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Variables to Predict Risk of Hospital Readmission

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Capstone

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Background

As the healthcare industry transitions toward accountable care and payment reform, the ability of health systems to creatively approach caring for patients is imperative. Changes in payment systems and a historically fragmented system have resulted in poorly coordinated care and shorter lengths of hospital stay. These payment changes, in conjunction with poorly coordinated care, have resulted in increased rates of readmission to the hospital soon after discharge. It is estimated that nearly one in every five Medicare patients returns to the hospital within 30 days of discharge (Rau, 2012). The national rate of hospital readmission is approximately 19 percent, but the rate of readmission varies throughout the country. This has large implications for hospitals and health systems as readmissions are costly and often result in poor outcomes for patients. These readmissions, many of which are preventable, are estimated to cost twelve billion dollars per year (Medicare Payment Advisory Commission, 2008).

The current payment system has created little incentive for hospitals to address readmissions since readmitted patients generate additional revenue. The Patient Protection and Affordable Care Act (ACA) modifies this reimbursement model and has dramatically increased attention to reducing hospital readmission rates. Medicare now has the authority to cut payments to hospitals when patients are readmitted to the hospital within 30 days of discharge. Medicare payments to hospitals could be cut by a maximum of one percent in 2013. This percent will increase to two percent in 2014 and to three percent in 2015. This penalty will be deducted from each Medicare payment to the hospital. Hospitals with high rates of readmission could lose a large amount of revenue, highlighting the need for system-wide transformation to address this problem. In Maine, Medicare is currently penalizing ten hospitals for their high rates of readmission. Many hospitals are struggling to adhere to the changing requirements for compliance with these new rules. In addition, hospitals, as well as many health systems, are dealing with financial losses in this economic environment. These Medicare rules, as well as the complexities that surround readmissions, mean that hospitals will need to dedicate a vast amount of resources to reducing this problem.

MaineHealth is a healthcare network comprised of eight member hospitals, HomeHealth, NordX, Synernet and the Maine Medical Center Physician Hospital Organization (MMC PHO). MMC PHO includes a large number of the practicing physicians, as well as Maine Medical Partners (MMP), which is a multi-specialty group of 300 Primary Care Physicians (PCP) that serves Southern Maine. MMC PHO and MaineHealth recently formed the MaineHealth Accountable Care Organization (MHACO). Under MHACO, physicians are held accountable for reaching financial and quality targets that will achieve better population health. One of the 33 quality measures primary care providers are held accountable for is all condition readmission within 30 days. Therefore, MMP is concerned with ensuring patients are treated in the primary care office and that they do not return to the hospital.

The need to focus on population health is even more critical given the intersection of increased regulation from the Centers for Medicare and Medicaid Services (CMS) and decreased resources. Many hospital readmissions would be prevented if patients were effectively managed within the ambulatory healthcare setting through increased care coordination. In addition, those who are consistently readmitted are often the most vulnerable members of society: the elderly, the chronically ill, and those with low incomes as they lack consistent, coordinated, and timely care. This population is often forced to seek treatment through Emergency Departments (ED) for conditions that could be treated in the ambulatory care setting. These individuals do not receive necessary and effective care and continue to perpetuate the cycle of ED overuse.

Many organizations have been trying to decide where to focus their scarce resources and have tried to develop a prediction model to identify patients at highest risk for readmission. These models use patient variables to try to predict the patient's risk of readmission. Prediction models pose many challenges because there are a multitude of factors that lead to a readmission, and each readmission being unique and often very complicated. However, there are many models currently being used to predict readmission. These models take patient variables and calculate a risk score based on the presence or absence of the variables. The variables and number of variables utilized in a specific model differ, but there are commonalities among the most popular models. Most often, the model's performance is evaluated based on a *c* statistic. The *c* statistic, in logistic regression, is a standard test of the predictive accuracy of a model's performance and can range from 0.5 to 1.0, with 1.0 being the highest possible value. A *c* statistic of 0.5 would suggest that a model does not perform any better than chance, while the 1.0 would suggest that the model perfectly predicts the measure of interest.

By employing a predictive model, providers can better understand their patients' risks and be more prepared to provide the patient with the appropriate treatment and resources. With the loss of Medicare revenue and our current economic situation, developing a successful model to predict hospital readmission is critical. Finding that model requires identifying the variables that are present in readmissions. However, the complexity of readmission, which is often specific and unique to each patient, makes this extremely challenging and organizations have been trying to adapt these quickly occurring changes.

While other industries have used risk prediction models, applying these models to the clinical setting of health care has created challenges. To date, there is no standard approach to prediction modeling or a model that can fit all of the nuances surrounding a patient's readmission. One problem with this new field is limited use of real-time data. Many doctors have to use claims data that can be delayed by weeks or even months. However, increased use of Electronic Medical Records (EMR) provides the opportunity to use real-time data to inform automated predictive models. With real-time models, clinical providers could use the prediction risk of the patient and treat the patient in the manner best suited for the patients' needs at the first hospital admission.

Patients are extremely vulnerable at discharge and are often confused and lack the ability to adhere to all of the instructions given to them. Giving providers the ability to fully understand the needs of their patients by alerting them to patients at high-risk of readmission is critical in reducing the risk. Understanding the risk could help providers better coordinate the discharge planning of the patients and tailor it to their specific needs and addressing any issues before the patient leaves the hospital. For example, problems with obtaining medication prescribed in the hospital could be anticipated and a solution found before discharge. Unfortunately, few models currently used take into account all of the medical and social factors that often cause readmissions (Kansagara, et al., 2011).

Practical Application of Predicting Readmissions: Maine Medical Partners (MMP)

MMP, which is part of the MaineHealth healthcare network, developed a Care Transition Program (CTP) in response to an identified gap in effectively transitioning patients from the hospital to the home and the need for coordinated care within MHACO. This program was created to meet the needs of the patients that they serve more effectively by placing telephone calls to patients that are recently discharged from Maine Medical Center. During the telephone conversation, the care transition nurse completes medication reconciliation, alerts the PCP of any immediate or alarming problems since discharge, and schedules an appointment for the patient to see their PCP. MMP conducted a pilot program that yielded promising results, which showed that the telephone calls helped to reduce the number of readmissions.

The number of discharged patients requiring a transition phone call exceeds the resources available. Due to limited resources, MMP developed a semi-automated model that categorizes a patient's risk for readmission as high, medium, or low. This model requires manual entry of data to capture a risk score. This model is based on five risk variables that were corroborated by the literature on readmission. The variables included in the scale are: source of admission (Emergency Department (ED), direct from primary care office (PCP), or scheduled), number of hospital visits within the last six months, number of ED visits within the last six months, on more than five medications, and any problem medications. Because this model is not automated within a patient's chart, the discharge nurse has to manually read through the patient's chart and then enter data into a worksheet that calculates the risk score. For example, if the patient has three to 30 ED visits within the last six months, this is considered a higher risk and one point will be added to the overall risk score. The scoring continues through all five variables. A total score of zero is given if no risks are found, and one point is added for each risk present for each variable. A total score of three or higher is considered to put a patient at high risk for readmission. With this scale, MMP can focus the care transition resources to those patients who are determined to be at a high level of readmission.

