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A Predictive Model for Readmissions Among Medicare Patients in a California Hospital

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Abstract

Predictive models for hospital readmission rates are in high demand because of the Centers for Medicare & Medicaid Services (CMS) Hospital Readmission Reduction Program (HRRP). The LACE index is one of the most popular predictive tools among hospitals in the United States. The LACE index is a simple tool with 4 parameters: **L**ength of stay, **A**cuity of admission, **C**omorbidity, and **E**mergency visits in the previous 6 months. The authors applied logistic regression to develop a predictive model for a medium-sized not-for-profit community hospital in California using patient-level data with more specific patient information (including 13 explanatory variables). Specifically, the logistic regression is applied to 2 populations: a general population including all patients and the specific group of patients targeted by the CMS penalty (characterized as ages 65 or older with select conditions). The 2 resulting logistic regression models have a higher sensitivity rate compared to the sensitivity of the LACE index. The C statistic values of the model applied to both populations demonstrate moderate levels of predictive power. The authors also build an economic model to demonstrate the potential financial impact of the use of the model for targeting high-risk patients in a sample hospital and demonstrate that, on balance, whether the hospital gains or loses from reducing readmissions depends on its margin and the extent of its readmission penalties.

Keywords: HRRP, LACE index, logistic regression, sensitivity rate, specificity rate, economic model

Introduction

Reducing readmission rates among hospitals across the United States has become a high priority because of the Hospital Readmission Reduction Program (HRRP), which was established in 2012 by the Centers for Medicare & Medicaid Services (CMS).[1,2–4] Hospital readmissions are disruptive for both patients and hospital administration. Readmissions can lead to longer stays and put patients at additional risk of hospital-acquired infections and complications. Meanwhile, hospital readmissions are often costly to the nation's health care system. An analysis of 2005 Medicare claims by the Medicare Payment Advisory Commission concluded that avoidable readmissions within 30 days of discharge resulted in an estimated $12 billion in Medicare spending.[5] According to the Agency for Healthcare Research and Quality, between January and November 2011 (before HRRP became effective), hospitals spent $41.3 billion to treat patients readmitted within 30 days of discharge.[6] Thus, in order to promote better quality of care, increase hospital efficiency, and to reduce health care costs, HRRP was put into effect in November 2012.

HRRP imposes penalties on hospitals with high readmission rates. Hospitals with readmission rates exceeding the national average for certain conditions (initially heart failure, pneumonia, and acute myocardial infarction) have their total Medicare reimbursement (all discharges, not just the target conditions) reduced. Initially, the reduction in funding was capped at 1% of Medicare reimbursement but it increased to 3% as of 2015. Under this financial pressure, hospitals are making significant progress with different strategies to reduce their readmission rates. According to CMS, the national readmission rate fell to 17.5% in 2013, whereas for many years before HRRP the readmission rate was steady at 19.5%.[1] An example of the calculation of the CMS penalty is provided in Supplementary Data (Supplementary Data are available online at www.liebertpub/pop).

Currently, the LACE index is a readmission model that is widely used in the United States because of its simplicity and moderate predictive power. LACE scores every patient on the risk of readmission upon discharge based on the following parameters: **L**ength of stay, **A**cuity of admission, **C**omorbidity, and **E**mergency department visits in the previous 6 months.[7] LACE scores range from 0–19. A score between 0–4 means the patient

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is at low risk of readmission, a score of 5–9 indicates a moderate risk of readmission, and LACE scores ≥10 represent a high risk of readmission to the hospital. In order to achieve better outcomes for patients, a simple and practical predictive tool such as the LACE index can prove helpful.

