Modeling Heart Failure Predictive Mortality in Skilled Nursing Facilities

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MODELING HEART FAILURE PREDICTIVE MORTALITY IN SKILLED NURSING FACILITIES

by

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A Dissertation submitted to the Faculty of the Graduate School, Marquette University, in Partial fulfillment of the Requirements for the Degree of Doctor of Philosophy

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Problem: Approximately 25% of skilled nursing facility (SNF) patients are diagnosed with heart failure (HF). The heart failure mortality trajectory is non-linear and there are no useable mortality models from clinical records for use by healthcare providers in the SNF setting. A mortality risk model for patients with HF is important so that palliative care interventions may be offered to improve patients’ quality of life during the end stages of dying. Assessment items captured routinely by the SNF Resident Assessment Instrument – Minimum Data Set 3.0 (RAI-MDS) instrument may be useful in identifying those patients whose declining condition warrants discussion of palliative care.

Methodology: Data from 1827 eligible HF patient’s RAI-MDS assessments, who resided in Midwest SNFs during 2013-14, were investigated in a retrospective cross-sectional exploratory method. Discrete survival analysis and logistic regression were used to determine which factors predict mortality so as to allow future creation of a model to prompt palliative care discussions.

Results: Nine variables embedded in the RAI-MDS were selected based upon a literature review of HF mortality prediction models. Five of the nine variables demonstrated predictive hazard ratios (HR) in the SNF setting. These included re-admission after hospitalization (HR 1.323), reduced renal function (HR 1.187), presence of dyspnea (HR 1.285), age 85 and older (HR 1.828), and having three or more diagnoses (HR 1.345). Not predictive were having diagnoses of diabetes or hypertension, being sixty-five to eighty-four years of age, and gender.

Conclusions: The mortality predictors identified in this study may facilitate development of a HF mortality risk model specific to patients in SNFs. Such a model may be useful in making decisions regarding when to institute palliative care discussions with SNF patients and their families.
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Stephen Biondi

I am extremely grateful to have had the opportunity to continue to learn throughout my life and achieve a PhD in Nursing. Achieving this milestone was something that I had dreamed about for years. I am hopeful that having this increased knowledge and understanding of the nursing profession will allow me to continue to find ways to give back to my colleagues and advance the profession.

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Chapter 1: Introduction

Background and Significance

Heart failure is a chronic debilitating terminal illness that affects over 5.1 million people in the United States, or about 2.1% of the population (Go et al., 2014; Mozaffarian et al., 2015; Yancy et al., 2013). There are 650,000 new cases diagnosed each year with prevalence increasing as the population ages. Heart failure is one of the top leading causes of mortality with one in nine deaths directly attributed to heart failure (Go et al., 2014). As heart failure is a progressive terminal condition, it is imperative that the health care team discuss palliative care with this population during the course of their illness.

The Institute of Medicine defines palliative care as “providing relief from pain and other symptoms, supporting quality of life, and focused on patients with serious advanced illnesses and their families” (Institute of Medicine, 2014, p 2-12). Presently, there are no known models to predict heart failure mortality specific to the skilled nursing facility (SNF) setting. Therefore, the ability to promote palliative care in this setting is limited. Having a viable SNF predictive mortality risk model could foster that discussion and prompt the planning for improved quality of care at the end stages of life.

Heart failure (HF) is defined as a “complex clinical syndrome that results from any structural or functional impairment of ventricular filling or ejection of blood” (Yancy et al., 2013). The term heart failure presently is the preferred medical description for this syndrome over the more commonly used term congestive heart failure. As no single test can determine this diagnosis, it is a syndrome diagnosed from data obtained from a health
history, physical examination, and clinical testing. Classically, HF manifests with symptoms of dyspnea and fatigue (Yancy et al., 2013).

The syndrome of HF bifurcates into two main diagnostic components: a) patients with reduced ejection fraction (HFrEF) labelled systolic heart failure, and b) patients with preserved ejection fraction (HFpEF) labelled diastolic heart failure. Ejection fraction (EF) is the measure of blood ejected from the left ventricle with each heartbeat into the aorta to feed the circulatory system. The American Heart Association (AHA) defines 50-70% EF as normal range ejection volume (AHA, 2016).

Heart failure is preceded by many health conditions that cause the myocardium to stretch and thicken (hypertrophy). This reduced pumping capacity is evident in HFrEF with <40%EF which comprises about 50% of cases of heart failure (Owan et al., 2006). Borderline HF patients have EF’s between 40 and 50% and may have no symptomology. Left-sided HF is more common than right-sided failure and is usually present prior to both ventricles being affected (AHA, 2016).

**Heart Failure Mortality**

The lifetime risk for developing the syndrome is 20%, making HF a priority of the Centers for Medicare and Medicaid Services (CMS), the primary payer of care for this population (Djousse et al., 2009). By the year 2050, one in five Americans over 65 years old will have HF (Yancy et al., 2013). Incidence for those between the ages of 65 to 69 is 20 cases per 1000 individuals compared to greater than 80 cases per 1000 for individuals greater than 85 years old (Curtis et al., 2008). From the Medicare population database (65 years old and greater and those on Social Security disability), the incidence of HF has
increased from 90 to 121 cases per 1000 individuals for the ten years preceding 2003 (Curtis et al., 2008).

Survival after diagnosis of HF has improved due to enhanced clinical interventions and medical technology. Absolute survival from time of diagnosis remains steady with approximately 50% dying within 5 years (Alter et al., 2012; Yancy et al., 2013). Those less than 50 years old had a longer life span (18.17 years +/- 6.99 years) compared to the octogenarian males that lived an average of 2.9 years (Atler et al, 2012). Pressler (2011) cited data from Get-With-The Guidelines – HF (an American Heart Association initiative) noting one-year post hospitalization skilled nursing facility (SNF) mortality was 53.5% compared to 29% for home bound discharges, reflecting greater frailty in the SNF care setting.

Heart failure is the primary Medicare hospital diagnosis in the United States representing greater than 1 million admissions annually (Allen et al., 2011; Yancy et al., 2013). Patients admitted with HF have a 30-day readmission rate of 25% for all cause re-hospitalization despite significant interventions to minimize that recidivism (Eapen et al., 2013; Feltner et al., 2014; Yancy et al., 2013). Furthermore, nearly 10% of the HF patients admitted to the hospital died within 30 days of admission (Eapen et al., 2013). Repeat hospitalization is common with 83% hospitalized at least once per year and 43% at least 4 times per year (Yancy et al., 2013) making heart failure one of the costliest diagnoses to the Medicare program. Charges to Medicare and Medicaid programs account for about $30 billion annually (Yancy et al., 2013). The yearly mean cost/patient of hospitalization is $23,077 and can be higher when HF is the secondary diagnosis.
Palliative care has been shown to reduce hospitalization and improve the health-related quality of life for heart failure patients (Zuckerman et al., 2016).

Zuckerman et al. (2016) identified that hospitalization length of stay for hospice patients was less (generally 1-5 days overall) and spending was $900-$5000 less when hospice was utilized. Medicare funded hospice is an approach to providing palliative care to those who have a terminal condition and a life expectancy of less than six months (CMS, 2016). It is reimbursed by Medicare and in some states, by Medicaid. Hospice care can be provided in SNFs, in a patient’s home, or in a designated hospice facility.

Palliative care is the holistic integration of symptom management that includes discussion and planning with the patient and their family. It may include curative care that can benefit the patient and family if expected to improve their quality of life (Hupcey et al., 2009). Thus, having a heart failure predictive mortality model available for HF patients in SNF’s has the potential to improve the quality of life for the frailest of the frail.

Because HF is a terminal condition, patient discussions about end of life preferences with their providers should occur early upon establishing a HF diagnosis (Hupcey et al., 2009; Whellan et al., 2014). Palliative care discussions should focus on the options and benefits of palliative care with the intent of identifying patient and family’s preferences to achieve the optimal quality of life for their remaining lifespan (IOM, 2014). Hupcey et al. (2009) identified in their systematic review of literature that patients with this diagnosis are not receiving palliative care, even at the end of life.
The Skilled Nursing Facility Heart Failure Patient

CMS defines skilled nursing facilities (SNFs) as centers that furnish short-term nursing and rehabilitation and long-term residential nursing care to their beneficiaries (CMS, 2016). These facilities provide care to those who are not able to be cared for at home or in another community-based setting. Medicare services in SNFs generally include skilled nursing care, medical care, and related services including rehabilitation for admissions caused by injury, disability, or illness. Medicaid services are identical to Medicare except rehabilitation is not generally provided. Care for all SNF patients is based upon a regulatory mandated Resident Assessment Instrument-Minimum Data Set 3.0 (RAI-MDS 3.0).

Today, there are 15,655 SNFs in the country providing care funded by Medicare, Medicaid, managed care, private insurers, Accountable Care Organization (ACO) networks, and private funding sources (American Health Care Association, 2020). Approximately 2.3 million patients were cared for in this setting in 2014 (Medpac, 2016). In fiscal year 2014, CMS provided coverage to 1.7 million fee for service (FFS) beneficiaries in SNFs with total costs at $28.6 billion (Medpac, 2016). These patients have multiple comorbidities and generate substantial costs to the Medicare program. These beneficiaries are older, frailer, predominantly female, disabled, and often dually eligible for Medicare and Medicaid payment (Medpac, 2016).

Approximately 24% of hospitalized HF patients are discharged to a SNF (Jung et al., 2012; Jurgens et al., 2015). The remaining 22.3% are referred to home health care and 53.6% to self-care at home (Allen et al., 2011). HF diagnosis is highly prevalent in SNFs with estimates of between 20% and 37.5% (Jurgens et al., 2015). For those admitted to a
SNF, repeat hospitalization is common with 83% re-hospitalized at least once per year and 43% at least four times each year (Heidenreich et al., 2011).

**Palliative Care in the Skilled Nursing Facility**

HF patients in SNFs have a 76% greater risk of 5 year mortality compared to those discharged home due to the presence of multiple comorbidities and their frailty (Allen et al., 2011). Jurgens et al. (2015) identified that 53.3% of SNF patients with heart failure die within one year of admission. Therefore, advance directives and palliative care planning for this population is essential for proving quality end of life care (Leclerc et al., 2014). Despite significant advances in the development of mortality prediction models for HF, little progress has been made in implementing these models in SNFs (Jurgens et al., 2015). While the Palliative Performance Scale is widely used in the hospice setting, the data directly obtained from the SNF assessment instrument does not correlate with this scale.

It is essential that clinicians discuss with patients and their families palliative care versus curative interventions in the SNF setting to improve understanding of patient and family’s wishes for quality at the end of life (Allen et al., 2011). Hospitalizations decrease as the needs and wishes of the HF patient are honored through palliative versus curative interventions. Butler et al. (2015) found that less than 20% of hospitalized heart failure patients have an advance directive (an indication of planning for end of life). Of these, less than 2.5% of HF patients are discharged to hospice for palliative care, a clear indication of the need for discussion regarding palliative and end of life care with this terminally ill population (Butler et al., 2015). Providing hospice and palliative care interventions improves quality of life through symptom and pain management using a
holistic multidisciplinary approach. This approach is best used throughout the course of caring for patients with any terminal illness (Whellan et al., 2012).

**Heart Failure Mortality Risk Models**

Despite significant advances in the treatment of HF in recent years, it is still uncommon for practitioners in any health care setting to discuss eventual mortality or palliative care with this population (Hupcey et al., 2009). Heart failure survival and mortality risk is widely discussed in current literature. However, existing mortality risk instruments/models are not easily implemented in the SNF setting due to limited availability of clinical data required in these models. In fact, most risk instruments are not easily implemented in the hospital setting for the same reason (Rahimi et al., 2014). The development of a SNF HF mortality risk model using data available in the SNF would facilitate palliative care planning with this population.

**The SNF Minimum Data Set Assessment Instrument (RAI-MDS 3.0)**

In 1990, CMS developed a universal assessment instrument titled the Resident Assessment Instrument-Minimum Data Set Centers for Medicare and Medicaid Services (2008). The intent was to standardize the data collected upon admission and throughout the patient’s stay in the SNF. This assessment instrument has been regularly updated and is currently in version 3.0. The RAI-MDS 3.0 must be completed by day five after admission, day 14, day 30, and then quarterly with an annual comprehensive assessment update. These assessment dates vary for type of admission but generally follow the preceding sequence. If the patient has a significant change in condition, as defined by the CMS RAI-MDS user’s manual, the assessment is updated and submitted to CMS for
notification of status change. The RAI-MDS 3.0 is completed on all patients regardless of payment source. It is also completed at time of death or discharge reflecting the end of the assessment cycle. This lengthy 40-page standardized assessment instrument provides a rich database to potentially identify mortality risk for HF patients in SNFs. Pocock et al. (2013) identified that many factors are present on this instrument that may be useful in mortality prognostication in this setting.

**Purpose and Aims of this Study**

The purpose of this study was to determine the predictive risk of mortality associated with variables linked to heart failure that are routinely assessed using the RAI-MDS. Knowledge of the mortality risk for patients with heart failure could be used to develop a model that improves care and quality of life for terminally-ill heart failure patients residing in SNFs.

