Title

Predicting 30-day Hospital Readmissions at a University Hospital: A Retrospective Study Utilizing the LACE index and HOSPITAL score

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Publication Date

2018

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA,
IRVINE

Predicting 30-day Hospital Readmissions at a University Hospital: A Retrospective Study Utilizing the LACE index and HOSPITAL score

THESIS

submitted in partial satisfaction of the requirements
for the degree of

MASTER OF SCIENCE

in Biomedical and Translational Science

by

Alexander Lin

Thesis Committee:
Professor Sherrie H. Kaplan, Chair
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Professor John Billimek

2018

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ABSTRACT OF THE THESIS

Predicting 30-day Hospital Readmissions at a University Hospital: A Retrospective Study Utilizing the LACE index and HOSPITAL score

By

Alexander Lin

Master of Science in Biomedical and Translational Science

University of California, Irvine, 2018

Professor Sherrie H. Kaplan, Chair

Background: Hospital readmissions are burdensome to patients and costly to the healthcare system. Readmissions may be the result of poor transitional care and targeted interventions may help prevent unnecessary hospitalizations. Identifying patients that are at high risk for hospital readmission could help hospitals focus their resources towards preventing these events.

Methods: In a retrospective study at the University of California, Irvine Medical Center, multiple patient-level variables, including the LACE index and HOSPITAL score, were collected on patient admissions from February 1, 2017 to April 30, 2017 to determine which variables were significant predictors of 30-day hospital readmission.

Results: The analysis included data for 827 discharges within the study period. The prediction model using the LACE index demonstrated a C-statistic of 0.83 (95% CI,

0.81-0.86). The C-statistic for the model using the HOSPITAL score was 0.77 (95% CI, 0.74-0.80). A prediction model that utilized the LACE index, plus two other significant variables (number of hospital admissions within the previous 12 months and presence of an abnormal vital sign within 24 hours of discharge), demonstrated a C-statistic of 0.91 (95% CI, 0.89-0.93). The Hosmer-Lemeshow goodness of fit test for the LACE "plus" model had a chi-squared value of 1.63 with a p-value of 0.99. The HOSPITAL score, plus three additional significant variables (the Charlson Comorbidity Index, discharge by the Hospitalist service, and an abnormal vital sign within 24 hours of discharge), showed a C-statistic of 0.88 (95% CI, 0.85-0.90). The Hosmer-Lemeshow goodness of fit test for the HOSPITAL "plus" model had a chi-squared value of 10.99 with a p-value of 0.20.

Interpretation: Both the LACE index and HOSPITAL score performed well in predicting hospital readmissions in this retrospective study. The addition of other significant variables to these scores improved the discrimination of the prediction models, suggesting that the addition of other variables may improve the ability of these scores to predict 30-day hospital readmissions.

INTRODUCTION

Hospitals have been focused on reducing 30-day hospital readmissions since the Centers for Medicare and Medicaid Services (CMS) introduced the Hospital Readmissions Reduction Program (HRRP) as part of the Affordable Care Act in 2012. According to data from the federal government, 20% of Medicare patients experience a hospital readmission at an estimated cost of $26 billion dollars per year, of which $17 billion is viewed as preventable. [1] According to CMS, while some readmissions are unavoidable, many may be the result of poor discharge planning, inadequate inpatient care, and lack of effective transitional care.

In the first two years of the program, the HRRP applied to three specific conditions: congestive heart failure (CHF), pneumonia, and acute myocardial infarction (MI). The program was then expanded to include chronic obstructive pulmonary disease (COPD) and elective total knee and total hip replacements. In 2017, coronary artery bypass grafting (CABG) was added to the list. In classifying readmissions, Medicare uses an “all-cause” definition for readmission, meaning that hospital stays within 30 days of an index admission are considered readmissions, regardless of the reason for readmission. [2] This information is used to calculate a hospital’s specific readmission rate, as well as the national average readmission rate for comparison. Hospitals that fare worse than the national average readmission rate are then subject to financial penalties. In addition, CMS adopted a 30-day all-cause hospital readmission measure as part of its value-based payment modifier program for physicians. Under this program, doctors under the Medicare Physician Fee Schedule would receive differential payments based upon the quality of care provided relative to the cost of care. [3]

The financial penalty that applies to hospitals that perform poorly on 30-day readmission rates can be substantial. In the fiscal year of 2013, shortly after the program was initiated, the maximum penalty was a 1% reduction in base payments for all Medicare inpatient admissions. For the year 2017, the maximum penalty was 3%. CMS estimates the financial penalties for hospital readmissions to cost $528 million dollars in 2017. [2]

Starting in 2012 when the HRRP was initiated, 30-day readmission rates have steadily fallen, suggesting that hospitals have adopted new interventions targeted at reducing hospital readmissions. Some of these programs have focused on nursing interventions, improved discharge planning, and improved medication management. Other transitional care initiatives have sought to improve aftercare such as follow-up telephone calls, improved skilled-nursing care, and close outpatient primary care follow-up visits. As the number of interventions aimed at preventing hospital readmissions has increased, so has the cost to implement these programs. Programs that have been specifically designed to reduce 30-day hospital readmissions have not consistently yielded economic savings for hospitals [4]. Faced with the reality of budget constraints, hospitals have sought to identify ways to accurately predict which patients are at highest risk for readmission, so that they can make informed decisions on how to best allocate their resources.

Identifying exactly which variables are most predictive of 30-day hospital readmissions has been a challenge. This study aims to build upon previous work by developing a prediction model to identify patients that are at risk for 30-day hospital readmission. An accurate prediction model could provide hospitals with a valuable tool to help improve quality of care, while simultaneously improving efficiency through cost-savings.

