

Translating Readmission Risk into Clinical Care:

Testing a Readmission Risk Calculator among Elderly Hospitalized Veterans

By

Nathan Brashares Sackett

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Thesis Committee:

Dr. John Balmes, Chair
Dr. Caroline Stephens
Dr. Doug Jutte
Dr. Susan Ivey

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I. Literature Review

Introduction

Hospital readmission within 30-days of discharge is increasingly used as an important hospital-level quality measure. Many believe that readmissions are a marker of ineffective and fragmented healthcare delivery and have led to health policy mandates aim to penalize hospitals and providers with readmission rates higher than their peers. Thus, getting to the root of the problem and offering evidence-based solutions that target the appropriate population is increasingly in the collective interest of patients, providers, and health systems. However, doing so is difficult due to lack of good models for many patient populations.

As an example, consider the case of Mr. D, a 65-year-old veteran admitted to the San Francisco Veterans Affairs Medical Center (SFVAMC) with worsening shortness of breath. He has a long history of heart failure, chronic obstructive pulmonary disease, psychiatric illness and substance abuse. This is his third hospital admission, and in the prior 90-days he has spent 32 days in the hospital. Mr. D is single, has no immediate family and is unable to name his primary-care provider or recall the names of his medications. When asked what he believes was the greatest contributor to his multiple hospital readmissions, he explains that limited finances negatively impact his ability pay for transportation to and from his primary care appointments.

Patients like Mr. D are frequently admitted to the SFVAMC medicine service. Indeed, Mr. D is a fictional compilation of 25 patients who were interviewed at SFVAMC to help better understand the complexities associated with hospital readmissions. The

identification of potential readmission risk factors have led to the development of interventions aimed at patients with the greatest risk. Numerous observational studies have identified risk factors associated with hospital readmissions. However, the majority of current research explores hospital readmission risk among the Medicare population, with only a small handful of researchers exploring hospital readmission risk among geriatric US Veterans. This paper provides the background for an observational, cohort study aimed to validate a risk calculator among geriatric Veterans at the San Francisco Veterans Affairs Medical Center.

Given the complexities associated with hospital readmission, it is necessary to review our current understanding of readmission risks and the associated implications in order to effectively design and target care interventions. To that end, this literature review has four main goals: 1) review and discuss the evidence around using 30-day readmission rates as a metric of hospital care; 2) review the formative literature that identifies hospital readmission risk factors; 3) explore three evidence-based care transitions-focused interventions and their associated outcomes; and 4) discuss methods currently used to identify high-risk patients with a specific focus on readmission risk-calculators.

Hospital Readmission and Quality of Care

A hospital readmission within 30 days of a hospital discharge is widely considered an indicator of poor quality care^{1,2}. Current literature suggests a wide range of factors contribute to a hospital readmission, spanning patient demographics^{3,4}, hospital characteristics and location^{2,5} and clinical care practices. Interventions aimed to improve care-delivery among specific patient-populations have convincingly demonstrated the ability to reduce hospital readmissions through structured care transitions and improved discharge planning and coordination⁶⁻⁸. These findings suggest that among high-risk patient populations, hospital readmissions may be reduced and thus can act as a proxy for quality.

The Institute of Medicine defines quality as *‘the degree to which health services for individuals and populations increases the likelihood of desired outcomes and are consistent with current professional knowledge’*⁹. Agreement between patients, providers and policy makers regarding the best measures of quality varies significantly and reflect different goals¹⁰. Quality care in the eyes of a policy-maker may focus on the appropriate utilization of resources. A provider may measure quality based on their understanding of best clinical practices, whereas a patient may measure quality based on their individual needs¹⁰. As a result, healthcare quality improvement is an iterative process that requires investment from all stakeholders. The remainder of this section reviews three related topics: A. how the quality improvement movement led to quality indicators, B. the current debate about hospital readmission rates as a reliable quality indicator and outcome measure, and C. the use of hospital readmission rates within the Veterans Health Administration (VHA).

A. How Quality Improvement led to Quality Indicators

The 1999 Institute of Medicine (IOM) report, *To Err is Human*¹¹ thrust the importance of quality improvement into the national spotlight when it estimated that 44,000 – 98,000 preventable deaths occurred annually due to medical errors in the hospital. Using the lower estimate of 44,000 preventable deaths placed *medical error as the 8th leading cause of death in the US*, ahead of mortality due to motor vehicle accidents, breast cancer and AIDS^{11,12}. The IOM report went on to discuss how medical errors and resultant poor quality healthcare contribute to rising healthcare costs. The sum of additional healthcare expenses related to errors, including income lost, reduced household productivity and disability costs, amount to \$17 - \$29 billion dollars a year¹¹. One of the most important contributions made by the 1999 IOM report was the assertion that poor quality of care is the result of a fragmented and complex healthcare system, not solely the result of bad-providers.

In 2001, the IOM published *Crossing the Quality Chasm: A New Health System for the 21st Century*, which aimed to advance the debate sparked by *To Err is Human* by providing a framework for improving the healthcare system¹³. This report resulted in the formation of the Agency of Healthcare Research and Quality (AHRQ). AHRQ was tasked with the identification, evaluation and implementation of innovative methods to aid in care-delivery redesign.

AHRQ devised Standardized Quality Indicators (SQIs) in four groups: 1) Prevention Quality Indicators, including readmission rates; 2) In-patient Quality Indicators, including in-patient mortality; 3) Patient Safety Quality Indicators, including iatrogenic events like hospital-acquired infections, and; 4) Pediatric Quality Indicators.

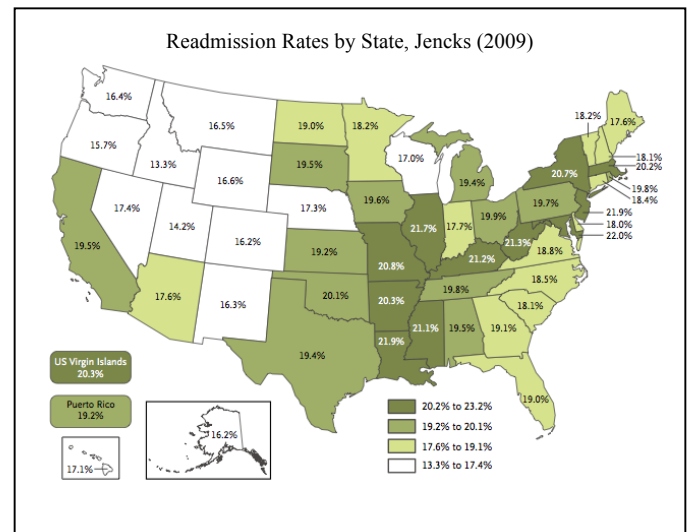
The implementation of reportable standard quality indicators has demonstrated a positive effect, improving hospital quality outcomes among the Medicare population ¹⁴ and the Veteran population ¹⁵ by identifying fragmented delivery-processes and standardizing evidence-based care. An observational study that examined Medicare data observed improved outcomes in 17 of the 18 quality indicators after 5 years of mandatory reporting ¹⁴. A study examining the effects of mandatory quality reporting among the VHA reported similar results, with hospital improvement observed over time and across regions ¹⁵.

The use of quality indicators also informs health-policy. The Patient Protection and Affordability Care Act of 2010 (PPACA) uses readmission rates as a proxy measure of healthcare quality. Under PPACA, the Center for Medicare and Medicaid Services (CMS) is authorized to reduce hospital reimbursement rates to hospitals with higher than expected risk-adjusted HRR among certain diseases ¹. Additionally, CMS publishes hospital-level readmission rates on a public website (www.hospitalcompare.hhs.gov/staticpages/for-consumers/ooc/readmission-measures.aspx), allowing the healthcare consumers to compare 30-day hospital readmissions rates between hospitals for three specific conditions: Congestive Heart Failure (CHF), Acute Myocardial Infarction (AMI) and Pneumonia. CMS's efforts to alter reimbursement based on hospital readmission rates, and make these rates available to the public, illustrate how quality indicators are currently used to better align financial and quality goals ¹⁶, thus meeting one of the major recommendations in *Crossing the Quality Chasm*.

B. Current Debate about Hospital Readmissions as an Outcome Measure

In 2009, a retrospective analysis of 2003-2004 CMS data found that 19.7% of Medicare patients were re-hospitalized within 30 days of hospital discharge, costing CMS \$17.4 billion dollars per year ². When further examined by state, 30-day readmission rates varied tremendously, from 13.1% in Idaho to 32.2% in Washington D.C ². This alarming distribution of hospital readmission by state seems to suggest a profound regional variation of quality of care.