In the literature, there are at least 117 HF mortality risk models and 249 predictive variables (Ouwerkerk et al., 2014; Rahimi et al., 2014). Presently, there are no known valid and reliable HF mortality risk instruments relevant to the SNF using data in the RAI-MDS 3.0 assessment tool. Creating a predictive model utilizing existing assessment data would facilitate adoption of palliative care practices in SNFs for the patient whose life expectancy is severely limited. Therefore, the specific aim of this study was: To determine which RAI-MDS 3.0 variables statistically predict heart failure mortality based on the domains of demographics, symptomology, diagnoses, and hospitalizations.
Significance to Nursing

The nursing profession, as defined by the American Nurses Association, is dedicated to “the protection, promotion, and optimization of health and abilities, prevention of illness and injury, facilitation of healing, alleviation of suffering through the diagnosis and treatment of human response, and advocacy in the care of individuals, families, groups, communities, and populations” (American Nurses Association, 2015). Registered nurses (RNs) identify and plan the care of patients in the SNF setting as required by CMS regulations (CMS, 2016). This is accomplished through interdisciplinary collaboration with the attending physician and other disciplines involved in the patient’s care. The Omnibus Budget Reconciliation (OBRA) Act of 1987 specifically states that each resident (patient) must “achieve the highest practicable physical, mental, and psychosocial well-being” (OBRA, 1987). Interpretation of this statutory requirement implies that care must be provided to meet the resident/patient’s needs and provide for optimum quality of life (OBRA, 1987).

Presently, CMS, the federal regulatory agency, has not specified palliative care assessment nor created a model using the RAI-MDS 3.0 assessment to prompt palliative care discussion. A mortality risk tool that identifies those HF patients who are nearing their end of life would provide a structured mechanism to implement palliative care interventions and improve patient quality of life.
Significance to Patients and Their Families

Implementation of a heart failure mortality risk tool has tremendous potential to positively affect the quality of life for the terminally ill HF patient and their family. Such a tool would facilitate engagement of the patient and their family in making personalized choices about their care and future. This has been emphasized in the 2016 CMS skilled nursing facility regulations requiring resident/patient centered care planning (CMS, 2016). Creation of a mortality risk model using identified RAI-MDS 3.0 factors would facilitate holistic systematic palliative care planning by nurses in the SNF care setting and provide opportunities to improve patient and family quality of life and care.

Summary

The prevalence of heart failure in the United States is significant and growing (Vigen et al., 2013). In the SNF care setting, HF accounts for approximately 25% or more of the patient population. HF is a terminal condition and patients can benefit from palliative care to improve quality of life at end of life. Limited tools or systematic approaches are available in the SNF care setting to guide nurses in identifying those HF patients nearing end of life. Creation of a heart failure mortality predictive risk model based on data from the RAI-MDS 3.0 assessment instrument is a viable approach to identifying terminally ill patients and improving quality care at end of life.
CHAPTER II: REVIEW OF THE LITERATURE

Philosophical Underpinnings and Conceptual Framework

The purpose of this research study was to identify variables in the RAI-MDS assessment tool that could be used to develop a mortality risk model for HF patients residing in SNFs. Such a model could ultimately be used to improve the patient’s quality of life. The purpose of conducting nursing research is to generate, test, and find applications of theoretical or conceptual approaches that will produce a benefit for the overall population (Fawcett, 1999). It is a systematic process that is formal, rigorous, and tests concepts and propositions with the goal of contributing to new nursing knowledge.

From an epistemological perspective, the positivist approach is warranted in this study as the researcher is seeking new knowledge pertaining to quantitative data contained within the RAI-MDS 3.0 instrument. Positivism uses observable data, and therefore, its end product can be generalized (Remenyi et al., 1998), which is the desired outcome of this study. Positivism uses objective reality and attempts to hold the researcher’s personal biases in check in the process of evaluating the phenomena (Polit & Beck, 2008). This approach allows the researcher to test the phenomena that is being studied to discover relationships about the studied data (Polit & Beck, 2008). One key component of positivism is the value-free nature in the way the research is undertaken. As this study utilizes tangible data from an existing instrument that is valid and reliable, and these data were collected by registered nurses not associated with the researcher, the potential for biasing the data is limited.
The Conceptual Model

This research study aimed to analyze the RAI-MDS 3.0 patient data and identify variables that predict heart failure mortality in a subgroup of skilled nursing facility patients. This study is framed in a conceptual model that drives quality improvement of care and services. “A conceptual model is a set of abstract and general components and propositions that integrate into a meaningful configuration: synonymous with conceptual framework, conceptual system, paradigm, and disciplinary matrix (Fawcett, 1997, p13-14)”. The conceptual framework for this study is Donabedian’s Quality of Medical Care Model, which provides a framework to examine health care services and the quality of care that those services provide. Donabedian (2005) developed this model for evaluating and improving the quality of health care including systems of care delivery.

The Donabedian Quality of Medical Care model includes three components. The first component is described as structure or the setting in which care is provided that includes such elements as adequacy of the facility, staffing, qualifications of staff, and equipment. The second component that is necessary in this approach is processes of care, which are the mechanisms by which care is delivered to the patient. These processes include how care is systematically provided, what is done by each care participant, and the underlying supportive process to assure consistency. Care providers rely on the organization’s structural and systems framework to produce the desired quality result. The last component of Donabedian’s model is outcomes, defined as the relevant measure of the success of the systematic approach and identifies the expected result (Donabedian, 2005).
The Agency for Healthcare Research and Quality publication “Closing the Quality Gap: A Critical Analysis of Quality Improvement Systems” (McDonald et al., 2007) exemplifies the application of the Donabedian model. It demonstrates that the underlying framework of a quality improvement focus is on systems of care to drive quality outcomes. The agency’s approach applying the Donabedian model is further supported by the Andersen Behavior Framework (McDonald et al., 2007). This study utilizes a combined approach at the system level of quality improvement within an organization and the desired behavior of nurses in applying the risk model with their patients.

Utilizing Donabedian’s conceptual model, *structure* in this research study is exemplified by the clinical setting in which care is provided; the SNF facility. This includes the physical environment, the staff involved in delivering care, and the patients who receive that care. The *process* in this study is the analysis of key health status indicators provided in the RAI-MDS 3.0 assessment instrument that are utilized across all SNF settings. This is the extracting of identified RAI-MDS 3.0 variables within the context of a HF mortality risk model. The *outcome* in this study was directed towards improved quality of life at end of life for heart failure patients by having a HF risk mortality model. Figure 1 reflects the conceptual empirical structure of this research study within the framework of Donabedian’s model of quality of medical care (Donabedian, 2005).
Moorhouse, Mallery, and Kolcaba are clinical theorists who frame the logic in this research study and support the need to develop a heart failure mortality risk model. Each of their philosophies embody the perspective that care should be rendered to patients within the framework of comfort and harmonization of their wishes.

Moorhouse and Mallery (2012) developed a model entitled “Palliative and Therapeutic Harmonization (PATH)”. PATH was developed based on initially evaluating frailty among the elderly. This model takes into account patient and family preferences for ethical consideration evaluating whether care at end of life should indiscriminately provide aggressive curative treatment or foster discussion around palliative care in the decision-making process (Mallery and Moorhouse, 2011). Moorhouse and Mallery (2011) consider the ethical responsibility of respecting that patients want and deserve valid, honest, and forthright information about their prognosis. These authors purport that
the best health care decisions are made when full consideration is given to the risks and
benefits of treatment and the empowerment of patients and families in the decision-
making process.

Moorhouse and Mallery (2012) refined their ethical model and developed a
PATH model for long term care with the intent of improving quality of geriatric care.
They recognized that frailty was a key predictor in the elderly that created additional
vulnerability for the patient and family. The model notes that frail elderly are faced with
multiple comorbidities, subject to poor outcomes, and unfavorable responses to
traditional medical treatment. The researchers identified that: (a) there was a lack of a
systematic approach in addressing the patient’s care needs in the context of comorbid
conditions, (b) they needed to find a way to communicate sound information to the
patient and family, and c) to empower these patients and families to determine their care
and fate (Moorhouse and Mallery, 2012).

The PATH model determines frailty utilizing the Clinical Measure of Fitness and
Frailty Scale (Rockwood et al., 2005). This is in combination with a comprehensive
geriatric assessment, the first step in the process is gaining an understanding of the
patient’s health status and disease trajectory. This assessment includes major
comorbidities, functional status, social isolation or inclusion, mobility, cognitive status,
and their degree of frailty. With this comprehensive understanding of the patient’s status,
the next step in the PATH model is to communicate pertinent information in a semi-
structured manner to ensure that the patient and family have a comprehensive
understanding of their status and options (Moorhouse and Mallery, 2012).
The last step in the PATH model is the *empowerment* stage. Clinical practitioners discuss the foreseeable future with the patient and family and encourage their empowerment to make health care decisions for their future. The key component of these three steps in the model is communication with the patient and family about their decisions at each encounter and transferring that information to all care providers. This last component is essential in the ability of the health care team to develop and implement a care plan that is reflective of the wishes of each patient and their family (Moorhouse and Mallery, 2012). This model is aligned with the goals of this study in empowering the nurse and health care team to have open and honest discussions about a patient’s future.

Moorhouse and Mallery (2012) describe current end of life for frail adults as: (a) complex with comorbidities that are not always treated with evidence based medicine, sometimes leading to avoidance of the discussion of prognosis, (b) having limited awareness of the patient’s frailty, (c) having a lack of attention to the terminal condition, (d) the potential and usual withholding of comfort measures including pain management, (e) futile treatment being continued, and, (f) insensitivity to the needs of the patient and family.

The PATH model is a theoretical and practical framework for holistically addressing patient frailty and the appropriateness of a care plan for each patient based upon comprehensive assessment, effective and realistic communication, and lastly, patient empowerment to make sound decisions that are right for each patient. This provides a standardized approach to include the heart failure patient and family in the
decision-making process at end of life applied in this study model within the conceptual framework of Donabedian’s model for quality of care.

Katherine Kolcaba, a middle range nursing theorist, espoused a vision for holistic health care addressing comfort. Kolcaba (2003) describes her Theory of Comfort as patient centered, important to the patient and their health, and lastly, important to the viability of the care institutions where comfort should be a major driver in care delivery. From an ethical perspective, comfort care provides beneficence for the patient and allows nurses’ autonomy in addressing each patient’s needs. Her theoretical model also frames this study as the purpose of palliative care is to provide comfort and quality of life to the dying patient. The foregoing theorists provided great insight and guidance to this study and frame the rationale for the study.

**Literature Review**

As there is a plethora of literature on models to predict either HF survival or mortality risk, the literature review focused on the most relevant research studies applying mortality risk models to heart failure patients. However, none of the literature reviewed identified a model that could be readily utilized in the SNF setting. The search for this study was initiated beginning with the year 2000 until present to identify current HF mortality prediction models. The following key words were used to search for articles in CINAHL and PubMed databases: end stage heart failure, mortality risk, heart failure models, and palliative care. Key words were truncated where appropriate to explore all related possible articles. Abstracts of articles were reviewed for relevance and appropriate articles were obtained for review.
Review of key clinical practice guidelines from the American College of Cardiology Foundation in partnership with the American Heart Association (Yancy et al., 2013) were also included as these are updated every five years and provide evidence-based practice guidelines (AHA/ACCF, 2013) for the care of the heart failure population across all disciplines. Additional references from these guidelines were reviewed so as to provide pertinent concepts, facts, and additional relevant evidence.

*Heart Failure Risk Factors Identified*

The overarching purpose of this literature review was to identify HF mortality risk models and their predictive factors within the domains of demographic characteristics, symptomology, and comorbidities. Heart failure is a syndrome of many different and yet related risk factors and diagnoses that affect the optimum functionality of the heart and survival of the patient. As heart failure develops and evolves over time, it is essential to evaluate the etiology of this syndrome from disease precursors and other known comorbid diagnoses identified in the AHA/ACCF (Yancy et al., 2013) guideline and related literature.

*Hypertension*

Elevation of both systolic and diastolic blood pressure (BP), particularly untreated hypertension, are major etiologic risk factors for the development of HF (Yancy et al., 2013). While 82% of patients with hypertension are aware of the risks that their diagnosis has on mortality, only 75% are using prescribed antihypertensive agents, and 25% are not being treated for this diagnosis known to lead to HF. Only 53% of these patients diagnosed with hypertension are considered to be controlled to target normotensive
guidelines (Baker, 2002) which reduces their risk of HF. Effective BP treatment can influence and significantly reduce the potential to develop HF by about 50% (Baker, 2002). Those diagnosed with hypertension have a significantly greater chance of developing HF than those with normotensive blood pressure (Baker, 2002).

**Diabetes Mellitus**

Diabetes mellitus (DM), an etiologic risk factor causing microvascular damage, greatly impacts the progression of HF and the mortality of those diagnosed with the HF syndrome (Shindler et al., 1996). DM increases the propensity of developing HF even for those patients who do not have previous cardiac issues (Krumholz et al., 2000). Clinically, the heart of a patient with diabetes will show cardiac hypertrophy, dilation, and depressed vascular performance, all evidence of heart failure. These changes are accelerated in the presence of hypertension (Frustaci et al., 2000; Nasir & Aguilar, 2012).

**Obesity**

Obesity is also a significant etiological risk factor for HF. Increased body mass is associated with increased risk of heart failure (Kenchaiah et al., 2002). Compared to those with ideal body mass, those who were obese had double the potential for heart failure. In the United States, 154.7 million adults are overweight or obese representing 68.2% of the population with 35% being defined as obese (Go el al., 2014).
**Atherosclerotic Heart Disease**

The last major etiologic risk factor identified by the 2013 American College of Cardiology Foundation/ American Heart Association clinical guideline for the management of heart failure is atherosclerotic heart disease. Patients with atherosclerotic disease are more likely to develop HF (Yancy et al., 2013).

