk prediction model within a defined period of readmission of 30 days; and (c) generalizability to other HF populations, because a number of the included risk prediction models further restricted cohorts by age and diagnosis. Finally, only the primary author abstracted and screened full-text articles. Thus, there was no consensual validation of article selection and thematic analysis of results.

Despite the limitations, this study was innovative in that it explored the risk factors for 30-day readmission by categorizing risks according to the ABM. This review provides a comprehensive report addressing individual-level and contextual-level risk factors for patients who might benefit from an intervention that builds on the ABM. This study's results could be useful in the design of future interventions that take account of individual- and contextual-level factors.

Conclusion

This review provides a comprehensive overview of individual- and contextual-level factors associated with 30-day readmission during the post-discharge vulnerable phase. These factors were summarized and discussed according to the conceptual framework of the ABM. The following conclusions can be drawn. First, the results from the reviewed studies showed that individual-level factors were more likely to be reported than contextual-level ones. There is a lack of a clear understanding of contextual-level factors' roles in the variation of 30-day readmission during the post-discharge vulnerable phase. Second, the results showed greater inclusion of the traditional needs domain (e.g., medical comorbidity and prior utilization factors) and less inclusion of the other needs domain (e.g., overall health and function and illness severity) or the enabling domain (e.g., social determinants of health) associated with 30-day

readmission during the post-discharge vulnerable phase. Finally, reducing readmission risks requires adequate identification of factors at the contextual-level associated with 30-day readmission including geographic region risk factors, which can potentially be prevented via targeted patient interventions. Future quantitative studies could elucidate the validity or the appropriateness of the use of the ABM for examining the associations between individual- and contextual-level risk factors associated with 30-day readmission during the post-discharge vulnerable phase.

References

1. Virani SS, Alonso A, Benjamin EJ, et al. Explaining the slowdown in medical spending growth among the elderly, 1999-2012. Circulation. 2020;141(9): e139-e596.
2. Cowie MR. Post-discharge assessment and management of patients with heart failure. Medicographia. 2015;37(2):155-62.
3. Dharmarajan K, Krumholz HM. Strategies to reduce 30-day readmissions in older patients hospitalized with heart failure and acute myocardial infarction. Curr Geriatr Rep. 2015;3(4):306-15.
4. Kociol RD, Hammill, BG, Fonarow GC, et al. Generalizability and longitudinal outcomes of a national heart failure clinical registry: comparison of acute decompensated heart failure national registry (ADHERE) and non-ADHERE Medicare beneficiaries. Am Heart J. 2015;160(5):885-92.
5. Kumholz HM, Merrill AR, Schone EM, et al. Patterns of hospital performance in acute myocardial infarction and heart failure 30-day mortality and readmission. Circ Cardiovasc Qual Outcomes. 2009;2(5):407-13. doi:10.1161/CIRCOUTCOMES.109.883256
6. Bradley EH, Curry L, Horwitz LI, et al. Hospital strategies associated with 30-day readmission rates for patients with heart failure. Circ Cardiovasc Qual Outcomes. 2013;6(4):444-50.
7. Benjamin EJ, Virani SS, Callaway CW, Chamberlain AM, Chang AR, Cheng S, . . . de Ferranti SD. 2018. Heart disease and stroke statistics—2018 update: a report from the American Heart Association. Circulation.

8. Dharmarajan K, Hsieh AF, Lin Z, et al. Hospital readmission performance and patterns of readmission: retrospective cohort study of Medicare admissions. BMJ. 2013;347:f6571. Published 2013 Nov 20. doi:10.1136/bmj.f6571
9. Wallmann R, Llorca J, Gómez-Acebo I, Ortega AC, Roldan FR, Dierssen-Sotos T. Prediction of 30-day cardiac-related emergency readmissions using simple administrative hospital data. Int J Cardiol. April 2013;(164):93-200.
10. Meadow A, Sangl J. Hospital readmissions in Medicare home healthcare: what are the leading risk indicators? Home Healthc. Nov. 2019;37(4):213-21.
11. Cox ZL, Lai P. Lewis CM, Lenihan DJ. Centers for Medicare and Medicaid Services' readmission reports inaccurately describe an institution's decompensated heart failure admissions. Clinical Cardiol. 2017;40(9):620-25.
12. Greene SJ, Fonarow GC, Vaduganathan M, Khan SS, Butler J, Gheorghiade M. The vulnerable phase after hospitalization for heart failure. Nat Rev Cardiol. 2015;12(4):220-29.
13. Desai AS. The three-phase terrain of heart failure readmissions. Circ: Heart Fail. 2012;5(4):398-400. doi:10.1161/CIRCHEARTFAILURE.112.968735
14. Chun S, Tu JV, Wijeysundera HC, Austin PC, Wang X, Levy D, Lee DS. Lifetime analysis of hospitalizations and survival of patients newly admitted with heart failure. Circ: Heart Fail. 2012;5:414-21.
15. Vaduganathan M, Michel A, Hall K, et al. Spectrum of epidemiological and clinical findings in patients with heart failure with preserved ejection fraction stratified by study design: a systematic review. Eur J Heart Fail. 2016;18(1):54-65. doi:10.1002/ejhf.442

16. Mueller C, Bally K, Buser M, Flammer AJ, Gaspoz JM, Mach, F, . . . Fay B. Roadmap for the treatment of heart failure patients after hospital discharge: an interdisciplinary consensus paper. Swiss Med Wkly. 2020;w20159-w20159.
17. Krumholz HM. Post-hospital syndrome: an acquired, transient condition of generalized risk. N Engl J Med. 2013;368(2):100-102.
18. Mesquita ET, Jorge ET, Rabelo LM, Souza CV Jr. Understanding hospitalization in patients with heart failure. International Journal of Cardiovascular Sciences. 2017;30(1):81-90.
19. Lopatin YM, Rosano GM. Treatment of patients in the vulnerable phase (at discharge or early after discharge). J Am Coll Cardiol. 2017 June;(10).
20. Bocchi EA, Brito DA, Chioncel O, et al. Can biomarkers guide the assessment and management of heart failure patients after discharge from hospitals? Medicographia. 2005;37(2):171-84.
21. Fudim M, O'Connor CM, Dunning A, et al. Aetiology, timing and clinical predictors of early vs. late readmission following index hospitalization for acute heart failure: insights from ASCEND-HF. Eur J Heart Fail. 2018;20(2):304-14.
22. Maggioni AP, Greene SJ, Fonarow GC, et al. Effect of aliskiren on post-discharge outcomes among diabetic and non-diabetic patients hospitalized for heart failure: insights from the ASTRONAUT trial. European Heart Journal. 2013;34(40):3117-27.
23. Desai AS, Stevenson LW. Rehospitalization for heart failure: predict or prevent? Circulation. 2012;126:501-506.
24. Calvillo-King LD, Arnold D, Eubank KJ, et al. Impact of social factors on risk of readmission or mortality in pneumonia and heart failure: systematic review. J Gen Intern

Med. 2013;28(2):269-82.

25. Damiani G, Salvatori E, Silvestrini G, et al. Influence of socioeconomic factors on hospital readmissions for heart failure and acute myocardial infarction in patients 65 years and older: evidence from a systematic review. Clin Interv Aging. 2015;10:237.
26. Hawkins NM, Jhund PS, McMurray JJ, Capewell S. Heart failure and socioeconomic status: accumulating evidence of inequality. Eur J Heart Fail. 2012;14(2):138-46.
27. Gheorghiade, Mihai. A comprehensive, longitudinal description of the in-hospital and post-discharge clinical, laboratory, and neurohormonal course of patients with heart failure who die or are rehospitalized within 90 days: analysis from the EVEREST trial. Heart Fail Rev. 2012;17:485-509.
28. Kansagara H, Englander A, Salanitro D, Kagen C. Theobald M. Freeman S. Kripalani. Risk prediction models for hospital readmission: a systematic review. JAMA. 2011;306:1688-98.
29. Amarasingham R, Moore BJ, Tabak YP, et al. An automated model to identify heart failure patients at risk for 30-day readmission or death using electronic medical record data. Med Care. 2010 Nov;48(11):981-88.
30. Hammill BG, Curtis LH, Fonarow GC, et al. Incremental value of clinical data beyond claims data in predicting 30-day outcomes after heart failure hospitalization. Circ Cardiovasc Qual Outcomes. 2011;4(1):60-67. [PubMed: 21139093].
31. Van Walraven C, Dhalla IA, Bell C, et al. Derivation and validation of an index to predict early death or unplanned readmission after discharge from hospital to the community. Cmaj. 2010;182(6):551-57.

32. Colavecchia AC, Putney DR, Johnson ML, Aparasu RR. Discharge medication complexity and 30-day heart failure readmissions. Research in Social and Administrative Pharmacy. 2017;13(4):857-63.
33. Andersen RM. Revisiting the behavioral model and access to medical care: does it matter? J Health Soc Behav.1995;36:1-10.
34. Ross JS, Mulvey GK, Stauffer B, et al. Statistical models and patient predictors of readmission for heart failure: a systematic review. Arch Intern Med. 2008;168(13):1371-86.
35. Hersh A, Masoudi F, Allen L. Post-discharge environment following heart failure hospitalization: expanding the view of hospital readmission. J Am Heart Assoc. 2013;2(2):E000116.
36. Arksey H, O'Malley L. Scoping studies: towards a methodological framework. Int J Soc Res Methodol. 2005;(8):19-32. doi:10.1080/1364557032000119616
37. Moher D, Liberati A, Tetzlaff J, Altman DG, Prisma Group. Reprint—referred reporting items for systematic reviews and meta-analyses: the PRISMA statement. Phys Ther. 2009;89(9):873-80.
38. Colquhoun HL, Levac D, Brien KK, et al. Scoping reviews: time for clarity in definition, methods, and reporting. J Epidemiol. 2014;67(12):1291-94.
39. Levac D, Colquhoun H, O'Brien KK. Scoping studies: advancing the methodology. Implement Sci. 2010;5(1):1-9.
40. Peters MD, Godfrey CM, Khalil H, McInerney P, Parker D, Soares CB. Guidance for conducting systematic scoping reviews. J Evid Based Healthc. 2015;13(3): 141-46.
41. Daudt HM, Van Mossel C, Scott SJ. Enhancing the scoping study methodology: a large,

interprofessional team's experience with Arksey and O'Malley's framework. BMC Medical Research Methodology. 2013;(13):48-56. doi:10.1186/1471–2288–13–48

42. Joanna Briggs Institute, Moola S, Munn Z, Sears K, Sfetcu R, Currie M, Lisy K, . . . Mu P. Conducting systematic reviews of association (etiology): the Joanna Briggs Institute's approach. International Journal of Evidence–Based Healthcare. 2015;*13*(3):163-69.
43. Hsieh HF, Shannon SE. Three approaches to qualitative content analysis. Qual. Health Res. 2005;15:1277-88.
44. Lim NK, Lee SE, Lee HY, Cho HJ, Kim H, Choi JO., . . . Chae SC. Risk prediction for 30-day heart failure-specific readmission or death after discharge: data from the Korean Acute Heart Failure (KorAHF) registry. J Cardio. 2019;73(2):108-113.
45. Di Tano G, De Maria R, Gonzini L, et al. The 30-day metric in acute heart failure revisited: data from IN-HF outcome, an Italian nationwide cardiology registry. Eur J Heart Fail. 2015;17:1032-41.
46. Cubbon RM, Woolston A, Adams B, Gale CP, Gilthorpe MS, Baxter PD, . . . Kahn M. Prospective development and validation of a model to predict heart failure hospitalisation. Heart. 2014;100(12):923-29.
47. Hsiao J, Motta M, Wyer P. Validating the acute heart failure index for patients presenting to the emergency department with decompensated heart failure. Emerg Med J. 2012;29(12):e5–e5.
48. Hebert C, Shivade C, Foraker R, et al. Diagnosis-specific readmission risk prediction using electronic health data: a retrospective cohort study. BMC Med Inform Decis Mak. 2014;14:65.
49. Kossovsky MP, Sarasin FP, Perneger TV, et al. Unplanned readmissions of patients with

congestive heart failure: do they reflect in-hospital quality of care or patient characteristics? Am J. 2000;109(5):386-90.

50. Sudhakar S, Zhang W, Kuo YF, et al. Validation of the readmission risk score in heart failure patients at a tertiary hospital. J Card Fail. 2015;21:885-91.
51. Di Tano G, De Maria R, Gonzini L, et al. The 30-day metric in acute heart failure revisited: data from IN-HF outcome, an Italian nationwide cardiology registry. Eur J Heart Fail. 2015;17:1032-41.
52. Fleming LM, Gavin M, Piatkowski G, et al. Derivation and validation of a 30-day heart failure readmission model. Am J Cardiol. 2014;114:1379-82.
53. Au AG, McAlister FA, Bakal JA, et al. Predicting the risk of unplanned readmission or death within 30 days of discharge after a heart failure hospitalization. Am Heart J. 2012;164:365-72.
54. Chin MH, Goldman L. Correlates of early hospital readmission or death in patients with congestive heart failure. Am J Card. 1997;79(12):1640-4.
55. Huynh Q, Negishi K, De Pasquale C, Hare J, Leung D, Stanton T, Marwick T. Validation of predictive score of 30-day hospital readmission or death in patients with heart failure. Am J Card. 2018;121(3):322-29.
56. Raposeiras-Roubin S, Abu-Assi E, Cambeiro-Gonzalez C, et al. Mortality and cardiovascular morbidity within 30 days of discharge following acute coronary syndrome in a contemporary European cohort of patients: how can early risk prediction be improved? The six-month GRACE risk score. Revista Portuguesa de Cardiologia. 2015;34:383-91.
57. Cleland JG, Chiswell K, Teerlink JR, et al. Predictors of postdischarge outcomes from

information acquired shortly after admission for acute heart failure: a report from the placebo-controlled randomized study of the selective A1 adenosine receptor antagonist rolofylline for patients hospitalized with acute decompensated heart failure and volume overload to assess treatment effect on congestion and renal function (PROTECT) study. Circ Heart Fail. 2014;7:76-87.

58. Cubbon RM, Woolston A, Adams B, Gale CP, Gilthorpe MS, Baxter PD, . . . Kahn M. Prospective development and validation of a model to predict heart failure hospitalisation. Heart. 2014;100(12):923-29.
59. Felker GM, Leimberger JD, Califf RM, et al. Risk stratification after hospitalization for decompensated heart failure. J Card Fail. 2004;10(6):460-6.
60. Eapen ZJ, Liang L, Fonarow GC, et al. Validated, electronic health record deployable prediction models for assessing patient risk of 30-day rehospitalization and mortality in older heart failure patients. JACC Heart Fail. 2013;1:245-51.
61. Betihavas V, Frost SA, Newton PJ, et al. An absolute risk prediction model to determine unplanned cardiovascular readmissions for adults with chronic heart failure. Heart Lung Circ 2015;24:1068-73.
62. Krumholz, Chaudhry, Spertus, Mattera, Hodshon, Herrin. Do non-clinical factors improve prediction of readmission risk? results from the tele-HF study. JACC: Heart Failure. 2016;4(1):12-20.
63. Wang H, Robinson RD, Johnson C, et al. Using the LACE index to predict hospital readmissions in congestive heart failure patients. BMC Cardiovasc Disord. 2014;14:97.
64. Zai AH, Ronquillo JG, Nieves R, et al. Assessing hospital readmission risk factors in heart failure patients enrolled in a telemonitoring program. Int J Telemed Appl.

2013;2013:305819.

65. Watson AJ, O'Rourke J, Jethwani K, et al. Linking electronic health record-extracted psychosocial data in real time to risk of readmission for heart failure. Psychosomatics. 2011;52:319-27.

66. Mholz HM, Chaudhry SI, Spertus JA, Mattera JA, Hodshon B, Herrin J. Do non-clinical factors improve prediction of readmission risk? results from the tele-HF study. JACC: Heart Failure. 2016;4(1):12-20.