A good quality metric is one where the relationship between the chosen process (clinical care) and the outcome (hospital



readmission) is supported by empirical data ¹⁷. Although early theoretical work has suggested an association between hospital readmission to poor quality of care ¹⁸, the mechanism remains unclear. Many argue that 30-day hospital readmission rates, by definition, are not a quality metric, but rather a utilization metric. Critics suggest that utilization of healthcare services is influenced by healthcare policy and societal factors not directly linked to quality of care, including socioeconomic status, access to transportation, health insurance coverage, and geography ^{3,19,20}. If readmission rates are indeed a reflection of access to services and socio-cultural determinants linked to geography, then the ability of readmission rates to measure quality of care is limited ¹⁹. Several studies ²¹ ^{3,22} have argued that poor agreement in the definition of a preventable hospital admissions, the inherent challenge in measuring readmission as an outcome, and the assertion that

non-modifiable risk factors are a greater influence in readmissions than modifiable risk factors, all make readmission a poor proxy of quality.

In a systematic review of 34 studies by van Walraven and colleagues estimates of an institution's 'avoidable' readmissions rate across studies found tremendous variation: rates of 5% - 78.9%, with a mean of 27.1%. The authors assert that such a wide range of reported 'avoidable' admission demonstrates a lack of agreement in both the definitions and measures used in reporting hospital readmission rates. Further analysis identified three research-design characteristics associated with higher reported 'avoidable' admission rates, including: 1) use of retrospective evaluation of administrative data, 2) using readmission outcomes over a longer period of time, i.e., 30, 60, 90-day, or 1-year time horizons; and 3) studies performed at teaching institutions. Consequently, the authors caution policy makers about the use of hospital readmission rates as a proxy for quality of care given the lack of agreement across the literature in how to precisely define an avoidable readmission ²¹.

Another systematic review sought to identify determinants of avoidable readmission using 37 studies conducted between 2000-2009. Vest and colleagues found variation in the concept of 'avoidable' readmission consistent with van Walraven. Vest and colleagues report that the heterogeneity of study design, outcomes selected (30, 60, and 90-day readmissions) and variation in the clinical cohorts examined make it difficult to clearly identify determinants of a avoidable admission ²².

Epstein and colleagues further suggest that a hospital's 30-day readmission rates are a poor quality metric because they reflect regional characteristics more than modifiable clinical-care practices ³. Using a national Medicare data set from 4432

hospitals, the analysis used geographic region as a predictor of 30-day hospital readmissions. In the analysis the authors reported that the hospital location, hospital characteristics (private, public, or academic) and the number of practicing cardiologists in the region were highly predictive of readmissions for congestive heart failure (CHF) in the US. This analysis undermines the assumption that a hospital's readmission rate reflects poor clinical-care processes in the hospital³ and asserts the notion that hospital readmissions may be a reflection of regional characteristics and practice patterns.

These three studies collectively argue that varying definitions of 'avoidable' hospitalizations, the unclear relationship with quality of care³, inconsistent study design²¹, variable outcomes measured²² and the influence of geographical factors beyond the control of hospitals³ make hospital readmission rates a complex and suboptimal endpoint for measuring quality of care.

C. Veterans Affairs Health Administration and Hospital Readmission

The Veteran's Affairs Health Administration (VHA) is the nation's single largest provider of healthcare, serving at estimated 37% of the estimated 22.7 million veterans²³ in 2011. Although the overall Veteran population is steadily declining, the cost of medical services related to chronic diseases has increased²⁴. The San Francisco Veterans Affairs Medical Center (SFVAMC) is part of the federally integrated VHA, with a 124-bed hospital and multiple ambulatory care services and supporting services. SFVAMC delivers care to more than 310,000 Veterans living in eight counties in Northern California.

In 1996, the Veteran's Health Care Eligibility Act was implemented²⁵ aimed at reducing cost while maintaining patient-centered quality care. This legislation was part of the VHA's effort to contain hospital cost and improve care by improving ambulatory care services with the goal of reducing the reliance on more expensive and less patient-centered inpatient care services. As a result, the 'ambulatory-care-sensitive' condition was developed, defined as *a medical condition that can be well managed with timely and effective outpatient services and thus, when a patient is hospitalized, may have been prevented*²⁶.

Although current CMS policy does not directly affect VHA through reduced hospital reimbursement for readmissions²³, the VHA has made hospital readmission and improving quality of patient care a core strategic goal. The VHA is interested in addressing hospital readmissions and improving quality for several reasons. First, historical studies suggest that hospital readmission rates among VA patients are higher than private hospitals, placing a greater financial burden on the VHA and implying poor quality^{27,28}. Second, the demographics of VA patients are rapidly changing due to an aging Vietnam Veteran population and an increase in recent global conflicts. Almost a quarter of VA patients are over 75, and 22% of veterans have four or more chronic conditions²⁴. Third, close to 40% of VA patients are covered by both Medicare and VHA²⁴. These 'dual-users' pose a unique challenge because their patterns of utilization and access to services may negatively impact health outcomes, with some reports of increased mortality among 'dual-users' when compared to non-dual users²⁹. The recent implementation of PPACA may motivate private hospitals to send 'dual-users' to the

VHA if this is perceived as a means to reliably reduce a hospital's 30-day readmission rates.

Recent data suggest that Veterans over the age of 65 seeking care at SFVAMC have a 30-day readmission rate of 16.8%, up 3% over the prior 5 years. In response to this increase, SFVAMC partnered with the Avoid Readmission through Collaboration (ARC) initiative (<http://www.avoidreadmissions.com/>) to reduce SFVAMC's all-cause 30-day readmission rates by 30% by 2013. The ARC is a learning network funded by the California Quality Collaborative and Center for Quality System Improvement, aimed at increasing awareness of current evidence and best practices and supporting implementation and evaluation of efforts to redesign care transitions (discussed in Section III).

In the summer of 2011, SFVAMC performed a needs assessment exploring the unique concerns of its veteran population using both qualitative and quantitative methods. The findings of this assessment were presented to SFVAMC leadership and key-stakeholders, resulting in the selection of an intervention aimed to reduce readmissions by improving care-transitions among vulnerable veterans. However, the majority of interventions aimed at reducing hospital readmission rates were developed and tested among Medicare populations, and methods for identifying patients at the greatest risk were primarily derived from retrospective studies using Medicare data. Currently, it is not clear which readmission risk factors and assessment tools are most appropriate for veterans.

Readmission Risk Factors

Numerous studies identify patients at increased risk for hospital readmission, principally assessing observational data on patients with specific diseases. Risk factors associated with hospital readmission include intuitive factors, such as patient age, disease, and severity of illness, and the less obvious causes, such as the role of residency (trainee) work hours³⁰, availability of prior hospitalization discharge summary³⁰, and the location where services are received². The body of literature identifying readmission risk factors is broadly divided into three domains: (A) patient-level predictors, (B) delivery-system predictors and (C) clinical predictors. The remainder of this section reviews the core literature in each of the three domains.

A. Patient-Predictors: Age, Race and Geography

Age

Age is a strong predictor of 30-day hospital readmission in both Medicare populations and VA populations. Most studies use either large administrative data sets from CMS or the VHA or analyze disease-specific cohorts. Silverstein conducted a large (n = 29,292) retrospective cohort study using CMS administrative data from seven hospitals in the Dallas-Fort Worth area and found a positive linear association between readmission risk and age. Using 65 as the baseline, they reported that patients between 70-74 had an increase in relative risk (RR) of 1.11(95% confidence interval [CI] 1.00-1.12). Older patients had steadily increasing risks: 75-79 years - RR of 1.35 (95% CI 1.22-1.49); 80-84 years - RR of 1.40 (95% CI 1.27-1.55), and patients > 85 years - RR 1.55 (95% CI 1.40-1.71)³¹. Among only VA patients, Smith used electronic medical record data from

nine VA hospitals and found patients over 80 years of age have the highest rates of hospital readmissions within 60 days of discharge³². These findings are consistent with early work by Jencks, Marcantonio, Corrigan, and Frankl who also reported age as a positive predictor of readmission^{2,33-35}.

With disease-specific diagnoses, however, the findings are mixed. Age remains predictive among studies examining cohorts of patients with pneumonia^{36,37}, but loses its predictive value in studies examining chronic obstructive pulmonary disease³⁸, percutaneous coronary interventions³⁹ and CHF⁴⁰. Meta-analyses examining both general medicine populations⁴¹ and post-acute myocardial infarction cohorts⁴² were unable to demonstrate age as a predictor of readmission. However both these meta-analyses caution that final analysis was difficult due to the heterogeneous nature of the studies included.

Race

Race is a predictor of 30-day hospital readmission among the Medicare population. Joynt and colleagues examined a large CMS data set (n = 3,133,011) of hospital discharges between 2006-2008 and found black patients over 65 years of age discharged with myocardial infarction (MI), CHF and pneumonia were 13% [OR 1.13, 95% CI 1.11-1.14] more likely than whites to be readmitted within 30 days⁴. In additional analysis, Joynt found that patients discharged from a hospital that serves predominantly non-white patients had a 23% increased risk of being readmitted within 30-days when compared to patients discharged from hospitals serving predominantly white patients⁴. Philbin examined New York State hospital administrative data and, in a multivariate analysis, found that black patients are readmitted 28% more frequently than whites [OR

1.28, 95% CI 1.16-1.41] ⁴³. Silverstein reported in the study cited earlier that non-whites have a 24% greater risk of 30-day readmission than matched whites [RR 1.24, 95% CI 1.13-1.36] ³¹. Consistent with these findings are those of a smaller observational study that found black patients with CHF were 7% more likely to be readmitted to the hospital compared to whites with CHF ⁴⁴. Interestingly, the literature examining race as a predictor of readmission examines race in two forms, white versus non-white, or white and black patient populations, often failing to examine other racial groups in the analysis.

