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The Identification of Clinically Relevant Readmission Risk Factors in Previously Hospitalized Albertan Heart Failure (HF) Patients: A Modified Delphi Process

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The Identification of Clinically Relevant Readmission Risk Factors in Previously Hospitalized Albertan Heart Failure Patients (HF): A Modified Delphi Process

by

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Abstract

Introduction: Heart failure (HF) is a leading national cause of hospitalization. Canadians hospitalized with HF have a 20% 30-day readmission rate. Readmission risk prediction (RRP) helps providers plan follow-up patient care, decreasing readmission risk. Current RRP models have low predictive ability. There is poor consensus on variables to include in RRP models. RRP models often use clinician-derived variables. However, including patient perspectives encourages the integration of sociodemographic and healthcare utilization variables in RRP models. To our knowledge, there are no previously published works on clinician/ non-clinician derived variables for an RRP. The aim was to formulate a list of variables deemed necessary for inclusion in an RRP model by both clinicians and non-clinicians.

Methods: An in-depth literature review revealed variables associated with readmission risk in HF patients. A modified Delphi process was used as the consensus-reaching method. A survey was administered to 13 panelists for a total of 3 rounds. Panelists included clinicians who varied in clinical expertise, profession, and years of practice. Also included were patients with HF and their caregivers. Results were summarized using medians, interquartile range (IQR) and narrative synthesis.

Results: A total 61 of 99 original variables reached consensus for association with readmission risk in HF patients. Variables were grouped into 6 domains. The domains with the lowest consensus were *Clinical Features* and *Treatment*. *Comorbidities* and *Sociodemographic* reached high levels of consensus. Within the systematic reviews, of the 19 variables not reaching agreement on association with readmission risk, 10 reached consensus in the Delphi. The five variables that were heavily reported in the literature and reached high % consensus in the Delphi

were: “follow-up with a multi-disciplinary team”, “elevated BNP” ,“elevated Creatinine”, “ACE-I” and “ARB” prescriptions upon discharge.

Conclusion: The combination of clinicians and non-clinicians using a Delphi method to establish variables associated with readmission risk in HF patients proved to be productive. A final list of 61 variables has been proposed for inclusion in RRP models. These variables may be able to be abstracted from the electronic medical record (EMR) and will be included in an RRP model in the province of Alberta using local EMR systems.

Keywords:
Heart failure, readmission risk prediction, rehospitalization, Delphi, patient-derived

Preface

This thesis is original, independent work by the author, Natalie Kristen Wiebe. The study was covered by Ethics Certificate number REB20-0684, issued by the University of Calgary Conjoint Health Ethics Review Board on August 31, 2020.

A shorter, focused version of Chapter 2 of this thesis will be submitted for publication as Wiebe, N., Eastwood, C., Ah-Chi Leung, A., Howlett., J. Thiebe, C., Martin, E., Quan, H. "Identifying clinically relevant readmission risk factors in previously hospitalized Heart Failure patients: a literature review and modified Delphi process" to *Canadian Journal of Cardiology*.

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Whatever is true, honorable, just, pure, lovely, commendable, anything of excellence, anything worthy of praise, center your mind on them, and implant them in your heart.

~To God be all the glory.

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HF: heart failure

EMR: electronic medical record

RRP: readmission risk prediction

AHS: Alberta Health Services

IQR: interquartile range

KT: knowledge translation

CHAPTER I.

Background

1.1 The Disease and Burden of Heart Failure

Heart Failure (HF) is caused by a deterioration of the heart muscle, leading to ineffective pumping of blood. Due to the heart's inability to circulate oxygenated blood to the body, patients with HF often experience injury to other bodily organs (e.g. kidney or liver disease). They also suffer from fluid build-up and decreased lung function (1). Given the multi-organ involvement of HF, the disease and its symptoms can be difficult to manage and treat, leading to decreased quality of life (1). HF is a common disease, with over 600,000 Canadians currently affected (2). Not only is HF difficult to manage and common, but in those >65 years, it is the national leading cause of hospitalization (2). Further, Canadians hospitalized with HF have a 20% readmission rate within 30 days of discharge, with risk of mortality increasing two-fold with each subsequent readmission (2). Each admission costs approximately $15,000; therefore, reducing the readmission rate from 23% to 15% would save Canadians up to $54 million annually. Hence, readmission rate reduction for HF patients is a priority for our healthcare system.

1.2 Readmission due to HF

Readmissions due to HF are one of the most avoidable readmission events given easily detectable symptomatology of worsening HF (3). Once a patient has been discharged following a hospitalization due to HF, access to regular follow-up appointments in the community is crucial for monitoring and treating HF progression. This mitigates acute decompensation of HF, which is characterized by feelings of shortness of breath, fatigue, or swelling in the limbs, to name a few. By implementing routine interactions with the appropriate care team, changes in the patient's clinical features can be detected, and treated. This can in turn help avoid subsequent re-hospitalization (4). However, the high readmission rate for patients previously hospitalized with HF suggests that decompensation can occur rapidly, and necessary follow-up care is currently not in place for newly discharged HF patients (4). This is largely due to a lack of community HF clinics. In the province of Alberta, HF specialists and the provincial health authority's, (Alberta Health Services (AHS)) representatives are preparing the launch of several HF clinic branches across Alberta(5). Deciding which patients need to be seen immediately following discharge, or the frequency with which a patient should be seen, are factors that can be decided prior to discharge. According to the patient's risk of readmission, appropriate discharge planning can be put into place. Therefore, predicting the risk of readmission for a HF patient facing discharge could potentially decrease readmission rates.

1.3 Readmission Risk Prediction (RRP)

Currently, readmission risk prediction (RRP) tools are dependent on variables available within the patient's electronic medical record (EMR) (6). Automated RRP algorithms are embedded within the EMR, and draw necessary variables from said EMR. For example, a commonly used EMR RRP model in the Canadian HF population is the LACE index. It uses the variables: "Length of stay", "Acuity of admission", "Number of Comorbidities", and "Number of Emergency visits in past year". Each of these 4 variables can be abstracted from the EMR using the patient's Discharge Summary and other available data. However, the LACE index has been shown to have a low predictive ability (C-statistic of 0.5) among HF patients (7). A recent study by Amarsingham et al. from the United States (US) demonstrated the potential that resides within an EMR-integrated RRP algorithm using a vast array of EMR-available sociodemographic and clinical variables representative of HF readmission risk (8). Two recent studies utilizing advanced statistical techniques found that between 12 and 18 clinical and sociodemographic variables are needed for the RRP model to have moderate-high predictive ability (9, 10). The LACE index, however, is constrained to using 4 clinical variables. Yet, Canada continues to use LACE due to the country's limited capabilities to abstract other variables necessary for high quality RRP. Within EMR systems in Canada, one of the barriers to achieving high power RRP is the limited amount of data available in the patient's EMR (6). Throughout Canada, there are multiple EMR systems, and many provinces are still using hybrid paper/electronic charting. A standardized EMR system across provinces is needed to transition out of hybrid paper/electronic charting, and to improve variable availability for RRP. It would also ensure standardized data entry between individual

physicians, hospitals, and provinces which would increase data quality (11). Improved data quality leads to improved prediction.

1.4 Electronic Medical Record (EMR) Systems

Many US states use an EMR reporting system called Epic (12). Epic popularity has risen due to its attention to variable integration and enrichment of data for researchers (13). Researchers can request the addition of variables to its front-end infrastructure, which then prompts the healthcare provider to enter patient information for these variables. These variables also require healthcare providers to limit free-text entry and use structured data elements instead (i.e. checkboxes). Structured data is easier to standardize and facilitates variable abstraction, rather than applying advanced text mining mechanisms for data abstraction from free-text. Epic roll-out has begun in some Canadian cities and institutions, with Alberta being the only province to incorporate province-wide roll-out. With its adoption across AHS, our team is taking advantage of the opportunity to request variable integrations into the EMR system (13). This function will allow for important RRP variables to be readily available within the EMR, thus decreasing the barriers of limited data availability and lack of standardization. Deciding which variables to request is the primary aim of this study.

1.5 Sociodemographic and Clinical Variables

Retrospective cohort studies (14) and patient interviews (15) have assessed patient-perceived readmission risk predictors. These studies demonstrate that patient-perceived variables (often representative of sociodemographic variables) such as race, marital status, high risk behavior patterns and income are all highly predictive for HF readmission (14, 15). With regards to clinical variables, RRP models have been proving their predictive power for decades. Well-known provider-derived predictive variables include, but are not limited to, low cardiac muscle function (ejection fraction <40%), weight gain during hospitalization, on >3 cardiac medications, high levels of serum brain natriuretic peptide (BNP) and history of a heart attack (16).

The high predictive power of variables derived by these two unique parties (patients and providers) is reason enough for attempts to merge the two into one robust RRP model. In 2018, Ahmad et al. from Chicago, USA integrated patient-described and clinically-derived HF variables into an EMR system's RRP algorithm (17). The patient-described variables were pooled from a patient survey, and added to a pre-existing clinical HF RRP model (18). The patient-described variables did not enhance model prediction. This, however, has not discounted the high prediction repeatedly shown in studies focused on patient-derived variables (14, 15). Rather, it has encouraged efforts to find a different method of merging patient and provider-derived variables into one predictive model. Unfortunately, the tendency has become to select a few predictive

sociodemographic variables using clinician's discretion and expertise (as done by Amarasingham), and incorporating them into an RRP model. However, this dehumanizes prediction efforts by minimizing the importance of including variables that equally reflect clinical judgement and patient perspectives. Within patient-centered care models (seen in the majority of healthcare systems worldwide), researchers should aim to assign equal weight to patient-derived variables and clinically-derived variables/clinician preference. It is important to include and respect the patient's ability to uniquely identify variables relevant to their readmission. The challenge is thus to preserve the predictive power of patient-identified variables, while merging them with clinically-derived variables commonly used in RRP. Additionally, the role of the caregiver cannot be overlooked when gleaning insight from the patient.

1.6 Integration into the EMR using Consensus

Though it is important to gather different opinions (i.e. survey methods), or to engage in discussion with providers and patients/caregivers (i.e. focus group methods), the existing knowledge gap in this area of study is in the identification of a summary of RRP variables derived from patients/caregivers and providers, which can be integrated into an EMR system. Therefore, it is most appropriate to use consensus-reaching methods from a diverse group of providers/patients/caregivers. To our knowledge, no efforts have been made to reach consensus on this matter between patients/caregivers and providers. Accordingly, the Delphi method is proposed as the appropriate method to attain consensus from these two groups. The accumulation of necessary variables through a Delphi panel has not been done for HF or any other disease. Without consensus, results such as those seen by Ahmad et al. can be expected (17). However, with the

opportunity for patients/caregivers and providers to work in tandem on compiling a list of essential variables for RRP, contradiction between the two parties is decreased. Further, consensus enhances the balance of perspectives, and validates the opinions of those most affected by readmission (i.e. patients), without discarding the extant clinician experience. Lastly, we suspect that if consensus were not to be of priority, we, the researchers, would have to judge which party to adhere to in the case of a disagreement. Given our desire to focus on the patient/caregiver and provider experience, our judgement would not be favorable or appropriate for the study aim. With the incoming Epic platform, there is a need and an opportunity to compile essential patient- and provider-driven variables which should be included in the EMR and in future HF RRP. The integration of patient- and provider-driven variables will allow for a richer database, greater variable availability, and a potentially more holistic and highly predictive RRP for HF patients. If successful, this enhanced RRP could be distributed globally to geographical locations with similar healthcare systems, EMR systems, patient populations/demographics, and disease prevalence.

1.7 Research Question and Objectives

The study's research question is: "Through consensus among Albertan healthcare professionals and heart failure patients and their caregivers, what are the variables most likely to contribute to hospital readmission for patients previously hospitalized for heart failure?" The aim of this project was to describe provider and patient/caregiver derived variables contributing to all-cause readmission risk in patients previously hospitalized with HF. From this point forward, the patient and caregiver population will be described as patients. There were three objectives to the study. The first was to search the literature and gather evidence for potential variables contributing

to RRP in HF patients. The second was to identify appropriate questions and panelists for the Delphi panel. The third objective was to obtain consensus from a panel of healthcare providers and patients on the list of variables contributing to readmission risk in HF patients using three rounds of questioning.

CHAPTER II.

Identifying clinically relevant readmission risk factors in previously hospitalized Heart Failure patients: a literature review and modified Delphi process

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2.1 Background

Heart Failure (HF) is a debilitating disease with complex, multi-organ involvement (1). It is difficult to manage, and unfortunately, it has become common in the Canadian population. Over 600,000 Canadians are currently affected (2). Due to its prevalence and complexity, healthcare systems have seen an increase in hospitalizations due to HF; it is now the second national leading cause of hospitalization in those ≥65 years. In addition to high hospitalization rates, patients discharged after a HF hospitalization have a 20% readmission rate within a month. (2). Each admission costs approximately $15,000 CAD; therefore, reducing readmission rates is a priority for national and international healthcare systems and government institutions.

Readmissions due to HF are often avoidable events given easily detectable clinical features of worsening HF (3). However, the high readmission rate for patients previously hospitalized with HF suggests that decompensation can occur rapidly, and necessary follow-up care is currently not in place for newly discharged HF patients (4). It has proven to be difficult to triage appropriate follow-up care in a setting where community clinics are scarce. Accordingly, the province of Alberta has invested in the expansion of community heart function clinics, as well as the development of readmission risk prediction (RRP) tools. RRP is dependent on variables available within the patient's electronic medical record (EMR) (6). Current RRP models have a low predictive ability (7). Within EMR systems in Canada, one of the barriers to achieving high power RRP is the limited amount of data available in the patient's EMR (6). Alberta is in the process of

launching a province-wide EMR reporting system called Epic, commonly used in the US. (12). Epic popularity has risen due to its attention to variable integration and enrichment of data for researchers (13). This function will allow for important RRP variables to be readily available within the EMR, thus decreasing the barriers of limited data availability and lack of standardization.

Enhancing the predictive ability for personalized medicine is a focus of RRP initiatives worldwide. A recent study by Amarsingham et al. demonstrated the potential high predictive ability that resides within an EMR-integrated RRP algorithm using a sociodemographic and clinical variables representative of HF readmission risk (8). Recently, retrospective cohort studies (14) and patient interviews (15) have assessed patient-perceived readmission risk predictors. These studies demonstrate that patient-perceived variables (often representative of sociodemographic variables) such as race, marital status, high risk behavior patterns and income are all highly predictive for HF readmission (14, 15). With regards to clinical variables, RRP models have been proving their predictive power for decades.

Unfortunately, the tendency has become to select a few predictive sociodemographic variables using clinician's discretion and expertise (as done by Amarasingham), and incorporating them into an RRP model. However, this dehumanizes prediction efforts by minimizing the importance of including variables that equally reflect clinical judgement and patient perspectives. It is important to include and respect the patient's ability to uniquely identify variables relevant to their readmission. We used a consensus-reaching method, namely the Delphi method, to achieve this.

The aim of this study was to describe provider and patient derived variables contributing to all-cause readmission risk in patients previously hospitalized with HF. The study was three-fold in objective: the first was to search the literature and gather evidence opinions for potential variables contributing to readmission in HF patients; the second was to identify panelists for the Delphi; and the third was to obtain consensus on a set of variables contributing to readmission risk in HF patients using a heterogenous panel of clinicians and non-clinicians.

2.2 Methods

A qualitative methodology was used to reach consensus, primarily the Delphi method. The preliminary variable list was ascertained from the literature. Consensus on these variables was sought through the use of an ad-hoc Likert scale response to a question derived by experts on the team. The ratings were summarized using medians and interquartile ranges. A narrative synthesis was used to describe responses, and report patterns seen in responses throughout panelists.

2.2.1 Methods for the Literature Review

A rapid review was conducted; however, due to time constraints, a systematic review has not be produced. The largest distinction between the rapid review conducted and a traditional systematic review was the absence of peer-review in the full-text stage. Additionally, there was no assessment of study quality for included studies.

a) Search Strategy

Derivatives of the following keywords were searched: "congestive heart failure", "readmission", "association", "risk factor". A list of relevant clinical and sociodemographic variables were compiled through a search of 3 peer-reviewed databases (Medline, Embase, and Cochrane Database for Systematic Reviews) from the year 2015 until present. A commonly referenced literature review among our team reporting on HF readmission risk factors was published in 2015 (19). Therefore, the search did not expand prior to 2015.

b) Inclusion and Exclusion Criteria

Titles and abstracts were independently screened by two reviewers, to assess eligibility of inclusion, followed by independent review of full-text by one reviewer. The inclusion and criteria for title and abstracts and full-text screening is reported in Table 2.1.

Table 2.1 Inclusion criteria for title and abstract and full-text screening

Inclusion Criteria	Title and Abstract	Full Text
English	✓	✓
Specific to patients with HF	✓	✓
Association with readmission	✓	✓
Not reporting on sub-condition	✓	✓
Variable available in EMR	✓	✓
Full Text available		✓
Systematic review		✓
Large cohort study (n >8, 000)		✓

Due to the broad scope of our research question, any studies investigating a feature of heart failure, or a condition leading to the development of heart failure, were considered to be "sub-conditions", and were excluded. As an example, a study investigating the effect of a cardiac ablation on readmission in patients with an arrhythmia and heart failure would be considered too specific, and was excluded. Additionally, variables that were not easily accessible from the EMR system currently used in Calgary were excluded. This decision was made in consultation with team members who have in depth knowledge of the data contained in the EMR. This was done to ensure that the variables used in the Delphi process were accessible to the panel, and not hypothetical in nature.

Lastly, expert opinion was sought for the inclusion of relevant HF Clinical Guidelines. The literature review is the foundational tool used to identify the variable list which was presented to panelists for consensus. The screening process lasted 6 months, with an additional search for newly published material completed in December, 2021.