BACKGROUND

A systematic review published in the Journal of the American Medical Association examined the subject of prediction models for hospital readmission. [5] This review found that of the prediction models available at the time, most demonstrated poor discriminative ability. Available models at the time used a variety of different variables to attempt to predict hospital readmission. Some of the models could be used to identify high-risk patients during a hospitalization, some used administrative data, while others could be used at time of hospital discharge. Few studies examined variables that were associated with overall health and function, illness severity, or social determinants of health.

The studies highlighted in the systematic review covered a broad range of possible variables that could predict hospital readmission. In 1999, researchers were looking at heart failure readmissions and found hospital readmissions to be higher in African-American patients, patients with Medicare and Medicaid insurance, patients with a greater number of medical comorbidities, and patients that had the use of telemetry during their hospitalization. [6] Patients were less likely to be readmitted if they were treated at a rural hospital, discharged to a skilled nursing facility, or if they had an echocardiogram or cardiac catheterization during hospitalization. Another study done on heart failure patients considered 32 different variables and found that 4 were significantly associated with hospital readmission. These were prior admission within one year, prior heart failure, diabetes, and a serum creatinine > 2.5 at time of discharge. [7]

One of the variables associated with higher readmission rates in a 2005 study from Switzerland was the Charlson Comorbidity Index. [8] The Charlson Comorbidity Index was developed as a prognostic tool to predict mortality in patients with different levels of medical comorbidities. Higher scores on the Charlson Comorbidity Index scores correspond with more medical comorbidities. The index factored in a patient's age, as well as the presence of multiple medical conditions such as diabetes, liver disease, malignancy, acquired immune deficiency syndrome (AIDS), moderate to severe chronic kidney disease, CHF, MI, COPD, peripheral vascular disease, cerebrovascular accident (CVA) or transient ischemic attack (TIA), dementia, hemiplegia, connective tissue disease, and/or peptic ulcer disease. [9] In addition to the Charlson Comorbidity Index, this study identified previous admission, male gender, and other specific diagnoses such as malignancy, sepsis, and anemia, among others, as significant predictors of hospital readmission.

In other studies, demographic and prior utilization variables were important in predicting hospital readmission. A 2006 study done in England identified age, gender, ethnicity, and the number of previous hospital admissions as significant predictors of readmission. In addition, specific conditions such as alcohol use, central nervous system (CNS) disorder, COPD, rheumatoid arthritis (RA), developmental disability, diabetes, peripheral vascular disease, renal disease, sickle cell disease, and ischemic heart disease were all associated with higher risk of readmission. [10]

In 2007, a Medicaid study done in the United States developed a prediction model for predicting future readmissions in patients. While researchers did include variables for medical comorbidities, they also incorporated variables that focused on prior utilization history. Specifically, these variables included frequency of hospital admission, number of Emergency Department (ED) visits, number of primary care and specialty care visits, use of broad range of other services such as home care, personal care, rehabilitation services, substance abuse services, and use of prescription drugs. In addition to prior utilization variables, socioeconomic status was considered by looking at census data based on a patient's ZIP code. [11]

A Baylor Health Care System study also found that readmission within 30 days was higher in patients with certain characteristics. Researchers looked at many of the other variables studied previously, such as age, ethnicity, and comorbidities and found readmission to be higher in patients that were older than 75, patients that were African-American, and patients with certain specific medical conditions such as lymphoma/leukemia, metastatic cancer, renal failure, and diabetes with chronic complications. This study also looked at insurance status, discharge disposition, and discharge specialty service and found higher risk in patients who had Medicare with no other health insurance, those who were discharged to home with home care or to a long-term care facility, and those patients with an index admission to a medical service (i.e. not surgical service). [12]

In 2009, a study done in Australia investigated many of the same variables including age, comorbidities, and number of previous admissions (within one year and three years) and also found them to be predictive of hospital readmission. In addition to these variables, researchers used a composite measure determined from census data and found that levels of economic disadvantage also predicted readmission. However, their model performed modestly in identifying patients at risk for readmission and while many comorbidities previously identified in other studies, such as anemia, COPD, and heart failure were associated with higher risk for readmission, many others were not (cardiac arrhythmias, hypertensive diseases, asthma, dementia, mental disorders due to other drug use, acute renal failure, lower respiratory tract infections, systemic connective tissue disorder, HIV, falls, cerebrovascular diseases, bronchiectasis, Parkinson's disease, inflammatory arthritis, schizophrenia, chronic rheumatic heart disease, pancreatic disease, and osteoporosis).[13]

In 2010, the LACE index was developed by van Walraven et al. [14] The LACE index has become one of the more widely used tools in assessing risk for hospital readmission. The LACE index has 4 components: *L*ength of stay, *A*cuity of Admission (emergent vs. elective), *C*harlson Comorbidity Index, and number of *E*R visits within the previous 6 months. (Table 1)

Table 1. LACE index

	Points
Length of Stay <1 0 1 day +1 2 days +2 3 days +3 4-6 days +4 7-13 days +5 ≥ 14 days +7	
Acuity of Admission Emergent +3 Elective (non-emergent) 0	
Charlson Comorbidity Index 0 points 0 1 point +1 2 points +2 3 points +3 ≥4 points +5	
ER visits within previous 6 months 0 0 1 +1 2 +2 3 +3 ≥4 +4	

The LACE index score range is from 0-19, with 0-4 indicating low risk, 5-9 indicating moderate risk, and ≥ 10 indicating high risk for readmission. The LACE index was derived from a sample of 4,812 patients from 11 different hospitals in Ontario, Canada. One of the primary advantages of the LACE index is ease of calculation. The index does not require area-level information (such as neighborhood socioeconomic status) that may not be readily available and the score can be calculated at the time of discharge, allowing hospitals to make timely decisions on interventions that may prevent hospital readmission.