Whereas most papers examining race among Medicare samples demonstrate that black patients are readmitted more frequently than whites, VA-cohort studies are unable to demonstrate race as an independent predictor of hospital readmission ^{5,45,46}. This is most likely the function of that VA studies have been conducted using relatively small populations at a single institution, but this issue needs to be further explored.

Geography

Geography is a positive predictor of hospital readmission in both Medicare and VA populations. Work by Weeks, Epstein and Billings found that geography is a predictor of hospital readmission ^{3,28,47}. As previously mentioned, Jencks examined national CMS data (n = 11,855,702) and found 30-day readmission rates vary from 13.3% in Idaho to 23.2% in Washington DC². Jencks and colleagues found one of the strongest predictors of readmission was the number of discharges a hospital performs annually. Patients discharged from a hospital with less than 1000 discharges had an observed readmission rate of 44.2%, whereas hospitals with more than 1000 discharges per year had an observed readmission rate of 24.4% ². Krumholz also performed an analysis using CMS data of

patients over 65 years but limited the study population to patients with CHF and acute MI and reported significant variation in both mortality and 30-day readmission based on region, varying from 20.1% - 29%⁴⁸. Although Jencks examined all cause readmissions and Krumholz only CHF and acute MI readmission, the trend in variation among Medicare patients implies that geography is a strong independent predictor of readmission.

Among Veterans, geography is a significant predictor of readmission. Veterans living in rural environments have been shown to have higher readmission rates than urban-living veterans²⁸, and work by Holloway demonstrated that increased distance to healthcare services was associated with increased risk of readmission⁵.

B. Delivery-System Predictors: Prior Utilization, Continuity and Coordination

Prior Utilization

Several studies suggest that prior utilization of healthcare services is a strong predictor of hospital readmissions. Studies typically employ secondary analysis of large data sets from CMS^{33,41} or the VHA^{32,46} and find that a history of hospitalization within the prior month³³, prior 6 months^{32,46}, or previous year⁴¹ is associated with increased 30-day hospital readmission risk in both Medicare and VHA populations.

Continuity and Coordination

Continuity of care is understood as the relationship between a patient and a single provider⁴⁹. Continuity of care typically has an inverse relationship with care-

coordination; the less continuity a patient has, the greater care-coordination is required⁴⁹. Many researchers use primary-care follow-up after hospital discharge as a proxy for continuity. Sharma examined over 3 million Medicare hospital discharges from 1996 through 2006 and the associated billing data from primary care providers (PCPs) and found that one visit to a PCP within 1 year of a hospital discharge was associated with significantly reduced rates of readmission⁵⁰. Interestingly, Sharma also demonstrated that rates of patient follow-up after hospitalization by a PCP have dramatically fallen between 1996 and 2006, from 50.5% of patients visiting a PCP within 1 year of hospital discharge in 1996 to 39.5% in 2006⁵⁰.

A single-institution study found a similar relationship with PCP follow-up and hospital readmission. Misky reported that patients discharged from the hospital who did not see a PCP within 30 days of discharge were 10 times more likely to be readmitted than those who visited their PCP after discharge⁵¹. Among the Veteran population, Pracht and colleagues examined data from a single VHA hospital and found that Veterans who visited their PCP monthly for chronic care management had significantly fewer readmissions⁵².

Coordination of care is often examined as a predictor of readmission by using hospital discharge summaries as a proxy of communication patterns and provider coordination. Van Walraven examined hospital discharges at a single institution and found that the availability of a discharge summary to the patient's PCP at the time of post-discharge follow-up visit was associated with a reduced risk of readmission³⁰. However, in a retrospective study at a single institution, Hansen and colleagues were unable to

demonstrate any significant relationship between communication among inpatient and outpatient providers and readmission rates ⁵³.

C. *Clinical predictors: Disease, Co-morbidities, Laboratory and Pharmacy Data*

Approximately 50% of adults over 65 have three or more chronic illness and close to 20% have more than five chronic conditions ⁵⁴. However, patients with a small cluster of diseases disproportionately are readmitted to the hospital: patients with CHF, acute MI and pneumonia.

Diseases: CHF

Heart failure alone is responsible for 18% of all Medicare hospital admissions ⁵⁵ and current estimates claim that 50% of patients with heart failure are readmitted within 6 months of hospital discharge ⁵⁶. Philbin performed a retrospective cohort study examining NY State data and found that 96% of patients readmitted to the hospital had a diagnosis of CHF ⁴³. Silverstein reported a 34% increased relative risk of hospital readmission for patients with CHF (RR-1.35, [CI] 1.23 - 1.46) ³¹. Additional studies by Burns, Krumholz, Smith, Naylor, Halfon and Ross all demonstrate heart failure dramatically increases risk of hospital readmission ^{32,55,57-59}.

Disease: Acute MI

In 2005, AMI acute myocardial infarctions were the 5th leading discharge diagnosis and had a reported 13.4% 30-day readmission rate ⁴⁸. However, to date, few studies have examined readmission rates and predictive risk factors among AMI-patient

cohorts. Desia and colleagues performed a literature review of AMI patients and readmission risk factors and identified 35 studies with a mean sample size of 23. In their final analysis, they claim that insufficient data limited the ability to identify patient-specific risk-factors among AMI-patient cohorts to inform policy ⁴². Krumholz and colleagues examined Medicare claim data and performed multiple hierarchical regressions among AMI readmission patients to develop a standardized reporting method that could discriminate expected readmission rates controlling for over 189 candidate variables. Although it was not the aim of the research, the analysis identified demographic variables (age and race), cardiovascular variables (history of coronary artery bypass grafting, percutaneous coronary intervention, angina, acute coronary syndrome, CHF, valvular disorders and arrhythmias) and co-morbidity variables associated with higher readmission risk. However, due to the nature of the analysis, the model could only discriminate hospital-level readmission rates, not patient-level variables ⁴⁸. These findings are consistent with the analysis by Joynt and colleagues that reported the only significant predictor among AMI-cohorts was whether an institution served a predominantly minority population (25.5% readmission rate versus 22.6% at non-minority serving hospitals); patient-level predictors were not identifiable in this study ⁴.

Disease: Pneumonia

Pneumonia has been associated with increased risk of hospital readmission, with 18% of pneumonia patients reported to have been readmitted within 30 days ⁶⁰. Lindenauer used Medicare administrative data and conducted a review of 226,545 hospitalizations across 4675 hospitals examining patients over 65 years old with

pneumonia and found that 32% were readmitted within 30 days³⁶. In their final analysis, the strongest predictor of readmission among pneumonia patients was overall hospital performance, using a variety of institutional-level measures³⁶. In an additional study examining Medicare data, pneumonia patients with co-morbidities including chronic obstructive pulmonary disease and coronary artery disease were found to be readmitted 2-3 times more frequently than pneumonia patients without these co-morbidities⁶¹.

Co-morbidities

At first glance, identified risk factors associated with increased readmission risk such as prior utilization, lack of continuity of care and specific diseases may be explained by increasing disease burden or worsening functional status. To address this confounder, many researchers control for co-morbidities by using the Charleson Comorbidity Index (CCI)⁶², or other disease-specific severity scales. Several single-institution cohort studies have demonstrated that severity of illness as predicted by CCI, is predictive of future readmission risk^{57, 18 41}.

Specific co-morbidities among Veterans have been observed to correlate with increased hospital readmission. These include diabetes⁴⁵, hypertension⁶³, COPD^{57,63}, malignancy^{5 57} and mental health disorders^{5,32,64}.

Laboratory Data

In studies examining characteristics of patients who are readmitted using logistic regression, blood urea nitrogen, creatinine, albumin and hematocrit have been identified as predictive of readmission. Herrman and colleagues performed an analysis that

examined 15,511 readmitted patients >40 years of age at a single hospital and found that an albumin <34g/L two days after admission was associated with higher rates of mortality, longer lengths of stays and increased hospital readmission (29% vs. 26% readmission rates)⁶⁵. Among a large, multi-site study examining albumin as a predictor of mortality and morbidity among VA surgical patients, Gibbs and colleagues found that albumin concentration was the strongest predictor of both mortality and morbidity (including readmissions) in their final regression analysis⁶⁶.

In a large multi-site observational study of CHF patients over 65 years of age, the strongest predictor of readmission was creatinine level >2.5 mg/dl⁴⁰. In another observational study examining predictors of readmissions among Veterans admitted to a general medicine service, Smith and colleagues found that elevated creatinine and blood urea nitrogen are associated with increased hospital readmissions^{32 63}, supporting a previous study by Reed⁴⁶.