**Other Etiological Risk Factors**

Other HF risk factors identified in the AHA/ACCF guidelines that may or may not be listed on the RAI-MDS 3.0 are noted here and will not be expanded upon in this manuscript. Etiology of heart failure includes: (a) dilated cardiomyopathy, (b) familial cardiomyopathy, (c) endocrine and metabolic cardiomyopathy, (d) diabetic cardiomyopathy, (e) thyroid disease, (f) acromegaly, (g) toxic cardiomyopathy, (h) cocaine cardiomyopathy, (i) cardiotoxicity related to cancer treatments, (j) myocarditis, (k) AIDS, (l) Chagas disease, (m) hypersensitivity myocarditis, (n) rheumatological and connective tissue disorders, (o) amyloidosis, (p) cardiac sarcoidosis, and (q) Takotsubo, or stress related cardiomyopathy (Yancy et al., 2013).

**Frailty**

Frailty is defined as the compromised ability to cope with physiological stress and is common in the SNF patient (Jurgens et al., 2015). While comorbidity is not the same as frailty, two or more comorbid conditions creates a risk factor for frailty (Jurgens et al., 2015). One of those indicators of frailty for the HF patient is determined by using the New York Heart Association (NYHA, 2017) classification system. Heart failure functional capacity classification is based upon the New York Heart Association
functional limitation model (NYHA, 2017). This classification system evaluates functional capacity relative to symptom severity. Class one (I) indicates minimal to moderate limitation of functional capacity and activities, with class four (IV) indicating very limited exertion causing functional impairment and limited quality of life. Those HF patients classified as NYHA III –IV are impacted the most and those at class IV have limited ADL function and have poor health-related quality of life.

**Comorbid Diagnoses**

Murad et al. (2015) evaluated the burden of comorbidities relative to functional and cognitive impairment in patients initially diagnosed with heart failure and assessed the impact of these on mortality. Using data from the Cardiovascular Health Study (CHS), a population based longitudinal study evaluating various factors in adults over 65 years old with cardiovascular disease funded by the National Institute of Health, the authors examined the prevalence of nine comorbidities and four functional and cognitive impairments in 5888 subjects who developed HF between 1990 and 2002. The HF sample was extracted from 5,888 study participants (patients) from four counties. The participants were evaluated prospectively until mid-2008. The mean age at the time of HF diagnosis was 79.2 +/- 6.3 years and approximately half were male. Sixty percent of these patients had three or more comorbidities and only 2.5% had none. Seventeen percent had cognitive impairment. The mortality rate for the 504 subjects who died within one, four, and ten years were respectively 19%, 56%, and 83%. The median survival was 4.3 years. Using a multivariate adjusted model, the following diagnoses had the greatest mortality risk: (a) diabetes [HR 1.64, 95% CI: 1.33- 2.03], (b) chronic kidney disease [HR 1.32, 95% CI:1.07-1.62], (c) moderate kidney disease [HR 3.00, 95% CI:1.82-4.95], (d)
cardiovascular disease [HR 1.53, 95% CI: 1.22-1.92], (e) depression [HR 1.44, 95% CI: 1.09-1.90], (f) functional impairment of 1 IADL [HR 1.30, 95% CI: 1.04-1.63], (g) 2 or more IADL impairments [HR 1.49, 95% CI: 1.07-2.04], and (h) cognitive impairment [HR 1.33, 95% CI: 1.02-1.73]. Other comorbidities not associated with mortality in this study were hypertension, coronary artery disease, peripheral arterial disease, atrial fibrillation, obstructive pulmonary disease, and functional impairments. The authors concluded that elderly HF patients often have a high burden of comorbidities with functional and cognitive impairments that are associated with greater mortality risk.

Saczynski et al. (2013) studied the effects of comorbidities on mortality in 23,435 individuals diagnosed with heart failure using data from the National Heart, Lung, and Blood Institute sponsored Cardiovascular Research Network PRESERVE study, a large multicenter community-based study. The authors compared predictors and outcomes in both HFpEF and HFrEF patients. The Charlson/Deyo Comorbidity Index, which weights the sum of medical conditions (higher scores indicate more comorbidity), was used.

In this study, 53% of the sample had preserved EF, of which, 60% were female. Three quarters of the sample had three or more comorbid conditions and half had five or more. Common comorbidities included hypertension and dyslipidemia occurring in more than a quarter of the sample. Those with HFpEF had a slightly higher comorbid status of 4.5 versus 4.4 for HFrEF (P=.002). The authors determined that there was a high degree of comorbidity in both the HFpEF and HFrEF subgroups. The burden and pattern of comorbidity varied only slightly between the two groups.
**Advanced Heart Failure**

The European Society of Cardiology (Metra et al., 2007) definition of advanced HF is severe functional impairment (NYHA III-IV). Risk factors for advanced heart failure include: (a) dyspnea and/or fatigue at rest or with minimal exertion, (b) episodes of fluid retention, (c) objective evidence of severe cardiac dysfunction by at least one of the following (LVEF < 30%, mitral inflow pattern disruption, pulmonary capillary wedge pressure of > 16 Hg or RAP of > 12mm Hg by pulmonary artery catheterization, or high BNP plasma levels in the absence of non-cardiac causes, (d) severe impairment of functional capacity, (e) history of hospitalization in the past 6 months, and (f), the presence of all of the previous features in spite of attempts to optimize therapy and care (Metra et al., 2007).

Other clinical events that predispose a patient to being in the advanced stages of HF are: (a) greater than 2 hospitalizations or emergency department visits for HF symptoms in the past year, (b) progressive deterioration of renal function, (c) weight loss without other occurring causes, (d) intolerance to ACE inhibitors, (e) intolerance to beta blockers, (f) frequent systolic blood pressure of < 90 mm Hg, (g) persistent dyspnea with dressing or bathing needing rest, (h) inability to walk one block due to dyspnea, (i) recent need to escalate diuretics, (j) progressive decline in serum sodium, and, (k) frequent ICD shocks when devices were present (Yancy et al., 2013). These patients are terminal and are likely to die of sudden death and have extremely limited quality of life.
Mortality and Hospitalization

Foebel et al. (2013) studied mortality and hospitalization in the SNF population using data from the GOLD-HF (Geriatric Outcomes and Longitudinal Decline in Heart Failure) Study. They followed 546 patients admitted to SNFs for up to one year. Using multivariate regression modeling and Cox proportional hazards regression, they determined the time to mortality predictors. Mortality overall was 42% for HF patients and 31% were hospitalized within that year. Interestingly, the major predictor of greater mortality was use of tranquilizers. Peripheral vascular disease was the strongest predictor of hospitalization. While this study was performed using data from SNFs, it did not produce a HF mortality risk assessment tool that could easily be applied in SNF setting using existing clinical assessment data.

Age

Pocock et al. (2013) conducted a meta-analysis that included data from 39,372 subjects and found that one of the strongest predictors of mortality in HF patients is age. Jurgens et al. (2015) identified that as individuals age, the number of comorbid conditions increase, increasing the risk of mortality in those with heart failure. Rahimi et al. (2014) evaluated risk factors across 43 models predicting HF and identified that strong predictors of mortality included age and gender. Clearly, as individuals age, the risk of increased comorbidity, frailty, and other heart failure factors increases the likelihood of mortality in this population.


**Gender**

Klempfner et al. (2014) evaluated the effect of gender related to HF. The study showed that women [HR 1.16, 95% CI: 0.96-1.41, P = 0.13] tended towards an increased risk for early mortality versus men [HR 1.25, 95% CI: 1.09-1.43, P = 0.001]. Conversely, Chyu et al. (2013) evaluated four specific variables in modeling heart failure risk in men and women. Their study revealed that women had better survival than men at the one-year endpoint and had higher event free survival for all-cause mortality than men. As noted from the two preceding studies, it is equivocal whether gender is influential in predicting HF mortality.

**Risk Factor Conclusions**

In summary, variables described in aforementioned heart failure mortality risk models informed the variables selected for this study. Only those variables that are available on the RAI-MDS 3.0 instrument and those known to be predictive from the literature review were evaluated in this research study. While functional decline is utilized in some of the mortality risk models, all patients in this study had limited functionality, which required them to be placed in a SNF. Therefore, functional decline was not evaluated as part of this study since it is an underlying characteristic of the study population.

**Heart Failure Risk Models Compared and Contrasted**

Levy and Anand (2014) evaluated the value and benefits of heart failure mortality prediction models. Model validation is important both for discriminatory value and calibration with another cohort. This is significant in that factors such as ethnicity,
genetics, and lifestyle may limit the accuracy of risk scores across populations. For example, in the Framingham study, the risk score for Asian patients was raised/inflated due to cultural differences (Levy & Anand, 2014).

Levy et al. (2006) developed the Seattle Heart Failure Model (SHFM), the most widely known HF prediction model. The multivariate model predicts 1, 2, and 3-year survival of heart failure patients. The SHFM used data from 1,125 patients from the Prospective Randomized Amlodipine Survival Evaluation (PRAISE study) that was analyzed using Cox multivariate statistical methodology. This model was then validated prospectively in a sample of 9,942 patients from five other randomized controlled studies that included 17,307-person years. The strength of this model is the ability to add or delete medications and devices to observe the treatment effect using a calculator that can be loaded for free onto any computer or tablet. While this model is considered excellent and one of the easiest to use, the variables included in this model are not easily obtained in the SNF setting, such as biomarkers or diagnostic tests, and are not “captured” on the RAI-MDS 3.0 instrument. Capturing data from the RAI-MDS is part of the process whereby a date is selected and nurses finalize the assessment, thereby “capturing” or collecting a “snapshot” of assessment data that describes that patient at that one point in time. Further, the intent of this proposed study was to determine relevant mortality risk variables contained in the RAI-MDS instrument that does not require additional data capture or model input when used in a future predictive model.

Ouwerkerk et al. (2014) performed a systematic review of existing HF prediction models extracting the corresponding patient characteristics that have been used to predict HF mortality outcomes, or hospital readmission. Studies were included only if the results
reported C statistics or receiver operating curve values. In their analysis, they identified 117 HF mortality risk models in 55 papers reviewed. The models had a total of 249 different variables. The best mortality predictors were a patient’s serum blood urea nitrogen level (BUN) and serum sodium level. Mortality predictability was enhanced when using many clinical variables. Their mean C statistic for mortality was 0.68 +/-

value of chronic versus the acute heart failure in these models.

Pocock et al. (2013) conducted a meta-analysis using heart failure mortality risk studies with the aim of creating a generalizable mortality risk score for HF patients. The Meta-Analysis Global Group in Chronic Heart Failure (MAGGIC) data provided an opportunity for this research team to create an analysis that included data on 39,372 patients having both HFrEF and HFpEF from 30 different cohort studies. Six clinical trials comprised 75.8% of the sample and included the DIAMOND (Distensibility Improvement and Remodeling in Diastolic Heart Failure) study, DIG (Digitalis Investigation Group) study, CHARM (Candesartan in Heart Failure Assessment in Reduction) study, and ECHOS (Echocardiography and Heart Outcome Study) and In-CHF and HOLA registries. Methods were deployed to adjusted to account for missing data. Pocock et al. (2013) found that 42% of the patients died within the median follow up of 2.5 years.

In this meta-analysis, Pocock et al. (2013) performed a multivariate piecewise Poisson regression using time of death from any cause, and forward stepwise regression for variable selection using p < 0.01 to identify 13 highly significant independent predictors of mortality in this population. These include in order of predictive strength: (a) age, (b) lower EF, (c) NYHA class, (d) serum creatinine, (e) diabetes, (f) no
prescribed beta-blocker, (g) lower systolic blood pressure, (h) lower body mass, (i) time since diagnosis, (j) current smoker, (k) COPD, (l) male gender, and, (m) no prescribed ACE-inhibitor or angiotensin-receptor blocker. While age was most predictive in HFpEF, systolic blood pressure was less predictive in HFrEF. The Poisson model predictor was converted into an easy to use integer risk score with zero being lowest possible risk and 50 being the highest risk producing 3-year mortality rates of 10% bottom decile and 70% top decile. Risk was predicted using this tool for 1 and 3-year survival/mortality.

Rahimi et al. (2014) performed a systematic literature review and analysis of risk prevention models for HF patients attempting to identify the most consistently reported variables across models. This study gathered articles from MEDLINE and EMBASE for the period between January 1995 and March of 2013, yielding 2,678 abstracts with additional hand searches identifying other relevant studies. Eligibility for inclusion required that the published report have at least one multivariate model that predicted either death, hospitalization, or both in HF patients. However, none of these studies were conducted in the SNF population. Sixty-four models with 50 modifications were obtained and ranked from 48 studies that met this criterion. Forty-three models predicted death, ten predicted hospitalization, and eleven predicted death or hospitalization. Rahimi et al. (2014) observed wide variation in the study methodologies and settings, population characteristics, sample sizes, and variables included in the studies. Variables included diagnoses, psychological factors, and biomarkers (some captured from medical records, and others from administrative databases). A few strong risk predictor variables emerged from comparative analysis of risk assessment tools. These include: (a) age, (b) renal function, (c) blood pressure, (d) blood sodium levels, (e) left ventricular ejection fraction,
(f) sex, (g) brain natriuretic peptide level (BNP), (h) NYHA classification, (i) diabetes, (j) weight or BMI, and, (k) exercise capacity. Rahimi et al. (2014) concluded that development of automated systems to obtain risk variables and analyze them would help to facilitate user application and foster communication with patients and families regarding their risks.