2.2.2 Methods for the Modified Delphi Process

The modified Delphi process was used as the method for reaching consensus. This method was chosen because it can inform variable identification when scientific evidence is incomplete (20). There are 3 characteristics to a Delphi method: i) goal is to structure a group communication that allows individuals to solve complex problems, ii) feedback is provided to participants with opportunity to revise individual views, and iii) assessment of the group judgement or view is made by the researcher (21). The flexibility offered within each of these three characteristics (e.g. how group communication takes place, method of feedback, how consensus is reached) is what

modifies the Delphi, thus creating the modified Delphi method. The Delphi is one of two available methods used to reach consensus. The alternative consensus method is the RAND method, which follows strict guidelines pertaining to indications for use, type of questioning, or number of panelists (21). Given the niche area and purpose of questioning for this project, study objectives did not align with the criteria needed to use a RAND method (i.e. not creating best practice guidelines or indicators); instead, the Delphi method offers the flexibility needed for this research question. Due to the timeline of the thesis, a total of 3 rounds were administered to panelists.

a) Ethics

This project is a subset of a larger study, for which an ethics request was approved by the Conjoint Health Research Ethics Board (CHREB) (REB20-0684). Additionally, all panelists completed a consent form, which stated they understood their responses would not be made available to those outside of the research team, and clearly delineated their voluntary involvement and ability to withdraw. The consent form also specified that the patient's future care would not be altered by their participation.

b) Variables

Variables were categorized according to the health domain populated by the literature (e.g. laboratory measurement, clinical assessment). Where applicable, variables presented directionality. For example, "sodium level" as a variable is too generalized and is not likely to lead to consensus. However, an abnormally low serum sodium level can be dangerous for HF patients due to existing electrolyte imbalances. Therefore, the use of directionality was necessary. The research team decided it best to only list one direction for each variable, where applicable. This

would allow for brevity of the survey, decrease respondent fatigue, and also allow the panelist to frame his or her expertise around a question anchor.

c) Sampling Method

Typical Delphi panel numbers range from 9-20 (21). Given the time frame for this study and its provincial focus, a smaller subset of panelists was chosen. Four HF physician specialists, 2 HF patients, 2 caregivers, 1 internal medicine specialist, 1 general practitioner (GP) and 3 HF nurses were invited to participate in this Delphi process, for a total of 13 panelists. Through AHS, a provincial working group of HF physicians and nurses has been assembled to create a provincial HF "care pathway" (22). Some authors of this study are currently members of the working group. Therefore, opportunity existed to use purposive sampling to recruit panelists through this working group. Upon extending the invitations, snowball sampling was also used to access further potential panelists in the case of non-response, drop-out or inability to reach 13 panelists. With regards to the patient and caregiver population, existing collaborations existed between our research team and the Alberta Strategy for Patient Oriented Research SUPPORT Unit (SPOR) (23). The SPOR's Patient Engagement team offers the opportunity for researchers to involve patients and caregivers as partners in their projects, and is a primary resource for connecting researchers with appropriate patients and caregivers offering lived experience of a disease. Specific patients recommended by HF clinicians as well as SPOR resources were leveraged through purposive sampling to recruit patient and caregiver panelists. Additionally, pre-existing networks between the research team and heart function clinics across Alberta were used to perform in-person recruitment of patients and caregivers.

d) Panelists

Deliberation by the research team on which provider specialization to include, as well as ratio of each panelist type, was done over the course of several months. Internal medicine was included because acutely ill HF patients are often treated on non-cardiac internal medicine hospital wards. Thus, internal medicine specialists offer a perspective on the acutely ill HF patient that other specializations (including HF clinicians) might not regularly see. The GP was included based on the frequent outpatient visits made by HF patients to their family doctors. If HF symptoms worsen, patients are advised to visit their GP. GPs have a sound perspective on HF severity, and the respective triaging that needs to be done according to clinical features. They are also the first points of contact for patients struggling to manage their HF, and can therefore speak to some of the barriers experienced by patients in HF management. Registered Nurses (RNs) specialized in HF are either seen in specialized HF clinics, or on cardiac units within the hospital. Regardless of employment location, due to the extended period of time spent with each patient during an RN shift, RNs often interact with a patient, examine their symptom progression, and learn about the impact of sociodemographic variables on a patient's health status. Therefore, they offer a unique perspective gleaned through intimacy, longevity and relationship, that other specializations lack. The decision to include HF patients with previous history of readmission is self-explanatory. Lastly, caregivers are often responsible for identifying symptoms and managing patient care. Therefore, the inclusion of the selected patients' caregivers was deemed crucial for supporting the patient perspective.

The ratio of provider specializations and patients was established based on knowledge of HF. Those with an HF specialization and those experiencing HF themselves would be assumed to have a deeper understanding of physical, psychological, and social determinants of hospital

readmission. Therefore, the majority (11) of the 13 panelists had a specialized knowledge of HF. To accurately represent Alberta, concerted efforts were made to establish a balance between rural and urban Alberta. The HF specialist physicians practiced in central Calgary, Edmonton and Medicine Hat; the HF nurses practiced in Red Deer and central Calgary; both sets of patients and caregivers were from different regions of Calgary; the GP and the Internal Medicine specialist practiced in central and southeast Calgary, respectively. When from Calgary, efforts were made to include variation in the Calgary regions, since different patient demographics arise depending on sampling area. Given the array of patient characteristics/diseases seen by the GP, it was important for the GP to have experience working with HF patients. Therefore, HF experts on the research team were responsible for selecting a GP that commonly refers HF patients to them. Otherwise, selection criteria for provider panelists was strictly limited to specialization and location, as described above. Any other factors such as years of experience, gender, age, sub-specialty, or research involvement, were not taken into consideration. The aforementioned factors were assumed not to be influential on the panelist's ability to represent the perspectives of their respective group.

To capture the diversity seen in HF patients, sex, ethnicity, and age were diversified, when possible. Fluency in English was required. Further, patients needed to i) have a current diagnosis of HF, and ii) have a history of ≥1 HF readmission(s). Caregivers of selected patients were included, with no further criteria required, apart from fluency in English. Content validity of an expert panel can be ensured by having at least 50% of participants belonging to each unique group (in this case, non-clinicians versus clinicians) (24). Though this was intended, patient and caregiver recruitment throughout the pandemic proved to be difficult. Therefore, only 30% of panelists belonged to the non-clinician group. Contrarily, the opposite effect was seen in clinicians,

particularly nurses. Snowball sampling proved very effective in recruiting nurse participants, leading to more clinician panelists than originally intended.

e) Electronic Data Abstraction Tool

REDCap, a secure, user-friendly data abstraction tool, was used to collect panelist survey responses for Round 1 and Round 2 (25). Panelists received an e-mail link to the REDCap survey, which contained the question and variable list with available rating options as radio buttons. There was a free-text entry option next to each variable (referred to as an "Additional Comments" section). In Round 2, The REDCap form allowed panelists to add additional variables if they deemed the variable(s) as necessary for inclusion. Newly proposed variables were added to the original list for the third round survey. No new variables were added after the third round.

REDCap can be used to populate individual summary reports showing each respondent's answer in comparison to the rest of the group. This feature was used for feedback in Round 1 and Round 2. Since Round 3 was not based off of previous group responses (discussed in section 2.4.3c), a simpler instrument, SurveyMonkey® (www.surveymonkey.com, Palo Alto, California, USA), was used.

f) Delphi Question and Likert Scale

Experts in the field (i.e. HF specialists and Delphi method experts) were consulted to formulate an appropriate question for panelists. This question was amenable to comprehension by the layperson, suitable to a Grade 8 reading level. The question was posed as a statement to be agreed upon. The statement followed the format of "*Variable x* at *Time y* of a heart failure hospitalization is associated with a risk of readmission for any cause in the next 30 days." It was

to be answered with the following 5-point Likert scale: 1: Strongly Disagree; 2: Disagree; 3: Neutral; 4: Agree; 5: Strongly Agree. An additional response of "6: No Judgement" was available for each variable. If "Agree" or "Strongly Agree" were selected, an additional question was asked using branching logic within the REDCap instrument. The question asked: "Does this variable increase or decrease the risk of readmission?" The response options were 1) Increase, 2) Decrease, or 3) Other. If "Other" was selected, panelists were instructed to explain their selection.

Given the scope of our research question, the concepts of "all-cause" and "30 day" readmission were important to include. According to the literature, readmission rates are especially high at the 30-day mark, which influenced our decision to use that time period. An "all-cause" reason for readmission was selected in order to ensure that readmissions related to commonly seen comorbidities within the HF population would still be captured. Given the intricate connection between the state of comorbidities and the predominant disease (e.g. kidney disease and HF), it was important to have a robust understanding of the overall deterioration of the HF patient, even though the predominant reason for admission might not immediately present as HF. Importantly, the index hospitalization was considered to have been caused by HF.

The Likert scale is the recommended scale for responses in a Delphi panel (26, 27). The idea of "agreement" for the Likert scale was established as a concept that is well-understood, as opposed to using less accessible concepts such as "likelihood". This concept allowed for the question to be posed as a statement, facilitating sentence structure for a layperson's understanding. Additionally, each survey contained a list of definitions for each concept posed in the statement asked.

It was assumed that certain panelists (i.e. patients/caregivers) would not know the readmission risk contribution of certain variables (e.g. laboratory or medication), in the same manner that some providers would not know to what extent certain sociodemographic or healthcare use variables contribute to readmission risk. Because of the heterogeneity of the panel and the variable categories, we predicted that there would be quite a few "No Judgement" options selected from both groups of panelists. However, this was not seen as a limitation to our study, but rather what was to be expected when groups with different backgrounds were combined. It is for this reason that Neutral and No Judgement were assigned separate numbers, so as to flag the "No Judgement" responses in the analysis stage, and explore potential reasons for this response. The difference between Neutral and No Judgement was described repeatedly in each round as the following: "As a reminder, "No judgement" is to be used if you have no opinion or you do not know about a certain factor. "Neutral" is to be used if you have an opinion, but in your experience, you neither agree nor disagree with there being an association between the factor and risk of readmission."

In order to increase accessibility and comprehension for each statement (i.e. each variable), layman terms were used for clinical terminology when able. However, panelists were repeatedly encouraged to rely solely on pre-existing knowledge and experience, without consulting external sources. Therefore, if a panelist did not know the meaning of a specific variable, he or she was encouraged to select "No Judgement".

A cut-off of 75% was used to establish consensus. Given the exclusion of "No Judgement" in the analysis obtaining 75% was often not possible with a new denominator. Therefore, ≥73% cut-off was allowed in all three rounds. In Round 2, variables with an IQR >2.0 were included in Round 3. There were 14 variables included in Round 3, which used a different format of questioning. This is further described in section 2.4.2.

g) Data Collection and Handling

REDCap surveys have multiple functions to secure confidentiality, privacy, and anonymity. Entries were kept anonymous between participants throughout the entire consensus-reaching process, and participants were not able to see other responses until feedback was given. In order to facilitate this, REDCap offers the option to create a participant list allowing separate emails to be sent to each participant, ensuring that participants do not know who else is on the panel. Using this function allowed us to identify which panelists had not yet responded to the survey, and could send individual reminder emails to said panelists. In order to assure security of responses, the survey link initially e-mailed to the respondents expired within 5-7 days (according to the survey deadline of each Round). In the initial e-mail, panelists were instructed to "save and exit" the form if they did not plan on completing the survey in one sitting. If this option was selected, panelists were e-mailed an access code to be entered upon resuming the survey. This was put in place in order to ensure security of panelist responses.

Access to responses could only be requested by the administrator of the project (NW). Access requests were processed through the data holding center, the Clinical Research Unit at the University of Calgary. Requests were only made for those on the research team. No panelists had

access to the responses. For members of the research team who did not have a conflict of interest with panelists, survey responses were not anonymous. Identification facilitated analysis of responses based on panelist background/expertise, and allowed researchers to request clarifications from panelists if ambiguity existed. A new survey was created for each round, with variable inclusion/exclusion dependent on survey ratings from the previous round. Survey responses between each round were linked by respondent using the only identifiable information (name identifiers). A summary of panelist ratings were distributed to all panelists between each round. No identifiers were attached to ratings. Survey responses were monitored for missingness. All listed variables had a mandatory radio button rating field, which inhibited the panelist from submitting the form with empty ratings.

2.3 Results from the Literature Review

2.3.1 PRISMA, Included Studies and Study Characteristics

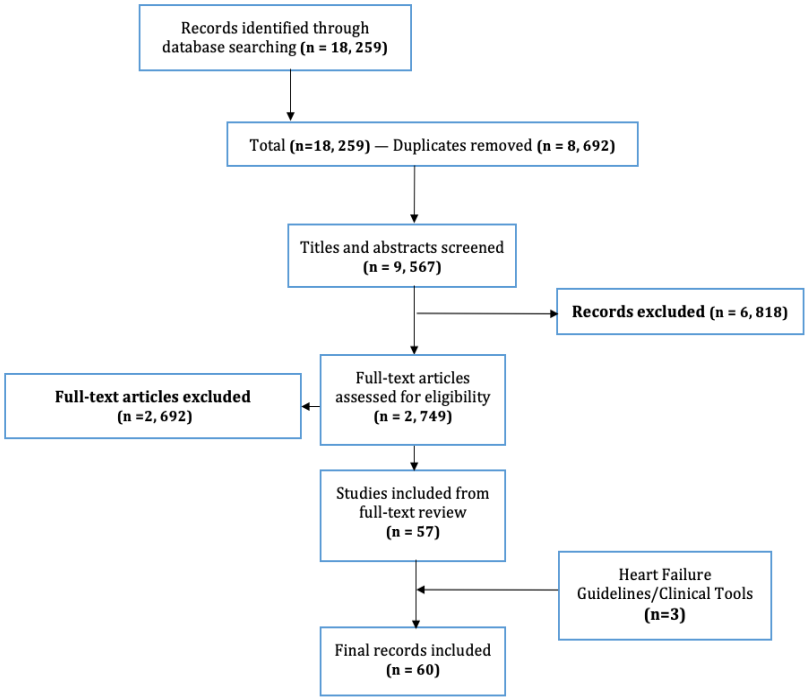

Figure 2.3 PRISMA Flow diagram for study inclusion from literature review

All records pulled from electronic databases were from Medline or Embase. Following the inclusion criteria for title and abstract, and full-text screening, a total of 57 studies were selected for inclusion in the Literature Review. Due to the mass amount of search results (2, 749 full-text), the authors decided to only include systematic reviews, large-scale cohort studies, and large scoping reviews. Forty-seven systematic reviews, 1 summary report, 1 scoping review, 7 large-scale cohort studies, and the 2015 reference article were included. An additional 2 Canadian Heart Failure Guidelines and 1 Readmission Risk Prediction Tool (LACE) were included. The Guidelines came as a recommendation from a heart failure specialist on the research team. Both guidelines describe clinical features to watch for in cases of worsening heart failure, thus increasing risk of readmission. The LACE prediction tool is a widely used scoring index for risk of readmission in HF patients. A total of 60 references were consulted for variable selection.

The oldest study was published in 2015, with the majority published in 2019-2020. Systematic reviews ranged on number of studies reported, with a minimum of 3 and maximum of 285 studies. Of note, though the statement posed to the panelists includes "30-day" readmission risk, the literature review was not limited to this time period. This decision was made in order to increase the scope of possible included variables. Reflecting the original research question, studies needed to report on heart failure patients or patients with an index hospitalization attributed to heart failure.

2.3.2 Literature Review Findings

The literature revealed 6 categories by which to group HF variables associated with readmission. The categories were *Peri-Hospitalization*, *Sociodemographic, Comorbidities, Clinical Features, Laboratory,* and *Treatment*. *Peri-Hospitalization* encompasses interactions with the healthcare system prior, during, and after the heart failure hospitalization. *Sociodemographic* included all variables affecting or affected by an individual's social, economic, and demographic status. *Comorbidities* referred to co-morbid conditions to heart failure. *Clinical Features* reflected symptomatology and clinical characteristics of heart failure. *Laboratory* data included relevant biomarker, serum or urinary findings. *Treatment* encompassed pharmaceutical and non-pharmaceutical clinical interventions for treating heart failure.

a) Variables Identified for Association with Readmission

From the 60 included studies and guidelines, 96 variables were found to be associated with readmission. Three additional variables were identified through expert opinion from the authors.

Protection or risk of readmission was established through hazards ratios, risk ratios, odds ratios, and additional measures of statistical significance. Within each of the 6 categories, the following number of variables were included: *Peri-Hospitalization* (n=16), *Sociodemographic* (n=15), *Comorbidities* (n=26), *Clinical Features* (n=22), *Laboratory* (n=7), *Treatment* (n=13).

Table 2.3.1 describes the definition for each variable, as well as the number of studies reporting on each variable. The most frequently reported variables (≥5 studies) were: *discharge to a home with assistance, multi-disciplinary follow-up, chronic obstructive pulmonary disease, chronic kidney disease, brain natriuretic peptide,* and *ultra-filtration.* Variables within the category *Clinical Features* were infrequently reported; 91% of variables were investigated by less than 3 studies each. Contrarily, the category with the highest number of frequently reported variables was *Treatment*; 62% of variables were investigated by at least 2 studies each.