Since the derivation of the LACE index by van Walraven, a number of other studies utilizing the LACE index to predict hospital readmission have been published, with varying results. One study found that a higher threshold, ≥13 rather than ≥10, was more accurate in predicting hospital readmission. [15] In other studies, the LACE index did not perform well in predicting 30-day hospital readmission. [16, 17] In 2012, the LACE+ index score was developed to augment the original LACE index and included other significant variables such as age, gender, number of admissions to the hospital in the year before the index admission, teaching status of the discharge hospital, number of days on alternative level of care during the index admission, and acute diagnoses and procedures performed during the index admission. [18]

In 2013, Donze et al developed a new score, called the HOSPITAL score. [19] The HOSPITAL score contains 7 variables: *h*emoglobin at discharge, discharge from an *o*ncology service, *s*odium level at discharge, *p*rocedure during index admission, *i*ndex type of admission (urgent/emergent vs. elective), number of *a*dmissions within the previous 12 months, and *l*ength of stay. (Table 2) The prediction score was derived in a sample of 2,398 patients at an academic medical center in Boston, Massachusetts.

Table 2. HOSPITAL score.

	Points if positive
Hemoglobin < 12 g/dL at discharge	1
Discharge from Oncology service	2
Sodium < 135 mEq/L at discharge	1
Procedure performed during hospital stay (ICD coded)	1
Index type of admission urgent or emergent	1
Admissions within previous 12 months	
0-1	0
2-5	2
>5	5
Length of stay ≥5 days	2

The HOSPITAL score maximum is 13 points, with 0-4 indicating low risk, 5-6 indicating intermediate risk, and ≥ 7 indicating high risk for 30-day hospital readmission. The HOSPITAL score performed well in a retrospective study of about 900 patients at a university affiliated community hospital [20] and in an international validation study done at 9 large hospitals, across 4 different countries including the United States, involving a retrospective cohort of 117,065 patients. [21] In a study comparing the HOSPITAL score to the LACE index at a community hospital in Illinois, the HOSPITAL score performed better than the LACE index. [22]

In addition to the LACE index and HOSPITAL score, attempts have been made to identify socioeconomic factors that may be important in predicting 30-day hospital readmissions. Accounting for socioeconomic status has garnered attention as data has shown that since the HRRP was initiated in 2012, major teaching hospitals and hospitals with more low-income beneficiaries have been more likely to incur financial penalties from excess 30-day readmissions. [2] In 2014, Kind et al published a study that showed higher readmission rates for patients who resided in the 15% most disadvantaged neighborhoods in the United States. [23] The study utilized an Area Deprivation index [24] based on 17 different variables that are available in the census data. (Table 3)

Table 3. Area Deprivation Index

Percent of the population aged 25 and older with less than 9 years of education
Percent of the population aged 25 and older with at least a high school diploma
Percent employed persons aged 16 and older in white-collar occupations
Median family income in US dollars
Income disparity
Median home value in US dollars
Median gross rent in US dollars
Median monthly mortgage in US dollars
Percent of owner-occupied housing units
Percent of civilian labor force population aged 16 years and older who are unemployed
Percent of families below federal poverty level
Percent of the population below 150% of the federal poverty threshold
Percent of single-parent households with children less than 18 years of age
Percent of households without a motor vehicle
Percent of households without a telephone
Percent of occupied housing units without complete plumbing
Percent of households with more than 1 person per room

One of the more recent studies took a different approach and looked at vital sign instability as a possible predictor of 30-day hospital readmission. [25] Abnormal vital signs were defined as temperature ≥37.8, heart rate ≥100, respiratory rate > 24, systolic blood pressure ≤ 90, and oxygen saturation <90% within 24 hours of hospital discharge. This study found increased 30-day readmission rates for patients who had any vital sign instability within 24 hours of being discharged from the hospital.

METHODS

Candidate independent risk prediction variables were identified from literature review. [26-37] From this list, candidate variables were categorized into one of seven categories: sociodemographic, medical comorbidities, mental health and substance abuse, illness severity, prior utilization, overall health and function, and social determinants of health.

The study site was the University of California, Irvine (UCI) Medical Center. UCI Medical Center is a 411-bed teaching hospital located in the city of Orange, California. Adults admitted at UCI Medical Center from February 1, 2017 to April 30, 2017 were included in the study. Pediatric patients, including newborns, as well as patients who left AMA were not initially excluded from the dataset and included as part of a sensitivity analysis. Deceased patients were excluded. Charts that could not be accessed or located because of inaccurate identifying information were also excluded from the study.

Available data from the electronic health record (EHR) included the LACE index score, the Charlson Comorbidity Index, length of stay, number of hospitalizations within the previous 12 months, and admission status (emergent vs. elective). Admission status was missing in 23 cases and coded as elective or non-emergent (score 0). Charlson Comorbidity Index scores were missing for 3 patients and coded as 0. Demographic data on age, gender, and ethnicity were collected. Payer data was available and categorized as Commercial, Medicaid, Medicare, self-pay/uninsured. A separate category was made for payer status that was identified as “other” in the database.

Information on specific diagnoses was obtained from available ICD-10 coding. Relevant diagnoses were chosen from a review of the literature and included CHF, COPD, MI, diabetes, history of psychiatric illness, end stage renal disease, pneumonia, and sepsis.

Area Deprivation Index score was determined by converting the patient’s address on file to a corresponding 9-digit zip code using United States Postal Service software that is available to the public. [38] Of the 936 cases, 111 were missing because of either missing address, invalid address on the USPS website, or because there was no corresponding 9-digit zip code available on the Area Deprivation Index database (available through the University of Wisconsin). [39] Missing values for ADI were assigned the median value for the entire dataset. Sensitivity analysis was performed excluding those cases with missing values.

