Predictive Validity of the Hospital Frailty Risk Score on Health Service Utilization Among Older Adults in New Brunswick

by

Jacques Al Alam

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Supervisors: Ted McDonald, PhD, Department of Political Science
Sandra Magalhaes, PhD, Department of Sociology

Examining Board: Pamela Jarrett, MD, FRCPC, Geriatric Medicine, Dalhousie University

Richard Audas, PhD, Division of Population Health and Applied Health Sciences, Memorial University

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Abstract

The Hospital Frailty Risk Score (HFRS) is a claims-based frailty algorithm designed to identify older adults at risk of adverse outcomes, but its performance in the Canadian healthcare context remains understudied. This study evaluated the predictive validity of the HFRS for adverse health service outcomes among adults aged 65 years and over in New Brunswick using linked administrative data from 2014-2018. Three-year intervals were constructed with a two-year exposure period to calculate HFRS and a one-year follow-up to assess outcomes. Adjusted logistic regression models examined associations between frailty risk (low, medium, high) and cumulative acute length of stay, alternate level of care (ALC) stays, and mortality. Among 57,730 observations, a clear dose–response relationship was observed, with progressively higher odds of prolonged hospitalization, extended ALC stays, and mortality across frailty categories. This study demonstrates the predictive validity of the HFRS for longer-term hospital utilization and ALC outcomes, supporting its use for health system planning and resource allocation.

Dedication

To my supervisor, Dr. Sandra Magalhaes, whose patience, guidance, and unwavering support never faltered, even when I was slow to find my footing in the world of research and thesis writing. Thank you for not giving up on me and for believing in my ability to grow into this work.

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1. Chapter 1, Introduction

1.1 Background and Context

As individuals age, they become increasingly susceptible to health issues. Naturally, there is a connection between a patient's age and the quantity (and cost) of healthcare services they utilise (Kalseth & Halvorsen, 2020). Older adults (65 and older), who make up only 15% of the total population account for nearly half of the costs associated with healthcare services (Kalseth & Halvorsen, 2020).

In addition to the high healthcare cost, the population in Atlantic Canada, and including in NB, is aging rapidly. According to recent reports from Statistics Canada in 2022, the elderly population in NB is growing faster than the national average in Canada (Government of Canada, 2022). This places increased pressure on the provincial healthcare system. Naturally, this also shows how crucial health services research on this demographic is, and we need a deeper understanding of the nuanced healthcare service challenges that this group faces, which will provide evidence that may support research that can lead to effective solutions and better healthcare policy plans.

One particularly important area of study when it comes to the healthcare utilisation of older adults is frailty. While the literature is generally divided when it comes to the definition of frailty, there is a common understanding that frailty is a medical condition consisting of an increased vulnerability to negative health outcomes. This combination of deficits leads to an increased vulnerability to negative health outcomes, making this population a very important group when it comes to studies involving healthcare use.

This high prevalence of frailty among the older adults, who are the primary users of healthcare services, as well as the strong connection between frailty and healthcare usage, shows why research in the topic of frailty is important, especially in NB.

Identifying frail individuals accurately can help guide healthcare resource allocation efficiently and improve patient outcomes. The Hospital Frailty Risk Score (HFRS) is a tool designed to measure frailty using previous electronic hospital records, enabling large-scale frailty assessments without in-person evaluations. While the current application of the HFRS in real-time patient assessment is limited, it remains a powerful tool for conducting retrospective research on frail individuals. Although the HFRS has been validated in various populations internationally(Gilbert et al., 2018; Sy et al., 2022), its effectiveness in NB, with its aging demographic, remains untested. This study aims to fill that gap by assessing the HFRS's ability to predict frailty-related adverse health outcomes among older adults in the province.

A recent population-based study examined the prevalence of frailty among hospitalized older adults in New Brunswick using administrative health data (Gallibois et al., 2022). The researchers applied the Hospital Frailty Risk Score (HFRS) to hospital discharge records for individuals aged 65 and older to identify levels of frailty across acute care admissions. Their findings revealed that 34.2% of hospitalized older adults in NB were classified as frail, while 38.9% were identified as pre-frail (with an HFRS score between 5 and 15), and only 26.9% were classified as not frail. These results demonstrate that frailty is highly prevalent among older inpatients in the province. The study highlighted the feasibility of using the HFRS with routinely collected data to monitor frailty trends at

the population level. It also reinforced the need for targeted interventions and healthcare planning to address the disproportionate burden of frailty in NB's aging population.

1.2 Problem Statement

Frailty in older adults is consistently associated with increased healthcare utilization, including higher rates of hospitalization, prolonged inpatient stays, unplanned readmissions, and mortality (Kim et al., 2016; Lee et al., 2023; Turcotte et al., 2023). However, much of the existing literature has focused on relatively short-term outcomes, such as 30-day readmissions, in-hospital mortality, or hospital stays of 10 or more days. While informative, these outcomes do not fully capture the sustained burden frailty places on health systems.

Outcomes that are particularly important, both for frailty research and in the Canadian healthcare system context have received little attention in relation to frailty measurement: very prolonged cumulative hospital stays (≥30 or ≥90 days across a year) and Alternate Level of Care (ALC) stays. Alternative Level of Care (ALC) refers to a designation applied to hospitalized patients who no longer require acute care services but remain in hospital while awaiting transfer to a more appropriate care setting (Canadian Institute for Health Information [CIHI], 2021). Both outcomes represent a substantial economic and operational challenge for healthcare systems, as they reflect not only high service utilization but also systemic issues in care transitions, discharge planning, and long-term care capacity. Despite their relevance, evidence is lacking on whether frailty tools such as the Hospital Frailty Risk Score (HFRS) can predict these outcomes.

New Brunswick (NB), being one of the faster aging populations in Canada, faces growing pressures on hospital resources and long-term care capacity. Validating whether the HFRS can predict outcomes such as extended cumulative hospital stays and ALC stays using administrative health data will provide critical evidence for frailty measurement in this setting. If successful, this approach would not only confirm the HFRS's predictive validity for conventional outcomes such as mortality, but also extend its utility to outcomes of direct policy and system relevance in NB.

By addressing this gap, this thesis contributes new evidence on the applicability of the HFRS in a Canadian context, while also highlighting its potential role as a tool that identifies, in existing data, frail individuals at risk of high healthcare utilization. This work has important implications for health system planning, as the HFRS can be used as a system-level tool that helps with allocating resources more effectively for an aging population.

1.3 Research aim and objectives

The aim of my thesis is to evaluate the predictive validity of the Hospital Frailty Risk Score (HFRS) in identifying frailty-related outcomes among older adults in New Brunswick (NB), with particular attention to outcomes of high relevance for the Canadian healthcare system. Specifically, this study examines whether the HFRS is associated with adverse outcomes including cumulative hospital length of stay, Alternate Level of Care (ALC) use, and short-term mortality. For cumulative hospital length of stay, thresholds of 10, 30, and 90 days are considered to capture varying degrees of hospitalization burden.

For ALC, the outcomes assessed include any ALC stay as well as stays lasting 10 days or longer and 30 days or longer. Mortality within 90 days of the start of the outcome year is also evaluated.

In addition to examining these individual outcomes, this thesis evaluates whether the associations between frailty and adverse events follow a dose–response gradient across low-, medium-, and high-risk categories of the HFRS. By doing so, the study not only validates the HFRS in the NB population but also provides insight into the extent to which frailty levels correspond to escalating risks of healthcare utilization and mortality. Finally, the study aims to demonstrate the utility of the HFRS for health system planning in NB by focusing on outcomes such as prolonged hospital stays and ALC use, which have rarely been studied in relation to frailty yet represent substantial economic and operational challenges. In the short term, this work will provide a validated tool for identifying frailty in NB using administrative data. In the longer term, it will inform strategies for resource allocation, discharge planning, and interventions aimed at reducing the healthcare burden associated with frailty.

1.4 Importance of the study

This study makes several important contributions to the literature on frailty and health services research. First, by evaluating the predictive validity of the HFRS in NB, it provides essential evidence on the applicability of this tool in a Canadian context. Demonstrating that the HFRS can predict adverse outcomes using administrative health

data supports its use for retrospective analyses, population surveillance, and health system planning.

Second, the study extends existing validation research by examining outcomes that have not been studied in relation to the HFRS but are important, both from the frailty research perspective and from a healthcare systems planning perspective: very prolonged cumulative hospital stays (≥30 and ≥90 days) and Alternate Level of Care (ALC) stays. Both outcomes represent considerable economic and operational burdens, reflecting not only high service utilization but also challenges in care transitions, discharge planning, and long-term care capacity. Evidence that the HFRS can predict these outcomes highlights its potential value in identifying patients most at risk of prolonged hospital dependence and delayed discharge.

Finally, the study reinforces the relevance of frailty as a central determinant of health outcomes for older adults in NB, a province facing rapid population aging. By validating the HFRS against outcomes that directly strain hospital and long-term care systems, this research provides actionable insights for policymakers, clinicians, and planners. In the short term, these findings can guide risk stratification and discharge planning. In the longer term, they can inform targeted interventions and resource allocation strategies to better support frail individuals and mitigate the health system pressures associated with an aging population.

1.5 Research Gaps

Although frailty has been widely studied and consistently linked to adverse outcomes such as mortality, readmissions, and prolonged hospital stays, important gaps remain in the validation of frailty measurement tools. Most existing studies validating the Hospital Frailty Risk Score (HFRS) have focused on relatively short-term outcomes, such as 30-day readmissions, in-hospital mortality, and cumulative hospital stays exceeding 10 days (Gilbert et al., 2018; Soong et al., 2018; Kundi et al., 2020). While valuable, these outcomes do not fully reflect the longer and more impactful consequences of frailty, especially outcomes that contribute to an increase in hospital strain and extended bed use. In particular, very prolonged cumulative hospital stays (≥30 or ≥90 days across a year) and Alternate Level of Care (ALC) stays have not been yet studied in relation to the HFRS. These healthcare outcomes are of substantial importance, both in the Canadian healthcare context, as well as in the frailty-related research context: they represent not only high service utilization but also systemic pressures around discharge planning, long-term care capacity, and the economic burden of hospital dependence. Addressing this gap provides an opportunity to extend the application of the HFRS to outcomes that are both novel to the frailty literature and directly relevant to healthcare policy.

A second gap lies in the regional application of the HFRS. Existing validation studies have been conducted primarily in international settings, such as the United Kingdom (Gilbert et al., 2018) or at a national level in Canada (Turcotte et al., 2023). While these studies confirm the utility of the HFRS in diverse populations, they do not account for the specific demographic and health system context of New Brunswick (NB), a province

with one of the fastest-aging populations in the country and persistent challenges with ALC and hospital capacity. Validation of the HFRS in this setting is therefore essential to determine its relevance and applicability for local health system planning.

By addressing these gaps, this study contributes both methodological innovations, through the inclusion of outcomes rarely studied in frailty research, and regional relevance, by validating the HFRS in the context of NB's aging population.

1.6 Primary Research Question:

Among older adults aged 65 and over in the province of NB, do those identified as more frail by the HFRS have higher healthcare utilization as compared to those at lower levels of frailty?

Chapter 2. Literature review

In this section, I present an in-depth summary of the existing literature related to the topic of frailty, delving further into measuring frailty, the prevailing definitions of frailty, and the approaches to quantify it. Additionally, I will detail the existing literature related to the Hospital Frailty Risk Score (HFRS), that I will be using in my quantitative study and exploring the existing evidence in literature on the validity of the HFRS. This literature review will also include an overview of the previous studies demonstrating the relationship between frailty and healthcare usage, and studies that have shown the demographic variables that impact frailty (such as age, and gender). A structured literature search was conducted to identify relevant studies related to frailty measurement, the Hospital Frailty Risk Score (HFRS), and its predictive validity. Electronic databases including PubMed, Scopus, and Google Scholar were searched using combinations of key terms such as “frailty,” “Hospital Frailty Risk Score,” “HFRS,” “predictive validity,” “healthcare utilization,” “length of stay,” “mortality,” and “older adults.” Studies were included if they (i) examined frailty measurement approaches, particularly those derived from administrative data, (ii) evaluated the predictive validity of the HFRS, or (iii) assessed associations between frailty and health service outcomes such as hospitalization, cumulative length of stay, alternate level of care stays, or mortality. Studies were excluded if they focused exclusively on clinical frailty instruments without relevance to administrative data, were not peer-reviewed, or were not published in English. Priority was given to studies conducted in high-income countries with health systems comparable to Canada.

2.1 Measurement of Frailty

Measuring frailty is an important step for identifying older adults that are more vulnerable to adverse health outcomes, such as hospitalisation, falls, mortality. Throughout the literature, the concept of frailty does not have one universally accepted definition, and each study focuses on different manifestations of this condition. However, there are commonly two approaches that are used to define frailty. Common to both studies is that frailty is conceptualized as a complex medical condition that reflects a decline in an individual's physiological reserve and function. This in turn is associated with an increased vulnerability to adverse health outcomes.

In the first approach, frailty is defined from a physiological point of view, in the second common approach, it was described as an accumulation of deficits. The first widely used definition of frailty, proposed by Fried et al., is one of the earliest and most widely recognized, which describes frailty as "*a clinical syndrome that is characterised by different physiological symptoms*" (Fried et al., 2001). The study conducted by Fried et al. in 2001 also introduced one of the most commonly used measures to quantify frailty: the "Fried Frailty Phenotype" (FFP).

The FFP quantifies frailty based on five physical criteria that can be assessed by a clinician or a registered nurse. If the patient meets three or more of the criteria, they are considered frail. These criteria include (i) unintentional weight loss, (ii) self-reported exhaustion, (iii) grip strength, (iv) gait speed, and (v) physical activity. The patient is assigned a score of 1 for every criterion they meet, and a score of 0 otherwise. The scores from each criterion are summed to calculate the frailty score (out of 5). If a person has a

score of 0, then they are considered not frail. A score of 1-2 indicates that they are pre-frail, and a score of 3 and above indicates that the patient is frail (Fried et al., 2001).

The second most common method used to describe frailty, it is the cumulative deficit model proposed by Rockwood et al. in 2005. This model considers frailty as an accumulation of deficits, which could be different symptoms, signs, disabilities, and diseases. The cumulative deficit model was also the basis for creating the widely used approach to quantify deficits known as the Frailty Index (FI) (Rockwood et al., 2005).

The Rockwood method of identifying frailty, calculates a FI, which is a proportion based on the number of deficits the patient possesses. These deficits can encompass a wide range of factors, such as clinical signs (e.g., tremor), physical symptoms (e.g., vision problems), functional limitations (e.g., difficulty with bathing, personal hygiene, or mobility), and chronic medical conditions. To ensure that the assessment of frailty is standardized, Searle et al. (2008) defines very specific criteria for constructing a FI. The first is that the deficit should be directly responsible for a decline in the patient's health status, meaning that it reflects a measurable deterioration in physiological reserve, functional ability, or overall health. In other words, included variables must represent health-related problems rather than neutral characteristics or stable traits. For example, chronic diseases, mobility limitations, or cognitive impairment qualify as deficits because they signal compromised functioning, whereas fixed demographic characteristics such as sex or education level would not. In addition, another criterion that needs to be met is that the deficit should be more prevalent the older the patients are, which ensures that it's directly related to the aging process. The deficit also needs to be associated with negative health outcomes (hospitalisation, mortality, increased morbidity) (Searle et al., 2008).