Table 2.3.1 Variable definition and number of studies reporting on each variable abstracted from literature review

Category	Variable	Definition	Number of Studies/Guidelines
Peri-Hospitalization	los_long	Long length of stay (>5 days) during hospitalization	3
	los_short	Short length of stay (<3 days) during hospitalization	3
	dc_teach	Discharge teaching completed prior to discharge	4
	dc_from	Discharged from a non-cardiac specialized facility	1
	er	>1 Emergency Department visit in year prior to hospitalization	1
	admit	>1 Hospital admission in year prior to hospitalization	2
	assist	Discharged to a home with assistance (assistance means long-term care facility, home with homecare, or assisted living facility)	7
	multi	Multi-disciplinary follow-up post hospitalization	6
	dc_sum	Communication of discharge summary to primary care provider	1
	fu_week	Follow-up with primary care provider 1 week post discharge	3
	transfer	Transfer between 2 or more healthcare facilities during hospitalization	2
	acp	Participation in Advanced Care Planning during hospitalization	3
	ama	Leaving against medical advice during hospitalization	3
	nut	Receiving nutritional teaching post hospitalization	2
	diet	Following a low-sodium diet post hospitalization	1
	fluid	Restricting fluid intake post hospitalization	3
		At the time of hospitalization:	
Sociodemographic	age	Age >75 years	3
	sex	Male	4
	race	Person of Colour	2
	esl	Poor/absent fluency in English	0
	distance	Living >40 kilometers from healthcare facility	1
	inc	Low income (< $30k/year for 1 person household)	3
	insur	Poor or absent prescription drug coverage	1

	employ	Unemployment (excludes retirement and those on short-term disability or sick leave)	1
	disable	Chronic disability	1
	comply	Poor medication compliance	2
	selfcare	Inadequate self-care	1
	purpose	Poor sense of purpose	1
	married	Unmarried (single, living alone, widowed, or divorced)	3
	smoke	Smoking (tobacco-like substances)	2
	ind	Possessing Indigenous status	1
		A history of:	
Comorbidities	cci	Charlson Comorbidity Index >3	1
	dep	Depression	3
	anx	Anxiety	1
	copd	Chronic obstructive pulmonary disease	5
	afib	Atrial fibrillation	4
	htn_hx	History of hypertension (more than 150 mmHg systolic, and more than 90 mmHg diastolic)	1
	pm	Pacemaker	2
	valve	Valve disease	3
	cong	Congenital heart defect	0
	peri	Pericarditis	0
	mi	Myocardial infarct	4
	cad	Coronary artery disease	4
	neo	Cancer	4
	chol	High cholesterol (total cholesterol greater than 6.2 mmol/L)	1
	pvd	Peripheral vascular disease	2
	diab	Diabetes Type 2	4
	liver	Liver disease	3
	kidney	Chronic kidney disease	6
	abuse	Substance use disorder (any substance excluding tobacco, marijuana, and vaping)	1
	pe	Clotting in the lungs (PE) or legs (DVT)	1
	obese	Obesity	2

	cmyo	Cardiomyopathy	1
	aflutter	Atrial flutter	1
	cog_imp	Cognitive impairment	2
	anemia	Anemia	3
	frailty	Frailty	3
		At the time of hospitalization:	
Clinical Features	hfpef	Heart failure with preserved ejection fraction (EF >49%)	2
	hfref	Heart failure with reduced ejection fraction (EF <40%)	3
	hfmref	Heart failure with mildly reduced ejection fraction (EF 40-49%)	2
	nyha	New York Heart Association functional classification score greater than III	2
	lowbp	Low blood pressure (systolic less than 90 mmHg, diastolic less than 60 mmHg)	1
	sob	Shortness of breath (abnormal feeling of shortness of breath on exertion or at rest)	2
	fatigue	Fatigue (abnormal feeling of exhaustion or low energy)	2
	weight	No weight change between admission and discharge	2
	rshf	Right-sided heart failure	1
	del	Acute delirium	2
	arf	Acute kidney failure	3
	tachy	High heart rate (more than 100 beats per minute)	2
	htn	High blood pressure (more than 150 mmHg systolic, and more than 90 mmHg diastolic)	2
	na	Low sodium (less than 135 mEq/L)	2
	pot	High potassium (greater than 5.0 mmol/L)	2
	edema	Peripheral edema (swelling of the extremities)	2
	jvd	Jugular vein distention	1
	pci	Receiving a coronary artery stent	2
	xray	Chest x-ray showing lung fluid	1
	us	Receiving an inferior vena cava (IVC) ultrasound	2
	pulm_us	Greater than 15 B-lines on pulmonary ultrasound	2
	walk	Six-minute walk test greater than 400 meters	1

		At the time of discharge:	
Laboratory	trop	High troponin (HS-cTn greater than 14 ng/L)	1
	ua	High serum uric acid (greater than 8 mg/dL)	2
	exc	Low sodium urinary excretion (less than 50 mmol/L)	1
	cys	Elevated Cystatin-C (greater than 1.2 mg/L)	1
	bun	High blood urea nitrogen (BUN) (greater than 2.5 mmol/L (45 mg/dL))	2
	bnp	High brain natriuretic peptide (BNP) or N-terminal BNP (BNP greater than 100 pg/mL, NT-proBNP greater than 300 pg/mL)	5
	cr	High creatinine (Cr) and low GFR (Cr greater than 120 mcmol/L, GFR less than 60)	2
		At the time of hospitalization:	
Treatment	uf	Receiving ultrafiltration	5
	soltn	Receiving a hypertonic saline solution and diuretic combination	2
		At the time of discharge:	
	acei	Receiving an ACE-I prescription (medication class often ending in "-pril")	4
	arb	Receiving an ARB prescription (medication class often ending in "-sartan")	4
	bb	Receiving a beta-blocker prescription (medication class often ending in "-lol")	3
	loop	Receiving a loop diuretic prescription (medication class often ending in "-mide")	3
	vn	Receiving a vasodilator/nitrate prescription (example: hydralazine, isosorbide)	3
	ino	Receiving an inotrope prescription (example: digoxin)	2
	lipid	Receiving a lipid-lowering medication prescription (medication class often ending in "-statin")	1
	mra	Receiving an MRA prescription (example: spironolactone)	3
	sglt	Receiving an SGLT-2 inhibitor prescription (medication class often ending in "-flozin")	1
	iva	Receiving an ivabradine prescription	4
	arni	Receiving an ARN-I prescription (example: sacubitril-valsartan)	1

b) Directionality and Association within Systematic Reviews

Given their superiority in quality within study hierarchy, the systematic reviews and scoping reviews were the focus of this analysis. Each review reported a variable as increasing and/or decreasing risk of readmission, or having no effect on risk of readmission. Table 2.3.2 shows the directionality and presence of association between the variable and readmission risk, according to each review. Additional information regarding number of studies included in each systematic review, as well as year of study publication can also be found in Table 2.3.2. Arrows pointing upwards indicate an increased risk of readmission with the associated variable. Arrows pointing downwards indicate a decreased risk of readmission. Bi-directional arrows indicate that the study found contradicting effects on readmission risk with the variable in question. "No effect" signifies the variable was found not to be associated with readmission.

Table 2.3.2 Summary table of findings from 60 included studies and guidelines

AUTHOR	YEAR	STUDY DESIGN (n included studies)	PERI-HOSPITALIZATION															
			los_long	los_short	dc_teach	dc_from	er visit	admission previous	dc to hc	multi-discipline	dc_sum to pcp	fu_week with pcp	transfer between hospitals	acp in hospital	left ama	nutritional teaching	low sodium diet	fluid restriction
Schjodt	2020	SR(52)	↓	↑				↑	↑									
Bielecka-Dabrowa	2018	Summary Report																
Covic	2020	SR(14)																
Hoang-Kim	2020	Scoping Review (34)																
Kimmoun	2021	SR(285)																
Takeda	2019	SR(10)								↓								
Kratka	2020	SR(20)			↓	**no effect**			↓	↓	↓	↓				**no effect**		
Wobbe	2021	SR(8)																
Zhong	2021	SR(21)			↓				**no effect**									
Habaybeh	2021	SR(5)														↓		
Oh	2021	SR(3)			↓													
Choi	2021	SR(18)																
Huang	2019	SR(10)																
Alkofide	2019	SR(6)																
Bejianki	2020	SR(14)																
Rice	2018	SR(7)								↓								
Feng	2021	SR(43)																
Kewcharoen	2019	SR(5)																
Kewcharoen	2020	SR(10)																
Zhou	2019	SR(7)												**no effect**				
Hou	2019	SR(3)												↓				
Kernick	2018	SR(8)																
HeidariGorji	2019	SR(13)																
Parenti	2020	SR(13)																
Guo	2020	SR(19)																
de Vecchis	2020	SR(6)																**no effect**
Bryan Richard	2021	SR(7)																
Chen	2019	SR(10)																
Toukhsati	2019	SR(4)																
Koroma	2020	SR(13)																
Larina	2020	SR(29)																
Qiu	2021	SR								↓								
Shi	2019	SR(14)																
Son	2020	SR(9)																
Li	2021	SR(38)								↓								
Zhang	2019	SR(20)																
Paredes	2018	SR(4)																
Kyriakou	2015	SR(26)																
Yusuffudin	2016	SR(26)																
Li	2015	SR(6)																**no effect**
Sterling	2018	SR(6)							↑↓									
Wang	2015	SR(7)																
Abshire	2015	SR(17)			↓												**no effect**	↓
Ontario Health	2017	SR(10)										↓						
Platz	2017	SR(13)																
Diop	2017	SR(15)												↓				
Jain	2016	SR(7)																
Ontario Health	2021	SR(8)																
Van Spall	2017	SR(53)							↓									
Eastwood	2014/2015	N/A							↑				↑		↑			
Sud	2017	Cohort(58230 pts)	↑	↑														
Kwok	2019	Cohort(8,342,383 pts)							↑				↑		↑			
Schjodt	2019	Cohort(17,122 pts)																
Kundi	2020	Cohort(348,649 pts)																
Huusko	2020	Cohort(20,878 pts)						↑										
Patel	2018	Cohort(116,789 pts)													↑			
Gulea	2019	Cohort(54,953 pts)																
3 Guidelines	2017/2021/2021									↓		↓						
LACE Index	2010		↑	↓			↑											
ExpertOpinion																		

AUTHOR	YEAR	STUDY DESIGN (n included studies)	SOCIODEMOGRAPHIC														
			age	sex	race	esl	distance from hospital	low income	prescription med coverage	unemployed	disability	med compliance	selfcare	purpose	unmarried	smoker	indigenous
Schjodt	2020	SR(52)		↑	↑												
Bielecka-Dabrowa	2018	Summary Report															
Covic	2020	SR(14)															
Hoang-Kim	2020	Scoping Review (34)		↑ ↓													
Kimmoun	2021	SR(285)															
Takeda	2019	SR(10)															
Kratka	2020	SR(20)															
Wobbe	2021	SR(8)															
Zhong	2021	SR(21)															
Habaybeh	2021	SR(5)															
Oh	2021	SR(3)															
Choi	2021	SR(18)	↑ ↓	↑ ↓					↑	↑							↑
Huang	2019	SR(10)															
Alkofide	2019	SR(6)															
Bejjanki	2020	SR(14)															
Rice	2018	SR(7)															
Feng	2021	SR(43)															
Kewcharoen	2019	SR(5)															
Kewcharoen	2020	SR(10)													↑		
Zhou	2019	SR(7)															
Hou	2019	SR(3)															
Kernick	2018	SR(8)															
HeidariGorji	2019	SR(13)													↑		
Parenti	2020	SR(13)															
Guo	2020	SR(19)															
deVecchis	2020	SR(6)															
Bryan Richard	2021	SR(7)															
Chen	2019	SR(10)															
Toukhsati	2019	SR(4)											↑				
Koroma	2020	SR(13)															
Larina	2020	SR(29)										↑					
Qiu	2021	SR															
Shi	2019	SR(14)															
Son	2020	SR(9)														↑	
Li	2021	SR(38)															
Zhang	2019	SR(20)															
Paredes	2018	SR(4)															
Kyriakou	2015	SR(26)															
Yusuffudin	2016	SR(26)															
Li	2015	SR(6)															
Sterling	2018	SR(6)															
Wang	2015	SR(7)															
Abshire	2015	SR(17)															
Ontario Health	2017	SR(10)															
Platz	2017	SR(13)															
Diop	2017	SR(15)															
Jain	2016	SR(7)															
Ontario Health	2021	SR(8)															
Van Spall	2017	SR(53)															
Eastwood	2014/2015	N/A	↑		↑		↑	↑			↑	↑		↑			
Sud	2017	Cohort(58230 pts)															
Kwok	2019	Cohort(8,342,383 pts)	↑	**no effect**				↑								↑	
Schjodt	2019	Cohort(17,122 pts)						↑							↑		
Kundi	2020	Cohort(348,649 pts)															
Huusko	2020	Cohort(20,878 pts)															
Patel	2018	Cohort(116,789 pts)															
Gulea	2019	Cohort(54,953 pts)															
3 Guidelines	2017/2021/2021																
LACE Index	2010																
ExpertOpinion						↑											

AUTHOR	YEAR	STUDY DESIGN (n included studies)	COMORBIDITIES																								
			cci	dep	anx	copd	afib	htn_hx	pacemaker	valve disease	congenital heart defect	pericarditis	MI	CAD	neoplasm/ cancer	dyslipidemia	PVD	diabetes	liver dx	kidney dx	substance abuse	pulmonary embolism/ dvt	obese	cardio-myopathy	aflutter	cognitive impairment	anemia	frailty
Schjodt	2020	SR(52)		↑	↑		↑		↑	↑			↑	↑						↑			↑	↑	↑			
Bielecka-Dabrowa	2018	Summary Report																		↑								
Covic	2020	SR(14)																										
Hoang-Kim	2020	Scoping Review (34)																										
Kimmoun	2021	SR(285)																										
Takeda	2019	SR(10)																										
Kratka	2020	SR(20)																										
Wobbe	2021	SR(8)																										
Zhong	2021	SR(21)																										
Habaybeh	2021	SR(5)																										
Oh	2021	SR(3)																										
Choi	2021	SR(18)				↑	↑			↑				↑	↑			↑		↑							↑	
Huang	2019	SR(10)																										
Alkofide	2019	SR(6)																										
Bejinki	2020	SR(14)																										
Rice	2018	SR(7)																										
Feng	2021	SR(43)																										
Kewcharoen	2019	SR(5)																								↑		
Kewcharoen	2020	SR(10)		↑																								
Zhou	2019	SR(7)																										
Hou	2019	SR(3)																										
Kernick	2018	SR(8)																										
HeidariGorji	2019	SR(13)																										
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Koroma	2020	SR(13)																										
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Qiu	2021	SR																										
Shi	2019	SR(14)																										
Son	2020	SR(9)																										
Li	2021	SR(38)																										
Zhang	2019	SR(20)																										↑
Paredes	2018	SR(4)																										
Kyriakou	2015	SR(26)																									↑	
Yusuffudin	2016	SR(26)																										
Li	2015	SR(6)																										
Sterling	2018	SR(6)																										
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Ontario Health	2017	SR(10)																										
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Jain	2016	SR(7)																										
Ontario Health	2021	SR(8)																										
Van Spall	2017	SR(53)																										
Eastwood	2014/2015	N/A				↑	↑						↑		↑			↑	↑	↑		↑						↑
Sud	2017	Cohort(58230 pts)																										
Kwok	2019	Cohort(8,342,383 pts)		↑		↑	↑	**no effect**	↑	**no effect**			**no effect**	↑	↑	↑	↑	↑	↑	↑	**no effect**		↑				↑	
Schjodt	2019	Cohort(17,122 pts)																										
Kundi	2020	Cohort(348,649 pts)																										↑
Huusko	2020	Cohort(20,878 pts)																										
Patel	2018	Cohort(116,789 pts)																										
Gulea	2019	Cohort(54,953 pts)				↑																						
3 Guidelines	2017/2021/2021													↑												↑		
LACE Index	2010		↑			↑							↑		↑		↑	↑	↑	↑								
ExpertOpinion								↑			↑	↑				↑					↑							

			CLINICAL FEATURES																			
AUTHOR	YEAR	STUDY DESIGN (n included studies)	hfpef	hfref	hfmref	NYHA >3	lowbp	SOB	fatigue	no weight change	RS heart failure	acute delirium	acute renal failure	tachycardia	HTN	low sodium	high potassium	edema	JVD	PCI	chest xray	IVC Ultrasound	pulmonary ultrasound	6 minute walk test
Schjodt	2020	SR(52)	↓	↑		↑						↑			↓	↑	↑			↑				↓
Bielecka-Dabrowa	2018	Summary Report											↑											
Covic	2020	SR(14)																						
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Zhong	2021	SR(21)																						
Habaybeh	2021	SR(5)																						
Oh	2021	SR(3)																						
Choi	2021	SR(18)	**no effect**	**no effect**	**no effect**	↑	**no effect**				↑		↑↓	↑	**no effect**			↑					↑	
Huang	2019	SR(10)																						
Alkofide	2019	SR(6)																						
Bejjanki	2020	SR(14)																						
Rice	2018	SR(7)																						
Feng	2021	SR(43)																						
Kewcharoen	2019	SR(5)																						
Kewcharoen	2020	SR(10)																						
Zhou	2019	SR(7)																						
Hou	2019	SR(3)																						
Kernick	2018	SR(8)																						
Heidari Gorji	2019	SR(13)																						
Parenti	2020	SR(13)																				↑↓		
Guo	2020	SR(19)			↓																			
de Vecchis	2020	SR(6)																						
Bryan Richard	2021	SR(7)																						
Chen	2019	SR(10)																						
Toukhsati	2019	SR(4)																						
Koroma	2020	SR(13)																						
Larina	2020	SR(29)																						
Qiu	2021	SR																						
Shi	2019	SR(14)																						
Son	2020	SR(9)																						
Li	2021	SR(38)																						
Zhang	2019	SR(20)																						
Paredes	2018	SR(4)																				↓		
Kyriakou	2015	SR(26)																						
Yusuffudin	2016	SR(26)																						
Li	2015	SR(6)																						
Sterling	2018	SR(6)																						
Wang	2015	SR(7)																						
Abshire	2015	SR(17)																						
Ontario Health	2017	SR(10)																						
Platz	2017	SR(13)																					↑	
Diop	2017	SR(15)																						
Jain	2016	SR(7)																						
Ontario Health	2021	SR(8)																						
Van Spall	2017	SR(53)																						
Eastwood	2014/2015	N/A						↑	↑	↑		↑									↑			
Sud	2017	Cohort(58230 pts)																						
Kwok	2019	Cohort(8,342,383 pts)											↑			↑	↑			↑				
Schjodt	2019	Cohort(17,122 pts)																						
Kundi	2020	Cohort(348,649 pts)																						
Huusko	2020	Cohort(20,878 pts)																						
Patel	2018	Cohort(116,789 pts)																						
Gulea	2019	Cohort(54,953 pts)																						
3 Guidelines	2017/2021/2021			↑				↑	↑	↑				↑				↑	↑					
LACE Index	2010																							
Expert Opinion																			↑					

AUTHOR	YEAR	STUDY DESIGN (n included studies)	LABORATORY						
			troponin	high serum uric acid	urinary sodium excretion	cystatin-c	BUN	BNP	Creatinine
Schjodt	2020	SR(52)					↑	↑	
Bielecka-Dabrowa	2018	Summary Report						↑	↑
Covic	2020	SR(14)							
Hoang-Kim	2020	Scoping Review (34)							
Kimmoun	2021	SR(285)							
Takeda	2019	SR(10)							
Kratka	2020	SR(20)							
Wobbe	2021	SR(8)							
Zhong	2021	SR(21)							
Habaybeh	2021	SR(5)							
Oh	2021	SR(3)							
Choi	2021	SR(18)		↑				↑	↑
Huang	2019	SR(10)		↑					
Alkofide	2019	SR(6)							
Bejjanki	2020	SR(14)			↑				
Rice	2018	SR(7)							
Feng	2021	SR(43)							
Kewcharoen	2019	SR(5)							
Kewcharoen	2020	SR(10)							
Zhou	2019	SR(7)							
Hou	2019	SR(3)							
Kernick	2018	SR(8)							
HeidariGorji	2019	SR(13)							
Parenti	2020	SR(13)							
Guo	2020	SR(19)							
de Vecchis	2020	SR(6)							
Bryan Richard	2021	SR(7)							
Chen	2019	SR(10)				↑			
Toukhsati	2019	SR(4)							
Koroma	2020	SR(13)							
Larina	2020	SR(29)							
Qiu	2021	SR							
Shi	2019	SR(14)							
Son	2020	SR(9)							
Li	2021	SR(38)							
Zhang	2019	SR(20)							
Paredes	2018	SR(4)							
Kyriakou	2015	SR(26)							
Yusuffudin	2016	SR(26)	↑						
Li	2015	SR(6)							
Sterling	2018	SR(6)							
Wang	2015	SR(7)							
Abshire	2015	SR(17)							
Ontario Health	2017	SR(10)							
Platz	2017	SR(13)							
Diop	2017	SR(15)							
Jain	2016	SR(7)							
Ontario Health	2021	SR(8)						**no effect**	
Van Spall	2017	SR(53)							
Eastwood	2014/2015	N/A							
Sud	2017	Cohort(58230 pts)							
Kwok	2019	Cohort(8,342,383 pts)							
Schjodt	2019	Cohort(17,122 pts)							
Kundi	2020	Cohort(348,649 pts)							
Huusko	2020	Cohort(20,878 pts)							
Patel	2018	Cohort(116,789 pts)							
Gulea	2019	Cohort(54,953 pts)							
3 Guidelines	2017/2021/2021						↑	↑	
LACE Index	2010								
ExpertOpinion									