67. Yamokoski L, Hasselblad V, Moser D, Binanay C, Conway G, Glotzer J . . . Leier C. Prediction of rehospitalization and death in severe heart failure by physicians and nurses of the ESCAPE Trial. J Cardi Fail. 2007;13:8-13.

68. Keenan PS, Normand SL, Lin Z, et al. An administrative claims measure suitable for profiling hospital performance on the basis of 30-day all-cause readmission rates among patients with heart failure. Circ Cardiovasc Qual Outcomes. 2008; 1:29-37.

69. Silverstein, MD, Qin H, Mercer SQ, Fong J, Hayda Z. Risk factors for 30-day hospital readmission in patients ≥ 65 years of age. In Baylor University Medical Center Proceedings. 2008;21(4):363-72. Taylor & Francis.

70. Allen LA, Smoyer Tomic KE, Smith DM, et al. Rates and predictors of 30-day readmission among commercially insured and Medicaid-enrolled patients hospitalized with systolic heart failure. Circ: Heart Fail. 2012;5(6):672-9.

71. Kutyifa V, Rice J, Jones R, Mathias A, Yoruk A, Vermilye K., . . . Lowenstein C. Impact of noncardiovascular disease burden on thirty-day hospital readmission in heart failure patients. Cardiology Journal. 2018;*25*(6):691-700.

72. Davidson PM, Macdonald P, Moser DK, et al. Cultural diversity in heart failure management: findings from the DISCOVER study (part 2). Contemp Nurse. 2007 May–June;25(1-2):50-61.

73. Dickson VV, McCarthy MM, Howe A, Schipper J, Katz SM. Sociocultural influences on heart failure self-care among an ethnic minority black population. J Cardiovasc Nurs. 2013 Mar–Apr;28(2):111-18.

74. Retrum JH, Boggs J, Hersh A, Wright L, Main DS, Magid DJ, Allen LA. Patient-identified factors related to heart failure readmissions. Circ: Cardiovasc Qual Outcomes. 2013;6(2):171-77.

75. Phillips KA, Morrison KR, Andersen R, Aday, LA. Understanding the context of healthcare utilization: assessing environmental and provider-related variables in the behavioral model of utilization. Health Services Research. 1998;33(3 Pt 1): 571.

76. Lindenauer PK, Lagu T, Rothberg MB, Avrunin J, Pekow PS, Wang Y, Krumholz M. Income inequality and 30-day outcomes after acute myocardial infarction, heart failure, and pneumonia: retrospective cohort study. BMJ. 2013;346:f521.

77. Pencina MJ, D'Agostino RB. Evaluating discrimination of risk prediction models: the C statistic. JAMA. 2015;J314(10):1063-64.

78. Joynt KE, Orav EJ, Jha AK. Thirty-day readmission rates for Medicare beneficiaries by race and site of care. JAMA. 2011;305(7):675-81.

79. Philbin EF, Dec GW, Jenkins PL, DiSalvo TG. Socioeconomic status as an independent risk factor for hospital readmission for heart failure. Am J Card. 2001;87(12):1367-71.

80. Wu JR, Holmes GM, DeWalt DA, Macabasco-O'Connell A. Bibbins-Domingo K, Ruo B, . . . Erman B. Low literacy is associated with increased risk of hospitalization and death among individuals with heart failure. J Gen Intern Med. 2013;28(9):1174.

Table 1. Database Searches for All Included Databases

pubmed	("patient readmission"[mesh] or readmi* or re-admi* or rehospital* or re-hospital*) and ("30 day" or "30-day" or "thirty day" or "thirty-day") and ("risk"[mesh] or risk) and ("models, statistical"[mesh] or model or predic*) and ("heart failure"[mesh] or "heart failure" or "myocardial failure" or "cardiac failure")
medline	(mh "patient readmission" or readmi* or re-admi* or rehospital* or re-hospital*) and (“30 day” or “30-day” or “thirty day” or “thirty-day”) and (mh "risk+" or risk) and (mh "models, statistical+" or model or predic*) and (mh "heart failure+" or "heart failure" or "myocardial failure" or "cardiac failure")
psycinfo	(de "hospital admission" or "patient readmission" or "patient re-admission" or readmi* or re-admi* or rehospital* or re-hospital*) and ("30 day" or "30-day" or "thirty day" or "thirty-day") and (de "risk assessment" or de "risk management" or risk) and (de "models" or de "statistical analysis" or de "predictability (measurement)" or model or predic*) and ("heart failure" or "myocardial failure" or "cardiac failure")
cinahl	(mh "readmission" or readmi* or re-admi* or rehospital* or re-hospital*) and ("30 day" or "30-day" or "thirty day" or "thirty-day") and (mh "risk assessment" or mh "cardiovascular risk factors" or risk) and (mh "models, statistical+" or model or predic*) and (mh "heart failure+" or "heart failure" or "myocardial failure" or "cardiac failure") excluding medline records
embase	('hospital readmission'/exp or readmi* or 'hospital readmission' or re-admi* or rehospital* or re-hospital*) and ("30 day" or "30-day" or "thirty day" or "thirty-day") and ('risk'/exp or risk) and (model or predic*) and ('heart failure'/exp or ' heart failure' or ' myocardial failure' or 'cardiac failure')
web of science	("patient readmi*" or readmi* or re-admi* or rehospital* or re-hospital*) and ("30 day" or "30-day" or "thirty day" or "thirty-day") and (risk) and (model or predic*) and ("heart failure" or "myocardial failure" or "cardiac failure")

Table 2. Andersen's Behavioral Model of Health Services Utilization Constructs Definitions

Evaluated health outcome	Hospital readmissions, 30-day readmission
Individual level	Identifies risk factors that predispose the patient to readmission (eg, demographics) and that interact with enabling factors (eg, SES) and needs factors (eg, disease severity) to affect behaviors and outcomes (30-day readmission)
Individual predisposing domain	Refers to basic characteristics of the population and can be identified as the most frequent factors associated with health and the need for health services
Demographic factors	Includes risk factors such as sex, age, ethnicity or racial group membership
Social structure risk factors	Includes risk factors such as educational and marital status
Health beliefs factors	Includes risk factors such as attitudes, values, and knowledge about health and health services
Individual enabling domain	Refers to conditions that may be changed by individual and social efforts and can be identified as moderate factors associated with health and health services (can facilitate or inhibit individuals' ability to access the health care system)
Financial enabling resources factors	Includes risk factors such as health insurance or income as well as occupation
Personal/familial enabling resources factors	Includes risk factors such as patients living alone or with others and/or the presence of a caregiver
Individual needs domain	Refers to the most direct/proximate causes associated with health and health services and reflects disease characteristics; factors in this domain can be identified as those that act as the most immediate cause of the use of health services
Disease characteristics factors	Includes risk factors such as comorbidities, clinical, vital signs, laboratory measures, medical procedures, and medication
Perceived health factors	Includes risk factors related to how individuals view their own health and functional state or as assessed by a professional or by means of objective measures
Self-reported health status factors	Includes risk factors related to how someone describes their health and functional needs
Individual health behaviour	Can be identified as personal health practices or medical care processes risk factors
Personal health practices /medical care processes domains	Includes risk factors such as diet, use of tobacco, or medical care processes, refusing health services, or missing appointments
Contextual level	Identifies risk factors that are related to demographic and social characteristics at the community level: includes the external environmental and health care systems domains

Note: All variables were based on the Andersen's Behavioral Model of Health Services Utilization.[33]

Table 3. Characteristics of the Included Studies on 30-Day Hospital Readmission Predictive Models

Reference **Model name**	**Study design/data source** **Data collection period** **Country**	**Population**	**Study outcome**	**Sample size**	**Age group (years)**	**Readmission rate (%)**	**Discrimination methods** **C-statistic** **(95% CI or SE if reported)**
Lim, 2019 KorAHF Risk score	Prospective, observational study 10 tertiary hospitals Korean Acute Heart Failure (KorAHF) registry 2011–2014 Korea	ACHF patients >40 years	30-day HF-specific readmission or death	4566 patients Original sample* (n = 430) Validation sample (n = 1046)	Mean=70.3 ±12.1	9.8% (9.1% in men and 10.5% in women)	AUC of 0.710 Basic model: 0.647 Clinical model: 0.679 Complex model: 0.711
Huynh, 2018 The non-clinical model The clinical model The combined model	Retrospective cohort study State-wide data in teaching hospitals in 5 Australian capital cities 2014–2015 Australia	HF patients	30-day readmission for HF Composite outcome within 30 days of discharge for HF	1046 patients Non-clinical—1537 patients Clinical—977 patients available	Mean=80	25.4%	Non-clinical model 0.66 Clinical model 0.72 Combined model 0.76 C-statistic: 0.77 Very good discriminatory power in the prediction of 30-day readmission or death

Raposeiras-Roubin, 2015 Six-month GRACE risk score (Related references: Eagle, 2004 Granger, 2003)	Retrospective cohort study Academic teaching hospital single center with an established specialized HF and heart transplant program 2004–2010 Spain	Patients readmitted for HF after acute coronary syndrome	30-day post-discharge death and 30-day cardiovascular readmission for HF after acute coronary syndrome	4429 patients	Mean=77 (UHRs); 68 (no UHRs)	1.3%	Discrimination: 0.79 Calibration: p=0.83 Overall performance: 0.83 Good fit 30-day events for HF discrimination: 0.83 ± 0.02 Goodness of fit: 0.78 Sensitivity and specificity
Sudhakar, 2015 RR score	Retrospective cohort study Tertiary hospital/ chart review 2011–2013 US	CHF patients	30-day risk-standardized all-cause readmission rates for patients with CHF	1046 admissions from 712 patients	Mean=65.2 65.2±16.6	35.28%	Performance / discrimination (ROC) AUC for all age group: 0.61 ≥65 years—0.59 Random selection—0.58 Sensitivity and specificity of the RR score: 33/80 % poor
Betihavas, 2015 WHICH/ Unnamed	Retrospective cohort study Multicenter RCT NR Australia	CHF patients	Cardiovascular readmission and death 28-day readmission	280 patients	Mean=79 (UHRs); 69 (no UHRs)	13%	Discrimination C-statistic: 0.80

Di Tano, 2015 Unnamed	Prospective cohort study National Registry Database 61 Italian cardiology centers including academic and community hospitals NR Italy	Acute HF	30-day readmission for acute HF Time to all-cause mortality or readmission after discharge (*A*) and for time to all-cause readmission after discharge (*B*) according to clinical presentation (worsening chronic HF or *de novo* HF) at the index admission	1520 patients	Mean=72	6.25% (91% for cardiovascular causes; 60% for recurrent HF) 1-year readmission rate was 30.7% (8.3%) met the combined endpoint	Discrimination (ROC) 0.695
Cleland, 2014 Unnamed	Placebo-controlled randomized PROTECT study NR North America, Europe, Israel, and Argentina	Acute HF patients/ pre-existing HF	All-cause readmission or death outcomes at 30 days were death or rehospitalization for any reason; death or rehospitalization for cardiovascular or renal reasons; and, at both 30 and 180 days, all-cause mortality	2033 patients	Median=72	30-day death or all-cause rehospitalization : 382/2033 30-day death or CV/renal rehospitalization : 326/2033	0.79 No variable: >0.70 few >0.60

Hebert, 2014 Unnamed	Retrospective cohort study Large Midwestern tertiary care medical center 2 years of data collected from the IW at the OSUWMC 2009–2011 US	Patients with a primary discharge diagnosis of CHF	All cause 30-day readmission	3572 patients 1354 patients in CHF	Mean=61	16.4% readmission rate in CHF	Random sample: AUC 0.63 Validation cohort: AUC 0.64 Poor
Fleming, 2014 Unnamed	Retrospective cohort study 1 tertiary medical center 2007-2011 US	HF patients	30-day readmission on patients with HF	3413 admissions Derivation: Validation =3:1 (2566:847)	Mean=74 derivation cohort; validation cohort: 74.6	24.2% (derivation)	AUC: 0.69 AUC: 0.66
Wang, 2014 LACE index score	Retrospective cohort study Urban publicly-funded hospital ED with CHF exacerbations 2012–2013 US	Acute CHF exacerbation	30-day readmission for patients with CHF	253 patients	Mean= 57.67 (no UHRs); 56.17 (UHRs)	24.5%	Derivation cohort: 0.59 Validation cohort: 0.59

Cubbon, 2014 Unnamed	Prospective cohort study Specialist physician-led cardiology outpatient clinics in National Health Service tertiary or district hospitals in West Yorkshire Derivation cohort: 2006–2009 Validation cohort: 2009–2011 UK	AHFS patients stable with CHF secondary to left ventricular systolic dysfunction	Death and AHFS hospitalization in stable outpatients with CHF secondary to left ventricular systolic dysfunction	Derivation cohort (n=628) Validation cohort (n=462)	All: 67 No AHFS: 67.1 AHFS: 65.3	7% (patients were hospitalized as a result of AHFS during 1 year of follow-up)	Calibration: Hosmer–Lemeshow p=0.38 Discrimination: C-statistic 0.77 Validation cohort: Satisfactory calibration: Hosmer–Lemeshow p=0.15 Discrimination: C-statistic 0.81
Eapen, 2013 Unnamed	Retrospective cohort study Centers for Medicare database Utilizing data elements readily available in EHRs GWTG-HF registry 2005–2009 US	HF patients 65 years of age with a hospitalized episode of worsening HF or developed significant HF symptoms during a hospitalization for which HF was the primary discharge diagnosis	30-day readmission for HF 30-day mortality after admission, 30-day rehospitalization after discharge 30-day mortality/ rehospitalization after discharge	33349 patients 70% in derivation cohort; 30% in validation cohort 33349 patients 70% in derivation cohort; 30% in validation cohort	Median= 80	22.8%	Derivation cohort: 0.59 Validation cohort: 0.59 0.62 The rehospitalization: C-indices 0.59 Death/rehospitalization models: C-indices 0.62 Modest discrimination

Zai, 2013 Unnamed (Original Watson, 2011)	Cohort study The telemonitoring-based readmission model Partners Center for Connected Health and Partners Home Care MGH 2008–2011 US	HF population	30-day readmission for HF	100 patients	Mean=66.8	38%	The telemonitoring-based readmission model 0.21 The psychosocial model (validation) 0.67 Sensitivity 0.87 Specificity 0.32
Au, 2012 LaCE+ score (used different score: Charlson score (Charlson, 1987) LACE score (van Walraven, 2010) CMS-endorsed Krumholz (Krumholz, 2006) Keenan scores (Keenan, 2008)	Retrospective cohort study 4 health databases 1999–2009 Canada	HF population	30-day post-discharge death or unplanned readmission	59652 patients	Mean=76	19% death or unplanned readmission	Five administrative data-base models .57–.61
Hsiao, 2012 AHFI (Validation study: Hsieh, 2008)	Prospective cohort study Urban university hospital EDs with DHF 2007–2009 Canada	ED HF population with DHF	Secondary outcomes were all-cause mortality within 30 days of admission and hospital readmission within 30 days because of AHF	259 patients	Mean=68	Low-risk subgroup: 8.3% Higher-risk subgroup: 27.6%,	Combined secondary outcome rate: 30.2% (CI 23.9– 37.0)

Hammill, 2011 Unnamed Claims-only model Claims-clinical model	Cohort study GWTG-HF data 2004–2006 US	Patients with new or worsening HF in patients 65 years or older	All-cause readmission or death	24163 patients from 307 hospitals	Median= 81	21.9% overall	0.60 Claims-only readmission model: AUC, 0.587 Claims-clinical readmission model: AUC, 0.599
Watson, 2011 The psychosocial readmission model	Retrospective cohort study Psychosocial-related predictors available in the EHR MGH Institutional Review Board 2007–2008 US	HF patient	All-cause 30-day readmission on HF	729	Mean= 71.4	13.3% (all female)	0.67
Amarasingham, 2010 Unnamed	- Single center urban hospital Parkland Memorial Hospital 2007–2008 US	HF patients	All-cause readmission or death	1372	Mean= 56.5	24.1% overall	0.72 (0.70-0.75)
Krumholz, 2016 Unnamed	Tele-HF trial The Human Investigation Committee at the Yale University School of Medicine approved the study US	HF patients	All-cause 30-day hospital readmission	1004 patients	Mean= 62	17.1%	0.62

