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Correlation of the Boost Risk Stratification Tool as a Predictor of Unplanned 30-Day Readmission in Elderly Patients

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CORRELATION OF THE BOOST RISK STRATIFICATION TOOL AS A PREDICTOR OF UNPLANNED 30-DAY REAMDISSION IN ELDERLY PATIENTS

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To my husband, Tad and my children Alyssa & Lindsey

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ABSTRACT

Risk stratification tools can identify patients at risk for 30-day readmission but available tools lack predictive strength. While physical, functional and social determinants of health have demonstrated an association with readmission, available risk stratification tools have been inconsistent in their use of variables to predict readmission. One of the risk stratification tools targeted at 30-day readmission is the Better Outcomes by Optimizing Safe Transitions (BOOST) 8 P's tool which includes and social variables but this was not validated. This quantitative dissertation consists of nine research questions, eight of these measured the strength of their association with 30-day readmission and the ninth question measured the combined predictive strength of these variables with 30-day readmission.

The sample included one year of hospitalized patients (n=6849) from a tertiary hospital in the Midwest. The sample was divided into two groups, those that were readmitted or not to this same hospital within 30 days using an electronic medical record. Univariate and multivariate odds ratios were used to determine the strength of the association between variables individually with readmission. Multivariate logistic regression was used to evaluate the predictive strength of the BOOST risk stratification tool with 30-day readmission.

This study demonstrated that six of the eight variables in the BOOST risk stratification tool showed a significant association with 30-day readmission that included the social variables of health literacy (p=.030), depression (p=.003) and isolation (p=.011). Other significant variables included problem medications ($p=.001$), physical limitations ($p=<.001$) and prior hospitalization ($p=<.001$). Combining these variables using multivariate logistic regression, the BOOST risk stratification tool had limited predictive capability with a C-statistic of .631.

This study was the first attempt to validate the BOOST 8 P’s tool and to utilize nursing documentation within an electronic medical record to capture social determinants of health. Findings demonstrated the need to continue research on variables, especially social factors of depression, health literacy and isolation to predict 30-day readmission, especially for the growing population of elderly patients with chronic illness.

CHAPTER ONE

INTRODUCTION

Risk Stratification for Hospital Readmission

Hospital risk stratification tools have the potential to identify elderly patients at risk for unplanned hospital readmission (Kansagara, Englander, Salanitro, Kagen, Theobald, Freeman, & Kripalani, 2013; Peskin, 2013). Risk stratification is defined as a systematic process for identifying and predicting patient health risks (Just, 2014; Peskin, 2013). The population of the United States is shifting toward a greater number of seniors that have chronic illness and require more health care (Center for Disease Control (CDC), 2013c). Unfortunately, the U.S. healthcare delivery system is not designed to care for patients with chronic conditions (Institute of Medicine, 2012b). Instead, it has focused on episodic acute care, rather than long-term management required for patients with chronic illness (World Health Organization (WHO), 2013). Elderly patients with chronic conditions represent a population at risk due to their reliance on a variety of medical providers and fragmented health systems that lack interoperability (Naylor, Hirschman, O'Connor, Barg, & Pauly, 2013). This disjointed support system has been linked to adverse outcomes including preventable and costly unplanned hospital readmissions (Horwitz, Partovian, Lin, Grady, Herrin, & Conover, 2014). One solution to this problem is to identify chronically ill patients during vulnerable periods when they have complex or intensive needs (e.g., post hospitalization) using risk stratification tools (Kansagara et al., 2013). Research has identified that clinicians have been unable to accurately predict patients at risk for readmissions and need predictive tools (Allaudeen, Schnipper, Orav, Wachter, & Vidyarthi, 2011). Risk stratification approaches hold promise to identify patients at risk for adverse events including unplanned readmission but little research exists to support the predictability of these tools (Kansagara et al., 2013). There is a need for more research in developing risk stratification tools based on the variables associated with unplanned readmission for a growing population of elderly patients with chronic illness and complex needs (Choudhry, Li, Davis, Erdmann, Sikka, & Sutariya, 2013).

What is Risk Stratification?

Risk stratification is a process that categorizes a population into groups based on the level of risk or probability of adverse outcomes (Just, 2014; Peskin, 2013). An example of an adverse outcome for elderly patients with chronic disease is unplanned readmission to a hospital within 30-days of a previous hospitalization (Centers for Medicare and Medicaid (CMS), 2016c). Risk stratification tools and models are composed of variables that attempt to identify patients at greatest risk for adverse events, for example, future hospitalizations (Hummel, Katrapati, Gillespie, Defranco, & Koelling, 2014; Lemke, Weiner, & Clark, 2012; Levine, Steinman, Attaway, Jung, & Enguidanos, 2012). After at-risk patients are targeted, there may be an opportunity to provide preventive interventions within the primary care setting; for example, care coordination through a patient-centered medical home care delivery model (American Nurses Association (ANA), 2012b; Cipriano, 2012; Institute of Medicine (IOM), 2011; Lamb, 2013).

Risk stratification variables associated with predicting readmission include diagnosis, co-morbidities and demographics (Haas, Takashi, Shah, Stroebel, Bernard, Finnie, & Naessens, 2013; Kansagara et al., 2013). However, research has failed to demonstrate that any of these are strong predictors for readmissions (Choudhry et al., 2013; Kansagara et al., 2013). In addition, social factors or social determinants of health seem to be associated with unplanned readmissions (Haas et al., 2013). These potential predictors, including socioeconomic status, lifestyle, community and level of education, lack sufficient research to predict readmission (Joynt & Jha, 2012; Kansagara et al., 2013). Overall, the lack of research on the association between risk variables and unplanned readmissions demonstrates a need for tool development to identify at-risk patients. Having this knowledge can lead to targeted and preventive interventions and reduce the burden of unplanned hospital readmissions (Allaudeen et al., 2011; Choudhry et al., 2013; Hammill, Curtis, Fonarow, Heidenreich, Yancy, Peterson, & Hernandez, 2011; Kansagara et al., 2013; Silow-Carroll, Edwards, & Lashbrook, 2011).

Changing Elderly Demographic Resulting in High Healthcare Needs

Several healthcare population trends that have magnified the demand for healthcare resources include an expanding elderly population with complex medical, economic and social needs (Centers for Disease Control and Prevention, Quality, & Services, 2011; Centers for Medicare and Medicaid Services, 2011; CMS, 2015; Commonwealth, 2014). These trends include the growth in the elderly population, the growing prevalence of chronic conditions, the unique health issues of minority elders, and the importance of social determinants of health when identifying health risk. These trends indicate that elderly require increasing levels of health care to manage chronic conditions in the community, which involve social factors.

Elderly Population is Expanding

Americans are living longer with an average life span of 78.7 years, compared to 71 years in 1950 (CDC, 2012; Data360, 2012; IOM, 2013). The combination of a longer life expectancy plus aging baby boomers is predicted to double the population of seniors in the next 25 years to 72 million (CDC, 2013b). It is projected that older adults will represent 20% of the U.S. population by 2030 (CDC, 2013b).

Elderly Have a High Prevalence for Chronic Illness

Older adults have an increased incidence of chronic disease (CDC, 2012). Projections are that by 2030, more than half of seniors will be managing more than one chronic disease (IOM, 2012b). Chronic illness is expected to increase to 20% by 2020 (Keehan, Sisko, Truffler, Poisal, Cuckler, & Madison, 2011). Heart disease, stroke, cancer, and diabetes are associated with up to 70% of all deaths in the United States (Bloom, Cafiero, Jané-Llopis, Abrahams-Gessel, Bloom, Fathima, ... Mowafi, 2012; CDC, 2011; IOM, 2012a). Causes of mortality over the past century has dramatically shifted from infectious disease and acute illness to chronic and degenerative disease (CDC, 2013b).

Minorities Have Unique Health Care Needs and are Often Impacted by Economic Barriers

While in 2010, the majority or 80% of seniors were non-Hispanic white, it is estimated that by 2030 this will decline with significant increases in Hispanic, non-Hispanic Blacks and Asian older adults (CDC, 2013b). Black non-Hispanic seniors have a greater risk of high frequency chronic illnesses including heart disease and diabetes compared to other races (CDC, 2013b). In addition, between 2007-2011, over 14% of U.S. adults had income levels below poverty level with the highest poverty rates for minorities including American Indians, Alaska Natives, Blacks or African Descent, and Hispanics (Census Bureau, 2013). Private health insurance coverage declined among adults between 2000-2010 with an increase in the percentage of uninsured from 13% to 16% impacting the access to medical care due to costs (National

Center for Health, 2011). Thus, low-income racial and ethnic minorities are often disproportionately affected by chronic illness and may face social and economic barriers to accessing preventive care (Centers for Disease Control and Prevention et al., 2011).

Elderly are Highly Impacted by Social Determinants

Social factors or social determinants represent the conditions and communities in which patients live, work and socialize (CDC, 2013b). Social determinants of health are important to seniors with chronic illness potentially impacting their use of health care resources and risk for adverse outcomes (Institute of Healthcare Improvement, 2016h). Research has identified that seniors are at an increased risk of social isolation and loneliness, which has been associated with an increased risk of mortality (Pantell, Rehkopf, Jutte, Syme, Balmes, & Adler, 2013a). In addition, older adults that are minorities, often demonstrate disproportionately poorer health outcomes, which may be due to social barriers including language, cultural norms and access to a primary care provider (CDC, 2013b). Collectively, these demographic changes for seniors have magnified the need for responsive healthcare.

U.S. Health Care System Not Designed to Support Chronic Care

The national healthcare delivery system and the focus on acute decentralized care has failed to align with the healthcare needs of an expanding elderly population managing chronic illness (Institute of Healthcare Improvement, 2016i). These trends include a health care infrastructure that supports acute care, a low utilization of preventive and chronic care in the primary care setting, and high use of expensive acute care services due to poor chronic care management. Unplanned hospital readmission has been identified as an important quality indicator for seniors that has gained momentum due to the high frequency and associated hospitalization costs (CMS, 2016c).

Health Care Systems Focus on Acute Care

Historically, the U.S. healthcare delivery system and the insurance industry were designed to support an acute care model focusing on emergent care (Institute of Medicine, 2012b; WHO, 2013). This model relied on a fee-for-service model in which providers were reimbursed for the quantity rather than the quality of care delivered by providers (CMS, 2015). This quantity-based healthcare delivery structure has been blamed for the upward spike that has allowed healthcare costs to represent 18% of the U.S. gross national product (CMS, 2016a). Acute services include a range of healthcare services that require prompt responses to prevent death or disability (WHO, 2013). Clinical care settings that provide acute care services include emergency rooms, trauma centers, critical care, and, inpatient surgical or medical care (WHO, 2013). However, the acute care delivery system has been blamed for fragmented and disconnected care between settings and providers especially for chronically ill seniors (Lamb, 2013).

Primary Care Services are Often Underutilized

Seniors require a range of preventive and potentially lifesaving services including screenings for cancer, blood pressure and lipid disorders and immunizations ideally coordinated through a primary care provider but these are often not utilized (Centers for Disease Control and Prevention, 2011). It is estimated that about 50% of Americans use recommended preventive services impacted due to deductibles, co-insurance and co-payments (CDC, 2013a). In addition, seniors may not be aware of recommended services or coverage of those services by Medicare if they are not visiting their primary provider routinely. In addition, physical and social barriers may compromise access to primary care especially for minorities including transportation, disabilities, health literacy and fears around pain or test results (Centers for Disease Control and Prevention, 2011).

Need a Health Care System Targeted to Support Chronic Care

Elderly patients with exacerbations of chronic illness often rely on episodic acute care systems rather than relying on primary care providers to coordinate preventive interventions (WHO, 2013). The nature of chronic illness for seniors typically involves intensive episodes with ongoing preventive care including monitoring, follow-up, and education to help them manage their disease over a lifetime (WHO, 2013).

Mismatch in Healthcare Delivery Systems Has Resulted in Quality/Safety Problems

National studies of the U.S. healthcare system have demonstrated significant quality and safety gaps especially for elderly patients with chronic disease resulting in adverse events including unplanned hospital readmission, morbidity and mortality (Institute of Healthcare Improvement, 2016f; Institute of Medicine, 2001; Kansagara et al., 2013). An important safety gap is that the health care system is not designed to support elderly patients with chronic conditions (Centers for Disease Control and Prevention, 2011). Reasons cited included a lack of the following: continuity of care between health care providers, coordination from acute care to home, and sufficient preventive services to support chronic conditions over a lifetime (CDC, 2013b). One of the nationally recognized quality indicators for seniors that has drawn national attention are unplanned hospital readmissions within 30-days of post-acute care, when the patient is most vulnerable for a health complication (CMS, 2016c). Health care reform efforts, including the Patient Protection and Affordable Care Act, have targeted the reduction of barriers to wellness and preventive interventions for seniors (Office of the Legislative Counsel, 2010).

Need for Health Care System Reform: Implementation of the Affordable Care Act (ACA)

Compared to other industrialized countries, the U.S. healthcare system has been unable to compete and ensure access, equity and outcomes of healthcare services for vulnerable patients (Commonwealth, 2014). Reasons for this difference include the lack of universal healthcare coverage impacting the accessibility of care between patients and providers that serve as the medical home (Commonwealth, 2014). The Affordable Care Act (ACA) launched in 2010 (Office of the Legislative Counsel, 2010), focused on increasing reducing Medicare costs and improving access to care especially for seniors through a coordinated payment model focused on reimbursing providers for quality rather than the quantity of care under the fee for service model (CMS, 2012b).

Medicare has estimated the burden of 30-day readmission hospital penalties to be over 41 billion annually impacting 3.3 million adults and the majority or 55.9% were Medicare patients (Hines, Barrett, Jiang, & Steiner, 2014). The top three conditions for seniors with readmission were congestive heart failure, septicemia and pneumonia. Unplanned readmissions have been associated with inadequate transitions in care between providers and healthcare systems (Lamb, 2013). Several ACA programs were directed at reducing the 30-day readmission rates (CMS, 2012c). Programs targeted removing cost barriers to preventive services such as wellness visits and rewarding coordination of care though primary care providers (CMS, 2012c). These programs have begun to demonstrate improved use of preventive services with over 30 million Medicare beneficiaries reporting at least one no-cost preventive service in 2012 (CMS, 2012c).

As part of the ACA health reform, unplanned hospital readmissions were identified as an important patient quality issue for seniors, as those who are well managed in the community after hospitalization should not return to the hospital during this 30-day vulnerable time. The CMS "Readmission Reduction Program," implemented in 2012, reduced Medicare hospital reimbursements for individuals who experienced a 30-day unplanned readmission (CMS, 2016b). The CMS readmission program began with high prevalence for diagnoses of heart failure, myocardial infarction and pneumonia, which were associated with heavy costs of admissions and readmissions (CMS, 2016b). This was expanded in between 2014 and 2016 to include more chronic illness diseases associated with readmissions within 30-days for Medicare patients (CMS, 2016c).

Several other CMS programs were targeted at reducing the fragmented of care and encouraging coordination between healthcare providers including, "Partnership for Patients," which established public-private partnerships hospital engagement networks (CMS, 2012c). Also, the "Transforming Clinical Practice Initiative" was established as a collaborative learning initiative to encourage an appreciation for coordinated care for seniors with chronic disease to reduce their risk of unplanned hospital readmissions (CMS, 2016d).

In summary, the U.S. health system has not been designed to meet the needs of elderly patients with chronic conditions. However, new federal programs and incentives have targeted the need to reduce 30-day unplanned hospital readmissions to improve quality outcomes. While preventive interventions are important to reduce the risk of unplanned readmission, there is a need to identify vulnerable patients using risk stratification tools.

Risk Stratification Tools

Risk stratification tools and models are composed of variables that attempt to measure which patients are at greatest risk for adverse events, including future hospitalizations (Hummel et al., 2014; Lemke, Weiner, & Clark, 2012; Levine et al., 2012). There is a need for risk stratification tools that identify vulnerable elderly patients that could benefit from interventions and care coordination strategies to prevent 30-day readmission (Kansagara et al., 2013). Variables associated with unplanned readmissions are complex and include a range of medical, social and economic factors (Haas et al., 2013; Kansagara et al., 2013). In addition, of the many risk stratification tools available, none have emerged as the gold standard for predicting readmission.