Pharmacy Data

Polypharmacy, the prescription of multiple medications for multiple conditions (possibly by more than one physician), is associated with increased hospital readmission^{53,67}. As many as 50% of adults discharged from a hospital report an adverse event, with medication-related events causing the majority of readmissions among the elderly^{68 69}. Single institution studies report a linear relationship between the number of medications at discharge and the probability of hospital readmission⁶⁷, with patients discharged with 12 or more medications at discharge associated with increased mortality and worsening functional status⁷⁰.

Additionally, the numbers of medications at discharge and the class of medications are both strong predictors of readmissions. Budnitz performed an analysis of emergency department visits (n= 99, 628) examining over 5000 documented adverse medication events and found that four medications account for 67% of the events. The medications most often associated with readmission included the use warfarin (33.3%), insulin (13.9%), oral anti-platelet medications (13.3 %) and oral hypoglycemic agents (10.7%)⁶⁸.

Summary

In summary, a number of risk factors are associated with increased risk of hospital readmissions, spanning patient demographics, delivery-system factors and healthcare-practices. The majority of identified risk factors associated with hospital readmissions are derived from either large Medicare administrative data sets or single-institution cohort studies.

The multiple drivers of hospital readmission make the isolation of a single cause virtually impossible and have resulted in the development of various theories to help explain factors that drive hospital readmission. Further complicating the issue, few studies have examined how the identified risk factors interact with one another, potentially altering the overall risk profile of an individual patient. Nonetheless, these observational studies lay the foundation for interventions aimed at vulnerable patient populations.

III. Transitional Care Interventions

Transitions in care occur whenever a patient is moved between care settings and includes hospital admissions, discharges and transfers⁷¹. These transitions represent two

critical events: 1) a change in a patient's healthcare needs and, 2) a transfer of responsibility between providers ⁴⁹. A recent observational study examining a large Medicare data set found that 22% of patients over 65 years of age had at least one care transition annually ⁷², with the most common transition observed between home and the hospital. An additional observational study of Medicare patients found over 46 unique transitions in care among enrollees in 1997-1998 with 61% reporting at least one transition in care, 17.9% reporting two transitions, 8.5% reporting three transitions and 4.1% reporting four or more transitions in care ⁷¹. Each transition represents a critical event that may put patient safety at risk and thus represents a modifiable risk factor that may reduce hospital readmissions ^{1,73}. Given the nature of these transitions, interventions typically bridge the gaps across care settings and providers. The next section provides an overview of three transitional-care interventions, examining the design, measurable outcomes and challenges associated with each.

A. Transitional Care Model

Mary Naylor at the University of Pennsylvania developed the Transitional Care Model as follows: *“Transitional care is defined as a broad range of time-limited services designed to ensure health care continuity, avoid preventable poor outcomes among at-risk populations, and promote the safe and timely transfer of patients from one level of care to another or from one type of setting to another. Transitional care is complementary to but not the same as primary care, care coordination, discharge planning, disease management, or case management”*. ¹

Dr. Naylor's intervention is designed around the use of an advanced practice nurse (APN) leading an interdisciplinary team focusing on high-risk seniors. The APN meets the patient in the hospital to discuss the plan with the in-patient medical team, reviews the discharge plan with the family, and assess home-safety⁷⁴. Immediately after discharge, the APN visits the patient weekly to ensure proper medication and supplies are available and connect the patient and caregivers to available community resources. The patient has around-the-clock telephone support from nurses to address any urgent issues that may arise. The APN accompanies the patient to the first follow-up visit to ensure continuity and make any adjustments to the care-plan as needed.

A clinical trial conducted examining 30-day readmission rates among CHF patients enrolled in Dr. Naylor's transitional care model demonstrated a reduction in 30-day hospital readmissions by 48%, compared to matched controls⁷⁵. Health care cost savings (estimated savings from prevented readmission minus the cost of intervention) associated with this model tested on CHF patients reported a cost savings at 52 weeks of \$5000 per patient (\$7,636 vs. \$12,481)⁸. An NIH-funded clinical trial comparing Medicare enrollees and patients with common medical and surgical conditions found that cost savings for enrollees were \$3,000 dollars at 24 weeks, per patient (\$3,630 vs. \$6,661)⁸.

B. Care Transition Intervention

Eric Coleman at the University of Colorado developed an intervention termed the *Care Transition Intervention* (CTI). At the core of this intervention is a transition coach, who educates patient and caregivers about self-management. The transition coach is derived from the understanding that most patients and caregivers feel ill prepared at the

time of discharge ^{18,76}. The transition coach provides education and self-advocacy resources for patients and caregivers to better support patients at hospital discharge.

Experimental trials examining the effects of the CTI program demonstrate reduced hospital readmission at 6 months post-discharge and cost savings ⁷. A clinical trial conducted in 2006 demonstrated a reduced rate in 30 and 90-day readmission (intervention group, n = 379 and control group n = 371) with the intervention group demonstrating a 30 and 90-day readmission rate of 8.3 and 16.7% compared to the control group with 30 and 90-day rates of 11.9 and 22.5%. An additional analysis examined cost savings per transition coach and found a yearly cost savings of \$330,000 (with one transition coach responsible for 350 chronically ill patients) ⁷⁷. A more recent trial by Voss and colleagues examined the effects of health-coaching and reported results consistent with prior work, reporting a 30-day readmission rate of 13% for those receiving the intervention versus 20% for the control ⁷⁸.

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| <p>Project RED and Discharge Advocate</p> <ol style="list-style-type: none">1. Educate patient about his or her diagnosis throughout the acute-care hospitalization2. Make follow-up appointments and coordinate the collection of post-discharge test results;3. Discuss with the patient tests that are pending and ensure responsibility to act is clarified;4. Organize any post-discharge services, including home nursing, physical therapy, occupational therapy etc;5. Confirm with patient the post-discharge medication list;6. Reconcile discharge plan to follow national guidelines;7. Review with patient actions to take if problem arise;8. Expedite transmission of discharge summary to accepting primary care provider and other services;9. Assess the patients understanding of the care plan at discharge using teach-back methods10. Ensure patient has written copy of discharge plan at time of hospital discharge. <p>Pharmacist</p> <ol style="list-style-type: none">11. Provide 2-3 day follow-up phone call to ensure patient understanding of current medications and treatment plans. |
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C. Project Red

Dr. Brian Jack at Boston University developed an intervention termed *Project Re-Engineering Discharge*, or Project RED. At the core of this intervention is the use of ‘discharge’ advocates (DA). The discharge advocate is expected to focus on 11 points, listed in Box 1. Unlike Dr. Naylor’s transitional care intervention with an APN and Dr.

Coleman's Care Transition Intervention, Project RED puts greater emphasis on ensuring communication between primary care providers and outpatient services prior to discharge. The DA functions to fill the communication gap and provide patient education while a pharmacist calls patients 2-3 days after discharge to address any medication concerns or questions. A randomized trial of the Project RED intervention recently demonstrated a 30% reduction in 30-day readmissions compared to controls with an average cost saving of \$412 dollars per patient who received the intervention ⁶.

D. Challenges in the Study of Transition Interventions

Just as studies of readmission rates vary greatly and utilize multiple methods of assessment, so do the studies used to examine the effects of transition focused interventions. A recent literature review by Dr. Naylor identified 21 interventions, with a wide range of study designs ¹. Fourteen of the studies were single-site studies, while seven were multisite interventions. Interventions included either discharge planning or follow-up or both. In this analysis, Naylor identified five outcomes of interest including: (1) health status, (2) quality of life, (3) patient satisfaction (4) resource utilization (including readmissions) and (5) cost. As a result, Naylor concludes that the multitude of outcomes measured across different interventions make it difficult to clearly measure and implement interventions ¹.

Hasan et al. conducted a literature review examining 43 unique studies examining transitional interventions ⁴¹. Of the 43 studies, 26 studies did not account for missing data or incomplete outcome measures, 24 of the studies examined a single-component

intervention and of these, only seven studies were randomized. Of the interventions examined, most were termed ‘bundled discharge services’, or the sum of the intervention was a variety of smaller, more focused interventions. No studies were able to determine if there were any interactions between specific elements of the intervention, nor was there any agreement on the elements of the intervention that showed the greatest effect ⁴¹.

Among Veteran populations, there are no studies demonstrating the implementation of a transitional model and reduced hospital readmission rates. However, despite clear evidence that transitional models can result in cost savings, several questions remain. What sub-populations would best be served by a transitional model intervention? Is there a standardized patient risk assessment for hospitals interested in reducing readmission? And what research has examined risk assessments among the VA population?

IV. Readmission Risk Calculators

Readmission risk calculators create a patient risk index (risk of a patient being readmitted) by compiling identified risk factors in the three domains mentioned earlier; patient-level (demographic data), delivery-level (utilization, continuity and coordination) and clinical data (disease, co morbidities, laboratory and pharmacy data) to quantify the risk of a patient being readmitted. Increasing interest in readmission risk calculators have emerged to help target transitional care interventions aimed at vulnerable populations. The following section aims to: A) review current understanding of readmission risk calculators in both Medicare and VA populations and, B) introduce the IPEC calculator tested in this study.