Searle et al. also included that the deficits need to cover several body systems (cognitive, physical, social), reflecting the multifaceted nature of frailty. These deficits also need to not be redundant and should each reflect unique information regarding the patient's health status. Other criteria defined by Searle et al. (2008) include that the deficit should represent a chronic condition, or a long-term health issues rather than acute problems, and that the deficit needs to be measurable in a clinical or research setting. Last, deficits need to be sensitive to change over time, which would allow for proper measurement of how frailty is progressing in response to interventions (in case the health of the patient is deteriorating or improving).

2.2 Hospital Frailty Risk Score (HFRS)

Several new approaches for quantifying frailty using routinely collected administrative healthcare hospital records have been more recently developed, reducing the dependence on individualised examination of patients. This has in turn led to the ability to quantify frailty on a larger scale, allowing easier assessment of frail patients. This is the frailty measurement approach that I chose to use, the Hospital Frailty Risk Score (HFRS).

In Section 2.2 I review the existing literature on the HFRS, highlighting its development, validation, and application in clinical practice and research. The Hospital Frailty Risk Score (HFRS) is a validated measure designed to identify frail older adults at risk of adverse outcomes following hospitalisation, based on specific diagnostic codes (ICD-10) in routinely collected administrative data from hospitalisation claims records. Developed by Gilbert et al. (2018), the HFRS assigns weighted values to diagnostic codes, providing

a cumulative score representing the patient's level of frailty, with higher scores indicating greater frailty and risk of poor health outcomes.

2.2.1 Development

Gilbert et al. (2018) derived the HFRS from a large cohort study in the UK, including patients aged 75 years and older who were hospitalised. The score is calculated based on the presence of one or more of 109 International Classification of Diseases, 10th Revision (ICD-10) diagnostic codes that are associated with frailty. These codes cover a wide range of conditions, including mobility issues, cognitive impairment, and chronic diseases. The development study cohort consisted of 22,139,805 hospital admission records of patients (aged 75 and older), between January 1, 2014 and December 31, 2014. This cohort was solely used to create and derive the HFRS. It was first used to identify the relevant diagnosis codes (ICD-10 codes) from the electronic hospital records (EHR) that are associated with frailty, assign weights to these codes and formulate the initial version of the HFRS (Gilbert et al., 2018).

Each code was assigned a specific weight based on how strongly it is associated with adverse outcomes, and the HFRS would then be calculated as a summation of these weights (Gilbert et al., 2018). Some conditions had higher weights than others, as they were more closely related to frailty. These highly weighted conditions included chronic diseases that have a significant negative impact on recovery and health status of a patient, such as heart failure, chronic obstructive pulmonary disease (COPD), dementia, as well as some mobility impairment conditions, such as gait instability, reduced walking endurance, recurrent falls, and functional dependence in activities of daily living (e.g.,

transferring or climbing stairs). To reiterate a critical point, several of these chronic conditions are especially prevalent in New Brunswick, which shows why further investigation in the topic of frailty is particularly important in this province.

2.2.2 Validation

The HFRS has been validated in multiple cohorts, demonstrating good predictive validity for adverse outcomes such as prolonged hospital stay, readmission, and mortality. To validate the HFRS, routinely collected electronic hospital records from the National Health Service (NHS) in England were used (Gilbert et al. 2018).

Two validation cohorts were then used to test the validity of the HFRS, both using electronic hospital records (EHR) from the NHS of patients that are 75 and older. The first was an internal validation cohort, consisting of 1,013,590 hospital admission records within the same time period as the development cohort (i.e. January 1, 2014, and December 31, 2014). This first cohort was used to test the HFRS on a subset of the same population, allowing for a confirmation that the score works consistently within the same overall population (Gilbert et al., 2018). The second was an external validation cohort, consisting of 1,739,354 hospital admission records collected from January 1, 2015 to December 31, 2015. This second validation cohort was used to test the HFRS on new EHRs and ensure that the HFRS is robust and generalisable across different samples of hospital admissions and over time.

The validation of the HFRS and how accurately it could represent frailty, the study considered the following primary frailty-related adverse outcomes: 30-day in-hospital mortality, long hospital stays (more than 10 days), and 30-day readmission rates. To

quantify the association between the HFRS and these various adverse outcomes, Gilbert et al. (2018) used logistic regression that is adjusted for age, gender, and other covariates that account for patients' medical history, income, and accessibility to medical consultation in their area.

Patients from the validation cohorts were separated into three different categories, based on their HFRS (Gilbert et al., 2018). The following specific cut-off values were determined based on the distribution of HFRS scores within the study population and their association with clinical outcomes: patients that had an HFRS ranging from 0 to 5 were considered "Low risk", while patients with an HFRS between 6 and 15 were considered to be "Medium risk", and patients with an HFRS of 16 and above are considered to be "High risk". The results indicated a strong relationship between the HFRS and adverse health outcomes (Gilbert et al, 2018). For the outcome 30-day in-hospital mortality, low risk patients had approximately 1.5% mortality rates, while medium risk patients had a 4.5% mortality rate and high-risk patients had a13% mortality rate. In terms of long hospital stay (more than 10 days), low risk patients had a 21% probability of long hospital stays, whereas medium risk patients had a 31% probability and high-risk patients had a 49% probability of staying in the hospital for more than 10 days (Gilbert et al, 2018). A similar trend was also found for 30-day readmission rates, as low risk patients had a 9.5% readmission rate, while medium risk patients had a 14% readmission rate and 19% of high risk patients were readmitted to a hospital within a 30-day period.

In the Canadian context, the Hospital Frailty Risk Score (HFRS) was validated in a large cohort study using Ontario administrative health data (McAlister & van Walraven, 2019).

In Ontario, this study externally validated the HFRS in patients ≥75 years with urgent non-psychiatric admissions (2004–2010). They compared HFRS with the hospital-patient one-year mortality risk (HOMR) score for three outcomes: prolonged length of stay (LOS) >10 days, 30-day mortality after admission, and 30-day post-discharge urgent readmission/ED visits. HFRS best identified risk of prolonged LOS (C-statistic ≈0.71); HOMR better predicted 30-day mortality (C-statistic ≈0.71); both scores performed poorly for 30-day readmission (C-statistics ≈0.52–0.54). Patients with higher HFRS had markedly higher odds of prolonged hospitalization and slightly higher 30-day mortality, but lower 30-day readmission/ED rates. This supports using HFRS to flag risk of long stays in Canadian administrative data, while cautioning against using it to predict readmission.

An important recent contribution to the Canadian validation literature on the HFRS is the study by Turcotte et al. (2023), which conducted an external validation of the score among hospitalized home care clients. Using a retrospective cohort design, the study linked interRAI home care assessment data (a standardized comprehensive clinical assessments data used across Canada to evaluate functional status, cognition, comorbidities, and care needs among home care clients) with hospital discharge records across multiple provinces in Canada, focusing on older adults who were receiving home care services prior to hospitalization (Turcotte et al., 2023). The authors examined the ability of the HFRS to predict key outcomes, including in-hospital mortality, 30-day mortality, and long hospital stays, and compared its performance to the interRAI-based Frailty Index (FI). The results showed that while the HFRS could moderately predict adverse outcomes, it underperformed compared to the FI, particularly for outcomes like

functional decline. The area under the curve (AUC), a measure of a model's ability to correctly discriminate between individuals who do and do not experience an outcome, ranged from 0.60 to 0.69 for the HFRS across different outcomes. An AUC of 0.5 indicates no discriminative ability beyond chance, whereas values closer to 1.0 reflect stronger predictive performance; therefore, these results suggest modest discrimination.. Despite its limitations, the study emphasized the utility of the HFRS as a scalable tool when clinical assessment data like interRAI are unavailable, and it highlighted the need for frailty tools to be validated in more diverse, community-based populations.

2.2.3 Comparative Studies and Meta-Analyses

Several comparative studies and meta-analyses have also evaluated the performance of the HFRS against other frailty assessment tools, to show its efficiency and accuracy at identifying frail patients. For instance, a meta-analysis by Thompson et al. in 2019 compared the predictive accuracy of the HFRS with other commonly used frailty indices, such as the Fried Frailty Phenotype (FFP) and the Frailty Index (FI). This study showed that the HFRS had comparable or superior predictive accuracy for adverse outcomes, particularly in hospital settings. This involved a retrospective cohort analysis, where the HFRS was derived from EHR of patients using their ICD-10 codes, and its predictive accuracy was then compared to the FFP and FI using area under the receiver operating characteristic (AUROC) curves (Thompson et al., 2019); higher values of AUROC indicate better prediction. Results showed that the HFRS had similar predictive ability as the FFP and FI. HFRS had an AUROC of 0.72 for predicting 30-day mortality, 0.68 for predicting hospital readmissions and 0.70 for 1 year mortality, which were similar to

those of the FFP and FI, 0.70 and 0.71 respectively for 30-day mortality, 0.67 and 0.66 for hospital readmissions, 0.69 and 0.68 for 1-year mortality.

Another comparative study by Kundi et al. (2020) assessed the HFRS alongside the Clinical Frailty Scale (CFS) and the Frailty Index based on Comprehensive Geriatric Assessment (FI-CGA). This study used a similar comparison method to Thompson et al., (2019) that involved a comparison of the AUROC for different health outcomes. The results showed that, on average, the AUROC curves showed that the HFRS was comparable to the CFS for predicting 30-day mortality, 30-day readmission, and 1-year mortality in patients (Kundi et al., 2020). This also supports that the HFRS is a valuable tool for identifying frail patients in clinical settings, and it has the advantage of being easily implementable using existing administrative data, as opposed to the CFS which requires a more in-person assessment.

2.2.4 Application of HFRS

The HFRS has been widely adopted in research to identify frail older adults using previous hospitalization data and assess their risk of adverse outcomes. The ability to use routinely collected data makes it a practical tool for widespread implementation without the need for additional data collection or in-person assessments (Gilbert et al., 2018).

Another study applied the HFRS to a cohort of hospitalised older adults and found that the score was a strong predictor of in-hospital mortality and 30-day readmission rates (Kundi et al., 2020). Specifically, the results showed that patients with an HFRS greater than 15 had a 3.6 times higher risk of 30-day mortality after being readmitted to a hospital, and 4 times higher risk of post-discharge mortality. Additionally, they were at a

3 times higher risk of 30-day readmission compared to those with an HFRS less than 5. In the future, if data containing ICD10 codes becomes accessible to physicians in real time, there is a number of interventions that can potentially improve the healthcare outcomes for patients with a higher frailty risk score. In one of the studies that shows the impact of different interventions, Parker et al. (2018) used the HFRS to identify frail patients who were at high risk of hospital readmission and demonstrated that targeted interventions for these patients could reduce readmission rates and improve health outcomes. Interventions ensuring the continuity of care for high-risk patients mainly fell under two categories: pre-discharge, and post-discharge interventions. The predischarge interventions included a comprehensive patient education about their diagnosis and medical condition, medication reconciliation, discharge planning involving caregivers, and tailored exercise programs. The post-discharge interventions included regular follow-up phone calls by a geriatric nurse, home visits within 48 hours of discharge and continued in-home visits and support over a 24-week period. These interventions led to a significant reduction in unplanned hospital readmissions, where the unplanned readmissions rate within 28 days of discharge was significantly less for patients who had some or several of these interventions.

Parker et al. (2018) conducted a randomized controlled trial using the HFRS to identify frail patients at high risk of hospital readmission, and the control group consisted of high-risk older adults who received standard care, similar to the intervention groups, ensuring a valid comparison. The results of this study showed that the group of patients that were given tailored physical exercise program only had a 14% readmission rate, compared to the control group that had a 25% readmission rate. Similarly, the group of patients that

had the interventions of home visits and telephone follow-up care had a readmission rate of 10%, and those that had both exercise and follow-up care interventions had an 8% readmission rate. This highlights the importance of conducting frailty research at a population level to allow for better healthcare policy design to improve the healthcare outcomes of frail older adults.

The HFRS has also been used in various healthcare settings, including long-term care facilities (Barker et al, 2021) and primary care (Boyd et al, 2019). In the context of long-term care facilities, the HFRS was used to assess the frailty of residents (Barker et al., 2021). These HFRS scores were then used to stratify the residents based on their frailty risk, which helped in care planning, since the medical staff can focus more resources to monitor high-risk residents to prevent hospital admissions. Additionally, primary care providers also used the HFRS to analyse patients' hospital electronic medical records, assessing their frailty risk scores, which was then used to prioritise high-risk patients for geriatric assessments, follow-ups and preventative care measures (Boyd et al., 2019). This not only enabled precise and easy identification of frail patients but also facilitated interventions that reduced the progression of frailty and subsequent hospital admissions (Boyd et al., 2019).

2.2.4.1 Feasibility of Real-Time HFRS Implementation in New Brunswick:

While the Hospital Frailty Risk Score (HFRS) has shown strong predictive validity for short-term adverse outcomes in this study, its use in real-time clinical decision-making within New Brunswick is currently limited by the structure of available diagnostic coding. Although hospital discharge data submitted to the Discharge Abstract Database (DAD) includes detailed ICD-10-CA diagnostic codes (CIHI, 2022), these are typically

coded after discharge and are not accessible to clinical teams at the point of care. Similarly, physician billing data—another potential source of diagnostic information—has traditionally used ICD-9 coding in New Brunswick, which lacks the specificity required to calculate the HFRS (Government of New Brunswick, 2024). Recent developments, such as the integration of ICD-10 codes into shadow billing for nurse practitioners (Government of New Brunswick, 2025) and within Velante electronic medical record systems (Velante, 2025), mark important progress. However, these changes are not yet system-wide. Until ICD-10 coding is implemented consistently and made available in near real-time across all care settings, the HFRS is best suited for retrospective analysis, risk stratification, and discharge planning infrastructure development, rather than point-of-care clinical decisions.

2.3 Frailty and Healthcare Utilisation

There is a large body of research that is related to the relationship between frailty and healthcare service use. In the context of Canada, some studies by the Canadian Frailty Network were conducted on large-scale data and focused on a population-based approach, mainly in the province of Ontario. One of the most notable studies by the Canadian Frailty Network in this context is the "Frailty Screening & Management in the Community" guidance document, which was published in December 2023. This study emphasized the importance of early identification and comprehensive management of frailty in a community setting, to prevent adverse health events of patients. It also presented an important five-step approach, which starts with understanding population demographics, identifying screening triggers, utilizing validated screening tools such as the Pictorial Fit-Frail Scale, performing detailed assessments, and implementing tailored

interventions. The document also highlights the importance of addressing frailty across multiple domains, including physical, cognitive, mental, and social health, while emphasizing strategies like physical activity promotion, nutritional support, and enhanced social engagement to maintain functional independence and reduce adverse health outcomes (Geriatrics Ontario, 2023).