Purpose

The purpose of this Capstone is to inform MMP of evidence for variables that effectively predict a patient's risk of readmission so they will be able to lower their readmission rates resulting in improved patient care, decreased costs and reduced hospital utilization. This Capstone provides an analysis of predictive variables and concludes with a recommendation of variables for MMP to analyze for their predictive model.

Framework and Methods

This Capstone was conducted using a systematic literature review to identify variables associated with readmission rates. Informative interviews were used to gather qualitative information about readmission rates at MMP to answer the following research questions:

1. Is the use of the current variables in the MMP scale supported by the literature?
2. Are there variables that should be added to the current MMP scale based on evidence from the literature and stakeholder interviews?

The framework for this capstone was based on the systematic review conducted by Kansagara that identified two top performing scales for predicting readmission: the

Coleman Administrative and Self-Report Model and the Amarasingham Electronic Readmission Model. The twelve variables identified in these models formed the basis of the literature review. This literature review also incorporated the top three answers found by a survey of PCPs at MMP to be the most prominent reasons that their patients are readmitted.

Variables were selected in two top performing scales through a review of the literature. The database Ovid MEDLINE was used to search for evidence supporting the efficacy of utilizing these variables in a prediction scale. Search terms were each of the identified variables used in separate searches and the variable title was used as the major header. To narrow the search results, both hospital readmission and patient readmission were included as a secondary search term. The search was limited to articles published between the years 2000 to 2013.

After completing the literature review, interviews were conducted to gather evidence for support of the variables. All the interviewees gave verbal consent to be interviewed. The interviews were not recorded, but notes were taken and themes were coded into categories related to the variables after the interviews were completed. The identities of the individuals were kept confidential. The interview questions were not related to the interviewees' job performance or the organization's performance and should not be seen as threatening to the participants. This Capstone received Institutional Review Board exemption from the University of Southern Maine for this project. Appendix A provides the questions that were asked during the interview.

Finally, evidence gathered from the literature and through the stakeholder interviews was used to identify the efficacy of the current variables and to propose variables that MMP could incorporate into their current prediction model into a document.

Results

Literature Review Findings

A total of 172 articles were collected to review, with 126 of the articles excluded, for a total of 45 articles used to inform this paper. The criteria used to exclude literature was unit-based, disease specific, or regarded as a specific surgery. Dates were also considered when analyzing articles with a preference to recently published articles. The inclusion criteria for articles selected was analysis completed of the variable, the sample size used and the *c* statistic score. However, for some of the variables, literature was used that had a small sample size, often referred to as N, due to the limited research available. The table in Appendix B displays the articles that were reviewed to inform this paper. During the literature search, it was clear the variables identified through the 2 top performing models, referred to as the researched variables, consisted of similarly themed variables. Additionally, certain variables did not have evidence that supported the utilization of the variable within a predictive model. Therefore, for this Capstone, variables were combined, and coded by themes, into one variable referred to as the final variables. To view the researched variables and the final variables please see table 1 – “list of variables”.

Table 1 – List of Variables

Researched Variables	Final Variables
Limited Social Support	Limited Social Support
Single Status	
Self-rated health	Self-rated health
Activities of daily living	
Functional Status	
Age	Age
Sex	Gender
Prior Medical Service Use	Prior Medical Service Use
Number of Prior Admissions	
Presented to ED b/w 6 A and 6 P for index admission	
Problem Diagnosis	Problem Diagnosis
Heart Disease	
Cancer	
Diabetes	
Charlson Index	Charlson Index
History of Depression/Anxiety	Mental Health
Medicaid Status	Low Socioeconomic Status
Residential Stability	
Medicare Status	
Residence in Lowest SES Quartile	
History of Confirmed Cocaine Use	Risky Behaviors
History of Missed Clinic Visit	
Health Literacy	Health Literacy
Problem Medication	Problem Medication
Use of Health System Pharmacy	Excluded
Visual Impairment	
Tabak Mortality Score	

Models

Kansagara and colleagues found that none of the prediction models used to date have performed remarkably well at predicting readmission risk (Kansagara, et al., 2011).

Through the literature search, other evidence was found that supported this finding. In fact, clinical data did not add to risk prediction for readmission, and while clinical factors do well at predicting mortality, they do not do well when predicting readmission (Hammill, et al., 2011) (Amarasingham, et al., 2010). Additionally, most models available are scored around a *c* statistic of .6. Two factors can be deduced from those scores: first, important predictors of readmission are missing from the models and, second, non-medical factors have a larger role in the risk of readmission (Giamouzis, et al., 2011). This suggests that more testing of models that focus on the inclusion of non-medical variables is needed. Kansagara and colleagues discussed social factors often contribute to readmission, but do not always make it into the final predictive model and adding these factors has not been studied extensively (Kansagara, et al., 2011). Kansagara found models that assign patients into high and low-risk categories are clinically meaningful, demonstrating the benefit of categorizing patients despite the evidence of performance of scales.

Despite that evidence, there are many models being used and the most common include: the Coleman Administrative Model, Patients at Risk of Re-hospitalization (PARR), LACE Index, Probability of Repeat Admissions (Pra), and Predicting Emergency Admissions over the Next Year (PEONY).

Eric Coleman and Colleagues have developed two models, the Coleman Administrative Data Model and a second model which includes the former with the addition of self-reported information. The variables included in the first model were: age, sex, prior medical services use, Medicaid status, Charlson Index, heart disease, cancer and diabetes. The second model incorporates additional data, including: self-reported health, activities of daily living assistance need, visual impairment, and functional status. The additional variables improved the model's *c* statistic score from 0.77 to 0.83, which demonstrates that the addition of the self-reported variables resulted in a more effective prediction model (Coleman, Sung-joon, Chomiak, & Kramer, 2004).

The PARR 1 model, developed by Billings and Colleagues, was built for ease of implementation, using data already collected at the time of admission and at the bedside of the patient. The model looks at the patient's history of Congestive Heart Failure, Chronic Obstructive Pulmonary Disease (COPD), Diabetes, and Sickle Cell Anemia, along with 21 other variables that score patients according to the number of risks they have. This model scored a *c* statistic score of 0.70 (Billings, Blunt, Steventon, Georghiou, Lewis, & Bardsley, 2012). Billings has recently developed a model that advances his earlier model called PARR 2 that was expanded to include hospitalizations. The Combined Model was formed to include data from other sources whereas PARR 1 and 2 include only inpatient data (Billings, et al.). The goal in developing a model based on data outside of inpatient stays is to begin to look at the general population, not just a sample of individuals readmitted, in an attempt to best match resources to the need of the population.