Using the Seattle Heart Failure Model (SHFM), Fink et al. (2012) prospectively evaluated the impact of fatigue and depressive symptoms, along with immune biomarkers, relative to prognosis. The study included 59 patients with HFrEF that were attending outpatient clinics in the Midwest under the care of a cardiologist. The data suggest that fatigue (measured on the NYHA classification) with a covariate of depressive symptoms was positively associated with the SHFM score. Further, fatigue and depressive symptoms were important covariates in predicting poorer prognosis in the HFrEF population.

Chyu et al. (2013) developed a four-variable risk model to predict mortality for heart failure patients. A sample of 2,255 HF patients were stratified by sex into both derivation and validation cohorts. The initial analysis consisted of 39 variables that were mainly non-invasive scores. Cox regression methodology was utilized to determine key variables predictive of either death/urgent transplant/or left ventricular assist device (LVAD) augmentation. The survival rate for the overall sample was 83.5%, 69.9%, and 58.4% for years 1, 3, and 5 respectively. Despite some differences in the baseline data, the four strongest predictors of mortality were: (a) B-type natriuretic peptide, (b) peak oxygen consumption during cardiopulmonary exercise testing, (c) NYHA class, and (d) the use of Angiotensin Converting Enzyme-Inhibitors (ACE-I) or Angiotensin Receptor
Blockers (ARBs). The four-variable model was then converted into a point-based risk score. The C index was 0.79 for the Heart Failure Survival Score compared to the Seattle Heart Failure Model (SHFM) C index of 0.76. Both these scores indicate a good model.

Betihavas et al. (2015) evaluated absolute risk prediction to determine unplanned cardiovascular readmissions for adult HF patients. The study included 280 subjects in a prospective multiple center randomized controlled trial comparing home versus clinic-based interventions. Cox proportional hazards statistical modeling was employed to account for the competing risk of death. Results indicated that 13% were readmitted to the hospital within 28 days and 53% within 18 months. It should be noted that this study included home based subjects who were not considered overtly frail or in need of SNF care. This particular model had a C statistic of 0.80 with the following results: (a) age [HR 1.07, 95% CI: 0.90-1.26] for each 10-year increase in age, (b) living alone [HR 1.09, 95% CI: 0.74-1.59], (c) living a sedentary lifestyle [HR 1.44, 95% CI: 0.92-2.25], and (d) the presence of multiple (5 or more) comorbidities [HR 1.69, 95% CI: 0.38-7.58]. While this model identifies short term risk of hospitalization, it is useful in this study in understanding the pre-acute risk factors prior to a SNF admission.

Kommuri et al. (2012) evaluated 2,221 HF patients admitted to 14 Michigan hospitals during 2002-2004. The researchers used the EFFECT (Enhanced Feedback For Effective Cardiac Treatment) model that stratifies patients into low, medium, and high risk of hospitalization. The study found that for otherwise low risk patients, a history of two or more HF hospitalizations within the last year significantly increased one-year mortality.
Zomer et al. (2013), analyzed the frequency of HF admission to acute care and the mortality risk after first admission. The study sample consisted of 10,808 adult HF patients with a median follow up period of 21 years. Incidence of first time HF hospitalization was 1.2 per 1000 patient-years. Patients admitted for HF had a five-fold higher mortality risk than those not admitted or maintained through closer clinical management. The hazard ratio was 5.3 [95% CI:4.2-6.9]. One and three-year mortality for those admitted was 24% and 35%, respectively. The conclusion of their research indicated that the mortality risk is greatly increased after a HF hospital admission signifying the need to manage the patient closer medically and utilize medical interventions for stability.

Corrao et al. (2015) studied a cohort of 13,171 Italian patients aged 50 and older that survived their first hospitalization for HF. These researchers found that using a 30-day post hospital period, 4.7% died 30 days post hospital discharge, and 4.3% were readmitted to the hospital. Additionally, 22.6% died and 57.2% were readmitted to the hospital within one year for any cause. They concluded that both short and long-term risk of mortality was high for this population.

Chaudhry et al. (2013) evaluated the risk factors for hospitalization in 758 patients newly diagnosed with HF. The mean hospitalization rate was 7.9 per 10-person years [95%; CI: 7.4-8.4]. The independent risk factors were; (a) diabetes [HR:1.36, 95% CI: 1.13-1.64], (b) NYHA class III or IV [HR 1.32; 95% CI:1.11-1.57], (c) chronic kidney disease [HR 1.32, 95% CI:1.14-1.53], (d) slow gait [HR 1.28, 95% CI:1.06-1.55], (e) depressed EF [HR 1.25, 95% CI:1.04-1.51], (f) depression [HR 1.23, 95% CI:1.05-1.45] and (g) muscle weakness [HR 1.19, 95% CI:1.00-1.42]. The authors concluded that
if these conditions were modifiable through treatment, they should be assessed and treated when appropriate.

In a study of 3,830 HF patients from the CORONA (Controlled Rosuvastatin Multinational Trial in Heart Failure) study, Perez-Moreno et al. (2014) identified that greater fatigue correlated with worsened clinical outcomes. The key predictor variable was dyspnea which correlated with left ventricular ejection fraction (LVEF). Dyspnea symptom severity was associated with higher risk of cardiovascular death and/or hospitalization. After adjusting for other variables, such as LVEF, NYHA class, and B-type natriuretic peptide level, fatigue was associated with higher risk of hospitalization, and dyspnea increased the risk of worsened clinical outcomes.

As there are almost equal percentages of HFP EF and HFrEF patients, it is important to identify which type of HF was included in the study sample. Sherazi et al. (2015) followed 191 patients with HFP EF of >40% with a mean age of 70+/-14.6 years, for 4.0 +/- 2.8 years. The 5-year mortality was 59% for men and 57% for women. Using multivariate Cox regression analysis, predictors were: (a) BUN > 25 mg/dL (HR 1.77, p = 0.002), (b) absence of hypertension (HR 1.58, p = 0.032), (c) left ventricular end diastolic dimension (LVEDD) ≤ 4.1cm (HR 1.73, p = 0.011 and (d) LVEF ≤ 45% (HR 1.69, p = 0.027). They concluded that patients hospitalized for HFP EF had a high risk of mortality. Absence of hypertension, elevated BUN, and lower LVEF increased the risk for short and long-term mortality. A lower LVEDD was an independent predictor of mortality for this population.

Senni et al. (2013) identified that the existing risk models had multiple limitations. They developed a simple model using existing clinical information including
cardiac and comorbid conditions that predicted all cause 1-year mortality. This tool was titled the Cardiac and Comorbid Conditions HF (3C-HF) Score. The tool was developed with a derivation cohort of 2,016 subjects and a validation cohort of 4,258 subjects. The median age was 69, about one third were female, 20.6% had a normal EF, and 65% had at least one comorbidity. The study results after 5,861 person-years of follow-up had 12.1% meet the end point of all cause death. The variables that best predicted one year all-cause mortality included in descending order: (a) NYHA class III-IV, (b) LVEF<20%, (c) no beta blocker medication, (d) no renin angiotensin system inhibitor, (e) severe valve disease, (f) atrial fibrillation, (g) diabetes with micro and macroangiopathy, (h) renal dysfunction, (i) anemia, (j) hypertension, and (k) older age. The C statistic was 0.87 for the derivation and 0.82 for the validation group. This research team believed that this tool would be simple and easy to implement to improve the prognostication of disease progression in daily practice. While that may be the case in physician offices or in acute care settings, many of the variables are not easily obtained in settings like SNFs that universally use the RAI-MDS 3.0 instrument.

Eapen et al. (2013) sought to develop heart failure prediction models using data elements from an electronic health record database to assess risk of 30-day re-hospitalization and mortality of older HF patients. Their study extracted data from a large Medicare claims database so as to create and validate heart failure risk prediction tools. The study evaluated Get With the Guidelines-Heart Failure (GWTG-HF) subjects using claims data from January 2005 to December 2009. Eapen et al. (2013) selected variables based upon availability within the electronic health record (EHR) and prognostic value in
prediction. The models were randomly selected and contained both HFrEF and HFpEF. Sample size was 33,349 patients in 160 hospitals.

Mortality rate was 9.1% within 30 days of hospital admission, 22.8% were hospitalized again within thirty days of discharge, and 27.2% died or were hospitalized within 30 days combined. High risk patients had a significantly higher odds ratio (8.82) of death with a); rehospitalization [OR 1.99, 95% CI:1.86-2.13] and the combination of both being [OR 2.65, 95% CI: 2.44-2.89]. This mortality model had a C statistic of 0.75 with the rehospitalization and death/rehospitalization a more modest discrimination of 0.59 and 0.62. The study determined that having predictive models for risk stratification for 30-day rehospitalization outcomes for HF patients could provide a validated point of care tool for clinicians to foster better decision making for this population.

In a study by Sartipi et al. (2014), the researchers validated the MAGGIC (Meta-Analysis Global Group in Chronic Heart Failure) risk score that utilized thirteen routinely available patient characteristics. The MAGGIC variables included: (a) age, (b) gender, (c) BMI, (d), current smoker, (e) systolic blood pressure, (f) diabetes, (g) NYHA class, (h) ejection fraction, (i) COPD, (j) HF duration, (k) creatinine, (l) beta blocker use, and (m) ACE inhibitor or ARB. The sample included 51,043 patients from the Swedish Heart Failure Registry and calculated the MAGGIC score using three-year mortality as the outcome metric. The study group had a mean age of 75 with 40% being female and 56% having HFpEF. The NYHA classification of the group was 57% class I or II, 38% class III, and 5% class IV. They compared the actual three-year mortality to the predicted three-year mortality of the MAGGIC score. The overall outcome for actual mortality of the patient group was 39.4% versus the predicted mortality of 36.4%. The observed to
expected ratio was 1.08. The C index was good at 0.741. It appeared that the MAGGIC risk calculation performed well in predicting mortality in this population. Overall survival was 80% at year one, and 61% at year three and one predictive variable identified was rehospitalization.

Giamouzis et al. (2011) performed a literature review of the rehospitalization of HF patients. The review focused on risk factors, knowledge gaps, and risk prediction tools. Factors identified in the literature that prompted re-hospitalization included sociodemographic indicators including advancing age, socioeconomic status, racial heritage, smoking, and alcohol use. Other factors were clinical laboratory testing results, comorbidity burden, cardiovascular status, other clinical conditions, and some quality of life factors. Some of the studies examined reported higher risk of hospitalization for reduced EF, increased heart rate, higher NYHA functional classification, and prior hospitalizations for HF. The comorbidity burden increased the HF admission rate with 39% having five or more comorbidities and only 4% with just a diagnosis of HF (Giamouzis et al., 2011).

Giamouzis et al. (2011) also identified that one half of hospitalized HF patients were readmitted within six months. Seventy percent of those readmitted to the hospital were due to worsening of the previously treated HF. Further, Jenks et al. (2009) identified through Medicare data that this diagnosis is the number one cause of hospital readmission. Giamouzis et al. (2011) identified that more needed to be done to understand high risk HF mortality and how to improve the quality of life of this frail population.
Identification of Study Variables

Variables for this study were selected based upon the identified factors most predictive of HF mortality and decline found in the previously cited literature review and were found in the RAI-MDS 3.0 instrument dataset. Table 1 in Appendix A lists the key variables that are contained within the RAI-MDS 3.0 either directly or via proxy variable, which was identified. While the RAI-MDS 3.0 has 41 potential variables, this study tested the identified variables to evaluate whether a SNF heart failure mortality risk model can be created using data from RAI-MDS 3.0, a required assessment instrument for residents of SNFs. The following represents the variables that were examined followed by the references of the studies that support their inclusion as found in Table 1 in the Appendix.

1. Hospital admission. Hospitalization and rehospitalization are variables that consistently appear in the literature on risk factors for mortality in the heart failure population (Betihavas et al. (2015); Eapen et al. (2013); Giamouzis et al. (2011); Heidenrich et al. (2011); Kommuri et al. (2015); Ouwerkirk et al. (2014), and Zomer et al. (2013), Because this study utilized a statistical methodology that requires a defined starting point, it included data from patients initially admitted to the SNF following an acute episode requiring hospitalization. This was indicated by a completed full RAI-MDS 3.0 assessment.

2. Expiration. The study attempted to define mortality prediction variables and expiration is the crucial dependent variable. Expiration may or may not have occurred in the SNF (potential hospital admission and subsequent expiration)
but is documented on the instrument to close out the RAI-MDS assessment series submitted to Medicare and Medicaid if occurring during the window of 2013-14. The study also defined expiration as discharged to an acute hospital return anticipated but not re-admitted in 14 days. (Betavius et al., 2015; Chaudry et al., 2013; Chyu et al., 2013; Eapen et al., 2013; Fonorow et al., 2005; Giamouzis et al., 2011; Levy et al., 2006; Murad et al., 2015; Pocock et al., 2012; Rahimi et al., 2014; Sartipi et al., 2014; Senni et al., 2013; Yancy et al., 2013; Zomer et al., 2013).

3. **Age.** Age was included as published HF risk models indicate HF mortality increases as a person ages. In this study, because it is not known when a patient was initially diagnosed with HF, it was assumed that it was prior to the most recent hospitalization causing SNF admission (Betihavas et al., 2015; Levy & Anand, 2014; Pocock et al., 2013; and Rahimi et al., 2014).