In another population-based cohort study conducted in Australia using linked hospital and aged care administrative data, Hubbard et al. (2017) examined the relationship between a deficit accumulation frailty index derived from routinely collected data and subsequent healthcare utilization among older adults. Although this measure differs conceptually from the Hospital Frailty Risk Score (HFRS), which is based on weighted diagnostic codes, both approaches aim to quantify vulnerability using administrative data and have demonstrated similar associations with adverse health outcomes. The results showed that frailty significantly impacts various aspects of healthcare use, including hospitalizations, emergency department visits, and long-term care (LTC) admissions (Hubbard et al., 2017). The key findings of the study show that a 0.1 increase in the frailty index (FI) was associated with increased odds of hospital stays exceeding 28 days (Odds Ratio [OR]: 1.29; 95% Confidence Interval [CI]: 1.10–1.52), a higher likelihood of new discharges to residential aged care facilities (OR: 1.31; 95% CI: 1.10–1.57), and a significantly higher risk of mortality during hospitalization for frail individuals (OR: 2.01; 95% CI: 1.66–2.42). Studies with smaller cohorts also exist in the literature, but they examine a more specific groups of frail patients, such as those living in rural areas. While these studies do not use a very large sample, they provide more detailed insights about frailty. One such study found frail older adults in rural areas in Canada face a lot of

challenges such as limited availability of services, long travel distances to healthcare providers, and a shortage of healthcare professionals that can help with their condition (Rosenberg et al., 2011).

A review of existing frailty research by Clegg et al. (2013) found that frail older adults are more likely to be hospitalised compared to their non-frail counterparts, with frailty being a strong predictor of both the frequency and duration of hospital stays. Similarly, Rockwood et al. (2012) reported that frail individuals had higher rates of acute care hospitalizations, often resulting in prolonged hospital stays and increased healthcare costs.

Long-term care (LTC) admissions are also significantly influenced by frailty. Frail older adults are more likely to require LTC services due to their diminished functional abilities and increased need for assistance with activities of daily living (ADLs). A longitudinal study by Theou et al. highlighted that frailty was a strong predictor of LTC admission, with frail individuals being more likely to transition to nursing homes or assisted living facilities compared to non-frail older adults(Theou et al., 2013).

The Canadian Study of Health and Aging (CSHA), a seminal longitudinal cohort study of older adults in Canada, found that frailty was associated with higher healthcare costs, primarily due to increased hospital and LTC admissions (Rockwood et al., 2005). Although the CSHA findings are based on earlier waves of data, the study remains foundational in establishing the relationship between frailty and healthcare utilization in Canadian populations.

Despite the extensive evidence linking frailty with increased healthcare utilisation, there is limited research on frailty-related healthcare use specific to NB. While it is expected to see a similar pattern in the province of NB, the population is much more susceptible to being frail, due to the higher-than-average prevalence of chronic conditions directly linked to frailty, such as diabetes, cardiovascular disease, and hypertension (Frohlich et al., 2017). This specific demographic in the province might cause an increase in the burden on the healthcare system, especially in terms of economic resources and access to healthcare for the general population. This thesis will therefore serve as a starting point to quantify this burden on the healthcare system, allowing future research to properly assess the resources used by the frail population in NB. Previous literature showed that targeted interventions can in fact decrease the healthcare services usage of frail patients significantly (Hubbard et al., 2019). This is why quantifying the healthcare usage of frail patients in NB and having a measurement for these patterns is the first step for developing targeted interventions and optimising healthcare delivery by reducing the economic impact of frailty-related health service use. This thesis aims to fill this gap and provide valuable insights for healthcare planning and resource allocation.

Chapter 3. Methodology

The research methodology section outlines the approach and techniques employed to evaluate the predictive validity of the Hospital Frailty Risk Score (HFRS) in identifying frailty-related adverse health outcomes among older adults (aged 65 and over) in New Brunswick. First, the study design is described, specifying the retrospective cohort approach and the criteria used for sample selection. Second, the data sources are outlined, including the Citizen Registry dataset and the New Brunswick Discharge Abstract Database accessed through the DataNB (formerly New Brunswick Institute for Research, Data and Training (NB-IRDT). Third, Section 3.1.2 details the process of estimating frailty using the HFRS and the classification of individuals into low-risk, medium-risk, and high-risk categories. The subsequent section defines the adverse outcomes used to evaluate predictive validity, with a focus on cumulative hospital length of stay (≥10, ≥30, and ≥90 days), alternate level of care (ALC) stays (any, ≥10 days, and ≥30 days), and 90-day mortality. Finally, the analytic strategy is described, including the use of logistic regression models to assess the association between frailty risk categories and adverse outcomes, adjusting for age, sex, comorbidity, hospitalization history, and medical accessibility.

3.1 Study Design

Retrospective Cohort Study Design

This study employs a retrospective cohort design. Two years of data are required by the HFRS algorithm to calculate a frailty score (exposure period) and one-year after this

period will be used to assess the adverse health outcomes of cohort members as shown in Figure 1 below. The cohort includes individuals aged 65 and over who were discharged from hospitals in NB between fiscal years 2014, and 2018. This includes any individuals who turned 65 during the study period and were discharged from hospital after their 65th birthday. Individuals that die or leave the province during the exposure period are excluded from the cohort. Individuals not covered in the provincial administrative data were also excluded from the cohort. This includes members of the Canadian Armed Forces, Royal Canadian Mounted Police (RCMP), individuals incarcerated in federal correctional facilities, and residents of First Nations communities.

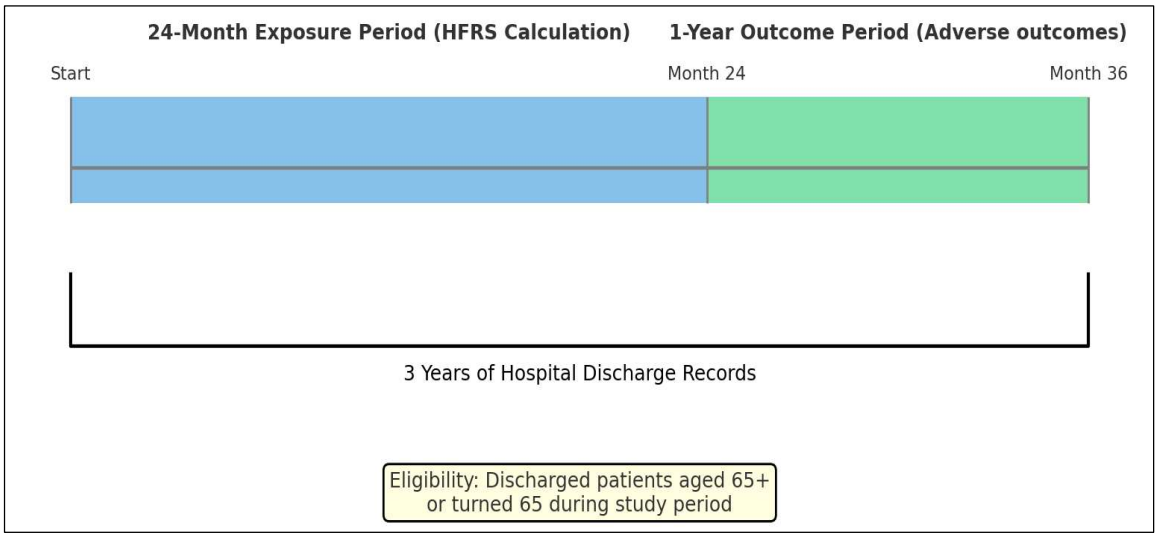

Figure 1: Analytical Timeline Showing HFRS Exposure Period and Outcome Assessment Window

3.1.1 Validity framework used for this study:

In health measurement research, validity refers to the extent to which an instrument accurately measures the concept it purports to assess. In the context of frailty, several types of validity are relevant. Construct validity assesses whether the measure reflects the

theoretical construct of frailty, often evaluated by comparing it with other known frailty tools or related health indicators. Predictive validity, by contrast, refers to the ability of a measure to accurately forecast future outcomes that are theoretically linked to the construct (in this case, adverse health outcomes such as mortality, hospital readmission, or long hospital stay).

My thesis study focuses on predictive validity, aiming to determine whether the HFRS, originally developed by Gilbert et al. (2018), can effectively predict a range of adverse outcomes in an older adult population in New Brunswick.

The validity of a measurement tool can be conceptualized as part of a broader framework that includes content validity, construct validity, criterion validity, and predictive validity. Content validity refers to how well a measure captures the theoretical construct it is intended to represent, while construct validity assesses whether the measure behaves as expected in relation to other constructs. Criterion validity typically requires comparison with a gold standard, which is often unavailable in frailty research because there is no single universally accepted definition or clinical measure of frailty.

In the absence of a definitive gold standard, predictive validity becomes an especially important approach. Predictive validity refers to the extent to which a score or measure can accurately forecast future outcomes that it is theoretically expected to predict. Unlike criterion validity, which relies on comparison to an external standard, predictive validity is established when a tool behaves in accordance with theory. In the case of frailty, theory and prior research indicate that frail individuals are more likely to experience adverse health outcomes such as prolonged hospitalizations, delayed discharges,

institutionalization, and mortality. Therefore, if a frailty measure such as the Hospital Frailty Risk Score (HFRS) is valid, it should be able to predict these outcomes.

The present study adopts this predictive validity framework. By examining whether the HFRS, applied to administrative health data in New Brunswick, predicts outcomes including cumulative hospital length of stay, Alternate Level of Care (ALC) use, and mortality, this study contributes to understanding how well the HFRS functions as a frailty measure in this setting. This approach is consistent with previous validation studies of the HFRS, which have relied on predictive validity to establish its utility across healthcare systems (Gilbert et al., 2018; Soong et al., 2018; Kundi et al., 2020).

3.1.2 Defining the cohort

Fiscal years will be used to define the time periods of the study, which starts on April 1st of every year and ends on March 31st of the next year.

Five years of available hospital discharge data were used for the study, starting 2014-04-01 and ending 2019-03-31. Twenty-four months of hospital records are required to calculate the HFRS of individuals in the study cohort. The one year that follows the HFRS calculation period will be used to define the frailty-related healthcare outcomes of individuals in the cohort. The data available from 2014-2019 will be separated into 3-year intervals, as shown in Figure 2 below.

The first interval would be from 2014-2016, the second interval being from 2015-2017 and the third interval from 2016-2018 (fiscal years).

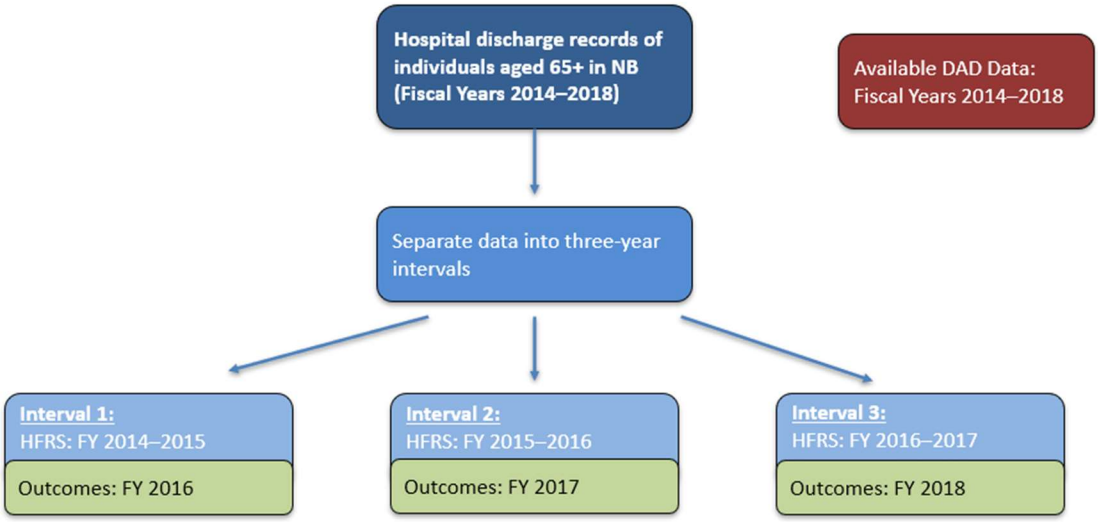

Figure 2: Flow Diagram of Cohort Selection and Time-Interval Assignment

3.1.3 Estimation of Hospital Frailty Risk Scores

For each cohort member, frailty will be assessed using the available hospitalization records. The HFRS is calculated based on the presence of one or more of 109 ICD-10 diagnostic codes that are associated with frailty. These codes cover a wide range of conditions, including mobility issues, cognitive impairment, and chronic diseases. Each ICD code is assigned a specific weight based on how strongly it is associated with adverse outcomes, and the HFRS would then be calculated as a summation of these weights (Gilbert et al. 2018) across 24 months of available hospitalization data. The weights assigned to each ICD-10 code in the Hospital Frailty Risk Score were derived using logistic regression. Specifically, the authors identified ICD-10 codes that were significantly more common in a cluster of hospitalized patients exhibiting frailty-related

characteristics. They then used logistic regression to estimate the strength of association between each code and membership in this frail cluster. The resulting regression coefficients were scaled to create the final weights used in the score (Gilbert et al., 2018). Some conditions had higher weights than others, as they were more closely related to frailty. These highly weighted conditions included chronic diseases that have a significant negative impact on recovery and health status, such as heart failure, chronic obstructive pulmonary disease (COPD), dementia, as well as mobility impairment conditions. The cut-off values that were determined by Gilbert et al. based on the distribution of HFRS scores within the study population and their association with clinical outcomes will be used in my thesis study. Gilbert et al. (2018) defined the HFRS cut-off values based on the distribution of scores and their observed association with clinical outcomes in the derivation cohort. The HFRS is calculated using ICD-10 diagnostic codes recorded in hospital discharge data. Each frailty-related condition is assigned a weighted value based on its statistical association with adverse outcomes in the derivation study. A patient's total HFRS is obtained by summing the weights of all qualifying diagnostic codes present in all their hospital discharge records over a 24-month period. For example, if a patient has diagnostic codes corresponding to dementia (weight ≈4.0), heart failure (weight ≈1.2), and a history of falls (weight ≈3.2), their total HFRS would be approximately 8.4, placing them in the intermediate-risk category. Patients with scores ≤5 had relatively low rates of adverse outcomes and were classified as 'low risk', those with scores between 6 and 15 showed a moderate increase in risk and were labelled 'intermediate risk,' and those with scores >15 had substantially higher rates of 30-day mortality, prolonged hospitalization, and readmission, warranting a 'high risk' classification.

3.2 Data sources:

Section 3.2 will detail the data sources that will be used to answer my research questions, including: (i) how data will be accessed, (ii) description and purpose of each dataset, as well as (iii) how the data will be linked at the individual-level.

3.2.1 Data Access:

Data will be accessed at DataNB at the University of New Brunswick (UNB) Fredericton. DataNB is the administrative data custodian for the province of NB. DataNB handles linked pseudonymised personal administrative data, ensuring that the privacy of New Brunswick residents is safeguarded. A primary purpose of DataNB is to support research that contributes to informed and effective government decision-making. Researchers can access the DataNB data to conduct studies on any topic of interest using specific datasets that are needed solely for the research question proposed. My thesis research in frailty will contribute to the existing knowledge about the topic in the province, as well as help inform future frailty-related research that helps address policy relevant questions.

DataNB manages over 100 interconnected data sets, to access the data needed for my thesis. I went through a rigorous application process, which includes data privacy training that is repeated every year, as well as a background check. The ability to link de-identified personal information across these data sets enables a thorough, population-level analysis using large samples and corresponding control groups, and it is what makes research such as this possible.