Need for Risk Stratification Tools for Readmission

There is a paucity of risk stratification tools for seniors with chronic illness to target preventive interventions, and those that exist have demonstrated limited predictive capability (Kansagara et al., 2013). Variables associated with unplanned readmission are a combination of diagnosis, demographics and social factors (Hu, Gonsahn, & Nerenz, 2014; Joynt & Jha, 2012; Shier, Ginsburg, Howell, Volland, & Golden, 2013).

The Importance of Including Social Determinants of Health in Risk Stratification Tools

Social determinants that may be factors associated with readmission include poverty, lack of medical insurance, limited education, poor health literacy, social isolation, substance abuse, mental illness and discharge to a community that has poor access to healthcare after hospital discharge, such as a rural setting (Hu et al., 2014; Kansagara et al., 2013). There is a lack of research demonstrating the predictive association between social factors and readmission risk (Hu et al., 2014; Kansagara et al., 2013; Parikh, Kakad, & Bates, 2016).

Risk stratification models used to predict readmission typically included variables of age and gender along with diagnosis and co-morbidity but few include social determinants (Joynt & Jha, 2012; Kansagara et al., 2013). Social factor variables lacked adequate validating studies on their predictive strength (Kansagara et al., 2013). In addition, the majority of risk stratification tools used to predict readmission were designed to predict different adverse outcomes including mortality, resource use, care coordination and hospitalization. Yet, these variables may be valuable in identifying elderly patients at risk for unplanned readmission. Psychometric studies are needed to evaluate the ability of these tools to predict 30-day readmission.

In a group of nine risk stratification tools used to predict readmission, only four included some social determinant variables. The Elder Risk Assessment (ERA) included the presence of an informal caregiver (Boult, Dowd, McCaffrey, Loult, Hernandez, & Keulewitch, 1993). The Hierarchical Condition Categories incorporated the ERA tool to assess the presence of informal caregivers (Mosley, Peterson, & Martin, 2009). The Minnesota Tiering Model included health literacy and severe and persistent mental illness (MHCP Minnesota Department of Human Services, 2011). Finally, the Heart Failure Model included socioeconomic status, insurance status, cocaine use and marital status (Amarasingham, Moore, Tabak, Drazer, Clark, Zhang, ... Halm, 2010). There is a need for more comprehensive risk stratification tools that consider the range of variables associated with readmissions including social determinants (Hu et al., 2014; Institute of Healthcare Improvement, 2016h; Kansagara et al., 2013).

BOOST Includes Social Determinants but Lacks Validating Studies

One risk stratification tool, called the Better Outcomes by Optimizing Safe Transitions (BOOST) 8P's instrument, combines social determinants including depression, functional ability, problem medications, recent hospitalization and medical diagnoses and holds promise for providing a more holistic and accurate risk assessment (Kansagara et al., 2013; Society of Hospital Medicine, 2015). BOOST is a comprehensive approach for hospitals that includes both a risk stratification tool and a toolkit of evidence-based clinical interventions to reduce patient risk during transitions of care (Society of Hospital Medicine, 2015). One of the focus areas within the toolkit is to prevent unplanned readmissions within 30-days after hospital discharge (Society of Hospital Medicine, 2015). BOOST could potentially serve as a comprehensive, more holistic and accurate risk assessment tool (Society of Hospital Medicine, 2015).

Research is Needed to Determine the Predictive Validity of BOOST

While the majority of readmission risk stratification tools have focused on medical diagnosis groups, the BOOST 8 P's tool includes social variables, but lacks predictive validating studies (Allaudeen et al., 2011; Choudhry et al., 2013; Kansagara et al., 2013; Society of Hospital Medicine, 2015). The research question for this dissertation is to measure the 30-day readmission predictive ability of the BOOST risk stratification tool.

Overall Purpose of the Study

The U.S. healthcare delivery system struggles to achieve patient outcomes that meet or exceed other countries (Commonwealth, 2014). Seniors with chronic illness represent a growing population that has created challenges for the U.S. healthcare delivery system (Centers for Medicare and Medicaid Services, 2011; CMS, 2015; Commonwealth, 2014). Healthcare financing was designed to support acute care rather than the ongoing preventive care needed to support patients with chronic illness (Institute of Medicine, 2012b; WHO, 2013). The most vulnerable population at risk for fragmentation of care are chronically ill elderly adults especially those with economic barriers (IOM, 2001; Naylor et al., 2013). Patients with chronic illness are at an increased risk of hospital readmission (Centers for Medicare and Medicaid Services (CMS), 2011; Commonwealth, 2014; Hines et al., 2014). Unplanned 30-day hospital readmission following discharge is an important quality measure associated with high costs and adverse events (CMS, 2012a; Horwitz, 2011). Readmission solutions include the implementation of financial incentives, care coordination interventions, and risk stratification tools that include social determinants (Commonwealth, 2014; Institute of Medicine, 2013; Parikh, Kakad, & Bates, 2016).

Risk stratification or assessment tools can improve the value of scarce healthcare resources by targeting fragile patients, yet the majority of tools demonstrate poor predictive capability (Herbert, Shivade, Foraker, Glasserman, Roth, Mekhijan, . . . Embi, 2014; Kansagara et al., 2013; Parikh, Kakad, & Bates, 2016). While most risk stratification tools focus on diagnosis groups, there is a need for more research on the predictability of social determinants in risk stratification tools (Hu et al., 2014; Kansagara et al., 2013; Parikh, Kakad, & Bates, 2016). One of the risk stratification tools that integrates social determinants is the BOOST 8P's tool (Society of Hospital Medicine, 2015) but there is a need for validating studies. The aim of this study is to determine the degree to which the variables in the BOOST 8P's risk stratification tool can predict 30-day unplanned readmission of elderly patients compared to elderly patients without readmission. The following are the study hypotheses:

- **H1:** Compared with ≥ 65-year-old patients without 30-day unplanned readmissions after an index admission over the past year, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with polypharmacy or the use of high-risk medications.
- **H2:** Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with a diagnosis or history of depression.
- **H3:** Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with specified chronic illness (cancer, stroke, diabetes, chronic obstructive pulmonary disease or heart failure).
- **H4:** Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission over the past year, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with physical limitations (including frailty, malnutrition and weakness).
- **H5:** Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission over the past year, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with poor health literacy.
- **H6:** Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission over the past year, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with patients that lack social support.

- **H7:** Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission over the past year, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with a previous hospitalization within the previous six months.
- **H8:** Compared with ≥ 65-year-old patients without 30-day unplanned readmission over the past year, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with a diagnosis of palliative or hospice care.
- **H9:** Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with some or all of the eight BOOST variables.

CHAPTER TWO

LITERATURE REVIEW

Chapter Two will present the conceptual framework to understand the use of risk stratification within the context of healthcare needs of elderly patients with chronic illness. In addition, this chapter will present a synthesis of relevant literature, a discussion of risk stratification tools, and gaps in the literature.

Theoretical Framework: Wagner's Care Model

Wagner's Care Model (The MacColl Center, 2002) will be used as the overarching theoretical framework for this study. The Care Model represents an expansion of the Chronic Care Model, which illustrated the interconnected nature of acute and preventive care needed by chronically ill patients over a lifetime, as shown in Figure 1 (Wagner, 1998).

Wagner's original Chronic Care model was based on several assumptions: highest cost chronically ill patients benefit most from an integrated approach orchestrated by primary care providers; care management is ideally directed by a lead manager or advocate and improved patient outcomes are associated with potential cost savings (Wagner, 1998). Wagner's model demonstrated the interactive and collaborative nature of care for chronic illness to prevent complications and adverse events (Improving Chronic Illness Care, 2016d). This model was recognized for shifting the focus from acute or episodic care to a population health approach that demonstrated the interdependence between health systems and communities to support patients to manage their chronic illness (Cramm & Nieboer, 2013). This interdependent model provides an ideal conceptualization to guide this study.

The Care Model, as shown in Figure 1, has four larger concepts that demonstrates the interface of healthcare surrounding the chronically ill patient: (1) community/health systems; (2) services; (3) patient and healthcare practice team engaged in ongoing interactions and (4) improved clinical outcomes (Improving Chronic Illness Care, 2016g). The idea is that there is dynamic flow between an informed patient and proactive healthcare team to navigate the myriad of healthcare services, systems, providers and services through "productive interactions" or communications that result in improved patient outcomes. The following sections describe each concept within the model and characteristics of the concepts.

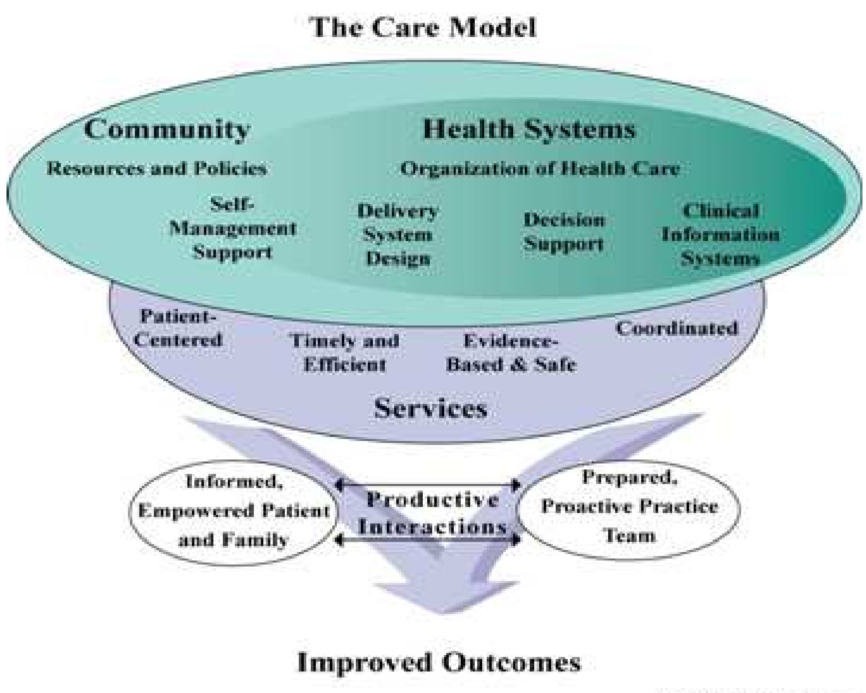

Figure 1. Wagner's Care Model

Community and Health Systems

The first larger concept describes the nature, interactive relationship and direction of the sub-concepts of community and health systems.

Community

Community represents supports for the patient including programs and partnerships for filling gaps in services and advocating for expanded resources (Improving Chronic Illness Care, 2016b). Organizations involved could include local, state and national patient organizations. Policies were added in 2003 and include those that advocate and protect chronically ill patients such as civil rights laws and disability provisions. An example of resources and policies would be the requirement for handicap access for entertainment and dining establishments.

Health Systems

Health systems represent the organization of health care services available to the patient. Health systems represents the culture, structure and mechanisms that promote safe and high-quality care (Improving Chronic Illness Care, 2015, 2016e). Characteristics of a health system include leaders that recognize the importance of improvement strategies targeted at system change to support patient outcomes (Improving Chronic Illness Care, 2015). Leadership promotes an atmosphere that encourages open and systematic reviews of errors (updated in 2003) and quality problems to assure patient safety (Improving Chronic Illness Care, 2015). Effective health systems change their care processes in response to patient safety issues and adverse events. Communication and coordination of care is assured through agreements (updated in 2003) between different organizations and providers (Improving Chronic Illness Care, 2015).

An example of a healthcare system would be an academic medical health system that incorporates other acute hospitals, emergency services, specialty care and primary care services.

The gradation between the health system and the community is intentional. The health system exists within the community, but includes a graded separation and connection with the community. There are four sub concepts that represent structures that support the provision of health care within the health care system, but can be connected to the community: self-management support, delivery system design, decision support, clinical information system.

Self-management support. Self-management supports represent resources within the community and/or health system to help patients manage their chronic illness. The patient is in a central role of managing their care and participating in goal setting, problem solving and creating a treatment plan with supports that are accessible (Wagner, Austin, Davis, Hindmarsh, Schaefer, & Bonomi, 2001). Due to the nature of chronic illness that includes a prolonged course with fluctuating healthcare needs, patients need systematic interactions and follow-up with their healthcare team (Wagner et al., 2001). Self-management implies that patients control their decisions and behaviors, including lifestyle, that may impact their ability to manage their chronic illness (Improving Chronic Illness Care, 2016f). An example of self-management support would be introducing a medication reminder box to help patients remember to take their routine medications in order to manage their hypertension or asthma.

Delivery system design. Delivery system design is the structure of how health care is provided, which may include an interconnection with community resources. Systems are designed to maximize effective, efficient clinical care processes to support patients to manage their own health between healthcare providers and settings including local services (Improving

Chronic Illness Care, 2016d). Team members utilize a proactive approach by anticipating problems and following up rather than simply reacting when a patient is acutely ill. Clinicians recognize potential cultural (updated in 2003) and linguistic limitations that may affect patients with chronic disease. There is an understanding that patients that are more complex may require episodes of intensive management using care management to optimize their ability to return to self-management (updated in 2003). An example of delivery system design would be providing interprofessional teams within the primary care setting especially for elderly patients with chronic disease.

Decision support. Decision support represent the clinical processes to support care based on evidence-based guidelines, highest quality medical research and specialist expertise along with patient preferences (Improving Chronic Illness Care, 2016c). Guideline recommendations are incorporated into clinical processes such as reminder systems, standing orders and protocols. Clinician and patient research-based education is available to improve practice and compliance. Providers rely on these tools to tailor care for individual patients that may require more intensive care. An example of decision support would be using a risk stratification tool to identify patients at risk for hospital readmission.

Clinical information systems. Information systems represent the flow of medical information that support efficient and effective care (Improving Chronic Illness Care, 2016a). These systems should be interoperable to allow coordination of individual patient care between different practice teams and providers (updated in 2003). These systems should provide reminders for needed services to allow monitoring and planning care. In addition, these systems should identify groups of patients that require additional care or quality improvement interventions. An example of clinical information systems would be the integration of a risk stratification tool as part of a shared electronic medical record by the primary care provider in targeting chronically ill patients at risk for readmission.

Services

The second construct in the Wagner Care Model is Services. Services are the activities provided by a healthcare system to support patients within the context of the health system and community. The expanded Wagner Model has included service characteristics described in the Institute of Medicine Crossing the Quality Chasm report (2001). Given the structure of the health system, services need to be patient-centered, timely and efficient, evidence-based, safe and coordinated (Institute of Healthcare Improvement, 2016f). The following sections define each sub concept and relate these sub concepts to this study.

Services Should be Patient-Centered

Patient centered care is defined as interventions that consider the patients cultural beliefs, preferences, lifestyle and values (Institute of Healthcare Improvement, 2016c). Although risk stratification tools are decision support tools, the BOOST tool can support patient centered care because it includes social determinants of health. This information can inform a strategy to identify patient risk levels by incorporating individual variables including social isolation and health literacy.

Services Should be Timely and Efficient

Timely and efficient care is defined as care that is provided at the right time with the appropriate amount of resources (Institute of Healthcare Improvement, 2016d). The complexity of the healthcare system has been blamed for the lack of efficiency and waste in the ways in which care is delivered (Institute of Healthcare Improvement, 2016e). Risk stratification can improve both the timeliness and efficiency of interventions through the identification of vulnerable patients that could benefit from preventive interventions at the time and magnitude required (Kansagara et al., 2013).

Services Should be Evidence-Based and Safe

Research based interventions are defined as clinical activities grounded in scientific evidence to reduce the risk of harm (Institute of Healthcare Improvement, 2016a). Medical errors have been estimated to represent the third leading cause of death (Makary & Daniel, 2016). Hospitalized patients are at a high risk of medication errors impacting 7 out of 100 patients (Institute of Healthcare Improvement, 2016a). Safety can be impacted by creating a culture in which mistakes are recognized as opportunities to improve systems and processes (Institute of Healthcare Improvement, 2016a). The use of an evidence-based approach is also referred to as an "effective" approach (Institute of Healthcare Improvement, 2016b). Clinical processes need to change as medical knowledge advances impacting both the overuse or underuse of techniques, processes and technologies (Institute of Healthcare Improvement, 2016b). Risk stratification can identify patients that could benefit from evidence-based interventions to protect patients from adverse events such as readmissions (Institute of Healthcare Improvement, 2016a).