4. **Gender.** Risk models indicate gender may influence HF mortality time frames. (Chyu et al., 2013; Levy & Anand, 2014; Pocock et al., 2013; Rahimi et al., 2014, and Sartipi et al., 2014).

5. **Hospitalization after SNF admission.** This variable was captured by analyzing discharge and readmission to the SNF. The RAI-MDS data base does not contain information on prior hospital admissions before the SNF admission, but does include readmissions subsequent to initial SNF admission. (Betihavas et al., 2015; Eapen et al., 2013; Giamouzis et al., 2011; Heidenrich et al., 2011; Kommuri et al., 2015; Owerkirk et al., 2014; Zomer et al., 2013, and Yancy et al., 2013).
6. **Comorbidities.** Total number of comorbid conditions were included. (Allen et al., 2015; Betihavas et al., 2015, and Murad et al., 2015).

7. **Diabetes Mellitus (DM).** While diabetes is also counted in the total comorbidity calculation, evidence supported capturing and evaluating this variable independent of the other comorbidities (Chaudhry et al., 2013; Murad et al., 2015; Rahimi et al., 2014; Senni et al., 2013, and Sartipi et al., 2014).

8. **Hypertension.** Hypertension is an etiologic factor for the development of heart failure and was evaluated independent of the comorbidities in total. (Chyu et al., 2013; Fonorow et al., 2005; Levy & Anand, 2014, and Senni et al., 2013).

9. **Renal function.** While serum laboratory results are not captured on the RAI-MDS, this variable is specifically noted on the RAI-MDS 3.0 instrument as renal insufficiency, renal failure, or End Stage Renal Disease (Chaudhry et al., 2013; Murad et al., 2015; Rahimi et al., 2014; Senni et al., 2013, and Yancy et al., 2013).

10. **Dyspnea.** Shortness of breath with exertion, when sitting, and when lying flat was used to define dyspnea in this study. Dyspnea is a classic symptom of this syndrome and is indicative of NYHA class III and IV. It is a predictive variable in multiple risk models (Chaudhry et al., 2013; Chyu et al., 2013; Murad et al., 2015; Pocock et al., 2013; Rahimi et al., 2014; Sartipi et al., 2014, and Senni et al., 2013).

**Study Assumptions**

To conduct a study that defines the variables for a heart failure mortality risk model, the author made assumptions that form its foundation. Therefore, this study assumed that:
1. The RAI-MDS 3.0 data were accurately obtained by nurses.
2. The data obtained were accurately entered into the RAI-MDS 3.0 instrument.
3. The existing heart failure mortality risk models are valid and reliable.
4. The proxy variables adequately represent the mortality risk model variables.
5. The obtained database reflects the heart failure population in SNFs across the United States.

This research study is unique in that statistical evaluation of presumed predictive variables that can be used to create a mortality risk model for HF patients residing in SNFs has not previously been published in scientific literature or made available in the SNF health care setting. It was assumed that incorporating variables included in published valid and reliable HF mortality/survival risk models would ultimately lead to the development of a valid and reliable tool that can be used in the SNF setting to improve quality of end of life care for HF patients in this setting.

**Research Question and Aims**

The overarching aim of the study was to examine factors associated with heart failure and determine their respective risk for mortality for those who reside in SNFs. Based on this, the research question guiding this study was: Which factors associated with heart failure included in the RAI-MDS had the greatest risk to cause death in skilled nursing home patients? The elucidation of these predictive factors has the potential to enable the creation of a heart failure mortality risk model and future mortality risk tool for individuals with HF. Based on the review of the literature the following variables were explored:

- hospital re-admission
• diagnosis of renal failure, renal insufficiency, or being on dialysis
• diagnosis of hypertension
• diagnosis of dyspnea
• diagnosis of diabetes
• age of 65 to 84 years old
• age 85 years old and older
• male gender
• presence of three or more diagnoses

Gaps in the Literature

While there has been extensive research and publication of valid and reliable HF mortality risk tools, none have been created or published using data from the RAI-MDS 3.0 instrument in the SNF setting. Each of the published risk models utilize different and unique variables, many of which are not captured in the SNF setting. If these variables are captured in the SNF, they are not consistently documented or transferred in the transition from acute care to post-acute care (SNF) and are not found on the RAI-MDS 3.0 instrument.

It is important to note that the SNF health care setting has extensive statutory and regulatory requirements of participation in the Medicare, Medicaid, and state licensure programs. These requirements create an extensive burden of documentation, systems design, and execution. In this practice setting, it would increase the nursing work burden if the mortality risk model is not derived from an existing patient assessment instrument. Requiring an additional assessment tool would most likely not be accepted or embraced in this setting.
CHAPTER 3: Research Design and Methods

This study was a retrospective cross-sectional exploratory analysis of factors embedded in the RAI-MDS 3.0 instrument that predict mortality in patients with heart failure who reside in SNFs. The study sample was comprised of a cohort of patients with a primary or secondary diagnosis of heart failure who were admitted to SNFs which were part of a multi-facility organization in the Midwest during the years 2013-2014. Based on the review of published studies and heart failure mortality models, relevant variables associated with HF mortality were extracted from an existing RAI-MDS 3.0 database from 24 SNFs. It should be noted that mortality risk factors in this study are synonymous with the term “variables”. The participants in the study are referred to as patients or residents, which are synonymous.

Based on the literature review, selected variables were identified for evaluation of their predictive value in determining heart failure mortality in residents of SNF. These variables were evaluated simultaneously using multivariate regression methodologies to quantify their predictive value in the SNF care setting. Methodologies included survival analysis with calculation of hazard ratios that are described later in this chapter.

Dataset Quality

Since the data for this study were extracted from existing RAI-MDS databases across multiple SNFs, the following criteria were used to select organizations from which to extract their data so as to ensure dataset quality: (a) data must come from a facility organization that has a regional operational leadership, (b) R.N.’s completing the RAI-MDS 3.0 instrument must have had proper training and credentialing, (c) the organization
has stable facility leadership, (d) the organization has engaged the services of a data analytics firm that cross validates the data for consistent item response, (e) the organization utilized current standards of practice, and (f), the facility must be operated by one leadership team.

Based on these criteria, a multi-facility organization was selected for the data sample. This facility operated 24 SNF’s in the Midwest, had a stable regional and facility leadership with consistent direction, and was respected as quality facility operators by the state licensure and certification agency. This organization employed R.N.’s that were trained on completion of the RAI-MDS and credentialed by the American Association of Registered Nurse Assessment Coordination (2016) which designates them as Registered Nurse Assessment Coordinators (RNACs). These R.N.s were required by law to indicate that the information contained in the assessment was accurate and represents the patient and are presumed to understand the nuances of the instrument completion process. This is important since responses are not always self-evident and must be consistent with the RAI-MDS 3.0 User Manual definitions and criteria.

All the completed assessment instruments were screened by proprietary software for accuracy, completion, and consistent item response. Since completed assessments are forwarded to the state and CMS, the software allows the RNACs to correct or improve their responses on the instruments based on this software’s feedback to obtain the best description of the patient at that point in time, thereby improving the accuracy of the assessment.

This organization utilized national standardized professional care guidelines. Further, the SNFs in this organization did not use temporary staffing, and therefore, may
have greater consistency in care delivery and documentation. It is believed that the deliberate process of selecting this organization and the number of SNFs that drawn from enhanced the internal and external validity of the study and thereby increases the potential to generalize the results of this study to other SNFs in the United States.

**Instrument Reliability and Validity: RAI-MDS 3.0**

The RAI-MDS 3.0 instrument and user manual were extensively tested by CMS prior to implementation in the SNF care setting. RAND Health Corporation conducted an extensive evaluation of the validity and reliability of the updated RAI-MDS 3.0 instrument published in 2008 (Saliba & Buchanan, 2008). The intent of updating the RAI-MDS from the 2.0 to 3.0 version was to bring voice to the patient (resident) and better capture the care needs of this population. This third version increased focus on patient-centered concerns and needs.

Assessment items on the RAI-MDS 3.0 instrument were tested for interrater reliability. Beta testing revealed kappa statistics to be very good to excellent for both the gold-standard to gold-standard nurse assessment and the gold-standard to facility-nurse assessment comparisons. Generally, the reliability statistics were higher than those published for RAI-MDS 2.0 version, particularly when the facility nurse performing the assessment was compared to the gold-standard nurse’s documentation (Saliba & Buchanan, 2008).

National validation testing for MDS 3.0 for the cognitive, depression, and behavior items showed significantly higher agreement with criterion measures than did MDS 2.0 items collected on the same residents. These categories were tested specifically as they were new to the instrument and incorporated reliable and validated instruments
such as the PHQ-9 (Patient Health Questionnaire - 9, Resident Mood Interview) and BIMS (Brief Interview for Mental Status) assessment tools.

The RAI-MDS 3.0 has 17 defined demographic and clinical assessment sections covering categories such as patient identification, cognition, mood, behavior, functional status, pain, skin integrity, nutritional status, active diagnoses, and essential components for planning care for the patient. A link to this instrument is found at:


When the RAI-MDS 3.0 instrument is completed, specified response factors can trigger up to 20 additional high-risk assessment protocols, defined as Care Area Assessments (CAA). CAA examples include delirium, ADL functional potential, nutritional status, pain, and others. These CAA are completed by the interdisciplinary team and augment the process of formulating a comprehensive individualized care plan.

Study Database

The database for this study was in an Excel spreadsheet obtained from the multifacility SNF organization that included the RAI-MDS assessments of all patients diagnosed with heart failure (HF) in the midwest SNFs in 2013-2014. The data file contained 10,336 RAI-MDS 3.0 completed instruments representing 3208 HF patients. Each patient’s assessment data were noted on a separate row of the database with columns representing each RAI-MDS 3.0 assessment component. Data included assessments where the patient had a primary or secondary diagnosis of heart failure and excluded all other patient assessments if the HF diagnosis was not present. The two-year timeframe was selected to adequately capture a sufficient sample size that would include the event of expiration for many subjects based on literature describing HF mortality.
Approval to use the database was obtained from the SNF organization and documented in a letter of support. The organization was provided a detailed description of how the data would be maintained according to HIPAA and corporate compliance expectations. Patient data utilized for the study was de-identified prior to analysis.

Protection of this database was on a password protected computer and will be retained for five years after completion of this study for additional analysis if desired, and then the data will be destroyed. The rationale for keeping the data is to allow other potential statistical approaches to be applied as deemed useful by this researcher in furthering the work of improving the quality of life and care for HF patients in SNFs.

Prior to obtaining the data, an Institutional Review Board (IRB) application was submitted to Marquette University to determine whether the proposed research methodology was ethically sound. The IRB approved the study in 2015 and a continuing approval was obtained prior and subsequent to initiation of the study and data analysis.

Data were evaluated and cleaned to produce a data set that met the requirements of this study. Patients who did not have HF as one of their diagnoses were removed from this database. While the sampled subjects have other diagnoses, all participants in this sample had an underlying primary or secondary diagnosis of heart failure. The RAI-MDS 3.0 instruments obtained were all complete with no known missing data as the analytic files. CMS submission software does not allow incomplete assessments to be submitted. Participants in this database included patients that were: a.) initially admitted from a hospital to the facility, b.) had two or more assessments completed, and c.) were living at the end of the study or had expired prior to the end of the study time period or were discharged to the community.
**Study Variables**

As noted in Chapter Two, variables shown to predict HF mortality were identified through a careful and deliberate review of published heart failure mortality models. Variables present within the RAI-MDS 3.0 instrument that have been shown to correlate with heart failure mortality were included in the present study. They include:

1. *Hospital Admission* (study entrance). As all subjects in the database were admitted initially after an acute hospital stay. Subjects were evaluated from the first full RAI-MDS 3.0 assessment occurring after January 1, 2013. This assessment may not represent the first admission to the SNF. This variable was captured from the RAI-MDS 3.0 and signified the starting point for each subject in the study. Subjects were also started in the study beginning with an annual assessment if previously residing in the facility. This was represented on the RAI-MDS instrument as data point A 0310 B 01 or A0310 A 3.

2. *Expiration*. Expiration was defined as the death of a subject and reflected as the end of the assessment cycle. If a subject was discharged to an acute care facility and was expected to return but does not return within 14 days, the subject was counted as expired. Each subject either continued to be living at the end of the study or had expired. This was represented on the RAI-MDS instrument as data point A 0300 F 12. Therefore, the event of death is defined as either death in the facility or a discharge to an acute hospital with no readmission within 14 days.
3. **Age.** Age was captured in the following manner: (a) 65 years old to 84 and (b) 85 and older. This is represented on the RAI-MDS instrument as data point A 0900.

4. **Gender.** This variable was coded as either male or female. This was represented on the RAI-MDS instrument as data point A 0800.

5. **Number of hospitalizations since initial SNF admission.** Future hospital admissions were captured and identified as a readmission to the facility. This variable was represented in the following manner: one additional hospital admission after initial admission to the SNF represented by readmission. This was represented on the RAI-MDS instrument as data point A 1800 03 for each admission.

6. **Comorbidities.** Total number of comorbid conditions were evaluated in this variable. Comorbidities are diagnoses that are present for each patient and captured from the medical record to the RAI-MDS 3.0. These were represented in the following manner: three (3) or more comorbid diagnoses. This variable was utilized as the literature indicates that greater comorbidity increases mortality in this population (Murad et al., 2015). These were represented on the RAI-MDS instrument as those listed in data points I 10100 – I8000.