The LACE Index has been cited in published research a number of times. This model includes only four variables: length of stay, acuity of admission, Charlson Index, and use of ED in the past 6 months (van Walraven, et al., 2010). The simplicity of the model makes it easy to use for practitioners, as there is a point system for each variable. If a patient scores higher than 11, it is suggested that the patient be referred to case management. Evidence shows that for each one-point increase in the patient's LACE

Index score, the risk of unplanned admission increases by eighteen percent (Au, McAlister, Bakal, Ezekowitz, Kaul, & van Walraven, 2012). However, in a study by Cotter, only ED use was a predictor of readmission and the overall tool was considered a poor predictor (Cotter, Bhalla, Wallis, & Biram, 2012). Some of the criticism of LACE is that the tool does not take into consideration the patient's severity of illness, which can be a large factor in the hospitalization and readmission of a patient.

The Pra model calculates a score for risk of readmission using eight measurements to predict the probability of repeat admission. The eight variables include: older age, male, poor self-rated health, informal caregiver, history of CAD, diabetes, hospital admission within past year, and more than six doctor visits (Allaudeen, Schnipper, Orav, Wacther, & Vidyarthi, 2011). Pra and administrative data were tested for performance and the article concluded that combining administrative data and a survey-driven model might be helpful in trying to find a more accurate prediction model (Vojta, Vojta, TenHave, Amaya, Lavizzo-Mourey, & Asch, 2001).

The Predicting Emergency Admission over the Next Year (PEONY) model uses a number of variables and the final model includes 39 variables. The development of this model was different from other models in two aspects: the sample included those aged forty and older and was derived from the general population. Many other samples use a cohort of those previously readmitted.

Review of Variables

In the review of the literature, researchers evaluated several variables to determine whether or not they effectively predicted readmission risk. The following section on variables is presented in order of support from the literature based on the statistical report given by the study author. Each variable evaluated in each article was identified and was then compiled into Table 2 shown below. This section also contains evidence regarding variables collected from the stakeholder interviews. Table 2 displays the variables evaluated from the articles evaluated. The first columns refer to what variables were found to be significant during quantitative analysis. The second column refers to the variables that were quantitatively tested but found to not be significant.

Table 2 – Variable Table

	Statistically Significant	Evaluated, but not significant
Problem Diagnosis	31	24
Prior Medical Service Use	14	8
History of Depression/Anxiety	10	11
Age	9	15
Sex	8	15
Charlson Score	3	1
Low Socioeconomic Status	6	5
Problem Medication	3	2
Limited Social Support	3	0
Risky Behavior	3	2
Self-rated health	3	6
Health Literacy	0	1
Visual Impairment	Excluded from literature search	
Tabak Mortality Score		
Use of Health System Pharmacy		

Problem diagnosis

For this Capstone, problem diagnoses includes some of the most frequently cited diagnosis for readmission, which are heart failure (HF), diabetes, Chronic Obstructive Pulmonary Disease (COPD), and stroke. Evidence suggests that the problem diagnosis at discharge focuses on too much and due to this complexity, the cause of readmission is missed. For example, only 37 percent of HF patients are readmitted for the same condition (Krumholz, 2013). That is a small percent of readmissions as 63 percent admitted of patients are readmitted for other reasons. Because readmission is so unique and complicated, when readmission data is compiled by causes of readmission, heart failure is the most frequent readmission, and, therefore, the easiest to target. It is hard to ignore focusing in on a specific issue that garners such high of a level of readmission. However, there is the need to look at characteristics and variables that transcend all diseases.

- Heart failure is often associated with readmission as patients with heart failure are hospitalized over a million times each year and of those patients, almost fifty percent, will return to the hospital within six months (Giamouzis, et al., 2011) (Aranda, Johnson, & Conti, 2009). Additionally, heart failure was shown to be the cause of 28 percent of all readmissions (Aranda, Johnson, & Conti, 2009).
- Diabetes is a common cause of readmission. The medication therapy can increase patients' risk of readmission due to adverse effects (Morrisey, 2003). The expense of the therapy can be prohibitive causing patients to not adhere to treatment plans because they cannot afford the medication.
- COPD is the third most common cause of readmission (Sharma, Kou, Freeman, Zhang, & Goodwin, 2012). Half of patients with hypercapnia on admission will be readmitted to the hospital and seven percent will be readmitted three or more times within six months.

- The rates of readmission for stroke range from 20 to 27 percent in the first year. In a study of 2,603 patients, less than 15 percent survived admission-free five years after the initial stroke (Bravata, Ho, Meehan, Brass, & Concato, 2005).

Prior medical service use

Much of the evidence suggests that a having a hospital readmission within the past year increases the odds of a readmission (Billings, Blunt, Steventon, Georghiou, Lewis & Bardsley, 2012). Many models include previous readmission as a variable. In research on a prediction model for ED use, the most powerful predictive factor was two or more unplanned admissions within the previous year (Giamouzis, et al., 2011). Additionally, number of prior admissions was a recurring theme in the interviews, and all of those interviewed mentioned the importance.

There is evidence that access to services during the night or weekend is related to PCP offices being closed. In an analysis of over 20,000 patients conducted by Kirby and colleagues, there was no significant difference between time or and presentation to the ED, which could suggest that access may not be an issue. This study suggested that use of the ED was related to the type of care that was needed and suggested that presentation to the ED can be related to inability to access specialists through other means, such as through primary care. Evidence also suggests that having a PCP is associated with readmission risk as those who had a PCP could be sicker and more likely to be readmitted (Hasan, 2011). Additionally, much of the care that is provided in the ED can be treated in primary care, which suggests that chronic conditions are not being treated and properly managed in the appropriate setting.

Mental health

Mental health can have serious effects on the overall health status of a patient. All forms of mental disorders are associated with higher levels of readmission. Mental health can impact readmission as those who struggle with mental illness can be less likely to have the ability to adhere to treatment (Dossa, Glickman, & Berlowitz, 2011). Many providers described history of depression and anxiety as very important, as patients with co-existing mental conditions often present at the ED. Depression is present in almost half of all patients with heart failure, and while often associated, it is not often regarded in treatment or care (Giamouzis, et al., 2011). A positive effect has also been found between depression and social support; Frassier-Smith found that depression decreased as social support increased. There is also the increase in likelihood of spending increased inappropriate days in the hospital (Cornette, D'Hoore, Malhomme, Van Pee, Meert, & Swine, 2004). Many articles included in this review have expressed the connection between depression and higher rates of readmission. Understanding patient's mental health, especially during discharge, is extremely important.

Age

As the age of the patient increases, the risk of readmission increases as well. Age is a variable that is easily collected and can help to inform providers of increasing risk of readmission as those that are older access a higher level of resources. However, this variable creates challenges, as there are those who are chronically ill that utilize many resources, but would not be considered in an age group that is at more risk due to their younger age.

Gender

In most of the research collected, males are cited as more likely to be readmitted. However, there were articles reviewed that showed woman are also at a higher risk of readmission.