Services Should be Coordinated

Care that is coordinated is defined as supporting connections between providers and settings and aligning quality processes that is part of the fabric of policies, procedures, systems and leadership (Institute of Healthcare Improvement, 2016f, 2016i). Readmissions have been associated with inadequate transitions in care (Lamb, 2013). Care coordination is an example of a proactive dialog between providers across systems and settings with a focus on prevention especially for seniors with chronic disease (Institute of Healthcare Improvement, 2016i). Risk stratification represents a decision support tool that alerts clinicians between healthcare settings of patients that could benefit from care coordination interventions. An example of this would be tracking vulnerable heart failure patients for preventative interventions within the primary care setting.

Informed Patient and Proactive Team Connected Through Interactions

The third construct in the Wagner Care Model is an informed patient and proactive team connected through interactions. There are three sub concepts within this construct: an informed patient, proactive team, and productive interactions.

Informed Empowered Patient and Family

An "informed empowered patient and family" have the motivation, information, tools, and confidence to make decisions concerning the management of their or their family members' chronic condition (Improving Chronic Illness Care, 2016f). The patient and/or caregivers have an adequate understanding of the trajectory of their chronic disease, treatment plan and an understanding of when to alert providers or seek complex or emergency services. An example could be a family who attends care conferences, asks questions, and follows an individualized care plan.

Prepared Productive Practice Team

The "prepared productive practice team" ideally represents the primary care team that coordinates the information between alternate providers and levels of care from acute to community supports. This team would provide resources to support the chronically ill elderly patient that includes providing patient information and decision supports (Improving Chronic Illness Care, 2016f). Risk stratification represents a systematic decision support tool that can help provide valuable information for the practice team by identifying patients at risk for an adverse event such as re-hospitalization to guide the team toward preventive interventions (Just, 2014).

Productive Interactions

Productive interactions link patients and providers in effective communications that share an understanding of the patient's self-management skills and confidence, tailoring of interventions recognizing individual needs and values, collaborative goal setting and sustained follow-up (Improving Chronic Illness Care, 2015). Patients are included in developing a shared care plan to set short and long-term goals throughout the course of their chronic illness.

Improved Outcomes

Improved outcomes represent the fourth construct and ultimate goal of the Care Model, which is described as meeting the triple aim of healthier patients, improved satisfaction and cost savings (Improving Chronic Illness Care, 2015). Readmissions are often due to multiple factors, especially for patients with chronic illness (AHRQ, 2016). While readmissions can represent the "outcome measure" of changes in the health state of a patient, it may also be associated with a lack of social supports such as caregivers in the home or misunderstanding of discharge instructions due to poor health literacy (AHRQ, 2016). In addition, readmissions can occur due to poor care during the first admission that may require rescue or negative outcomes (AHRQ, 2016). Thus, 30-day readmission can be a proxy measure for health outcomes.

Applying the Wagner Care Model to Risk Stratification

Risk stratification is a form of "decision support" within the health system and community. This decision support can be integrated into the clinical information system. Specifically, the BOOST risk stratification tool incorporates both medical and social factors that can inform the provider team about both medical and social risks for more productive interactions between the provider and patient. A well-designed risk stratification tool has the potential to predict poor outcomes. Providers that know patient risk can intervene with interventions to mitigate poor outcomes.

The Wagner Model provides an overall theoretical framework for care management, but this study more specifically measures the degree to which the eight predictors identified in the BOOST risk assessment tool lead to 30-day readmissions. The Wagner Care Model provides the context for using and applying the BOOST tool. Each of the predictors are conceptually defined later in this chapter.

Measures of Risk Stratification

This section will describe and evaluate current risk stratification tools associated with unplanned 30-day readmission. These tools can be evaluated based on their targeted population, variables and predictive strength (Steyerberg, Vickers, Cook, Gerds, Gonen, Obuchowski, ... Kattan, 2010). The targeted population is the sample used for the study. Variables represent the outcome that is measured. Predictive capability or model discrimination is the strength of the association between variables and the outcome, which is typically presented as a c-statistic or the probability of an outcome that is better than chance (Hosmer & Lemeshow, 2000).

Operationally, risk stratification models are tested for discrimination ability using the c-statistic or area under the curve with 95% confidence level (Kansagara et al., 2013; Steyerberg et al., 2010). It measures the estimated conditional probability or predicted risk for binary outcomes (Uno, Cai, Pencina, Agostino, & Wei, 2011). C-statistics provide the proportion of time the model correctly identifies high and low risk with the following criteria: 0.50 indicating that the model is equivalent to chance; less than 0.70 indicating poor discriminative ability, 0.70-0.80 indicating modest discriminative ability; and, a threshold of 0.80 demonstrates good discriminative ability (Kansagara et al., 2013; Steyerberg et al., 2010).

Risk Stratification Tool Search Strategy

In a review of over 20 studies of risk stratification tools associated with readmission, only four measured 30-day readmission and three of these also measured the risk of death. These all demonstrated moderate to poor predictive strength with c-statistics between 0.78-0.56. The Heart Failure Model was the only tool of this group that included social variables (Amarasingham et al., 2010). Table 1 below and the following section describe each tool, target population, predictive variables, and discrimination ability.

The remaining six risk stratification tools detailed in Table 2 had different targeted outcomes including mortality, repeated hospitalization, and complexity of care and resource utilization and were used in one comparative study to predict 30-day readmission (Haas et al., 2013). Three of the tools included social variables. Their collective predictive strength of these risk tools when applied to the 30-day readmission was modest to strong with c-statistics of 0.83-0.73.

Table 1. Risk Stratification Tools Predicting 30-day Readmission.

Model	Outcome	Variables	Social Factors	C-Statistic
ACC (Choudhry et al., 2013)	Readmission	Discharge Model: Demographics including age, gender and race/ethnicity Utilization Laboratory tests Exploratory tests Medications Conditions LOS Discharge disposition		0.76 & 0.78 (Modest)
LACE + Index (van Walraven, 2012)	Readmission or Mortality	Demographics including senior age & male gender Teaching status hospital Acute diagnosis Procedures Number of admissions		0.771 (Modest)
LACE Index (van Walraven, Dhalla, Bell, Etchells, Stiel, Zamke,…, Forster, 2010)	Readmission or death	Length of stay in the hospital Acuity of the admission Comorbidity ED use in previous 6 months		0.684 (Moderate/Poor)
Heart Failure Model (Amarasingham et al., 2010)	Readmission or mortality	Diagnosis of heart failure Severity of illness Number of ED visits in previous. year	Socioeconomic status (history of home address changes in previous year) Risky health behavior (cocaine use) Insurance status Single marital status Male gender	0.56-0.66 (Poor) Addition of social factors increased to 0.72 (Modest)

Risk Stratification Tools Targeting 30-Day Readmission

Four tools specifically measure risk for 30-day readmission: The Advocate Health Care in Chicago and Cerner Admission and Discharge Models (ACC), LACE + Index, LACE Index, and the Heart Failure Model.

Advocate Health Care in Chicago and Cerner Admission and Discharge Models (ACC)

Advocate Health Care in Chicago and Cerner (ACC) Admission and Discharge Models represent a partnership between a healthcare system and a healthcare data management provider to measure the risk of 30-day unplanned readmission to identify vulnerable patients that could benefit from preventive interventions to support transitions in care (Choudhry et al., 2013). The population was 126,479 adult patients discharged over a year from eight Advocate hospitals located in the Chicago market. The tools were created using a retrospective cohort study of adult inpatients from March 1, 2011-July 31, 2012. The admission and discharge cohorts shared six variables including demographics, resource utilization, laboratory and exploratory tests, medications and conditions. The discharge model added length of stay and discharge disposition variables. These models demonstrated modest discrimination ability with c-statistics of 0.76 for the admission cohort and 0.78 for discharge cohort (Choudhry et al., 2013).

The Lace Index Models

The LACE Index was developed as a tool to predict the risk of readmission or death within 30-days of discharge to identify vulnerable patients that could benefit from intensive preventive interventions (van Walraven et al., 2010). The population included 4,812 medical and surgical adult patients discharged to home from 11 community hospitals in Ontario. The tool was created using a prospective cohort survey and splitting the sample for death or discharge using

48 patient-level and admission level predictive variables collected over a four-year period. Predictive variables independently associated with these outcomes included the mnemonic "LACE" or length of stay in the hospital [L], acuity of the admission [A], comorbidity in which they used the Charlson comorbidity index Score [C] and emergency department utilization in the six months before admission [E]. Predictive capability was moderate/poor for readmission or death with a c-statistic of 0.68 (van Walraven et al., 2010).

The LACE + Index

The LACE index was enhanced into a LACE + in an effort to measure readmission death within 30-days of discharge while adjusting for risk and improving the capability to compare hospital readmission rates between facilities (van Walraven, 2012). The population included 500,000 medical and surgical adult patients discharged to home from any community hospital in Ontario between April 1, 2003-March 31, 2009. The tool was created using a logistic regression model on 250,000 randomly selected patients from the population and expanding the LACE index predictive variables. The original "LACE" predictive variables were kept with the addition of demographics of age and male gender, acute diagnosis and use of emergent and acute services in the year previous to the index admission (van Walraven, 2012). Validation of the LACE + model was conducted using the remaining 250,000 patients. This revised model exceeded the predictive capability of the original model moderate/strong c-statistic of 0.77 (van Walraven, 2012).

The Heart Failure Model

The Heart Failure Model was developed by Parkland Health and Hospital System in Texas as a real-time predictive model to identify heart failure patients at high risk for 30-day readmission or death (Amarasingham et al., 2010). The population was 1,372 heart failure patients at a major urban hospital from January 2007-August 2008. Predictive variables included diagnosis of heart failure, severity of illness, number of emergency room visits, socioeconomic status, and cocaine use, insurance and marital status. The tool was created, derived and validated using logistic regression comparing performance with readmission and mortality models developed by CMS, and a heart failure model was derived from the Acute Decompensated Heart Failure Registry (ADHERE) (Amarasingham et al., 2010). While the c-statistics for mortality were moderate at 0.72-0.73, readmissions demonstrated poor predictive capability with c-statistics at 0.56-0.66. When social determinants including single marital status, male gender, risky behavior, insurance status and socioeconomic status were added, the predictive capability for readmissions improved from poor with c-statistics of 0.56-0.66 to modest with a c-statistic of 0.72 (Amarasingham et al., 2010).

Alternate Risk Stratification Tools Used to Predict 30-Day Readmission

Other risk stratification tools to consider that were not designed to predict 30-day unplanned readmission, but were used in studies that predicted 30-day readmissions, include Charlson Comorbidity Index, Ambulatory Clinical Grouping (ACG), Chronic Condition Count (CCC), Minnesota Tiering Model (MT), Elder Risk Assessment (ERA) and Hierarchal Condition Categories (HCC).

Table 2. Alternate Risk Stratification Tools Used to Predict 30-day Unplanned Readmission.

Model	Target Outcome	Variables	Social Factors	C-Statistic Readmission Risk (Haas et al., 2013)
Charlson (Charlson, Pompei, Ales, & MacKenzie, 1987)	Mortality	Diagnosis codes Mortality		0.73- (Modest)
ACG (Weiner, Starfield, Steinberg, & Steinwachs, 1991)	Resource Utilization	Age Gender ICD-9		0.80-0.83 (Strong)
CCC (Naessens, Strobel, & Finnie, 2011)	Resource Utilization	Number of chronic conditions Total insurance payments		0.76-0.79 (Modest)
MT (MHCP Minnesota Department of Human Services, 2011)	Care Complexity & Care Coordination Needs	Complexity tiers	Non-English speaking patient's/sign language and communication devices Serious mental illness	0.78-0.81 (Modest-Strong)
ERA (Boult et al., 1993)	Repeated hospital admission	Older age Male gender History of coronary artery disease/DM Previous hospital admission last year More than 6 physician visits in the previous year Condition codes Poor self-rated general health	Availability of informal caregiver	0.76-0.79 (Modest)
HCCs (Mosley, Peterson, & Martin, 2009)	Hospitalization & Care Coordination Needs	Older age Male gender History of coronary artery disease/DM Previous hospital admission last year More than 6 physician visits in the previous year Condition codes Poor self-rated general health	Availability of informal caregiver	0.73-0.77 (Modest)

The Charlson Comorbidity Index

The Charlson Comorbidity Index was developed to classify comorbid conditions that may increase the risk of mortality over time (Charlson et al., 1987). This was tested on two cohorts to measure one-year and ten-year mortality in a sample of 559 medical patients and 685 patients respectively. Predictive variables were the number and acuity of comorbid disease classified into groups. Comparison of the cohorts demonstrated a stepwise increase in the weighted index of comorbid disease with an associated increase in cumulative attributable mortality short and long-term mortality (log rank chi 2=165; p <0.001).

The Charlson Index was more recently tested comparing ICD-9 to ICD-10 coding systems to predict in-hospital and one-year mortality post hospitalization (Li, Evans, Faris, Dean, & Quan, 2008). This involved a population of five cohorts of Canadian adult patients between 1997 and 2004 targeting patients with congestive heart failure, diabetes, chronic renal failure, stroke and patients undergoing coronary artery bypass grafting. C-statistics between the cohorts of ICD-9 and ICD-10 codes demonstrated similar risks of mortality ranging from 0.82 to 0.62. However, when it was used in a large comparative study for 30-day readmission, it demonstrated moderate predictive ability with c-statistics of 0.73 compared to eight tools described in Table 2 (Haas et al., 2013).

The Ambulatory Care Groups

The Ambulatory Care Groups (ACG) was developed by Johns Hopkins to measure the utilization of ambulatory care services (Weiner et al., 1991). The tool was validated using 160,000 continuous primary care adult enrollees in four large HMO's and a state Medicaid program. Predictive variables were the age, gender and ICD-9 codes associated with the presence or absence of broad clusters of diagnoses and conditions that categorized patients into one of 51 ACG categories over extended periods (i.e., one year). This variable reflected the patient's pattern of disease rather than a specific diagnosis and was used to predict use of ambulatory services. The ACG system predicted more than 50% of variance in ambulatory resource use in retrospective studies (Weiner et al., 1991). This tool had modest predictability of healthcare expenditures with a c-statistic=0.76. However, when it was used in a large comparative study for 30-day readmission, it demonstrated strong predictive ability with c-statistics of 0.80-0.83 compared to eight tools described in Table 2 (Haas et al., 2013).

The Chronic Condition Count (CCC)

The Chronic Condition Count (CCC) measures the longitudinal effect of healthcare costs of multiple chronic conditions (Naessens, Strobel, & Finnie, 2011). The population was 33,324 adult employees and their dependents of the Mayo Clinic in Rochester, Minnesota aged 18 to 64 years in a self-funded healthcare insurance plan from January 1, 2004, to December 31, 2007. The study measured how well the number of chronic conditions per patients predicted healthcare costs using secondary data from medical and pharmacy claims in a retrospective cohort study. The results demonstrated that 75.3% of the adult population had at least one chronic condition and 54% had multiple chronic conditions that were associated with persistent increases in healthcare costs across all age groups (Naessens, Strobel, & Finnie, 2011). Mean costs for patients with no chronic conditions was $2,137 compared to patients with five or more chronic conditions, which was over $21,000/year. However, when it was used in a large comparative study for 30-day readmission, it demonstrated moderate predictive ability with c-statistics of 0.76-0.79 compared to eight tools described in Table 2 (Haas et al., 2013).

The Minnesota Tiering Model

The Minnesota Tiering Model measures the complexity of patient needs as part of a state healthcare reform effort, called the "Minnesota Health Care Programs (MHCP) Health Care Homes," to reimburse primary care providers for providing care coordination for patients with multiple chronic conditions (MHCP Minnesota Department of Human Services, 2011; MHCP Minnesota Department of Human Services, 2012). The MHCP model was developed under 2008 Legislature to reimburse primary care providers to coordinate care. Beginning July 1, 2010, MHCP provided payment to primary care providers that coordinated care within a medical home model (MHCP Minnesota Department of Human Services, 2012). Predictive variables include grouping patients into "complexity tiers" based on major chronic conditions; severity or potentially unstable conditions that could lead to severe illness or death; the need for care team to coordinate care; the need to communicate in a non-English language; and, serious and persistent mental illness diagnosis (Minnesota Department of Health, 2016a). This tool was recognized for reducing inpatient admissions by over 30% between 2010 and 2014 (Minnesota Department of Health, 2016b). When used in a large comparative study for 30-day readmission, it demonstrated a moderate to strong predictive ability with c-statistics of 0.78-0.81 compared to eight tools described in Table 2 (Haas et al., 2013).