7. **Diabetes Mellitus (DM).** The presence of a diagnosis of diabetes mellitus was captured as either present or not present. This was represented on the RAI-MDS instrument as data point I 2900.
8. **Hypertension.** The presence of a diagnosis of hypertension was captured as either present or not present. This was represented on the RAI-MDS instrument as data point I 0700.

9. **Reduced renal function.** While biological serum laboratory results are not captured on the RAI-MDs, this variable is specifically noted on the RAI-MDS 3.0 instrument as renal insufficiency, renal failure, or End Stage Renal Disease (dialysis). The presence of one of these diagnoses indicated a reduced renal function. This was represented on the RAI-MDS instrument as data point I 1500.

10. **Dyspnea.** Shortness of breath with exertion, when sitting, and when lying flat was used to define dyspnea in this study. Presence of one or more of these indicates the presence of dyspnea in the subject. This was represented on the RAI-MDS instrument as data point J 1100 A and/or B and/or C.

**Data Analytical Methodology and Procedures**

This study used data collected from January 1, 2013 through December 31, 2014. During this two year time period, patients were entered in the study as they were admitted to the SNF for the first time after an acute hospital stay within those years, or began the study at their first full RAI-MDS 3.0 assessment if already a patient. Therefore, the study began January 1, 2013 and ended December 31, 2014.

Discrete survival analysis was the statistical method employed in this study. Survival analysis is the study of the distribution of periods of time beginning with a defined starting period and measured over time until a terminal event occurs (Allison, 2010). Survival analysis asks the question of whether and when the event of death
occurred (Singer & Willett, 2003), which is the intent of this study. Therefore, the researcher must ask what target event is occurring, define a beginning of time for the study, and a metric that represents the passage of time.

The statistical analysis was a multistep process that initially performs logistic regression, modeling whether the patient died within a window of time at 60, 90, 120, and 180 days following the first full MDS assessment as the logical probable death window. The first analytical step in this process was defining the \textit{time of origin} for each patient that signifies the beginning of the study. The \textit{time of origin} was defined as the first full RAI-MDS 3.0 assessment completed in year 2013 or 2014, either as an annual assessment or a new admission assessment. This was captured from A 310 as either A 01 or 03. It may occur at any time during the study period.

For the purpose of the logistic regression analysis, different primary analytic data files were created from the original data set as follows. Each row in a primary analytic file, that is, each new case record in the Excel spreadsheet, was generated by a full MDS assessment for which the life-death status can be measured at two, three, four, and six months after admission. Each new record case does not represent a patient but rather an uninterrupted stay of a patient in the SNF.

Stepwise methods were employed to develop predictive models for proximity to death using different MDS risk factors as explanatory variables. Subsequent to that analysis, discrete survival analysis and Cox proportional hazards models were explored. Unlike logistic regression, which examines the overall probability of an event without regard to the timing of that event, survival analysis allows the examination of the longitudinal progression of the probability that the event (i.e. death) occurs (Allison,
Hence, analysis occurs in terms of the hazard at a point in time, namely, the risk of the event of death occurring per unit of time elapsed, given that the patient has survived up to that time. The hazard function expresses the hazard of death as it changes over time and was modeled using the MDS risk factors.

The statistical program SAS was used to analyze this data set. Survival analysis was performed using survival time as the dependent variable and exploring the explanatory variables impact on the hazard rate function. A special feature of survival data, called censoring, indicates that the event of death is not observed for a number of patients, but instead we know that it has not yet taken place, due to the study ending, or to discharge for reasons other than death. In most survival analysis methods, as in the Cox proportional hazard models, the survival time is assumed to be a continuous variable.

In this analysis, it was reasonable to split the two-year observation period of the study in several time intervals and to consider discrete-time survival methods (Allison, 2014). More explicitly, each survival time then represents a set of indicators of whether or not a patient failed in each time unit until a person either experiences the event of death or is censored. This allows the researcher to perform the discrete time survival analysis with standard logistic regression procedures. The methodology included the extra effort of entering the data in a “long person-period” format so that each patient’s survival history is broken down to a set of discrete time units. For example, if a patient dies at the fourth time unit, four different observations (i.e. rows in the person-period data set) will be created. For the fourth observation, the dependent variable will be coded “1” indicating death, and for the previous three observations, it will be coded “0”. Hence, the patient’s one record will yield four records in the person-period format. Then the
researcher can estimate a logistic regression model predicting whether the death event did or did not occur in each time unit.

Specifically, estimates were generated for as many probabilities as time units. That is, for each time unit, an estimate will generate the conditional probability that a patient will experience the event of death at that time unit, given that the patient did not experience the event prior to it. These conditional probabilities are the fundamental parameters of this analytic process. Analysis will estimate their values and investigate their dependence on the MDS risk factors (i.e. explanatory variables). This is referred to as the set of these conditional probabilities as the discrete-time hazard function. Figure 2 represents the methodological modeling employed in this study.

**Figure 2: Modeling Heart Failure**

![Modeling Heart Failure Predictive Mortality in Skilled Nursing Facilities Study Diagram.](image)

**Methodological Rigor**

As the data set is comprised of historical data obtained in a methodologically rigorous process following the RAI-MDS 3.0 user’s manual, it was presumed that the
dataset met the standard for quality quantitative research. This researcher maintained the rigors of the process of analyzing the data through a careful and conscientious method when sorting the database to extract only the variables and information that were pertinent to this study. The data were organized in an Excel spreadsheet and columns of data not needed for this analysis were hidden but maintained for other purposes if needed.

It is important to assure statistical validity in the process of evaluating the data output (Polit & Beck, 2017). Conclusions reached must be valid inferences from the analysis and deployment of appropriate statistical methods. In conducting this research, the internal validity must also be evaluated to assure that the relationships among variables are truly due to their unique interactions rather than caused by other variables.

Construct validity of the instrument allows the researcher to infer from the study results and determine their outcome value (Polit & Beck, 2017). It is believed this study had construct validity and was unbiased in producing valid reliable results. Lastly, external validity concerns whether study results can be generalized to other setting and populations. As the data instrument is consistent across all SNF’s and the variables were based on published predictive models, the generalizability of the findings to other SNFs is purported to be good. This researcher also engaged the services of a statistician who is Ph.D. educated and experienced in working specifically with this database and skilled in logistic regression and survival analysis. Together with the statistician, this researcher properly organized and analyzed the data using procedures defining the episodic data for each subject and evaluating explanatory variables from pertinent sections of the RAI-MDS 3.0 instrument.
CHAPTER IV: RESULTS

The purpose of this study was to analyze specific variables to determine their relative risk of causing mortality in patients with heart failure who resided in skilled nursing facilities during a two-year period. Analysis was performed to determine the trajectory of mortality for the study sample at 60, 90, 120, and 180 days. Table 2 reflects the number of patients who died and those who were alive or censored at each of the time periods over the two-years of data collection. Since patients were admitted at various points throughout this two-year period, the number of patients at 60, 90, 120 or 180 days diminished accordingly. Consequently, the number of patients alive at 60 days (1,827) is larger than at 90, 120, and 180 days. As outlined in Table 2, the number of participants who died increased over time, with 337 participants dying within 60 days, and 526 who died dying within 180 days.

Table 2: Number of Patients Alive vs. Death at 60, 90, 120, and 180 Days

<table>
<thead>
<tr>
<th>Days</th>
<th>Eligible Patients</th>
<th>Patients Who Died</th>
<th>Patients Who Didn’t Die</th>
</tr>
</thead>
<tbody>
<tr>
<td>60</td>
<td>1,827</td>
<td>337</td>
<td>1,490</td>
</tr>
<tr>
<td>90</td>
<td>1,640</td>
<td>398</td>
<td>1,242</td>
</tr>
<tr>
<td>120</td>
<td>1,483</td>
<td>447</td>
<td>1,036</td>
</tr>
<tr>
<td>180</td>
<td>1,283</td>
<td>526</td>
<td>757</td>
</tr>
</tbody>
</table>

Using the data analysis software SAS, the PROC PHREG (Cox Proportional Hazard Modeling) procedure was used to compare the survivor functions across the two groups of patients in the analysis, those that died, and those that survived or were censored for the given period of time. PROC PHREG is an analytic procedure that implements the Cox model to generate the hazard ratio estimate of a given variable. The
output reflects the results of the statistical survival analysis and logistic regression methodologies. For each of the variables, survival product limit curves were created and analyzed. Table 3 presents the model of the analysis that evaluated the study variables to determine the Cox proportional hazard function of each variable. In survival analysis, using the Cox proportional hazard model, the interpretation of the analytical output is the hazard ratio. The hazard is described as the expected number of deaths or events in a unit of time, or, the probability of the event happening in that time interval.

Survival Analysis Model Results

Table 3. Model Results

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Analysis of Maximum Likelihood Estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Log Rank Statistic</td>
</tr>
<tr>
<td>----------------------------------</td>
<td>--------------------</td>
</tr>
<tr>
<td>Hospital Readmission</td>
<td>52.528</td>
</tr>
<tr>
<td>Reduced Renal Function</td>
<td>21.919</td>
</tr>
<tr>
<td>Hypertension</td>
<td>-40.043</td>
</tr>
<tr>
<td>Dyspnea (short of breath)</td>
<td>45.0</td>
</tr>
<tr>
<td>Diabetes</td>
<td>-33.0</td>
</tr>
<tr>
<td>Age 65 to 84</td>
<td>-40.0</td>
</tr>
<tr>
<td>Age 85 and greater</td>
<td>105.66</td>
</tr>
<tr>
<td>Male Gender</td>
<td>6.8002</td>
</tr>
<tr>
<td>3+ Diagnoses –</td>
<td>26.684</td>
</tr>
</tbody>
</table>
Table 3 represents the Cox proportional model results. The parameter estimate along with the standard error and Chi-Square value are shown. The PR> ChiSq represents the $p$ value for each factor. The hazard ratio for each factor is shown in the last column on the right. Negative parameter estimates and those factors with $p$ values greater than 0.05 are not significant (hypertension, diabetes, age 65-84, male gender). As observed in the table, five of the nine variables were significant. The following section presents the analysis for each of these variable and includes the product limit survival estimate curves, the number of deaths, and the associated risk of mortality.

**Hospital Readmission**

Hospital readmission was defined as those patients who were previously admitted to the SNF, subsequently hospitalized, and then re-admitted to the SNF for care. For this variable, there were 728 who were hospitalized and returned to the SNF and 2,480 patients who were not hospitalized. For those hospitalized, there were 290 (39.8%) deaths and 461 (18.5%) deaths in the group that were not hospitalized. As noted on Figure 3 that follows, there is visual evidence of the hospitalization and readmission effect. The survival curve for those hospitalized and readmitted to the SNF declined more steeply. The graph indicates plus signs whenever there are censored projected observations when the event of death did not occur.

The x axis is segmented for modeling purposes into time increments of 200 days for each segment for the two-year observation study (maximum observations of 730 days, therefore graph reflects 800 days). Along the x-axis, the number of patients still at risk (not yet dead or censored) are indicated separately for each patient group in the model. The blue curve represents the patients who did not have a hospital readmission
and the red indicating those that did. The y axis represents that model’s proposed survival probability curve for each group.

Figure 3: *Survival Curve for Hospital Readmission*

![Survival Curve](image)

Note: Hospital Readmission is “re-entry”. 0 = not hospitalized nor readmitted (blue); 1 = readmission (red)

For the readmission group, the log-rank statistic is 52.528. The log-rank test is the most widely used test for differences in the survivor function. The log-rank test can be represented as the sum of the deviations of observed numbers of events (i.e. deaths) from expected numbers of events, where the summation is over all unique event times in both groups. The Wilcoxon test differs from the log-rank test only by the presence of some weights. That is, it is a weighted sum of the above deviations, giving more weight to the early times than to the late times. The p-values for both tests are significant at p < 0.0003.
The hazard ratio for this variable is 1.323 indicating that readmission increases the risk of mortality by 32.2% for those with HF in SNFs.

**Reduced Renal Function**

Reduced Renal Function is defined as the patient having a diagnosis of renal failure, renal insufficiency, or was on dialysis, reflecting total renal failure. For this variable, there were 1,110 patients who had reduced renal function and 2,098 who did not have reduced renal function. For those with reduced renal function, there were 268 deaths (24%) and 483 (23%) deaths for those without reduced renal function.

**Figure 4: Survival Curve for Reduced Renal Function**

*Note.* Dialysis on graph indicates Reduced Renal Function. 0 = no reduced renal function (blue); 1 = reduced renal function (red)
As can be noted on Figure 4, there is a visual difference in the effect for both groups. The survival curve for those with reduced renal function (red indicators) declines quickly then resumes a more steady decline with plus signs noting those censored. Along the x-axis, we have noted the number of patients in the model still at risk (not yet dead or censored) indicated separately for each patient group. For reduced renal function, the log-rank statistic is 21.919. The p-values are significant for both tests at < 0.0272. The hazard ratio for this variable is 1.187 indicating that reduced renal function increases the risk of mortality by 18.7% for those with HF in SNFs.

**Hypertension**

This variable reflects whether the patient had a diagnosis of hypertension or not. There were a total of 2,719 patients with hypertension and 489 patients that did not have hypertension. For those with hypertension, there were 610 (22%) deaths with 141 (29%) deaths if hypertension was not a defined diagnosis.