AUTHOR	YEAR	STUDY DESIGN (n included studies)	TREATMENT												
			ultra-filtration	hypertonic saline solution	acei	arb	bb	loop	vasodilator/ nitrate	inotrope	lipid	MRA	SGLT-2	ivabradine	arni
Schjodt	2020	SR(52)			↓	↓			↓		↓	↑			
Bielecka-Dabrowa	2018	Summary Report	↓	↓											
Covic	2020	SR(14)		↓											
Hoang-Kim	2020	Scoping Review (34)													
Kimmoun	2021	SR(285)			**no effect**	**no effect**	**no effect**	**no effect**		**no effect**					
Takeda	2019	SR(10)													
Kratka	2020	SR(20)													
Wobbe	2021	SR(8)	↓												
Zhong	2021	SR(21)													
Habaybeh	2021	SR(5)													
Oh	2021	SR(3)													
Choi	2021	SR(18)													
Huang	2019	SR(10)													
Alkofide	2019	SR(6)												**no effect**	
Bejjanki	2020	SR(14)													
Rice	2018	SR(7)													
Feng	2021	SR(43)			↓	↓	↓					**no effect**			
Kewcharoen	2019	SR(5)													
Kewcharoen	2020	SR(10)													
Zhou	2019	SR(7)													
Hou	2019	SR(3)													
Kernick	2018	SR(8)													
HeidariGorji	2019	SR(13)													
Parenti	2020	SR(13)													
Guo	2020	SR(19)													
de Vecchis	2020	SR(6)													
Bryan Richard	2021	SR(7)												↓	
Chen	2019	SR(10)													
Toukhsati	2019	SR(4)													
Koroma	2020	SR(13)												**no effect**	
Larina	2020	SR(29)													
Qiu	2021	SR													
Shi	2019	SR(14)	↓												
Son	2020	SR(9)													
Li	2021	SR(38)													
Zhang	2019	SR(20)													
Paredes	2018	SR(4)													
Kyriakou	2015	SR(26)													
Yusuffudin	2016	SR(26)													
Li	2015	SR(6)													
Sterling	2018	SR(6)													
Wang	2015	SR(7)							↓	↑					
Abshire	2015	SR(17)						↓							
Ontario Health	2017	SR(10)													
Platz	2017	SR(13)													
Diop	2017	SR(15)													
Jain	2016	SR(7)	↓												
Ontario Health	2021	SR(8)													
Van Spall	2017	SR(53)													
Eastwood	2014/2015	N/A													
Sud	2017	Cohort(58230 pts)													
Kwok	2019	Cohort(8,342,383 pts)													
Schjodt	2019	Cohort(17,122 pts)													
Kundi	2020	Cohort(348,649 pts)													
Huusko	2020	Cohort(20,878 pts)													
Patel	2018	Cohort(116,789 pts)													
Gulea	2019	Cohort(54,953 pts)													
3 Guidelines	2017/2021/2021		↓		↓	↓	↓	↓	**no effect**			↓	↓	↓	↓
LACE Index	2010														
ExpertOpinion															

The literature showed vast amounts of heterogeneity in establishing the direction of readmission risk of any given variable. Nearly 20% of the 99 variables lacked agreement on their association with and/or directionality of readmission risk, as indicated in Table 2.3.4 by a shaded cell in > 1 column for a particular variable. The number of studies addressing each variable is represented here by the cell's colour. The higher the number of studies, the darker the colour. The number of studies was taken to signify the certainty of conclusion from the literature. The higher the number, the more certain the literature's conclusion on any given association or direction for a variable's readmission risk. The number of studies for a particular variable was also taken to indicate the level of importance assigned to that variable across academic institutions. The higher the number, the more attention that variable was receiving from researchers investigating readmission risk factors.

The categories with highest degree of disagreement on directionality of risk or association of a variable with readmission were *Peri-Hospitalization, Clinical Features,* and *Treatment*. There was no apparent correlation between number of studies reporting on a specific variable, and the level of agreement among studies on association/directionality of risk.

c) Agreement among Systematic Reviews

Tables 2.3.3 and 2.3.4 correspond to the variables reaching agreement and not reaching agreement among and/or within systematic reviews. Agreement among and within systematic reviews on association and/or directionality was seen in 54 variables. Seventeen (31%) of these variables had ≥ 2 studies reporting them. The majority of variables reaching agreement in the reviews were found to increase risk. Only 3 variables found no association with readmission, all

of which had only 1 systematic review reporting them. Of note, 26 of the original 99 variables included from the literature review were not referenced by a systematic review.

Legend:

↑	Increases risk of readmission
↓	Decreases risk of readmission
↑ ↓	Both increases and decreases risk of readmission
No Effect	No effect on risk of readmission
	Reported by 1 systematic review
	Reported by 2 systematic reviews
	Reported by ≥ 3 systematic reviews

Table 2.3.3 Association and direction of readmission risk for variables (n=54) according to systematic reviews reaching agreement

	VARIABLE	↑	↓	↑ ↓	NO EFFECT
Peri-Hospitalization	los_long		↓		
	los_short	↑			
	dc_teach		↓		
	dc_from				NO EFFECT
	admission previous	↑			
	multidisciplinary		↓		
	dc_sum to pcp		↓		
	fu_week with pcp		↓		
	low sodium diet				NO EFFECT
Sociodemographic	race	↑			
	prescription med coverage	↑			
	unemployed	↑			
	med compliance	↑			
	selfcare	↑			
	unmarried	↑			
	smoker	↑			
	indigenous	↑			
Comorbidities	dep	↑			
	anx	↑			
	afib	↑			
	pacemaker	↑			
	valve disease	↑			

	MI	↑			
	CAD	↑			
	neoplasm/cancer	↑			
	diabetes	↑			
	kidney dx	↑			
	obese	↑			
	cardiomyopathy	↑			
	aflutter	↑			
	cognitive impairment	↑			
	anemia	↑			
	frailty	↑			
Clinical Features	NYHA >3	↑			
	lowbp				NO EFFECT
	RS heart failure	↑			
	acute delirium	↑			
	tachycardia	↑			
	low sodium	↑			
	high potassium	↑			
	edema	↑			
	PCI	↑			
	pulmonary ultrasound	↑			
	6 minute walk test		↓		
Laboratory	troponin	↑			
	high serum uric acid	↑			
	urinary sodium excretion	↑			
	cystatin-c	↑			
	BUN	↑			
	Creatinine	↑			
Treatment	ultrafiltration		↓		
	hypertonic saline solution		↓		
	vasodilator/nitrate		↓		
	lipid		↓		

Table 2.3.4 Association and direction of readmission risk for variables (n=19) according to systematic reviews not reaching agreement

CATEGORY	VARIABLE	↑	↓	↑↓	NO EFFECT
Peri-hospitalization	dc to ltc	↑	↓	↑↓	NO EFFECT
	acp in hospital		↓		NO EFFECT
	nutritional teaching		↓		NO EFFECT
	fluid restriction		↓		NO EFFECT
Sociodemographic	sex	↑		↑↓	
Clinical Features	hfpef		↓		NO EFFECT
	hfref	↑			NO EFFECT
	hfmref		↓		NO EFFECT
	acute renal failure	↑		↑↓	
	HTN		↓		NO EFFECT
	IVC Ultrasound		↓	↑↓	
Laboratory	BNP	↑			NO EFFECT
Treatment	acei		↓		NO EFFECT
	arb		↓		NO EFFECT
	bb		↓		NO EFFECT
	loop		↓		NO EFFECT
	inotrope	↑			NO EFFECT
	MRA	↑			NO EFFECT
	ivabradine		↓		NO EFFECT

The remaining 19 variables did not reach agreement among or within the systematic reviews. Of these 19, 7 were in the *Treatment* category. None of the variables within the *Comorbidity* category lacked agreement among systematic reviews. Additionally, only one of the variables in *Sociodemographic* lacked agreement. This correlates with the opposite finding of high levels of agreement within systematic reviews on variables within the *Comorbidity* and *Sociodemographic* categories. Sixteen of the 19 variables not reaching agreement among systematic reviews possessed a "No Effect" rating. Eight (42%) of the 19 variables had ≥ 2 studies reporting them.

2.4 Results from the Modified Delphi Process

2.4.1 Panel Characteristics

Job Title	
Nurse Educator	1
Registered Nurse	1
Nurse Clinician	1
Clinician Researcher	5
Physician	1
Specialization	
Cardiac Sciences	2
Heart Failure Medicine	5
Internal Medicine	1
Family Medicine	1
Organization	
University Affiliate	
Yes	6
No	3
Years of Practice	
1-9	2
10-19	3
20-29	2
30-39	2
Sex	
Male	5
Female	4
Region	
Red Deer	1
Calgary	7
Edmonton	1
Medicine Hat	1

Table 2.4.1 Characteristics of healthcare provider panel members (n=9)

There were a total 2 patients and 2 caregivers included in the panel. Patient A was an 80 year old female with a <10 year history of heart failure. Her caregiver (Caregiver A) was her

adult daughter. They had previously been involved in research. Patient B was a 60 year old female with a <10 year history of heart failure. Her caregiver (Caregiver B) was her husband. Both Patient A and B had an index heart failure hospitalization with a subsequent readmission. A time period between index admission and readmission was not specified due to the potential difficulty in recruiting patient participants that have experienced readmission within a specific time frame.

2.4.2 Variable Selection from the Modified Delphi Process

Panelists reached consensus on 61 variables, 58 of which were deemed to be associated with risk of readmission for any cause within 30 days of discharge. Figure 2.4 shows the process of obtaining this final set of variables through 3 rounds of questioning.

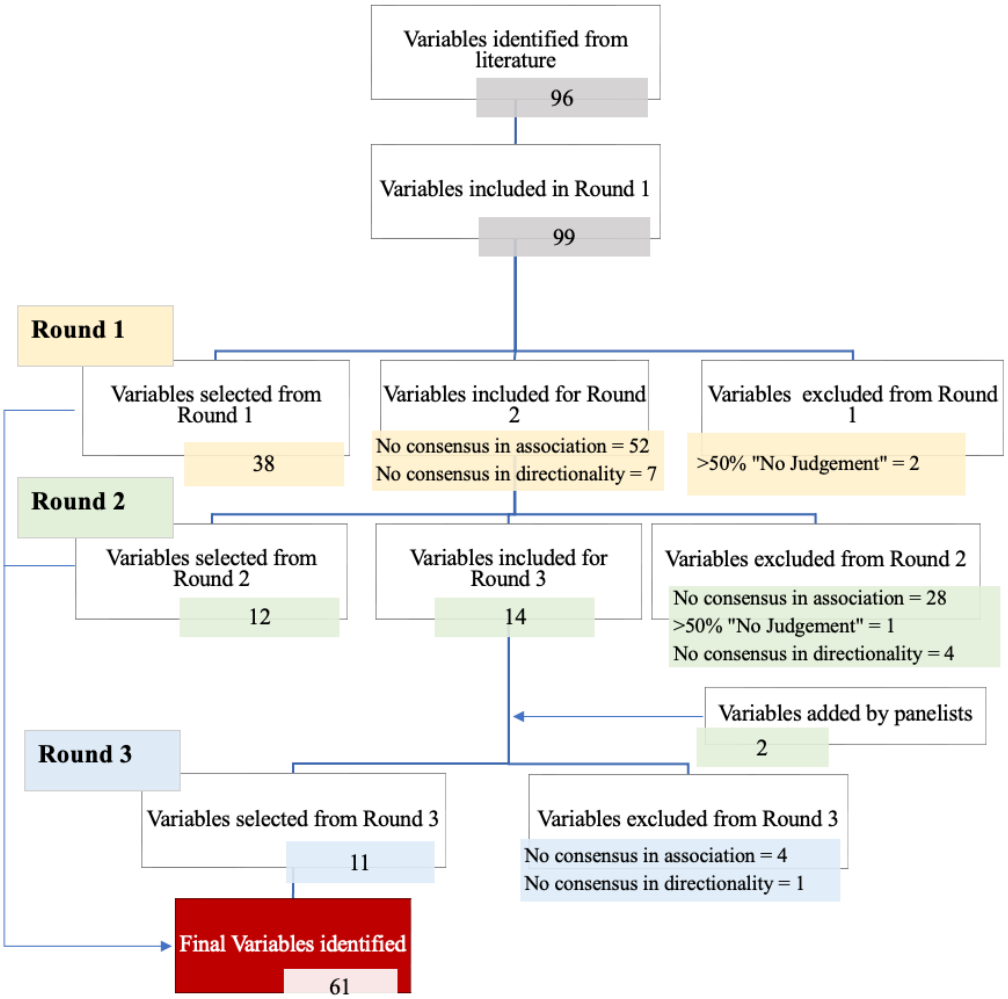


Figure 2. 4 Flow diagram of selection process for variables associated with heart failure readmission

a) Consensus of Association

Each round used ≥73% as the threshold for achieving consensus. For each variable, scores with 4 and 5 ("Agree" and "Strongly Agree") were summed and labeled "agreement"; similarly, scores of 1 and 2 ("Strongly Disagree" and "Disagree") were summed and labeled "disagreement". The average percent of responses falling into each category ("agreement", "neutral" (score of 3),

and “disagreement”) was calculated for each variable. If ≥75% of scores fell into one category of responses, that variable was said to have reached consensus.

The “No Judgement” response option was calculated separately. If ≥50% of scores were a 6 (“No Judgement”), then that variable was considered to have reached consensus and was excluded from the next round. Throughout all three rounds, 3 variables were excluded for this reason. If <50% of scores were a 6, then those individual responses were removed from the calculation of means. Figure 2.4.1 shows an example of this process, using a variable from Round 1. Thirteen panelists responded, 9 (69%) of which responded as “disagreement”, 2 (15%) of which responded “agreement”, and 1 of which responded “No Judgement”. The latter was removed from the pool of respondents, allowing for a new denominator of 12, and 75% of respondents (9 of 12) reaching consensus on “disagreement”. With a new denominator, the consensus cut-off was set at ≥73% where applicable.

STRONGLY AGREE (5)	1
AGREE (4)	1
AGREE %	0.15
NEUTRAL (3)	1
NEUTRAL %	0.08
DISAGREE (2)	7
STRONGLY DISAGREE (1)	2
DISAGREE %	0.69
NO JUDGEMENT (6)	1
NO JUDGEMENT %	0.08
NEW DENOMINATOR	12
PERCENT	0.75
CONSENSUS?	yes

Figure 2.4.1 Example of scoring analysis for establishing consensus

b) Consensus of Directionality

Consensus was also calculated for directionality. Once the variable was identified as being associated with readmission risk, the scores for increased or decreased risk of readmission were summarized. In Round 1, 7 of the variables that reached consensus in association varied in directionality (e.g., at least one panelist stated the variable increased readmission risk when other panelists stated the variable decreased readmission risk). In Round 2, panelists were explicitly asked if these 7 variables increased or decreased readmission risk. If there was still disagreement in directionality by Round 3, these variables were excluded. Both Round 2 and Round 3 had one variable where panelists disagreed on directionality. From all 3 rounds, a total of 5 variables were excluded for lack of consensus in directionality.

2.4.3 The Modified Delphi Process

a) Rounds 1 and 2

Prior to the first round, panelists were given a reminder for the upcoming survey. They were given one week for completion of Round 1. In Round 1, 38 variables reached consensus of both association and directionality. The remaining variables were re-assessed in Round 2.

In preparation for Round 2, panelists were e-mailed two documents; the first was a detailed report for each factor not reaching consensus in Round 1. Each panelist received a histogram of the group's anonymous responses. The histogram also indicated where he or she scored in comparison. This visual representation was chosen due to its accessibility to both clinicians and non-clinicians. The goal of this visual was to encourage panelists to consider adjusting their

responses to help the group reach consensus. However, panelists were to remain partial to their personal experience and knowledge; if they felt strongly about a particular response and were not willing to adjust, they were encouraged to make a comment about this in the survey.

The second document in the e-mail contained a bar graph with the group's anonymous responses to the 7 variables where consensus of directionality was not obtained. This graph also indicated the panelist's previous response. Panelists were given 5 days to complete Round 2, which contained 59 variables. A one-day reminder was given to outstanding participants.

b) Feedback from Panelists

For each variable, there was an option to "add Additional Comments". In Round 1, only one comment was made with regards to how a specific variable was being measured. This was specific to the variable "assist" which asked about the association between readmission and being discharged home with assistance. "Assistance" included long-term care facilities and homecare. The comment addressed the difference in readmission association between these two types of assistance. However, for the sake of survey brevity, the variable remained unchanged for subsequent surveys.

In Round 2, one panelist gave feedback with regards to how the questions had been interpreted. It was made known that this panelist (panelist x) had interpreted the original question of association as asking whether the variable was associated with *increased* risk of readmission. This feedback influenced the structure of Round 3. Two variables were added by panelists into Round 3 that had not been included in previous rounds.

c) Round 3

In Round 2, 28 variables did not reach consensus of association and 4 variables did not reach consensus of directionality. Of the 59 variables included in Round 2, 14 were included in Round 3. After discussion with the research team, these 14 variables were selected because of their large IQR. A large IQR indicated a wide distribution of responses on the Likert scale. This was taken to represent a misunderstanding of the question, as indicated by panelist x. For Round 3, each variable had 2 questions; one asked if the variable increased risk of readmission, the other asked if the variable decreased readmission risk. In preparation for Round 3, panelists were given a summary of their responses to these 14 variables in previous rounds, with no mention of the group's responses. Since the group's responses from previous rounds were so varied, and the variation was thought to be attributed to a misunderstanding of the question, the feedback did not include the group's responses. Panelists were given 5 days to complete Round 3. A total of 16 variables were included in Round 3, of which 11 reached consensus.

d) Attrition

During Round 2, one panelist (clinician) was unable to complete the survey; the total number of participants in Round 2 was 12. However, since the feedback from Round 2 did not contain the group's ratings, this panelist was invited to complete Round 3. Therefore, the final number of panelists for Round 1 and Round 3 was 13.