The Elder Risk Assessment (ERA)

The Elder Risk Assessment (ERA) measures the risk of repeated hospital admissions (Boult et al., 1993). The population included 5,876 non-institutionalized U.S. civilians ≥ 70 years old in 1984. Subsequent hospital admissions and mortality were tracked through Medicare records and the National Death Index over four years. Predictive variables included older age, male gender, history of coronary artery disease or diabetes, previous hospital admission in the last year, more than six physician visits in the previous year, major conditions, poor self-rated general health and the availability of an informal caregiver. Logistic regression of a split sample was used to compare the presence or absence of these factors for cumulative predictive variance of repeated admissions (41.8% vs. 26.2%, $p<0.0001$) and mortality (44.2% vs. 19.0%, $p<0.0001$). When used in a large comparative study for 30-day readmission, it demonstrated moderate to strong predictive ability with c-statistics of 0.76-0.79 compared to eight tools described in Table 2 (Haas et al., 2013).

The Hierarchical Condition Categories (HCC's)

The Hierarchical Condition Categories (HCC's) measures the probability of hospitalization to evaluate the need for care coordination resources (Mosley, Peterson, & Martin, 2009). This model was developed by the Centers for Medicare & Medicaid Services (CMS) to predict the probability of hospitalization of Medicare Advantage Plan enrollees with chronic illness to determine hierarchical condition categories (HCC). The population was 4,506 newly enrolled beneficiaries. Predictive variables included older age, male gender, history of coronary artery disease or diabetes, previous hospital admission in the last year, more than six physician visits in the previous year, major conditions, poor self-rated general health and the availability of an informal caregiver (Mosley, Peterson, & Martin, 2009). Logistic regression was used to assess the predictive capability of the variables to hospitalization. Predictive capability was poor with c-statistic at 0.603-0.674, 95% CI. However, when it was used in a large comparative study for 30-day readmission, it was moderately predictive with c- statistics of 0.73-0.77 compared to eight tools described in Table 2 (Haas et al., 2013).

Risk Stratification Tool Analysis

Two large comparative studies of risk stratification tools associated with hospitalization readmission demonstrated that the majority of tools demonstrated poor to moderate predictive validity (Haas et al., 2013; Kansagara et al., 2013). Kansagara et al. compared 26 risk stratification tools. The majority used predictive variables of medical comorbidity and the use of previous medical services but very few considered social determinants of health. Haas et al. (2013) compared six risk stratification tools for various outcomes including readmission which are outlined in Table 2. Predictive strength for readmission was moderate with c-statistics of 0.75-0.81. However, the addition of age, gender and marital status improved the c-statistic for all outcomes including readmission. Few risk stratification tools used for readmission used alternate variables including severity of illness, functional status, problem medications and social determinants of health (Choudhry et al., 2013; Haas et al., 2013; Kansagara et al., 2013).

While there is a paucity of social variables in risk stratification tools used to assess readmission, there is also a lack of consistency on what social factors are most predictive. In Tables 1 and 2, only four included social variables, and it was unclear which had greater predictive strength between marital status, use of informal caretakers, communication compromises, frequency of changes of address, presence of severe mental illness and the use of cocaine as a risky behavior. There needs to be a greater understanding of which social variables are significant predictors for hospital readmission.

Barriers in using social variables in research may be associated with the difficulty in extracting this information consistently from the medical record (Choudhry et al., 2013; Pantell et al., 2013a). Social determinants of health represent a wide range of variables that are frequently documented in nursing or case management narrative notes, which are difficult to extract from the patient medical record.

Better Outcomes by Optimizing Safe Transitions (BOOST)

Better Outcomes by Optimizing Safe Transitions (BOOST) represents a comprehensive hospital-based implementation tool kit that links risk stratification variables gathered on admission with preventive interventions to reduce 30-day readmissions for adults with chronic disease (Society of Hospital Medicine, 2015). BOOST was created through a grant from the John A. Hartford Foundation in 2008 and lead by Dr. Eric Coleman’s Care Transitions Program and Dr. Mary Naylor’s Transitions of Care Model to reduce unnecessary readmissions and improve the coordination of care (Society of Hospital Medicine, 2015). The model was designed based on population health research on the causative factors of readmission including medical factors and social determinants. One of the instruments in the toolkit is the 8P’s risk stratification or identification tool, which screens patients for social determinants associated with readmissions along with their diagnosis, medications, physical limitations and prior hospitalizations (Society of Hospital Medicine, 2015).

BOOST Research

There were only two studies on the implementation of the BOOST toolkit within hospitals and only one mentioned the use of the BOOST risk stratification tool (Landman, 2013; Williams, Li, Hansen, Forth, Budnitz, Greenwald, ... Coleman, 2014). These both used testing sites that included Illinois testing sites.

Chicago study. In a 2009 Commonwealth Fund Study, “Aiming Higher: Results from a State Scorecard on Health System Performance,” Illinois ranked 44 out of 50 states on 30-day readmissions (Commonwealth, 2009). As a result, three organizations, BlueCross BlueShield of Illinois (BCBSIL), Northwestern University's Feinberg School of Medicine and the Illinois Hospital Association, worked with the Society of Hospital Medicine (SHM) to reduce the state's readmission rate (Landman, 2013). In 2011, the group launched Preventing Readmissions through Effective Partnerships (PREP) with five objectives (1) redesign of hospital discharge processes; (2) improve transitions in care; (3) enhance the delivery of patient-centered care; (4) strengthen hospitalist program; and, (5) measure reductions in readmissions with standard metrics.

As part of this initiative, the BOOST mentoring program was used to support improved dissemination of program objectives. In one of the hospitals, Sherman reduced their readmission rates from 26% in 2009 to 11% in 2013, which they attributed to the BOOST mentoring program (Landman, 2013). In 2013, almost 90% of Illinois hospitals have participated in the PREP program and demonstrated significant reductions in readmission rates.

Six hospital multi-state pilots. The second research study of the implementation of the BOOST toolkit included the use of the BOOST risk stratification tool (Williams et al., 2014). This was a qualitative study of 27 hospitals reviewing BOOST interventions involving various levels of staff at the hospital sites. Qualitative results were gathered by focusing on perceptions of successes and failures of the pilot. Findings substantial barriers to adopting the BOOST included an inadequate understanding of the discharge process, lack of resources, lack of protected time and ambiguous leadership support. Themes of successes included the value of mentorship, teamwork and the engagement of the patient.

The BOOST risk stratification tool was implemented in 77% and 79% of the two cohorts but there was no detail describing the successful use of preventative interventions or the psychometrics of the BOOST risk stratification tool. While the BOOST toolkit seemed to be well regarded, there were significant barriers in implementation (Williams et al., 2014).

BOOST Structure

The BOOST toolkit was built around core principles including patient centeredness, empowerment, risk appropriateness, team oriented and bridging (Society of Hospital Medicine, 2015). “Patient centeredness” focuses communicating the needs, abilities and desires of patients with their caregivers and providers across settings and time (Society of Hospital Medicine, 2015). “Empowerment” prepares patients and caregivers to advocate for appropriate care and warning signs for adverse events (Society of Hospital Medicine, 2015). “Risk appropriateness” is a discharge intervention that directs resources to patients with identified potential for poor outcomes (Society of Hospital Medicine, 2015). “Team oriented” is the multidisciplinary team ideally organized by a lead advocate to ensure a successful discharge (Society of Hospital Medicine, 2015). Interventions, termed “bridging interventions” are directed to three phases or touch points including hospital admission, nearing discharge, and at discharge (Society of Hospital Medicine, 2015).

Part of the BOOST toolkit is the 8P’s risk stratification tool, which suggests screening all hospitalized seniors to identify at-risk patients that could benefit from preventive interventions. The eight variables in the tool reflect those associated with readmission including diagnosis, medications, mental health, physical limitations, poor health literacy, social isolation, previous hospitalizations and palliative care. The BOOST 8P’s tool includes several social variables including poor health literacy (Cloonan, Wood, & Riley, 2013), depression (Cancino, Culpepper, Sadikova, Martin, Jack, & Mitchell, 2014) and lack of patient supports (Mistry, Rosansky, McGuire, McDermott, & Jarvik, 2001).

Since there is limited research to support the validity of the BOOST risk stratification tool, there is an opportunity to study the predictive association between the variables and the readmission. The eight assessment areas of the Boost tool are defined in Table 3 and further described below (Society of Hospital Medicine, 2015).

Table 3. BOOST 8P's Risk Stratification Variables.

Variable	Conceptual Definition
Problem Medication	Polypharmacy OR High-risk medications
Psychological	History OR positive screen for depression
Principal Diagnosis	Cancer OR stroke OR diabetes OR COPD OR heart failure
Physical Limitations	Deconditioning, frailty, malnutrition
Poor Health Literacy	Inability to do Teach Back
Poor Social Support	Absence of spouse or caregiver to assist with discharge and home care
Prior Hospitalizations	Within previous six months
Palliative Care	Perception patient could die within the upcoming year OR if the patient has advanced or progressive terminal illness

Problem medications are defined as either the use of ≥ 10 routine medications or polypharmacy associated with readmission (Santos, Silva, Alves-Conceicao, Antoniolli, & Lyra, 2015; Society of Hospital Medicine, 2015). The use of high-risk medications in the elderly has been associated with an increase in adverse events after discharge (Marcum, Handler, Boyce, Gellad, & Hanlon, 2010; Society of Hospital Medicine, 2015). The American Geriatric Society (ACG) has established a categorization process, “Beers Criteria,” to define a wide range of potentially high-risk medications. The BOOST risk stratification tool recognizes problem medications as polypharmacy, or the use high-risk medications.

Psychological problems are defined as a diagnosis of depression described by the American Psychological Association as a serious medical illness and mood disorder associated with feelings of sadness and loss of interest in formerly enjoyable activities (2016). Depression is often undiagnosed in older patients and has been associated with an increased rate of rehospitalization (Cancino et al., 2014; Society of Hospital Medicine, 2015).

Principal diagnosis is defined as selected chronic illnesses associated with an increased risk of adverse events including rehospitalization (Ford, 2015; Hijjawi, Abu Minshar, & Sharma, 2015; Linden & Butterworth, 2014). The BOOST risk stratification tool recognizes principal diagnoses as including cancer, stroke, diabetes, COPD, and heart failure.

Physical limitations are defined as compromises in the ability to perform activities of daily living that have been associated with readmission (Agarwal, Ferguson, Banks, Batterham, Bauer, Capra, & Isenring, 2013; Craven & Conroy, 2015). The BOOST risk stratification tool recognizes physical limitations as deconditioning, frailty, malnutrition and other physical compromises that may impair the patient’s ability to participate in their care or perform activities of daily living.

Poor health literacy is defined as difficulty with understanding language and has been associated with an increased risk of readmission (Cloonan, Wood, & Riley, 2013; Society of

Hospital Medicine, 2015). The BOOST risk stratification tool recognizes poor health literacy as the inability to perform a “teach back.” This is defined as having a patient communicate in their own words what instructions are being taught by clinical staff (Institute of Healthcare Improvement, 2016g).

Poor social support is defined as the lack of psychological, spiritual or medical supports that has been associated with higher rehospitalization rates (Mistry et al., 2001; Society of Hospital Medicine, 2015). The BOOST risk stratification tool recognizes poor social support to include lack of patient support to include social isolation, absence of support to assist with care, and insufficient or absent connection to primary care.

Prior hospitalizations is defined as a prior unplanned hospitalization which represent the single and most predictive factor in re-hospitalization (Garrison, Mansukhani, & Bohn, 2013; Hummel et al., 2014; Society of Hospital Medicine, 2015). The BOOST risk stratification tool recognizes prior hospitalization as a non-elective prior hospitalization in the previous six months.

Palliative care is defined as an approach to care for patients with a terminal illness, which has been associated with improved symptom management, patient satisfaction and has been associated with reducing rehospitalizations for patients nearing the end of life (Nelson, Chand, Sortais, Oloimooia, & Rembert, 2011; Ranganathan, Dougherty, Waite, & Casarett, 2013; Society of Hospital Medicine, 2015). The BOOST risk stratification tool recognizes palliative care as the perception that a patient could die in the upcoming year or if the patient had advanced or progressive illness.

Gaps in Research

Readmission is an important quality indicator for elderly patients with chronic disease, but more research is needed to determine what variables predict readmission and their predictive strength to target preventive interventions for at risk patients (American Nurses Association, 2012a; Cipriano, 2012; Lamb, 2013). Risk stratification tools associated with readmission have poor to modest predictive strength and the majority lack variables representing social determinants of health (Kansagara et al., 2013). Predictive readmission variables for elderly patients with chronic disease seem to require a multidimensional approach that considers a range of associated variables (Haas et al., 2013). There is a gap in research on the association of social determinants of health with 30-day readmissions, which may be due in part to the difficulty in extracting this information from the patient health record (Choudhry et al., 2013; Mosley, Peterson, & Martin, 2009).

There are gaps in understanding the association of problem medications as either polypharmacy or the use of high risk medications with readmission (Santos et al., 2015). The Advocate Health Care in Chicago and Cerner (ACC) risk stratification model used medication as a variable, but it is unclear from the study on how this was defined or the predictive strength of this variable with 30-day readmission (Choudhry et al., 2013).

There are gaps in understanding the association of mental and emotional health with readmission (Cancino et al., 2014; Society of Hospital Medicine, 2015). Psychological variables were considered in two of the risk stratification tools. The Minnesota Tiering Model incorporated the concept of assessing the existence of serious and persistent mental illness and provided support through the use of “Behavioral Health Homes” as part of their Integrated Care Model

(Minnesota Health Care Financing Task Force, 2016). The Heart Failure Model included risky behavior, which was defined as the abuse of cocaine (Amarasingham et al., 2010). However, these definitions failed to consider moderate or acute episodes of mental illness or all forms of substance abuse that could impact judgment and self-care.

There are gaps in understanding the association of severity/acuity of illness with readmission (Choudhry et al., 2013; van Walraven et al., 2010). The majority of the risk stratification tools included complexity of care variables using proxy measures of diagnosis groupings, comorbidities and resource use. In addition, the LACE Index and the Heart Failure Model included acuity as variables to predict readmission (Amarasingham et al., 2010; van Walraven et al., 2010). There are gaps in understanding the association of physical limitations with readmission (Agarwal et al., 2013). The Elder Risk Assessment (ERA) model and the Hierarchical Condition Categories models asked for patients to rate their perception of their health as a proxy for functional status (Boult et al., 1993; Mosley, Peterson, & Martin, 2009).

There are gaps in understanding the association of health literacy with readmission (Cloonan et al., 2013). Health literacy variables were included in the Minnesota Tiering Model, which was defined as a primary language other than English, including sign language and the use of communication devices but nothing about cognitive or perceptual variables that could impact the understanding of health information (MHCP Minnesota Department of Human Services, 2012).

There are gaps in understanding the association of unexpected hospitalization within the previous six months with readmission (Garrison, Mansukhami, & Bohn, 2013; Hummel et al., 2014). While none of the reviewed risk stratification tools included this variable, the LACE

Index and the Heart Failure Model included variables on the use of emergency services within the previous six months and one year, respectively (Amarasingham et al., 2010; van Walraven et al., 2010). It is unclear if a six-month time previous unplanned hospitalization predicts 30-day readmission.

There are gaps in understanding the association of the need for palliative care with readmission (Haas et al., 2013; Ranganathan et al., 2013; Society of Hospital Medicine, 2015). The use of anticipated palliative, comfort or hospice care was not included in the variables for the nine reviewed risk stratification tools.