Information on the discharge specialty service was available. The services identified were Cardiology, Cardiothoracic surgery, Colorectal surgery, Emergency

Medicine, Radiology, Family Practice, Neurology, General Surgery, Pediatrics, Psychiatry (including Geriatric, General, and Child/adolescent), OB/GYN, Hospitalist, Internal Medicine, Infectious Disease, Hematology/Oncology, Maternal and Fetal, Neonatal/Perinatal medicine, Neurosurgery, Vascular surgery, Urology, Trauma, Transplantation, Pulmonary/Critical Care, Plastics, ENT, Orthopedics, and Oncologic Surgery. Hospitalist and Internal Medicine were combined into one discharge service.

Information on the discharge disposition was also available and categorized into the following groups: discharge to home, discharge to skilled-nursing facility (SNF), home health, hospice, against medical advice (AMA), and transfer to a long-term rehabilitation facility.

UCI medical center utilizes 3M software that categorizes admission severity of illness into 4 categories: 1 = Minor; 2 = Moderate; 3 = Major; 4 = Extreme. The 3M system is based on CMS diagnosis-related group (DRG) information and ICD coding that stratifies the admission severity of illness (SOI) in an attempt to capture "the extent of physiologic decompensation or organ system loss of function" [40] This information was coded as 1, 2, 3, or 4, corresponding to the 4 categories set by the 3M software.

The 7 variables of the HOSPITAL score were obtained. Last known hemoglobin and sodium were extracted from the patient's chart. Missing data was coded as normal. Oncology service patients were identified by ICD coding or admission specifically to the Hematology/Oncology or Oncologic Surgery service. UCI has a specific Hematology/Oncology admitting service that occasionally admits patients to the hospital (in this study, less than 1% of admissions). However, many of the patients with oncologic-related illness are admitted through the general internal medicine service with Oncology serving as a consult service. Similar to other studies, this study included oncology patients as those with a cancer-related ICD-10 diagnosis code. [20] Procedure was coded from available ICD-10 coding. Length of stay, number of hospitalizations within the previous 12 months, and index type of admission (emergent vs. elective) were available through the EHR and a HOSPITAL score was generated using this information.

Vital signs within 24h of discharge was obtained through the EHR and coded as abnormal if any of the vitals were out of range ($T \geq 37.8$, $HR \geq 100$, $RR > 24$, $SBP \leq 90$). Information on oxygen saturation, however, was not available. If vital sign information was not available for the patient, it was coded as normal.

Table 4 shows the final variables list used for this study.

Table 4. Final variables list.

LACE index
Charlson Comorbidity Index
Vital Sign Instability
Area Deprivation Index
Age
Gender
Ethnicity Hispanic White, Non-Hispanic African-American Asian
Payer Commercial Medicare Medicaid Self-pay/uninsured Other

Discharge specialty service Cardiology Cardiothoracic Surgery Colorectal surgery Emergency Medicine Radiology Family Practice Neurology General Surgery Pediatrics Psychiatry (including Geriatric, General, and Child/adolescent) OB/GYN Hospitalist/Internal Medicine Infectious Disease Hematology/Oncology Maternal and Fetal Neonatal/Perinatal medicine Neurosurgery Vascular surgery Urology Trauma Transplantation Pulmonary/Critical Care Plastics ENT Orthopedics Oncologic Surgery
Admit Severity (1: minor, 2: moderate, 3: major, 4: extreme)
HOSPITAL score Hemoglobin Oncology Service Sodium Procedure Index Admission type (emergent vs elective) Number of inpatient admissions within previous 12 months
Specific Diagnoses: CHF Pneumonia COPD Sepsis History of Psychiatric Illness MI Diabetes ESRD

Logistic regression was used with the dependent variable being patient-level 30-day all-cause readmission (dichotomous: not readmitted, readmitted). Including pediatrics cases, 936 cases were available for review. Statistical analyses were performed using SPSS version 25.

RESULTS

During the study period, from February 1, 2017 to April 30, 2017, 1284 admissions (including pediatrics and newborns) were available from the database. Of these, 348 recorded admissions did not correspond to a valid chart, could not be located or accessed, or the patient was deceased. Of the remaining 936 cases, 109 were pediatric (age < 18) or newborn cases and excluded from the initial analysis.

The overall study population was 49% female, had an average age of 53 years, and spent an average of 5.6 days in the hospital. The patients readmitted had higher LACE index scores and HOSPITAL scores and those differences were statistically significant. Readmitted patients had more emergent admissions and were more likely to be categorized in the top 2 levels of severity of illness (major, extreme) according to the 3M severity of illness classification. In addition, readmitted patients had more hospitalizations within the previous year than patients who were not readmitted and were more likely to have one or more abnormal vital sign abnormality within 24 hours of discharge. Other baseline characteristics are shown in Table 5.

Table 5. Baseline Characteristics of Study Population by 30-day Readmission Status

	Not Readmitted (N=421)	Readmitted (N=406)	p-value
Age, mean (SD)	52 (22)	54 (19)	0.157
Male	188 (45%)	213 (53%)	0.025
Hispanic	148 (36%)	141 (36%)	0.926
Medicaid	143 (34%)	162 (40%)	0.077
Medicare	142 (34%)	159 (39%)	0.104
Commercial insurance	120 (29%)	82 (20%)	0.005
Self-pay/Uninsured	9 (2%)	0 (0)	0.003
Urgent or emergent admission	313 (74%)	347 (86%)	<.001
Admit Severity 3, 4 (major, extreme)	22 (5%)	61 (15%)	<.001
Oncology service or cancer diagnosis (ICD-10 coded)	43 (10%)	78 (19%)	<.001
Length of stay in days, mean (SD)	3.8 (4.0)	7.4 (8.6)	<.001
Hospital admissions in the last year, mean (SD)	.00 (.07)	1.82 (2.78)	<.001
Procedure during hospitalization (ICD-10 coded)	297 (71%)	264 (65%)	0.089
Hgb < 12	192 (46%)	276 (68%)	<.001
Na < 135	59 (14%)	121 (30%)	<.001
Charlson Comorbidity Index, mean (SD)	1.52 (2.04)	4.36 (2.86)	<.001
LACE index, mean (SD)	7.9 (2.7)	12.2 (3.4)	<.001
HOSPITAL score, mean (SD)	2.7 (1.5)	4.9 (2.3)	<.001
Area Deprivation Index, mean (SD)	87 (19)	88 (19)	0.646