Yamokoski, 2007 Unnamed	RCT cohort ESCAPE trial 26 academic heart failure and transplantation centers US and Canada	Severe advanced HF	All-cause readmission	373	Mean = 56.16±13.9	184 were rehospitalized	0.60 Model: C-index 0.59
Kossovsky, 2000 Unnamed	Case-control study General internal medicine wards of the Hospital Cantonal 1993 - 1998 Switzerland	HF patients	All-cause 30-day readmissions	Cases: 91 Controls: 351	Cases: 76.4 (10.0) Controls: 75.3 (11.6)	Unplanned readmissions related to HF or to its treatment: 60 not related to HF: 31	Only readiness for discharge: ROC curve for all-cause readmissions: 0.57 ROC curve for heart-failure-related re-admissions 0.59 For models with age and medical history variables, ROC curve for all-cause readmissions: 0.67 ROC curve for heart-failure-related readmissions: 0.74 Models with both types of variables: For all-cause readmissions: 0.69 For heart-failure-related re-admissions: 0.75

Note: Discrimination is the ability of the test to correctly classify those with and without the quantified using the Area Under the Receiver Operating Characteristic Curve (AUROC or AUC). Calibration is the accuracy of risk estimates, relating to the agreement between the estimated and observed number of events. Goodness of fit is a model calibration, which reflects how well the model-specified outcome probabilities agree with people's subsequent observed outcomes. C-statistic is a measure of concordance; it measures the ability of a model to rank patients from high to low risk (generally ranging from 0.5 (random concordance) to 1 (perfect concordance)). (AUC) Area Under the Curve, (CI) Confidence intervals, (N) Sample, (SE) Standard error, (M) Male, (NR) Not reported, (US) United States, (RCT) Randomized controlled trial, (EHRs) Electronic health records, (KorAHF) The Korean Acute Heart Failure registry, (CHF) Chronic heart failure, (ACHF) Acute congestive heart failure, (HF) Heart failure, (DHF) Decompensated heart failure, (AHFS) Acute heart failure syndrome, (AHFI) The Acute Heart Failure Index,

(GRACE) The Global Registry of Acute Coronary Events risk score, (UHRs) Unplanned hospital readmissions, (RR score) The Readmission Risk score, (WHICH) WHICH Trial, (Tele-HF) Telemonitoring to Improve Heart Failure Outcomes Trial, (ESCAPE) The Evaluation Study of Congestive Heart Failure and Pulmonary Artery Catheterization Effectiveness Trial, (Eds) Urban university hospital emergency departments, (PROTECT) Selective A1 Adenosine Receptor Antagonist Rolofylline for Patients Hospitalized with Acute Decompensated Heart Failure and Volume Overload to Assess Treatment Effect on Congestion and Renal Function Study, (OSUWMC) The Ohio State University Wexner Medical Center, (LACE) Index of: Length of stay (L), Acuity of the admission (A), Comorbidity of the patient (C), and Emergency department use in the duration of 6 months before admission (E), (ESCAPE) The Evaluation Study of Congestive Heart Failure and Pulmonary Artery Catheterization Effectiveness Trial, (MGH) Massachusetts General Hospital, (GWTG-HF) Get With the Guidelines-Heart Failure registry.

Table 4. The Number of Risk Factors Associated with Hospital Readmission Within 30 Days by the Andersen's Behavioral Model Domains

	Structural Risk Factors		References	Total Number of Factors Included
Individual level				
Predisposing domain				
	Demographic factors	Factors (eg, age, sex, race/ethnicity, marital status)	Lim, 2019 Huynh, 2018 Roubin, 2015 Cleland, 2014 Fleming, 2014 Eapen, 2013 Hammill, 2011 Watson, 2011 Amarasingham, 2010 Krumholz, 2016	Demographic factors: n=13
	Socioeconomic factors	Factors (eg, education, social class, and employment status)	Krumholz, 2016	Social structure factors: n=1
	Health beliefs factors	Factors (eg, attitudes, values, and knowledge of health and health services)	na	Health beliefs factors: n=0
Enabling domain				
	Structural risk factors	Financial situation (eg, health insurance or income, occupation) factors	Eapen, 2013 Watson, 2011 Amarasingham, 2010 Krumholz, 2016	Financial situation factors: n=4
		Social support factors	Betihavas, 2015 Krumholz, 2016	Social support factors: n=2
Needs domain				
	Disease-related factors	Comorbidities factors	Lim, 2019 Huynh, 2018 Roubin, 2015	Comorbidities factors: n=13

		Betihavas, 2015 Di Tano, 2015 Cleland, 2014 Hebert, 2014 Cubbon, 2014 Eapen, 2013 Zai, 2013 Hammill, 2011 Krumholz, 2016	
	Clinical factors	Lim, 2019 Betihavas, 2015 Cleland, 2014 Hebert, 2014 Fleming, 2014 Eapen, 2013 Amarasingham, 2010 Krumholz, 2016	Clinical factors: n=8
	Vital signs factors	Hammill, 2011 Krumholz, 2016	Vital signs factors: n=5
	Laboratory measures factors	Cleland, 2014 Hebert, 2014 Eapen, 2013 Hammill, 2011	Laboratory measures factors: n=4
	Medical procedures factors	Lim, 2019 Roubin, 2015 Sudhakar, 2015 Hammill, 2011 Krumholz, 2016	Medical procedures factors: n=5
	Medication factors	Roubin, 2015 Di Tano, 2015 Hebert, 2014 Cubbon, 2014 Eapen, 2013 Zai, 2013	Medication factors: n=6
Perceived health related factors	Objective factors	Cleland, 2014 Eapen, 2013	Objective factors: n=3

		Krumholz, 2016	
	Symptoms factors	Di Tano, 2015 Zai, 2013 Krumholz, 2016	Symptoms factors: n=3
Self-reported health status related factors	Self-reported health status factors	Krumholz, 2016	Self-reported health status factors: n=1
	Psychological disorder factors	Krumholz, 2016	Psychological disorder factors: n=2
	Physical factors	Krumholz, 2016	Physical factors: n=1

Note: The table depicts all the candidate variables (significant and non significant).

Table 5. Health Behavior and The Number of Contextual Risk Factors Associated with Hospital Readmission Within 30 Days by the Andersen's Behavioral Model Domains

Structural risk factors	References	Total Number of Factors Included
Health behavior		
Personal health practices domain	Di Tano, 2015 Hebert, 2014 Zai, 2013 Hammill, 2011 Amarasingham, 2010 Krumholz, 2016	Personal health practices factors: n=6
Use of personal health services domain	Watson, 2011 Amarasingham, 2010 Krumholz, 2016	Use of personal health services factors: n=3
Contextual level		
External Environmental domain	Huynh, 2018 Krumholz, 2016 Silverstein, 2008 Betihavas, 2015 Krumholz, 2016	External environmental factors: n=3
Health care systems domain	Watson, 2011 Krumholz, 2016 Silverstein, 2008	Health care systems factors: n=3

Note: The table depicts all the candidate variables (significant and non significant).

FIGURES

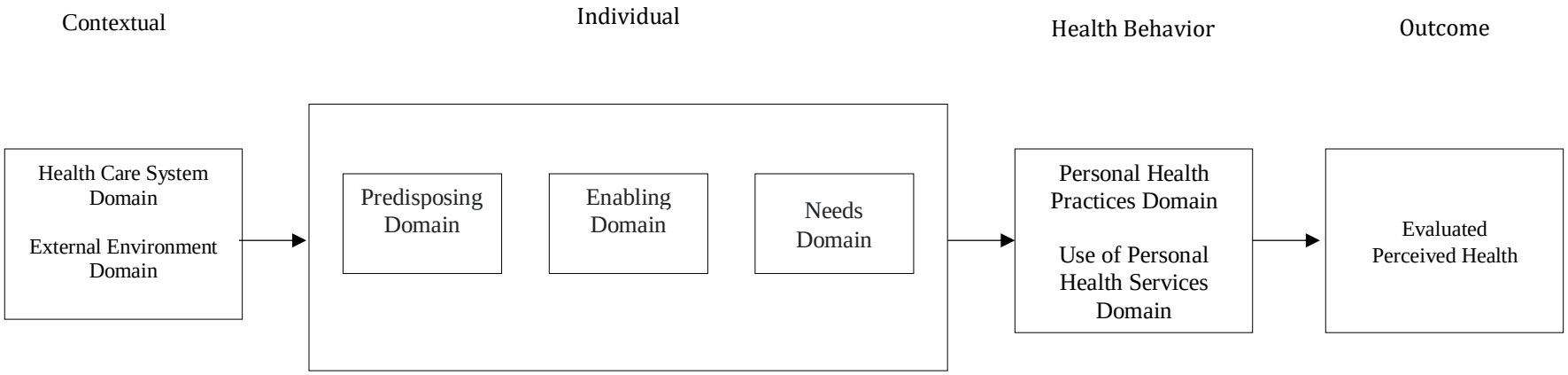


Figure 1. Andersen's Behavioral Model of Health Services[33]

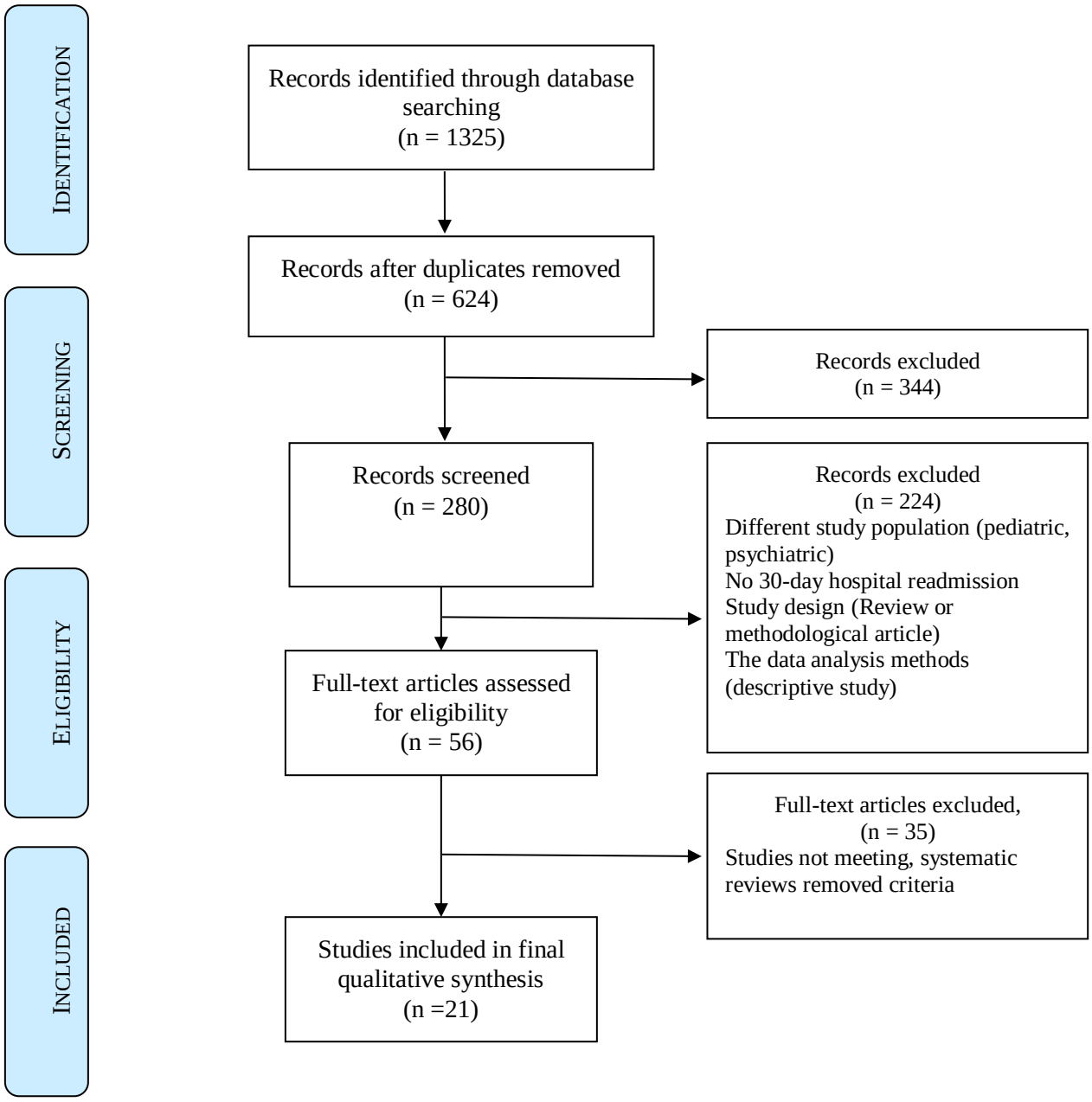


Figure 2. Flow Chart of Literature Search Indicating Exclusion Criteria and the Number of Included Articles

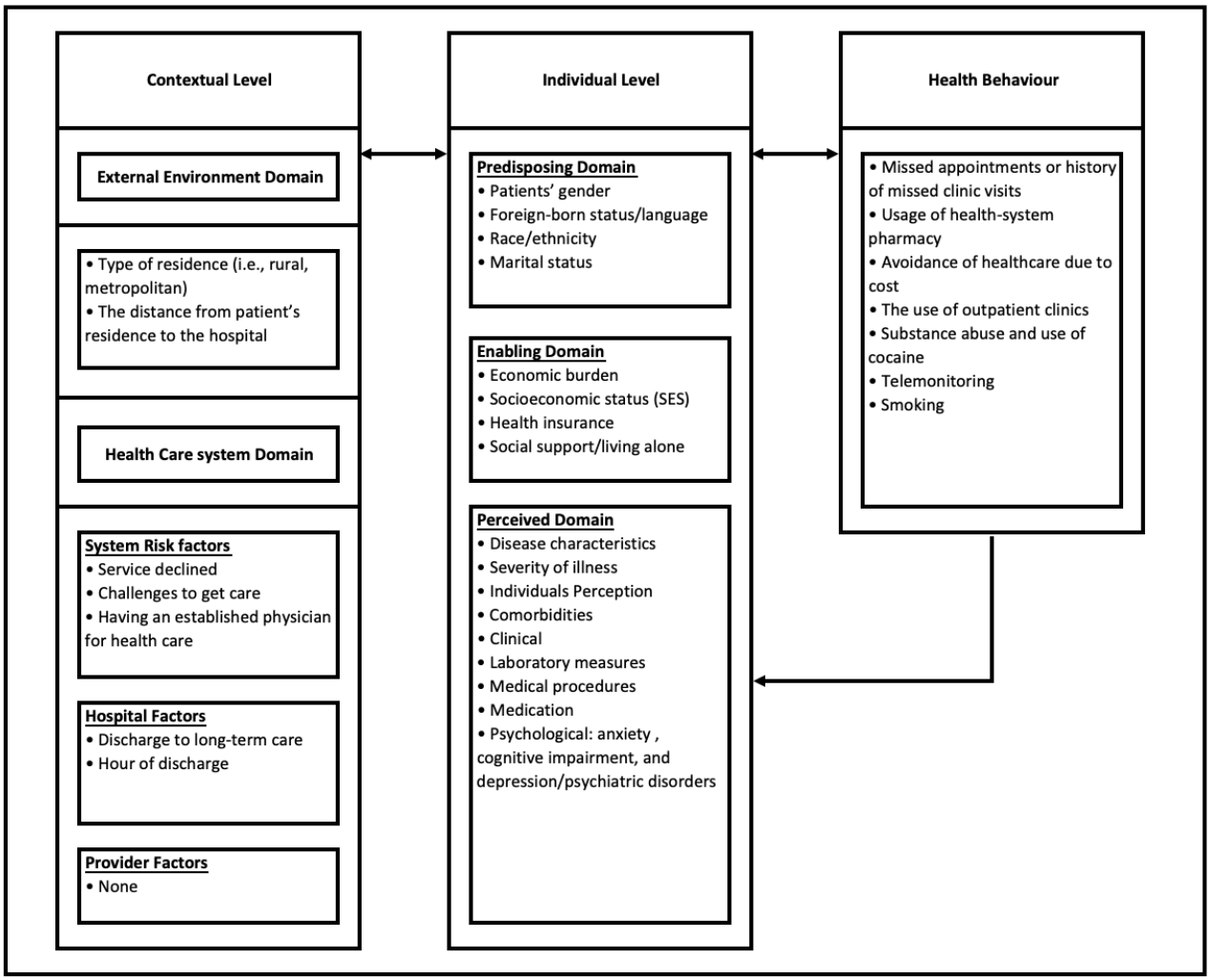


Figure 3. Map of Identified Individual and Contextual Factors Associated with Readmission during the Post-Discharge Vulnerable Phase