Finally, there are gaps in understanding the association of patient support with readmission (Mistry et al., 2001). Three risk stratification tools included variables concerning patient supports. The Elder Risk Assessment (ERA) and the Hierarchical Condition Categories used the availability of an informal caregiver and the Heart Failure Model measured marital status (Amarasingham et al., 2010; Boult et al., 1993; Mosley, Peterson, & Martin, 2009). However, these definitions failed to consider the value of formal caregivers or community supports. There is a need for increased research on each of these eight variables with particular attention to the role of social determinants of health to improve the predictive capacity of risk stratification tools for chronically ill seniors.

Gaps outside of the scope of this study include the efficiency of the electronic medical record in capturing and sharing variables associated with readmission across providers and mechanisms to more effectively capture social determinant variables within the medical record. Finally, more research is necessary on the value of care management or coordination once vulnerable chronically ill seniors are identified to mitigate potential readmissions and improve quality outcomes. This study will attempt to validate the BOOST 8P's risk stratification tool to measure the risk of 30-day hospital readmission.

CHAPTER THREE

METHODS

This chapter will review the study purpose in relation to the research questions, study design, characteristics of the sample, methodology, conceptual and operational definitions of the variables, instrumentation, data collection and management, data analysis and ethical considerations. This study will measure the association between the Boost 8P's and 30-day readmission.

Study Purpose

The purpose of this research is to study the strength of the association between the individual and collective variables in the BOOST risk stratification tool to predict 30-day readmission for seniors$\geq$ 65 years old.

Sample

This study will use one year of patient records from one Midwestern, tertiary care hospital in an urban area. The sample includes all senior's $\geq$ 65 years who were admitted to the hospital. Hospital admission or "index admission" is defined as any eligible admission to the study acute care hospital. Exclusion criteria for the index admission were defined based on criteria from other readmission studies and included the following: patients admitted for an elective hospitalization; observation care; emergency care only; inpatient admission for psychiatry; if the patient expired; left against medical advice; had a permanent address outside of Illinois; or, was transferred to another hospital or long-term care facility (Horwitz, 2011). The sample was divided into two groups for purposes of the analysis: seniors with an unplanned readmission within 30-days after the index admission and seniors without a readmission within 30-days after the index admission.

Study Design

This is a descriptive, retrospective, quantitative study using secondary data from the electronic health record to measure the degree to which each of the variables in the 8P's predicts 30-day unplanned hospital readmission. De-identified data were extracted from the Epic electronic health record using only the medical record number to insure privacy and compliance with the Health Insurance Portability and Accountability Act (HIPAA). Before data extraction began, Loyola University Health System IRB provided full approval for this study to ensure ethical integrity and the protection of human rights. Systematic and appropriate scientific technique was used in the study approach, as described in this chapter. Significance was defined as p-values$<.50$.

Variables

Dependent Variable

The dependent variable for this study is unplanned hospital readmission within 30-days of discharge from an "index" or eligible hospital admission from January 1, 2016 to December 31, 2016.

Independent Variables

The independent variables are the eight variables included in the BOOST risk stratification tool (Society of Hospital Medicine, 2015). The BOOST 8P's risk stratification items are nominal variables that are either found to be present or absent in the electronic health record associated with the index admission (Berkman & Reise, 2012; Society of Hospital Medicine, 2015). Variables were operationalized with the assistance of an Epic expert that extracted samples on each within the medical record to assess if these could adequately represent the intent of each variable. Samples varied between 500 and 100 cases to determine if an adequate data pool could be obtained.

BOOST Item One: Problems with (High-Risk) Medications or Polypharmacy

Conceptual definition. Problem routine medications taken by the patient at home are defined as either (1) the use of $\geq$10 routine medications or (2) the use of the high-risk medications (Society of Hospital Medicine, 2015).

Operational definition. Medication records were reviewed for documentation of over ten routine prescribed medications (i.e., polypharmacy) and/or documentation of any of the HEDIS identified high-risk medications at discharge for the index hospitalization as follows: http://www.ncqa.org/hedis-quality-measurement/hedis-measures/hedis-2016/hedis-2016-ndc-license/hedis-2016-final-ndc-lists. Categories of drug classes include medications for the following: antianxiety; antiemetics; analgesics; antihistamines; antipsychotics; amphetamines; barbiturates; long-acting benzodiazepines; calcium channel blockers; gastrointestinal anti-spasmodics; belladonna alkaloids; skeletal muscle relaxants; oral estrogens; oral hypoglycemics; narcotics; vasodilators; and, others including androgens, anabolic steroids; thyroid drugs; and, urinary anti-infectives. Meeting one or more of these criteria would meet the BOOST item criterion.

BOOST Item Two: Psychological (Depression)

Conceptual definition. Psychological problems for the BOOST tool is defined as a diagnosis or history of depression (Society of Hospital Medicine, 2015). While anxiety and substance abuse are optional interpretations of psychological compromise in the BOOST risk stratification tool, depression is the central concept that will be used in this study.

Operational definition. Patient records at any time during the index hospitalization would be reviewed for ICD codes for a diagnosis or history of depression. These would include ICD-9 codes 296, 290, 301, 311 & ICD-10 codes F32, 33. Meeting one or more of these diagnoses meets criterion for this BOOST item.

BOOST Item Three: Principle Diagnosis

Conceptual definition. Chronic illness for the BOOST tool is defined as the patient diagnosed with at least one of five chronic conditions: cancer, stroke, diabetes, COPD and/or heart failure (Society of Hospital Medicine, 2015).

Operational definition. Billing records for any time during the index admission were used to identify ICD-10 codes of cancer, stroke, diabetes, COPD and heart failure. These codes are detailed with exclusions in Appendix C. Meeting any of these diagnoses meets the criterion for this BOOST item.

BOOST Item Four: Physical Limitations

Conceptual definition. Physical limitation for the BOOST tool is defined as being compromised as deficits in activities of daily living, medication administration, and organizing follow-up with their primary physician (Society of Hospital Medicine, 2015).

Operational definition. Patient records for any time during the index hospitalization were searched using several different approaches. One criterion would be the presence of referrals for physical, occupational or nutritional therapy at any time during the index hospitalization. Another criterion would be nurses' documentation on the "Functional Assessment" form indicating mobility issues at any time during the index hospitalization. Meeting one or both criteria would meet the criterion for this BOOST item.

BOOST Item Five: Poor Health Literacy

Conceptual definition. Poor health literacy for the BOOST tool is defined as the patient, family or caregivers inability to perform a "teach back" of discharge education (Society of Hospital Medicine, 2015). Teach back is defined as the ability of a patient to repeat in their own words what is being taught at discharge (Institute of Healthcare Improvement, 2016g).

Operational definition. Patient records for any time during the index hospitalization were searched using several different approaches. One criterion searched the patient education documentation for using teach back as an education method. For these patients, the BOOST item criterion is met if the nurse documented "no evidence of learning" or "needing reinforcement." Another criterion would be documentation in the nursing "Learning Assessment Sheet" indicating that there were barriers to learning and/or the need for an interpreter. Finally, the "disease/condition" section of nurse's notes includes categories of compromised learning readiness including "non-acceptance" or "refusal." Meeting one or more of these criteria meets the criterion for this BOOST item.

BOOST Item Six: Patient Support

Conceptual definition. Lack of patient supports for the BOOST tool is defined as the absence of a reliable caregiver to assist with the discharge, living alone or without needed assistance, and/or lack of connection to the primary care provider (Society of Hospital Medicine, 2015).

Operational definition. Patient records were searched at any time during the index hospitalization using several different approaches. One criterion was documentation of being single or widowed under marital status. Another criterion was a response that the patient lived alone on the, "Domicile Problems Assessment Sheet." Another criterion on the same form is a response that no one would help the patient at home after hospitalization. Finally, on the same form, a response that the patient was not receiving care from healthcare agencies. Meeting one or more of these criteria meets the criterion for this BOOST item.

BOOST Item Seven: Prior Hospitalizations

Conceptual definition. Prior hospitalization for the BOOST tool is defined as documentation of a previous hospitalization prior to the index readmission within the past 6 months (Society of Hospital Medicine, 2015).

Operational definition. Patient medical records were searched for documentation at any time during the index hospitalization for a previous unplanned admission within six months of the index hospitalization. Documentation of a previous hospitalization within the previous six months of the index admission meets the criterion for this BOOST item.

BOOST Item Eight: Palliative Care

Conceptual definition. Palliative care for the BOOST tool is defined as an anticipated death within an upcoming year or an advanced/progressive illness (Society of Hospital Medicine, 2015).

Operational definition. Patient medical records were searched for documentation at any time during the index admission for a physician's order or current status as patient receiving palliative care or hospice services at any the time during the index admission. Meeting one or more of these criteria meets the criterion for this BOOST item.

Covariate Variables

The literature indicated that other variables may affect readmission (Boult et al., 1993; Choudhry et al., 2013; Mosley et al., 2009; van Walraven, 2012). These include age, gender, race and ethnicity and will be included in the analysis of covariates. The following will provide the rationale for each covariate, as well as conceptual and operational definitions.

Covariate: Age

Conceptual definition. Age may be defined as a stage of life (Merriam-Webster, 2017a). Seniors ≥65 years-old have been identified as having a higher risk of readmission (Office of the Legislative Counsel, 2010). Age was used as a predictive variable in five of the risk stratification tools used to predict readmission, ACC, LACE+, ACG, ERA and HCC as detailed in Table 2. Except for ACC and ACG, the remaining tools showed that older patients demonstrated significant associations with readmission.

Operational definition. Patient age is indicated on the admission form for the index admission.

Covariate: Gender

Conceptual definition. Gender may be defined as the sex of the patient associated with physical, psychological and cultural traits (Merriam-Webster, 2017c). Male gender has been associated with higher readmission (Haas et al., 2013). In addition, five of the ten risk stratification tools (i.e., ACC, LACE+, ACG, ERA and HCC) included gender as a variable in measuring readmission risk (see Table 2).

Operational definition. Gender is indicated on the admission form for the index admission.

Covariate: Race

Conceptual definition. Race when used as a noun, may be defined as grouping humans by specific physical traits (Merriam-Webster, 2017d). The variable of race was included in over 49 predictors used in the ACC risk stratification tool and demonstrated significant associations with readmission (Choudhry et al., 2013).

Operational definition. Race is indicated on the admission form of the index admission. The form includes the following five categories for race: white, black, Asian, and other.

Covariate: Ethnicity

Conceptual definition. Ethnicity may be defined as an affiliation or group (Merriam-Webster, 2017b). Ethnicity was only included as a variable in the ACC risk stratification tool and demonstrated significant associations with readmission (Choudhry et al., 2013).

Operational definition. Ethnicity is included on the admission form of the index admission. The form includes the following four categories for ethnicity: Hispanic origin, non-Hispanic origin, prefers not to answer and unknown.

Data Extraction and Cleaning

When identifying strategies to operationalize the BOOST items, an Epic expert at the health system was consulted to pilot the data extraction. The expert was able to perform preliminary data pulls using a sample of between 500-900 seniors$\geq$65 years old for each variable in the first quarter of 2016. These findings were used to ensure that the operational definitions for the BOOST variables for this study accurately represented the concept and that data existed in the specified databases. In cases in which there were multiple sources of information (i.e., health literacy, social isolation and physical limitations), we were able to locate adequate data sources within Epic to avoid manual medical record review. A preliminary data extraction table was developed based on these pilot findings.

The Principle Investigator (PI) met with University Epic expert to review the preliminary data extraction rules and further refine the rules for each BOOST item and covariate variables. The University Epic expert has over 14 years of experience in extracting data from the health system's electronic health records for research, which supports the content validity in the extraction process. Data were extracted from the Epic electronic healthcare record (EHR) using a data extraction tool, called Clarity Reports. Some of the variables required extracting data from a variety of fields including nursing assessment and teaching forms, consultation orders and billing records, which are all accessible through Clarity Reports. The Epic expert and researcher further refined and verified variable data extraction procedures throughout the study by e-mail. The final data extraction rules are summarized in Table 4.

The initial data extraction was analyzed using cross tabs to calculate odds ratios. Initial findings demonstrated uniformly significant results for all independent variables with unlikely large odds ratios. For example, patients with H1 were 2,028 times more likely than those without H1 to be readmitted. These findings suggested a possible data extraction error. Procedures were reviewed and indicated an error, which was corrected. In addition, the researcher discovered that high-risk medications were not included in the medication variable (H1). A Health System clinical pharmacist was consulted to determine the best way to identify high risk medications. It was decided to use the HEDIS list of high risk medications, as that is list is a nationally recognized list of high risk medications. This list was added to the Polypharmacy BOOST item operational definition.

The second data extraction demonstrated plausible findings. Per institutional protocol and post IRB approval, the data extraction expert with access to Epic data extracted the de-identified data using the data extraction rules in Table 4. Data extraction and cleaning is important to ensure the accuracy and utility of the data especially using secondary data sets (Andersen, Prause, & Silver, 2011). For this study, the extracted data was reviewed for any missing fields and gross errors.

Data Analysis Plan

The research hypotheses for this dissertation is to identify the degree of predictive association between the BOOST 8P's risk stratification tool and 30-day unplanned readmission of elderly patients compared to hospitalized patients that did not have a readmission within the previous 30-days. The hypothesis is that the BOOST tool can predict 30-day readmission for >65-year-old patients.

Table 4. Hypotheses, Data Sources, and Data Extraction Rules.

Hypothesis	Data Sources from Index Hospitalization	Data Extraction Rules
H1: Compared with ≥ 65-year-old patients without 30-day unplanned readmissions after an index admission over the past year, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with polypharmacy or the use of high-risk medications.	Epic medication documentation index hospitalization	Discharge medication sheets for ≥10 routine medications at discharge of the index admission Identified as meeting the HEDIS definitions of high-risk medications provided at discharge of the index admission
H2: Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with a diagnosis or history of depression.	Epic record index hospitalization	Diagnosis or history of depression at any time during the index hospitalization using ICD-9 & 10 codes-provided
H3: Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with specified chronic illness.	Hospital discharge billing- index hospitalization	Diagnosis of any of the following: cancer, stroke, diabetes, chronic obstructive pulmonary disease or heart failure at any time during the index hospitalization See Appendix C
H4: Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission over the past year, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with physical limitations including frailty, malnutrition and weakness.	Epic record, orders & notes index hospitalization	"Functional Status Sheet" with a "Yes" or fill-in answer for "Mobility issues" at any time during the index hospitalization Physician orders for consultations for physical, occupational, or nutritional therapy at any time during the index hospitalization
H5: Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission over the past year, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with poor health literacy.	Epic record index hospitalization	Nurse patient education documentation of the use of the Teach back method with a patient response of either "no evidence of learning" or "needs reinforcement" at any time during the index hospitalization Under the "Learning Assessment Sheet," indicates yes for "Does the primary learner have any barriers to learning?" and "Is an interpreter required?" at any time during the index hospitalization Under "Learning Assessment Sheet" indicates "non-acceptance" or "refuses" under Documentation of learning

		readiness at any time during the index hospitalization
H6: Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission over the past year, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with patients that lack social support.	Epic record index hospitalization	Documentation that patient “lives alone”; “Marital status.” indicates widowed or single at any time during the index hospitalization Domicile Problems Assessment Sheet, “Lives alone?” if “yes”; “Who will help you at home after your hospitalization?”; if answers, “no one” “Are you receiving care/services from agencies”; if answers “none” at any time during the index hospitalization
H7: Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission over the past year, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with a previous hospitalization within the previous 6 months.	Epic records	Documentation of a previous non-elective hospital admission within 6 months of the index admission
H8: Compared with ≥ 65-year-old patients without 30-day unplanned readmission over the past year, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with a diagnosis of palliative or hospice care.	Epic orders & notes index hospitalization	Documentation of orders or notes of hospice or palliative care at any time during the index hospitalization
H9: Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with some or all the eight BOOST variables.		Comparison of H1-H8 variable data for admitted and non-readmitted patients. In addition, covariates will be compared including age, gender, race and ethnicity on the index hospitalization admission form.

Odds ratios were used to evaluate H1-H8. Multivariate logistic regression and C-statistic calculations were used to evaluate H9. Each statistical method is described below.

Odds Ratios

Odds ratios were used to estimate the univariate odds of 30-day readmission due to each BOOST item (“P”). Confidence intervals and p-values were provided to indicate statistical significance. Each odds ratio is presented individually in two ways: when the other P’s are not held constant and when the other P's and covariates are statistically controlled. The latter was calculated using multivariate logistic regression.