	Not Readmitted (N=421)	Readmitted (N=406)	p-value
At Least One Abnormal Vital Sign Prior to Discharge	122 (29%)	217 (53%)	<.001
Hospitalist/Internal Medicine	100 (24%)	145 (36%)	< .001
Discharge to Home	304 (72%)	251 (62%)	0.001
Discharge to SNF	37 (9%)	54 (13%)	0.039
Home Health discharge	44 (11%)	79 (20%)	< .001

* Table entries are number of patients and percentage unless otherwise noted. p-values computed using independent samples t-test for continuous variables and Fisher's exact test for dichotomous variables.

A prediction model was generated starting primarily with the LACE index. Age was not included in this model as age is already a component of the Charlson Comorbidity Index. Having Medicare insurance also was excluded as part of the LACE index model because of the association between Medicare and age as, with the exception of certain patients such as those with a disability or a diagnosis of ESRD, Medicare beneficiaries generally must be older than age 65 to qualify for the program. In addition, the list of specific diagnoses that included variables such as CHF and MI were also not included as most are already components of the Charlson Comorbidity Index. In the model using the LACE Index, gender, ethnicity, payer status, admit severity, discharge disposition, and discharge specialty service were not significant predictors of 30-day hospital readmission. The Area Deprivation Index also was not predictive of hospital readmissions. The HOSPITAL score itself was not added to this model because the HOSPITAL score contains two identical components of the LACE index (length of stay and index admission type). The remaining 5 components of the

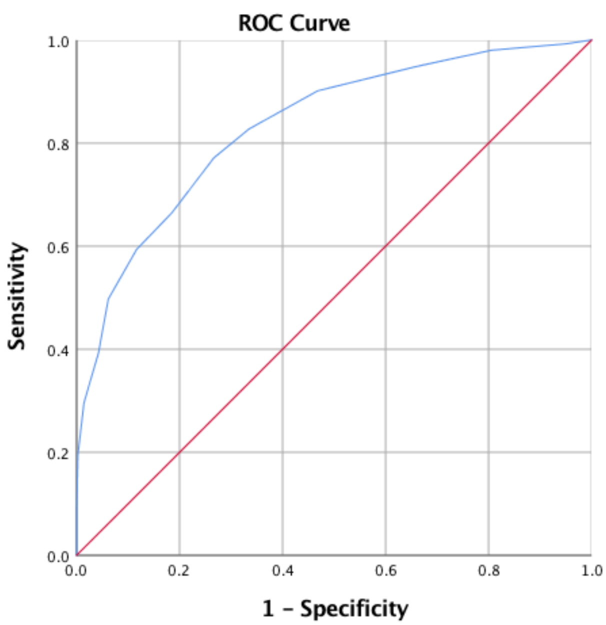
HOSPITAL score were added to the model and only number of hospital admissions within the previous 12 months was a significant predictor. The final model is shown in Table 6.

Table 6. LACE "plus" model using logistic regression, including Odds Ratio

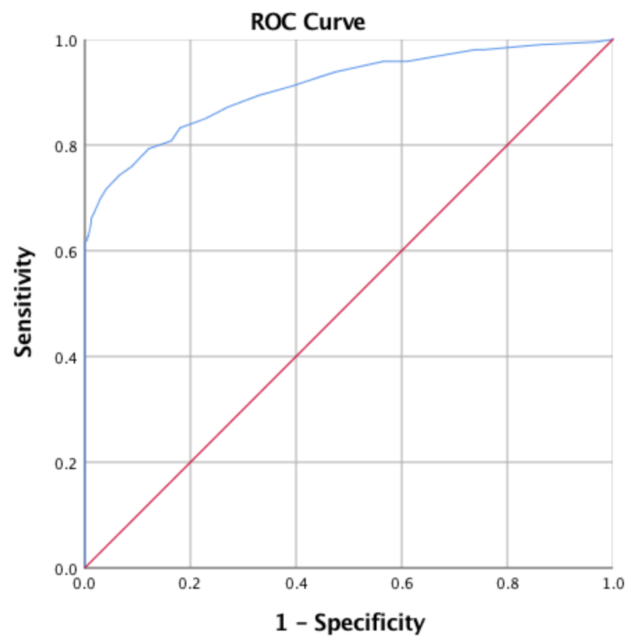
	Odds Ratio	95% Confidence Interval	p-value
LACE index	1.38	1.28-1.48	<.001
Number of hospital admissions within previous 12 months	77.02	18.64-318.29	<.001
Vital sign instability	2.26	1.49-3.44	<.001

Receiver operating characteristic (ROC) curves were generated using the LACE index as the sole independent variable, as well as for the LACE "plus" model. (Figure 1) The C-statistic for the model using only the LACE index was 0.83 (95% CI, 0.81-0.86), while the C-statistic for the LACE "plus" model was 0.91 (95% CI, 0.89-0.93). The Hosmer-Lemeshow goodness of fit test had a chi-squared value of 1.63 with a p-value of 0.99.

Figure 1. ROC curves for LACE index and LACE “plus” model



LACE index, C-statistic 0.83



LACE “plus”, C-statistic 0.91

Another prediction model was developed starting primarily with the HOSPITAL score. Many of the variables that were not significant in the LACE model also were not significant using the HOSPITAL score. These included age, gender, ethnicity, insurance status, and discharge disposition. The Area Deprivation Index also did not improve the prediction model. Specific diagnoses that were significant and included in an initial version of the model were CHF, diabetes, ESRD, and history of psychiatric illness. However, the model had improved discrimination with a higher C-statistic when these 4 specific diagnoses were replaced by the Charlson Comorbidity Index score, which also takes into account many of these specific diagnoses.