DataNB supports governments, communities, and partners in making reliable, evidence-based decisions for the welfare of New Brunswickers. While DataNB operates

independently from the government, it is a key institution that provides policy-oriented research, in collaboration with the government, to guide the future of programs, policies, and healthcare system improvements in NB.

To maintain the privacy and security of the data, DataNB implements stringent safeguards. These include removing direct identifiers (such as names, Medicare numbers, and addresses) from the data, assigning unique file numbers for data linkage between departmental datasets, and operating within a highly secure facility with restricted external access. Researchers wishing to access the data undergo a rigorous application process to ensure the minimal amount of the information is disclosed to address their research questions. The data required for the analysis of my thesis research has been approved through this rigorous application process.

3.2.2 Description of the Data Sources

My study utilises two datasets accessible through DataNB: Citizen Data and Discharge Abstract Data.

Citizen Data: The Citizen Data (CD) is a Government New Brunswick Department of Health (DH) administrative dataset that contains basic demographic and residential information on all residents of NB who have been issued with a provincial Medicare card between January 1, 1971, and January 31, of 2021. This dataset also includes Medicare card eligibility information of individuals, which gives valuable information indicating if an individual is eligible for Medicare or not, and the reason behind the termination of their coverage in case they are no longer eligible. The citizen data also includes valuable

information, which will be used to identify the define cohort membership, outcomes and population sub-categories.

Discharge Abstract Data (DAD): The Discharge Abstract Database (DAD) is a Department of Health (DH) administrative dataset on separations/discharges and day surgeries from acute care institutions in NB. It captures administrative, diagnostic, clinical interventions, demographic and residential information as well as discharges, deaths, sign-outs, and transfers. The diagnostic information in DAD for each hospital record is coded using the International Classification of Diseases, 10th Revision (ICD-10). These codes are crucial for this study, as they allow for the identification of specific chronic conditions and comorbidities associated with frailty. The Hospital Frailty Risk Score (HFRS) used in this study is calculated based on the presence of 109 ICD-10 diagnostic codes that are strongly linked to frailty. There is one DAD dataset per fiscal year (April 1 to March 31 of each year), which we appended covering all 5 years of the study. DAD is reported to the Canadian Institute for Health Information (CIHI) for editing, preparation and generation of knowledge products, allowing for national comparisons. The data that are returned to the DH from CIHI are available for use at DataNB. This dataset is instrumental in assessing exposure (in my thesis, this is represented by HFRS scores) and different frailty-related healthcare outcomes.

3.2.3 Data Linkage

Pseudonymized versions of datasets which are held at DataNB are linkable at the individual level across datasets using scrambled unique identifiers. The linkage done with personal identifiers is performed at the Department of Health (DH) using a crosswalk

process. This crosswalk process is used to ensure that there is no direct way of identifying individuals or Medicare numbers. The crosswalk process starts with data owners who assign an interim ID for each record in the data and the dataset is split into two data files: one data file that is sent to DataNB with the interim IDs and the variables in the dataset, and the identifying file that has both the interim IDs and the identifiers (e.g., Medicare number) is sent to the DH. Upon receiving this data file, DataNB replaces the interim IDs with corresponding Institute ID, use a crosswalk file created by DH for the dataset. The Institute ID enables data linkage across different providers. Across projects, Institute IDs are also scrambled to create project specific IDs. These steps are completed to safeguard against reidentification of individual records.

The datasets utilised in this study can be linked through project specific individual ID variables. The process of data linkage involves combining information from the CD, and DAD through the unique individual identifiers. This linkage enables the integration of demographic data, and hospital discharge information, providing a merged data that would serve two purposes: (i) it will be used to calculate an HFRS for each individual to quantify their frailty; and (ii), it will be used to define frailty-related adverse health outcomes. This integrated approach allows for a detailed analysis of the interplay between the HFRS and the frailty-related adverse health outcomes.

3.3 Definition of Health Outcomes

A range of frailty-related adverse health outcomes were used to evaluate the predictive validity of the HFRS. These outcomes were selected based on their relevance to frailty and their established use in previous studies evaluating healthcare utilization among older

populations (Gilbert et al., 2018; McIsaac et al., 2020; Clegg et al., 2013). They include both short-term outcomes (mortality within 90 days) and longer-term outcomes reflecting healthcare resource use (cumulative hospital length of stay and Alternate Level of Care stays).

Although a 30-day outcome window has been commonly used in previous frailty research (e.g., Gilbert et al., 2018), this study adopted a 90-day timeframe for assessing short-term mortality. This decision was informed by both methodological and clinical considerations. Frailty reflects a chronic, progressive vulnerability rather than an acute episode, and its effects may unfold over a longer period. A 90-day window captures a broader range of adverse events that are still temporally and clinically related to the index period, particularly in populations with complex health profiles (Turcotte et al., 2023). This timeframe has also been used in other frailty studies to evaluate mortality (Kim et al., 2016), reinforcing its validity as a meaningful short-term outcome. From a data-driven perspective, preliminary testing with a 30-day window in the New Brunswick data produced substantially fewer cases, which limited statistical power and model stability. The 90-day period therefore allowed for more robust modeling and greater consistency across outcomes.

Frailty has also been consistently associated with prolonged hospital length of stay (LOS) across multiple studies. In their seminal validation of the HFRS, Gilbert et al. (2018) found that patients classified as frail had substantially increased odds of experiencing hospital stays longer than 10 days, making prolonged LOS one of the score's key

predictive outcomes. Similarly, Soong et al. (2018) demonstrated that higher frailty scores were correlated with longer inpatient stays, while (Lin et al., 2016) concluded that frailty is a robust predictor of extended LOS across diverse clinical contexts. Building on this evidence, the present study extends the literature by examining cumulative hospital length of stay across the outcome year at three thresholds: ≥10 days, ≥30 days, and ≥90 days. This approach captures not only moderate hospital use but also very prolonged stays that represent a substantial burden to patients and the health system.

A further novel outcome in this study is Alternate Level of Care (ALC) stay, which has not previously been examined in relation to the HFRS. ALC refers to the period in which a patient remains in hospital despite no longer requiring acute care, typically due to delays in transitioning to long-term or community care. ALC represents a major systemic challenge in Canada, especially in provinces like New Brunswick with limited long-term care capacity and is a key driver of hospital congestion. By assessing any ALC stay as well as ALC stays of ≥10 and ≥30 days, this study introduces an outcome that is highly relevant to Canadian healthcare planning and extends the scope of frailty validation research.

Frailty-related outcomes examined in this study therefore include mortality within 90 days, cumulative hospital length of stay (≥10, ≥30, and ≥90 days), and ALC stays (any, ≥10, and ≥30 days). These outcomes, along with their definitions and data sources, are summarized in Table 1 below.

Table 1: Frailty-related healthcare outcomes and their definitions

Outcome	Term (Short/Long)	Definition/Description

Mortality	Short-term (90 days)	Death (including community-based) within 90 days of the outcome period, identified by a termination code (52) in the Citizen Dataset.
Cumulative length of stay	>= 10 days >= 30 days >= 90 days	This is derived from the variable of total length of stay in the DAD. Over the outcome year, the total length of stay of all hospital admissions of an individual is summed up and then compared to the thresholds.
Alternative Level Care stay	Any ALC stay >=10 ALC days >=30 ALC days	Hospital stay in the Alternative Level of Care, this uses the ALC length of stay variable in the DAD: - Any ALC stay if an individual has any admission with

		ALC length of stay >0 - if an individual has an admission with ALC length of stay >= 10 days - if an individual has an admission with ALC length of stay >= 30 days.

As table 1 shows, outcomes related to cumulative hospital length of stay and Alternate Level of Care (ALC) will be derived from the Discharge Abstract Database (DAD), while short-term mortality will be identified using the Citizen Registry. Each outcome was coded as a binary variable, with 0 indicating no occurrence and 1 indicating the presence of the outcome for a given individual in the cohort. This binary approach facilitates statistical modeling and the interpretation of predictive validity.

In the following sub-sections, I describe how each outcome was derived and the specific variables used within the datasets. Individuals meeting the criteria for a given health outcome were flagged as either having that outcome (1) or not having the outcome (0). An illustrative example is provided in Table IV.

3.3.1 Mortality

All-cause mortality included both in-hospital and community-based deaths. This outcome was also measured - within 90 days of the start of the outcome period. Deaths were identified using the Citizen Dataset, specifically derived from the variable of termination code, where an eligibility status of '52' indicates death for an individual. Any individual with that status for a given outcome year (the year following the exposure period) will be labelled as 1, and those not having that will be coded as 0.

3.3.2 Cumulative Hospital Length of Stay

Cumulative hospital length of stay (cumLOS) was defined as the total number of days an individual spent in hospital during the outcome year, across all admissions. This measure reflects the overall burden of hospitalization rather than the duration of a single stay. For the purposes of this study, three binary outcome variables were created to capture different thresholds of hospitalization burden: ≥10 days, ≥30 days, and ≥90 days. Although cumulative length of stay can be analyzed as a continuous measure, binary thresholds were used in this study to enhance clinical interpretability and align with prior research examining prolonged hospitalization outcomes (Gilbert et al., 2018; McAlister & van Walraven, 2019). Thresholds such as ≥10 days have been used to capture extended hospital utilization, while higher cut-points (≥30 and ≥90 days) reflect progressively greater healthcare burden and resource intensity. Categorizing cumulative length of stay also facilitates comparison across outcomes and supports clearer interpretation of frailty-related risk in a policy and health system planning context. Continuous modelling of length of stay represents a complementary analytical approach and may be explored in future work. These thresholds were derived using the discharge and admission dates

available in the Discharge Abstract Database (DAD). An individual was flagged as having met an cumulative hospital days if their during the outcome year met or exceeded the specified threshold (value = 1), and were given a value of 0)otherwise.

3.3.3 Alternate Level of Care (ALC)

Alternate Level of Care (ALC) refers to the period of time during which a patient occupies a hospital bed but no longer requires acute medical treatment, typically due to delays in accessing community or long-term care resources. ALC status is recorded in the Discharge Abstract Database (DAD) for hospitalizations where patients remain in hospital after being designated as requiring an alternate level of care. For this study, three binary outcome variables were created to capture the burden of ALC: any ALC stay, an ALC stay of ≥10 days, and an ALC stay of ≥30 days. Individuals were flagged as having met the outcome (value = 1) if their total recorded ALC days during the outcome year met or exceeded the specified threshold, and as not having the outcome (value = 0) otherwise.

Table 2: Simplified example of data used for the regression models

Individual ID	Fiscal year	Any ALC stay	Mortality (within 90 days)	Cumulative LOS >= 30 (in the following year)
1	2016	1	1	0

2	2016	0	1	1
3	2016	1	1	1

3.4 Data Analysis

Logistic regression models will be used to estimate the strength of the association between HFRS and each adverse health outcome, while adjusting for confounding variables.

3.4.1 Covariate Definitions

To account for potential confounding and isolate the effect of the Hospital Frailty Risk Score (HFRS), a set of covariates were included in the regression models. These variables were selected based on their known relationship with health outcomes and frailty in older adults. Below is a description of each covariate, including how it was defined, categorized, and derived.

3.4.1.1 Age Group

Age was calculated using the individual's date of birth, obtained from the Citizen Database. For each outcome year, age was determined based on the fiscal year of observation, by subtracting the year of birth from the fiscal year. Age groups were then categorized into three levels: i) 65–74 years, ii) 75–84 years, and iii) 85 years and older. This variable was modelled as a categorical covariate.

3.4.1.2 Gender

Gender was extracted from the Citizen Database. It is a categorical variable with two levels: i) M for male and ii) F for female, this is simply linked to each individual by using their unique individual ID.

3.4.1.3 Charlson Comorbidity Index (CCI)

Comorbidity was measured using the Charlson Comorbidity Index (CCI), which was derived from diagnostic codes in the Discharge Abstract Database (DAD). The CCI is a widely used measure of comorbidity burden that accounts for the number and severity of chronic conditions and has been validated for use with administrative data. For this study, the CCI was categorized into levels (0, 1, 2, 3, 4, 5, and ≥6) to facilitate adjustment for general health status in regression models. The index was already available within the DAD dataset, and therefore did not require additional derivation or linkage from other sources. Although the CCI and HFRS both incorporate diagnostic information and reflect aspects of health vulnerability, they capture distinct constructs. The CCI primarily measures disease burden and mortality risk associated with chronic conditions, whereas the HFRS reflects broader frailty-related vulnerability, including functional decline and geriatric syndromes. Adjustment for CCI was therefore included to account for comorbidity burden and to better isolate the independent contribution of frailty to the outcomes examined.

3.4.1.4 Area-Level Income

Area-level income was extracted from the Citizen Database using the Dissemination Area Unique Identifier (DAUID), which corresponds to the individual's geographic area. This identifier was linked to income quintile data derived from the QATIPPE variable, a

component of the Postal Code Conversion File Plus (PCCF+), which provides area-based socioeconomic indicators. The resulting income variable has five levels: i) 1 (lowest income) to v) 5 (highest income) and was modelled as a categorical variable. Area-level income represents a proxy for individual socioeconomic status and may be subject to misclassification due to within-area income heterogeneity. However, dissemination-area income measures are widely used in administrative health research and capture important neighbourhood-level socioeconomic influences that may independently affect health outcomes.

3.4.1.5 Medical Accessibility

Medical accessibility was measured using the number of physicians per dissemination area. Data were obtained from the New Brunswick Health Council (NBHC) Community Profiles website (https://nbhc.ca/info/communities-health-zones-nb), which provides physician counts at the community level. This information was first matched to dissemination areas using community-level geographic boundaries and then merged into the analytic dataset via the Dissemination Area Unique Identifier (DAUID). The resulting variable captures healthcare service availability at the area level and was linked to each individual based on their residential DAUID. Physician density was included as a proxy for healthcare service availability and geographic accessibility, as variation in provider supply may influence hospitalization patterns and healthcare utilization independent of individual health status. Although this measure does not capture all dimensions of access, such as transportation barriers or wait times, physician-to-population ratios reflects area-level healthcare resource availability. Gilbert et al (2018) adjusted for medical

accessibility in their study, and in NB, this is the available variable to closely represent this variation.

3.4.1.6 Number of Hospitalizations in the Exposure Period

This variable reflects the total number of acute care hospitalizations an individual experienced during the two-year exposure period prior to the outcome year. Hospitalization counts were derived from the Discharge Abstract Database (DAD) by summing all admission records for each individual over the exposure period. The variable was modelled as a continuous measure and used to adjust for prior healthcare utilization, providing additional context on baseline hospitalization patterns before the outcomes of interest were observed.

Although frailty is conceptually related to age and comorbidity, these variables capture distinct constructs. Age represents chronological aging, whereas the HFRS reflects accumulated health deficits derived from diagnostic codes. The stability of coefficient estimates, and absence of inflated confidence intervals suggest that multicollinearity was not substantial in the final models.

3.4.2 Base models description

The base logistic regression model aims to assess the relationship between the Hospital Frailty Risk Score (HFRS) and various adverse health outcomes, while adjusting for potential confounders. The primary predictor in all models is HFRS. Covariates included in the base model are age group, gender, comorbidity level, length of hospital stay in the previous year, medical accessibility (measured by the number of physicians per dissemination area), and area-level income.