Odds ratios measures the odds that an outcome will occur given exposure to a variable of interest (Szumilas, 2010). Presence or absence of a positive odds ratio is further supported by evaluating its significance, which requires *p* values. These are calculated as follows using a two-by-two frequency table, which were performed using crosstabs in SPSS and 95% confidence intervals:

Table 5. Two-Way Frequency Readmission 30 Days.

Variable (H1-H8)	No=0	Yes=1	Totals
No=0	A	B	E
Yes=1	C	D	F

Where

A= Number of patients without meeting criteria for the "P" and were not readmitted

B= Number of patients without meeting criteria for the "P" and were readmitted

C= Number of patients meeting criteria for the "P" and were not readmitted

D= Number of patients meeting criteria for the "P" that were readmitted

Odds Ratio = D/C divided by B/A

Odds Ratio = 1 implies the "P" does not affect the odds of a 30-day readmission

Odds Ratio > 1 implies the "P" is associated with higher odds of a 30-day readmission

Odds Ratio < 1 implies the "P" is associated with lower odds of a 30-day readmission

Multivariate Logistical Regression

Multivariate logistical regression was used to calculate the adjusted odds ratio of each BOOST item H1-H8 holding all other independent variables (i.e., 8P's) and covariates including age, gender, race and ethnicity constant. Multivariate logistical regression was also used to determine the ability of all BOOST items in predicting 30-day readmission using the C-statistic (i.e., H9). The C-statistic was used to compare the BOOST with other risk stratification tools.

One assumption of logistical regression is that the natural log of readmission (i.e., outcome) shares a linear relationship with any continuous covariate (i.e., age) (Bewick, Cheek, & Ball, 2005). This model identifies the equation that best predicts the value of the 30-day readmission related to the values of the 8 P's. These equations are expressed as slopes (b_1, b_2, etc.) and intercept (a) or the best-fitting equation. In other words, the target is to find the "perfect line that best represents the data," or the value of the parameters with which you would most likely find the observed results. The statistical model for the curve for this study is:

$\ln(\pi/1-\pi) = \exp\ (\text{intercept} + \beta(\text{BOOST}))$

Where π = The probability of readmission; β(BOOST) = the log odds of readmission when the BOOST item is positive (1) rather than negative (0). The exponentiation of β will reveal the odds ratio of readmission for those who are positive for the BOOST item rather than negative for the BOOST item. The ability for the independent variables (or P's) to predict the dependent variable (or 30-day readmission) is the area under the logistical curve, also called the C-statistic. Therefore, H9 will be evaluated using the C-statistic.

In these models, each parameter estimate will be exponentiated and represented as a standard odds ratio for 30-day readmission (along with its 95% confidence interval). Multivariate logistic regression models will be used to determine the adjusted odds of 30-day readmission as a function of each BOOST item controlling for the other BOOST items and important covariates such as age, gender, race, and ethnicity. The predictive capability of the BOOST model will be will be reported using C-statistic, which is defined as the area of the regression curve. The null hypothesis (H_0) was that the risk of 30-day readmissions would not be greater in elderly patients with physical, functional and social factors, when demographic factors were controlled. Computation of the analyses for this study will be conducted using SPSS version 24 (IBM, Armonk, NY) with additional statistical support provided by a trained Biostatistician in Loyola's Health Sciences Division (Mr. William Adams).

CHAPTER FOUR

RESULTS

The hypothesis is that the BOOST risk stratification tool has predictive capability in 30-day readmissions of elderly patients. This chapter describes the sample and explores each hypothesis.

Sample

The sample consists of 6,872 adults≥65 years-old who were admitted to a Midwestern health system from January 1, 2016 to December 31, 2016. As shown in Table 6, most of the patients were white, non-Hispanic patients with a median age of 74 years old. Readmissions for these demographics demonstrated that all covariates were associated with non-readmission rather than readmission. Sixteen percent of the patients were readmitted within 30-days of an index admission. There were missing, unknown and no answers which impacted 28 responses.

Covariates

As shown in Table 7, patient characteristics were not statistically significant predictors of 30-day readmission (all p values > .05). However, there may be additive effects of the demographic variables. Therefore, these characteristics will be included as covariates in the multivariable logistical regression analysis.

Table 6. Frequency and Percent of Sample Demographics.

Covariate	Total Frequency	Readmit Frequency	Percent of Readmit	No Readmit Frequency	Percent of No Readmit
Total	6872	1083	16%	5805	84%
Gender					
Female	3524	543	15%	2981	85%
Male	3370	540	16%	2830	84%
Race					
White	5160	792	15%	4368	85%
Black	1162	207	18%	955	82%
Asian	140	30	3%	110	79%
Other	426	54	13%	372	87%
Missing	6				
Ethnicity					
Hispanic	833	114	14%	719	86%
Non-Hispanic	6039	968	16%	5071	84%
No answer	6				
Unknown	16				

Table 7. Adjusted Odds of 30-day Readmission as a Function of Patient Characteristics While Controlling for their BOOST Variables.

Variable	Adjusted Odds Ratio	CL-Upper	CL-Lower	*P-value*
Age	.994	.985	1.003	.191
Female vs. Male	.950	.829	1.087	.455
Black vs. White	1.181	.992	1.407	.062
Asian vs. White	1.303	.852	1.993	.222
Other vs. White	.817	.579	1.153	.251
Hispanic vs. Non-Hispanic	.840	.647	1.090	.189

Note: These estimates are further adjusted for patients' BOOST assessments, including lives alone ($p = .01$), educational status ($p = .03$), and, patient comorbidities including depression ($p = .003$), cancer, stroke, diabetes, COPD (all $p = .35$), lives alone ($p = .01$), physical limitations ($p < .001$), polypharmacy ($p = .001$), prior inpatient admission ($p < .001$), and palliative care ($p = .07$)

Findings per Hypothesis

The following describes the findings per hypothesis. Hypotheses one through eight were evaluated using cross tabs, which were performed manually and verified with SPSS, to calculate the univariate odds ratios. Multivariable logistic regression was also used to calculate adjusted odds ratios, holding all other BOOST variables and covariates constant, per hypothesis.

Hypothesis 1

Compared with ≥ 65-year-old patients without 30-day unplanned readmissions after an index admission over the past year, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with polypharmacy or the use of high-risk medications.

Findings. As shown in Tables 8 and 9, on univariable analysis, patients with polypharmacy or use of high-risk medications were statistically significantly more likely to be readmitted than patients without polypharmacy or high-risk medications. That is, compared to patients without polypharmacy or high-risk medications, those with polypharmacy or high-risk medications were 1.57 (95% CL: 1.37-1.80) times more likely to be readmitted (p=<.001). When controlling for covariates, there remained a statistically significant association between polypharmacy or use of high-risk medications and 30-day readmission (p=.001), but with a lower odds ratio (1.28). This demonstrates that polypharmacy and use of high risk medications predict 30-day readmission.

Table 8. Cross Tabulation of Problem Medications and 30-day Readmission.

	Not Admitted	Admitted	Total
Non-problem meds	2645 (45%)	376 (35%)	3021(44%)
Problem meds	3166 (54%)	707 (65%)	3873 (56%)
Total	5811	1083	6894

Table 9. Odds of 30-day Readmission as a Function of Problem Medication Status.

	N	Odds Ratio	CL-Upper	CL-Lower	*P*
Univariate	6894	1.57	1.37	1.80	<.001
Adjusted*	6894	1.28	1.11	1.48	.001

*This estimate is adjusted for patient age, sex, race, ethnicity, education status, whether the patient lives alone, and patient comorbidities including depression, cancer, stroke, diabetes, COPD, physical limitations, prior readmission, and palliative care

Hypothesis 2

Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with a diagnosis or history of depression.

Findings. As shown in Tables 10 and 11, on univariate analysis, patients with depression were statistically significantly more likely to be readmitted than patients without depression. That is, compared to patients without depression, those with depression were 1.61 (CI:1.37-1.90) times more likely to be readmitted (*p*=<.001). When controlling for covariates and the other BOOST items, there remained a statistically significant association between depression and 30-day readmission (*p*=.003), but with a lower odds ratio (1.30). This demonstrates that depression predicts 30-day readmission.

Table 10. Cross Tabulation of Depression and 30-day Readmission.

	Not Admitted	Admitted	Total
Non-depression	5018 (86%)	863 (79%)	5881 (85%)
Depression	793 (14%)	220 (20%)	1013 (15%)
Total	5811	1083	6894

Table 11. Odds of 30-day Readmission as a Function of Depression Status.

	N	Odds Ratio	CL-Upper	CL-Lower	*P*
Univariate	6894	1.61	1.37	1.90	<.001
Adjusted*	6895	1.30	1.09	1.55	.003

*This estimate is adjusted for patient age, sex, race, ethnicity, education status, whether the patient lives alone, and, patient comorbidities including cancer, stroke, diabetes, COPD, physical limitations, prior readmission, has polypharmacy or high-risk medications and palliative care.

Hypothesis 3

Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with specified chronic illness (cancer, stroke, diabetes, chronic obstructive pulmonary disease or heart failure).

Findings. As shown in Tables 12 and 13, on univariate analysis, patients with selected chronic diagnoses were less likely to be readmitted than patients without those diagnoses and the results were statistically insignificant (p=.235). When controlling for covariates and the other BOOST items, there was statistically insignificant association between diagnosis and 30-day readmission (p=.348). Both these results demonstrate that primary diagnosis of a chronic condition (cancer, stroke, diabetes, chronic obstructive pulmonary disease or heart failure) failed to predict 30-day readmission.

Table 12. Cross Tabulation of Diagnosis and 30-day Readmission.

	Not Admitted	Admitted	Total
Non-diagnosis	4852 (83%)	920 (84%)	5772 (84%)
Diagnosis	959 (17%)	163 (15%)	1122 (16%)
Total	5811	1083	6894

Table 13. Odds of 30-day Readmission as a Function of Diagnosis Status.

	N	Odds Ratio	CL-Upper	CL-Lower	*P*
Univariate	6894	.896	.748	1.074	.235
Adjusted*	6894	.916	.762	1.100	.348

*This estimate is adjusted for patient age, sex, race, ethnicity, education status, whether the patient lives alone, and, patient comorbidities including depression, physical limitations, prior readmission, has polypharmacy or high-risk medications and palliative care.

Hypothesis 4

Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission over the past year, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with frailty, malnutrition and weakness.

Findings. As shown in Tables 14 and 15, on univariate analysis, patients with physical limitations were statistically significantly more likely to be readmitted than patients without physical limitations. That is, compared to patients without physical limitations, those with physical limitations were 1.62 (CI:1.42-1.85) times more likely to be readmitted (*p*=<.001). When controlling for covariates and the other BOOST items, there remained a statistically significant association between physical limitations and 30-day readmission (*p*=<.001), but with a lower odds ratio (1.30 odds ratio). This demonstrates that physical limitations predict 30-day readmission.

Table 14. Cross Tabulation of Physical Limitations and 30-day Readmission.

	Not Admitted	Admitted	Total
Non-limitations	3469 (60%)	517 (48%)	3986 (58%)
Limitations	2342 (40%)	566 (52%)	2908 (42%)
Total	5811	1083	6894

Table 15. Odds of 30-day Readmission as a Function of Physical Limitations Status.

	N	Odds Ratio	CL-Upper	CL-Lower	*P*
Univariate	6894	1.62	1.42	1.85	<.001
Adjusted*	6894	1.46	1.27	1.68	<.001

*This estimate is adjusted for patient age, sex, race, ethnicity, education status, whether the patient lives alone, and, patient comorbidities including depression, cancer, stroke, diabetes, COPD, previous readmission, polypharmacy or high-risk medications and palliative care.

Hypothesis 5

Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission over the past year, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with poor health literacy.

Findings. As shown in Tables 16 and 17, on univariate analysis, patients with poor health literacy were statistically significantly more likely to be readmitted than patients without poor health literacy. That is, compared to patients without poor health literacy, those with poor health literacy were 1.22 times more likely to be readmitted (p=.019). When controlling for covariates and other BOOST items, there remained a statistically significant association between health literacy and 30-day readmission (p=.030). This demonstrates that poor health literacy predicts 30-day readmission.

Table 16. Cross Tabulation of Health Literacy and 30-day Readmission.

	Not Admitted	Admitted	Total
Non-Poor Literacy	4859 (84%)	874 (81%)	5733
Poor Literacy	952 (16%)	209 (19%)	1161
Total	5811	1083	6894

Table 17. Odds of 30-day Readmission as a Function of Health Literacy Status.

	N	Odds Ratio	CL-Upper	CL-Lower	*P*
Univariate	6894	1.22	1.03	1.44	.019
Adjusted*	6894	1.22	1.02	1.47	.030

*This estimate is adjusted for patient age, sex, race, ethnicity, whether the patient lives alone, and, patient comorbidities including depression, cancer, stroke, diabetes, COPD, physical limitations, prior readmission, polypharmacy or high-risk medications and palliative care.

Hypothesis 6

Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission over the past year, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with patients that lack social support.

Findings. As shown in Tables 18 and 19, on univariate analysis, patients with social isolation were statistically significantly less likely to be readmitted than patients without isolation. That is, compared to patients without being socially isolated, those with social isolation were .723 (CI: .608-.860) times less likely to be readmitted (p<.001). When controlling for covariates and other BOOST items, there remained a statistically significant lower risk of 30-day readmission (p=.011), albeit with a slightly higher odds ratio (0.792). This demonstrates that social isolation predicts fewer 30-day readmissions.

Table 18. Cross Tabulation of Isolation and 30-day Readmission.

	Not Admitted	Admitted	Total
Non-isolation	4582 (79%)	907 (84%)	5489
Isolation	1229 (21%)	176 (67%)	1405
Total	5811	1083	6894

Table 19. Odds of 30-day Readmission as a Function of Isolation Status.

	N	Odds Ratio	CL-Upper	CL-Lower	*P*
Univariate	6894	.723	.608	.860	<.001
Adjusted*	6894	.792	.663	.948	.011

*This estimate is adjusted for patient age, sex, race, ethnicity, educational status, and, patient comorbidities including depression, cancer, stroke, diabetes, COPD, physical limitations, prior readmission, polypharmacy or high-risk medications and palliative care.

Hypothesis 7

Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission over the past year, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with a previous hospitalization within the previous six months.

Findings. As shown in Tables 21 and 22, on univariate analysis, patients with a previous admission within 6 months prior to the index admission were statistically significantly more likely to be readmitted than patients without a previous admission. That is, compared to patients without a previous admission, those with a previous admission were 2.079 times more likely to be readmitted within 30 days of the index admission (p<.001). When controlling for covariates and the other BOOST items, there remained a statistically significant risk of 30-day readmission (p <.001), albeit with a lower odds ratio (1.84). This demonstrates that previous admission prior to six months of the index admission predicts 30-day readmission.

Table 20. Cross Tabulation of Previous Admission and 30-day Readmission.

	Not Admitted	Admitted	Total
Non-Prev Admission	3503 (60%)	457 (42%)	3960
Prev Admission	2308 (40%)	626 (58%)	2934
Total	5811	1083	6894

Table 21. Odds of 30-day Readmission as a Function of Previous Admission Status.

	N	Odds Ratio	CL-Upper	CL-Lower	*P*
Univariate	6894	2.079	1.82	2.37	<.001
Adjusted*	6894	1.84	1.60	2.11	<.001

*This estimate is adjusted for patient age, sex, race, ethnicity, lives alone, educational status, and, patient comorbidities including depression, cancer, stroke, diabetes, COPD, lives alone, physical limitations, polypharmacy or high-risk medications and palliative care.

Hypothesis 8

Compared with ≥ 65-year-old patients without 30-day unplanned readmission over the past year, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with a diagnosis of palliative or hospice care.

Findings. On univariate analysis, patients with palliative or hospice care were statistically significantly more likely to be readmitted than patients without palliative or hospice care. That is, compared to patients not receiving palliative or hospice care, those receiving palliative or hospice care were 2.077 times more likely to be readmitted (*p*=<.001). However, when controlling for covariates and other BOOST items, there was no statistically significant difference between receiving palliative or hospice care and 30-day readmission (*p*=0.67). The sample of both readmitted and admitted patients was low representing a small portion of the population. This demonstrates that palliative or hospice care failed to predict 30-day readmission.