2.4.4 Variables Reaching Consensus

Table 2.4.2 Variables reaching consensus (n=61) by % consensus obtained

Variable (n=61)	Consensus	Increases Risk	Decreases Risk	Neutral Direction
poor medication compliance	100%	100%		
inadequate self-care	100%	100%		
high BNP	100%	100%		
multi-disciplinary follow-up	100%	0%	100%	
pcp follow-up post discharge	100%	0%	100%	
ARB prescription	100%	0%	100%	
ARNI prescription	100%	0%	100%	
follow-up with cardiologist	96%	0%	92%	8%
COPD	92%	100%		
Beta-Blocker prescription	92%	0%	83%	17%
discharge summary sent to pcp	92%	0%	92%	8%
diabetes	91%	100%		
ACEI prescription	91%	0%	91%	9%
SGLT-2 inhibitor prescription	91%	0%	91%	9%
unemployed	90%	100%		
low sodium	90%	100%		
high creatinine	90%	100%		
low proficiency in english	90%	100%		
walk test >400 meters	90%	0%	100%	10%
high charlson comorbidity index	88%	100%		
left against medical advice	85%	100%		
no prescription coverage	85%	100%		
atrial fibrillation	85%	100%		
frailty	85%	100%		
tachycardia	85%	100%		
coronary artery disease	82%	100%		
anemia	81%	100%		
depression	80%	100%		
high troponin	80%	100%		
chronic disability	80%	100%		

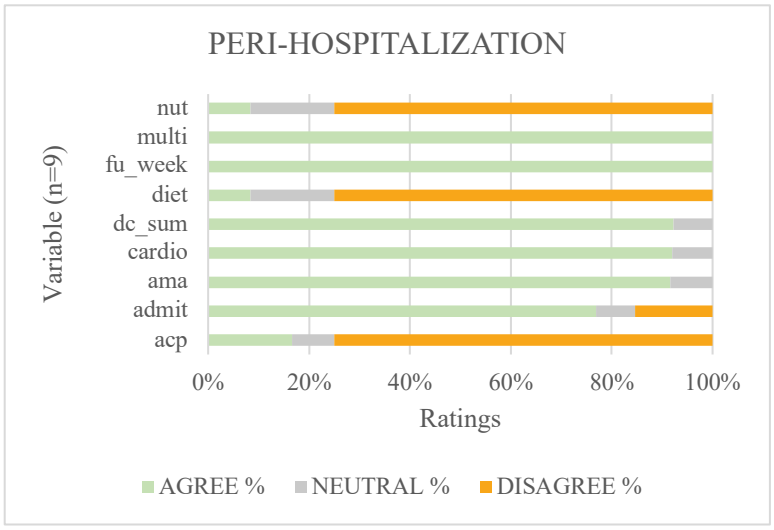
unmarried	80%	100%		
anxiety	80%	100%		
pulmonary embolism	80%	100%		
MRA prescription	79%	0%	75%	25%
peripheral edema	78%	100%		
admission in past year	77%	100%		
valve disease	77%	100%		
myocardial infarction	77%	100%		
substance abuse	77%	100%		
cardiomyopathy	77%	100%		
Atrial flutter	77%	100%		
hfpef	77%	100%		
hfref	77%	100%		
new york heart association >3	77%	100%		
low blood pressure in hospital	77%	100%		
acute renal failure	77%	100%		
age>75	75%	100%		
low income	75%	100%		
smoker	75%	100%		
kidney disease	75%	100%		
cognitive impairment	75%	100%		
high BUN	75%	100%		
person of colour	75%	100%		
advanced care planning in hospital	75%	Disagree		
nutritional teaching in hospital	75%	Disagree		
low sodium diet	75%	Disagree		
indigenous status	73%	100%		
history of high blood pressure	73%	100%		
congenital heart defect	73%	100%		
high potassium	73%	100%		
jugular vein distention	73%	100%		

A variable data dictionary is available in Table 2.3.1. Of the 61 variables reaching consensus, 3 (“advanced care planning in hospital”, “nutritional teaching in hospital”, “low sodium diet”) were thought to have no association with readmission risk. Of the remaining 58 variables

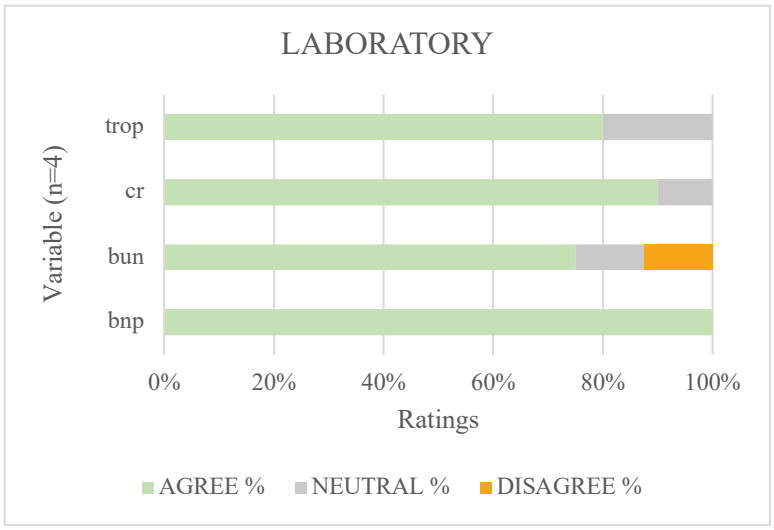
associated with readmission risk, 11 were thought to decrease readmission risk, while the remaining 47 increased readmission risk.

Variables with lower % consensus (73% - 80%) were those in the "Clinical Features" category. Variables with higher % consensus were in the "Treatment" category. All other categories had a seemingly equal distribution in % consensus reached. Of the variables included in the Delphi, 80% Sociodemographic, 67% Comorbidities, 57% Laboratory, 53% Peri-hospitalization, 50% Clinical Features, and 46% Treatment variables reached consensus.

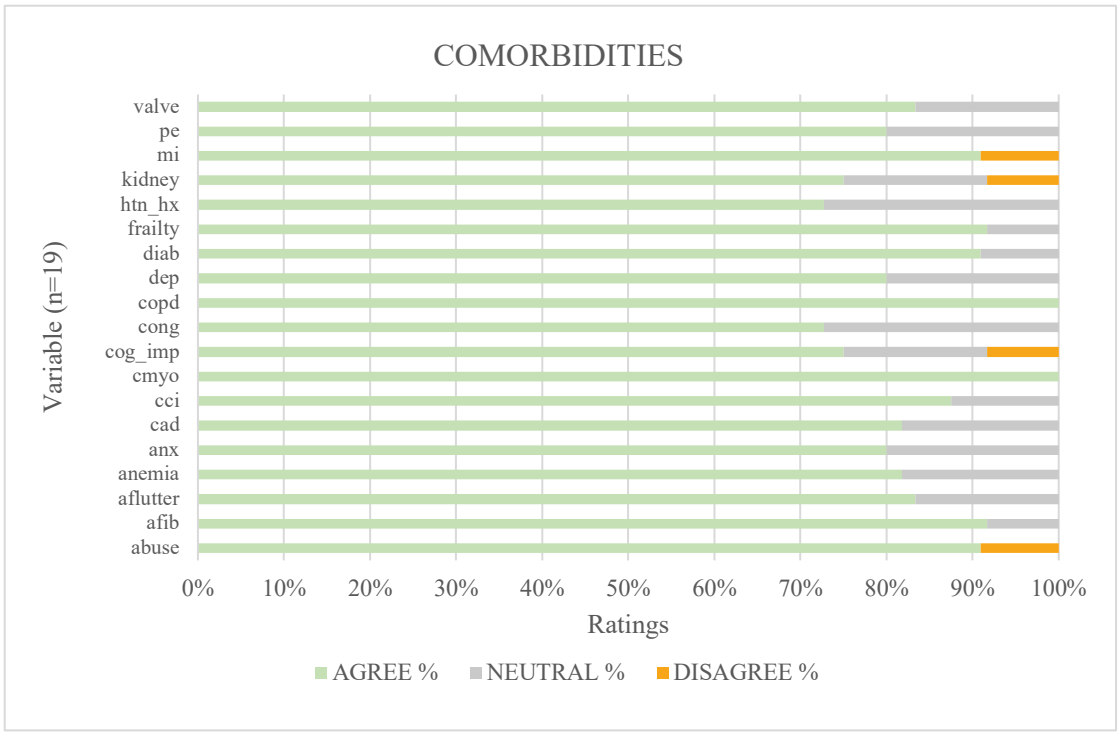
Despite 80% of the total sociodemographic variables included in the Delphi reaching consensus, these variables had the highest number of "disagree" ratings of all categories. Figure 2.4.2 depicts the ratings for each variable obtaining consensus.


PERI-HOSPITALIZATION
Variable (n=9)
nut
multi
fu_week
diet
dc_sum
cardio
ama
admit
acp
0%
20%
40%
60%
80%
100%
Ratings
AGREE %
NEUTRAL %
DISAGREE %

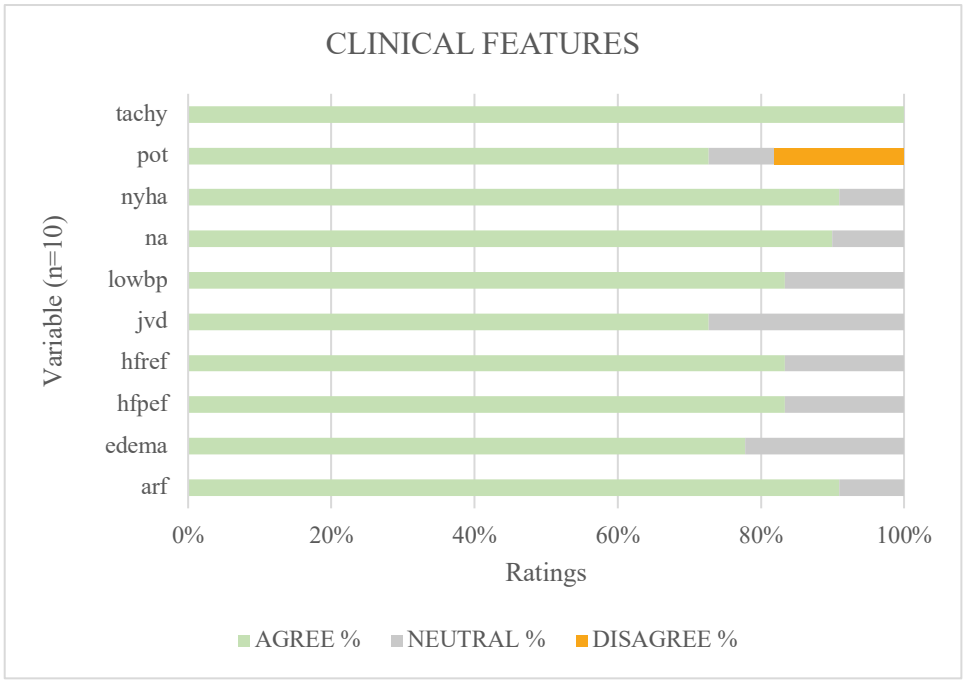
A.


LABORATORY
Variable (n=4)
trop
cr
bun
bnp
0%
20%
40%
60%
80%
100%
Ratings
AGREE %
NEUTRAL %
DISAGREE %

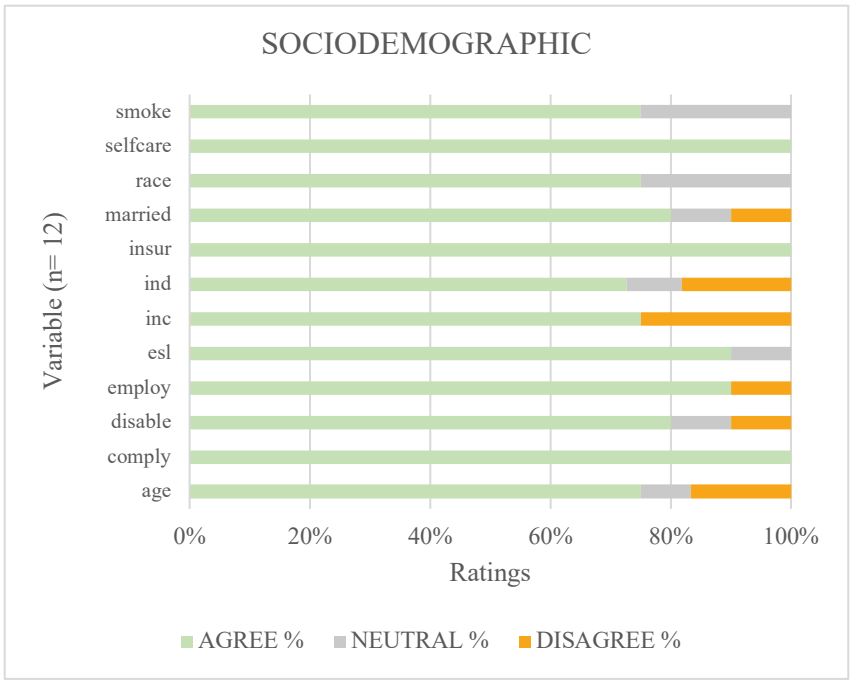
B.


COMORBIDITIES
Variable (n=19)
valve
pe
mi
kidney
htn_hx
frailty
diab
dep
copd
cong
cog_imp
cmyo
cci
cad
anx
anemia
aflutter
afib
abuse
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Ratings
AGREE %
NEUTRAL %
DISAGREE %

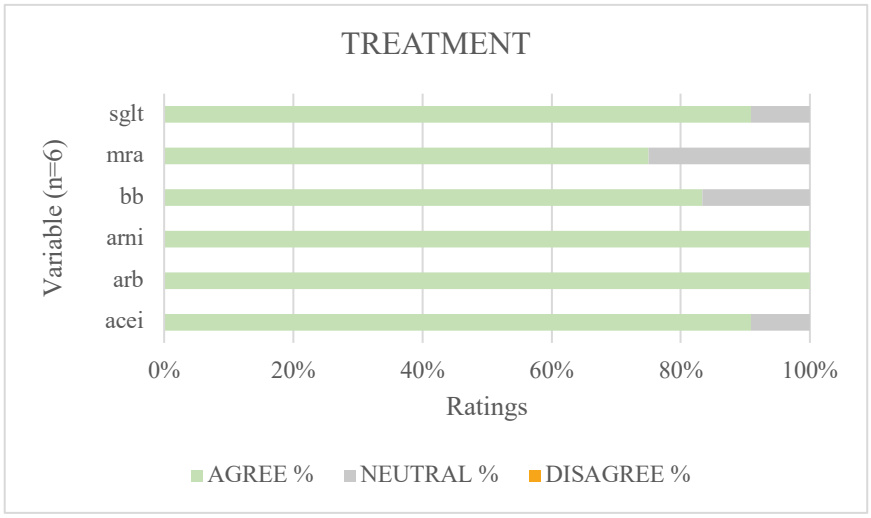
C.


CLINICAL FEATURES
Variable (n=10)
tachy
pot
nyha
na
lowbp
jvd
hfref
hfpef
edema
arf
0%
20%
40%
60%
80%
100%
Ratings
AGREE %
NEUTRAL %
DISAGREE %

D.



E.



F.

Figure 2.4.2 Summary of ratings for variables reaching consensus by category

2.4.5 Variables Not Reaching Consensus

Table 2.4.3 Variables not reaching consensus (n=32) by % consensus obtained

Variable (n=32)	Agree	Neutral	Disagree	No judgement
dementia	69%	31%	0%	0%
sense of purpose	67%	33%	0%	0%
right sided HF	67%	33%	0%	0%
shortness of breath	67%	25%	8%	0%
discharged from	58%	25%	0%	17%
liver disease	58%	25%	0%	17%
delirium	58%	25%	0%	17%
emergency visit	58%	33%	8%	0%
neoplasm/cancer	58%	17%	8%	17%
xray showing lung fluid	58%	17%	17%	8%
long length of stay	58%	17%	25%	0%
peripheral valve disease	50%	25%	0%	25%
urinary sodium excretion	50%	25%	0%	25%
distance from hospital	50%	17%	17%	17%
inotrope	42%	25%	0%	33%
pericarditis	42%	33%	8%	17%
high cholesterol	42%	25%	8%	25%
transfer between facility	42%	25%	17%	17%
pacemaker	42%	33%	17%	8%
high serum uric acid	33%	25%	0%	42%
ultrafiltration	33%	25%	8%	33%
fatigue	33%	42%	17%	8%
weight	33%	33%	17%	17%
vasodilator/nitrate	25%	33%	0%	42%
pci (stent)	25%	33%	8%	33%
sex	25%	25%	17%	33%
home with assist	23%	23%	46%	8%
HFmrEF	17%	42%	8%	33%
IVC ultrasound	8%	50%	17%	25%
fluid restrictrion	8%	38%	54%	0%
lipid lowering med	0%	67%	25%	8%
loop diuretic	0%	31%	62%	8%

The 32 variables not reaching consensus do not include the 3 variables that were excluded from the analysis (Figure 1) due to >50% No Judgement responses. As seen in Table 2.4.3, the 32 variables can be segregated into 3 sections: i) those with ≥50% agreement and few disagree responses. These indicate variables where panelists were not in disagreement with the association of a variable with readmission, but were not in full agreement with it either; ii) those with >25% agreement. These variables have more varied responses, and had a large IQR. There are larger quantities of "No Judgement" responses here, indicating respondents were more unsure of an association between a variable and readmission; and iii) those with ≤25% agreement. Variables in this section have higher quantities of disagreement responses, indicating that panelists were more likely to disagree with the association of a variable with readmission. This disagreement could be attributed to question formatting, as was seen in Round 3. Of note, the variable that received feedback from a panelist in Round 2 ("assist") had a high percentage of disagreement, and an even spread of responses among agreement and neutral.

Around 50% of no-consensus variables were in section i), with the remaining 50% spread equally between the other two sections. The majority of variables in the categories *Comorbidities, Sociodemographic, Peri-Hospitalization,* and *Laboratory* found in section i). Interestingly, both *Clinical Features* and *Treatment* had higher amounts of variables in the latter sections.