A. Readmission risk calculators: Medicare and VA

The most common calculators of readmission risk are the healthcare providers themselves. Interestingly, very little research has examined the accuracy of providers in predicting patients at the greatest risk of hospital readmission. In a single-institution survey of nurses, social workers and physicians working in an inpatient general medicine unit, no single group could accurately predicted the patients who were readmitted within 30 days ⁷⁹. In an additional single-site study, nurses and physicians were surveyed to assess readmission predictive accuracy of Class IV CHF patients and readmission risk within 6 months of discharge and found that neither nurses nor physicians could accurately assign risk based on clinical judgment alone ⁸⁰

Given the lack of provider reliability to discriminate patients at high risk of readmission, various predictive models have been developed to flag vulnerable patients that may benefit from enrollment into an intervention. A systematic review of readmission risk prediction models was performed by Kansagara and colleagues and identified 26 unique models in 30 primary studies, with sample sizes from 173 to 2.7 million subjects⁸¹. Of the 26 models examined, only one study examined potentially preventable readmissions and six included models were derived and tested in non-US institutions.

They further divided the models by data source, including retrospective administrative data (14 models), real-time clinical data (3 models) and retrospective primary data collection (chart-review) (7 models) to better identify models with clinical utility and those used for evaluation purposes ⁸¹. To rank the models, the authors used the Receiver Operator Curve (ROC), a plot of sensitivity versus 1 minus specificity. A plot

with an area under the curve (AUC) of 0.5 represents a model with no discrimination, while a plot with an AUC of 1 demonstrates perfect discrimination⁸². Among the 26 models examined by Kansagara, a range in AUC was observed, from 0.5⁷⁹ to 0.83⁷¹.

In the analysis, Kansagara and colleagues highlighted that half of the examined models were developed for hospital comparison purposes and have little clinical utility. The remaining half were developed to identify high-risk patients, although no single model demonstrated strong predictive ability across the population. They chose a cut-point of 0.7 and 0.8, with models demonstrating an AUC above 0.7 considered to demonstrate modest discrimination and 0.8 demonstrating a clinically useful model.

VA-Specific Models

Of the 26 models examined by Kansagara, four were tested or derived from a VA population. The four studies are single-institution studies^{57,63,64,83}, range in outcomes measured (30, 60 and 90-day readmissions) with sample sizes of 134⁶⁴, 532⁵⁷, 2790⁵ and 662⁶³. Of the four models derived from a Veteran population, the Smith index is the best studied and has reported a C-stat of 0.66 when using 90-day readmissions as an outcome⁶³.

The Smith index was derived examining 1396 subjects at nine VHA hospitals and examined a broad spectrum of dependent variables to develop a set of predictive variables. In their analysis, the authors used a step-wise Cox regression to identify four variables that were associated with increased readmission risk, including hospitalization or emergency room visit in the prior 6 months, higher blood urea nitrogen, lower mental health function,

a diagnosis of chronic obstructive pulmonary disease (COPD) and increased patient satisfaction with access to emergency room care.

C.VA Readmission Risk Calculator

As previously mentioned, the SFVAMC and ARC collaboration resulted in the selection of Project RED, targeting high-risk Veterans receiving general medicine care. To assist in appropriately enrolling patients, a risk calculator derived based on national VA data was used that has not been validated among SFVAMC general medicine patients.

The VA-derived risk calculator uses the following variables (see image): age (70-80 years or >80 years); surgical admission (yes/no); length of stay > 7 days (yes/no); admission in prior 180-days (yes/no); number of medications at discharge; presence of high-risk laboratory indicators including albumin, creatinine, glucose and hematocrit; and presence of high-risk primary or co-morbid diagnosis (anemia, cancer, CHF, COPD, diabetes and/or renal failure).

Each of these variables is weighted and compiled into a raw score that is then correlated with an expected probability of a 30-day hospital readmission (See image).

Calculation of Modified Risk Score	
Patient Demographics (select only one)	Lab Values
<input checked="" type="checkbox"/> Age 70 - 80 years	<input checked="" type="checkbox"/> Albumin <= 3.2 g/dL
<input type="checkbox"/> Age > 80 years	<input type="checkbox"/> 1.5 mg/dL < Creatinine <= 2 mg/dL
Hospitalization Information	<input type="checkbox"/> Creatinine > 2 mg/dL
<input type="checkbox"/> Operative	<input checked="" type="checkbox"/> Glucose < 60 mg/dL or Glucose > 180 mg/dL
<input type="checkbox"/> Length of stay 7 days or more	<input type="checkbox"/> HCT % <= 25 or HCT % >= 55
Previous Admission	Primary or Comorbid Diagnosis
<input type="checkbox"/> 0 - 180 Days prior	<input type="checkbox"/> Anemia
Medications (select only one)	<input checked="" type="checkbox"/> Cancer
<input type="checkbox"/> 1 - 5	<input type="checkbox"/> CHF
<input type="checkbox"/> 6 - 17	<input type="checkbox"/> COPD
<input type="checkbox"/> More than 17	<input type="checkbox"/> Diabetes
	<input type="checkbox"/> Renal Failure
30 Day Readmission Risk Score	7
Probability of Readmission	11.5%

Conclusion and Summary

To date, no studies have examined the clinical applicability of a VA-specific readmission risk calculator, nor used it to identify patients who would benefit from a transitional care intervention. This paper reviewed four large topics: 1) the use of hospital readmission rates as a quality indicator, 2) the formative literature identifying readmission risk factors, 3) three evidence-based transitional care interventions aimed at reducing hospital readmissions and, 4) current research on readmission risk calculators among the Medicare population and the VA population. A major gap in the literature includes the lack of validation of a risk calculator that can assist clinicians in enrolling patients into a transitional care intervention. Previous work has been limited by data collection techniques, with many studies using retrospective data to examine hospital readmissions.

The SFVAMC is focusing on methods to reduce hospital readmissions as part of the strategic goals of the medical center. My collaboration with the Avoid Readmission through Collaboration has resulted in a needs assessment, the selection of a transitional care intervention and a commitment from leadership and key stakeholders to address hospital readmissions. However, currently there are no validated patient-level risk calculators available to assist clinicians in deciding which patients deserve enrollment into the selected intervention. The purpose of the study proposed here is to examine the clinical applicability of a VA-derived risk-calculator in triaging patients into transitional care interventions.

Section II. Original Research

Background

A hospital readmission within 30 days of discharge is seen as a marker of poor healthcare quality that is both expensive and potentially avoidable. Current observational studies report hospital readmission rates as high as 20% among all Medicare patients² and as high as 50% among specific patient populations^{46,57,84}. Among Veterans using the Veteran Health Affairs (VHA) system, similar observations have been reported³². As the nation's single largest provider of healthcare, the VHA serves approximately 37% of the estimated 22.7 million veterans²³.

The 2010 Patient Protection and Affordable Care Act legislates that hospitals address 30-day readmission rates to avoid significant financial penalties^{16,85}. Although this legislation will not directly affect the VHA, there is a shared concern among VHA administrators and providers to improve quality and reduce cost, particularly with the growth of patients with multiple chronic conditions²⁴. Current literature suggests a wide range of factors contribute to hospital readmissions, spanning patient demographics^{3,4}, hospital characteristics, location^{2,5,28} and clinical care practices^{18,22,86}.

Although the list of identified risk factors believed to contribute to 30-day hospital readmission is substantial, transition between healthcare settings have increasingly been the focus of interventions⁶⁻⁸. Termed Transitional Care Interventions^{1,51,87,88} (TCI), these evidence-based programs aim to reduce 30-day hospital readmission by improving care and communication from discharge to the return to the community^{7,71,89,90}. Many of these interventions utilize the use of nurse practitioners^{54,91},

home care nurses, social workers and pharmacists⁶ to address any urgent medical or unmet social needs after hospital discharge. TCI's are increasingly being utilized among specific patient populations, particularly patients with chronic diseases such as congestive heart failure and chronic obstructive pulmonary disease. However, hospitals are challenged with appropriately identifying patients with the highest risk of 30-day readmissions so that interventions may be targeted accordingly.

The VHA has made the reduction of hospital readmissions and improvement of quality care a core strategic goal²³. Although the overall Veteran population is steadily declining the cost of medical services related to chronic diseases has increased²⁴. Studies further suggest that hospital readmission rates among VHA patients are higher than reported rates for private hospitals, placing a greater financial burden on the VHA and implying poor quality^{27,28}.

Recent quality improvement data suggest that Veterans over the age of 65 seeking care at the San Francisco VA Medical Center (SFVAMC) have a 30-day readmission rate of 16.8%, up by 3% over the prior 5 years, representing a 22% rise. This increase in readmissions has led to SFVAMC exploring interventions to reduce hospital readmissions. Unfortunately, the majority of interventions aimed at reducing readmission rates have been developed and tested among Medicare populations, and methods for identifying patients at the greatest risk have been primarily derived from retrospective studies using national Medicare administrative data^{2,4,43}. As a result, it is currently not clear which readmission risk factors and assessment tools are most appropriate for use among the Veteran population. A small body of literature explores readmission risk

prediction among veterans in four single institution cohort studies,^{5,57,63,64}, yet no study to date has tested a specific readmission risk calculated derived from national VHA data.