2 medical services, specifically Family Practice and Hospitalist/Internal Medicine were significant in the model and remained so, even after controlling for admit severity. The Family Practice and Hospitalist/Internal Medicine services admitted more patients with class 3 or 4 severity on the 3m index than non-Family Practice/Hospitalist/Internal Medicine services (16% to 7%, p-value <.001). In addition, Family Practice/Hospitalist/Internal Medicine services admitted patients with higher Charlson Comorbidity Index than the other specialty services (3.7 vs. 2.5, p-value <.001). However, when controlling for admit severity in the prediction model, Family Practice and the Hospitalist/Internal Medicine service still remained significant predictors of hospital readmissions, while admit severity did not. In total, Family Practice patients accounted for 35 cases, compared to 245 for the Hospitalist/Internal Medicine service. At UCI Medical Center, and at many other hospitals, Family Practice functions as a general admitting service similar to a hospitalist or Internal Medicine service. In the final model, they were combined into a single “Hospitalist” variable (Table 7).

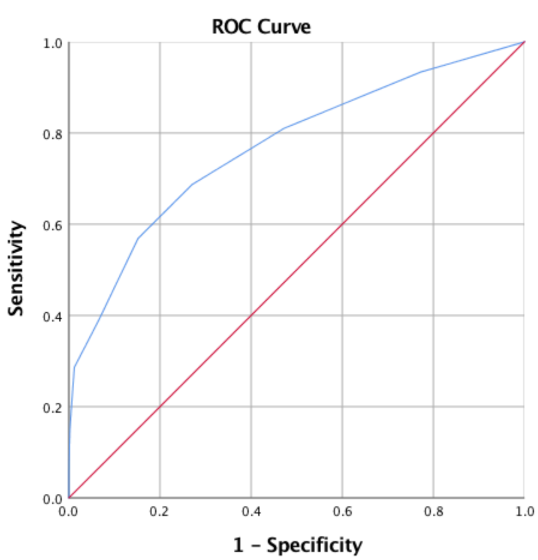
Table 7. HOSPITAL “plus” model using logistic regression, including Odds Ratio

	Odds Ratio	95% Confidence Interval	p-value
HOSPITAL score	1.67	1.51-1.84	<.001
Charlson Comorbidity Index	1.47	1.37-1.58	<.001
Hospitalist	1.98	1.35-2.90	0.001
Vital Sign Instability	2.95	2.03-4.28	<.001

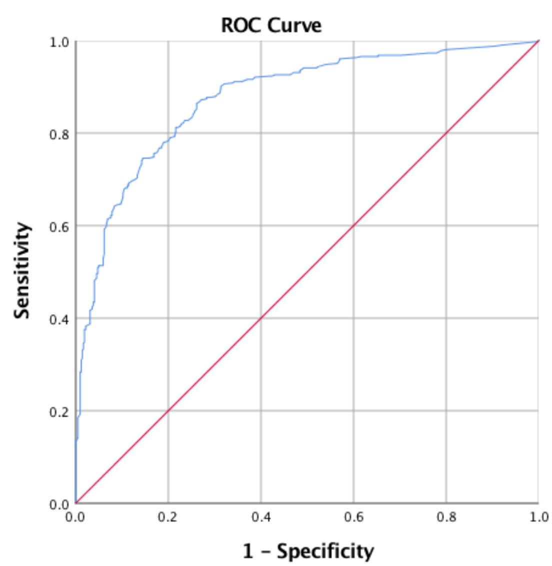
Using only the HOSPITAL score, ROC curve analysis demonstrated a C-statistic of 0.77 (95% CI, 0.74-0.80). The HOSPITAL “plus” model (HOSPITAL score plus Charlson Comorbidity Index, Hospitalist, and vital sign instability) showed a C-statistic of 0.88 (95% CI, 0.85-0.90). (Figure 2) The Hosmer-Lemeshow goodness of fit test for the HOSPITAL “plus” model had a chi-squared value of 10.99 with a p-value of 0.20.

Sensitivity analyses that excluded AMA cases or included pediatrics cases did not significantly alter any of the prediction models.

Figure 2. ROC curves for HOSPITAL score and HOSPITAL “plus” model



HOSPITAL score, C-statistic 0.77



HOSPITAL “plus”, C-statistic 0.88

DISCUSSION

This retrospective, single-center study demonstrates that both the LACE index and HOSPITAL score have good discrimination in predicting 30-day hospital readmission at a university-based hospital.

In this study, the addition of variables to each model improved performance of the prediction models, suggesting that the original models derived by van Walraven et al and Donze et al may perform better if additional variables are considered. The LACE "plus" model in this study included a variable (number of hospital admissions within the previous 12 months) that was also a part of the follow-up LACE+ study by van Walraven et al that added variables to the original LACE index prediction model. This variable (number of previous hospital admissions) was considered when the LACE index was originally derived, but a significant association was not found at that time for it to be included in the original model.

The HOSPITAL "plus" model also performed better, suggesting that variables accounting for comorbidities, whether by specific diagnoses such as CHF and ESRD, or through an index such as the Charlson Comorbidity Index, may improve the performance of the HOSPITAL score.

In addition, the significance of vital sign instability potentially adds an important element for hospitals to consider as they are in the process of discharging patients. Electronic Health Records have the capability of flagging charts with abnormal vital signs, alerting physicians in real-time about a potentially high risk patient that may need hospital readmission or experience an adverse outcome. Physicians could then consider additional treatment or prolonged hospital stay. However, the potential impact on inpatient lengths of stay and associated costs would need further study.