2.4.6 Comparison of Responses Among Panelists

a) Differences between Rounds

Eight variables could be assessed for adjustment in ratings between Round 1 and Round 2. Upon receiving feedback from Round 1, panelists repeated their ratings for the 8 variables shown in Figure 2.4.3

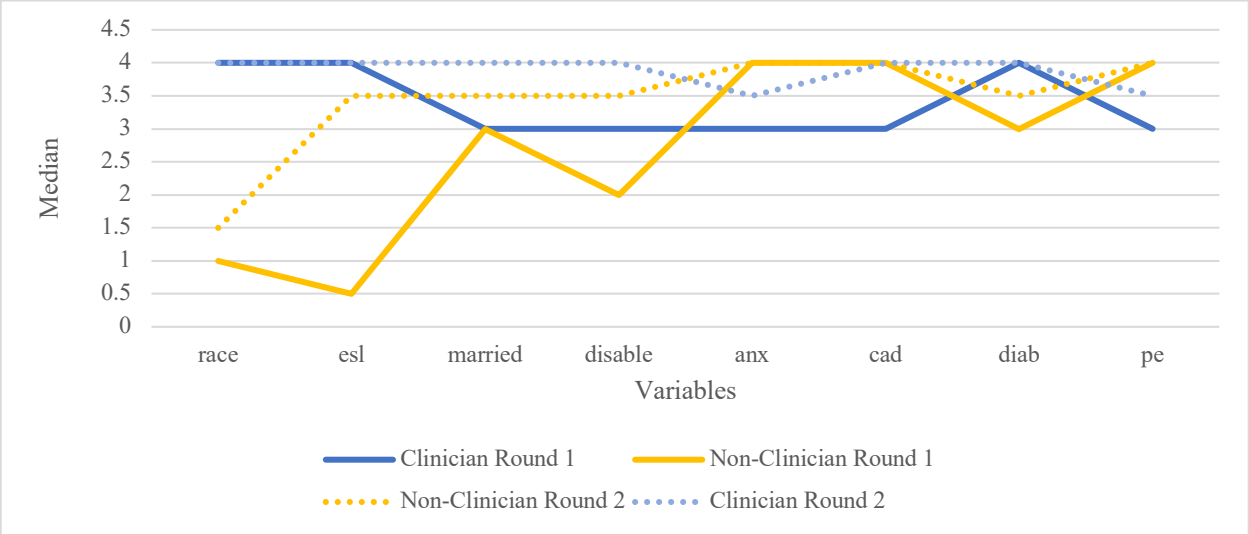


Figure 2.4.3 Rating differences from round 1 to round 2 among clinicians and non-clinicians

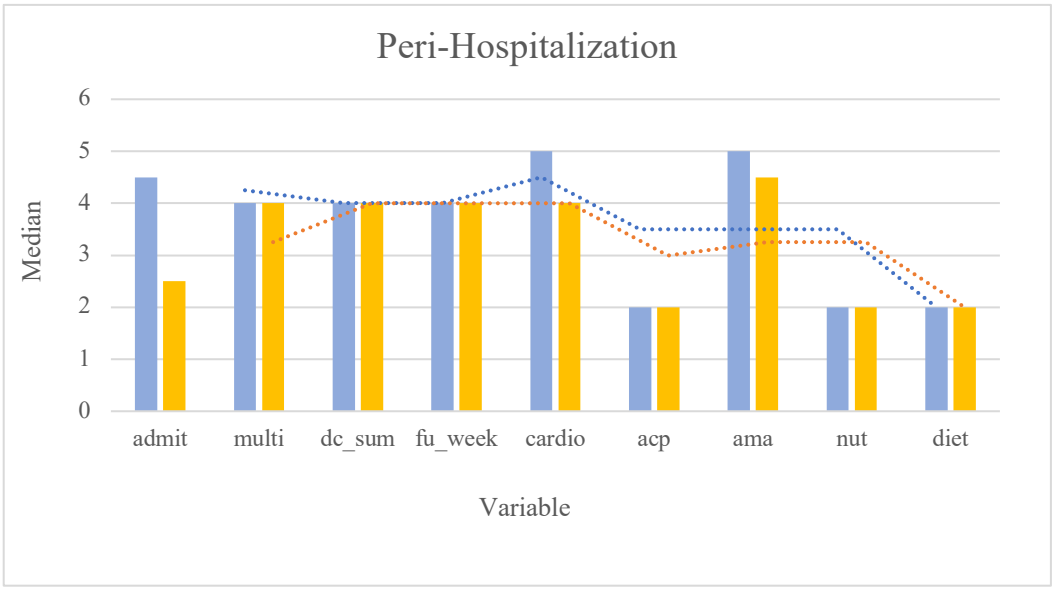
Non-clinician ratings tended to increase in score, flattening out the medians. Scores changed from "disagree" or "strongly disagree" to "neutral" or "agree". On the contrary, clinician ratings that were in "neutral" in Round 1 unanimously increased to "agree" or "strongly agree".

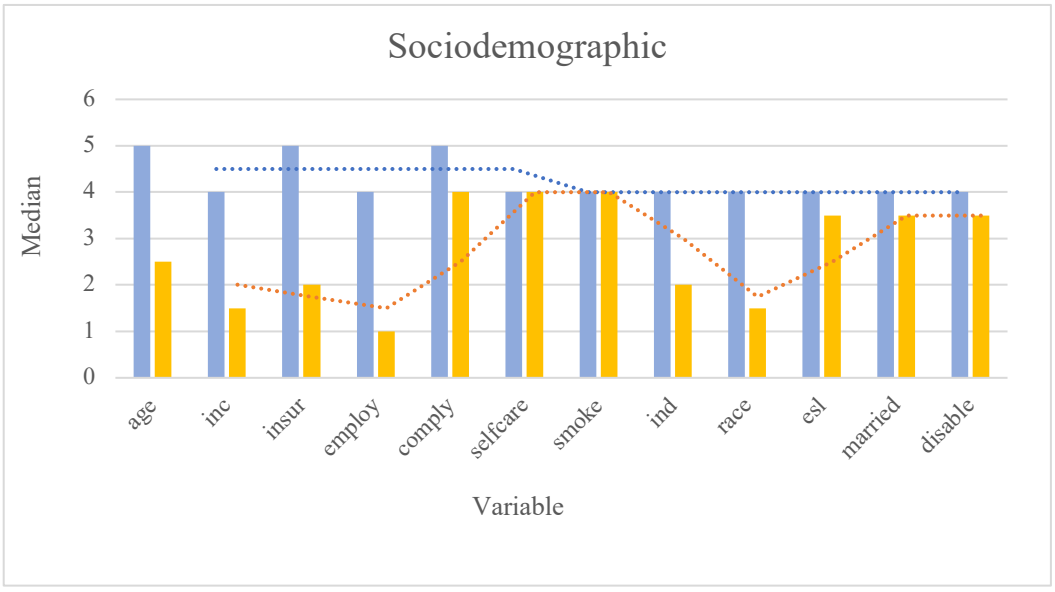
c) Variables Reaching Consensus through Delphi, Differences among Panelists

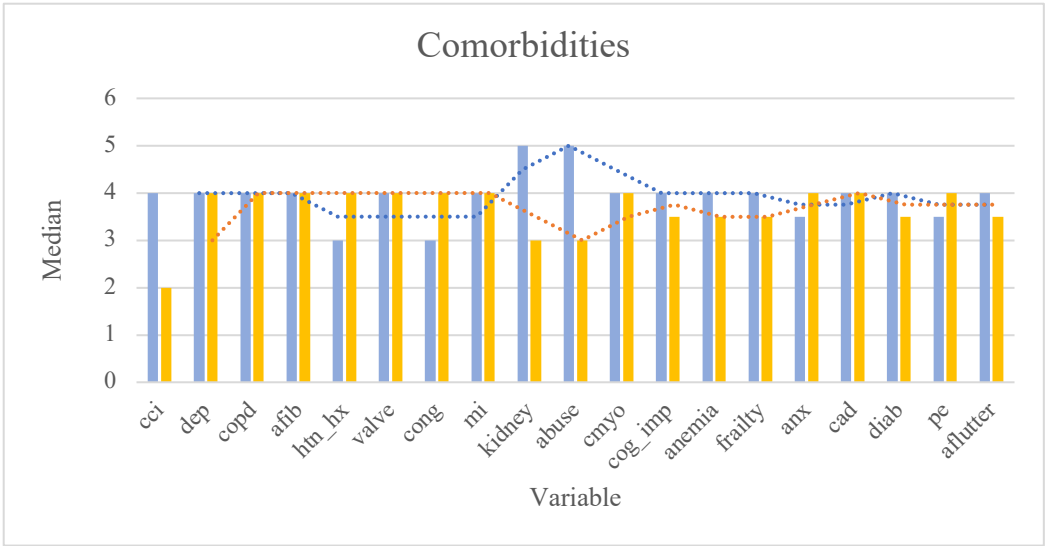
The median scores and their trajectories for clinicians and non-clinicians were plotted together in Figure 2.4.4.

Legend:


Clinician
Non-Clinician
Median Trajectory (Clinician)
Median Trajectory (Non-Clinician)


Peri-Hospitalization
Median
0
1
2
3
4
5
6
admit
multi
dc_sum
fu_week
cardio
acp
ama
nut
diet
Variable


Sociodemographic
Median
0
1
2
3
4
5
6
age
inc
insur
employ
comply
selfcare
smoke
ind
race
esl
married
disable
Variable


Comorbidities
Median
6
5
4
3
2
1
0
cci
dep
copd
afib
htn_hx
valve
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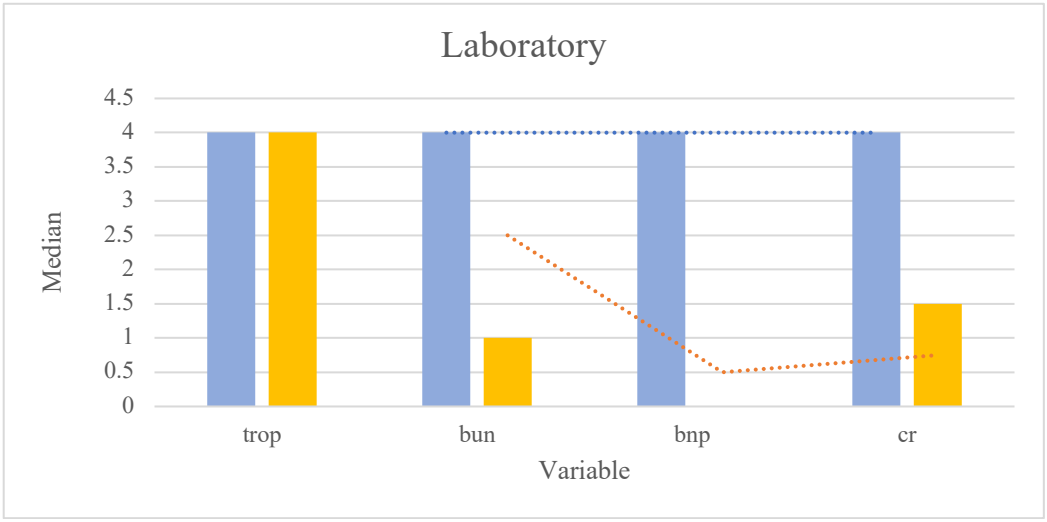
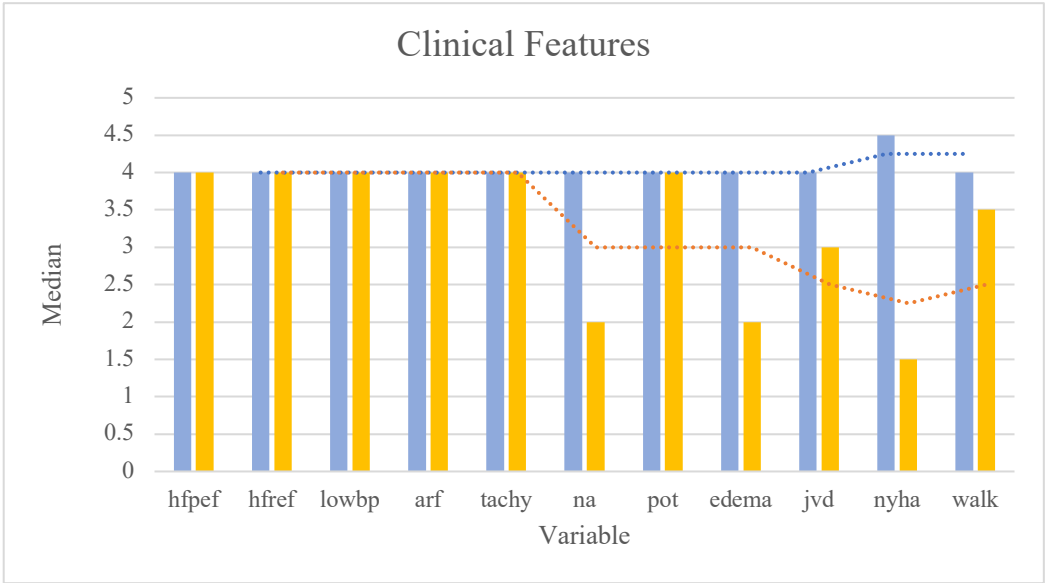
kidney
abuse
cmyo
cog_imp
anemia
frailty
anx
cad
diab
pe
aflutter
Variable


Laboratory
Median
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
trop
bun
bnp
cr
Variable


Clinical Features
Median
5
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
hfpef
hfref
lowbp
arf
tachy
na
pot
edema
jvd
nyha
walk
Variable

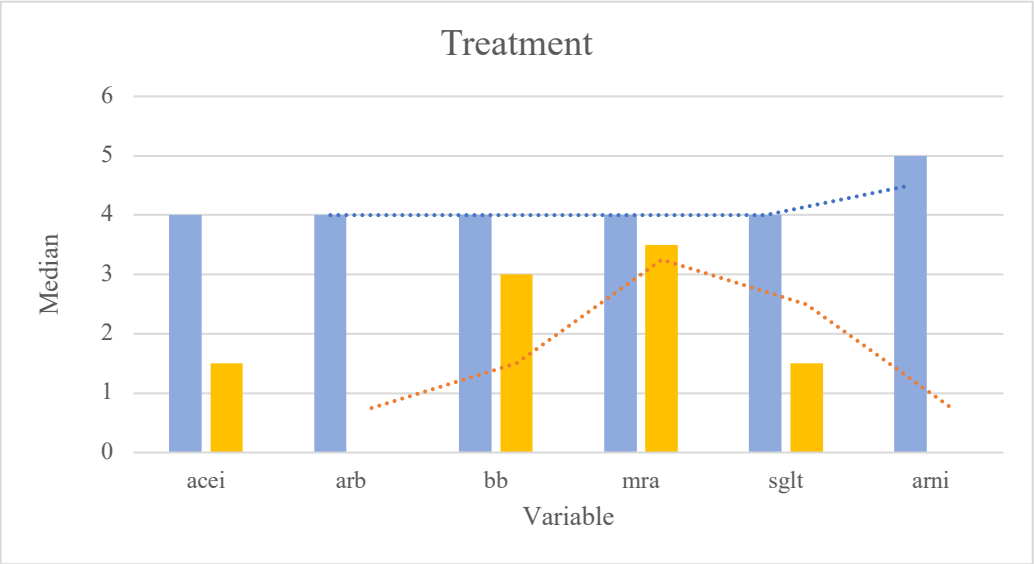


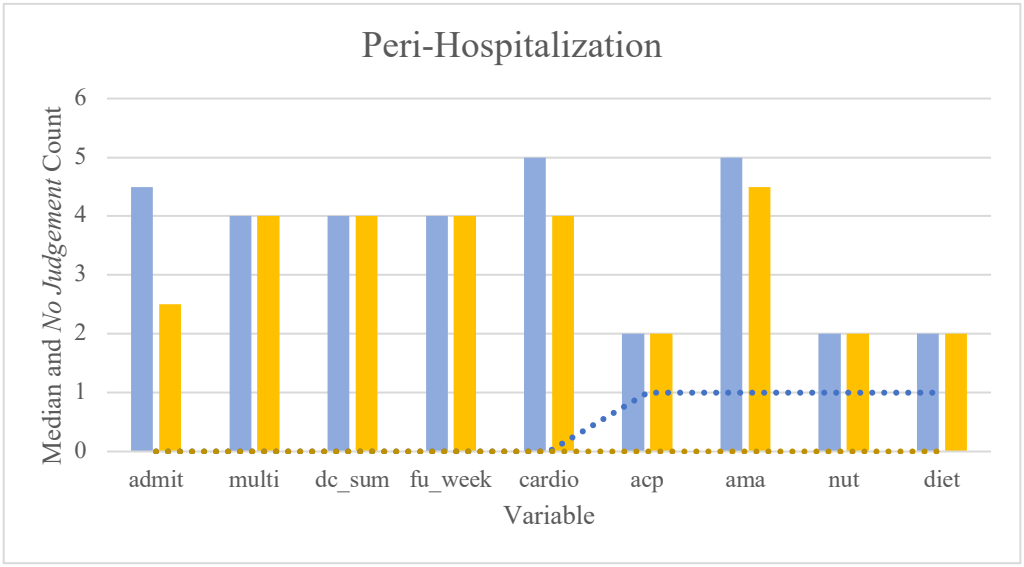
Figure 2.4.4 Median responses of clinicians and non-clinicians for included variables, by category

The purpose of this analysis was to compare responses based on clinical expertise; each category is displayed in its own graph to facilitate analysis. Where the medians differed, clinician medians were consistently higher than non-clinicians, indicating a higher tendency for clinicians to rate the statements with "Agree" or "Strongly Agree". Among clinicians, the category with the highest median trajectory (meaning trend of the median) was *Sociodemographic*, with the lowest score being "Agree". In comparison, *Sociodemographic, Laboratory,* and *Treatment* had the lowest median trajectories among non-clinicians. In fact, although these variables obtained consensus, 50% of the variables in *Sociodemographic* were rated < 3 (either "Disagree" or "Strongly Disagree") by non-clinicians.

The categories where medians between clinicians and non-clinicians were closer together were *Peri-Hospitalization, Comorbidities,* and *Clinical Features.* Interestingly, items within *Clinical Features* which might not be intuitive to the layperson, yet received similar medians between the two groups, were "hfpef" and "hfref" (2 definitions of heart failure based on ejection fraction seen in an echocardiogram). Similarly, a cardiac biomarker such as "troponin" is not common knowledge. However, compared to all other laboratory variables reaching consensus, this value received a median score of 4 ("Agree") from both groups of panelists. Assessing the knowledge gap, or lack thereof, in non-clinicians was the incentive for the following analysis.