CHAPTER 2: Contextual Risk Factors in Heart Failure Readmission: A Multilevel and Geospatial Analysis

Target Journal: Journal of Cardiovascular Nursing

CONTEXTUAL RISK FACTORS IN HEART FAILURE READMISSION: A MULTILEVEL AND GEOSPATIAL ANALYSIS

Afnan Hamad Al Swyan,[1] MEd, MSN, CCRN, Barbara Cochrane,[2] PhD, RN, FAAN, FGSA, Min Li,[3] PhD, Brenda Zierler,[1] PhD, RN, FAAN

Affiliations
[1]Department of Biobehavioral Nursing and Health Informatics, University of Washington, Seattle, Washington [2]Child, Family, and Population Health Nursing, University of Washington, Seattle, Washington, [3]College of Education, University of Washington, Seattle, Washington

Corresponding author:
Afnan Hamad Al Swyan MEd, MSN, CCRN
University of Washington
Department of Biobehavioral Nursing and Health Informatics
1959 NE Pacific St.
Seattle, WA, 98195
afswyan@uw.edu

Alternative corresponding author:
Brenda Zierler PhD, RN, FAAN
University of Washington
Department of Biobehavioral Nursing and Health Informatics
1959 NE Pacific St.
Seattle, WA, 98195
brendaz@uw.edu

Citation: (to be Submitted to Journal of Cardiovascular Nursing)

Abstract

Background: Little improvement has been made in understanding how contextual factors and neighborhood socioeconomic disadvantages are associated with hospital readmission. **Objective:** The purpose of this study was (1) to assess the effect of individual- and contextual-level risk factors on 30-day readmission among heart failure (HF) patients using the Andersen's Behavioral Model (ABM) conceptual framework as a guide, and (2) to measure the impact of neighborhood disadvantage (contextual factor) on early (30-day) readmission for patients previously hospitalized with HF. **Methods:** This is a retrospective secondary data analysis of an existing dataset. This study was implemented using a hierarchical linear modeling and a multilevel survival approach with right censoring to model readmission risk as a function of fixed and random effects that combine individual and contextual characteristics. Also, a spatial analysis technique was used to evaluate the effect of neighborhood disadvantage on 30-day readmission among patients with HF. **Results:** With regard to individual-level risk factors, the study found that longer lengths of stay (LOS), being in the surgical unit, and non-cardiac admissions were associated with a significantly shorter time to all-cause readmission (increased risk). With regard to contextual-level risk factors, low household income and households with only high school education had a significantly shorter time to all-cause readmission (increased risk). Lastly, those who lived in the most disadvantaged neighborhoods had a higher risk of all-cause readmission than those living in less disadvantaged neighborhoods. **Conclusions:** Living in a disadvantaged neighborhood brought a higher risk for 30-day readmission following hospitalization for HF. Thus, the findings of the multilevel and multifaceted factors associated with 30-day readmission suggest the importance of developing effective, patient-centered health care interventions based on the patient's social context to target the individual (patient) and

contextual (neighborhood) factors to reduce 30-day readmissions among patients with HF.

Keywords: Contextual-level factors, neighborhood, socioeconomic, readmission, spatial analysis

What's New?

- Compared to hospital-level and Individual-level factors, the source of variation in early (30-day) readmission was primarily attributable to contextual-level risk factors.
- Living in a disadvantaged neighborhood was associated with a higher risk of 30-day readmission following hospitalization for heart failure.
- The study findings suggested that Contextual-level factors like neighborhood like neighborhood-level factors should be considered along with individual-level factors, providing opportunities for future studies.

Introduction

Heart failure (HF) is a growing health concern and costly condition.[1] The growing medical and economic burden of hospitalizations for HF is a significant health problem for patients, their families, and the United States (US) health care system.[2-6] The projected economic impact on the US health care system of Medicare beneficiaries who were readmitted within 30-days of hospital discharge was estimated to exceed $17 billion a year.[1,7] Patients discharged after HF remain at high risk for frequent readmissions, with approximately 25% being readmitted early, within 30 days of discharge.[8,9] Reducing hospital readmissions has become an important national priority[10] because of the economic impact. To curb the health care burden and to improve the quality of health care delivery, the Affordable Care Act established the Hospital Readmissions Reduction Program, under which the Centers for Medicare and Medicaid Services (CMS) issued financial penalties to hospitals with excessive 30-day readmissions.[11]

The transition period following discharge from the hospital has been described as a vulnerable phase for HF patients.[12] Therefore, identifying factors associated with 30-day HF readmission is essential to better support patients during the high-risk post-discharge vulnerable phase and to develop effective interventions for those most likely to be readmitted. An extensive amount of research has focused on understanding individual demographic characteristics, such as increasing age, being male, and having clinical risk factors, such as illness severity and extended hospital stays, in predicting 30-day HF readmissions.[13-19] These common factors are more likely to be included in risk prediction models.[20-23] However, another category of factors, called contextual-level risk factors, may contribute to a high risk of 30-day readmission, but they have not been included frequently in HF prediction models.[20-23] Contextual-level risk factors are

those that operate within a social context and include political and socioenvironmental factors. These factors create the contexts in which health problems arise as well as barriers to and opportunities for addressing them. In this study, the contextual-level risk factors included economic, social, and physical environments for HF patients.[20,21] Contextual-level risk factors could increase 30-day readmission likelihood because of gaps in the availability of equitable access to key resources critical for patients with HF.[24] Such inequality is triggered by health care service availability or the availability of healthy foods.[24]

However, on a broader level, little improvement has been made in understanding how contextual-level risk factors influence the likelihood of readmission.[20,21] There are challenges associated with treating patients in disadvantaged neighborhoods, characterized by unemployment status, limited education, and substandard living accommodations.[25,26] Patients living in disadvantaged neighborhoods are more likely to be readmitted compared to those who are not socioeconomically deprived. There are interactions between individual- and contextual-level risk factors and 30-day readmission outcomes.[26] However, there is inconsistent evidence about the role of neighborhood disadvantage on readmissions.[26,27] One reason is that patients living in disadvantaged neighborhoods may have relatively poor access to health care resources.[26] The composite measure of neighborhood disadvantage, the area deprivation index (ADI) created by Singh,[28] may help to characterize the role of disadvantaged neighborhood risk on several health care outcomes, including 30-day readmission risk.[26,28]

Another contributing factor to 30-day hospital readmission is where patients live in relation to the health care facilities from which they seek care. Few studies have explored the detrimental effects of geographic variation, such as distance to health care facility, in identifying HF patients at high risk of 30-day hospital readmission.[21] Geographic information systems

(GIS) have not commonly been included in 30-day readmission risk prediction models as the data are not readily available in clinical databases.[20,21] While many studies examined the association of census-driven neighborhood deprivation with HF risk, few studies to date have examined the mechanisms by which the hierarchical and unique contributions of contextual-level risk factors affected 30-day readmission.[15,22,29] Integrating the Andersen's Behavioral Model of Health Services Use (ABM) with a review of the literature related to 30-day HF readmission facilitated the development of a conceptual framework to guide the study of contributing factors to 30-day HF readmission (Figure 1).[30]

The goal of this study is to use the ABM to better understand and define the individual- and contextual-level risk factors that contribute to 30-day HF readmission in order to identify effective interventions.[20,21,31] Using inpatient data from an academic medical center, this study has two aims:

1. To assess the effect of individual- and contextual-level risk factors on 30-day readmission among HF patients using the ABM conceptual framework as a guide.
2. To measure the impact of neighborhood disadvantage (contextual-level) on 30-day readmission for patients previously hospitalized with HF.

Conceptual Framework

This study tests competing hypotheses by examining the associations between individual- and contextual-level risk factors and 30-day HF readmission to determine critical predictors of 30-day readmission (Figure 1). The modified multilevel conceptual framework based on the ABM (Figure 2) illustrates the relationships between the two primary level risk factors to 30-day readmission: (1) *individual-level factors* and (2) *contextual-level factors*.

Early readmission within 30 days can be partially explained by the combined effects of the 3 domains of *individual-level factors*: predisposing characteristics, needs, and enabling resources.[32] The first individual-level domain, *predisposing*, included characteristics before the onset of an encounter that may predispose some individuals to delay seeking treatment. The second individual-level domain is *enabling* resources, which can often be influenced by tailored interventions to target at-risk populations to improve access to care policies.[30,33] The third individual-level domain is the *needs* for care, which include clinical characteristics and a set of indicators for the index hospitalization factors.

It is also essential to consider the 2 domains of *contextual-level factors*, subdivided into the health care system and the external environment domains, that may predispose specific populations to 30-day readmission. This study considered hospital census tract data (census-level demographic and socioeconomic census tract factors), urban/rural residence, distance to the closest health-care facility, and neighborhood-level characteristics as possible contextual-level factors affecting 30-day readmission. Also, neighborhood disadvantage is an aggregate-level measure reflecting the population means of individuals living in a defined geographic area.[33]

Methods

Study design

This study is a retrospective secondary data analysis of an existing dataset. This study was implemented based on the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) criteria to improve observational research reporting (Table S1 in supplemental files).

Setting. The populations of interest in this study are patients diagnosed with HF. These patients were admitted to an academic medical center[34] between 2013–2018 (a single-center study of a large urban hospital).

Study population. This is a secondary data analysis of 1950 HF patients hospitalized with congestive HF (CHF).[34] These patients originated from 3167 inpatient admissions. Patients younger than 18 years old, those who died during their index hospitalization, and those admitted and discharged on the same day were excluded. Finally, patients who died during the index admission were excluded. Figure 3 shows an overview of the specific inclusion and exclusion criteria for the sample.

Data sources and management. To illustrate this method, the individual-level data for all hospitalizations during the study period derived from the HF Datamart dataset was considered. Study data involved in the data analysis was exempt from institutional review board approval, which granted a waiver of informed consent. To qualify for inclusion in this study cohort, patients with HF must have had a discharge diagnosis of HF as defined by the International Classification of Diseases, Ninth Revision and Tenth Revision, Clinical Modification (ICD-9-CM and ICD-10-CM) code (Table S2 in supplemental files). Also, zip code level information was linked to the discharge HF Datamart data observations, and individual-level data was aggregated to larger spatial units utilizing census tract-level data for analysis. Information was extracted at the zip code tabulation area (ZCTA) level. In addition to the census-level data, to identify urban/rural residence, the ten-tiered federal US Rural-Urban Commuting Area (RUCA) codes of patient zip codes were converted from their claims to a two-level and four-level definition and classification method (see Tables S3 and S4 in supplemental files) recommended by RUCA Codes definitions of urbanized areas and urban clusters RUCA 3.10 framework.[35]

Lastly, spatial information was added to the latest census data using geocoding analysis. The US national database, the Neighborhood Atlas, was used to assess the ADI to reflect neighborhood disadvantage at a granular census block group level (aggregated neighborhood characteristics)[26,28] (see Table 1). The distribution of ADI values was examined and neighborhoods were sorted into percentiles of increasing ADI.

Variables

Dependent variable. In the study, each inpatient admission episode was considered as the analytic unit. A patient could have multiple readmissions during the study period, and each hospital admission stay date served as a new index admission for subsequent readmissions. The dependent outcome was time to hospital readmission (measured in days) defined as any repeat admission after being discharged from an index hospital stay for any reason within the time period of data collection. Also, 30-day readmission, defined as any repeat admission after being discharged from an index hospital stay for any reason within 30-days, was tested.

Covariates of readmission. For a more precisely meaningful classification, candidate factors were grouped a priori based on the ABM (see Figure 2). For *individual-level factors*, the individual- *predisposing domain* included patient age, gender (male as the reference group), and race. Race was categorized as "White," "Black," or "other." The *enabling domain* included "living alone" and "primary payer." Living arrangement factors were defined as "living alone," "living with family," or "health facility." For patients who did not have Medicare, Medicaid, or private insurance, their primary payer was categorized as "other." The *Needs domain* included clinical factors and index hospitalization level factors, such as admission source, admission type, hospital service, accommodation type, discharge disposition, the reason for readmission, placement of the cardiovascular device, and HF type. Comorbid conditions were identified using

the ICD-9-CM and ICD-10-CM. For *contextual-level factors*, measures of contextual-level census tract data (census-level demographic and socioeconomic census tract factors) were assessed. Also, access to care at the center's main hospital, nearest hospitals, and clinics was calculated. Lastly, the clustering of social and economic indicators based on the individual's residence at the index admission time, namely, neighborhood disadvantages using the ADI, was measured (see Table 1).

Bias. To reduce the sample bias, as the uninsured could have fewer planned readmissions, planned and previously scheduled readmissions were excluded. Missing values can occur in the level-1 factors or the level-2 factors. Although individual-level data was abstracted rigorously, there were missing values for some patients for individual-factors with low missing rates. The multilevel model can handle missing observations without making biased estimates on any of the risk factors or the outcome (by removing the row of values that contain NAs in R when an observation is missing). All cases with missing zip code data were removed (see Figure 3).

Statistical analyses

Descriptive sample characteristics. Descriptive statistics were calculated to summarize patient and admission characteristics using the chi-square test for categorical variables and the *t*-test for continuous variables.

Covariates of readmission. Candidate risk factors were drawn based on the ABM conceptual framework, as described earlier in the Methods section. A *p*-value with <0.05 significance was used as a criterion for selecting risk factors in the multivariable model (see Table S5 in supplemental files).

Hierarchical linear modeling and multilevel survival analysis. First, to aid understanding of readmissions that happen after discharge from the index (i.e., initial) admission, 3 separate

analyses were performed to examine the association of readmission separately for each level (see Figure 4). Due to the complexity of the models in which the survival data are right-censored, a multilevel survival analysis was run using the 'frailty.gaussian' function to allow for the hierarchical, random-intercepts domain separately for 3 levels of risk factors: (a) individual characteristics (including demographic factors, such as age and gender), (b) clinical and index hospitalization characteristics (eg LOS and admission unit), and (c) contextual characteristics (including census-level factors, such as income) (see Figure 4, A).

Then, multilevel mixed models (also known as hierarchical linear modeling [HLM]) were employed to model individual-level factors. First, individuals' various explanatory factors were included, including age, gender, marital status, and ethnicity and race characteristics in the predisposing model. Then, health needs (clinical characteristics and a set of indicators for the index hospitalization factors) and enabling (insurance, living situation, and employment status) factors were sequentially added. Lastly, a hierarchical 1-level logistic model (Model 1, collapsed model) was run, including all predisposing, enabling, and needs factors (see Figure 4, B).

Also, a HLM (Model 2) was run to include only variables that examine the contextual-level factors (see Figure 4, C). Then, multilevel mixed models were employed to model (2-level logistic model) readmission risk as a function of fixed and random effects that combine individual and contextual characteristics. Specifically, the fixed effects included all individual-level factors. The models' random-effects aspect estimated the expected readmission by nesting the models at the individuals' contextual level (see Figure 4, D).