Categorical variables with more than two levels are represented in the model using dummy variables. For each variable with *k* levels, *k-1* dummy variables were created using one level as the reference category. The reference categories are as follows: HFRS Level 1, Gender: Male, Age Group: 65–74 years, Comorbidity Level 1, and Income Quintile 1.

The logistic regression equation is structured as follows:

$$
\begin{aligned}
&\textit{logit(Adverse Health Outcome)} = \beta 0 + \beta 1(\textit{medium_risk}) + \beta 2(\textit{high_risk}) \\
&+ \beta 3(\textit{Gender_F}) + \beta 4(\textit{Age75_84}) + \beta 5(\textit{Age85plus}) \\
&+ \beta 6(\textit{Comorbidity2}) + \beta 7(\textit{Comorbidity3}) + \beta 8(\textit{Comorbidity4}) + \beta 9(\textit{Comorbidity5}) \\
&+ \beta 10(\textit{Comorbidity6}) + \beta 11(\textit{Comorbidity7}) + \beta 12(\textit{Comorbidity8}) + \beta 13(\textit{Comorbidity9}) \\
&+ \beta 14(\textit{Income2}) + \beta 15(\textit{Income3}) + \beta 16(\textit{Income4}) + \beta 17(\textit{Income5}) \\
&+ \beta 18(\textit{Medical_Accessibility}) \\
&+ \beta 19(\textit{Length_of_Stay_Prior_Year}) \\
&+ \varepsilon
\end{aligned}
$$

Where each coefficient (β) represents the log-odds associated with that variable, relative to its reference category for categorical variables. Continuous covariates such as medical accessibility and prior year length of stay are included directly in the model.

3.5 Software

To perform the data cleaning and analysis for this study, I will be utilising the statistical programming language R, version 3.6.1 (R Core Team, 2019), with RStudio as the primary programming environment (RStudio Team, 2020). This software ensures a robust and flexible analysis framework capable of handling the complexities of the data and the proposed statistical methods.

Several R packages were employed to support data preparation, transformation, and modelling. This includes the tidyverse collection of packages (Wickham et al., 2019), including dplyr, ggplot2, and tidyr, which was used extensively for data wrangling and visualization. The dplyr package (Wickham et al., 2023) was especially essential for filtering, summarizing, and transforming large datasets efficiently. The haven package (Wickham & Miller, 2020) was used to import data from SAS formats, enabling compatibility with administrative health datasets. In addition, data.table and readr were occasionally used to process large data files more efficiently. For modeling, functions from the base R stats package were used, particularly the glm() function for fitting logistic regression models. Logistic regression was selected due to the binary nature of the study outcomes and its suitability for estimating adjusted associations between frailty and the likelihood of experiencing adverse events. The resulting odds ratios provide an interpretable measure of relative risk that is widely used in health services and epidemiologic research. Alternative modelling approaches, including count models for length of stay or survival analyses for time-to-event outcomes, were considered; however, the use of clinically meaningful binary thresholds facilitated comparability

across outcomes and supported clearer interpretation of frailty-related risk within a health system planning context.

3.6 Interpreting Predictive Validity

The predictive validity of the Hospital Frailty Risk Score (HFRS) in this study will be assessed by examining whether higher frailty risk categories are associated with increased odds of adverse health outcomes. Predictive validity refers to the extent to which a measure forecasts outcomes that it is theoretically expected to predict, rather than to its correspondence with a gold standard. In the case of frailty, adverse outcomes such as prolonged hospitalizations, Alternate Level of Care (ALC) stays, and short-term mortality are well established in the literature as consequences of increasing frailty. Demonstrating that the HFRS predicts these outcomes in New Brunswick would therefore provide evidence of its predictive validity in this setting.

Interpretation will be based on the odds ratios (ORs) and 95% confidence intervals (CIs) obtained from logistic regression models. A positive finding of predictive validity will be indicated when medium- and high-risk HFRS groups have significantly higher odds of experiencing adverse outcomes compared to the low-risk reference group. Particular emphasis will be placed on identifying dose–response patterns, where the odds of an outcome increase progressively across frailty categories, as this pattern strengthens the case for validity.

By focusing on these associations, this study provides a direct test of whether the HFRS operates as intended in the NB population. Namely, whether increasing frailty risk corresponds to escalating healthcare utilization and mortality. This approach situates the

HFRS within the broader framework of measurement validity, emphasizing its ability to predict meaningful and policy-relevant outcomes rather than replicate an unavailable clinical gold standard.

3.6.1 Interpreting the Regression Models

The regression models used in my thesis include HFRS frailty category as the primary predictor and adjust for demographic and health-related covariates. Associations are reported as odds ratios (ORs) with 95% confidence intervals (CIs), which indicate both the magnitude and the statistical significance of the relationship between frailty level and each adverse health outcome.

These odds ratios represent the relative likelihood of an outcome for individuals classified as medium- or high-risk frailty groups compared to those classified as low-risk. For example, an odds ratio of 2.0 for the high-risk group in the model for cumulative hospital length of stay ≥30 days would indicate that individuals at high frailty risk are twice as likely as those at low risk to accumulate 30 or more days in hospital during the outcome year, after adjusting for other covariates.

The analysis therefore addresses the central question of whether the HFRS meaningfully predicts adverse outcomes, and how strong those predictions are. Strong and consistent associations across cumulative hospital length of stay thresholds, ALC stays, and short-term mortality would provide robust evidence of the HFRS's predictive validity as a frailty measure in this context. Evidence of a dose–response pattern, where the odds of adverse outcomes increase progressively across frailty categories, would further strengthen support for the validity of the tool.

Chapter 4. Results:

This chapter presents the descriptive statistics and the regression model results of the predictive analysis between the Hospital Frailty Risk Score (HFRS) and increasing levels of healthcare services utilization. Descriptive statistics are used to illustrate the distribution of covariates across frailty risk categories in the study cohort, including age categories, gender and Charleson Comorbidity Index (CCI) levels. Descriptive statistics of the frequency of each outcome studied will also be presented in this section. Logistic regression model odds ratio estimates and 95% confidence intervals (CI) are then presented, with results reported separately for each outcome.

4.1 Descriptive statistics

The analytic dataset included 57,730 person-interval observations of adults aged 65 years and older. Individual characteristics stratified by frailty risk group are presented in the figures 3, 4 and 5. The majority were classified as low-risk (78.3%), followed by medium-risk (18.9%) and high-risk (2.8%). Frailty was more prevalent among females (medium-risk: 54.3%; high-risk : 60.1%), than in males (Figure 3).

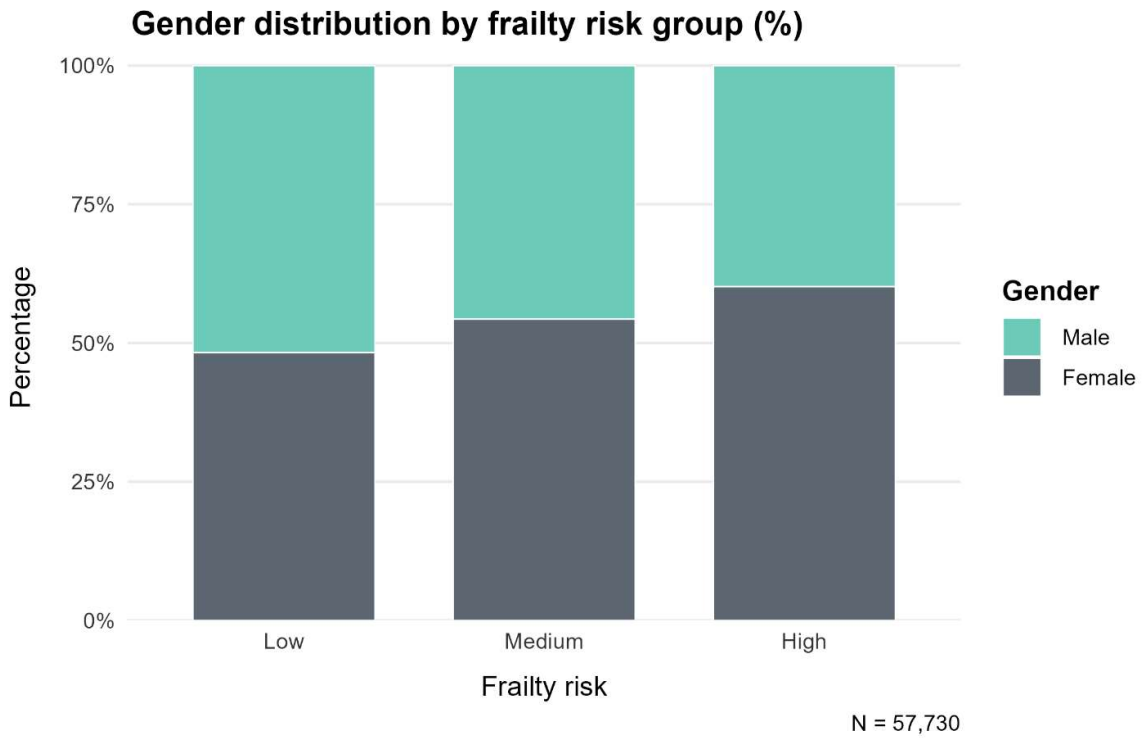

Figure 3: Stacked bar chart displaying the percentage of individuals within each Hospital Frailty Risk Score (HFRS) category (low, medium, and high risk frailty) for males and females.

As expected, figure 4 shows that frailty-risk increased with age. The proportion of individuals classified as high-risk increased with age, rising from 1.9% among those aged 65–74 years to 4.3% among those aged 85 years and older. Conversely, the share of individuals classified as low-risk declined with increasing age group, from 86.4% for age 65–74 years to 75.2% for age 75–84 years and 61.1% for age 85 years and older.

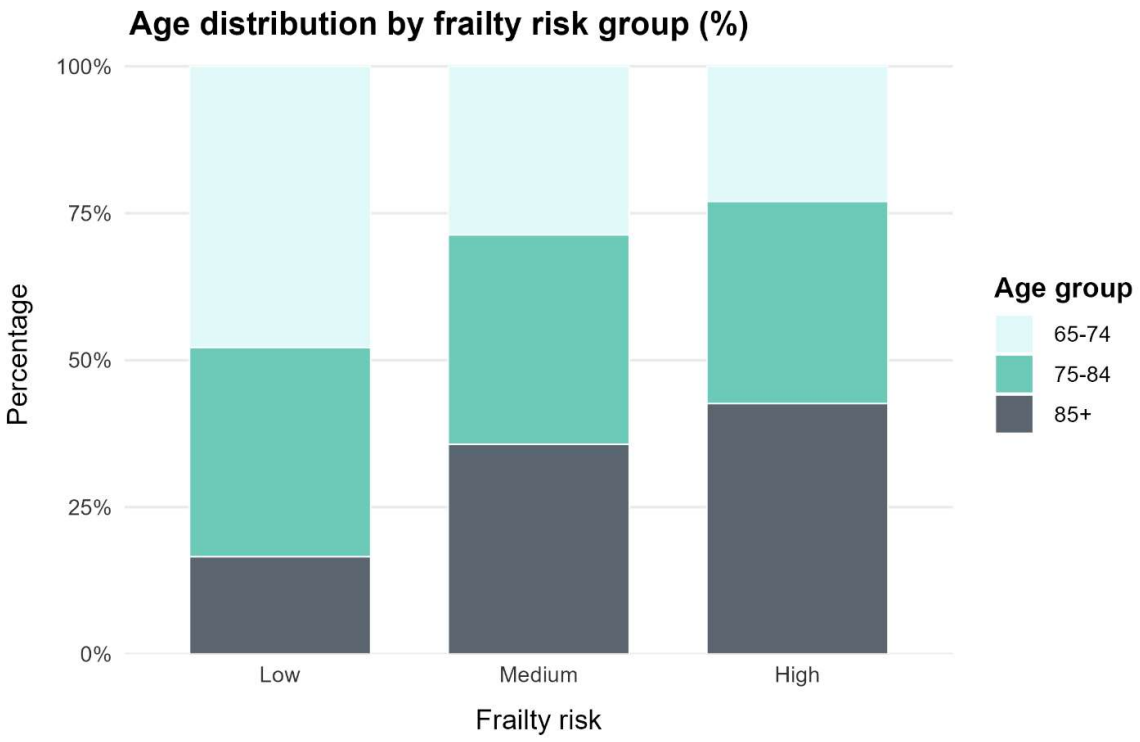

Figure 4: Stacked bar chart displaying the percentage of individuals within each Hospital Frailty Risk Score (HFRS; low, medium, and high frailty) categories across age group (65–74, 75–84, and 85+).

Figure 5 shows that high-risk frailty groups were also found to have greater comorbidity. Only 2.8% of individuals in the high-risk group had no comorbidities (CCI = 0), whereas 44.9% of those in the low-risk group fell into this category. In contrast, among those with a CCI score of 4 or more, the prevalence of frailty was substantially higher with 17.4% of medium-risk and 23.5% of high-risk individuals had a CCI ≥4, compared with only 6.1% of the low-risk group.

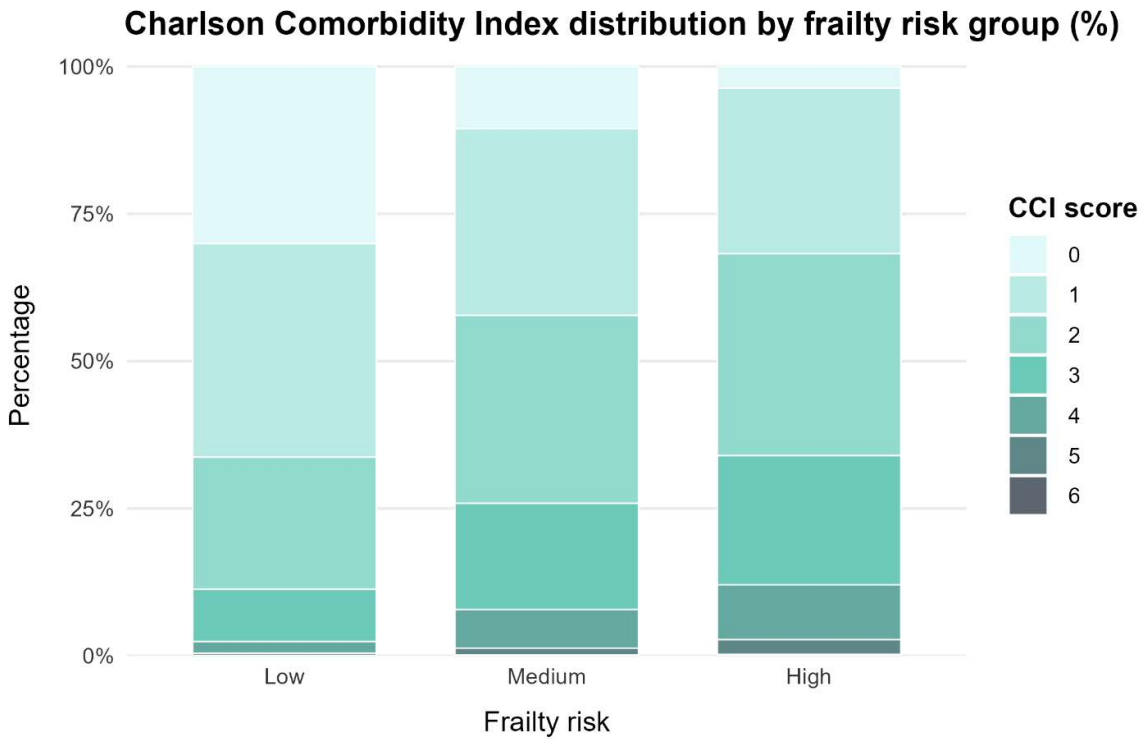

Figure 5: Stacked bar chart displaying the percentage of individuals within Hospital Frailty Risk Score (HFRS) categories (low, medium, and high frailty) for each Charlson Comorbidity Index (CCI) score (0–6).