Legend:


Clinician median
Non-Clinician median
No Judgement (Clinician)
No Judgement (Non-Clinician)


Peri-Hospitalization
Median and No Judgement Count
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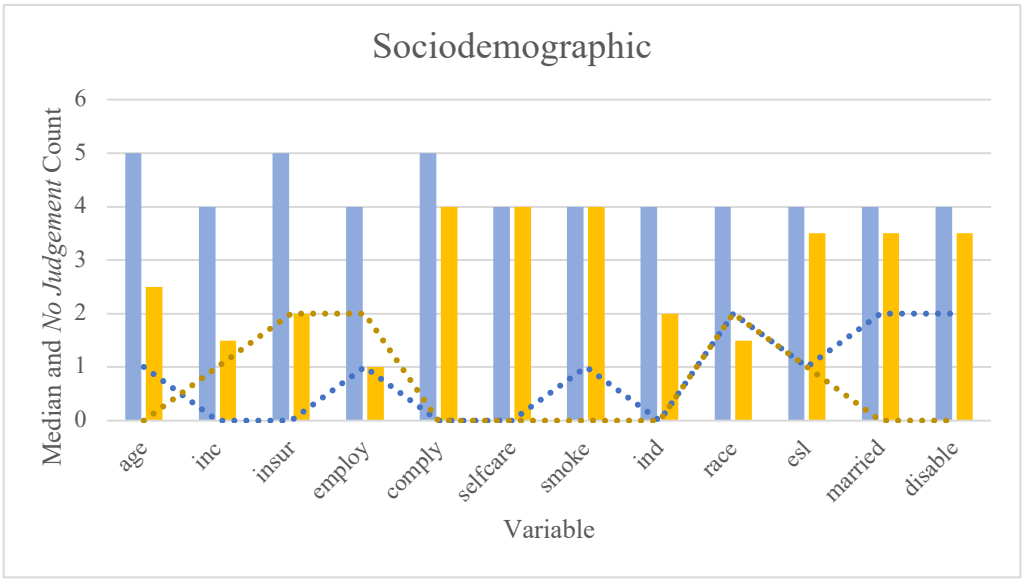
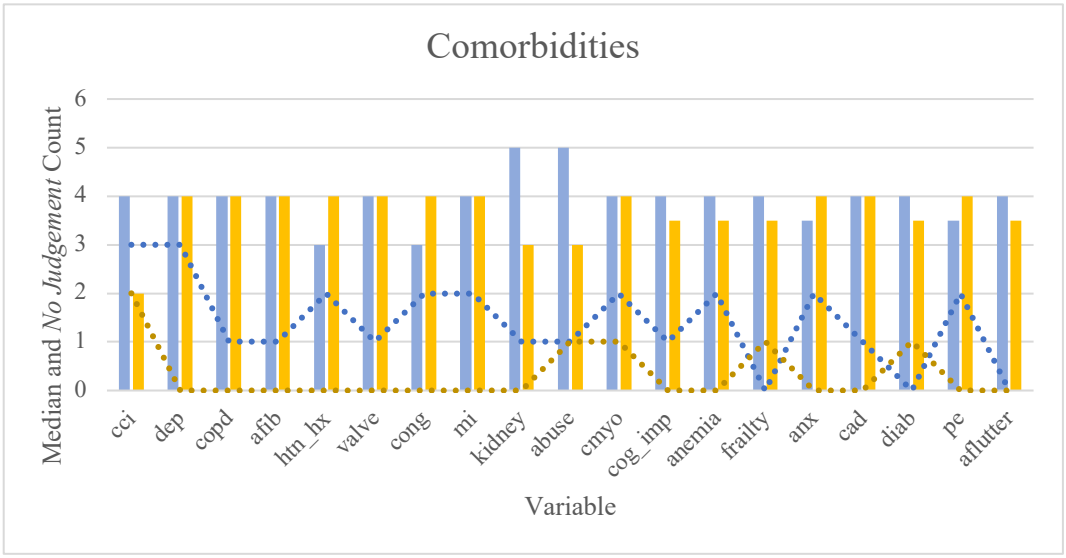
1
2
3
4
5
6
admit
multi
dc_sum
fu_week
cardio
acp
ama
nut
diet
Variable


Sociodemographic
Median and No Judgement Count
0
1
2
3
4
5
6
age
inc
insur
employ
comply
selfcare
smoke
ind
race
esl
married
disable
Variable


Comorbidities
Median and No Judgement Count
6
5
4
3
2
1
0
cci
dep
copd
afib
htn_hx
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cong
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kidney
abuse
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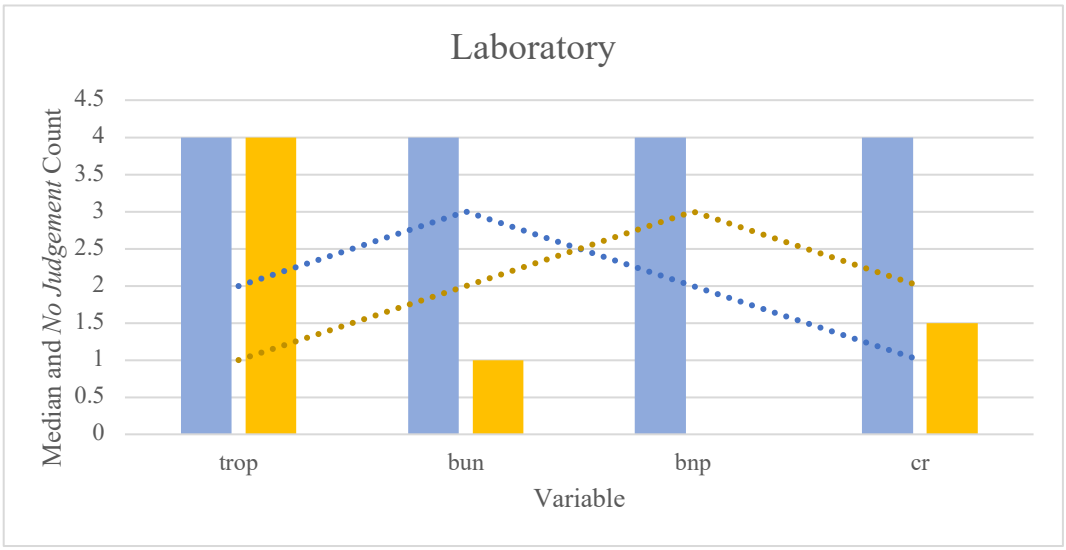
cog_imp
anemia
frailty
anx
cad
diab
pe
aflutter
Variable


Laboratory
Median and No Judgement Count
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
trop
bun
bnp
cr
Variable

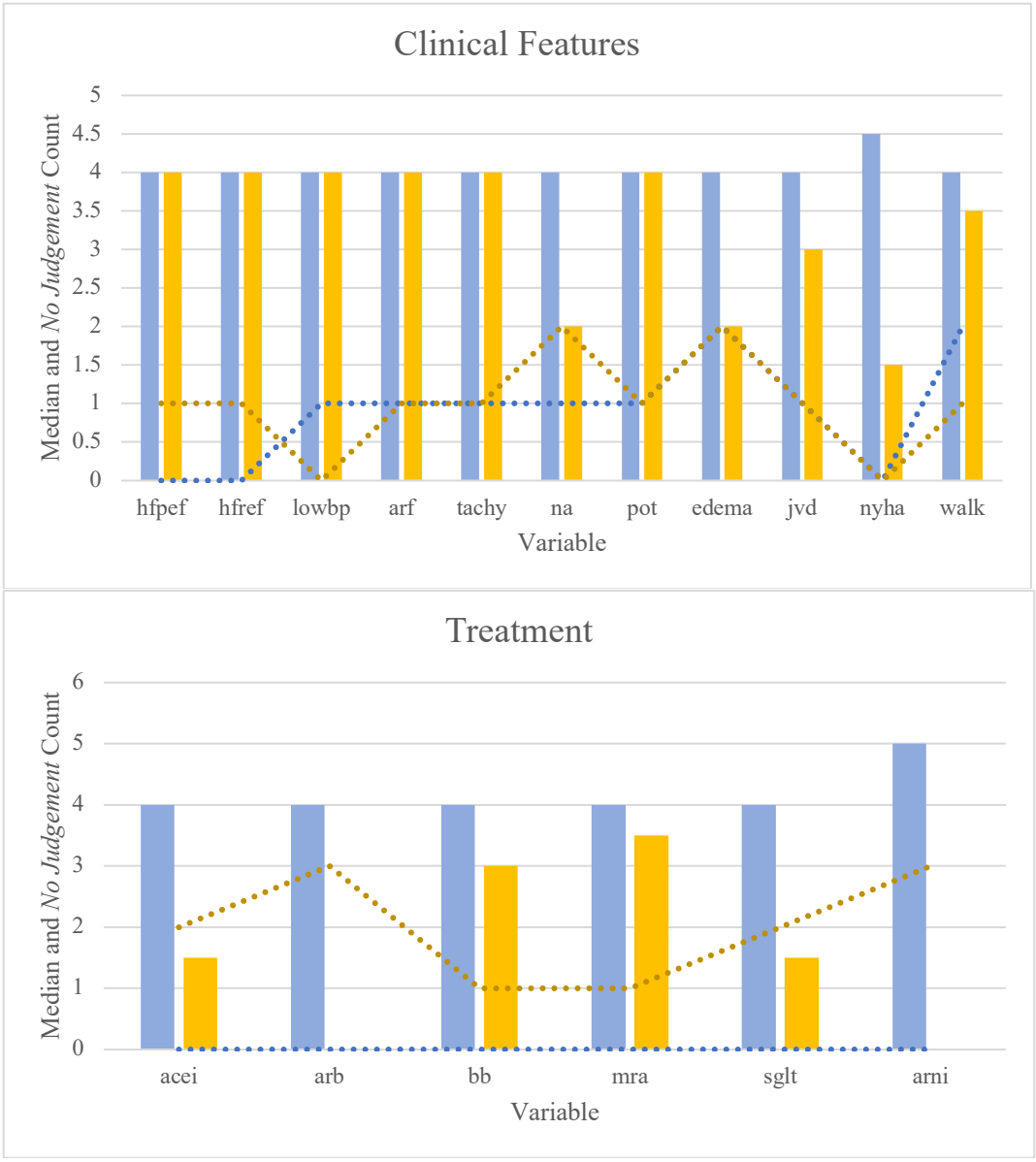


Figure 2.4.5 Median responses of clinicians and non-clinicians for included variables, with "No Judgement" responses

2.4.7 Results from "No Judgement" Ratings

A potential indicator of an existing knowledge gap for panelists is the amount of "No Judgement" ratings selected. These ratings were excluded from the median calculations to avoid a false median, and because the nature of the "No Judgement" rating is separate from the 1-5 Likert scale options.

In the variables where non-clinicians had a low median (*Sociodemographic)*, Figure 2.4.5 also demonstrates a high number of "No Judgement" ratings. Typically, for non-clinicians, where a low median was seen, a higher number of "No Judgement" ratings were also seen. This pattern was also seen with clinicians, albeit a fewer quantity of "No Judgement" ratings were available for comparison. This pattern correlates with the weak confidence seen in lower medians (moving towards the "Neutral"). However, because of the small sample size, it could also be a result of one or two panelists having strong opinions in the "Disagree" or "Strongly Disagree" camp, and the remainder of participants having no judgement. Interestingly, in the *Comorbidities* category, the amount of "No Judgement" ratings seen among clinicians was consistently higher than non-clinicians. Comparatively, "No Judgement" was seldom used in this category amongst non-clinicians.

2.5 Results from the Literature Review and the Modified Delphi Process

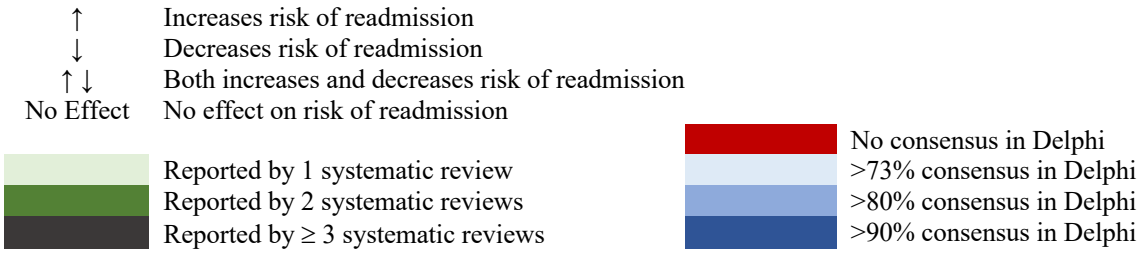
Forty-three of the 79 (59%) included variables from systematic reviews reached consensus in the Delphi process., seen in Table 2.5.3. Of these, there was lack of agreement among systematic reviews regarding directionality/association. However, if the Delphi agreed with one of the directions investigated in the systematic reviews, it was considered to have reached consensus with the systematic review. Eighteen of the 26 (69%) variables drawn from other literature sources reached consensus in the Delphi.

The majority of the variables where the Delphi and reviews agreed were in the *Sociodemographic* and *Comorbidity* categories. Strength of consensus in the Delphi was often matched by number of reviews reporting on a particular direction/association, as indicated by

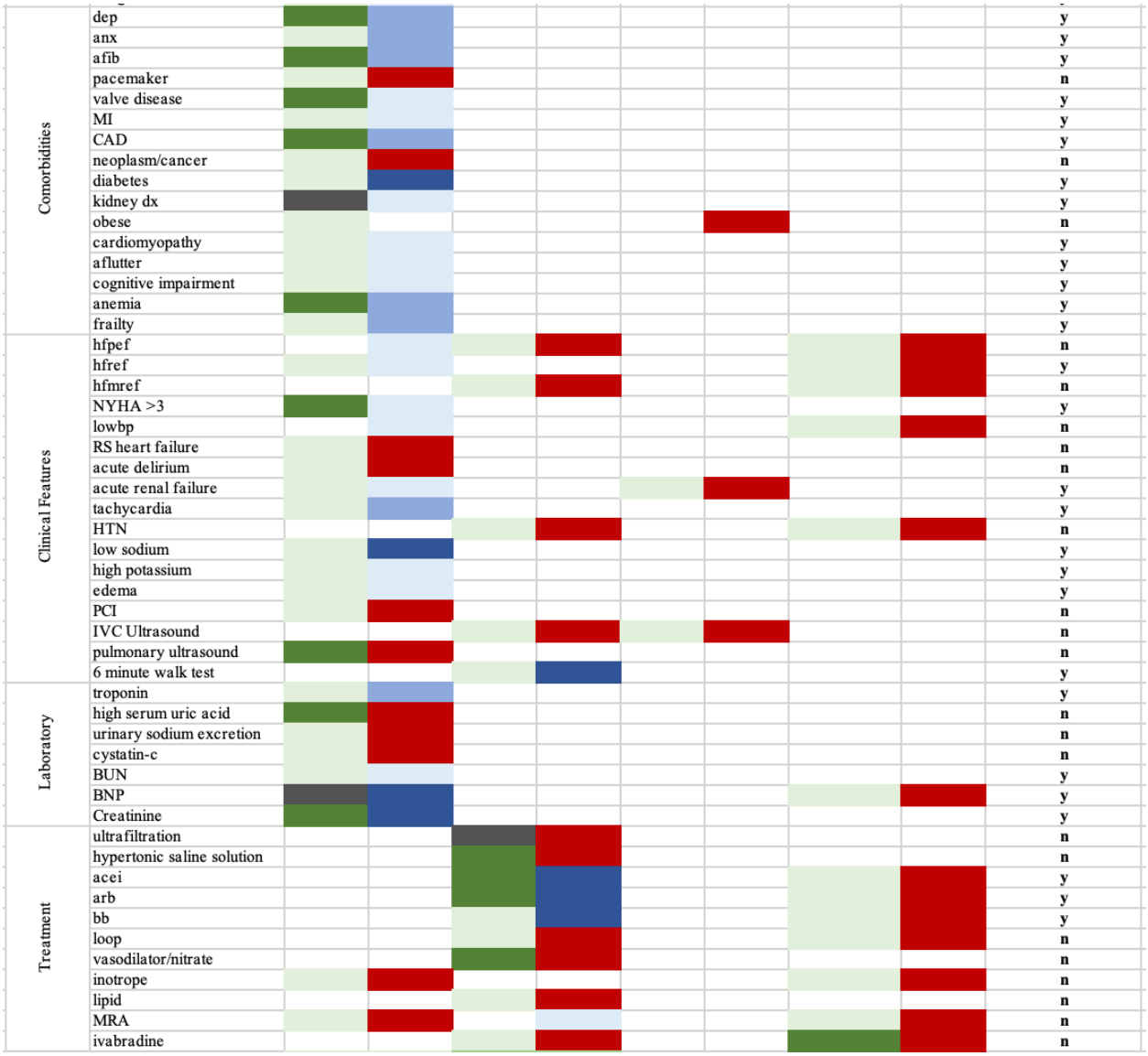
darker hues in both the systematic review and Delphi columns. Among those variables where the Delphi and systematic reviews did not agree on association or direction, the majority were in the *Treatment* category. The five variables that were heavily reported in the literature and reached high consensus % were “multi-disciplinary”, “BNP” ,“Creatinine”, “ACE” and “ARB”.

Table 2.5.3 Relationship between Delphi and systematic review variables

Legend:



	VARIABLE	↑		↓		↑↓		NO EFFECT		CONSENSUS between Delphi and SR?
Peri-Hospitalization	los_long									n
	los_short									n
	dc_teach									n
	dc_from									n
	admission previous									y
	dc to ltc									n
	multidisciplinary									y
	dc_sum to pcp									y
	fu_week with pcp									y
	acp in hospital									y
	nutritional teaching									y
	low sodium diet									y
	fluid restriction									n
Sociodemographic	age									n
	sex									n
	race									y
	prescription med coverage									y
	unemployed									y
	med compliance									y
	selfcare									y
	unmarried									y
	smoker									y
	indigenous									y
Comorbidities	dep									y
	anx									y
	afib									y
	pacemaker									n
	valve disease									y
	MI									y
	CAD									y
	neoplasm/cancer									n
	diabetes									y
	kidney dx									y
	obese									n
	cardiomyopathy									y
	aflutter									y
	cognitive impairment									y
	anemia									y
	frailty									y



Of the 19 variables not reaching consensus in the systematic reviews, 10 (52%) reached consensus in the Delphi (Table 2.5.4). Eight of these variables agreed with at least one of the measures of association identified in the systematic reviews. When this occurred, the strength of consensus correlated with the number of studies reported. For example, “BNP” had >3 studies reporting on its increased risk of readmission. Accordingly, “BNP” reached >90% consensus in

the Delphi. Seventeen of the 54 variables reaching agreement in the systematic reviews did not obtain consensus in the Delphi.