Consequently, the purpose of this retrospective cohort study is to examine the predictive ability of a VHA derived 30-day readmission risk calculator in a cohort of Veterans over the age of 65 who were discharged from the general medicine service at an urban, academic-affiliated VHA Medical Center.

METHODS

Study Setting and Population

This is a retrospective cohort study using a sample of Veterans discharged from the general medicine service at the SFVAMC, an urban, academic-affiliated center within the VHA system. This acute care facility includes a 124-bed hospital and multiple ambulatory care services and supporting services aimed at delivering care to more than 310,000 Veterans living in eight counties in Northern California. The inpatient general medicine service at the SFVAMC is a large teaching medical service engaged in the training of medical students, residents and fellows and is the primary acute-care facility for Veterans in the area.

Data for this study was derived from a large quality improvement (QI) dataset that included patient clinical data, as well as hospital census and utilization for general medicine patients who were discharged between March 2, 2011 and April 28, 2011. Two physicians and two medical students (including the primary author - NS) abstracted electronic medical records based on the discharges between the defined date-ranges.

For this study, the QI data set was queried for patients that met the following conditions; were over 65 years old, were documented to live in the primary service area, and survived for at least 30 days after the original hospitalization discharge date. Patients discharged on hospice care or with a primary psychiatric discharge diagnosis were excluded from this analysis. Applying the above selection criteria resulted in 140 unique patients (n = 140). Due to the nature of the data and analysis, institutional review board approval was not required as there was no direct access to patient identifiers in this study.

Primary Predictor

The primary predictor of interest was the risk of readmission calculated using a Veteran's Readmission Risk Calculator (VRRC). This calculator constructs risk % from the following variables: (a) patient age (in years), 70-80 or > 80 y.o (y/n); (b) hospitalization information including if the admission was surgical (y/n) and if the length of stay (LOS) ≥ 7 days (y/n); (c) if there were any previous admissions in past 0 -180 days (y/n); (d) number of medications at discharge (1-5,6-17, or >17); (e) lab values, including albumin ≤ 3.2 g/dL (y/n), creatinine 1.5 mg/dl - 2mg/dL (y/n) and/or creatinine >2 mg/dL (y/n), glucose <60 mg/dL or glucose > 180 mg/dL (y/n), Hct% ≤ 25 (y/n) or Hct % ≥ 55 (y/n); and (f) primary or co-morbid diagnosis, including anemia (y/n), cancer (y/n), CHF (y/n), COPD (y/n), diabetes (y/n) and renal failure (y/n).

These patient specific variables were collected in the original QI dataset and were tabulated from hospital discharges that met inclusion criteria during the study period.

These variables were then entered into the VRRC using a model derived from national

VHA data and the readmission risk % evaluated as a continuous variable. Due to patient privacy concerns, only the risk % was extracted for analysis.

Primary Outcomes

The primary outcome of interest was the patient acute-care utilization of medical services after index hospitalization. Acute care utilization was defined as (1) hospital readmission at the SFVAMC within 30 days of index hospital discharge and (2) emergency department (ED) visits at SFMVAC not resulting in hospital admission within 30 days of hospital discharge. Patients who were seen in the ED and then admitted were counted as readmissions to prevent counting them twice.

Possible Confounding Factors

Additional confounding variables identified in the literature were examined as potential cofounders, including age, severity of disease⁹² and the availability of follow-up care^{86,93} at hospital discharge. Severity of disease was assessed using the Charleson Comorbidity Index (CCI), a proxy measure of disease burden that has been validated and well tested⁶². Follow-up care for patients included in the sample was defined as discharged with any follow-up appointment, including those for both primary and specialty care.

Statistical Analysis

Descriptive statistics were used to evaluate demographic characteristics of the cohort, including gender, age, CCI, length of stay (LOS) in days of the index hospitalization, and the recording of a follow-up visit at time of discharge.

Logistic regression was performed to examine any association between the dichotomous outcome variables (readmission, ED visit) and the continuous predictor variable (readmission risk percentage) calculated by the VRRRC. Additional associations between patient demographic variables and utilization variables were examined using logistic regression, reporting odds ratios in both an unadjusted model and adjusted model, controlling for age, CCI, LOS and if the Veteran was discharged with a follow-up appointment.

Likelihood ratios (LRs) of hospital readmission were calculated for multiple risk percentages allowing for the construction of a receiver operator characteristic (ROC) curve. ROC curves are often used to examine the clinical utility of both diagnostic and prognostic models. The ROC is a plot of sensitivity versus 1-specificity and is a measure of a model's discrimination and calibration. Discrimination refers to a model's ability to accurately discern test subjects with or without a known variable^{82,94}. Calibration refers to a model's ability to predict an observed outcome in the future and is thus referred to as a calibration-statistic (C-stat)⁹⁵. The area under the curve (AUC) is the calculated area under the plot and is often used to compare predictive models. A C-stat with an AUC of 0.5 indicates that a model performs no better than chance. A C-stat with an AUC closer to 1 indicates better calibration.

The VRRS calculated readmission risk was stratified into low, medium and high risk based on the distribution of calculated risk, ranging from 1-45%. Low readmission risk was defined as a calculated risk between 1-16%, medium risk ranging between 17-33% and high risk ranging from 34-45%.

RESULTS

Table 1 shows the demographics of the cohort, including patient age, gender, CCI, LOS and follow-up appointment scheduled at discharge, stratified by readmission risk. Of the 140 patients included in this analysis, 38 (27.1%) utilized acute care services within 30 days of index hospitalization. Acute-care utilization included 18 (12.9%) readmissions within 30 days of index hospitalization and 20 (14.3%) ED visits within 30 days of index hospitalization.

When the VRRC readmission risk score was examined as a continuous predictor, the association between the risk score and 30-day hospital readmission in both the unadjusted (OR 1.08 [CI 1.01-1.14]) and adjusted models (OR 1.10 [CI 1.01-1.18]) was significant. When the VRRC readmission score was examined as a continuous predictor for ED readmission, significance was observed in the unadjusted model (OR 1.05 [CI 1.00-1.11]) but lost significance in the adjusted model. Readmission risk was not associated with 30-day acute care utilization when risk was examined as a categorical variable (low, medium, severe). Table 2 shows the odds ratios of 30-day hospital readmission and 30-day ED visit for multiple predictor variables. Predictors were examined as both continuous and categorical variables.

When CCI was examined as a categorical variable, a score between 0-2 was protective for 30-day readmission in both unadjusted (OR 0.28, [CI 0.09 – 0.85]) and adjusted models (OR 0.11 [CI 0.01 – 0.68]). When the length of stay of the index hospitalization was examined categorically, a LOS of 4-7 days was associated with an increased risk of 30-day ED visit in both unadjusted and adjusted models (OR 2.18, [CI 1.05 – 4.53]) and (OR 2.47 [CI 1.10 – 5.64]) respectively.

Figure 1 reflects the result of the ROC curve analyses examining readmission risk as the predictor for three outcomes, 30-day readmissions, 30-day ED visits and total acute care utilization. Using C-stat, the AUC of the VRRC risk prediction for 30-day readmissions was 0.63. The ROC for ED-visit was 0.59 and the ROC for the total acute care utilization was 0.6.

Table 3 shows sensitivity, specificity, positive predictive value (PPV) and negative predictive values (NPV) of the VRRC risk prediction for 30-day readmissions. There is an increased PPV and reduced NPV as the risk % is increased. The greatest PPV and NPV corresponds to a risk % of 32.2%, with a PPV of 41.4%, NPV of 89.9 and a sensitivity of 11.1% and specificity of 98.4%.

DISCUSSION

Among a cohort of geriatric Veterans discharged from a general medicine service, over one-fourth utilized acute care services within 30 days of hospital discharge. Close to 13% of the cohort was readmitted to the hospital within 30 days of original hospitalization and 14% were seen in the ED within 30 days of hospital discharge. The results of this study demonstrate that the VA readmission risk tool using both clinical and patient

demographic data has a calibration statistic of 0.63 when using 30-day readmission as the outcome. This finding confirms that the VA readmission risk calculator is able to predict 30-day readmissions among geriatric Veterans better than chance (C-stat >0.5), although the small sample size limits the power of these findings.

Perhaps the most common readmission “risk calculators” are healthcare providers. While not typically described as ‘risk calculators’, clinicians are often tasked with rapidly deciding who is ready to be discharged from the hospital based on a mixture of clinical factors and provider experience. In a recent study of staff nurses, social workers, and physicians working in an urban Veteran Health Affairs, inpatient general medicine service, no group of providers could accurately predict which patients were readmitted within 30 days⁷⁹. When stratified by profession and analyzed using C-stat and associated AUC, nurses were found to have a C-stat of 0.55, social workers 0.5, interns 0.58, residents 0.58 and attending physicians 0.57. This poor predictive ability of health care providers may be a reflection of the diagnostic heterogeneity among general medicine patients. However, in a similar study examining the predictive accuracy of nurses and physicians for a cohort with a specific diagnosis of Class IV congestive heart failure (CHF) patients, neither professional group could accurately assign risk based on clinical judgment alone⁸⁰.