Charlson index

The Charlson Index is a tool that assists in measuring comorbidities and involves weighting 17 co-morbid conditions by assigning a number to the comorbidity resulting in score which is often referred to as the Charlson score. Comorbidities are increasingly common in our population and the literature demonstrates that this is a common factor in prediction models. This tool is used frequently for ease of implementation and is inclusive of the major disease states that are prevalent in readmission literature. This tool can be electronically coded from previous diagnoses within the patient's medical record. For every one-point increase on the patient's Charlson score, there was a 15 percent increase in a poor outcome at discharge (Goldstien, Samsa, Matchar, & Horner, 2004). Additionally, for every one-unit increase in comorbidity, the risk for readmission increases by 47 percent (Wong, Gan, Burns, Sin, & Eeden, 2008). A recent study found that 39 percent of the elderly population had 5 or more non-cardiac comorbidities, where 4 percent had only heart failure demonstrating the need to treat patients in broader contexts, which the Charlson Index does, and is increasingly important in our population (Giamouzis, et al., 2011). Understanding this can help to guide clinical decisions and discharge planning. Additionally, by using a tool that is less focused on one specific disease state, the whole patient can be assessed.

Low socioeconomic status

Those living in a low socioeconomic class are at risk for a plethora of health problems. This is not a new problem or surprise as a survey conducted in 1989 indicated that low socioeconomic status (SES) and poor patient health were predictors of problems for patients after discharge (Strunin, Stone, & Jack, 2007) Those with lower SES had higher risk of one-year mortality and readmission within one year of discharge. Individuals unemployed with lower incomes or residing in deprived areas have higher rates of readmission (Rathore, et al., 2006). These patients are more likely to have more coexisting conditions than higher income level patients (Wang, Conroy, & Zuckerman, 2009). Low-income individuals are predisposed to a number of illnesses, often having more severe forms of illness when finally arriving for medical help (Wang, Conroy, & Zuckerman, 2009). One reason for this is that many individuals with a lower SES delay seeking treatment due to a number of factors, such as cost, access, or a lack of insurance.

In the literature, zip codes were used to understand the SES of patients. In a location like Portland, Maine, which has only three zip codes, a different approach may be needed to identify what addresses could be considered lower SES. Other identifiers that could be utilized are type of insurance such as Medicare or Medicaid. Despite having either Medicaid or Medicare access to providers can be an issue; many providers limit the number of Medicare or Medicaid patients seen, which results in many patients being marginalized to receive treatment at emergency rooms. Patients that have fewer resources will have less access to health care services.

Problem medication

Use of many medications is common, especially among the aging population. Medications usually have side effects that could cause negative consequences for patients; there are medications that have been noted as causing a higher number of problems or adverse effects and noted for predictive models, such as the one currently in use by MMP. Additionally, polypharmacy refers to those who are taking five or more medications. In prediction models, many will use five or more medication to denote a high risk of readmission. However, for those 65 and older, the average number of medications taken is eight to ten medications (Ferrell, 2011). With eight to ten being the average number of medications consumed, raising the number of medications that indicates higher risk might be necessary. Being on multiple medications can have consequences, such as adverse drug reactions or increases in the likelihood of falls.

Limited social support

Social isolation can be categorized in a number of ways; living alone, marital status, social isolation, being single. However, a critical message is shown throughout the different categories: the relationship between social isolation and increased risk of readmission. Social support or isolation is often regarded in the literature, but very few models incorporate the variable into the final model. Inadequate regard for social needs accounts for 36 percent of the missed opportunities in preventable readmission (Feigenaum, et al., 2012). The absence of a partner is associated with readmission regardless of age. Studies found that those who live alone are three times more likely to be readmitted (Murphy, et al., 2008). The greater the degree of social isolation, the greater the risk of re-hospitalization; the risk of social isolation in readmission was found to be equivalent to the risk of previous hospital utilization (Rodriquez-Artalejo, et al., 2006). Absence of social support was shown to increase readmission, especially among woman with additional articles finding clear relationships between lack of social support and readmission (Giamouzis, et al., 2011) (Luttick, Jaarsma, Moser , Sanderman, & van Veldhuisen, 2005). On the contrary, having a partner can increase compliance to care plans and medication, physical activity, healthy diet and help deal with anxiety, fears, adversity and troubles (Gallagher, Luttick, & Jaarsma, 2011). Living alone also has a number of implications for patients' health as those who live alone are more likely to smoke, drink, have a second myocardial infarction, present later for issues, and not adhere to care plans. Additionally, economic disadvantage and low education are associated with living alone, both of which are linked to poorer health outcomes (Mitchell, Sadikova, Jack, & Paasche-Orlow, 2012).

However, other authors point out that being married can be associated with an increased risk of readmission (Hasan, 2011). The increased risk is related to the care provided; many elderly couples age together in place and it is challenging for the caregiver in the relationship to keep up with the duties needed to provide adequate care. Secondly, patients who are married may be more likely to be discharged to home despite being frail and sick, where those without support at home may be referred to a nursing home. Caring for a sick partner can create high levels of stress and depression among caregivers can increase risk of hospitalization (Saunder, 2008). An interviewee discussed the importance of the support system and understanding what the caregiver has the ability to provide, as it was stated that sometimes the caregivers are frailer than the patient. It is important for providers to assess the level of care provided at home by a partner.

Limited social support was a theme in the interviews and brought up by each interviewee. Marital status was discussed and the point was made that incorporating just the marital status will not capture the actual home life of patients. The question needs to be broader to incorporate the different support systems and lifestyles that the population lives in today.

Risky behaviors

Amarasingham's Electronic Readmission model includes variables that can be seen as risky health behaviors; which were history of confirmed cocaine use and history of missed clinic visits. Substance abuse was discussed in the literature and those with substance abuse are more likely to seek care in the ED, which creates care that is fragmented and unable to meet the needs of the patients. Studies suggest that those with comorbidities that have substance abuse issues are at increased risk of readmission. Those with substance abuse are often very complex patients and create challenges to medical staff trying to assist with treatment and incorporating this factor into a prediction model can help to factor such risks and treat the patient more comprehensively.

Self-rated health

Assessments of patients Activities of Daily Living (ADL) can assist providers in treating patients as providers can gauge how dependent the patient is on obtaining care from others and ensure that the level of care necessary for the patient is available upon discharge. Evidence has shown that decreased ability to perform ADL increases readmission risk (Cornette, D'Hoore, Malhomme, Van Pee, Meert, & Swine, 2004). Functional status can help to predict readmission while also assisting providers to assess the care the patient needs, can adhere to and tolerate (Yamada, Shimizu, Suzuki, &

Izumi, 2011). Individuals lacking functional ability are 48 percent more likely to be readmitted; individuals without self-management skills may be at a similar risk of being readmitted (Arbaje, Wolff, Yu, Powe, Anderson , & Boult, 2008). Those who perform more tasks independently have lower rates of readmission.