Table 2.5.4. Relationship between Delphi and variables not obtaining agreement in systematic reviews

	VARIABLE	↑	↓	↑↓	NO EFFECT	Delphi consensus obtained?
Peri-hospitalization	dc to ltc					no
	acp in hospital					yes
	nutritional teaching					yes
	fluid restriction					no
Sociodemographic	sex					no
Clinical Features	hfpef					yes
	hfref					yes
	hfmref					no
	acute renal failure					yes
	HTN					no
	IVC Ultrasound					no
Laboratory	BNP					yes
Treatment	acei					yes
	arb					yes
	bb					yes
	loop					no
	inotrope					no
	MRA					yes
	ivabradine					no

2.6 Discussion

Identifying readmission risk variables in patients with heart failure has been a longstanding, complex and arduous process for the cardiac research community. This study aimed to establish a set of variables associated with readmission in heart failure patients, using a modified Delphi process that included clinicians and non-clinicians. A final set of 58 variables were found to be associated with readmission risk, with 47 increasing the risk of readmission, and 11 decreasing the readmission risk. For the most part, variables were analyzed according to their category (pre-determined through the literature review).The original list of variables was drawn from a literature review summarizing key systematic reviews, large-scale cohort studies, and clinical guidelines. The review revealed vast heterogeneity in several aspects of readmission risk

variable identification. Discrepancies existed among and within systematic reviews on the i) association of any given variable with readmission risk, ii) direction of association for a variable contributing to readmission risk, and iii) strength of association between variables and readmission risk. Nonetheless, all variables extracted from the review were included in the modified Delphi process. Thirteen panelists in Round 1 and 3, and 12 panelists in Round 2, rated 99 variables for association with readmission risk, as well as direction of associated readmission risk where applicable. Despite the intended heterogeneity in panelist background, education-level, and clinical expertise, the panel had a high level of consensus, with close to 40% of variables reaching consensus in the first round.

2.6.1 Interpretation of Findings by Category

a) Clinical Features and Treatment

Variables in *Clinical Features* were the most infrequently reported among systematic reviews. Contrarily, *Treatment* variables had the highest frequency of reporting. These two categories, however, had some of the highest levels of disagreement among systematic reviews with regards to their variables' associations and/or directions of association with readmission risk. With regards to the Delphi panel, variables within *Clinical Features* had the lowest % of consensus among variables obtaining consensus. Additionally, variables in *Treatment* were the least likely to obtain consensus. Accordingly, variables from these two categories had the widest IQR among those not obtaining consensus, signifying lack of certainty surrounding their association with readmission risk. This corresponds with the high levels of disagreement among systematic reviews for these two categories.

Interestingly, despite both the Delphi and systematic reviews independently indicating low levels of consensus for *Treatment*, when compared against each other, there was minimal consensus between the Delphi and systematic reviews on association and directionality. These two categories have proven to be highly heterogeneous in association with readmission risk, as well as direction of association. Despite being quite frequently reported in the literature (*Treatment)*, neither the systematic reviews nor the Delphi were able to reach consensus on many variables within these two categories.

Clinical Features were not as heavily reported in the literature, with almost every variable being reported on by only one systematic review. The inclusion of these variables was in large part attributed to clinical guidelines and cohort studies. The oldest studies reporting on these variables were from 2017, therefore some time has passed since the establishment of these variables within the literature. A potential reason for lack of consensus in this category from both Delphi and literature lies in the subjective nature of clinical features. For instance, the presence of jugular vein distention might not be an abnormal finding for a patient with longstanding congestive heart failure. In the Delphi, each variable was meant to be treated uniquely, with no regard for other variables. This was in efforts to decrease the influence of other variables (especially clinical features) on the relevance of any given variable and its association with readmission risk. However, despite these efforts, consensus was still not obtained in the Delphi.

Likewise, with the *Treatment* category, asking panelists to ignore clinical presentation might have led to decreased consensus. Within the literature, similar findings were seen, with

reviews contradicting one another on a medication's effect on readmission risk. Further exploration is needed to identify the best way to measure severity of heart failure based on medications prescribed. For instance, perhaps being on >1 medication to treat heart failure is an indicator of increased readmission risk. In this case, number of medication classes present in a patient's pharmacy record could be indicative for readmission risk. However, for the sake of simplicity, and the need to integrate these variables into the EMR, "number of medication classes" could not be used as a variable in this study.

b) Comorbidities and Sociodemographic

One of the hypotheses of this study was that *Sociodemographic* variables would be less likely to obtain consensus. However, results from the systematic review, Delphi process, and both the review and Delphi combined, demonstrated the opposite. Within the systematic reviews, there was scarce, if not absent, disagreement in association and directionality for *Comorbidities* and *Sociodemographic.* These two categories also had the highest amount of variables obtaining consensus in the Delphi.

However, despite a large amount of variables reaching consensus within *Sociodemographic,* 50% of these variables were rated < 3 ("disagree" or "strongly disagree") by non-clinicians. Comparatively, clinicians had the highest median trend for *Sociodemographic* variables. This difference was not expected between the two groups, primarily because non-clinicians were thought to have a robust and personal experience with variables within the *Sociodemographic* category, and the impact of these variables on their heart failure journey. Unfortunately, this might have been attributed to the small sample size of the study. Diversity in

the non-clinician group's background, living conditions, or socioeconomic status, could not be accounted for. Future research should aim to recruit a larger patient sample with a focus on socioeconomic diversity.

Nonetheless, many *Sociodemographic* variables were included in the final list of variables. With regards to *Comorbidities*, clinicians selected "No Judgement" more frequently than non-clinicians, indicating a knowledge gap. This was not expected, given the exposure clinicians have to a diverse set of diseases when assessing their patients. Once again, the notion of determining the association of a variable with readmission risk without accounting for any other variable, poses challenges to the panelists. Particularly in the case of co-morbidities, where the emphasis is on diseases that accompany the primary condition, the best indicator of readmission risk might be one that allows for a holistic view of the patient's disease processes. The Charlson Comorbidity Index (CCI) would be of use here. Fittingly, the panel decided a CCI score >3 was associated with increased risk of readmission.

2.6.2 Knowledge Gaps in the Literature, and Among Panelists

a) No Effect

One of the findings in the literature was that the higher the amount of reviews identifying a variable as having "no effect" on readmission, the less likely that variable was to obtain consensus among systematic reviews regarding association with readmission risk. Sixteen of the 19 variables where "no effect" was reported in the systematic reviews, did not reach consensus among systematic reviews. However, 9 out of 16 of the variables with "no effect" that did not

reach consensus in the systematic reviews, did reach consensus in the Delphi. Ultimately, the amount of "no effects" mentioned in the literature did not impact the Delphi's consensus. However, the high amount of "no effect" findings in variables not reaching agreement in the systematic reviews suggests a need for clarification among studies reporting on variables associated with readmission risk in HF. A follow-up study investigating systematic review quality might reveal why so many variables were found to have "no effect" on readmission risk, when other reviews cited the opposite.

b) No Judgement

The use of "No Judgement" proved to be highly revealing on panel knowledge, particularly in comparison to the literature, and when analyzed between clinicians/non-clinicians. With regards to the literature, one of the heaviest cited variables was "ultrafiltration"; >3 systematic reviews cited this treatment as beneficial for decreasing risk of readmission in heart failure patients. However, this variable in the Delphi accumulated 40% "No Judgement" ratings and was ultimately excluded. Similarly, the use of hypertonic saline solution with a diuretic was found to decrease readmission risk in the literature. However, this variable also scored >50% "No Judgement' and was excluded. Interestingly, "No Judgement" was hardly selected by both clinicians and non-clinicians for the category *Peri-Hospitalization*. This indicates certainty of association between these variables and readmission risk. Variables within this category also had the highest % consensus in those obtaining consensus in the Delphi.

The use of "No Judgement" highlighted areas of heart failure management that panelists lacked knowledge in, particularly in the *Treatment* category. Conversely, it also highlighted areas

where panelists felt quite knowledgeable and confident in their answers. With regards to non-clinicians, there is a possibility that they did not know what they did not know. For instance, the lack of "No Judgement" scoring in categories that are heavily medical, such as *Comorbidities*, could indicate false certainty. However, given the small sample size, it is not possible to ascertain whether this finding was due to a lack of power.

2.6.3 Strengths and Limitations

There are several strengths to the Delphi method, many of which can be limitations as well. An anonymous panel provides the panelists the opportunity to freely share opinions. However, anonymity can also contribute to a loss of ownership of ideas which can increase lack of interest and commitment to the panel, and consequent drop-out. However, panelists were being asked to contribute their expertise to the project. This offered panelists a sense of value, compelling them to stay involved. Additionally, reminder emails were sent to panelists to keep them engaged, and only one panelist withdrew for one round. The Delphi panel's anonymity can also detract from lively in-person discussions and the group-think mentality, which can contribute to consensus building. However, given the potential sources of bias (discussed below) when using a heterogenous panel, the feedback provided was sufficient to influence scores. Additionally, had the panel met in person, the diversity of the panel would most likely have led to dominance and submission from panelists based off their self-perceived expertise or lack thereof. This is evidenced by the magnitude and direction of median change from one round to the next in non-clinicians. By completing the survey online, we were able to maintain the anonymity that is so crucial for independent, non-biased, well thought-out opinions when formulating consensus (27).

A potential limitation of this study was the selection of variables available in the current EMR used in Alberta. Missingness of data might be revealed when a new EMR system with richer data is introduced. However, the goal of the current study was to establish variables that could be incorporated into a prediction model at this present moment. Another potential limitation can be found in the use of a rapid review rather than a systematic review for the literature review (28). Due to the lack of peer-review, there is potential for bias in study inclusion/exclusion. However, given the objectivity of the research question (i.e. which variables were statistically found to be associated with readmission risk), risk for bias was limited. Assessment of study quality and rigor was not done, and should be considered for future studies using a literature review as a comparator for Delphi panel results.

Another issue that could arise using the present EMR system is that some variables deemed important for inclusion by panelists are simply not predictive for readmission. It will be important to document reasons for inclusion of this variable by the panel, and explore the variable's inclusion further. For example, if the variable was deemed important by patients with limited access to healthcare services, one could further explore perceived barriers and facilitators to healthcare access, and how these perceptions might amplify the contribution of said variable in increased readmission risk. There is opportunity for a qualitative study compiling this evidence for the panelist's inclusion of certain variables demonstrating poor predictive power.

2.6.4 Bias

The majority of questions posed in Round 3 with the new format (two separate questions per variable for each direction of association) were from the *Treatment* category. Interestingly, this category had the highest % consensus among variables obtaining consensus. This raises the question of whether the previous rounds were optimally formatted in the statements posed. Though the statements was explicitly phrased as asking first about association with readmission risk, then about directionality, it is apparent that the differentiation between these two concepts was not clear to many panelists. However, due to the heterogeneity found in the literature review, for many variables, a direction of association was not made obvious. Therefore, a broader question of association was needed to be asked.

Further, the concept of introducing bias into the survey was heavily considered in the formatting of the questions. Concerted efforts were made to avoid bias: i) since it was decided that only one statement would be offered per variable (unlike Round 3), a direction was not inserted into the original question (no leading questions) to avoid swaying panelist responses in favor of agreement with the question's direction (acquiescence bias); ii) questions where a direction needed to be made explicit with regards to the variable itself (e.g. high versus low sodium) were kept to a minimum; iii) no information was given with regards to pre-existing associations in the literature between a variable and risk of readmission; iv) surveys were intentionally shortened as much as possible to avoid non-response bias; v) survey questions were in no particular order within their designated categories to avoid question order bias; vi) all responses were kept anonymous to decrease conformity bias.

Response bias (specifically conformity bias, the tendency to respond in a way that benefits how they might appear to others) was thought to likely occur within the non-clinician population, given their insight of not understanding medical jargon in the questions asked, or not knowing about risk of readmission for a specific variable (29). Consequently, we expected to see higher numbers of "No Judgement" among non-clinicians. Surprisingly, there was no obvious difference in the use of "No Judgement" between clinicians and non-clinicians. To this regard, those who have a tendency to be involved in patient research and are more vocal in the HF community might have opted to be involved with our sampling platform (SPOR) or have been more amenable to participate in the survey. These patients/caregivers might be more involved in their HF management and care and therefore may not represent the general HF population. If replicated in a larger study setting, perhaps an alternate sampling method could be used to identify patients/caregivers which might minimize this bias.

We also expected to see a bigger change in ratings between Round 1 and Round 2 with non-clinicians as opposed to clinicians. This was indeed the case, with median ratings increasing among non-clinicians towards the neutral score. This finding was representative of potential conformity bias for non-clinicians; however, given the nature of the method, where changes in ratings was encouraged, this could not be avoided.

Of peculiarity was the response from clinicians to the feedback between Round 1 and Round 2. Rather than attempt to neutralize their responses in order to increase the likelihood of consensus, clinicians uniformly increased their median ratings, moving towards more extreme

responses. This pattern could be a representation of another form of response bias, specifically acquiescence bias, the tendency to respond on the affirmative side of the scale (29). Once clinicians saw the high amount of "agree" responses in Round 1, they might have been tempted to lean even further towards that pole. Again, because of the nature of the consensus-reaching methodology, influence between rounds is to be expected, and cannot be mitigated.

With regards to survey brevity, the impact of this choice was seen in the variable "assist". As gleaned from a panelist's feedback, the risk of readmission might have differed between different aspects of the variable (home with assistance). However, because we combined these aspects into one variable to keep the survey concise, we potentially sacrificed an opportunity for consensus among panelists. Perhaps maintaining the balance between assessing as many variables as possible, while keeping the survey short so as to avoid attrition, and simultaneously representing each variable well, should be the focus of future Delphi processes in this area.

2.7 Conclusion

The literature review and survey data contributed to the compilation of a list of 61 variables thought to be associated with readmission risk in heart failure patients for any cause within 30 days of discharge. Results can inform RRPs using EMR systems that possess the capability to abstract sociodemographic, peri-hospitalization, co-morbidity, clinical feature, laboratory and treatment variables from structured or free-text electronic documents. The current study is unique in that these variables were compiled using a heterogenous panel of clinicians and non-clinicians, offering diverse experiences related to HF management, treatment, and factors for readmission.

CHAPTER III.

Implications of Findings

3.1 Research Significance and Impact

The derivation of patient- and provider-driven variables that contribute to readmission risk for HF patients has a significant impact on the future of readmission risk prediction, and consequent improved patient health outcomes. This list will be the first among its kind to incorporate a patient and provider perspective on readmission risk variables in HF patients. Independent of EMR integration, this list will provide a rigorous clinically-relevant Albertan reference for future RRP endeavours.

This list will advance scientific knowledge on the topic of RRP in HF by bringing attention to the perspectives of patients and providers in determining predictors for readmission. With this list, certain variables previously unconsidered in RRP can be incorporated into RRP, and not only improve prediction, but also reflect the patient-centered philosophy of many healthcare systems worldwide- something not frequently seen with prediction modeling. If these variables are integrated into the EMR system, then international EMR users can use these variables as guidelines for creating databases amenable to clinically-relevant RRP tools.

This project will also impact EMR technicians, information technologists, and analysts involved in the creation and implementation of these EMR variables; they will all have the opportunity to be on the front-end of innovation for risk prediction. Health systems

administrators will also benefit from this project, given that they will hopefully see a decrease in hospital bed use from readmissions, allowing them to better allocate resources to hospital admissions unrelated to preventable readmissions. Lastly, with future inclusion of these variables into prediction tools, patients can be confident that their voice has been heard in their care process and planning, which increases self-advocacy and improves patient health outcomes. Additionally, more accurate risk prediction due to improved variable selection will lead to decreased hospitalization, and improved health and quality of life for HF patients.

3.2 Future Research Directions

3.2.1 Panel

Future research endeavors might involve replicating the study with a larger sample. This would allow for increased power in summary statistics, as well as increased diversity in panelist specialty, experience, background, and socioeconomic status. Importantly, an analysis of non-clinician demographic information including health literacy, social deprivation index, and education level would be of interest. This would allow for a robust understanding of the non-clinician's baseline understanding of medical jargon, as well as personal biases that might influence survey responses. For example, one panelist had immigrated to Canada, and their rating for the association of "esl" (English as a second language) with readmission risk was significantly lower than the rest of the panel. Though these dynamics can be difficult to control for in a survey with heterogenous respondents, they can help frame our understanding of ratings, and perhaps make necessary adjustments to better suit this heterogeneity.

3.2.2 Integration into the EMR

Several steps need to be taken prior to the integration of these variables into the EMR. First, validating each variable takes concerted effort and time. Particularly with regards to variables abstracted from free-text (i.e. ejection fraction % abstracted from a History & Physical document), there are complex and highly technical data analytic techniques that need to be refined.

Second, ensuring high quality data for the development of a risk prediction model is essential. As mentioned in Chapter II, Alberta is fortunate to be moving towards one standardized EMR system used across all hospitals in the province. However, currently several healthcare facilities use a hybrid paper-electronic charting system, signifying missing electronic data. Additionally, when training a model, one needs to ensure there is an appropriate gold-standard database to which to train to the model to. The cardiac database, APPROACH (Alberta Provincial Project for Outcome Assessment in Coronary Heart disease) incorporates some sociodemographic, clinical, laboratory, treatment, and peri-hospitalization data. It can be a useful reference standard for validation due to its structure format and standardized data validation processes (30).

Third, the actual embedding of a risk prediction model into an EMR system needs to take several factors into consideration; i) validation techniques to ensure accurate and reliable data are entered on the front-end, ii) appropriate use of alerts and pop-ups for end-user to avoid alert

fatigue, and iii) real-time data abstraction from the EMR to add to the current admission's EMR. Since this RRP model is to be used prior to the patient's discharge, any data from previous interactions with the healthcare system, as well as past pharmacy data and sociodemographic data needs to be pulled in real-time. This could allow the RRP to influence healthcare decisions in actuality; however, this poses a challenge to an EMR system like the current one in use in the city of Calgary. It only possesses hospital data; therefore, laboratory, pharmacy, and community healthcare utilization data would need to be linked in real-time to the patient's current admission. Current work is being done to expedite the data linkage process, but there is still work to do prior to the realization of our readmission risk prediction model.

3.3 Knowledge Translation Plan

Knowledge exchange, dissemination and application will be key components of KT for this study. The use of providers and patients as panelists will allow for the sharing of knowledge between researchers on the team, and users (providers and patients). Additionally, allowing end users (providers and patients) to be active members of the research process (panelists) enabled integrated KT. The list of variables will be published in a scientific journal (i.e. Canadian Journal of Cardiology) and presented at virtual scientific conferences (i.e. Heart Failure Update Conference, and Heart Failure Society of America Annual Scientific Meeting) to ensure knowledge dissemination. Panelists will also be made aware of study findings, and will be acknowledged in study publication.

Key stakeholders (HF specialists) involved in the panel will disseminate knowledge to their colleagues. These HF specialists are involved in the provincial HF "Care Pathway" working group. This working group is creating a roadmap for implementing order sets, cardiac clinic referrals, and prediction algorithms into clinician practice. Therefore, the actual use of the prediction algorithm, once implemented into Epic, will be spearheaded by this working group. Lastly, many members of the research team are involved in the roll-out for Epic provincially and nationally. Therefore, the opportunity to implement these variables into the EMR system will allow for knowledge application.

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