Table 22. Cross Tabulation of Palliative or Hospice Care and 30-day Readmission.

	Not Admitted	Admitted	Total
Non-Palliative/Hospice	5711 (98%)	1045 (96%)	6756
Palliative/Hospice	100 (2%)	38 (3.5%)	138
Total	5811	1083	6894

Table 23. Odds of 30-day Readmission as a Function of Palliative or Hospice Care Status.

	N	Odds Ratio	CL-Upper	CL-Lower	*P*
Univariate	6894	2.077	1.42	3.04	<.001
Adjusted*	6894	1.44	.975	.2.13	.067

*This estimate is adjusted for patient age, sex, race, ethnicity, lives alone, educational status, and, patient comorbidities including depression, cancer, stroke, diabetes, COPD, lives alone, physical limitations, polypharmacy or high-risk medications

Hypothesis 9

Compared with ≥ 65-year-old patients without 30-day unplanned readmission after an index admission, readmitted ≥ 65-year-old patients over that same year will have a stronger degree of association with some or all of the eight BOOST variables.

Findings. Using multivariable logistic regression and controlling for covariates and considering the collective ability of the BOOST items to predict the sensitivity and specificity of the model for 30-day readmission, the BOOST risk stratification tool demonstrated poor predictive capability with a C-statistic of .631, as shown in Table 24. The ROC curve below (see Figure 2) illustrates that using the BOOST risk stratification tool is only slightly more predictive than chance or .50 for readmission.

Table 24. Area Under the Curve: Predicted Probability for All BOOST Items.

Area	Std. Error	Asymptotic Sig	Asymptotic 95% Confidence Interval-Lower Bound	Asymptotic 95% Confidence Interval-Upper Bound
.631	.010	.000	.613	.650

BOOST Model C-statistic: .631

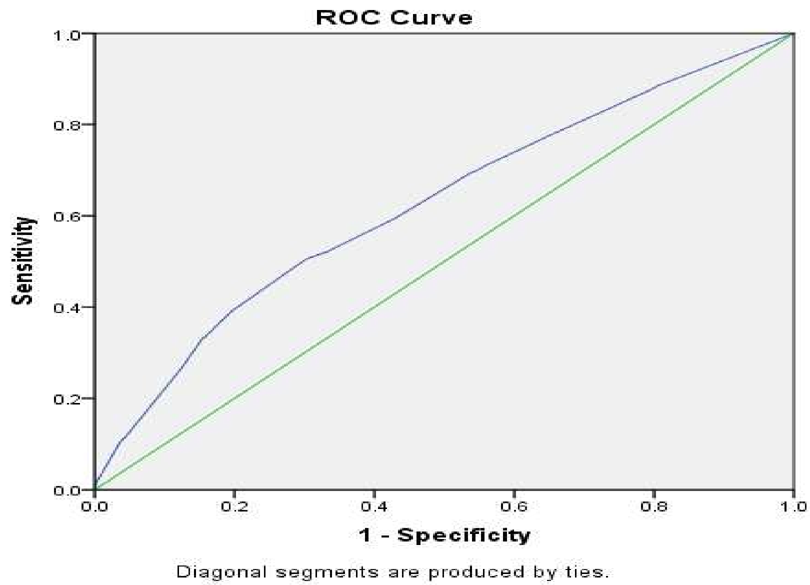

Figure 2. ROC Curve of the BOOST Risk Stratification Tool

Comparison all variable effect sizes. As shown in Figure 3, the Forest Plot Effect Sizes graphically illustrates the adjusted odds ratios of all covariates and the eight variables. None of the covariates, primary medical diagnosis and palliative/hospice care demonstrated predictive ability. Five of the eight variables demonstrated predictive capability for 30-day readmission.

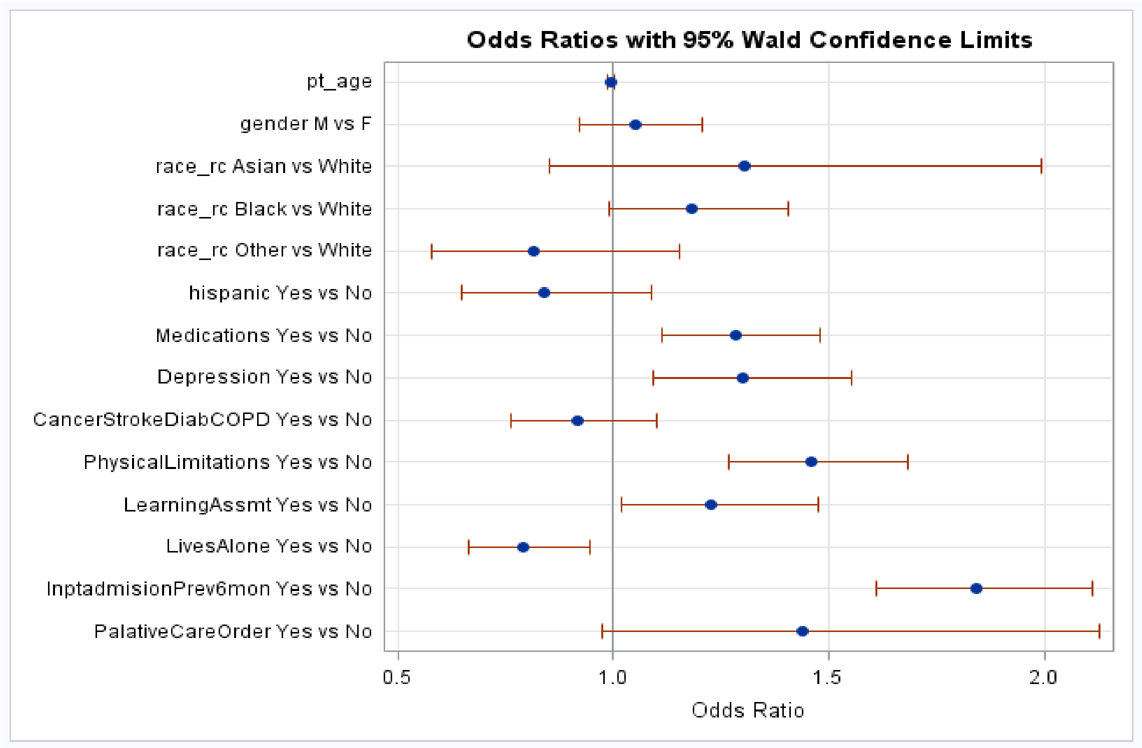

Figure 3. Forest Plot All Variable Effect Sizes

CHAPTER FIVE

DISCUSSION

This chapter has been organized into four sections. The first section will discuss the limitations of the study, followed by a discussion of the findings, implications for nursing practice, and opportunities for future research.

Limitations

Limitations of this study included (a) restriction of this sample to one hospital, setting, (b) limiting the data sample to one year, (c) use of secondary data, (d) reliance on the electronic medical record for data source which may have entry errors or incomplete documentation and (e) broadly defined independent variables, which may have been not been captured adequately through electronic methods. As illustrated in Table 4, data extraction involved finding multiple sources of data within the medical record. Each limitation is further discussed below.

With only one hospital used for this study, it is difficult to generalize results for other regions and communities, which may have resulted in different findings. In addition, the data sample was limited to one year which may not allow generalizability to previous years or the current year.

There are inherent limitations in using secondary data (Andersen et al., 2011). While secondary data offers the ability to survey large sets of data, variables used for this study were extracted from a variety of electronic data sources including physician orders, admission and discharge forms, patient education forms, nursing assessment forms, referrals, consultations and medication lists. These data fields would be at risk for missing or incomplete information due to human errors or incomplete sources of information within the electronic medical record, which could have limited validity. Readmission research have cited the difficulty of using the electronic medical record to gather data (Choudhry et al., 2013; Pantell et al., 2013b). In particular, research has cited the challenges of the lack of consistency between social variables (Chen, Manaktala, Sarkar, & Melton, 2011). There is a need to understand how variables associated with readmission, particularly social variables within nursing documentation, could be extracted more easily within electronic medical records to support the development of comparative predictive studies.

Operationalizing many of the proxy variables including social isolation, physical limitations, health literacy and palliative care required filtering multiple electronic data fields, which may have missed other documentation in free text, notes or referral requests within the Epic record. In addition, there may be information buried in historical paper-based charts or records that were brought with the family and not recorded in the Epic documentation extracted for this study. Any of these factors could have impacted the accuracy and generalizability of the results of this study.

Interpretation of Findings

This study is the first known to attempt to validate the BOOST risk stratification tool, which was developed in 2008 as part of the comprehensive BOOST toolkit targeted at improving the care of hospitalized chronically ill adults by reducing the risk of readmission (Society of Hospital Medicine, 2015). This study was also the first to use nursing documentation within an electronic medical record to capture physical limitations and social determinants of health, including isolation and health literacy.

This study demonstrated that although five out of the eight individual items in the BOOST tool predicted a higher rate of 30-day readmission, together, all eight items were poor predictors of 30-day readmission, with a C-statistic of 0.631 (Kansagara et al., 2013). Compared to the 10 other risk stratification tools used to predict readmission, nine out of the ten risk stratification tools demonstrated better predictive capability than BOOST, with the exception of the Heart Failure Model (Amarasingham et al., 2010).

The focus of the BOOST risk stratification tool as part of the larger BOOST Toolkit was to direct preventive interventions based on risk variables during an index hospitalization to avoid 30-day readmission, rather than validating the risk tool or variables within the risk tool. The next section will present each of the BOOST risk variables with their predictive strength and comparison to variables in other risk stratification tools used for readmission.

Problem with Medications (H1): Good Predictor

This study supported the ability of problem medications to predict 30-day readmission. This is consistent with research demonstrating a correlation between polypharmacy or high-risk medications and readmission (Marcum et al., 2010; Santos et al., 2015). Although research supports this relationship, problems with medications were not included as a variable in any of the other risk stratification tools that predict readmission. The BOOST risk stratification tool used a unique approach of combining two types of problem medications, polypharmacy and high-risk medication. This study supports the inclusion of medication variables in risk stratification tools. In addition, these findings support additional research in addressing medication issues post discharge, including research in developing preventive interventions for elderly patients with polypharmacy or use of high risk medications.

Psychological-Depression (H2): Good Predictor

This study supported the ability of a depression diagnosis to predict 30-day readmission. This finding is consistent with past research that demonstrated a correlation between a diagnosis or history of depression and readmission (Cancino et al., 2014). Only one other risk stratification tool, Minnesota Tiering Model, included a mental health variable, which was defined as “severe mental illness” (Minnesota Department of Health, 2016b). This study supports the inclusion of depression variables in risk stratification tools. These findings also support additional research in addressing depression issues post discharge, including research in developing preventive interventions for elderly patients with depression.

Principal Diagnosis (H3): Poor Predictor

This study did not support the ability of a primary diagnosis for chronic medical diseases to predict 30-day readmission. This is inconsistent with the literature that demonstrated an association of medical diagnosis with adverse events, which included readmission (Ford, 2015; Hijjawi et al., 2015; Linden & Butterworth, 2014). These findings are particularly notable, since nine out of the ten risk stratification tools used diagnosis of chronic disease as a predictor of 30-day readmission. Only the LACE tool (van Walraven et al., 2010) did not include diagnosis within their set of variables, but medical diagnosis was later added in their expanded model (van Walraven, 2012) and increased the predictive strength of the model. Since all ten of these risk stratification tools demonstrated strong to poor predictive capability between 0.83-.0.56., the role of medical diagnosis in predicting readmission requires more clarification and research. Since data were extracted using billing information at any time during the index hospitalization, patients may have been admitted for secondary issues or complications exacerbated by the underlying pathology of their chronic illness or the immunologic effects of an advanced chronic illness not captured in primary diagnosis billing codes. This study fails to support the inclusion of only the primary diagnosis as a chronic disease in a risk stratification tool. More research is needed to determine how data should be extracted to study the association of chronic medical diagnosis with 30-day readmission.

Physical Limitations (H4): Good Predictor

This study supports the ability of physical limitations to predict 30-day readmission. This is consistent with the literature that demonstrates the association between physical limitations and readmission (Agarwal et al., 2013; Craven & Conroy, 2015). Physical limitations were not included as variables in any of the ten risk stratification tools used for readmission. This study supports the inclusion of physical limitations in risk stratification tools. These findings also support additional research in addressing physical limitation issues post discharge, including research in developing preventive interventions for elderly patients with physical limitations.

Poor Health Literacy (H5): Good Predictor

This study supports the ability of poor health literacy to predict 30-day readmission. This is consistent with the literature that demonstrates the association between compromised health literacy and readmission (Cloonan et al., 2013). The only other risk stratification tool to use health literacy was Minnesota Tiering Model that used language barriers (Minnesota Department of Health, 2016b). This study supports the inclusion of poor health literacy in risk stratification tools. These findings also support additional research in addressing poor health literacy issues post discharge, including research in developing preventive interventions for elderly patients with poor health literacy.

Social Support (H6): Good Predictor Opposite Direction

This study demonstrated that poor social supports resulted in fewer 30-day readmissions. This study failed to support the research demonstrating a correlation between social isolation and readmission (Mistry et al., 2001). In other words, less social support seems to be related to fewer 30-day readmissions. In addition, three of the risk stratification tools in the literature defined social isolation in different ways. The Heart Failure Model (Amarasingham et al., 2010) used marital status, while the ERA (Boult et al., 1993) and HCC (Mosley, Peterson, & Martin, 2009) used access to an informal caregiver while BOOST used a combination of marital status and nurse's documentation on access to care.

It is unclear why this variable performed in the opposite direction, but it may be that single or isolated patients may have established adequate supports from their families, friends, community or primary care providers to reduce their use of hospitalization or they may have concerns about costs, limited access to transportation or fears around pain, or test results. This study supports the inclusion of the presence or absence of social supports to better understand the impact on readmission to allow for preventive interventions.

Prior Hospitalization (H7): Good Predictor

This study supports the ability of prior hospitalization to predict 30-day readmission. This is consistent with research demonstrating a strong correlation between prior hospitalization and readmission (Garrison, Mansukhani, & Bohn, 2013; Hummel et al., 2014). Hospitalization within the previous year rather than six months was included in two of the risk stratification tools used for readmission, ERA (Boult et al., 1993) and HCC (Mosley, Peterson, & Martin, 2009). This study supports the inclusion of prior hospitalization in risk stratification tools. These findings also support additional research in addressing prior hospitalization issues post discharge, including research in developing standardized preventive interventions for elderly patients with prior hospitalization.

Palliative Care (H8): Poor Predictor

This study fails to support the ability of palliative or hospice care to predict 30-day readmission. This is inconsistent with research demonstrating a correlation between palliative care and readmission (Nelson et al., 2011; Ranganathan et al., 2013). Palliative care was not used as a variable in the ten other risk stratification tools for readmission. Standardizing the documentation of palliative or hospice status within the electronic medical record may improve capturing this data.

It is important to note that only 100 out of 6894 patients received palliative or hospice care. The findings only refer to those who received that referral and does not include patients who were eligible or could benefit from palliative or hospice care. This low number could be due to provider awareness and comfort in using this end of life services which results in reduced admissions to the hospital.

The lack of significance of palliative/hospice care to predict 30-day readmissions may demonstrate that families are making appropriate but difficult decisions regarding hospitalization when dealing with the end of life of a loved one (Nelson et al., 2011; Ranganathan et al., 2013). Research has demonstrated the success of palliative/hospice care programs in the use of healthcare resources when outpatient palliative care was offered (Ranganathan et al., 2013) or inpatient consults on hospitalization for patients and their families facing end of life issues (Nelson et al., 2011). This study fails to support the inclusion of palliative or hospice care in risk stratification tools. These findings support the need for additional research in addressing palliative or hospice issues post discharge, including research in developing standardized preventive interventions for elderly patients with palliative or hospice care. However, continued work may be needed to help families handle pain management and decision making with hospitalization when faced with complex end of life issues.

Implications for Application to Nursing Practice

Nurses within health systems need to develop preventive interventions for vulnerable patients with chronic illness. The theoretical framework of the Care Model (Wagner, 1998) highlights the important role of health care providers in helping patients navigate healthcare resources to prevent unnecessary hospitalization (American Academy of Nursing, 2011; Cipriano, 2012; Institute of Medicine, 2001; Lamb, 2013).