Health literacy

Health literacy refers to patients' ability to understand health information and having the ability to make decisions regarding their health care. It is estimated that 26 percent of our population has low health literacy and those individuals are at increased risk of readmission as well as being extremely vulnerable within our society (Mitchell, Sadikova, Jack, & Paasche-Orlow, 2012). Those with low health literacy are 1.5 to three times more likely to experience adverse health outcomes, particularly patients with heart failure or chronic conditions (Dennison, et al., 2011). Additionally, those with low health literacy were 1.71 times more likely to return to ED and 1.67 times more like to be readmitted. In this study, low health literacy was associated with using Medicaid, being of African-American decent, being unemployed, having a low-income, and being less educated. Interestingly, those with low health literacy are more likely to report poor patient-doctor communication.

Qualitative Interview Findings

Six interviews were conducted with stakeholders that work in the field. There were five doctors interviewed; two were ED physicians, a primary care provider, a hospitalist and a doctor that is currently working in the research field. There was an ED nurse interviewed as well. There were a number of themes from the interviews, as well as new findings, that corroborate the literature.

As discussed in a few interviews, there is a pressure on providers from hospital administration to discharge the patients quickly for financial reasons. One interviewee detailed length of stay (LOS) and how it relates to hospital organization. Longer LOS could mean the individual's illness is more severe and the individual is more chronically ill, therefore, already at an increased risk of being readmitted. On the contrary, a short LOS could lead to an increase in readmission because many of the problems that arise occur within a short time period of the original hospitalization. Length of stay was discussed in this interview in regards to the hospital system organization and that organization structure can influence readmission rates. There is research that demonstrates that the number of beds in an area will increase the readmission rate per capita. Additionally, areas that have lower bed capacity will have a shorter length of stay because the beds are needed to admit other patients. This hospital organization and the financial reimbursement systems can influence LOS, however hospitals will now be held accountable for readmissions within thirty days and hospital administration will have to reorganize their focus to avoid costly and avoidable readmissions.

One concern expressed during the interview was how fragmented aspects of the care transition process are. Hospital discharge was discussed as being a task that falls on certain providers as discharge disposition was discussed as being the nurses' task at discharge. Social support or care that a patient has at home, which was also discussed as fragmented, often falls on the nursing staff to identify. This is troublesome because many providers are involved in caring for the patient, but often do not recognize the importance of social support. This interviewee felt the pressure providers are placed under to shorten length of stay even in the absence of adequate support at home. A few providers interviewed understand the housing status of patients, but did not understand what support was given in the home. Discharge is such a large factor that can cause a readmission and extremely important, particularly when coordinating the discharge process and making the transition home more efficient.

One interviewee mentioned an article recently published regarding the theory of post-hospital acquired syndrome, which is characterized by the time after discharge that creates a period of vulnerability for patients (Krumholz, 2013). During the much-discussed timeframe of 30-day post discharge period, many of these patients are suffering from physiological stress of the hospitalization. Krumholz's article discussed the disproportionate attention that is focused on the cause of the hospitalization instead of the overall picture of the patient. The stress created by staying in the hospital, having unusual sleep patterns, dealing with complicated medical issues and finally, trying to understand what the medical institution is trying to get them to do needs more attention. This article suggests the need to focus attention to health behaviors post-discharge, such as nutrition, sleep, and physical activity, which are more of a cause of readmission than is currently being attributed.

Care coordination plans have been highlighted in the literature and in practice as ways to improve care transitions. However, one provider mentioned that care coordination plans are not helpful to the provider during an ED visit. This provider asks patients during the visit about their address, employer, marital status, who will provide their care, how did they get here, where do they live, and do they smoke or drink. Two additional providers like to ask their patients a number of questions regarding their lives over the past year. These doctors mentioned addressing issues about spouses, care support, employment, and substance abuse. The hospitalist interviewed stated that psychosocial issues have to be known when treating the patient. However, when talking to a PCP, these issues are only known for about half of the patients, and providers often lack this information for newer patients. Another aspect of care transitions are the care managers that assist with discharging the patient. This provider feels like the skill sets differ and accountability per care manager that every patient at MMC is assigned. Addressing these shortcomings could increase consistency for other providers who are treating the patients.

Patients' lack of connection with their own primary care provider was discussed as a reason that some patients present to the ED, which is often discussed in the literature. One provider mentioned that the cost of going to a PCP's office is prohibitive for patients, and since there is no copayment at the ED, many patients will utilize the ED over going to a primary care office. The same provider discussed that the better care the patient receives in the ED, the more often patients will return to the ED for treatment. Additionally, one doctor pointed out that providers are bad communicators, which creates problems for patients when trying to understand the system and may be why some patients end up in the ED instead of at their PCP.

Additional factors that influence patient destination include health literacy effecting communication between PCP and patient, and poverty level correlating with ED use as a primary healthcare location. Decreased health literacy can impact the relationship with providers. Interestingly, four interviewees conveyed health literacy as a problem for providers, as there is no assessment, method, or documentation of patients' health literacy levels. One provider mentioned that health literacy is a factor that can be taught to patients, but that is currently not an area of focus or implemented at this time. The social determinants of health were a topic in one interview, with a focus on poverty. The interviewee stated that poverty is one of the top reasons for readmission, and it integrates many of the problems that increase readmission. One interviewee discussed how these individuals have trouble navigating the difficult health care system and the complexities faced when trying to do so. Due to these factors, many of these patients will present to the ED when the healthcare need could have been address in another setting, such as a PCP office. Collecting information in the chart was a struggle discussed by providers during the interviews. Additionally, the registration sheet that this provider can view to see demographic information is not reliable during the ED visit. One interviewee discussed struggling with how to determine what the patient understands during that interaction as the health literacy of the patient is never evaluated and documented in the charts. This interviewee suggested utilizing the Electronic Medical Record (EMR) alerts to understand patient's variables such as health literacy or a language barrier was discussed, which could be a great resource for MMP.

MMP is on the same EMR system as the hospital, called EPIC, which creates great potential to increase care coordination and could be very advantageous for MMP. Influencing order sets was a suggestion made in an interview. This provider discussed using a risk model within EPIC to influence care pathways in options of care, not as an absolute in treating care, but as a way to assist providers to incorporate socioeconomic information when treating patients. This is suggested in the literature as well as processes that identify patients immediately and accurately give providers the opportunity to treat the patient with the most appropriate care pathway before the patient is discharged. This immediate identification of risk could influence clinical decisions about care during the current hospitalization assisting providers to make decisions about the level of care needed and to whom to allocate care coordination resources.

One interviewee suggested that the new inpatient EPIC system attempts to incorporate social factors that can relate to readmission. During the ED visit, the provider can check that the patient's demeanor is either normal or abnormal. If abnormal is checked, the provider is prompted with a number of questions regarding visual impairment, thought process impaired, and use of a walker, among other identifiers. This information would be critical to creating a prediction model. Unfortunately, about 90 percent of ED providers will indicate that everything is normal in order to move forward with the assessment to save time, reduce workload, and avoid asking patients additional questions. This is a problem for many reasons; providers have not been educated on the importance of capturing these data points and the lack of support for the provider to spend the correct amount of time with the patient to obtaining this information, which would be extremely helpful to understanding the whole patient.