Retrospective geospatial analysis. A spatial analysis technique was used to calculate distances from patients' census tracts to the closest hospitals, clinics, and referral medical centers. I used GIS mapping to visualize areas with high 30-day readmission rates. ArcGIS software 10.7.1

(ESRI, Redlands, CA) was used. Choropleth maps in ArcGIS were used to generate GIS maps representing ADI scores and 30-day readmissions across Washington State. Frequencies of 30-day readmission were examined for each grouping. Logistic regression was used to assess the relationship between ADI groupings and 30-day readmission (see Figure 4, E).

All analyses were performed using R version 3.3.1. The "lmer()", "glmer()" (lme4 package), and "Surv()" (survival package) function in R were used to estimate the mixed model discreet and binary outcome. A *p*-value of <0.05 was considered statistically significant. To evaluate the model performance of each set of hospital-level variables and individual-level variables in explaining 30-day readmission variation, the readmission Akaike information criterion (AIC) was reported for each model. Since some patients may be counted more than once, a sensitivity analysis was performed comparing the above model fitting options, including the first eligible readmission for each patient.

Results

Descriptive sample characteristics. Table 2 provides sample mean values of the risk factors used in the analysis based on the ABM. The HF Datamart cohort consisted of 1950 patients admitted between 2013–2018 (see Figure 3). The patients' mean age was 60.42 years (SD 16.72) and 41.1% were male. More than 75.7% of the sample was White, 9.7% was Black, and 14.6% identified as other. Table 3 shows detailed estimates of demographic, social, economic, and housing characteristics at the census level (see Table 3). Table 4 shows the prevalence of readmission among patients with HF. It was observed that 30.5% of patients were admitted within 30-days, and 58.7% were admitted because of non-cardiovascular disease (CVD) related admissions.

Geospatial analysis of spatial pattern characteristics. The results show the geospatial analysis of spatial pattern characteristics, including distance to the centroid of the index hospital UWMC (32.68 ± 35.22), distance to any nearby hospital (4.68 ± 4.82), and distance to the nearest clinic (2.15 ± 3.46).

Multiple regression and multilevel modeling. Table 5 shows effects of the exploratory analysis for the 3 levels of individual, clinical, and index hospitalization characteristics, and contextual characteristics on time to all-cause readmission from the multilevel modeling. Several factors are associated with shorter or longer time to all-cause readmission during the post-discharge period (all *p*-values > 0.05). Only living alone, was identified as being associated with a longer time to all-cause readmission during the post-discharge period (β = 0.36, *p*-values <0.5). Living alone was more statistically significantly associated with a shorter time to all-cause readmission (increased risk) during the post-discharge period than living in a health care facility. The individual-level model AIC was 3866.81 during post-discharge. In Model 2, among hospital-level patient characteristics, patients admitted from a non-healthcare facility point of origin had a significantly longer time period before all-cause readmission during the post-discharge period (β = 0.22, *p*-value < 0.05). Also, patients admitted to a surgical unit were significantly more likely to be readmitted to the hospital early than those admitted to the medical or ICU unit (β = -0.37, *p*-value < 0.05). Hospital-level risk factors (predictors) to the multilevel model provided a higher AIC 3879.24 on all-cause 30-day readmission during the post-discharge period, indicating poorer fit as compared to the previous individual level. When patient information data was aggregated at the census and county level, contextual-level risk factors, such as low household income ($24,999 annually on average) and households with only high school education, married couples, and single parents with children all had a significantly shorter time to all-cause readmission

(increased risk) during the post-discharge period (-1.53, -3.46, -0.02, and -0.07 respectively, *p*-value = <0 .05). Examining the contextual-level risk factors provided a better fit to the data (AIC of 3026.95) on time to all-cause readmission during the post-discharge period, indicating a more favorable result for the model that was not accounted for in the previous model. Sensitivity analyses were conducted with no substantive difference (for the primary outcome) and therefore the results presented include all readmission data that was available. Table 6 shows the effects of risk factors associated with 30-day readmission using a multilevel model of the ABM conducted using an individual-level data source. According to the ABM, none of the included factors in the predisposing domain (Model 1) were significant in predicting all-cause readmission time during the post-discharge period (*p*-value > 0.05). The enabling domain alone was identified as being associated with a longer time to all-cause readmission during the post-discharge period (β = 0.36, *p*-values <0.5). The model's AIC fit was 4710.24. Regarding the individual enabling domain of proximal measures of personal resources, the enabling factors model's AIC fit was 4095.59, indicating a better fit. Regarding proximal measures of personal resources and access to care among the individual needs domain, the needs factors model's AIC fit was 4716.93. This indicates a lower fit as compared to the predisposing and enabling domains. The final all individual-level model's AIC fit was 4099.21. At the contextual level, Table 7 shows patient information data at the census- and county-level. The contextual factor model's AIC fit was 3717.61. Lastly, the 2-level risk factors' impact were compared to explore how contextual-level risk factors enhance or weaken individual-level risk factors. The full model AIC was low at 1097.73, indicating a better model fit (Table 8).

Neighborhood disadvantage. The association of neighborhood disadvantage was tested with all-cause readmission outcomes. The 100th percentile indicates the highest level of neighborhood

disadvantage. Figure 5 shows the distribution of ADI scores in disadvantaged neighborhoods in Washington State, with an average of 35% of neighborhoods indicating a moderately disadvantaged neighborhood. Figure 6 shows a map of the most disadvantaged neighborhoods and their prevalence. Those who live in the most disadvantaged neighborhoods have a higher risk of all-cause readmission than those who live in other regions with a lighter red color ($\beta = -1.2$, $p < 0.001$). The rate of all-cause readmission did not vary significantly across disadvantaged neighborhoods.

Discussion

This is a theory-informed analysis that used hierarchical linear modeling of all-payer data from an urban teaching hospital of HF cohorts, based on the index admission's primary diagnosis. This study demonstrated two principal results.

In the first aim, the effect of individual- and contextual-level risk factors on 30-day readmission was assessed among HF patients using the ABM conceptual framework as a guide. In the exploratory analysis, among clinical and index hospitalization characteristics, it was found that longer length of stay (LOS), admission to the ICU or a surgical unit (admission location), and discharge to the health care unit were significantly associated with an elevated risk of all-cause readmission. This finding is in line with a recent study reporting that longer LOS resulted in a higher likelihood of 30-day all-cause readmission among patients who are Medicare beneficiaries discharged after HF admission.[36] Among individual characteristics, it is surprising to note that patients who live alone—compared with patients living with family or at health care facilities—have longer readmission intervals. In contrast, previous reviews have identified the importance of social support to prevent 30-day readmission.[20,21,31,37,38] The available evidence concerning the effect of living alone and the risk for readmission is inconsistent; although some

previous studies have considered it to be a protective factor,[39] other studies have contradicted this finding.[40] In the study, the link between patients who live alone and the lower risk of having a shorter interval for readmission is unclear. However, several relevant factors may explain the study findings: examining living situations from electronic medical records and clinicians' documentation may involve a trade-off of not capturing the different perspectives of the actual complexity of the patient's living situation. In particular, the predictor of "lives alone" may not have captured the granularity of patient perception toward living alone.[41] Specifically, patients may live alone but are staying connected with other people in their community. Consequently, further research is needed to assess other patient-reported factors that reflect perceived social support and other social factors to capture data in relevant domains. Among contextual characteristics, people with the characteristics of residing in low-income neighborhoods, as measured by per capita income, being aged 25 and older without a high school diploma, and being married were more significantly linked to shorter readmission intervals of both outcomes. Emerging evidence has suggested that readmission rates and low socioeconomic status are associated with an increased risk of readmission.[42] Therefore, the ABM was used to understand how individual-level and contextual-level risk factors influenced the incidence of all-cause 30-day readmission among patients with HF.

The findings support the hypothesis that including contextual characteristics with the individual characteristics model would improve the ability to identify risk factors that predict all-cause readmission and HF-related readmission. When combined, it was found that individual sociodemographic, economic, and hospitalization characteristics explained individual-level variations in 30-day readmission rates. Ours results are in accordance with Hersh and colleagues,[21] who proposed a conceptual model for HF readmission, emphasizing the

importance of the post-discharge vulnerable phase as a critical time where patients are at high risk and prone to exacerbations. There is growing evidence that explains the role of social supports, a safe living environment, education level, economic stability, and access to care in the readmission of HF patients.[20,31,43] For example, Amarasingham et al[43] reported the limited ability of clinical factors to accurately predict the odds of readmission. Further, the Amarasingham et al[43] model focused on examining the synergistic effects of social, behavioral, and utilization factors (i.e., being single, male, using Medicaid, having an increased number of address changes, and average income level for zip code of residence) as predictors of readmission among patients with HF (C-statistic 0.72).[43] A systematic review of retrospective and prospective cohorts and case control and cross-sectional studies was conducted to assess the impact of social determinants of health on risk of readmission or on mortality after hospitalization for HF.[31] The results of the review emphasized the importance of studying social determinants of health that may affect the risk of post-discharge readmission for patients with HF. Specifically, social factors that were examined in relation to an increase in risk of readmission in HF were being elderly, being Black or Hispanic, using Medicare or Medicaid, being unmarried or single, and several measures of low socioeconomic status were also found to significantly increase readmission.[31]

The second aim attempted to determine whether neighborhood characteristics measured by the ADI had any significant effect on patient readmission risk. Awareness of the importance of assessing risk factor-related neighborhoods as well as the environment has grown steadily.[21] The Area Deprivation Index (ADI), developed by Singh et al, can be used to assess socioeconomic disadvantage.[28,44,45] The study shows that patients residing in a highly disadvantaged neighborhood had increased numbers of contextual and individual characteristics

that contributed to their readmission. The findings further support the notion that a high level of neighborhood disadvantage may influence the risk of readmission among patients with HF. This study aligns with previous research showing that residence in a zip code in the lowest socioeconomic quintile was associated with an increased risk of 30-day readmission.[15,26,42,43]

Taken together, the current study's findings show that focusing on individual-level data alone (including hospital-level data) in predicting patients at the highest risk of rehospitalization is not enough to address the issue of 30-day readmission. Therefore, in an effort to lower health care costs associated with excessive 30-day readmissions, there is a need for more theoretical studies to enrich our understanding of the individual- and contextual-level risk factors that might influence the risk of 30-day readmission in patient with HF. To prevent readmissions in a population, it is particularly important to move beyond assessing individual-level risk factors and to begin assessing multiple risk factors, such as social support, income level, and environment, on readmission. It is important for policymakers to integrate assessing contextual-level factors as a standard care transition practice of readmission reduction efforts to explain variations in hospital readmission rates. Living in socioeconomically disadvantaged neighborhoods may predispose HF patients to having limited access to essential resources, such as affordable, healthy foods. However, the underlying mechanisms for these associations remain unknown. More research is needed to examine readmission risk factors in post-discharge care facilities, such as skilled nursing facilities.

Limitations and Strengths

Several limitations should be acknowledged when interpreting the results. In the study, data extracted from a single academic medical center in Washington State was examined, limiting the generalizability of the findings. However, this study avoided the limitation of

previous studies in controlling for possible hospital-specific factors, such as discharge planning protocols, that might affect estimations of readmission rate. Also, it was not possible to examine imperative factors related to patient functional status and perceived patient-reported outcomes related to lifestyle behaviors, caregiver availability, and degree of social support because of the limitation of using routinely collected data in administrative databases. Another limitation of using routinely collected data from databases is that access was limited to a more comprehensive profile of risk factors related to hospital data (eg, hospital size) on adherence to treatment levels of variables that might influence risk of readmission.

Despite these limitations, the study has used a multilevel framework examining comprehensive variables, capturing patients' individual and contextual factors, to obtain patient characteristics across multiple readmission events.

Conclusion

The findings emphasize the importance of both individual- and contextual-level risk factors on readmission variations. From all the associations described, living in a disadvantaged neighborhood brought a higher risk for readmission following hospitalization for HF. The study's findings suggest that neighborhood-level factors should be considered along with individual-level factors. Ultimately, the findings of the multilevel and multifaceted factors associated with readmission suggest the importance of developing effective, tailored, patient-centered health care interventions based on the patient's social context to target the individual (patient) and contextual (neighborhood) factors to reduce readmissions among patients with HF.

References

1. Virani S, Alonso A, Benjamin E, Bittencourt M, Callaway C, Carson A, . . . Tsao C. Heart disease and stroke statistics—2020 update: A report from the American Heart Association. *Circulation*. 2020; 141(9): e139-e596
2. Chamberlain RS, Sond J, Mahendraraj K, Lau CS, Siracuse BL. Determining 30-day readmission risk for heart failure patients: The readmission after heart failure scale. *Int J Gen Med*. 2018 Apr 9 ; 11: 127-141.
3. Dharmarajan K, Hsieh AF, Lin Z, Bueno H, Ross JS, Horwitz LI, Barreto-Filho JA, Kim N, Bernheim SM, Suter LG, Drye EE, Krumholz HM. Diagnoses and timing of 30-day readmissions after hospitalization for heart failure, acute myocardial infarction, or pneumonia. *JAMA*. 2013 Jan 23; 309(4): 355-363
4. Meadow A, Sangl J. Hospital readmissions in Medicare home healthcare: What are the leading risk indicators? *Home Healthc Now*. 2019; 37(4): 213-221
5. Pedersen MK, Nielsen GL, Uhrenfeldt L, Lundbye-Christensen S. Risk assessment of acute, all-cause 30-day readmission in patients aged 65+: A nationwide, register-based cohort study. *J Gen Intern Med*. 2019; 34(2): 226-234
6. Wallmann R, Llorca J, Gómez-Acebo I, Ortega ÁC, Roldan FR, Dierssen-Sotos T. Prediction of 30-day cardiac-related emergency readmissions using simple administrative hospital data. *Int J Cardiol*. 2013; 164(2): 193-200
7. Zohrabian A, Kapp JM, Simoes EJ. The economic case for US hospitals to revise their approach to heart failure readmission reduction. *Ann Transl Med*. 2018; 6(15): 298

8. Fang J, Negassa A, Gern RW, Alderman MH. Access to revascularization among patients with acute myocardial infarction in New York City—impact of hospital resources. *J Urban Health*. 2006; 83(6): 1085-1094
9. Sokoreli I, Cleland JG, Pauws SC, Steyerberg EW, de Vries JJG, Riistama J.M . . . Clark AL. Added value of frailty and social support in predicting risk of 30-day unplanned re-admission or death for patients with heart failure: An analysis from OPERA-HF. *Int J Cardiol*. 2019; 278: 167-172
10. Cox SR., Liebl MG., McComb MN, Chau JQ, Wilson AA, Achi M, . . . Wallace, D. Association between health literacy and 30-day healthcare use after hospital discharge in the heart failure population. *Res Social Adm Pharm*. 2017; 13(4): 754-758
11. Hospital Readmissions Reduction Program (HRRP). The Centers for Medicare & Medicaid Services. Updated January 3, 2020. Accessed March 2, 2019. https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/Value-Based-Programs/HRRP/Hospital-Readmission-Reduction-Program
12. Mai Ba H, Son YJ, Lee K, Kim BH. Transitional care interventions for patients with heart failure: An integrative review. *Int J Environ Res Public Health*. 2020; 17(8): 2925
13. Arora S, Patel P, Lahewala S, Patel N, Patel NJ, Thakore K, . . . Gopalan R. Etiologies, trends, and predictors of 30-day readmission in patients with heart failure. *Am J Cardiol*. 2017; 119(5): 760-769. Doi:10.1016/j.amjcard.2016.11.022
14. Ayatollahi Y, Liu X, Namazi A, Jaradat M, Yamashita T, Shen, JJ, . . . Yoo JW. Early readmission risk identification for hospitalized older adults with decompensated heart failure. *Res Gerontol Nurs*. 2018; 11(4): 190-197. Doi:10.3928/19404921-20180322-01

15. Hu J, Gonsahn MD, Nerenz DR. Socioeconomic status and readmissions: Evidence from an urban teaching hospital. *Health Aff (Millwood)*. 2014; 33(5): 778-785.
16. Mirkin KA, Enomoto LM, Caputo GM, Hollenbeak CS. Risk factors for 30-day readmission in patients with congestive heart failure. *Heart Lung*. 2017; 46(5): 357-362. Doi:10.1016/j.hrtlng.2017.06.005
17. Nagasako EM, Reidhead M, Waterman B, Claiborne Dunagan W. Adding socioeconomic data to hospital readmissions calculations may produce more useful results. *Health Aff (Millwood)*. 2014; 33(5): 786-791
18. Philbin EF, DiSalvo TG. Managed care for congestive heart failure: Influence of payer status on process of care, resource utilization, and short-term outcomes. *Am Heart J*. 1998; 136(3): 553-561.
19. Rodriguez F, Joynt KE, López L, Saldaña F, Jha AK. Readmission rates for Hispanic Medicare beneficiaries with heart failure and acute myocardial infarction. *Am Heart J*. 2011; 162(2): 254-261.
20. Arbaje AI, Wolff JL, Yu Q, Powe NR, Anderson GF, Boult C. Postdischarge environmental and socioeconomic factors and the likelihood of early hospital readmission among community-dwelling Medicare beneficiaries. *Gerontologist*. 2008; 48(4): 495-504
21. Hersh AM, Masoudi FA, Allen LA. Postdischarge environment following heart failure hospitalization: Expanding the view of hospital readmission. *J Am Heart Assoc*. 2013; 2(2): e000116
22. Kansagara D, Englander H, Salanitro A, Kagen D, Theobald C, Freeman M, et al. Risk prediction models for hospital readmission: A systematic review. *JAMA*. 2011; 306(15): 1688-1698

23. Krumholz HM. Post-hospital syndrome—an acquired, transient condition of generalized risk. *N Engl J Med*. 2013; 368: 100-102.