Readmission risk calculators have been developed with different goals in mind. Some readmission risk calculators were developed using billing data and aggregated administrative data, which can only be used retrospectively. These calculators were designed to compare readmission rates between hospitals and cannot be used for individual patient risk stratification. Other risk calculators were designed using clinical

and patient data that can be collected as a patient receives care, termed ‘real-time’ data. For a readmission risk calculator to help a clinician, the readmission risk calculator needs to use data that is available on a patient-level and is immediately available as a patient receives care⁸¹.

Kansagara and colleagues⁴¹ recently conducted a comprehensive systematic review of 26 unique readmission risk calculators. Using ROC and C-stat for model comparisons, they argued that an acceptable C-stat of a readmission risk model is 0.7, however a value of 0.8 or above is preferred. Among the identified readmission models reviewed, C-stats ranged from 0.56 – 0.83⁸¹. To address readmission model differences, they divided the models by data source and corresponding analysis and found nine models reliant on retrospective administrative data collection, with a C-stat range of 0.55-0.65. The three most rigorous models used large Medicare datasets for disease-specific cohorts of patients with CHF, acute myocardial infarction (AMI) and pneumonia, with a reported C-stat of 0.61 for CHF and 0.63 for AMI and 0.63 for pneumonia.

Three models reviewed by Kansagara et al. used real-time administrative or clinical data allowing for potential clinical utility⁸¹. Real-time data can be captured and provided to clinicians as patient-care events occur. A single institution study of CHF patients developed a 30-day readmission model with a reported C-stat of 0.72⁹⁶. A study conducted by Billings and Mjanovich⁹⁷ in 2007 developed a model using Medicaid data to stratify high and low readmission risk with a reported sensitivity of 58% and specificity of 74% for readmission within 12 months of hospital discharge.

Along with the source of data mentioned above, Kansagara⁸¹ also stratified the readmission risk calculators by the type of patient population on which the models were

developed and tested. Of the 26 models identified, 14 were derived from and tested on patients over 65 and only four were derived from and tested on Veterans. Of the four studied with Veterans, all were single-institution, retrospective-cohort studies seeking to identify risk factors for early readmission.

Evans and colleagues studied 534 Veterans discharged from a single VA to a nursing home and using multiple medical, social and psychological variables identified during index admission and associated with readmission, including a diagnosis of two or more chronic conditions, altered mental status, psychiatric comorbidity, living alone and being unmarried⁶⁴. Holloway and colleagues conducted a similar study among a cohort of Veterans and identified primary diagnosis as the most predictive risk factor for readmissions within 60 days of index admission⁵. Burns and Nichols conducted a small cohort study at a VHA hospital in Memphis examining only elderly Veterans. In this analysis, the authors found three significant risk factors for hospital readmission, admission type (emergent vs. elective), diagnosis and severity of illness⁵⁷. Smith et al. conducted a study of the Smith Index, a risk-stratification index that compiles five risk factors, including an ED visit within 6 months of index admission, blood urea nitrogen, PaO₂, WBC count of >12,000/mm³ and a hemoglobin of <12g/dl. The authors found that this model had a sensitivity of 55% and specificity of 68% with a positive predictive value of 28%⁶³.

The existing literature suggests that clinicians are poor at predicting which patients are at the greatest risk for hospital readmissions^{79,80}. Although some risk calculator models have been shown to improve prediction of readmission, most of these models have not been derived from VHA patient data. Our study contributes to the relatively sparse data on

readmission risk among Veterans. To date, the Smith-Index is the only readmission risk predictive model that uses clinical data, with a PPV of 28%. The findings of this study using a model with a greater number of clinical variables suggest that the PPV may be improved upon. Although the data among the highest risk was too small for analysis, the trend suggests that PPV could exceed 28% with a larger sample.

Limitations and Future Directions

There are important limitations to this study, including the small sample size from a single institution, retrospective study design and the inability to alter the VRRC model and examine the relative contribution of each variable to the VRRC risk calculation. A larger sample size would allow for a more robust analysis that might show a significant trend across categories (low, medium, high) of predicted risk as well as potentially different effects for different strata of the patient population. The outcome of interest in this study, acute-care utilization, was only examined at a single VHA hospital. The SFVAMC may not be representative of VHA medical centers. The retrospective nature of this study precluded the follow-up of patients to determine they are utilizing acute care services outside of the VHA system. Further analysis of patient-level variables may provide an opportunity to improve the predictive ability of the VRRC.

Further studies are necessary to better understand the unique mixture of readmission risk factors that affect acute-care utilization among geriatric Veterans. In general, future studies of the VRRC should be prospective in nature to provide a more accurate assessment of its predictive ability and to ensure that Veterans are not seeking

acute care outside of the VHA system. More specifically, two areas of investigation have emerged as potential next steps.

First, additional research should examine unique social and demographic variables that disproportionally affect Veterans. For example, a recent qualitative study of frequently readmitted general medicine patients at the SFVAMC demonstrated that 80% of those readmitted had some sort of psychosocial stressor such as homelessness, psychiatric co-morbidities and substance use.

Second, the positive and negative predictive value of any readmission risk calculator should be examined as it relates to the clinical decision at hand. Deciding on a clinically acceptable set-point that will determine whether a patient has a risk profile deemed high enough to enroll them into an intervention must be examined against potential risks and perceived benefits, both from a clinical and financial perspective. This parallels the much larger debate about cancer prevention screening involving prostate-specific antigen (PSA) for prostate cancer screening, mammography for breast cancer screening and colonoscopy for colorectal cancer screening. All screening needs to take into account the potential harms of false-positives and the degree of acceptable sensitivity. However, the use of a readmission-risk calculator as a potential clinical decision-making tool is unique in that the relative harm of a false positive is low, particularly when compared to other screening methods like PSA and mammography. Arguably, a false positive in the context of readmission risk would result in potentially unnecessary enrollment in a transitional care intervention, interventions that are assumed to be safe.

In conclusion, the results of this study contribute to the literature on readmission risk, especially among hospitalized Veterans. Although the sample size is small, this is the first study to have assessed the readmission risk calculator designed specifically for use in hospitalized Veteran patients and examined the acceptable level of calibration and discrimination necessary to help clinicians enroll high-risk patients into transitional care interventions. While the calibration statistic analysis showed only modest predictive ability, the results nevertheless suggest that the VRRRC may be a useful tool in clinical practice. The VHA is in a unique position to further test this readmission risk tool at other facilities within its system. The necessary data are readily available within the VHA electronic medical record and the readmission risk calculation could be provided as a simple clinical-decision support tool at the time of discharge.

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Table 1. Characteristics of Geriatric Veteran Cohort Discharged from Inpatient General Medicine service by Calculated 30-day Readmission Risk, stratified into Mild, Moderate and High Risk Groups

Characteristic	Total Sample (n=140), %	Mild Risk (n=79), %	Moderate Risk (n=56), %	High Risk (n=5), %
Demographics				
Men	(n=130), 92.9	(n=72), 91.1	(n=53), 94.6	(n=5), 100
Age Group (in years)				
65-75	(n=88), 62.9	(n=56), 70.9	(n=32), 57.1	(n=0), 0
76-85	(n=30), 21.4	(n=15), 19.0	(n=13), 23.2	(n=2), 40.0
86+	(n=22), 15.7	(n=8), 10.0	(n=11), 19.6	(n=3), 60.0
Charleston Comorbidity				
0-2	(n=74), 52.9	(n=54), 68.4	(n=20), 35.7	(n=0), 0
3-5	(n=46), 32.9	(n=21), 26.6	(n=22), 39.3	(n=3), 60.0
6-8	(n=18), 12.9	(n=4), 5.1	(n=12), 21.4	(n=2), 40.0
9-10	(n=1), 0.7	(n=0), 0	(n=1), 1.8	(n=0), 0
Length of Stay (Days)				
1-3	(n=67), 47.9	(n=48), 60.8	(n=18), 32.1	(n=1), 20.0
4-7	(n=48), 34.3	(n=25), 31.6	(n=21), 37.5	(n=2), 40.0
8-10	(n=9), 6.4	(n=1), 1.3	(n=7), 12.5	(n=1), 20.0
11+	(n=16), 11.4	(n=5), 6.3	(n=10), 17.9	(n=1), 20.0
Follow-Up Appt at DC				
Yes	(n=65), 46.4	(n=35), 44.3	(n=28), 50.0	(n=2), 40.0
No	(n=72), 51.4	(n=42), 53.2	(n=27), 48.2	(n=3), 60.0
Utilization				
30-day Readmission	(n=18), 12.9	(n=7), 8.9	(n=9), 16.1	(n=2), 40.0
30-day ED Visit	(n=20), 14.3	(n=9), 11.4	(n=9), 16.1	(n=2), 40.0
Total ACU	(n=38), 27.1	(n=16), 20.3	(n=18), 32.1	(n=4), 80.0

Table 2. Calculated Odds Ratios of 30-day readmission and 30-day ED visit after index-hospitalization, stratified by cohort characteristics.