The providers interviewed also made a suggestion regarding care coordination, which was that MMP implement an alert that tells providers a care manager is actively working on preventing readmission. If an alert is not present, a provider knows to make a connection to a care manager for coordinated care. Additionally, a provider would like every discharged patient get follow-up call that is built into the system, which speaks to the success seen by providers of the MMP program. With many organizations working on care transitions, it can be extremely complicated to work together, but ultimately, working in a coordinated fashion will be providing the best care for the patient.

These interviews added greatly to the literature on variables that was already collected while also highlighting the current gaps. There are gaps that were evident in the interviews that should be addressed. These gaps include knowledge about their patients' lives that could help to prevent readmissions. There are also gaps in the collection of information that was discussed. The recommendations from providers to ease the transition of care from one provider to the next comes at a time when many changes are occurring and such changes could be incorporated into what is currently occurring. Fixing these gaps, collecting patient information regarding social factors and creating alerts for providers, will help to build an electronic prediction model that is embedded within the patient's medical chart.

Recommendations

Readmissions have a solid base of literature, but are missing consensus on variables that are effective at predicting them. However, based on the literature search and the information obtained through stakeholder interviews, I would recommend to MMP to test a number of variables to predict readmission including Charlson Index with age, previous admissions, social support, mental health, and low SES. Table 3 shows the variables currently in use as well as the recommended variables. These variables are very important elements that will help predict greater risk in a prediction model and can help providers to assist patients to avoid readmission.

Table 3 – Suggested Model

MMP Current Model	Suggested Model
Source of Admission	Charlson Index with Age
Number of Hospital Visits	Prior Medical Service Use
ED Visits in Past Six Months	Social Support
Five or More Medications	Mental Health
Problem Medications	Low Socio-Economic Status

The first research question asks if the variables that MMP is currently using should stay in the prediction model.

- Source of admission was not found to be significant in the literature that was located and was not mentioned during the stakeholder interviews and would not be recommended for the suggested model.
- Number of hospital visits and number of ED visits was combined into a final variable of prior medical service use and is recommended in the suggested model.
- Five or more medications and problem medication is challenging, however these two variables are not suggested in the final model, as there is evidence suggesting that this might not be as relevant as it once was, which was gathered from the interviews. Furthermore, there have been interventions that deal with medication reconciliation within the hospital and the MMP Care Transitions nurses complete medication reconciliation on the phone after patients are discharged. Additionally, the problem

medication list might signal someone with a chronic condition, which would be captured through the Charlson Index.

Comorbidities have a great influence on this field in the literature. The Charlson Index has been consistently used throughout the past few decades to determine patient's health. This tool has the ability to incorporate age into the score, which is another frequent determinant of readmission. This tool incorporates a number of the most frequent readmission causes and many of the chronic health problems that were identified by providers in the MMP physician survey. Comorbidities are a critical piece of the problems with the health of our country, and the ability to distinguish the individuals that have one or more comorbidity will be beneficial in the prediction model.

Prior medical service use, such as previous admissions, are highlighted in the literature and is often found to be significant and included in final prediction models. It was also one of the themes of the stakeholder interviews. There is not a great consensus on the time period to incorporate into the model. MMP is currently using the time period of previous six months and the LACE tool also incorporates the same time period in the model. However, it would be useful for the time period to be expanded to a year. It is important to think about the disease state and incorporate the trend of the disease and patient utilization patterns. There may be a benefit in testing utilization without a time period to increase the inclusion of patients as a small percent of the population us a large amount of services. Therefore it might make it more meaningful to exclude a defined time period and analyze all patients that utilize a high level of services. Analyzing these patients for inclusion in the predictive could focus more resources on this population and begin to see a difference in utilization patterns.

Social support is increasingly supported in the literature, but is often lacking in the final prediction models. There are a number of ways to try to incorporate social support. It can be identified by asking about marital status, living alone, or single status. But as one provider interviewed mentioned, the entire picture of the patient's support at home is necessary. Using one measure, such as marital status, might not show the whole picture of home life and support. This data can be pulled directly from an EPIC report. Primary care offices and the ED can work to collect this information on arrival to either location. This would be a great way to have medical assistants (MA) exert more authority. The MAs could ask patients questions about their lives to capture more information in the medical chart. Social support is critical to the success of patient, especially when leaving the hospital, which is shown in the evidence. This will also give the provider the ability to understand the patient and increase discussion about patients' home life. This could help providers develop a better relationship with the patient and could lead to increased patient satisfaction.

Addressing mental health treatment plays an important role in reducing readmission occurrence. Many individuals with mental health do not receive coordinated, comprehensive care, and often are forced to seek treatment through the ED. With a prediction model that incorporates ICD-9 codes that include mental health issues, an individual with higher risk could be streamlined to a higher level of care. Depression is much more prevalent in those with chronic illnesses and comorbidities and identifying that risk will help on the path to better treatment.

Low socioeconomic status has implications for the overall health of individuals, which can mean less access to care and can be prohibitive in obtaining comprehensive care. Incorporating this piece into the scale could help to identifying those at high risk and having the ability to connect such patients to more comprehensive services, such as a patient center medical home. Low SES is extremely important when attempting to achieve higher health care standards and being held accountable for population health. Incorporating this into a model can help to get our population better treatment.

Implementation

There were a number of gaps identified through this project, some of which have to do with the EMR system that is used both in the hospital and at MMP. Another gap has to do educating the staff to understand why it is important to know patients background and collect information in the patients’ chart to gather this data for the prediction model. It may be necessary to have hospital administration champion this project and address the problem to show support for staff to spend the appropriate time with patients. With financial reimbursements changing, there may be the opportunity to try different approaches to providing care to patients, one of which could be longer patient appointment to understand the social factors of the patient and document them into the medical chart.

MMP care transition teams could champion efforts to create alerts for providers as was expressed during the interviews. The EPIC system has the ability to create alerts for providers that could help the MMP care transition team coordinate these aspects of care for the providers. MMP could utilize all providers, such as MAs or care transitions nurses, to assist in collecting data from the patients during other points of care. MMP could add more questions to the care transition phone calls to collect many of the variables suggested. MMP could also utilize medical assistance and other office staff to assist doctors to get the information into the patient's chart. These care managers could assist providers, and the medical record, by having standards to approach the patient with. The care manager could help to assist within the medical record by completing an order set that was inclusive of a more comprehensive approach to the patient. Another area where MMP could try assist in providing more comprehensive care to patients is during the care transitions phone call. These points should be emphasized in every diagnosis or discharge and continued to advice given in the PCP office. MMP could also emphasize these points with education during the care transition phone call. By taking these issues into consideration, and giving providers a better picture of the patients, patients will get more comprehensive treatment.