As can be noted on Figure 5, there is visual evidence of the hypertension effect. The survival curve for those with normal function (no hypertension- blue) declines more rapidly than those with the diagnosis. The log-rank statistic is -40.043 for the hypertension group. As the parameter estimate is negative, the results indicate that this variable is not significant in predicting the mortality outcome for this variable. The p-values for both tests are < 0.0001 with a negative parameter estimate. The hazard ratio for hypertension is 0.672.
Figure 5: *Survival Curve for Hypertension*

Note: 0 = no hypertension (blue); 1 = hypertension (red)

**Dyspnea**

Regarding the variable of dyspnea, or shortness of breath, there were a total of 1,575 patients who had a diagnosis of dyspnea and 1,633 patients who did not. For those having dyspnea, there were 393 deaths (24.95%) compared to 358 (21.92%) deaths for those lacking the symptom of dypsnea. As noted in Figure 6, there is a minimal difference in the effect for both groups. The survival curve for those with a diagnosis of dyspnea declines at a slightly different and faster rate and progression than those without that diagnosis. The log-rank statistic is 45 for the those with a diagnosis of dyspnea. The p-values for both tests are significant at < 0.0011. The hazard ratio for this variable is
1.285 indicating that those with a diagnosis of dyspnea have a 28.5% greater chance of mortality than those that do not have the diagnosis.

**Figure 6: Survival Curve for Dyspnea**

![Survival Curve for Dyspnea](image)

*Note:* Short breath indicates dyspnea. 0 = no dyspnea (blue); 1 = dyspnea (red)

**Diabetes**

The variable of having the diagnosis of diabetes was also analyzed. There were 1,490 patients who had a diagnosis of diabetes and 1,718 patients who did not. For those having diabetes, there were 322 deaths (21.61%) and for those not diagnosed with diabetes, there were 429 deaths (24.97%). As can be noted on Figure 7, there is not a significant difference in the effect for both groups. The survival curve for those with a diagnosis of diabetes declines about the same as those without that diagnosis initially and then declines slightly more rapidly over time.
As the parameter estimate is negative, the results indicate that this variable is not significant in predicting the mortality outcome. The log-rank statistic is -33 for the those with a diagnosis of diabetes. The p-value for both tests is < 0.0725 which indicates that it is not statistically significant. A p-value higher than 0.05 indicates that this is not statistically significant. The hazard ratio for this variable is 0.863 indicating that having a diagnosis of diabetes may reduce the risk of mortality.

**Figure 7: Survival Curve for Diabetes**

![Survival Curve for Diabetes](image-url)

*Note.* 0 = No diabetes (blue), 1 = diagnosis of diabetes (red)

**Age 65 to 84**

The variable of age greater than 65 years to 84 years old was analyzed. This included those patients who were 65 and older yet not 85 years old. There were 2855 patients who were 65 years and under age 84 and 353 who were not yet 65 years old. For
those that were between 65 and 84, there were 722 deaths (25.29%) and for those under age 65, 29 (8.22%) deaths. As can be noted on Figure 8, there is a significant difference in the effect for both groups. The survival curve for those under 65 years old declines at a significantly slower rate and appears to project minimal deaths than the progression of those 65 and older. The log-rank statistic is -40 for the those 65 and older. As the parameter estimate is negative, the results indicate that this variable is not significant in predicting the mortality outcome for this variable. The p value is 0.0009. The hazard ratio for this variable is 0.524.

Figure 8: Survival Curve for Age 65 to 84

Note. Age 65 to 84 = 0 (blue); Under 65 = 1 (red)

Age 85 and greater

The variable of age greater than 85 was analyzed to determine predictive mortality for this population. There were 1,072 patients who were age 85 and older and
2,136 who were 84 and younger. For those 85 and older, there are 368 deaths (34.33%) and for those 84 and younger, 383 deaths (17.93%). As can be noted on Figure 9, there is a significant difference in the effect for both groups. The survival curve for those 85 years and older (red indicators) declines at a significantly faster rate and progression as those under 85 years old. The log-rank statistic is 105.66 for the those 85 and older. The p-values for both tests are significant at < 0.0001. The hazard ratio for this variable is 1.828 indicating that being 85 or older increases the risk of mortality by 82.8%.

**Figure 9: Survival Curve for Age 85 and Over**

![Image of survival curve](image)

*Note: 0 = under 85 (blue); 1 = 85 age and older (red)*

**Gender**

This variable was analyzed by indicating whether the patient was male or not male (female). There were a total of 1,282 patients who were of male gender and 1,925
who were of female gender. For the male gender, there were 281 deaths (21.92%) and 470 deaths (24.42%) of female gender. As can be noted on the graph, there is no significant difference in the effect for both groups. The survival curve for males declines at nearly the same rate and progression as those of female gender. The log-rank statistic is 6.8002 for the male gender. The p-values for both tests are 0.0598. A p-value higher than 0.05 indicates that this is not statistically significant.

**Figure 10: Survival Curve for Gender**

![Graph showing survival curve for gender](image)

**Note:** 0 = female gender (blue); 1 = male gender (red)

**Three or more diagnoses**

This variable reflects patients having three or more diagnoses compared to those having less than three. There were 568 patients with three or more diagnoses and 2,640 who had less than three diagnoses. For those with three or more diagnoses, there were
147 deaths (25.88%) and there were 604 deaths in patients with less than three diagnoses (22.9%). As noted in Figure 9, the survival curve for those with 3 or more diagnoses declines at a slightly faster rate and progression as those with less than 3 diagnoses. The log-rank statistic is 26.684 for the those with 85 and older. The p-values for both tests are significant at < 0.0001. The hazard ratio for this variable is 1.345 which indicates a 34.5% greater risk of mortality if the patient has 3 or more diagnoses.

**Figure 11: Survival Curve for Three or More Diagnoses**

Note: 0 = less than three diagnoses (blue); 1 = 3 or more diagnoses (red)

CHAPTER 5: Discussion
Of the nine variables evaluated using statistical survival analysis modeling, five variables predicted increased risk of mortality in the SNF heart failure patient. Hospital re-admission, presence of renal disease, presence of dyspnea, age 85 and older, and having greater than three diagnoses indicated increased risk of mortality. Four variables were not significant in predicting increased mortality risk. Those were diagnosis of diabetes, diagnosis of hypertension, being age 65 to 84, and male gender.

**Predictive Variables**

**Hospital Readmission**

The first predictive variable was hospital re-admission. Almost all SNF patients are initially admitted following a hospital stay. However, this variable represented a one-time rehospitalization during the patient’s SNF stay. This finding is supported by other studies which have found that declining patient health status caused hospitalization and ultimately mortality. Repeated hospital admission is indicated as a strong predictive variable (Eapen et al., 2013; Yancy et al., 2013). While the study patients may have had multiple hospital admissions, the present study analysis only captured one hospital readmission (binary variable), and therefore, does not capture the same patient having multiple re-admissions during their SNF stay.

Multiple hospital admissions due to exacerbation of the disease process are indicative of declining health. It is known that 83% of SNF patients are rehospitalized at least once per year and 43% at least four times each year (Heidenreich et al., 2011). Capturing multiple hospital readmissions could have provided additional mortality risk data. The hazard ratio for this variable was noted to be 1.323, or having at least one
hospitalization during the patient’s SNF stay would increase the risk of mortality by 32.3% compared to their peers in the sample. Further, providing palliative care may reduce hospitalization as patients’ end of life wishes are then honored.

Multiple studies indicate that hospitalization of HF patients increases the risk of mortality (Foebel et al., 2013; Kommuri et al., 2012; Metra et al., 2007). The present study assessing one hospital re-admission aligns with the previous studies indicating increased mortality risk. While other studies evaluated the impact of hospitalization, only one study evaluated this factor in the SNF setting. Foebel et al. (2013) evaluated predictors of SNF HF patient hospitalization and resultant mortality and found similar results. These findings add further support that hospitalization increases the risk of mortality for HF patients.

**Reduced Renal Function**

In the present study, renal disease was classified as renal insufficiency, renal failure, and/or being on dialysis. As renal disease is a comorbid condition prevalent in the HF population, it was evaluated to determine the significance of its impact on mortality. Prior studies have identified renal disease as a risk factor for mortality in this population (Chaudhry et al., 2013; Chyu et al., 2014; Fonarow et al., 2005; Giamouzis et al., 2011; Levy et al., 2006; Murad et al., 2015; Ouwerkirk et al., 2014; Rahimi et al., 2014; Senni et al., 2013; and Yancy et al., 2013). In the Murad et al. (2015) study, the comorbid condition of renal disease increased the risk of mortality by 32%. Whereas, in the present study, the mortality risk hazard ratio was lower at 18.7%. However, Murad and colleagues assessed mortality risk at the inception of a HF diagnosis of community-based participants which may explain the decreased risk in the present study of SNF patients.
Their patient population was evaluated based on a three-year retrospective review of clinical conditions that may have impacted the diagnosis of HF. As most diagnoses indicated in the medical record are captured from the previous acute hospital stay, the patients in the present study may or may not have a physician documented diagnosis of reduced renal function as the SNF attending physician is generally not the community primary physician. Therefore, the diagnosis of reduced renal function may not be captured on the RAI-MDS.

**Dyspnea**

Having dyspnea, or shortness of breath, increased the likelihood of mortality in the present study. The hazard ratio for dyspnea was 1.285 signifying that this group of patients have a 28.5% greater likelihood of mortality than those in the study population who did not have that coded condition. This finding was similar to the prospective study by Senni et al. (2013) that identified risk factors to create a mortality risk tool. In their study, the presence of a diagnosis of COPD had an odds ratio of 1.20 with a 95% confidence internal.

While this researcher expected a greater hazard ratio for this variable, it may be diminished due to data capture limitations of physician coding on the medical record as previously described. Further, in the present study, the variable COPD as a diagnosis was not used. While dyspnea may be present in the HF population due to COPD, or other comorbid conditions, evaluating the presence of COPD may be useful in mortality risk prediction.
85 Years Old and Older

Not surprising, being eighty five (85) years and older has an increased risk of mortality. The hazard ratio of 1.828 for those 85 and older increased the mortality risk by 82.8% compared to all those in the study. Therefore, age appears to play a significant role in predicting mortality in this population. This finding is supported by studies previously discussed in the literature review that found age to be a significant predictor of mortality. Pocock et al. (2013) conducted a meta-analysis and found that age was one of the strongest predictors of mortality in HF patients. Jurgens et al.(2015) also found that as individuals age, the number of comorbid conditions increase as does mortality. Rahimi et al. (2014) evaluated 43 risk models and identified that age and gender were significant predictors of mortality. Betihavas et al.( 2015) also identified a HR of 1.07 for each 10 year increase in age. In the present study, increased age greater than 85 demonstrated a HR of 1.828.

Three or More Diagnoses

This variable was selected for the study to represent, by proxy, the indication of frailty in this population as supported by Jurgens et al. (2015) and Murad et al., 2015. Betihavas et al.( 2015), Rahimi et al. (2014), and Senni et al.(2013) identified that comorbid conditions increased the risk of mortality. Murad et al. (2015) in their evaluation of the Cardiovascular Health Study HF participants examined the impact of comorbidities on the mortality of that population. Sixty percent (60%) of those patients had three or more comorbidities which contributed to their mortality risk.

The RAI-MDS assessment instrument does not have a specific variable that represents frailty which would signify a declining health status of the patient. To address
this, three or more comorbid diagnoses defined this variable. It is not uncommon to have significantly more diagnoses identified in the medical record. Furthermore, only specific diagnoses are indicated for inclusion on the RAI-MDS 3.0 instrument and thereby limits the potential to identify all that may be present. The hazard rate in this study for three or more diagnoses was 1.345 which is similar to other studies (Betihavas et al., 2015; Rahimi et al., 2014; and Senni et al., 2013). Therefore, this proxy variable appeared to be useful in representing frailty in this study. This study indicated that having three or more diagnoses increased the risk of mortality by 34.5% compared to their peers in the study group.

Non-Predictive Variables

The following variables were not significant in predicting mortality in this study population. While it was expected that these variables would be significant in increasing the mortality risk for HF SNF patients, the study results did not demonstrate such risk.

Hypertension

In the present study, the model’s survival curve indicated that those without a diagnosis of hypertension had a more significant decline leading to mortality than those with the diagnosis. This is perplexing since hypertension is a major etiologic risk factor for the development of HF (Yancy et al., 2013) and it is included in HF risk models as a predictive variable (Fonarow et al., 2005; Levy et al., 2006; and Senni et al., 2013).

A possible explanation of this is that patients in the study, were being treated for hypertension and therefore more clinically stable. It is known that about 25% of patients in the community that have hypertension do not comply with their prescribed medication
regimen or are not adequately treated (Yancy et al, 2015). Alternately, patients may have had hypertension but it was not indicated as a primary diagnosis by the attending physician, or that patients may have had hypertension yet not been diagnosed at the point of assessment. Another possible explanation is that roughly half of the patients have diastolic HF which is generally due to ventricular stiffening causing fluid balance issues, some of which are hypertensive. Because of this, further analysis is required to determine the viability of hypertension as a mortality predictor and to rule out alternative causes for this confounding finding.

**Diabetes**

Diabetes is a major etiologic risk factor similar to hypertension that causes microvascular damage impacting the mortality of those with HF (Shindler et al., 1996). In the Murad et al. (2015) study, the presence of diabetes in the community setting for adults 65 and older had a hazard ratio of 1.64. While it might be expected that this variable would be significant in this study, the results indicated that comparing those with and without the diagnosis of diabetes showed no significant difference between the groups. Similar to the findings related to hypertension, it is possible that patients with diabetes who are admitted to the SNF are being adequately treated and more closely monitored than if they were still living in the community. Another possible explanation is that the patient may not have had the diagnosis indicated in the medical record by the attending physician, or that the patient may not have yet been diagnosed. Based on this, further examination of the role of diabetes care in SNF should be examined, since proper management may have a protective effect.