One of the strengths of this study was that it looked at two of the primary models being used today by hospitals and unlike the Robinson study [22] where the HOSPITAL score outperformed the LACE index, both models performed well. Hospitals that have different levels of resources could consider using both models to target their interventions at reducing 30-day readmissions. For example, both models identified a cohort of the same 288 patients that were readmitted within 30 days. For a hospital with more limited resources, they could choose to focus their interventions on this group of patients.

For a hospital interested in increasing the sensitivity of their prediction tool, both models could be used in a way to expand the breadth of their interventions. For example, using a cut-off of 0.5 for predicted probability, the LACE "plus" model would have missed 98 of 416 readmission cases. The HOSPITAL "plus" model would have missed 89 cases. Using both models to identify high-risk patients would have missed a total of 36 cases. However, this would also come at the cost of identifying many more patients who ultimately may not be readmitted to the hospital within 30 days.

This study has several important limitations. It is a retrospective, single-center study with a relatively low sample size. There were a total of 827 patients in this study, compared to 4,812 patients in the original LACE study and 117,065 patients in the international validation of the HOSPITAL score.

Low sample size and the study being at one medical center may have contributed to the high C-statistics seen in this study's prediction models. The LACE index “plus” demonstrated a C-statistic of 0.91, compared to the original LACE index derivation study of 0.684. The HOSPITAL “plus” model from this study showed a C-statistic of 0.88, compared to the C-statistic of 0.71 in the original HOSPITAL score derivation study.

In addition, the number of records available in the UCI database for this study did not capture the entire set of patients with an index admission from February 1, 2017 to April 30, 2017. Over this time period, the available sample from the database had 801 total patients not readmitted and 483 readmissions, which would have yielded a readmission rate of 38%. UCI’s published hospital readmission rate for a range of medical conditions ranges from 5-12%. [41] In this particular sample of patients, after accounting for restricted access charts or records that could not be located, 49% of the patients were readmitted to the hospital within 30 days.

In terms of the Area Deprivation Index, there were also a number of cases where an ADI number could not be generated because there was no address on file, the address was invalid, or a corresponding 9-digit zip code could not be located in the existing database. In addition, the number of ADI cases that would have fallen into the 15% most disadvantaged neighborhoods (ADI score >113) was relatively small. In this sample, there were 43 total records with an ADI score > 113, 19 were readmitted and 24 were not. This could explain why no association between the Area Deprivation Index and 30-day hospital readmissions was found.

In this study using the HOSPITAL score, the Hospitalist service was a significant predictor of hospital readmissions. It is possible that some of the variance associated with sicker patients was captured by this variable. The Hospitalist service did admit patients with more comorbidities and higher admit severity of illness scores. In addition, the Hospitalist service was not a significant predictor of hospital readmissions using the LACE model, which already takes into account patient comorbidities as part of the Carlson Comorbidity Index. However, it is not entirely apparent why the Hospitalist variable remained a significant part of the prediction model, even after controlling for admit severity of illness. The significance of this finding would need further investigation.

This study demonstrates that both the LACE index and HOSPITAL score perform well in identifying high-risk patients for 30-day hospital readmission. The addition of other significant variables has the ability to potentially increase the accuracy of each prediction model. Further research would likely involve a larger prospective study to determine if these models can be used to prospectively identify high-risk patients and target effective interventions to reduce hospital readmissions. If shown to be effective at a single site such as UCI Medical Center, these models could be tested in a larger multiple-site study to determine their effectiveness in reducing hospital readmissions.

BIBLIOGRAPHY

1. Jencks, S.F., M.V. Williams, and E.A. Coleman, Rehospitalizations among patients in the Medicare fee-for-service program. N Engl J Med, 2009. **360**(14): p. 1418-28.
2. Boccuti, C. and G. Casillas, Aiming for Fewer Hospital U-turns: The Medicare Hosptial Readmission Reduction Program. Kaiser Family Foundation, 2017.
3. https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/PhysicianFeedbackProgram/ValueBasedPaymentModifier.html, accessed March 26, 2018.
4. Nuckols, T.K., et al., Economic Evaluation of Quality Improvement Interventions Designed to Prevent Hospital Readmission: A Systematic Review and Meta-analysis. JAMA Intern Med, 2017. **177**(7): p. 975-985.
5. Kansagara, D., et al., Risk prediction models for hospital readmission: a systematic review. JAMA, 2011. **306**(15): p. 1688-98.
6. Philbin, E.F. and T.G. DiSalvo, Prediction of hospital readmission for heart failure: development of a simple risk score based on administrative data. Rev Port Cardiol, 1999. **18**(9): p. 855-6.
7. Krumholz, H.M., et al., Predictors of readmission among elderly survivors of admission with heart failure. Am Heart J, 2000. **139**(1 Pt 1): p. 72-7.
8. Halfon, P., et al., Validation of the potentially avoidable hospital readmission rate as a routine indicator of the quality of hospital care. Med Care, 2006. **44**(11): p. 972-81.
9. Charlson, M.E., et al., A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. J Chronic Dis, 1987. **40**(5): p. 373-83.
10. Billings, J., et al., Case finding for patients at risk of readmission to hospital: development of algorithm to identify high risk patients. BMJ, 2006. **333**(7563): p. 327.
11. Billings, J. and T. Mijanovich, Improving the management of care for high-cost Medicaid patients. Health Aff (Millwood), 2007. **26**(6): p. 1643-54.
12. Silverstein, M.D., et al., Risk factors for 30-day hospital readmission in patients >/=65 years of age. Proc (Bayl Univ Med Cent), 2008. **21**(4): p. 363-72.
13. Howell, S., et al., Using routine inpatient data to identify patients at risk of hospital readmission. BMC Health Serv Res, 2009. **9**: p. 96.
14. van Walraven, C., et al., Derivation and validation of an index to predict early death or unplanned readmission after discharge from hospital to the community. CMAJ, 2010. **182**(6): p. 551-7.
15. Yazdan-Ashoori, P., et al., Utility of the LACE index at the bedside in predicting 30-day readmission or death in patients hospitalized with heart failure. Am Heart J, 2016. **179**: p. 51-8.
16. Cotter, P.E., et al., Predicting readmissions: poor performance of the LACE index in an older UK population. Age Ageing, 2012. **41**(6): p. 784-9.
17. Low, L.L., et al., Performance of the LACE index to identify elderly patients at high risk for hospital readmission in Singapore. Medicine (Baltimore), 2017. **96**(19): p. e6728.
18. van Walraven, C., J. Wong, and A.J. Forster, LACE+ index: extension of a validated index to predict early death or urgent readmission after hospital discharge using administrative data. Open Med, 2012. **6**(3): p. e80-90.
19. Donze, J., et al., Potentially avoidable 30-day hospital readmissions in medical patients: derivation and validation of a prediction model. JAMA Intern Med, 2013. **173**(8): p. 632-8.
20. Robinson, R., The HOSPITAL score as a predictor of 30 day readmission in a retrospective study at a university affiliated community hospital. PeerJ, 2016. **4**: p. e2441.
21. Donze, J.D., et al., International Validity of the HOSPITAL Score to Predict 30-Day Potentially Avoidable Hospital Readmissions. JAMA Intern Med, 2016. **176**(4): p. 496-502.