MMP could work with the EPIC build to incorporate measures and data points to capture into the Electronic Medical Record (EMR). MMP will have to advocate for these edits or alterations to the flow of EPIC in order for this to occur, but it will be extremely important to care coordination and providing the optimum level of care. There are currently efforts to build and revise order set. This is the perfect time for MMP to be involved and influence what is captured within patient's medical records. There is the potential to collect a number of measures within EPIC and pull from it to create a prediction model. MMP can develop a scale that pull data throughout the medical charts, either through medical notes or specific identifiers giving the ability to tier patients into categories of level of need before the patient leaves the hospital.

Furthermore, this would create the opportunity to build a prediction model similar to the Electronic Readmission Model, which has had much success due to the ability to use real-time data. MMP implementing an electronic prediction model, which is highly suggested in the literature, by using the EMR information to benefit care transitions, could help reduce the preventable, as well as overall, readmissions to the hospital.

Limitations

There are some limitations of the research completed. Many social factors would be beneficial in a prediction model, but as mentioned in this research, there is a gap in the literature for many of these variables. Many of the articles located in this search supported that conclusion. Some of the research articles were outdated, and it would have been helpful to have access to more current studies for certain topics. Some of the variables of interest also had small samples. Additionally, many of the samples used populations that are over 65 and might be different when applied to a younger subset of the population.

Conclusions

The variables that are recommended in this Capstone expand upon what MMP has already built through their experiences and testing. Some of the variables are commonly thought of within the medical and transition of care field, such as prior medical service use, comorbidity score, age and mental health. However, other variables incorporate aspects of the patient’s life that are not typically considered medical, such as social support and low socio-economic status. These factors contribute to readmissions and should help MMP identify those at higher risk of readmission.

This project's goal was to understand the variables that increased patients' risk of readmission, but through the research for this Capstone, it can be concluded that there are aspects of the system that need to be influenced in order to change the rate of readmission. MMP is in a great position to influence the system, both on the provider level as well as the technology and EPIC side. Implementing new methods is easier for providers when they are included in the discussion and decisions when changing practice behavior and requirements. MMP has a lot of providers at the table and the ability to help educate a large number of providers about why collecting information from patients, like these measures, is critical to providing better care.

With this knowledge, MMP can begin to test these variables to create a formal prediction model scale. By adjusting practices and workflows, MMP can collect additional data from EPIC. A prediction model could be incorporated using distinct variables from the order sets within the Electronic Medical Record while utilizing real-time data. This will assist providers as they treat the patients in the PCP's office or hospital setting. Giving the providers more information and working with providers to help them understand the needs of patients will increase their ability to treat the whole patient. Providing better care is necessary, given the timing of all of the changes occurring in our health care system and the transformation of reimbursement methods. Understanding the issues patients face will help to give better coordinated care in a fashion that suits providers' needs and most importantly, the needs of the patient. With this prediction model placing individuals into risk categories of low, medium, and high, patients will receive the right level of care that is most appropriate to their needs. It is a critical time to identify creative ways to improve population health.

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Appendix A - Interview Questions

1. In your opinion, what are the biggest factors (clinical and non-clinical) when individuals present to the emergency room/hospital?	
2. How often do you know the social factors of the patients, such as housing status, marital status or substance abuse issues?	
3. I'm going to read a list of patient characteristics. For each one, please tell me if it is a common problem among patients that you see in the ED or that are readmitted to the hospital.	
Limited social support	
Problem Diagnosis	
Health Literacy	
Problem Medication	
Self-rated Health	
Activities of daily living assistance need	
Functional status	
Age	
Sex	
Prior medical services use	
Medicaid status	
Charlson Index	
History of depression/anxiety	
Residential stability	
Medicare status	
Use of health system pharmacy	
# of prior admissions	
Presented to ED b/w 6 am & 6pm for index admission	
4. Is there information about social risks or clinical risks that is not currently included in the medical chart that should be included in order to better treat a patient?	
5. What would it take to implement incorporating patient risk of readmission scores in your work/department? What are the barriers?	
6. Would a tool located within the medical chart that states a patient's risk of readmission be useful for practitioners?	

Appendix B – Articles Reviewed

Insert Attached PDF File

Article Title	Source	Population and Setting	Derivation cohort	Validation cohort	Outcome	Actual Rate	Range of Rates	Model Discrimination
Redefining readmission risk factors for general medicine patients	Alluden	Dicharges from general medicine wards over a two year period from June 1, 2006 to May 31, 2008	6805	NA	30 Days	17%	Not Reported	NA
An automated model to identify heart failure patients at risk for 30 day readmission or death using EMR data	Amarasingham	Patients with CHF admitted to large teaching hospital between January 1. 2007 and August 31, 2008	1029	343	30 Day	24.1	12.2 - 45.7	0.72
Linking electronic health record-extracted psychosocial data in real-time to risk of readmission for heart failure	Watson	Patients discharged with HF between 2007 and 2008	729	NA	30 Day	Not Reported	Not Reported	0.67
Postdischarge environmental and socioeconomic risk factors	Arabeje	Community-dwelling Medicare beneficaries found from claims for 2001 to 2002	1351	NA	60 Day	15%	Not Reported	Not Reported
Current trends in heart failure	Aranda	Hospital discharge in 2003 with implant device or rhuematic HF	28919	NA	6-9 Months	60%	51-60	Not Reported
Predictors of early hospital readmission	Aujesky	Dicharges from 186 hospitals in Pennsylvania from 2000 - 2002	14426	NA	30 Day	14.6	10.7 - 18.1	Not Reported
Development of a predictive model to identify inpatients at risk of re-admission within 30 days of discharge	Billings	Hospital Episode Statistics from National Health Service from April 2008 - March 2009	576868	NA	30 Day	Not Reported	47.7 - 88.7	0.7
PARR combined predictive model	Billings	Data from Primary Care Trust	50% of sample	50% of sample	12 Months	Not Reported	Not Reported	Not Reported
Identifying patients at high risk of emergency hospital admissions- a logistic regression analysis	Bottle	Patients with emergcy admission to a National Health Service hospital between 4/2000 and 3/2001	50% of sample	50% of sample	12 Months	15.4	Not Reported	0.72
Depressive symptoms as a predictor of 6-month outcomes and services utilization in elderly medical inpatients	Bula	Patients 75 years or older admitted to academic hospital in Switzerland over a six month period	401	NA	6 Months	36%	Not Reported	NA
Correlates of early hospital readmission or death in pt with CHF	Chin	Patients admitted nonelectively with SOB/fatigue and evidence of heart failure in 1993 and 1994	257	NA	60 Day	31%	0-72	NA
Differential risk factors for early and later hospital readmission of older patients	Cornette	Patients age 70 or older admitted to two teaching hospitals from March 1998 to December 1998	596	NA	30, 60 and 90 Day	10.7, 12.4, 23.1	10.7 - 23.1	NA
Psychosocial risk factors for hospital readmission in copd	Coventry	Patienst with COPD were recruited by a respiratory specialist between May 2007 and August 2009	79	NA	365 Day	Not Reported	33 - 76	NA