4.1.1 Outcome frequency

Figure 6 shows the percentage of individuals that experienced each adverse health outcomes within each of the three frailty-risk categories. Overall, the percentage of individuals with adverse outcomes increased consistently with increasing frailty-risk scores, though the difference between medium and high-risk frailty was more similar as compared to low-risk frailty.

The percentage of individuals from each frailty-risk group experiencing cumulative lengths of stay outcomes increased with the frailty risk. Among those classified as high-risk, 41.1% experienced a hospital stay of 10 days or longer, compared to 40.0% in the

medium-risk frailty group and 23.1% in the low-risk frailty group. A similar gradient was observed for stays of 30 days or more (15.6%, 14.2%, and 6.7%, respectively). For cumulative length of stay of 90 days or more, proportions increased from 0.7% in the low-risk group to 3.0% in the medium-risk group and 7.2% in the high-risk group.

Similar patterns were also observed when examining increasing duration of ALC stays. The proportion of patients with any Alternate Level of Care (ALC) stay also rose with frailty risk level, from 7.1% among the low-risk group to 16.5% in the medium-risk group and 18.7% among the high-risk group. For ALC stays ≥10 days, the proportions were 3.9%, 9.8%, and 11.6%, for low, medium, and high-risk groups, respectively, while for longer ALC stays (≥30-day) the proportions were 1.7%, 5.0%, and 6.0%. These descriptive findings demonstrate a clear and monotonic association between frailty risk severity and the likelihood of experiencing adverse health outcomes, providing preliminary evidence of the ability of the HFRS to predict between individuals with increasing healthcare resource needs. However, the variation in frailty risk across demographic and clinical characteristics suggests the potential for confounding. As such, including these covariates that have been used in previous HFRS validation studies in the adjusted regression models will help ensure comparability with confounder adjustment used in prior studies and to isolate the independent predictive contribution of the HFRS.

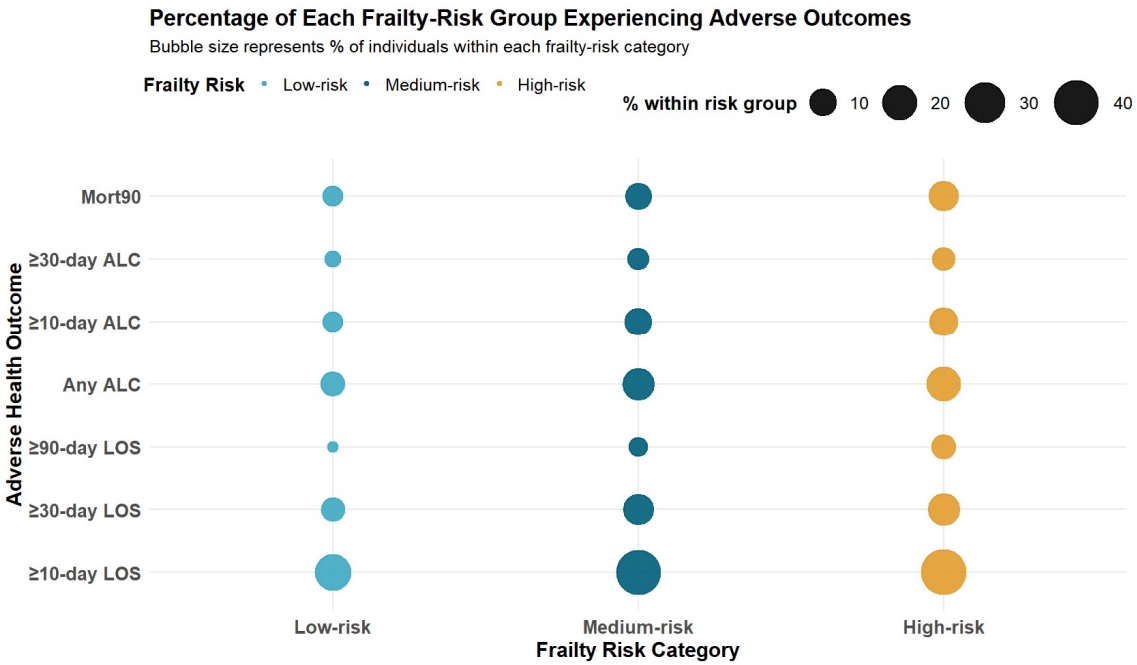

Figure 6: Bubble plot displaying the percentage of individuals within each Hospital Frailty Risk Score (HFRS) category experiencing adverse health outcomes, with the bubble size indicating the percentage of individuals within each HFRS group for each outcome.

4.2 Regression results

Adjusted logistic regression models results are presented as odds ratios (OR) with 95% confidence intervals (CI), using the low-risk group (HFRS <5) as the reference category. Models are reported separately for each outcome included three models for increasing duration of total cumulative length of stay in hospital (≥10, ≥30, and ≥90 days), three for alternate level of care days (any, ≥10 days, and ≥30 days), and one for mortality within 90 days of the start of the outcome period.

4.2.1 Cumulative acute length of stay in hospital

Regression models for total cumulative hospital length of stay in acute care during the outcome year showed a clear dose-response pattern between higher frailty risk groups

and the increasing number of days spent in hospital during the outcome year (≥10 days, ≥30 days, and ≥90 days). For lesser days in hospital, the two higher risk frailty groups were similar when compared to low risk, whereas differences between frailty-risk groups was more evident for longer durations spend in hospital.

Table 3: Adjusted odds ratios (ORs) for cumulative acute length of stay in hospital outcomes for Hospital Frailty Risk Score (HFRS) medium and high-risk categories, as compared to low risk frailty (reference group).

Outcome	Frailty risk group	Adjusted odds ratio*	95% CI
Acute LOS ≥10 days	Medium-risk	1.66	1.57–1.75
	High-risk	1.59	1.44–1.75
Acute LOS ≥30 days	Medium-risk	2.08	1.92–2.25
	High-risk	2.71	2.41–3.05
Acute LOS ≥90 days	Medium-risk	2.45	2.05–2.91
	High-risk	4.71	3.78–5.87

*adjusted for gender, age, income, comorbidity, medical accessibility, and number of hospitalization in the previous year

3.2.1.1 Cumulative hospital length of stay ≥10 days

Compared to the low-risk frailty group, those classified as medium-risk had 1.66 times higher odds of having a length of stay ≥10 days in hospital during the outcome year (95% CI: 1.57–1.76), which was similar to the high-risk frailty group (OR = 1.60, 95% CI: 1.45–1.76). Although the point estimate for the high-risk group was lower than that for the medium-risk group, the overlapping confidence intervals suggest that both frailty groups have similar likelihood of prolonged cumulative acute hospital stays for 10 or more days.

3.2.1.2 Cumulative hospital length of stay ≥30 days

Increasing level of frailty risk was more strongly and evidently associated with accumulating at least 30 days in hospital during the outcome year. Compared to the low-risk group, medium-risk frailty had a 2.08 times higher odds (95% CI: 1.92–2.25), while odds ratios in high-risk frailty had a greater magnitude and non-overlapping confidence intervals with medium-risk (OR: 2.71 (95% CI: 2.41–3.05)).

3.2.1.3 Cumulative hospital length of stay ≥90 days

The strongest association was observed between frailty-risk and the likelihood of most prolonged hospitalization outcome examined. Compared to the low-risk group, medium-risk had 2.45 times higher odds of being in hospital for 90 days or more during the outcome year (95% CI: 2.05–2.91). The most pronounce risk was among the high-risk group, with 4.71 times higher odds (95% CI: 3.78–5.87).

4.2.2 Alternate Level of Care (ALC) outcomes

Regression models examining the cumulative number of ALC days during the outcome year showed less pronounced differences across frailty-risk groups than was found for acute LOS. While medium and high-risk frailty groups generally demonstrated greater odds of accumulating ALC days compared to the low-risk group in the outcome year, there was no gradient between high- and medium-risk groups for ALC outcomes.

Table 4: Adjusted odds ratios (ORs) and 95% confidence intervals for alternate level of care (ALC) outcomes by Hospital Frailty Risk Score (HFRS) category, with low-risk frailty as the reference group.

Outcome	Frailty risk group	Adjusted odds ratio*	95% CI
An ALC stay	Medium-risk	1.61	1.50–1.72
	High-risk	1.62	1.44–1.82
ALC ≥10 days	Medium-risk	1.67	1.53–1.83
	High-risk	1.77	1.53–2.04
ALC ≥30 days	Medium-risk	1.89	1.67–2.15
	High-risk	2.03	1.66–2.47

*adjusted for gender, age, income, comorbidity, medical accessibility, and number of hospitalization in the previous year

3.2.2.1 An ALC stay

Frailty risk was significantly associated with the likelihood of having an ALC stay during the outcome year. The estimates for medium- and high-risk groups were nearly identical, suggesting that both HFRS categories predict a comparably elevated need of requiring ALC care. Compared to the low-risk group, medium-risk had 1.61 times higher odds of an ALC stay (95% CI: 1.50–1.72), and high-risk had a 1.62 higher odds (95% CI: 1.44–1.82).

3.2.2.2 ALC stay ≥10 days

Compared to the low-risk group, those with medium-risk had 1.67 times higher odds of experiencing an ALC stay of 10 days or longer (95% CI: 1.53–1.83). The high-risk group had a slightly greater increase, with 1.77 times higher odds (95% CI: 1.53–2.04).

3.2.2.3 ALC stay ≥30 days

Compared to the low-risk group, medium-risk had 1.89 times higher odds of having an ALC stay of 30 days or more (95% CI: 1.67–2.15). High-risk group had a similar increase compared to the low-risk group, with 2.03 times higher odds (95% CI: 1.66–2.47). These findings support that when looking at ALC in the outcome year, the HFRS best predicts when used as a binary measure.

4.2.3 Mortality within 90 days

Table 5: Adjusted odds ratios (ORs) and 95% confidence intervals for mortality within 90 days by Hospital Frailty Risk Score (HFRS) category, with low frailty as the reference group.

Outcome	Frailty risk group	Adjusted odds ratio*	95% CI
90-day mortality	Medium-risk	1.44	1.32–1.58
	High-risk	1.87	1.62–2.14

*adjusted for gender, age, income, comorbidity, medical accessibility, and number of hospitalization in the previous year

As expected, HFRS was predictive of increased risk of mortality within 90 days of the start of the outcome year. Compared to the low-risk group, medium-risk individuals had 1.44 times higher odds of death (95% CI: 1.32–1.58), whereas odds of death were

greatest in the high-risk group (OR: 1.87 95% CI: 1.62–2.14), with non-overlapping confidence intervals. These findings confirm the ability of the HFRS to predict short-term mortality risk in the NB population.

Chapter 5: Discussion

5.1 Summary of Findings

This study examined the predictive validity of the Hospital Frailty Risk Score (HFRS) and demonstrates its ability to predict longer-term adverse health service outcomes among older adults in New Brunswick, identifying those at increased vulnerability. Across all outcomes assessed, there is a consistent pattern: higher frailty-risk was associated with greater health service utilization and mortality.

The descriptive results show that frailty-risk followed expected patterns based on previous epidemiological studies, with higher prevalence among older age groups and among women, consistent with prior cohort studies of frailty (Gilbert et al., 2018; McAlister & van Walraven, 2019; Turcotte et al., 2023). Comorbidity burden also increased with frailty risk level; however, while notable overlap was found across categories, adjusted regression results indicate that elevated frailty risk is independent of disease comorbidity burden. This contextualizes the subsequent regression findings and reinforces the distinction between frailty and comorbidity: while related, they represent different dimensions of risk, with frailty reflecting a set of conditions associated physiological vulnerability beyond just the accumulation of conditions.

The regression analysis showed that frailty risk was consistently associated with all examined outcomes after adjustment for covariates. However, the pattern of association varied by outcome. For shorter durations of acute hospitalizations and for all the ALC outcomes, medium- and high-risk frailty categories predicted similar increases in the

outcomes compared to low-risk individuals. These results suggest that once individuals reach the HFRS threshold that defines them as frail, health service demands in the outcome year were increased regardless of further stratification of the higher frail groups. In contrast, the ability of HFRS to differentiate medium- and high-risk groups was more pronounced for increasing days of acute hospital stays. The discriminative capacity of the three-level HFRS improved with increasing duration of the acute hospitalizations (i.e., cumulative acute length of stays exceeding 10, 30 vs 90 days).

Overall findings demonstrate that the HFRS is a valuable tool to support health system-planning, however, it may perform better as a binary measure of frailty-risk for ALC outcomes, but as a 3-level measure for duration of acute hospitalization. Taken together, these findings indicate that the HFRS performs robustly across a range of health system-level outcomes, with particularly strong differentiation for the longer cumulative acute lengths of stay that exceed 30 and 90 days.

5.2 Interpretation of findings

In this section, I will discuss the consistency of my findings with the existing HFRS validation literature. Comparisons are made with the original validation study by Gilbert et al. (2018), and with more recent international validation cohorts. I will then discuss the novel contributions of my thesis, specifically the use of cumulative length-of-stay outcomes and inclusion of ALC. Finally, I will discuss implications for practical use of HFRS in future research and health service system planning.

My findings are consistent with those in the existing literature reporting on predictive validity of the HFRS. While similar in the overarching picture, several differences in

each study limits the ability to make direct comparisons with my own results. These differences vary between the studies, and they include: definition of frailty-related outcomes, cohort selection, geographic area, or study design.

5.2.1 Long length of acute hospital stay

A novel contribution of this thesis is the extension of the conventional definition of prolonged hospital stay used in prior HFRS validation studies. Existing literature has typically defined prolonged hospital use as a single acute hospitalization lasting 10 days or more within an outcome year. In contrast, my thesis examines the ability of the HFRS to predict cumulative hospital length of stay, reflecting the total number of inpatient days accrued across all admissions over the outcome year. From a health system surveillance and planning perspective, cumulative hospital stays exceeding 10, 30, and 90 days are particularly informative because they capture not only single prolonged admissions but also repeated patterns of acute care utilization. This approach allows assessment of whether the HFRS is sensitive to ongoing high-intensity hospital use over time, rather than being limited to identification of isolated long hospitalizations.

The original development study by Gilbert and colleagues used multiple external validation studies carried out in different jurisdictions and clinical populations (Gilbert et al., 2018). Similar to other existing literature validating the HFRS, they also defined "long length of stay" as having a single acute admission to the hospital with a duration of 10 or more days in the outcome year. Whereas in this thesis the outcome was cumulative length of stay over the outcome year. Patients in the high-risk group had markedly greater risk of having at least one hospitalization of 10 or more days, and mortality compared

with those in the low-risk group. Specifically, high frailty risk was associated with about three times higher odds of long length of stay (OR 3.2, 95% CI 3.1 to 3.4). While the cumulative hospital length of stay outcome definition used in my thesis is more stringent as it is based on cumulative days over a fiscal year rather than a single admission, my findings align with that magnitude and direction of effect.