Although the BOOST risk stratification tool demonstrated poor predictive capability, this study supported the predictive capability of variables associated with readmission, especially social variables captured in part within nursing documentation in the electronic medical record. There is an opportunity to use these sensitive variables to guide the development of targeted interventions that can guide nursing care. For example, for patients with compromised health literacy, nurses could offer interventions to promote teach back education or support during transitional care. For patients that live alone, nurses could work with families and patients to assure they have an adequate understanding of parameters for worsening symptoms to either notify their provider or go the emergency department. Also, to assure these patients have sufficient support systems to manage their chronic illness and activities of daily living. Risk stratification tools provide a starting point for nurses to plan preventive interventions, especially for chronically ill seniors.

Application of BOOST Risk Stratification to Promote Care Coordination/Collaboration

While the focus of this study was to determine predictors of 30-day, findings provide insight into preventive strategies. This includes a need for primary care nurses and health systems to develop care coordination processes including interprofessional collaboration to care for at-risk patients with chronic illness (Haas, Swan, & Haynes, 2013). This is particularly important given the national climate of quality-driven care (Office of the Legislative Counsel, 2010).

The American Academy of Ambulatory Care Nurses (AAACN) has identified the important role of nurses in coordinating care for vulnerable patients across different levels of care (American Academy of Ambulatory Care Nursing, 2017). The AAACN model illustrates the complex needs and opportunities to support patients between providers and settings to maximize clinical outcomes (American Academy of Ambulatory Care Nursing, 2017).

The BOOST tool can be used to screen and monitor risk variables using preventive and individualized care coordination interventions and interprofessional collaborative practice to reduce readmissions for at-risk patients. For example, while some of the variables such as diagnosis or physical limitations cannot be easily changed, there is an opportunity to target nursing interventions or referrals for depressed or health illiterate patients. Literacy issues could benefit from using a variety of teaching methods to promote effective patient understanding and adoption of individual plans of care for their chronic disease. Integration of risk stratification tools into care coordination processes across health care settings offer the potential to prevent hospitalization and modulate acute episodes of illness in the community, rather than the hospital.

Include Risk Stratification and Care Coordination in Nursing Education Programs

Risk stratification tools can help teach nursing students how to identify at risk patients with hospital or primary care visits and intervene to reduce the risk of readmission. AAACN has developed core competencies for care coordination and transitional care for nurses (American Academy of Ambulatory Care Nursing, 2017). One of the key competencies under the "Education and Engagement of Patient and Family" dimension is the skill to identify medical, functional, social and emotional problems that increase the patients' risk of adverse events. This study reinforces the usefulness of identifying predictive variables including social and emotional factors to reduce adverse events including readmission. Nurse competency skill building should include using risk stratification tools such as the BOOST tool to help clinicians identify important predictive variables associated with readmission.

Future Research

This study of the BOOST risk stratification tool underscores the paucity of strongly predictive tools for identifying patients at risk for 30-day readmission. In addition, there is a need for a greater understanding of a set of variables that are predictive across populations and settings. The ten risk stratification tools reviewed for this study used inconsistent variables, most of which did not include social determinants of health. There is a need for more research on combinations of variables, including social variables that can be incorporated into risk stratification tools targeted to support the reduction of readmission in seniors with chronic illness.

Integrate BOOST Risk Stratification Variables into the EHR

Operationalizing the variables in this study relied on the use of proxy measures within the medical record that included multiple data sources including billing records, consultations, medication sheets and nursing notes. There is a need for more accurate and complete variable information that could be easily accessed within the electronic medical record. Ideally, the BOOST risk stratification variables can be incorporated into the assessment screens in the electronic medical record to support the development of more timely preventive interventions for seniors with chronic disease, as well as study predictors for 30-day readmission.

Increase Research of Variables Associated with Readmission

There is a need for a greater understanding of the combination of variables most predictive of readmission for seniors with chronic disease (Haas et al., 2013; Kansagara et al., 2013). While this study supported the significance of physical and social factors, it is unclear why other variables associated with readmission including chronic illness, diagnosis; social support and palliative care were not stronger predictors. Implementation research is needed to determine the best ways to integrate these findings into practice and determine the best interventions that reduce risk of readmission.

Utilize BOOST Risk Stratification to Chronically Ill Seniors in Primary Care

This study used a sample of hospitalized seniors in one hospital. To understand the impact of chronic illness, there is a need to expand the use of risk stratification tools that include physical and social variables in primary care settings. Identifying at-risk patients earlier would support preventive care coordination interventions rather than waiting for a hospitalization to assess risk. Again, implementation research can identify successful interventions at primary care and community sites.

Promote Palliative/Hospice Care

There is a need for a better understanding on the potential success of palliative/hospice efforts in reducing readmission even though research has identified a gap in understanding how to support families in decisions regarding hospitalization (Ranganathan et al., 2013). Nurses caring for patients with chronic illness in primary or transitional care need to guide and support families in utilizing palliative or hospice care in concert with the individual needs of the patient. In addition, more research is needed on how to help families and patients with chronic illness make informed end of life decisions when faced with a potential hospitalization.

Conclusion

Despite the lack of predictive strength for the BOOST risk stratification tool for identifying patients at risk for 30-day readmission, the majority of the variables within the BOOST tool demonstrated predictive capability, consistent with previous readmission research. This study was the first to assess the validity of this tool using a large population of hospitalized patients. This study was also the first known to utilize nursing documentation within an electronic medical record to measure social variables associated with 30-day readmission.

There are important implications for nursing practice including expanding care coordination efforts and advancing nursing education and competencies in the use risk stratification tools and variables associated with readmission. Future research should consider integrating BOOST risk stratification variables into the electronic medical record, increase an understanding of the association of social variables with readmission, and expand the use of this risk stratification tool within primary care settings to avoid unnecessary readmission. Given the growing burden of seniors with chronic illness and the national move toward value-based care, nursing practice and future research needs to recognize the important role of risk stratification and predictive variables in conjunction with care coordination to reduce the burden of 30-day hospital readmissions.

APPENDIX A

RISK STRATIFICATION VALIDATED INSTRUMENTS ASSOCIATED WITH READMISSION

Author, Year, Location,	Tool	Design	Domain/ Construct	Methods	Statistical Analysis/ Validity	Limitations
Weiner, 1991 U.S.	Adjusted Clinical Groups (ACG)	Classification system by John Hopkins	Measure of ambulatory care resource use Delineates 93 patient categories based on presence or absence of diagnoses along with age & sex	Review of insurance and encounter documentation/claims over one year to develop inclusion into categories	ACG system had strong predictive C statistic at 0.73 for hospitalizations but also strong for predicting 30-day readmissions and healthcare expenditures Strongest predictive capability compared to other validated instruments in table	Method tied to software licensing and lack of social variables
Minnesota Department Human Services, 2012 U.S.	Minnesota (MN) Tiering Model	Five patient complexity levels based on Major Diagnostic Groups (MEDC's) also used by ACG method Condition groups served as a proxy for time and work required to coordinate patient care with assumptions based on literature review	To target vulnerable patients for care coordination outreach in the medical home model Tier 0: Low (no conditions) Tier 1: Basic (1-3 conditions) Tier 2: Intermediate (4-6 conditions) Tier 3: Extended (7-9 conditions) Tier 4: Complex (10+ conditions)	State healthcare reform 5-year effort with the University of Minnesota to introduce the concept of "medical homes" that promote the Triple Aim- currently over 300 practices are involved with this effort including small and large academic practices	MN had strong predictive capability with a C statistic of 0.78-0.81 similar to ACG but relied on ACG methodology for patient categorization; includes severe and persistent mental illness	Method tied to software licensing, few social variables
CMS, 2004 Crane, 2010 Mosley, 2009 U.S.	Hierarchical Condition Categories (HCC)	CMS implemented for Medicare Advantage Plan 191 condition categories representing diseases with high health costs plus age and gender	To target risk of hospitalization risk Incorporated the Elder Risk Assessment (ERA) Index for hospitalization in adults age 60 and over	Medicare Advantage Plan enrollees with chronic illness	HCC model explains 9.8% of the variance in future Medicare expenditures HCC compared to Probability of Repeated Admission (P_{RA}) tool	When compared to ACG & MN, HCC less robust in predictive capability, no social variables

			includes: age, sex, number of hospital days prior to 2 years, marital status and selected medical conditions Scoring -1 - 34		C statistic 0.638 and 0.654	
Naessens, 2011 U.S.	Chronic Condition Count	Based on Agency for Healthcare Research and Quality Clinical Classification Software-based on numbers of chronic conditions	To target the longitudinal healthcare costs Six categories summing chronic conditions scored from 0-5+ associated with persistent high costs	33,324 employees and their dependents 18-64 years old of the Mayo Clinic	Healthcare costs for patients with no chronic conditions was $2137, while patients with 5 or more chronic conditions was $21,183	When compared to ACG & MN, outcomes for HCC & CCC in the middle demonstrating fair validity, no social variables
Charlson, 1987 U.S.	Charlson Comorbidity Index	Designed for comorbidities affecting one-year mortality in cancer patients Sums weights for specific conditions	To target conditions impacting mortality 17 conditions Total sum of selected conditions	Two cohorts of adult patients (559) and (685) were tested for 1 year and 10-year mortality respectively; Stepwise regression	Validity established as prognostic measure of outcomes for various large populations has been demonstrated C statistic C 0.73- (Modest)	Some value compared to other validated tools but not as robust as other validated tools and specific to mortality of patients with cancer, no social variables
van Walraven, 2010 Canada	LACE Index/LACE + Index	Designed to predict readmission or mortality 30-days from hospital discharge	L (length of stay); A (acuity); C (comorbidities using Charlson), and E (use of emergency services with 6 months of hospital discharge). LACE + added additional variables Including Demographics Acute Diagnosis Use of acute services	4812 medical-surgical patients (2010)	Validity established across 11 hospitals and patient populations in Ontario Hosmer–Lemeshow goodness-of-fit statistic 14.1, $p = 0.59$ C-statistic 0.684 poor-moderate	Predictive capability poor but increased to moderate (C-statistic 0.771) with additional variables in the LACE + Model, no social variables
Choudhry, 2013 U.S.	ACC	Designed to predict readmission based on	Demographics Utilization Laboratory tests	126,479 hospitalized adults	C statistic 0.78 moderate	No social variables

		admission or discharge data	Exploratory tests Medications Conditions LOS Discharge disposition			
Boult, 1993 U.S.	Elder Risk Assessment (ERA)	Designed to predict hospitalization	Age Gender # Hospital Days prior 2 years Marital status Selected medical conditions	ERA had retrospective cohort study of 12,650 elder adults with primary outcomes of ER visits and hospitalization and patients in highest risk group had a relative risk of 9.5 for either hospitalization or ED visit and a relative risk of hospitalization of 13.3 in subsequent 2-year period C statistic 0.678- moderate predictive capability		Limited social variables
Amarasingham, 2010 U.S.	Heart Failure Model	Designed to predict readmission or death within 30-days of hospitalization	Diagnosis of heart failure Severity of illness Number of ED visits in previous year Socioeconomic status (history of home address changes in previous year) Risky health behavior (cocaine use) Insurance status Marital status	1372 heart failure patients over one year and one institution 0.72 (Modest) when social variables added		Limited social variables

APPENDIX B

READMISSION RESEARCH STUDIES

Author, Year, Location	Theoretical Base	Design	Independent Variables	Dependent Variables	Sample	Analysis	Limitations	Conclusions/ Implications
Stauffer, 2011	Transitional Care Program (TCP)-Naylor	RCT- prospective study with concurrent controls	APN-led transitional care program for patients with heart failure- series of 8 home visits including goal setting, education and encouraging supports	30-day readmission LOS 60-day from admission hospital system costs	56- Medicare patients with a principal diagnosis of heart failure from 8/09-4/10	48% reduction in 30-day readmission rates during post-intervention; little effect on LOS or 60 day costs	Limited sample	TCP programs can reduce 30-day readmission rates for HR patients
Voss, 2011 U.S.E	Care Transitions Intervention (CTI)-Coleman	Quasi-experimental prospective cohort study- logistic regression	Intervention group received Care Transition Intervention from trained transition coaches- hospital and home visits to provide education and follow-up encouraging self-management	30-day readmission	191 General medicine hospitalized Medicare beneficiaries	Intervention group 30-day readmission rate was 12.8% compared to control group with no intervention at 20%	Limited sample	CTI effective in reducing readmissions
Weiss, 2010 U.S.E	None noted	Hierarchical regression analysis	Nurse & patient assessments of discharge readiness within 4 hours of discharge	Readmissions & ED visits	162 adults from medical-surgical units from 4 Midwestern hospitals	Correlations between nurse and patient discharge readiness were low ($r = 0.15$-0.32); Nurses rated patient readiness higher than patients and nurse assessment had a higher association with post discharge utilization compared to	Limited sample	Need for formalizing nurse assessments of discharge readiness could facilitate the identification of patients at risk for readmission and ED use and avoid post discharge utilization

						self-assessment by patients		
Horowitz, 2011	CMS Measure Management System & AHA Standards for Statistical Models used for Public Reporting of Health Outcomes	Hierarchical regression generalized linear models	Seven cohorts of patients according to hospital service lines	Comparison of different hospitals and groups of patients for 30-day unplanned all-cause readmission after admission for any condition	181,203 readmission of Medicare beneficiaries over one year	c-statistics were consistently high for all 7 cohorts between 0.604-0.676 & captured 95% of eligible Medicare admissions and 88% of subsequent readmissions consistent with other public reporting measures	Need to test with randomly split samples and stability over time	Standardized hospital-wide (all-condition) risk-standardized readmission measures may assist in measuring quality and transitional care
French et al, 2014 U.S.	Collaborative Care Model	Cohort multivariate regression model	Healthy Aging Brain Center cohort of patients receiving disease management	Annual costs divided into inpatient and ED/outpatient costs	1756 patients in single center	Multivariate regression models, linear model with gamma distribution and log-link function, maximum likelihood technique	Single center	Improved care coordination and net savings of $980-2856 patient

APPENDIX C

DIAGNOSIS CODES ICD-9 AND ICD-10

Diagnosis	ICD-9 codes	ICD-10 codes	Notes
Depression	296.20-296.36, 311	F32.0 -F33.9	Exclude pediatric or post-partum
Cancer	Primary CA = 140 - 195.8 Secondary site = 196-198.89 Lymphatic CA = 200-208.92 CA in Situ = 230-234.9	Primary CA = C00-C76.8 Secondary site = C77-C79.9 Lymphatic CA = C81-C96.9 CA in Situ = D00-D09.9	Exclude benign & unspecified
Cerebrovascular Accident (CVA)	433.0 – 437.9	I63 – I63.9	
Diabetes – Adult	250.00-250.93 5th digit 0 = Type 2 5th digit 1 = type 1 5th digit 2 = type 2 uncontrolled 5th digit 3 = type 1 uncontrolled	DM Type 1 = E10- E10.9 DM Type 2 = E11 – E11.9 DM d/t underlying condition = E08-E08.9 DM d/t drugs = E09-E09.9	Exclude neonatal & gestational diabetes
Chronic Obstructive Pulmonary Disease	496	J44-J44.9	
Heart Failure	428.0 – 428.9	I50-I50.9	

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Carol has extensive professional experience in quality improvement and, the development of evidence-based guidelines, performance measures, federal regulations and research for business innovations. She is widely published in guidelines, performance measures and regulatory manuals. For many years, she worked at Walgreen Corporate Office in the development of clinical guidelines, ambulatory care measures and expanding participation into Medicare wellness programs for their retail health clinics. She also worked as a leader in quality, regulatory and research deliverables for a variety of organizations including University Health System Consortium (UHC) which is now Vizient, Resurrection Medical Center and the American Academy of Dermatology.

Currently, Carol is the Director of Quality and Performance Measurement at the American Society of Plastic Surgeons in Arlington Heights, IL. In this role, she supervises a team of research staff to develop clinical guidelines, physician performance measures, a Qualified Clinical Data Registry (QCDR) for reporting quality metrics and provides consultation on federal regulations impacting quality.