Adequate health literacy is associated with readmission	Dennison	Patients admitted to large urban teaching hospital with primary diagnosis CHF	95	NA	30 Day	16	2.3 - 18.3	NA
Diagnoses and timing of 30-day readmissions after hospitalization for HF, AMI or Pneumonia	Dharmarjan	2007-2009 Medicare fee-for-service claims data for patients readmitted for HF, AMI or Pneumonia	329308	NA	30 Day	24.8, 19.9, 18.3	Not Reported	NA
Development and validation of a model for predicting emergency admissions over the next year (PEONY)	Donnan	Patients 40 or older with a 3-year history of prescribed drugs or hospital admission from 1996 to 2004	90522	NA	365 Day	12.9	Not Reported	0.8
Association between mental health conditions and rehospitalization, mortality, and functional outcomes in patients with STROKE following inpatient rehabilitation	Dossa	Patients who underwent rehab at the Veterans Association Facilities in 2001	2162	NA	6 Months	27.11	12.9-27.11	NA
Factors contributing to all-cause 30 day readmissions	Feigenbam	30 of the most common readmission less than 6 weeks before study occuring between 2009 and 2010	537	NA	30 day (potentially avoidable)	50%	NA	NA
Socioeconomic status, medicaid coverage, clinical comorbidity	Foraker	Atherosclerosis Risk in Communities cohort participants enrolled 1997 - 1999 and censored until 2004	1342	NA	Readmission over time period	89	NA	NA
Social support and self-care in heart failure	Gallagher	Patients over the age of 18 and who were admitted for Heart Failure	333	NA	Social support	NA	28 - 42	NA
A simultaneous test of the relationship between identified psychosocial risk factors and recurrent events in coronary artery disease patients	Grewal	CAD patients who were patients of area cardiologists	1268	NA	Recurrent event	22.2	NA	NA
Hospital readmission in general medicine patients	Hassan	Patients discharged from six medical facilities	7287	3659	30 day	17.5	5 - 30	0.61
A multipurpose comorbidity scoring system performed better than the Charlson index	Holman	Patients admitted to hospital between 1989 and 1996	1118989	NA	12 Months	Not Reported	Not Reported	0.64
Using routine inpatient data to identify patients at risk of hospital readmission	Howell	Patients admitted who had at least one chronic medical condition between 2005 and 2006	13207	4492	12 Months	45.5	Not Reported	0.65
Association of partner status with heart failure patients	Howie-Esquive	Patients admitted to California Medical Center with primary or secondary diagnosis of heart failure in 2007	809	NA	90 day	32	49 - 62	NA

Factors associated with 30-day readmission rates after percutaneous coronary intervention	Khawaja	PCI hospitalizations from 1998 to 2008 at Rochester Hospital	15498	NA	30 day	9.4	Not Reported	0.65
Scheduled and unscheduled hospital readmissions among patients with diabetes	Kim	Patients 50 or older with primary or secondary diagnosis of diabetes admitted to California hospital between April and September 2006	124967	NA	90 day	26.3	NA	NA
Development of a model for predicting Inpatient hospitalization	Lemke	US Health plan outpatient claims data	4.63 million	4.7 million	12 Months	NA	NA	AUC = 0.8
Socioeconomic status and hospital utilization among younger adult pneumonia admissions at a Canadian hospital.	McGregor	Adult patients less than 65 years old admitted to a large teaching hospital in Vancouver	434	NA	30 day	12	NA	NA
Health literacy and 30-days postdischarge hospital utilization	Mitchell	Secondary data anlysis of clincial trial sets which included patients over 18 admitted to a general medicine unit at Boston Medical Center	703	NA	30 Day	Not Reported	NA	NA
Influence of drugs, demographics and medical history on hospital readmission of elderly patients- a predictive model	Morrissey	Unplanned general admission to hospital 1997-1998	487	732	12 Months	40.7	22.8-40.7	AUC= .65
Living alone predicts 30-days hospital readmission after coronary artery bypass graft surgery	Murphy	Patients on wait-list for CABGS between July 2001 and April 2004 at Royal Melbourne Hospital	181	NA	30 day	14.4	NA	NA
Prediction of early readmission in medical inpatients using the Probability of Repeated Admission instrument	Novonty	Patients 65 and older admitted to a Midwestern acute care hospital	1077	NA	41 day	14	NA	0.47
Prediction of hospital readmission	Philbin	Discharges assigned with ICD-9 codes for heart failure in 1995 in New York State	42731	21504	12 Months	21.3	NA	0.62
Socioeconomic status as an independent risk factor for hospital readmission for heart failure	Philbin	Patients discharged more than once during January to December 1995 with a principle diagnosis discharge of heart failure	41776	NA	Hospital readmission	NA	19-23	NA
Health services burden of heart failure	Robertson	Patients admitted at NSW Hospitals betwen 2000 and 2007	29161	NA	28 days / 12 months	27 / 73	11 - 73	NA
Social network as a predictor of hospital readmission and mortality among older patients with heart failure	Rodriguez-Artelejo	Patients admitted for HF emergencies at 4 spanish hospitals	371	NA	Time to first admission	Not Reported	Not Reported	NA

Health-related quality of life as a predictor of hospital readmission or death among patients with heart failure	Rodriguez-Artelejo	Patients admitted for HF emergencies at 4 spanish hospitals	394	NA	Time to first admission	Not Reported	Not Reported	NA
Family caregiver support and hospitalizations with patients with HF	Saunders	Patients who had a primary diagnosis of HF and over 40 years	41	NA	Patient hospitilizations	Not Reported	Not Reported	NA
Risk factors for 30-day readmissin in general medicine patients admitted from the ED	Shu	Patients admitted to general medicine ward from the ED in taiwan from 2009- 2010	2698	NA	30 day	16.7	Not Reported	NA
Derivation and validation of an index to predict early death or unplanned readmission after discharge from hospital to the community	Van Waldren	Medical and surgical patients d/c from 11 hospitals from 2004 -2008	4812	1000000	30 day	8	Not Reported	0.684
Unplanned readmissions after hospital discharge among patients identified as being at high risk for readmission using a validated predictive algorithm	Gruneir	Adult patients discharged from 6 Toronto hospitals in 2007	26045	NA	30 / 90 days	12.6 / 20.9	Not Reported	Not Reported
Patient Readmission and Mortality after Colorectal	Schneider	Patients with a diagnosis of colorectal cancer who underwent a colectomy between 1987 and 2005	149622	NA	30 Day	13	Not Reported	NA
Outpatient Follow-up Visit and 30-Day ED and Readmission for COPD	Sharma	Medicare beneficaries with an identifiable pcp who were hospitalized between 1996 and 2006	62746	NA	30 Day	66.9	8.8 - 10.5	NA