Cumulative lengths of stay were not studied in prior HFRS validation studies but are a very important indicator of hospital strain and extended care use of older adults. In line with Gilbert et al., my study found that medium frailty risk was associated with roughly doubling of the odds of accumulating prolonged hospital stays, and high frailty risk was associated with substantially higher odds again, particularly for cumulative stays of 30 and 90 days. Although the exact effect sizes are not directly comparable because of different outcome definitions as well as healthcare system (the Gilbert et al. study is based in Switzerland), the overall pattern suggests that once individuals cross the HFRS threshold for frailty, they are at significantly higher risk of prolonged hospital use, and my thesis research demonstrates that this gradient becomes even more pronounced for the longest stays.

Several recent external HFRS validation studies reinforce this bigger picture and provide useful benchmarks for the size of associations between the HFRS and long length of acute hospital stay, although in cohorts with different characteristics (aged 75 and older, with specific conditions). For example, Sy et al. examined in a cohort of critically ill older adults (above 75 years old) that are receiving mechanical ventilation in the United States Nationwide Readmissions Database and also defined prolonged hospitalization as

one hospitalization of 10 or more days, similar to Gilbert (2018). In that high-acuity cohort, hospitalizations in the high frailty risk category had an adjusted odds ratio of 5.59 (95 percent CI 5.24 to 5.97) for prolonged length of stay (defined as one hospitalization exceeding 10 days) compared with low-risk hospitalizations (Sy et al., 2022).

In a similar pattern, although the odds ratios differ, in a large Chinese hospital cohort of older adults aged 75 and older, Qiu et al. studied the predictive validity of HFRS on long length of stay (also defined as one hospitalization of 10 or more days) and found that, compared to patients with no frailty risk, the probability of long stay was 2.7 times higher for those with medium frailty risk, although their results for the high-risk group had wide confidence interval

5.2.2 Alternative Level of Care outcomes

Another novel element of my thesis research is the examination of ALC days as an outcome. To my knowledge, ALC has not been previously examined as an outcome in HFRS validation studies. ALC is an important outcome for older adults, especially frail individuals who need to be transitioned to proper care after hospitalization. My findings show that HFRS categories predict both a need for ALC, but also for more prolonged duration of ALC stays. Interestingly, these effects remained even after accounting for age and comorbidity,

Overall, these findings indicate that HFRS can not only predict the risk of acute events but can also predict the likelihood of requiring prolonged periods in hospital beds. Frailty as measured by the HFRS appears to signal both higher demand for acute care and a greater chance of experiencing system-level barriers to timely discharge, which is often a

reason for time in ALC, while waiting for discharge to more appropriate level of care settings. Higher demands for hospital health services has important implications for bed planning and system-level surveillance.

My thesis findings that increasing frailty-risk predicts need for ALC highlight a very important issue in the healthcare system in NB, which must be interpreted against the backdrop of the broader ALC situation in Canada. National data show that ALC has become a persistent structural issue. Recent Canadian analyses indicate that patients designated as ALC occupy between 10 and 20 percent of acute care beds at any given time and account for approximately 17 percent of all acute care bed-days in 2020–2021 (Durante et al., 2023). CIHI reports that, in recent years, about 6.2 percent of hospital stays in Canada included at least one ALC day, meaning thousands of patients are in hospital beds while waiting for more appropriate services in long-term care, rehabilitation, mental health, or home-based care settings (*Hospital Stays in Canada, 2023–2024 | CIHI*, n.d.). This pattern reflects a growing mismatch between the needs of older adults and the availability of community and residential care capacity.

Advocacy groups have noted that hundreds of seniors in the province are waiting for nursing home admission and that a large proportion of them are waiting in hospital rather than at home or in interim settings (*The New Brunswick Special Care Home Association*, 2025). These individuals do not require acute medical care but remain in hospital because there is no timely access to more appropriate care environments. As a result, hospitals operate at or near capacity, which restricts access for patients with acute needs and contributes to emergency department crowding, cancelled procedures, and difficulty

maintaining acceptable occupancy rates (*Hospital Stays in Canada, 2023–2024 | CIHI*, n.d.).

For older adults, prolonged ALC stays are not neutral holding periods. Canadian and international reports emphasize that remaining in hospital once acute medical needs have resolved is associated with increased risk of hospital-acquired infections, physical deconditioning, loss of mobility and independence, worsened cognition, and mental health decline (Covinsky et al., 2003; McCloskey et al., 2015).

Within this context, my study findings, that HFRS categories are strongly associated with both the need for and duration of ALC stays is particularly important. This indicates that frailty, as measured through routinely collected hospital data, is a key predictor of who ends up in ALC and who remains there for longer periods. In practical terms, this supports that ALC pressures in New Brunswick and across Canada are not random but are disproportionately generated by a subset of older adults living with frailty. This highlights the need for targeted transitional care interventions. Examples include early involvement of geriatric or specialized discharge teams, systematic assessment of long-term care and home support needs, and proactive coordination with community and residential care sectors(Tyler et al., 2023).

These study results also have implications for how governments and health authorities can monitor and evaluate system-level reforms. CIHI already reports indicators such as the percentage of patient days spent in ALC and the proportion of hospital stays with ALC days to help organizations monitor flow and bed use. By integrating HFRS into these monitoring frameworks, decision-makers could also track ALC use among frail

older adults. For example, if New Brunswick or Canada implements new policies to increase long-term care capacity, expand home care, or create dedicated transition units, these reforms are expected to provide better support for frail patients. Repeated measurement of ALC length of stay stratified by HFRS category over time could then help determine whether these interventions are effective and whether they are reducing ALC days among those most at risk.

In this way, the HFRS has potential to function as a surveillance tool, for assessing whether system changes lead to measurable improvements in flow for frail patients. If, over time, cumulative ALC days decline among individuals with medium and high frailty risk, this would provide evidence that transitional care reforms are effectively addressing the needs of the population that contributes most to ALC pressure. Conversely, if ALC use remains high among frail groups despite interventions, this would signal a need to reconsider policy design, resourcing, or implementation.

5.2.3 Practical implications for frailty categorization

Based on my research, and the findings of my study, I also want to point out a very important question in this topic: "*How many HFRS categories are needed for practical use?"*. Gilbert et al. proposed three categories (low, medium, high), and many validation studies have adopted this structure and reported clear gradients in risk across all three.

When these categories have been applied in validation studies, both medium and high frailty groups consistently show substantially higher odds of prolonged hospital stay compared with the low-risk group, while separation between medium and high risk is more modest. For example, Gilbert et al. reported odds ratios of approximately 1.7–2.0

for medium frailty and 2.8–3.3 for high frailty for stays ≥10 days with overlapping confidence intervals. Sy et al. found odds ratios of approximately 3.8–4.2 for medium frailty and 5.59 (95% CI 5.24–5.97) for high frailty in a high-acuity U.S. cohort (Sy et al., 2022).

Recent studies using the Hospital Frailty Risk Score (HFRS) have adopted simplified categorization strategies to facilitate analysis, with some combining medium and high risk groups into a single "frail" category, to simplify the use of HFRS. For example, research in cardiovascular and acute care cohorts has merged intermediate and high HFRS categories (e.g., HFRS ≥ 5) to compare frail versus non-frail outcomes, arguing that dichotomization retains clinical relevance while improving statistical power in settings with limited high-risk sample sizes(Sokhal et al., 2024). Another study similarly defined frailty-risk using a single threshold (e.g., HFRS ≥ 5) when evaluating associations with mortality or utilization, supporting the pragmatic use of two-level HFRS groupings in health services research where fine discrimination between moderate and severe frailty may be secondary to overall risk stratification(Van Nguyen et al., 2025).

In my study, medium and high frailty risk groups both had substantially higher odds of prolonged hospitalizations and ALC use compared with the low-risk group, and for several outcomes the confidence intervals around the medium and high risk estimates overlapped. This suggests that, for surveillance purposes, collapsing medium and high frailty risk into a single "frail" category may be sufficient to identify individuals at markedly increased risk of spending more time in ALC.

That conclusion is consistent this research showing that HFRS alone has good prediction for a range of long length of stay thresholds. From a system perspective, using two levels (not frail vs frail) could simplify implementation while preserving most of the prognostic information needed for planning and resource targeting.

5.2.4 Short-term mortality

While mortality was not a novel contribution of my thesis, I wanted to show that the HFRS does predict, as expected, short-term mortality in existing hospital administrative data. Mortality results in my study align with much of the existing HFRS literature. Gilbert et al. reported a 1.71 increase in the odds of 30-day mortality for those in the highest HFRS category compared with the low-risk group. In another validation study by Street et al., results also showed that medium and high-risk frailty categories were important predictors of in-hospital mortality, with only the Charlson Comorbidity Index contributing more strongly in their models(Street et al., 2025). Similarly, a recent nationwide heart failure cohort showed that frail patients identified by the HFRS had more than a four-fold increase in in-hospital death compared with non-frail patients (Bansal et al., 2025).

5.4 Strengths and Limitations

My study has several important strengths and limitations. Strengths include: the use of population-based administrative data for comprehensive provincial coverage; extension of HFRS validation to novel cumulative length-of-stay and ALC outcomes; and rigorous adjustment for demographic and comorbidity factors to isolate the independent contribution of frailty. Limitations include the short, fixed follow-up window, reliance on

administrative data without clinical or functional variables (only ICD10 codes), and reduced suitability for individual-level prognostic prediction despite strong system-level relevance.

First, the use of population-based administrative data provides broad, complete coverage of older adults in New Brunswick who are hospitalized, a core strength noted in other HFRS validation studies that also relied on administrative datasets for system-level generalizability (Gilbert et al., 2018; McAlister & van Walraven, 2019). This design supports reproducible health-system surveillance using routinely collected hospitalization records.

Second, this study extends prior validation work by examining cumulative LOS at multiple thresholds and by incorporating ALC duration, an outcome not previously assessed in HFRS research. Prior studies have focused predominantly on single-admission outcomes such as mortality, readmission, and standard LOS (Gilbert et al., 2018), whereas cumulative and ALC measures capture more sustained system dependency and delayed discharge pressures. These are key issues in Canadian hospital care (Canadian Institute for Health Information, 2023).

Third, adjustment for demographic characteristics and the Charlson Comorbidity Index aligns with analytical approaches used in previous HFRS studies, which similarly accounted for multimorbidity to validate the independent predictive contribution of frailty (McAlister & van Walraven, 2019; Soong et al., 2019). The persistence of strong associations after adjustment supports the construct validity of the HFRS as more than a marker of disease burden.

A primary limitation is the short, fixed follow-up window, which constrains cumulative LOS and ALC measurement. Similar challenges have been noted in studies where brief observation periods limited discrimination among frailty strata (Soong et al., 2019). Longer follow-up may reveal clearer separation between medium and high frailty categories, particularly when outcomes accumulate over the life course. Future research should consider extended or rolling windows to capture long-term utilization patterns.

Finally, although administrative data enable scalable system-wide monitoring, they lack granularity on functional status, cognition, and social vulnerability. These are factors shown in other frailty studies to improve individual-level prognostic accuracy (Rockwood et al., 2005). As a result, the HFRS cannot be used, currently, in individual-level assessment for frailty, especially since ICD10 diagnostic codes are not available to clinicians in real-time to be used as a discharge tool. Currently, until new data strategies are implemented, it is better suited for population-level risk stratification than for individualized prediction. Integrating administrative data with richer clinical or functional assessments may enhance future prognostic models.

6. Closing Statement

This study contributes to the growing evidence supporting the predictive validity of the Hospital Frailty Risk Score as a planning tool for identifying, in existing hospital administrative data, older adults at risk of adverse health system outcomes. Within a population-based cohort from New Brunswick, higher frailty risk was consistently associated with increased acute hospital use, delayed discharge as reflected by ALC stays, and elevated short-term mortality.

From a health system planning perspective, the observation that medium- and high-risk frailty groups demonstrated similar risks for several healthcare service use outcomes suggests that binary identification of frailty may be sufficient for population surveillance and resource targeting. Such an approach could simplify implementation within administrative health data systems while retaining the ability to identify groups most likely to benefit from early transitional care planning and supportive services. Integration of frailty-based monitoring could also support evaluation of policy initiatives aimed at reducing prolonged hospital stays and improving care transitions for older adults.

In a Canadian healthcare system facing persistent pressures from hospital crowding, delayed discharge, and long-term care capacity constraints, the findings from my thesis study underscore the relevance of frailty-based risk stratification as a crucial system performance indicator.

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Appendix A: Regression model outputs

This appendix presents the full adjusted regression model results for the specified outcome. Results are reported as odds ratios with corresponding 95% confidence intervals and p-values, as derived from multivariable regression analyses.

Cumulative length of stay >=10:

term	estimate	std.error	p.value	conf.low	conf.high	OR	CI_lower	CI_upper
(Intercept)	-2.9744	0.07664	0	-3.12512	-2.82466	0.05107	0.04393	0.05932
HFRS2	0.50931	0.02816	0.00E+00	0.45405	0.56448	1.66415	1.57468	1.75853
HFRS3	0.46742	0.04908	0.00E+00	0.37099	0.56343	1.59587	1.44918	1.75669
GENDER	0.15929	0.02505	0.00E+00	0.11019	0.20842	1.17268	1.11649	1.23173
age_groups75	0.1307	0.0292	0.00E+00	0.07345	0.18795	1.13962	1.07622	1.20678
age_groups85	0.26616	0.03205	0.00E+00	0.2033	0.32898	1.30494	1.22544	1.38955
TOT_GRP1	0.6481	0.04565	0.00E+00	0.55915	0.73817	1.9119	1.7492	2.09211
TOT_GRP2	0.964	0.04603	0.00E+00	0.8743	1.05482	2.62218	2.3972	2.87148
TOT_GRP3	1.19547	0.0506	0.00E+00	1.09668	1.29509	3.30511	2.99422	3.65133
TOT_GRP4	1.35444	0.06792	0.00E+00	1.22135	1.48767	3.8746	3.39178	4.42679
TOT_GRP5	1.72518	0.12712	0.00E+00	1.47602	1.9747	5.61354	4.37553	7.2045
TOT_GRP6	0.93903	0.35947	0.00899	0.20058	1.62013	2.55751	1.22211	5.05376
QABTIPPE2	-0.05177	0.03531	0.14263	-0.12104	0.01741	0.94954	0.88599	1.01756
QABTIPPE3	-0.06377	0.0361	0.07732	-0.1346	0.00693	0.93821	0.87406	1.00696
QABTIPPE4	-0.05369	0.0381	0.15877	-0.12847	0.0209	0.94772	0.87943	1.02112
QABTIPPE5	-0.21069	0.04138	0.00E+00	-0.292	-0.12976	0.81002	0.74676	0.87829
hospcount	0.339	0.00835	0	0.32267	0.35544	1.40354	1.38081	1.42681
Family.Physici	-0.01668	0.00374	0.00E+00	-0.02401	-0.00935	0.98345	0.97627	0.99069