Characteristic	30-day Readmissions OR		ED visit Only OR	
	(95% Confidence Interval)		(95% Confidence Interval)	
	Unadjusted	Adjusted*	Unadjusted	Adjusted*
Readmission Risk				
Low	0.93 (0.71 – 1.22)	0.94 (0.66 – 1.33)	1.00 (0.78 – 1.27)	0.96 (0.75 – 1.24)
Medium	1.12 (0.96 – 1.33)	1.1 (0.93 – 1.31)	1.1 (0.80 – 1.43)	1.02 (0.85 – 1.22)
Severe	NR	NR	NR	NR
Age				
65-75	0.98 (0.78 – 1.22)	0.98 (0.76 – 1.24)	1.03 (0.84 – 1.26)	1.03(0.84 – 1.27)
76-85	0.95 (0.75 – 1.20)	0.77 (0.51 – 1.15)	1.28 (0.97 – 1.71)	1.23 (0.90 – 1.70)
86+	1.05 (0.69-1.60)	1.33 (0.51 – 3.44)	1.05 (0.69 – 1.61)	1.33 (0.51 – 3.44)
CCI				
0-2	0.28** (0.09 – 0.85)	0.11** (0.01-0.68)	1.66 (0.72-3.85)	1.57 (0.64 – 1.86)
3-5	0.82 (0.35 – 1.93)	0.79 (0.32-1.97)	1.11 (0.36 – 3.41)	1.18 (0.37 – 3.81)
6-8	0.80 (0.19- 3.28)	1.85 (0.18 – 18.8)	0.86 (0.23-3.27)	1.02 (0.17 – 6.01)
9-10	NR	NR	NR	NR
LOS				
1-3	0.32 (0.08 – 1.28)	0.22 (0.03 – 1.60)	1.00 (0.31 – 3.21)	0.68 (0.20 – 2.37)
4-7	0.81 (0.40 – 1.65)	0.78 (0.34 – 1.79)	2.18** (1.05 – 4.53)	2.47** (1.10 – 5.64)
8-10	NR	NR	2.10 (0.26 – 16.1)	NR
11+	1.32 (0.83 – 2.10)	1.71 (0.72 – 4.10)	1.57 (0.92 – 2.69)	2.45 (0.91 – 6.59)
DCFU				
Yes	1.30 (0.50 – 3.56)	1.31 (0.45 -3.81)	1.13 (0.44 – 2.91)	1.23 (0.44 – 3.41)

* Adjusted for age, length of stay in days, Charleston Comorbidity Index and follow-up appointment at discharge

** Significance with p<0.05

NR – Not reported because of Insufficient sample size

Figure 1. ROC/AUC – 30-day readmission only, Fig 2) ROC/AUC – 30-day ED visit only , Fig 3) ROC/AUC of 30-day Acute Care utilization

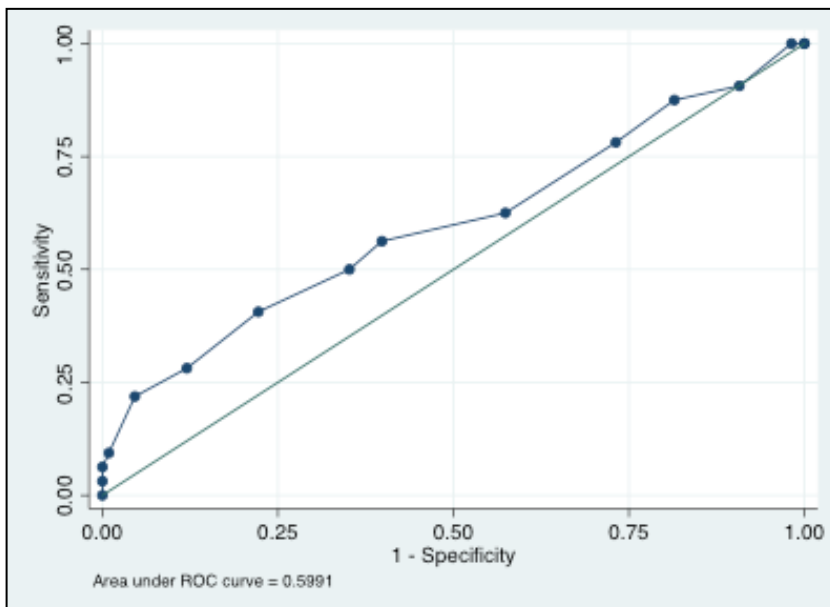
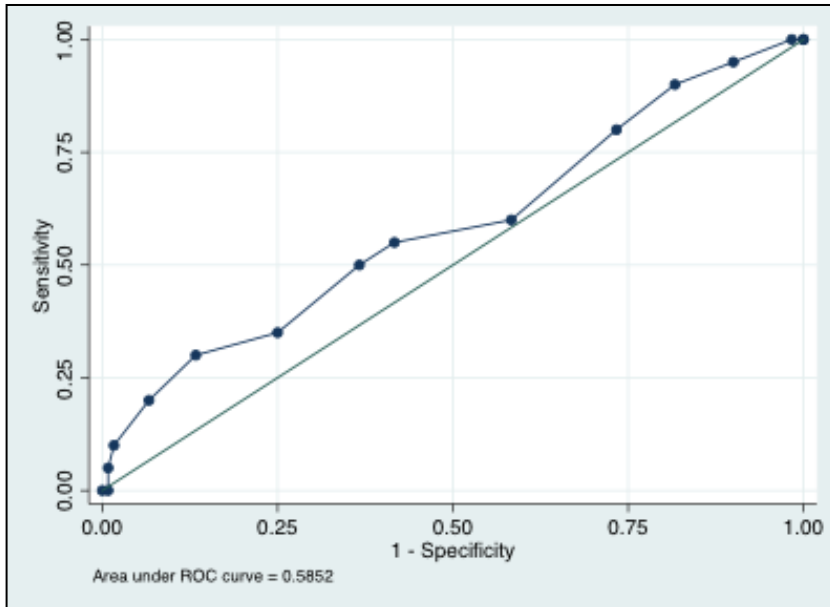
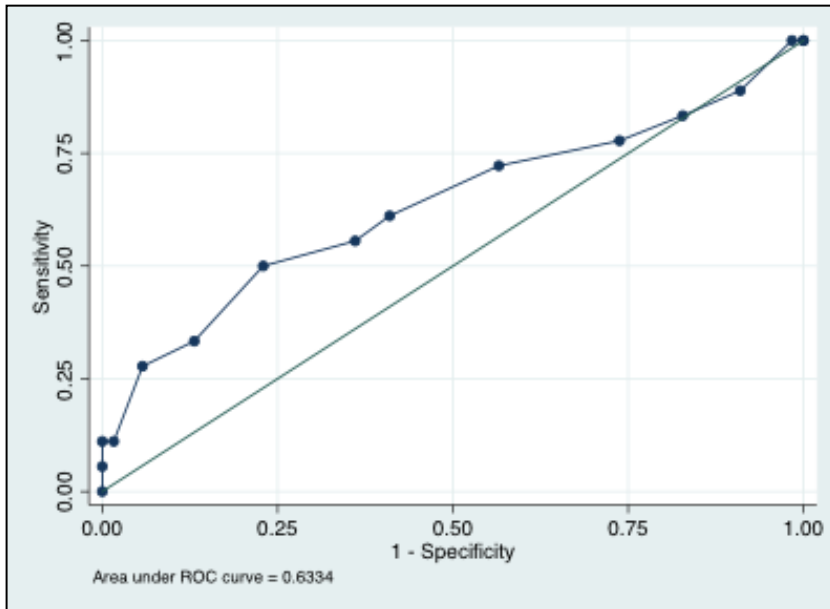


Table 3. PPV, NPV, Sensitivity and Specificity for different risk prediction cut-points using the 30-day Veteran's Readmission Risk Calculator (VRCC)

30-day Readmission Risk (%)	Positive Predictive Value (PPV - %)	Negative Predictive Value (NPV - %)	Sensitivity (%)	Specificity (%)
≥ 5.8	12.9	0.0	100	0.0
≥ 8.2	13.0	100	100	1.6
≥ 9.7	12.6	84.6	88.9	9.0
≥ 11.5	12.9	87.5	83.3	17.2
≥ 13.5	13.5	88.9	77.8	26.2
≥ 15.8	15.9	91.4	72.2	43.4
≥ 18.5	18.0	91.1	61.1	59.0
≥ 21.4	18.5	90.7	55.6	63.9
≥ 24.7	24.3	91.3	50.0	77.1
≥ 28.3	27.3	89.8	33.3	86.9
≥ 32.2	41.4	89.8	27.8	94.3
≥ 36.3	50.0	88.2	11.1	98.4
≥ 40.4	100	88.4	11.1	100.0
≥ 45.3	100	87.1	5.6	100.0