24. Bikdeli B, Wayda B, Bao H, Ross JS, Xu X, Chaudhry SI, Spertus JA, Bernheim SM, Lindenauer PK, Krumholz HM. Place of residence and outcomes of patients with heart failure. *Circ Cardiovasc Qual Outcomes*. 2014; 7(5): 749-756.

25. Joynt Maddox KE, Reidhead M, Hu J, Kind AJH, Zaslavsky AM, Nerenz D. Adjusting for social risk factors impacts performance and penalties in the hospital readmissions reduction program. *Health Serv Res*. 2019; 54(2): 327-336. Doi:10.1111/1475-6773.13133

26. Kind AJ, Jencks S, Brock J, Yu M, Bartels C, Ehlenbach W, et al. Neighborhood socioeconomic disadvantage and 30-day rehospitalization: A retrospective cohort study. *Ann Intern Med*. 2014; 161(11): 765-774.

27. Hu J, Kind AJ, Nerenz D. Area deprivation index predicts readmission risk at an urban teaching hospital. *Am J Med Qual*. 2018; 33(5): 493-501.

28. Singh GK. Area deprivation and widening inequalities in US mortality, 1969-1998. *Am J Public Health*. 2003; 93(7): 1137-1143.

29. Franco M, Diez Roux AV, Glass TA, Caballero B, Brancati FL. Neighborhood characteristics and availability of healthy foods in Baltimore. *Am J Prev Med*. 2008; 35(6): 561-567.

30. Andersen RM. Revisiting the behavioral model and access to medical care: Does it matter? *J Health Soc Behav*. 1995; 36(1): 1-10.

31. Calvillo-King L, Arnold D, Eubank KJ, Lo M, Yunyongying P, Stieglitz H, et al. Impact of social factors on risk of readmission or mortality in pneumonia and heart failure: Systematic review. *J Gen Intern Med*. 2013; 28(2): 269-282.

32. Andersen RM. Behavioral Model of Families' Use of Health Services. Research Series No. 25. Chicago, IL: University of Chicago Center for Health Administration Studies; 1968.

33. Andersen, R., Yu, H., Wyn, R., Davidson, P., Brown, E., & Teleki, S. (2002). Access to medical care for low-income persons: How do communities make a difference? Medical Care Research and Review, 59, 384–411.

34. Abu-Rish Blakeney E, Wolpin S, Lavallee DC, Dardas T, Cheng R, Zierler B. Developing and implementing a heart failure data mart for research and quality improvement. *Inform Health Soc Care*. 2019; 44(2): 164-175.

35. What is rural?. RUCA Codes definitions of urbanized areas and urban clusters RUCA 3.10 framework. WWAMI Rural Health Research Center. Department of Family Medicine. Accessed March 2, 2019. https://depts.washington.edu/uwruca/ruca-contact.php

36. Pham PN, Xiao H, Sarayani A, Chen M, Brown JD. Risk Factors Associated With 7- Versus 30-Day Readmission Among Patients With Heart Failure Using the Nationwide Readmission Database. *Medical Care*. 2019 Jan 1;57(1):1-7.

37. Baillie, Charles A., Christine VanZandbergen, Gordon Tait, Asaf Hanish, Brian Leas, Benjamin French, C. William Hanson, Maryam Behta, and Craig A. Umscheid. "The

readmission risk flag: Using the electronic health record to automatically identify patients at risk for 30-day readmission." *Journal of hospital medicine* 8, no. 12 (2013): 689-695.

38. Hoang-Kim, A., Parpia, C., Freitas, C., Austin, P. C., Ross, H. J., Wijeysundera, H. C., ... & Schull, M. J. (2020). Readmission rates following heart failure: a scoping review of sex and gender based considerations. *BMC Cardiovascular Disorders*, *20*, 1-19.
39. Ennis SK, Larson EB, Grothaus L, Helfrich CD, Balch S, Phelan EA. Association of living alone and hospitalization among community-dwelling elders with and without dementia. Journal of general internal medicine. 2014 Nov 1;29(11):1451-9.
40. Lu, M.L.R., Davila, C.D., Shah, M., Wheeler, D.S., Ziccardi, M.R., Banerji, S. and Figueredo, V.M., 2016. Marital status and living condition as predictors of mortality and readmissions among African Americans with heart failure. *International Journal of Cardiology*, *222*, pp.313-318.
41. Bucholz, E. M., & Krumholz, H. M. (2012). Loneliness and Living Alone: Comment on "Loneliness in Older Persons" and "Living Alone and Cardiovascular Risk in Outpatients at Risk of or With Atherothrombosis". *Archives of internal medicine*, *172*(14), 1084-1085.
42. Lindenauer PK, Lagu T, Rothberg MB, et al. Income inequality and 30 day outcomes after acute myocardial infarction, heart failure, and pneumonia: retrospective cohort study. *BMJ*. 2013;346(feb14 3):f521
43. Amarasingham R, Moore BJ, Tabak YP, Drazner MH, Clark CA, Zhang S, Reed WG, Swanson TS, Ma Y, Halm EA. An automated model to identify heart failure patients at risk for 30-day readmission or death using electronic medical record data. *Medical care*. 2010 Nov 1:981-8.

44. Singh GK, Miller BA, Hankey BF. Changing area socioeconomic patterns in U.S cancer mortality, 1950–1998: Part II--Lung and colorectal cancers. *J Natl Cancer Inst*. 2002; 94:916–925.

Figures

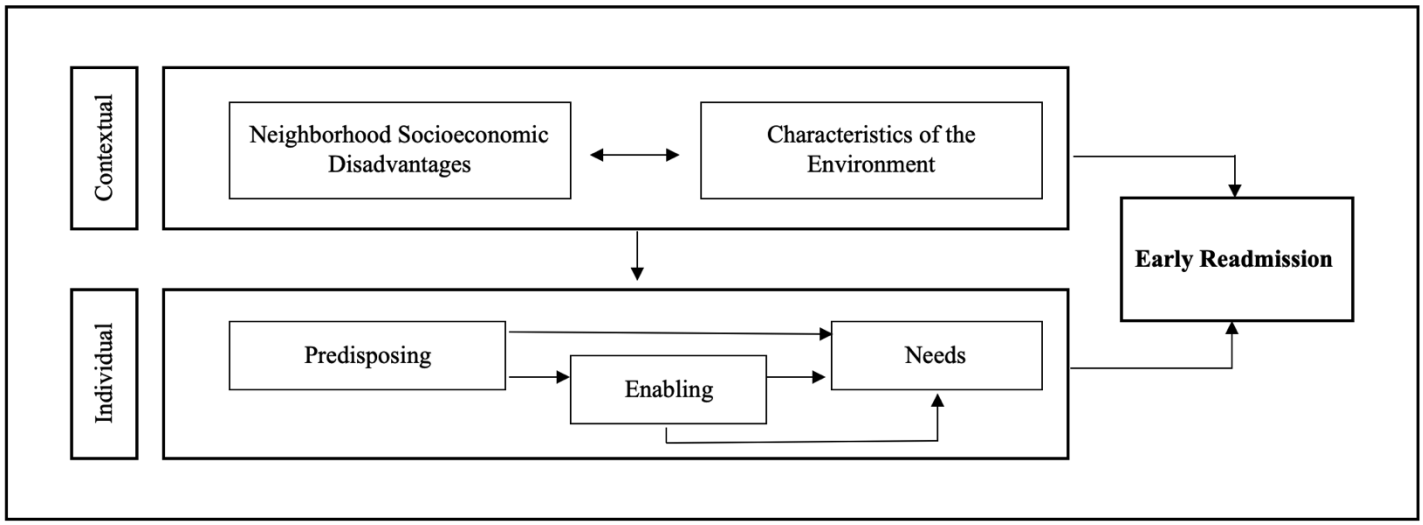


Figure 1. Multilevel Analysis Framework of the Readmission Rate of Residents in Washington State[30,32,33]

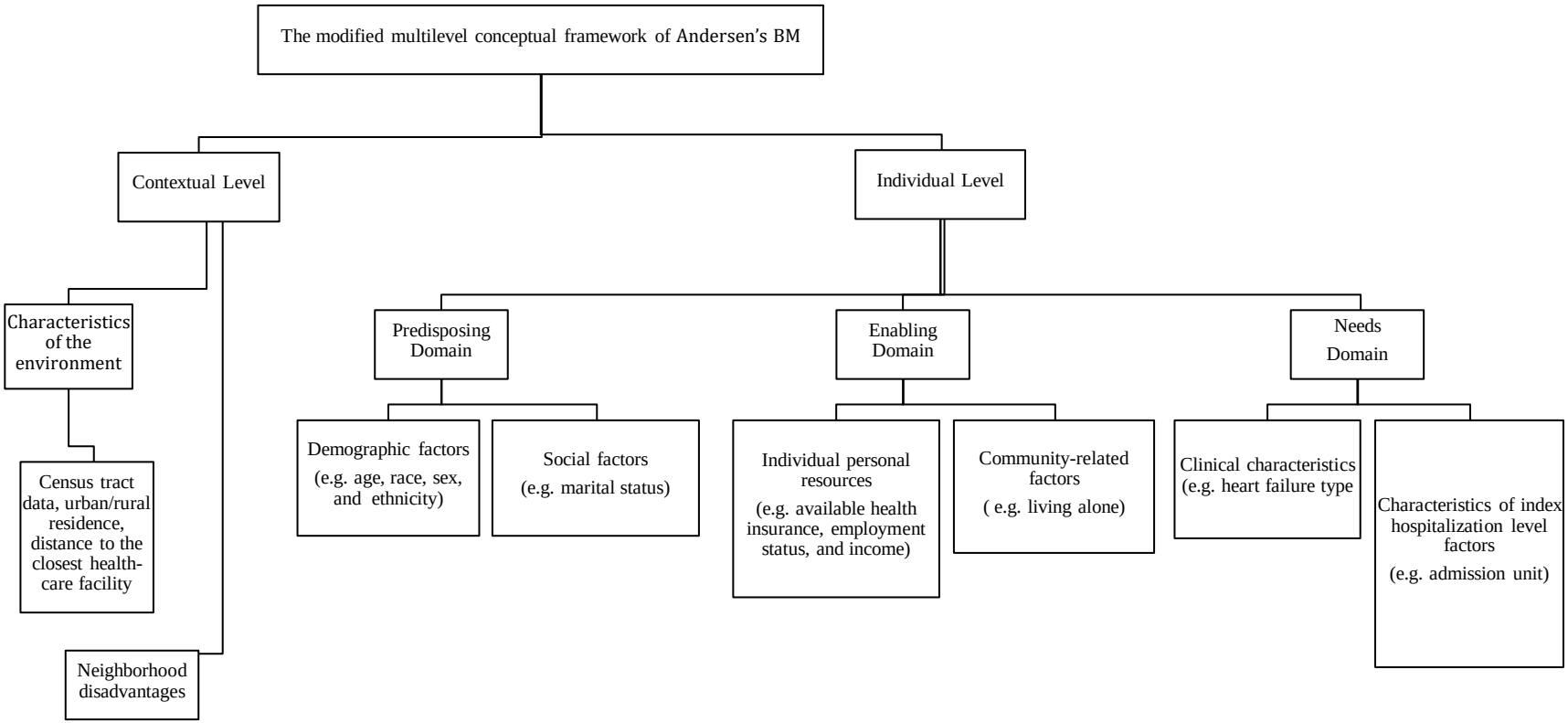


Figure 2. The Modified Multilevel Conceptual Framework of Andersen's BM[30]