Cumulative length of stay >=30:

term	estimate	std.error	p.value	conf.low	conf.high	OR	CI_lower	CI_upper
(Intercept)	-4.2281	0.11683	0.00E+00	-4.45865	-4.0006	0.01458	0.01157	0.0183
HFRS2	0.73016	0.04066	0.00E+00	0.65043	0.80983	2.07542	1.91637	2.24753
HFRS3	0.99642	0.06003	0.00E+00	0.87822	1.11359	2.70858	2.40663	3.0453
GENDER	0.20448	0.03646	0.00E+00	0.13307	0.27602	1.22689	1.14233	1.31787
age_groups75	0.04657	0.04273	0.27582	-0.03718	0.13035	1.04767	0.9635	1.13922
age_groups85	0.13436	0.04647	0.00383	0.04319	0.22537	1.1438	1.04414	1.25279
TOT_GRP1	0.58491	0.07685	0.00E+00	0.43626	0.73767	1.79483	1.54692	2.09107
TOT_GRP2	0.95567	0.07604	0.00E+00	0.8087	1.10691	2.60041	2.24499	3.02501
TOT_GRP3	1.19884	0.0803	0.00E+00	1.04319	1.35812	3.31627	2.83827	3.88889
TOT_GRP4	1.42157	0.09579	0.00E+00	1.2345	1.61015	4.14362	3.43667	5.00359
TOT_GRP5	1.54897	0.15674	0.00E+00	1.23767	1.8527	4.70665	3.44758	6.37702
TOT_GRP6	1.6695	0.40496	3.00E-05	0.8178	2.42144	5.30951	2.26552	11.26217
QABTIPPE2	-0.03453	0.05108	0.49895	-0.13481	0.06545	0.96605	0.87387	1.06764
QABTIPPE3	0.02414	0.05182	0.64121	-0.07759	0.12557	1.02444	0.92533	1.13379
QABTIPPE4	0.01144	0.05477	0.83449	-0.09621	0.1185	1.0115	0.90826	1.12581
QABTIPPE5	-0.23923	0.06217	0.00011	-0.36187	-0.1181	0.78722	0.69636	0.88859
hospcount	0.24314	0.0091	0.00E+00	0.22532	0.26103	1.27525	1.25272	1.29827
Family.Physic	-0.01327	0.00541	0.01422	-0.02386	-0.00263	0.98681	0.97641	0.99736

Cumulative length of stay >=90:

term	estimate	std.error	p.value	conf.low	conf.high	OR	CI_lower	CI_upper
(Intercept)	-5.35142	0.23855	0.00E+00	-5.82593	-4.89032	0.00474	0.00295	0.00751
HFRS2	0.8946	0.08915	0.00E+00	0.72	1.06964	2.44636	2.05444	2.91433
HFRS3	1.55034	0.11223	0.00E+00	1.32898	1.76917	4.71308	3.7772	5.86603
GENDER	0.11095	0.07591	0.14383	-0.03766	0.26001	1.11734	0.96303	1.29695
age_groups75-	-0.07638	0.08881	0.38972	-0.25064	0.09768	0.92645	0.77829	1.10261
age_groups85-	-0.01778	0.0965	0.85383	-0.20758	0.17093	0.98237	0.81254	1.18641
TOT_GRP1	0.43415	0.15759	0.00587	0.13349	0.75262	1.54365	1.14281	2.12256
TOT_GRP2	0.60455	0.15738	0.00012	0.30445	0.92274	1.83043	1.35588	2.51619
TOT_GRP3	0.82206	0.16568	0.00E+00	0.50424	1.15513	2.27519	1.65574	3.17445
TOT_GRP4	1.21934	0.18709	0.00E+00	0.85576	1.59079	3.38495	2.35316	4.90763
TOT_GRP5	1.75294	0.25358	0.00E+00	1.24461	2.24212	5.77155	3.47159	9.41328
TOT_GRP6	1.38192	0.7559	0.06752	-0.47252	2.64262	3.98254	0.62342	14.05008
QABTIPPE2	0.1208	0.10501	0.25	-0.08546	0.32651	1.1284	0.91808	1.38613
QABTIPPE3	0.22222	0.1053	0.03482	0.0154	0.42849	1.24885	1.01552	1.53494
QABTIPPE4	-0.04445	0.1185	0.70759	-0.27898	0.18601	0.95652	0.75654	1.20444
QABTIPPE5	-0.32294	0.13975	0.02084	-0.60272	-0.05402	0.72401	0.54731	0.9474
hospcount	0.12479	0.01442	0.00E+00	0.09633	0.15295	1.13291	1.10112	1.16526
Family.Physici	-0.01906	0.01116	0.08755	-0.04079	0.00295	0.98111	0.96002	1.00296

Any ALC stay:

term	estimate	std.error	p.value	conf.low	conf.high	OR	CI_lower	CI_upper
(Intercept)	-4.01341	0.10192	0	-4.21411	-3.81455	0.01807	0.01478	0.02204
HFRS2	0.47399	0.03606	0.00E+00	0.4032	0.54459	1.6064	1.49661	1.72391
HFRS3	0.48147	0.06014	0.00E+00	0.3628	0.59859	1.61845	1.43736	1.81956
GENDER	0.3214	0.03258	0.00E+00	0.25762	0.38534	1.37906	1.29384	1.47012
age_groups75	0.52129	0.041	0.00E+00	0.4411	0.60185	1.6842	1.55442	1.82549
age_groups85	0.95092	0.04198	0.00E+00	0.86883	1.0334	2.5881	2.38412	2.81062
TOT_GRP1	0.53608	0.05922	0.00E+00	0.42103	0.65325	1.7093	1.52354	1.92177
TOT_GRP2	0.79437	0.05976	0.00E+00	0.67825	0.91258	2.21306	1.97043	2.49074
TOT_GRP3	1.05146	0.06508	0.00E+00	0.92462	1.17982	2.86183	2.52091	3.25379
TOT_GRP4	1.23176	0.0847	0.00E+00	1.06536	1.3975	3.42728	2.90188	4.04508
TOT_GRP5	1.44056	0.15098	0.00E+00	1.13855	1.73121	4.22307	3.12225	5.6475
TOT_GRP6	1.80634	0.37165	0.00E+00	1.02737	2.49973	6.08814	2.79372	12.17921
QABTIPPE2	-0.02412	0.04543	0.59543	-0.1133	0.06482	0.97616	0.89288	1.06697
QABTIPPE3	0.00236	0.04613	0.95918	-0.08819	0.09265	1.00236	0.91558	1.09708
QABTIPPE4	-0.0011	0.04891	0.98194	-0.09722	0.09452	0.99889	0.90734	1.09913
QABTIPPE5	-0.17286	0.05407	0.00139	-0.27939	-0.06737	0.84125	0.75623	0.93484
hospcount	0.00294	0.00975	0.76274	-0.01639	0.02185	1.00294	0.98373	1.0221
Family.Physic	0.01167	0.00491	0.01749	0.00206	0.02133	1.01174	1.00206	1.02156

ALC stay >= 10:

term	estimate	std.error	p.value	conf.low	conf.high	OR	CI_lower	CI_upper
(Intercept)	-4.54538	0.13046	0.00E+00	-4.8027	-4.29127	0.01061	0.0082	0.01368
HFRS2	0.5127	0.04557	0.00E+00	0.42322	0.60189	1.66979	1.52687	1.82557
HFRS3	0.57134	0.07368	0.00E+00	0.42555	0.71446	1.77064	1.53044	2.04309
GENDER	0.27032	0.04133	0.00E+00	0.18942	0.35149	1.31038	1.20855	1.42118
age_groups75-	0.56285	0.05303	0.00E+00	0.45928	0.6672	1.75567	1.58293	1.94878
age_groups85-	0.92767	0.05416	0.00E+00	0.82189	1.03424	2.52861	2.27479	2.81297
TOT_GRP1	0.57196	0.07688	0.00E+00	0.4232	0.72471	1.77174	1.52684	2.06414
TOT_GRP2	0.73072	0.07794	0.00E+00	0.57982	0.88548	2.07658	1.78571	2.42415
TOT_GRP3	0.98525	0.08413	0.00E+00	0.8217	1.15167	2.67848	2.27438	3.16349
TOT_GRP4	1.1407	0.10775	0.00E+00	0.92875	1.35141	3.12897	2.53134	3.86289
TOT_GRP5	1.20829	0.19568	0.00E+00	0.81049	1.5797	3.34777	2.24901	4.85351
TOT_GRP6	1.73448	0.45191	0.00012	0.74669	2.54904	5.66598	2.11001	12.79485
QABTIPPE2	0.00728	0.05754	0.89924	-0.10571	0.11991	1.00731	0.89968	1.12739
QABTIPPE3	0.07195	0.05788	0.21385	-0.04171	0.18522	1.0746	0.95914	1.20349
QABTIPPE4	-0.0283	0.06277	0.652	-0.15187	0.09424	0.97208	0.85909	1.09883
QABTIPPE5	-0.17121	0.06932	0.01352	-0.30814	-0.03629	0.84263	0.7348	0.96435
hospcount	0.00685	0.0121	0.57092	-0.01725	0.03018	1.00688	0.98289	1.03064
Family.Physici	0.00899	0.00622	0.14888	-0.00317	0.02123	1.00903	0.99682	1.02146

ALC stay >= 30:

term	estimate	std.error	p.value	conf.low	conf.high	OR	CI_lower	CI_upper
(Intercept)	-5.33916	0.18789	0.00E+00	-5.71098	-4.97432	0.00479	0.0033	0.00691
HFRS2	0.63818	0.06459	0.00E+00	0.51138	0.76464	1.89303	1.6676	2.14823
HFRS3	0.7092	0.10161	0.00E+00	0.50727	0.9058	2.03236	1.66075	2.47393
GENDER	0.16841	0.05858	0.00404	0.05378	0.28347	1.18342	1.05526	1.32774
age_groups75-	0.51119	0.07551	0.00E+00	0.36393	0.66008	1.66728	1.43897	1.93495
age_groups85-	0.82621	0.07718	0.00E+00	0.67568	0.97835	2.28465	1.96537	2.66008
TOT_GRP1	0.59441	0.11312	0.00E+00	0.37717	0.82109	1.81196	1.45816	2.27297
TOT_GRP2	0.71282	0.11464	0.00E+00	0.49244	0.94232	2.03973	1.63631	2.56593
TOT_GRP3	0.92935	0.12308	0.00E+00	0.69134	1.17436	2.53288	1.99639	3.23609
TOT_GRP4	1.18824	0.1505	0.00E+00	0.89255	1.48333	3.2813	2.44136	4.4076
TOT_GRP5	1.00729	0.28745	0.00045	0.40609	1.54064	2.73819	1.50095	4.66758
TOT_GRP6	1.70992	0.61297	0.00527	0.27124	2.75904	5.52856	1.31159	15.78476
QABTIPPE2	0.09215	0.08	0.24938	-0.06498	0.24877	1.09653	0.93708	1.28245
QABTIPPE3	0.09239	0.08173	0.25828	-0.06828	0.25226	1.0968	0.93399	1.28693
QABTIPPE4	-0.14456	0.0925	0.11811	-0.32749	0.03534	0.8654	0.72072	1.03597
QABTIPPE5	-0.20918	0.10031	0.03704	-0.40838	-0.01485	0.81124	0.66472	0.98525
hospcount	0.01467	0.01636	0.36968	-0.01825	0.04585	1.01478	0.98191	1.04692
Family.Physici	0.02121	0.00893	0.01755	0.00378	0.0388	1.02144	1.00379	1.03956

Mortality within 90 days:

term	estimate	std.error	p.value	conf.low	conf.high	OR	CI_lower	CI_upper
(Intercept)	-3.9654	0.131849	1.02E-198	-4.22571	-3.7088	0.01896	0.014615	0.024507
HFRS2	0.367925	0.046654	3.12E-15	0.276282	0.459182	1.444734	1.318219	1.582779
HFRS3	0.624247	0.070917	1.34E-18	0.4841	0.762158	1.866839	1.622714	2.142895
GENDER	-0.12884	0.041462	0.00188673	-0.21014	-0.0476	0.879111	0.810468	0.953516
age_group	0.362295	0.054046	2.03E-11	0.256603	0.4685	1.436623	1.292531	1.597595
age_group	1.037044	0.053181	1.09E-84	0.933188	1.141689	2.820866	2.542603	3.132053
TOT_GRP1	0.564803	0.085098	3.20E-11	0.400476	0.734259	1.759101	1.492535	2.083937
TOT_GRP2	1.044507	0.083863	1.32E-35	0.882748	1.211682	2.841996	2.417534	3.35913
TOT_GRP3	1.158443	0.090222	9.79E-38	0.98365	1.337519	3.18497	2.674199	3.809581
TOT_GRP4	1.167171	0.114705	2.55E-24	0.941949	1.391906	3.21289	2.564975	4.022509
TOT_GRP5	1.162495	0.205588	1.56E-08	0.74401	1.552334	3.197902	2.104358	4.72248
TOT_GRP6	1.331975	0.538697	0.01341385	0.107593	2.274038	3.78852	1.113594	9.718568
QABTIPPE	-0.01092	0.058783	0.85264546	-0.12636	0.104117	0.989141	0.8813	1.109731
QABTIPPE	-0.01206	0.05974	0.84005497	-0.12943	0.104801	0.988015	0.878598	1.11049
QABTIPPE	0.049805	0.062507	0.42557879	-0.07315	0.171933	1.051066	0.929462	1.187598
QABTIPPE	-0.08269	0.068595	0.22803496	-0.21803	0.050934	0.92064	0.804098	1.052254
hospcount	0.059657	0.010867	4.02E-08	0.038083	0.08073	1.061472	1.038818	1.084078
Family.Phy	-0.00766	0.006215	0.21775085	-0.0198	0.004559	0.992369	0.980391	1.00457

Appendix B: Demographic distribution of cohort

Cohort Characteristics by Frailty Level (HFRS)

	Frailty Level		
Characteristic	**Low-risk**	**Medium-risk**	**High-risk**
Overall			
Number of observations (%)	44,395 (76.9%)	10,788 (18.7%)	2,547 (4.4%)
Mean age (years)	76.2	80.5	82.0
Gender (within HFRS %)			
Female (%)	48.3%	54.3%	60.1%
Male (%)	51.7%	45.7%	39.9%
Age groups (within HFRS %)			
Age 65–74 years (%)	47.9%	28.7%	23.0%
Age 75–84 years (%)	35.6%	35.6%	34.4%
Age ≥85 years (%)	16.6%	35.7%	42.6%
Charlson Comorbidity Index (within HFRS %)			
CCI = 0 (%)	30.1%	10.6%	3.7%
CCI = 1 (%)	36.2%	31.7%	28.0%
CCI = 2 (%)	22.4%	31.9%	34.3%
CCI = 3 (%)	8.9%	18.0%	21.9%
CCI = 4 (%)	2.0%	6.5%	9.3%
CCI ≥5 (%)	0.4%	1.3%	2.7%

All percentages are column percentages (within HFRS group).

Curriculum Vitae

Candidate's Full Name: Jacques Al Alam

Universities Attended (with dates and degrees obtained):

Lebanese American University (BSc. In Bioinformatics, 2017-2021)

Publications: N/A

Conference Presentations: ResearchNB poster presentation November 2025