**Age 65 to 84**
The influence of age was analyzed using two distinct groupings; the patient population aged 65 to 84, compared to those patients less than 65 years old. The mortality risk model survival estimates showed a somewhat linear decline of those in the 65 to 84 compared to those younger than 65 who showed more modest decline of projected mortality. This is expected and it supports findings of Betihavas et al. (2015) that identified a HR of 1.07 for each 10-year increase in age.

One possible explanation for the reduced mortality for this younger age group is that a majority of SNF admissions are admitted for short term rehabilitation. Those patients, while they may have a diagnosis of HF, are in the SNF for rehabilitation and return home after a brief stay. Therefore, the older the patient, the greater the risk of mortality. This younger age group variable is not significant in predicting mortality in the HF SNF population.

**Gender**

Gender was evaluated in this study as prior research suggested that being of male gender increased the risk of mortality for those with HF (Chyu, et al. (2013). Klempfner, et al. (2014) found the opposite in that female patients had a higher risk of mortality. However, the present study indicated that there was not a significant difference in gender relative to the risk of HF mortality in the SNF setting. As female patients comprise the majority of the SNF population, it is possible that males with HF have died in the community rather than in the SNF. Further evaluation of the gender variable is warranted as this study showed no significant difference.

**Theoretical and Practical Findings of Implications**
Of the nine variables selected for this study, five were significant in identifying a higher risk of mortality for SNF HF patients. These variables were selected based upon their significance and predictive value in multiple heart failure mortality risk models in other studies. Once examined through survival analysis and modeling, some variables became significant in predicting higher risk of mortality for those with HF residing in SNFs. Theoretically, a heart failure mortality risk model could be created from these variables with eventual development of a risk tool. As the variables selected for this study are included in the RAI-MDS 3.0 instrument and obtained through routine assessment, the ease of risk modeling could be put into place with minimal effort. Ideally, an additional assessment, RAI-MDS Care Area Assessment, could be generated electronically to identify potential additional risk assessment for the patient if triggered on the RAI-MDS.

Mortality risk identification has practical implications in the SNF setting as those patients are already compromised medically and physically. Creation of a risk model and tool would be useful for SNF nurses and other practitioners. Having the ability to utilize known mortality risk variables in a model that is directly obtained from the required assessment instrument could be highly valuable. Eliminating additional assessment data capture from other sources would facilitate an easily accessible risk assessment tool. Once mortality risk is identified for each patient, palliative care discussion could occur regarding treatment and quality of life preferences. As part of that discussion, nurses might consider the implications of how that information may affect the patient and family’s acceptance of the mortality risk. Guidance and structured processes as identified in Donabedian’s Quality of Medical Care model may be warranted.
Presently in the SNF setting, there is greater emphasis on obtaining an Advance Directive shortly after admission. While this process has improved the understanding of patient wishes, it could be expanded upon as part of the care plan process with discussion and further exploration of preferences for care direction. Palliative care consideration could be explored in that process. Ideally, the subject of palliative care for this population should be raised at each care plan conference with the patient and family and updated as needed.

From a patient and family perspective, knowing that their mortality risk is higher than their peer group would allow the patient and family to make care and quality of life decisions while they are still in control of their destiny. It is not uncommon for the HF patient to have an exacerbation of the syndrome forcing hospitalization with inherent acute care and treatment without having previous discussions and decisions regarding end of life care. With additional mortality risk information provided, having an advance directive discussion that considers this mortality risk would benefit care providers and ultimately the patients needing acute treatment.

**Methodological, Theoretical, and/or Statistical Importance of the Findings**

The approach to the present study was from a positivist framework and uses observable data allowing its end product to be generalized (Remenyi et al., 1998). While this researcher may have had biases towards the predicted results, objective reality held this researcher’s personal biases in check during the process of evaluating the phenomenon. As these predictive variables have been obtained utilizing survival analysis, they have statistical value as credible factors predicting increased mortality risk. The
variables have been used in other risk models that have been tested in the community setting. However, not all selected variables were found to be significant.

Methodologically, survival analysis was the most logical approach to analyze retrospective data to determine a predictive set of variables. Statistically, five predictive variables were significant in demonstrating a higher risk if the patient had one or more of these present in their assessment. With a sample size of greater than 3000 patients from 24 SNFs across both urban and rural settings, the results are generalizable to the SNF setting across the United States. As there are no known existing processes to use the RAI-MDS 3.0 instrument for the purpose of providing end-of-life care, there is value in the findings to enable the creation of a mortality HF risk model.

**Clinical Significance of the Findings**

Future development of a HF mortality risk model utilizing the predictive variables is clinically valuable allowing candid conversations with patients entering SNFs across the country. This discussion, as noted in the literature, and from this researcher’s professional perspective, rarely occurs prior to admission and often not in the SNF setting until a patient declines to obvious palliative care criteria. There has been recent improvement in SNFs to initiate conversations to obtain an advance directive shortly after admission. Having a viable risk model emanating directly from the RAI-MDS 3.0 assessment would enhance clinical care and seek to improve a patient’s quality of life. Once a patient’s end of life care preferences are known, there is potential to reduce hospital admissions allowing the patient to remain in the SNF for comfort care rather than have aggressive acute care that may or may not improve their quality of life or impact their mortality. Patient preferences discussed with their families being present and
engaged, if inclusion is desired by the patient, would improve the alignment of goals and assist the nursing care team to support the patient and family as the HF syndrome progresses.

**Relationship between the Findings, Previous Research, and the Theoretical/Conceptual Framework/Model**

This study was framed using Donnabedian’s quality of care framework (2005) incorporating both Moorehouse and Mallery’s PATH model (2012) and Kolcaba’s Comfort Theory (2003). Each of these frameworks proved valuable in guiding this study. Donnabedian’s structure, process, and outcome framework was used to guide the evaluation of these variables. From a structure perspective, the patient assessment process using the RAI-MDS 3.0 instrument is already in place in the SNF setting. Incorporating a future developed model and tool using the predictive variables will allow identification of increased mortality risk in those HF patients whose assessment includes positive responses of the predictive variables. From an outcome perspective, discussion with the patient and family will be fostered with newly identified information guiding the nursing process. Moorhouse and Mallery’s PATH framework (2012) is incorporated in this discussion of clearly assessing each patient and having forthcoming conversations with the patient, family, and the rest of the care team. Providing a palliative care discussion will allow the clinical team to provide comfort both physically and emotionally to support the patient as their health deteriorates in synchronization with their preferences as espoused by Kolcaba (2003) and Moorhouse and Mallery (2012).

While substantial research has been conducted to develop predictive HF mortality
models, none of these models have been developed specifically for the SNF setting. Each of these mortality risk models used similar and sometimes different predictive variables. Most of the data regarding these variables are not readily accessible in the SNF setting without further clinical testing or data extraction from an acute medical record. Ideally, when and if Electronic Health Records are shared among health care settings, the potential to incorporate other variables increases. Having a model that is derived directly from the RAI- MDS 3.0 assessment will streamline the nursing process, eliminate the hesitancy to evaluate the risk, and allow palliative care discussion to occur.

**Implications of the Research for Nursing Practice, Education, and Research**

While the nursing profession is improving efforts to engage in palliative care discussion with patients and families, a continued focus must occur. As there are various mortality risk models available, they are not utilized in most practice settings including acute care nor SNFs. Creation of an easy to use risk model can improve nursing practice over time as systemic processes become ingrained facilitating holistic care.

As identified in this study, there are variables contained in the RAI-MDS instrument that are predictive of increased mortality for HF patients. Mortality risk assessment is not present in SNFs and evaluation of HF risk and that of other chronic diseases would benefit the SNF patient population. COPD and diabetes are common in the SNF population and are worth further evaluation. Having other risk models that are directly obtained from the RAI- MDS instrument will foster enhanced palliative care opportunities and have the potential to improve the quality of life and care for SNF patients.

Education to support a better understanding of palliative care would benefit the
staff in SNFs and other care settings. Some nursing education curriculums now contain palliative care content and nurses are becoming more aware of the need to discuss end of life preference with patients. Further education and systemic processes will benefit and enhance these needed discussions.

Many of the nurses working in SNFs are licensed practical nurses. As their curriculum is focused on performance of nursing tasks, they have had little exposure to palliative care in their educational curriculum. While some progress has been made to incorporate palliative care education into the nursing curriculum, there is still much to be accomplished. Mason et al. (2020) identified that nursing education curriculums at the undergraduate and graduate level lack palliative care content. At the graduate nursing level, efforts are underway to address improving the knowledge of advance practice nurses. The American Association of Colleges of Nursing and the End of Life Nursing Education Consortium (2019) recently published a plan to address palliative care for graduate nurses in the “Preparing Graduate Nursing Students to Ensure Quality Palliative Care for the Seriously Ill & Their Families” (Butler et al, 2019).

Further research is needed to identify the most predictive variables of HF mortality risk. While this study identified five viable variables, there may be other variables that would add value to the the risk model. Analysis over time of patient functional decline is one example that could be extrapolated from the assessment data. As the SNF setting has a rich data collection and assessment instrument in place, there may be additional variables from other tools that can help quantify that risk and provide more meaningful information to nurses and patients in their disease progression.

Implications for Vulnerability and Vulnerable Populations
Patients with heart failure who reside in SNFs are extremely vulnerable due to their diminished functionality and health status. The opportunity for these patients and their families to converse with a health professional about their syndrome and probable progression would allow them to process that information and make informed decisions. Too often, the prognosis is not discussed, or clearly communicated so the patient and family can process it and have a secondary or tertiary discussion to clarify what they heard and what they understood. This could be structured using the Moorhouse and Mallery PATH model (2012) aligning the patient wishes with the clinical care teams support and plan.

**Strengths and Weaknesses or Limitations of the Study**

A significant strength of this study was that it used a diverse sample of heart failure patients residing in SNFs located in rural and urban locations. Due to this large sample size of SNF patients, there is enhanced external validity increasing the likelihood of generalization to the SNF population as a whole. While a similar RAI-MDS instrument is used in Canada, it is not clear that the results could be generalized to those populations since their health system is uniquely different than that of the United States. The acuity of the Canadian SNF population is lower compared to the United States and they rarely offer inpatient physical, occupational, or speech therapy as a means to transition back to the community.

Conversely, weaknesses or limitations of this study include that the sample was large and included a number of variables, this may have influenced the results. While the researcher was attempting to include many of the variables identified in prior studies, doing so may have weakened the model by diluting the hazard ratio results. Other
limitations result from the use of a pre-existing database and the RAI-MDS data was not collected specifically to address the particular research questions driving this study and data captured represented one snapshot/measurement point. Lastly, the RAI-MDS has specific coded responses that were designed to guide care and drive payment models. As such, the instrument lacked some key factors that are present on other HF risk models. The study results may not be applicable in other settings as the data was derived from SNF patients specifically.

**Suggestions for Future Research**

Research is needed to evaluate the impact of how a mortality risk tool in a care delivery system would improve the understanding of palliative care for SNF nurses and benefit the patient. The research questions driving this study could be: Does a mortality risk assessment tool increase the use of palliative care in SNFs and improve the patient’s quality of life? Does having this information influence a patient and their family in their decision making? What is the best method to deliver this information to guide the patient and their family in a supportive manner?

As the literature suggests that rehospitalization is a significant predictor of declining health and mortality, evaluating how each hospitalization increases the mortality risk would provide greater insight into the predictive value of this factor in the SNF setting. Clearly, the frailty of this population and increasing hospitalizations may shed light on whether that variable alone or in conjunction with other predictive variables could provide nurses with a tool to prompt palliative care discussion.

Conducting further statistical analysis using just the present study’s predictive variables could prove valuable in creating a mortality risk model and ultimately a tool. As
the variables are significant in predicting mortality risk, having a tool that is generated from the RAI-MDS 3.0 could prove to be an effective approach to prompt nurses to initiate palliative care discussions. Once developed and tested in SNFs, determining the value and benefit to the patient and family should be studied. Findings from the study can also be tested to determine if it improves patient’s quality of life through the initiation of palliative care and end of life decision making.

**Summary**

After identifying potential variables from the literature that can be captured in the MDS assessment instrument, this research study evaluated whether selected variables would predict increased risk of HF mortality in HF patients residing in SNF. Five of nine variables provided clear evidence that the RAI-MDS 3.0 assessment instrument contained relevant data that could be useful in development of a HF mortality risk model. As an administrator and nurse leader in the post-acute health care setting, identifying methods to drive quality outcomes is important and needed. Much of what is performed in a SNF setting is routine and dictated by regulatory requirements and guidelines. Any opportunity to structure a process that improves quality of care outcomes is desired. This aligns with the Donabedian Quality of Medical Care model of designing systems to drive the desired outcomes.

Additional research should be conducted to further test the variables in this model and determine the impact of mortality risk prediction in the SNF setting so as to improve the possibility of palliative care discussion in that setting. While this study obtained evidence of predictive variables, much is needed to further refine how these findings can
be used to impact quality of life for patients with heart failure who reside in skilled nursing facilities.
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Whellan, D. J., Goodlin, S. J., Dickinson, M. G., Heidernreich, P. A., Jaenicke, C.,


Appendix A

Table 1: Heart Failure Mortality Risk Variables

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<th>Variable</th>
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<th>Pocock et al., 2012</th>
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