22. Robinson, R. and T. Hudali, The HOSPITAL score and LACE index as predictors of 30 day readmission in a retrospective study at a university-affiliated community hospital. PeerJ, 2017. **5**: p. e3137.
23. Kind, A.J., et al., Neighborhood socioeconomic disadvantage and 30-day rehospitalization: a retrospective cohort study. Ann Intern Med, 2014. **161**(11): p. 765-74.
24. Singh, G.K., Area deprivation and widening inequalities in US mortality, 1969-1998. Am J Public Health, 2003. **93**(7): p. 1137-43.
25. Nguyen, O.K., et al., Vital Signs Are Still Vital: Instability on Discharge and the Risk of Post-Discharge Adverse Outcomes. J Gen Intern Med, 2017. **32**(1): p. 42-48.
26. Keenan, P.S., et al., An administrative claims measure suitable for profiling hospital performance on the basis of 30-day all-cause readmission rates among patients with heart failure. Circ Cardiovasc Qual Outcomes, 2008. **1**(1): p. 29-37.
27. Amarasingham, R., et al., An automated model to identify heart failure patients at risk for 30-day readmission or death using electronic medical record data. Med Care, 2010. **48**(11): p. 981-8.
28. Hasan, O., et al., Hospital readmission in general medicine patients: a prediction model. J Gen Intern Med, 2010. **25**(3): p. 211-9.
29. Hebert, C., et al., Diagnosis-specific readmission risk prediction using electronic health data: a retrospective cohort study. BMC Med Inform Decis Mak, 2014. **14**: p. 65.
30. Amarasingham, R., et al., Electronic medical record-based multicondition models to predict the risk of 30 day readmission or death among adult medicine patients: validation and comparison to existing models. BMC Med Inform Decis Mak, 2015. **15**: p. 39.
31. Shadmi, E., et al., Predicting 30-day readmissions with preadmission electronic health record data. Med Care, 2015. **53**(3): p. 283-9.
32. Agrawal, D., et al., Predicting Patients at Risk for 3-Day Postdischarge Readmissions, ED Visits, and Deaths. Med Care, 2016. **54**(11): p. 1017-1023.
33. Huynh, Q.L., et al., Mild cognitive impairment predicts death and readmission within 30days of discharge for heart failure. Int J Cardiol, 2016. **221**: p. 212-7.
34. Logue, E., W. Smucker, and C. Regan, Admission Data Predict High Hospital Readmission Risk. J Am Board Fam Med, 2016. **29**(1): p. 50-9.
35. Low, L.L., et al., Predicting 30-Day Readmissions in an Asian Population: Building a Predictive Model by Incorporating Markers of Hospitalization Severity. PLoS One, 2016. **11**(12): p. e0167413.
36. Morris, M.S., et al., Postoperative 30-day Readmission: Time to Focus on What Happens Outside the Hospital. Ann Surg, 2016. **264**(4): p. 621-31.
37. Greenwald, J.L., et al., A Novel Model for Predicting Rehospitalization Risk Incorporating Physical Function, Cognitive Status, and Psychosocial Support Using Natural Language Processing. Med Care, 2017. **55**(3): p. 261-266.
38. https://tools.usps.com/go/ZipLookupResultsAction!input.action?items=50&companyName=&address1=23412+pacific+park+dr&address2=&city=&state=Select&zip=92656.
39. Health Innovation Program. Area Deprivation Index. UW Health Innovation Program; 2014. Available at: http://www.hipxchange.org/ADI.
40. https://www.forwardhealth.wi.gov/kw/pdf/handouts/3M_APR_DRG_Presentation.pdf.
41. https://www.ucirvinehealth.org/-/media/files/pdf/quality/may-2017/30-day-hospital-readmissions.pdf?la=en, accessed March 27, 2018.
42. Agency for Healthcare Research and Quality. Statistical Brief #172, April 2014 Available from: http://www.hcup-us.ahrq.gov/reports/statbriefs/sb172-Conditions-Readmissions-Payer.pdf (Accessed December 9, 2014).
43. http://www.chiamass.gov/assets/Uploads/A-Focus-on-Provider-Quality-Jan-2015.pdf, accessed March 26, 2017.

44. https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/PhysicianFeedbackProgram/ValueBasedPaymentModifier.html, accessed March 24, 2017.