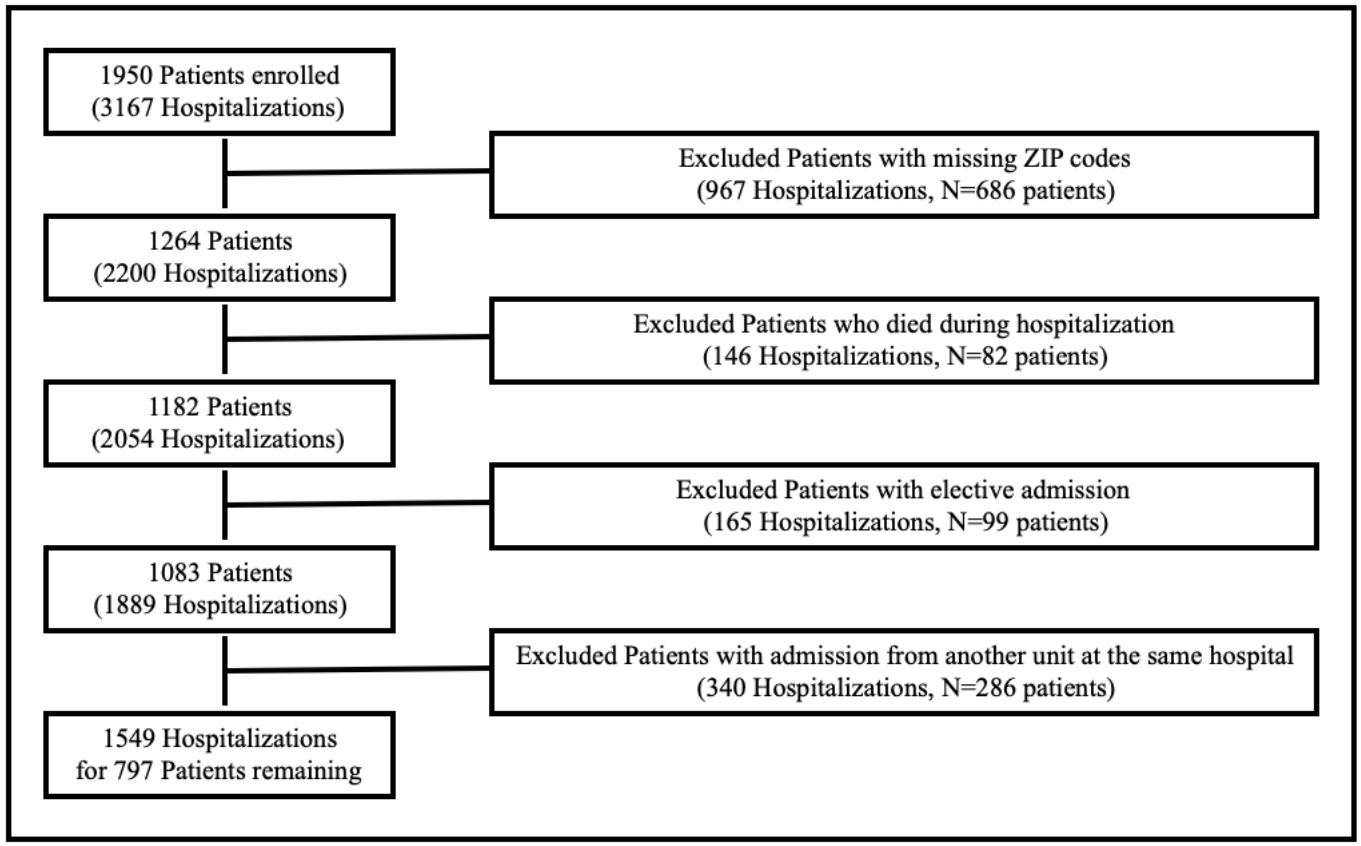
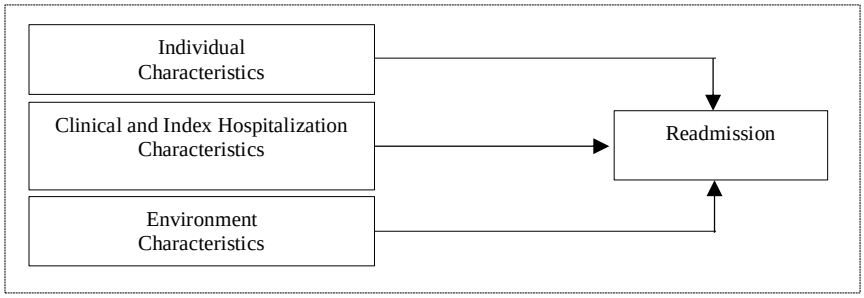
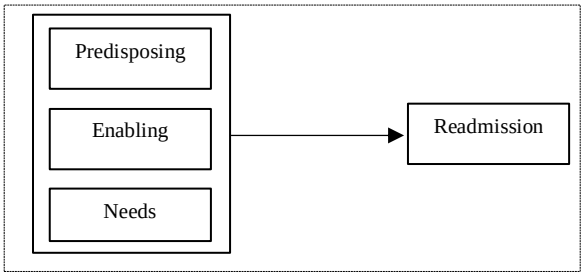


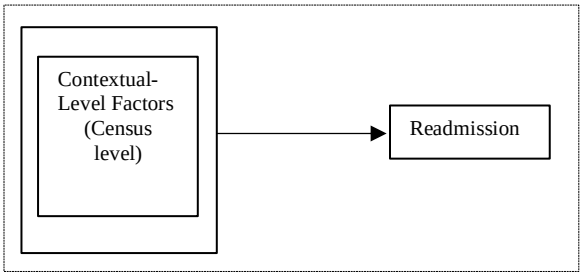
Figure 3. Study Chart Showing Numbers of Included, Excluded Patients, and Readmission Events



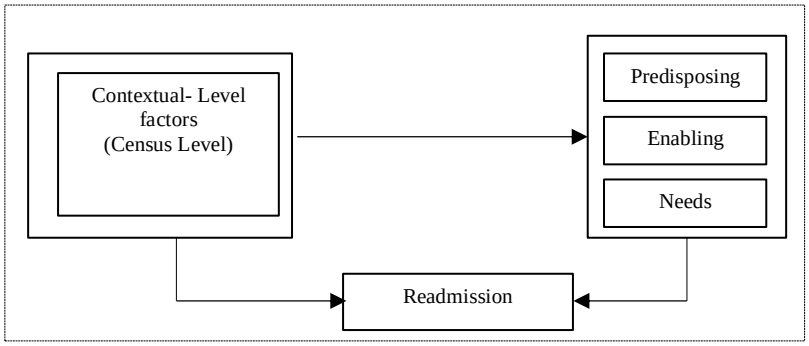
A. Model. The effect of individual, hospital related, and environmental risk factors separately on time to readmission (exploratory)



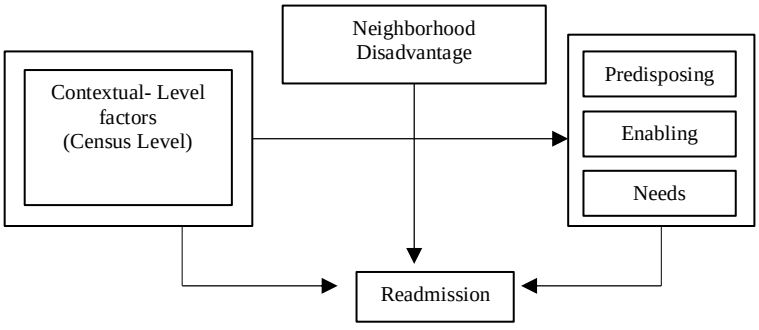
B. Model. Effect of individual predisposing, enabling, and needs risk factors on 30-day readmission based on Andersen's BM



C. Model. Effect of contextual-level risk factors on 30-day readmission based on Andersen's BM



D. Model. Effect of individual- and contextual-levels risk factors on 30-day readmission based on Andersen's BM



E. Model. Effect of neighborhood disadvantage on 30-day readmission

Figure 4. Competing Models for Understanding 30-day Readmission Using Andersen's BM

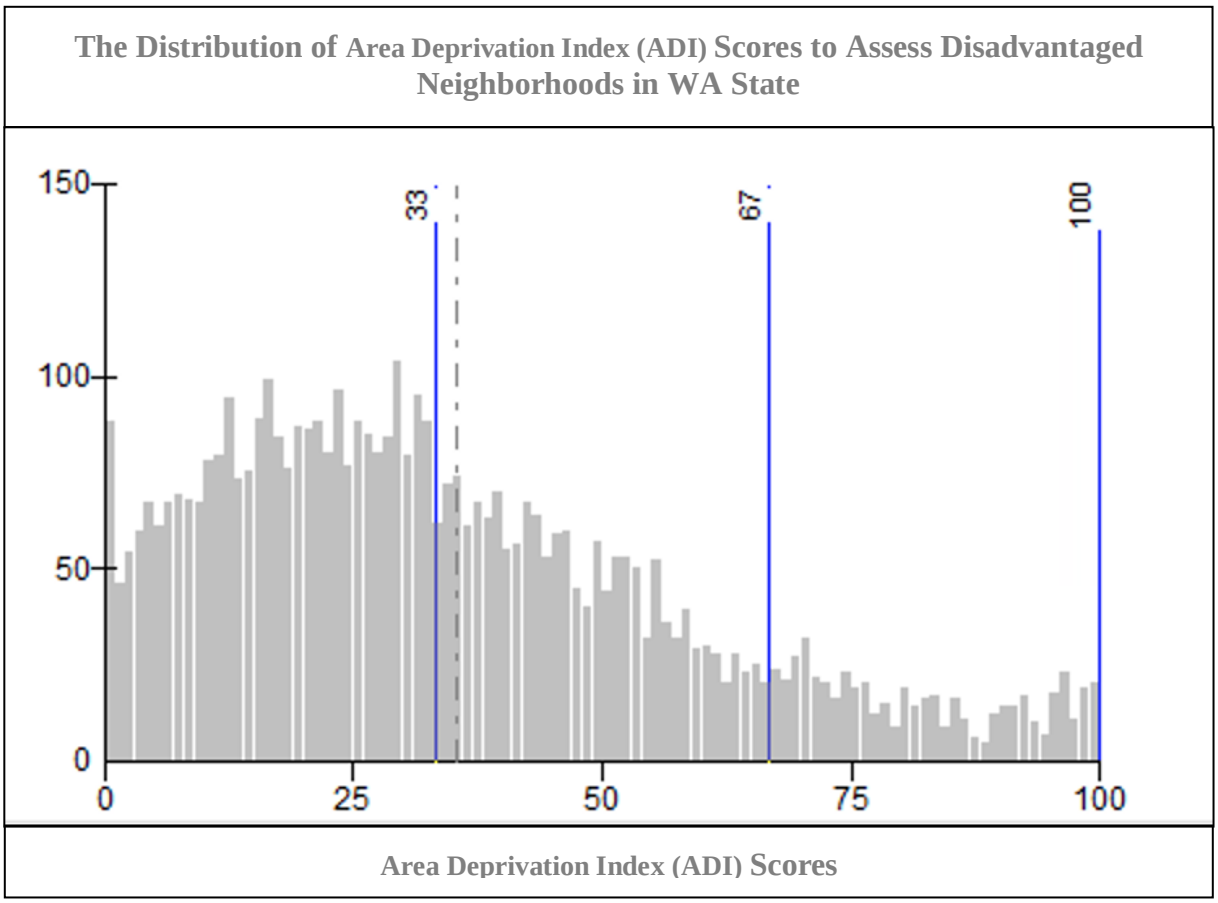


Figure 5. The Distribution of Area Deprivation Index (ADI) Scores to Assess Disadvantaged Neighborhoods in Washington State

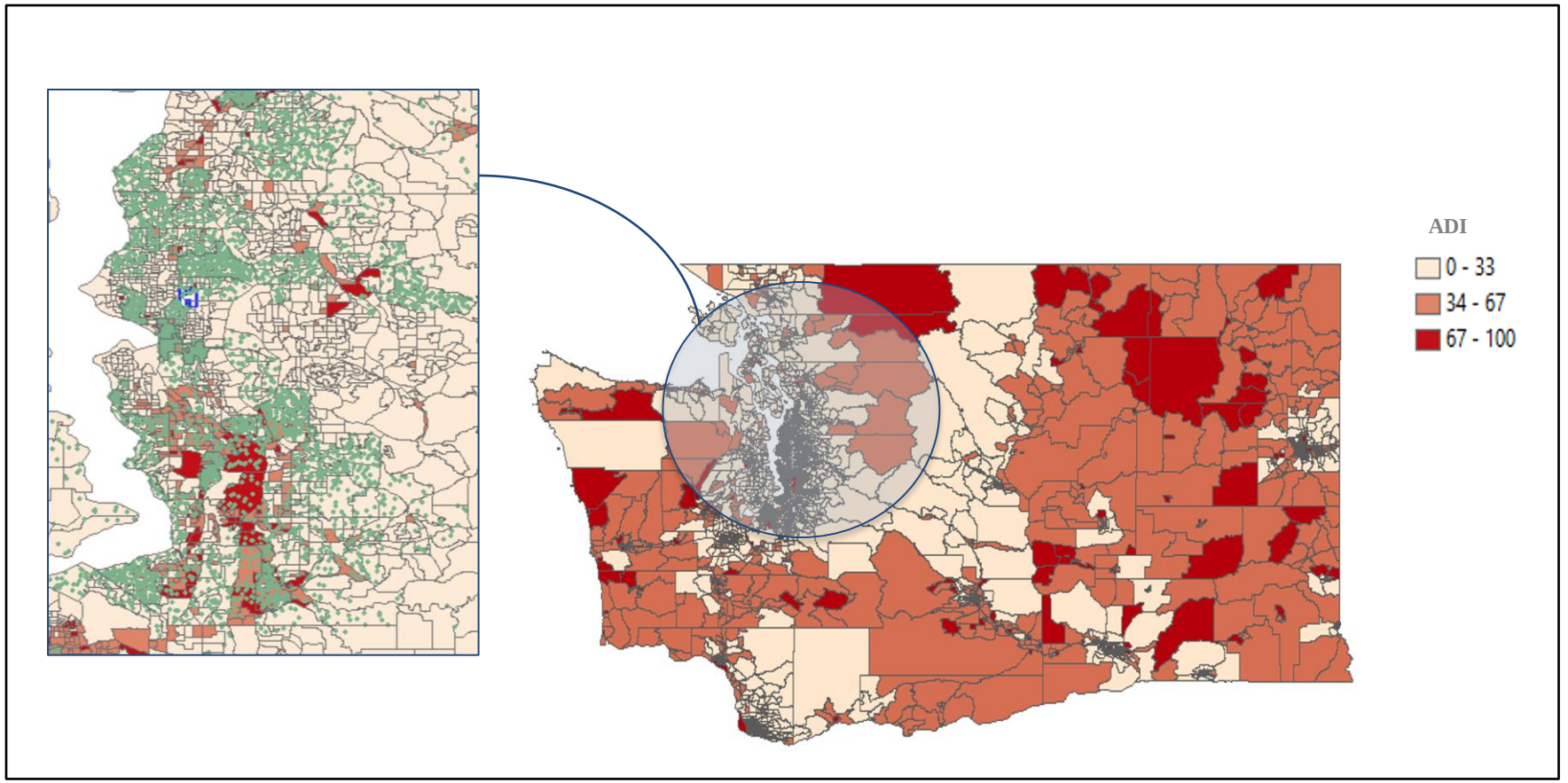


Figure 6. Neighborhood Socioeconomic ADI Score Characteristics and Readmission in Washington State

TABLES

Table 1. The 1-Factor Factor Analysis on 17 Composite Variables of the Area Deprivation Index (ADI) Score

Category	US Census Indicator
Poverty	Median family income, $
	Income disparity
	Families below poverty level, %
	% Population below 150% poverty threshold, %
	Single parent households with dependents <18%
	Households without a motor vehicle, %
	Households without a telephone, %
	Occupied housing units without complete plumbing, %
Housing	Owner occupied housing units, %
	Households with >1 person per room, %
	Median monthly mortgage, $
	Median gross rent, $
	Median home value, $
Employment	Employed person 16+ in white collar occupation, %
	Civilian labor force unemployed (aged 16+), %
Education	Population aged 25+ with <9yr education, %
	Population aged 25+ with at least a high school education, %

Note: Constructed using principal components analysis based on 17 census tract-level variables for a Census Block Group from four broad areas/ dimensions: poverty, housing, employment, and education. The ADI score variables at Block Group level used United States Census Bureau (CB) data for Washington State.

Table 2. Individual Predisposing, Enabling, and Needs at Index Hospitalization (N=1950)

Variable	Values N (%) or Mean ± SD
Individual predisposing domain	
Age (mean± SD)	60.42±16.72
Gender (n, %)	
Male (reference)	1249 (41.1%)
Marital status	
Single (reference, n, %)	964 (49.4%)
Race	
Black	189 (9.7%)
White	1476 (75.7%)
Other	285 (14.6%)
Ethnicity	
Hispanic (reference)	92 (4.7%)
Individual enabling domain	
Employment	
Employed (reference)	337 (17.3%)
Health Insurance	
Medicaid	104 (5.3%)
Medicare	434 (22.3%)
Private insurance	1085 (55.6%)
Other	327 (16.8%)
Living situation	
Living at facility or home (reference)	1492 (76.5%)
Individual needs domain	
LOS (mean ±SD)	13.19 ±16.29
Admission source	
Health care facility (reference)	1075 (55.1%)
Admission type	
Emergency	787 (40.4%)
Urgent	1006 (51.6%)
Elective	157 (8.1%)
Hospital services	
Cardiac unit	1387 (71.1%)
ICU unit	106 (5.4%)
Medical unit	255 (13.1%)
Surgical unit	202 (10.4%)
Accommodation type	
Non intensive telemetry units (reference)	1242 (63.7%)
Discharge disposition	
SNF	147 (07.5 %)
Routine discharge to home or self-care	1401 (71.8 %)
Home with health services	152 (07.8 %)
Hospice	44 (02.3 %)
Rehabilitation	33 (01.7 %)
Other	173 (08.9 %)
HF type	
HFpEF	222 (11.4 %)
HFrEF	1172 (60.1 %)

Unspecified	344 (17.6 %)
Combined	212 (10.9 %)
Cardiac device	
Having implantable device (reference)	22 (1.1%)
Comorbidity (secondary diagnosis)	
Neurological disorder	38 (1.9%)
CHF	129 (6.6%)
GI disorder	23 (1.2%)
CVD disease	801 (41.1%)
Renal disease	361 (18.5%)
Pulmonary disease	299 (15.3%)
Oncology	25 (1.3%)
Pancreas and liver disease	223 (11.4%)
Other	49 (2.5%)
Comorbidity (tertiary diagnosis)	
Neurological disorder	56 (2.9%)
HF	40 (2.1%)
GI disorder	43 (2.2%)
CVD disease	886 (45.4%)
Renal disease	348 (17.8%)
Pulmonary disease	217 (11.1%)
Oncology	35 (1.8%)
Pancreas and liver disease	228 (11.7%)
Other	97 (5.0%)

Note: N=1950. (LOS) length of stay, (ICU) intensive care unite, (SNF) transfer to skilled nursing facility, (HF) heart failure, (HFpEF) heart failure preserved ejection fraction (diastolic), (HfrEF) heart failure reduced ejection fraction (systolic), (CVD) cardiovascular disease.

Table 3. Detailed Estimates of Demographic, Social, Economic, and Housing Characteristics at Census Level

Rural residence	
Rural (reference)	278 (14.3%)
Poverty at family household (mean, SD)	3005.36 ±3655.26
Family pPoverty (mean %)	8.719%
Unemployment rate (mean %)	6.292%
Housing units	5079.47 ±5974.11
Median value of owner occupied units	256878.61±183793.15
Median household income	59070.36±28053.25
Mean income	76035.41±34870.98
Per capita income	31685.30±14889.648
Household income less than 24999 (mean)	19.41%
Race population (78767)	
White %	75%
Black %	1.89%
Population density (mean, SD)	1414.789±3533.80
Median age	41.89 ±11.99
High school (%)	25.28%
Married couple	52.54%
Single couple with children under18	7.19%

Note: Census-level data: n=600, total events=1216. Population density zip code missing available cases (935 events), missing n=281 (23%).

Table 4. Prevalence of Readmission among Patients with HF

Variables	Value N (%) or Mean
Reason for readmission (n, %) Secondary	
HF related admission	129(6.6%)
CVD related admission	800(41.0%)
Non-CVD related admission	1021(52.4%)
Reason for readmission (n, %) Tertiary	
HF related admission	53 (1.7%)
CVD related admission	1252 (39.5%)
Non-CVD related admission	1860 (58.7%)
All-cause readmission (Mean in days)	197.10
30-day readmission (Reference) (n, %)	371 (30.5%)
Death (n, %)	136 (7.0%)

Note: n=600. (HF) heart failure, (CVD) cardiovascular disease.

Table 5. The Effects of Individual, Clinical, and Index Hospitalization Characteristics and Contextual Characteristics on All-Cause Readmission

	Model 1 Individual characteristics	Model 2 Clinical and index hospitalization characteristics	Model 3 Contextual characteristics
	ß ± SD	ß ± SD	ß ± SD
(Intercept)	5.16±0.61 ***	4.40±1.32 ***	24.08±6.89 ***
Older adult (older)	-0.01±0.61		
Gender (Male)	-0.20±0.61		
Marital Status (Single)	-0.06±0.61		
Black race	-0.14±0.61		
White race	-0.21±0.61		
Hispanic	-0.30±0.61		
Retirement	0.06±0.61		
Living Situation (Alone)	0.36±0.61 *		
Insurance (Medicare)	-0.04±0.61		
LOS		-0.23±0.11 *	
Admission sources			
Non-healthcare facility		0.22±0.10 *	
ICU		-0.50±0.37	
Medical unit		-0.02±0.21	
Surgical unit		-0.37±0.16 *	
Discharge disposition to home self-care		0.18±0.14	
Combined HF		0.54±1.19	
HfpEF		0.51±1.19	
HfrEF		0.31±1.18	
Unspecified		0.35±1.20	
Secondary reason for readmission (none cardiac)		0.48±0.30	
Tertiary reason for readmission (none cardiac)		0.74±0.30 *	
Neurological disorder		-0.46±0.36	
GI		-0.59±0.41	
Heart disease		0.56±0.21 *	
Renal disease		-0.47±0.27 .	
Pulmonary disease		-0.28±0.29	
Oncology		-0.12±0.59	
Other		-0.49±0.28	
Pancreas and liver disorders		-0.56±0.35 .	
Rural			0.07±0.36
Unemployment			-0.00±0.07
Per capita income			-1.53±0.58 *
Household income <24999 ($)			-0.05±0.03 .
High education			-3.46±1.11 **
Married couple			-0.02±0.01 .
Single with children			-0.07±0.04 .
Access to nearest clinic			0.03±0.14
Access to UWMC			0.11±0.12
Access to nearest hospital			0.05±0.17
Model Fit			

AIC	3866.81	3879.24	3009.52

Note: Significant codes: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, '.' 0.1 ' ' 1. (AIC) Akaike information criterion. The optimal model is selected based on a minimum AIC. Null model AIC =4704.765.

Table 6. Individual Predisposing, Enabling, Needs and All Individual-Level Collapsed Factors for 30-Day Readmission

	Model 1 Predisposing	Model 2 Enabling	Model 3 Needs	Model 4 All individual level
	ß ± SD	ß ± SD	ß ± SD	ß ± SD
(Intercept)	0.22	0.33±0.04	0.48±0.32	0.27±0.04
Older adult	0.03			
Gender	0.02			
Marital status	-0.01			
Race White	0.06			
Race other	0.04			
Hispanic	-0.04			
Medicare		0.00±0.15		
Living situation		-0.09±0.1*		
Employment status		-0.03±0.16		
LOS			0.06±0.32	
Admission source			-0.03±0.03	
Hospital service - ICU			0.00±0.03	
Hospital service - Medical			0.03±0.07	
Hospital service - Surgical			0.10±0.05	
Accommodation type telemetry			0.03±0.04	
Discharge disposition to home self-care			-0.04±0.03*	
CVD device			-0.03±0.03	
Combined HF			-0.26±0.04	
HFpEF			-0.26±0.32	
HFrEF			-0.22±0.32	
Unspecified HF			-0.23±0.32	
Admission secondary to non-cardiac reasons			0.06±0.02	
Parsimony model				
Living situation - alone				-0.08±0.04
LOS - longer				0.07±0.041
Admission source from non-health care				-0.03±0.02
Hospital service - ICU				0.00±0.02
Hospital service - Medical				0.02±0.07
Hospital service - Surgical				0.12±0.052
Discharge disposition home self-care				-0.05±0.04
Admission secondary to non-cardiac reasons				0.06±0.03
Model Fit				
AIC	4710.24	4095.59	4716.93	4099.21

Note: Significant codes: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.(HF) heart failure, (LOS) length of stay, (CVD) cardiovascular device, (HFpEF) heart failure preserved ejection fraction (diastolic), (HFrEF) heart failure reduced ejection fraction (systolic), (AIC) Akaike information criterion. The optimal model is selected based on a minimum.

Table 7. Contextual-Level Characteristics and All-Cause Readmission

	Model 1 Contextual level
	ß ± SD
(Intercept)	-1.34±1.67
Rural	0.06±0.081
Unemployment	-0.01±0.09
Per capita income	0.15±0.13
Household income <24999 ($)	0.00±0.01
Race White	-0.01±0.00
Race Black	-0.01±0.01
High education	-0.02±0.015
Married couple	0.05±0.020
Single couple with children under18	0.34±0.26
Nearest clinic	0.00±0.00
Nearest UWMC	0.01±0.01
Nearest hospital	-0.04±0.03
Model Fit	
AIC	3717.609

Note: Significant codes: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. (HF) heart failure, (LOS) length of stay, (CVD) cardiovascular device, (HFpEF) heart failure preserved ejection fraction (diastolic), (HFrEF) heart failure reduced ejection fraction (systolic).

Table 8. Testing Model Fit of the Effects of the Individual and Contextual Risk Factors on All-Cause Readmission from the Multilevel Modeling

Model 1	Model 2	Model 3	Contextual risk factors
Predisposing	Enabling	Needs	
1592.407	1376.006	1611.693	
Individual risk factors			3717.609
1386.964			
1097.727			

Note: (AIC) Akaike information criterion. The optimal model is selected based on a minimum.

SUPPLEMENTAL FILES

Table S1. STROBE Statement—Checklist of items that should be included in reports of cohort studies

	Item No	Recommendation
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found
Introduction		
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported
Objectives	3	State specific objectives, including any prespecified hypotheses
Methods		
Study design	4	Present key elements of study design early in the paper
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection
Participants	6	(*a*) Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up
		(*b*) For matched studies, give matching criteria and number of exposed and unexposed
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group
Bias	9	Describe any efforts to address potential sources of bias
Study size	10	Explain how the study size was arrived at
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding
		(*b*) Describe any methods used to examine subgroups and interactions
		(*c*) Explain how missing data were addressed
		(*d*) If applicable, explain how loss to follow-up was addressed
		(*e*) Describe any sensitivity analyses
Results		
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed
		(b) Give reasons for non-participation at each stage
		(c) Consider use of a flow diagram
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders
		(b) Indicate number of participants with missing data for each

		variable of interest
		(c) Summarise follow-up time (eg, average and total amount)
Outcome data	15*	Report numbers of outcome events or summary measures over time
Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included
		(*b*) Report category boundaries when continuous variables were categorized
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses
Discussion		
Key results	18	Summarise key results with reference to study objectives
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence
Generalisability	21	Discuss the generalisability (external validity) of the study results
Other information		
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based

*Give information separately for exposed and unexposed groups.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at http://www.strobe-statement.org.

Table S2. Diagnoses of Heart Failure (HF) or Related Conditions, According to ICD-9-CM and ICD-10-CM Codes

ICD-10 diagnosis code	ICD-9 diagnosis code
I09.81	398.91
I10	402.91
I11.0	404.01
I13.0	404.91
I13.2	404.93
I34.0	428
I50.1	428.2
I50.20	428.21
I50.21	428.22
I50.22	428.23
I50.23	428.3
I50.31	428.31
I50.32	428.32
I50.33	428.33
I50.40	428.41
I50.41	428.42
I50.42	428.43
I50.43	428.9
I50.9	

Note: ICD-10 (International Classification of Diseases 10th Revision), ICD-9 (The International Classification of Diseases, 9th Revision).

Table S3. Urban/Rural Residence Status Based on the Definition and Classification Method Recommended by Rural Urban Commuting Areas (RUCA): Four-Tier Consolidation of Secondary RUCA Codes

Levels	RUCA	Population density
Level 1: Urban core	1.0, 1.1	
Level 2: Suburban	2.0, 2.1, 3.0	>100 residents/square mile
Level 3: Large rural	4.0, 4.1, 4.2, 5.0, 5.1, 5.2, 6.0, 6.1	>100 residents/square mile
Level 4: Small town/rural	7.0, 7.1, 7.2, 7.3, 7.4, 8.0, 8.1, 8.2, 8.3, 8.4, 9.0, 9.1, 9.2, 10.0, 10.1, 10.2, 10.3, 10.4, 10.5, 10.6	or not urban core with population density <100 residents/square mile

Table S4. Urban/Rural Residence Status Based on the Definition and Classification Method Recommended by Rural Urban Commuting Areas (RUCA): Two-Tier Consolidation of Secondary RUCA Codes

Levels	Codes
Urban	1 Metropolitan area core: primary flow within an Urbanized Area (UA) 1.0 No additional code 1.1 Secondary flow 30% through 49% to a larger UA 2 Metropolitan area high commuting: primary flow 30% or more to a UA 2.0 No additional code 2.1 Secondary flow 30% through 49% to a larger UA 3 Metropolitan area low commuting: primary flow 10% to 30% to a UA 3.0 No additional code
Rural	4 Micropolitan* area core: primary flow within an Urban Cluster (UC) of 10,000 through 49999 (large UC) 4.0 No additional code 4.1 Secondary flow 30% through 49% to a UA 4.2 Secondary flow 10% through 29% to a UA 5 Micropolitan* high commuting: primary flow 30% or more to a large UC 5.0 No additional code 5.1 Secondary flow 30% through 49% to a UA 5.2 Secondary flow 10% through 29% to a UA 6 Micropolitan* low commuting: primary flow 10% to 30% to a large UC 6.0 No additional code 6.1 Secondary flow 10% through 29% to a UA 7 Small town core: primary flow within an Urban Cluster of 2500 through 9999 (small UC) 7.0 No additional code 7.1 Secondary flow 30% through 49% to a UA 7.2 Secondary flow 30% through 49% to a large UC 7.3 Secondary flow 10% through 29% to a UA 7.4 Secondary flow 10% through 29% to a large UC 8 Small town high commuting: primary flow 30% or more to a small UC 8.0 No additional code 8.1 Secondary flow 30% through 49% to a UA 8.2 Secondary flow 30% through 49% to a large UC 8.3 Secondary flow 10% through 29% to a UA 8.4 Secondary flow 10% through 29% to a large UC 9 Small town low commuting: primary flow 10% through 29% to a small UC 9.0 No additional code 9.1 Secondary flow 10% through 29% to a UA 9.2 Secondary flow 10% through 29% to a large UC

10 Rural areas: primary flow to a tract outside a UA or UC (including self)
10.0 No additional code
10.1 Secondary flow 30% through 49% to a UA
10.2 Secondary flow 30% through 49% to a large UC
10.3 Secondary flow 30% through 49% to a small UC
10.4 Secondary flow 10% through 29% to a UA
10.5 Secondary flow 10% through 29% to a large UC
10.6 Secondary flow 10% through 29% to a small UC

Note: Based on Washington, Wyoming, Alaska, Montana, Idaho (WWAMI) Rural Health Research Center.[35]

Table S5. Study Variables

Dependent variable		
Time to hospital readmission	Any repeat admission after being discharged from an index hospital stay for any reason within the time period of data collection	
30-day readmission	Any repeat admission after being discharged from an index hospital stay for any reason within 30-days	
Covariates of 30-day readmission		
(Level 1) Individual-level factors		
Predisposing domain		
	Age	Older adult
	Gender	Male
	Marital status	Single
	Race	Black White Other
	Ethnic group	Hispanic
Enabling domain		
	Insurance	Medicare Medicaid Private insurance Other
	Living situation	Alone Living with family or health facility
	Employment status	Employed
Health needs domain		
	LOS	Length of stay in days
	Admition source description	Non-health care
	Hospital service	
	Accommodation type: Telemetry	Telemetry
	Discharge disposition	Home self-care
	CVD	
	Heart failure type Combined heart failure	Combined
	HFpEF	HFpEF
	HFrEF	HFrEF
	Unspecified heart failure type	Unspecified
	Comorbidity Neurological disorder GI Heart disease Kidney disease Lung disease Oncology Other Pancreas and liver disorders	
(Level 2) Contextual-level factors		
Census (ZIP code) level data		
	Rural/urban residence	Rural
	Census-level unemployment rate	

	Per capita income 12m	Income
	Percent of the population with incomes below the federal poverty level ($24999)	Poverty
	Race specific population Census-level race White	White
	Census-level race Black	Black
	Percent of the population over the age of 25 with no high school diploma	Highs school
	Married couple	Married couple
	Single parent with children under 18	Single parent
Spatial (GIS) level data		
	Nearest clinics	Nearest clinics
	Nearest hospitals	Nearest hospitals
	Access to care of the center's main hospital (UWMC)	Access to UWMC
Neighborhood (block level) disadvantage data		
	ADI	

Note: (LOS) Length of stay, (HFpEF) Heart failure preserved ejection fraction, (HFrEF) Heart failure reduced ejection fraction, (GI) Gastrointestinal, (UWMC) University of Washington Medical Center, (GIS) Geographic Information System, (ADI) Area Deprivation Index, (CVD) Cardiovascular device