An article published by the first US hospital to use the LACE index suggested that the LACE index should be combined with additional patient-level risk factors (eg, age, living situation, discharge status) to increase the discrimination and accuracy level of prediction.[8] Results were shown to be slightly better than those of the LACE index alone. Developing a more specific readmission risk prediction model could further explain causes of readmissions, as well as more accurately identify and stratify a population at risk of readmission for intervention. A study comparing an institution-specific model to the generic LACE model on 3 conditions (ie, heart failure, acute myocardial infarction, pneumonia), as well as a combined model, for 3 institutions found the C statistic for the area under the curve (AUC) to be higher for the specific models compared to LACE.[8]

Because lowering readmission rates requires dedication of case management resources, it is in part a financial issue. A complete evaluation of a model to predict readmissions would take into account the cost of intervening on a patient identified to have higher risk of readmission, together with the effectiveness of the intervention. In addition, the ''competing'' financial forces (a reduction in the hospital's revenue as a result of the avoided readmission, and the offsetting effect of the reduction in any penalties applied by CMS) need to be considered. The CMS penalty formula makes this a particularly difficult calculation, and one that is hospital specific. The ''business case'' of a model has proven to be an important factor in judging its effectiveness.[9]

This paper focuses on creating practical models that aid in the prediction of the risk of readmission to a specific hospital within 30 days of discharge, both for all patients and for target diagnosis Medicare patients, to aid in the identification and stratification of at-risk patients for intervention in a cost-effective manner.

Data

The data for this study were provided by a medium-sized, not-for-profit California hospital. The data set consists of admission, readmission, and emergency department visit records of 76,538 patients collected between 2010 and 2014. Readmission records were only available for the specific hospital, although as the only hospital in the area, the study team believes that the preponderance of readmissions will have occurred at the reporting facility. The explanatory variables that were provided by the institution are: race, age, sex, admit-from type (source of admission [eg, emergency, scheduled]), zip code, Diagnosis-Related Group (DRG), and number of emergency visits per year for 5 years. Table 1 summarizes the data provided.

Additional variables derived from the source data include: DRG class, length of stay, Chronic Illness and Disability Payment System (CDPS) risk score, and LACE index. DRG class is characterized as medical or surgical based on the DRG values provided by the hospital records; a small percentage of these admissions (approximately 6%) are for DRGs that are not classifiable (''Ungrouped''). Length of stay was calculated from provided admission and discharge dates. The LACE index was calculated using the 4 parameters required for the LACE model: length of stay, acuity of admission, comorbidity, and emergency department visits in the previous 6 months. Patient acuity in the LACE model is calculated by the Charlson index, which is a predictor of *mortality*, not morbidity.

Because extensive diagnostic data were available, the study team calculated a morbidity-appropriate measure of patient diagnostic risk, the CDPS risk score. CDPS is a risk-adjustment system tailored to adjust payments of health plans for a variety of illnesses (Chronic Disability Payment System, v 6 [UC San Diego, San Diego, CA[10,11]]). In addition to calculating a relative risk score, the CDPS system groups multiple diagnoses into hierarchical condition categories (HCCs). The CDPS system maps *International Classification of Diseases, Ninth Revision* (ICD-9) codes to 67 disease categories for risk adjustment purposes and generates a relative risk score for each patient based on the patient's diagnoses. (All diagnostic data were from prior to October 1, 2015, and therefore coded according to the ICD-9 system.) Risk scores can take a value from zero to infinity. ICD-9 mapping to CDPS categories is available at http://cdps.ucsd.edu/. More detail is provided in the Supplementary Data. The CDPS model has the additional benefit of applicability to working age adults, unlike other models such as CMS's HCC model, which is calibrated for seniors only. In the present study, the age range of patients was limited to 15 years or older, consistent with the specifications of CDPS.

The study team attempted to explore derived demographic variables such as educational levels and poverty from patients' zip codes available in the original data set. The zip code was matched to Internal Revenue Service and census data at the zip code level to identify, within zip code areas, the percentage of the population in poverty and the percentage with low levels of education. These socioeconomic variables were tested as risk factors to see whether they had any significant effects on hospital readmission. Specifically, the team tested the hypothesis that patients from areas with low levels of income or education would have a higher chance of being readmitted within 30 days after hospital discharge. However, these variables were not significant: the majority of patients admitted were from the same communities or nearby areas with negligible differences in socioeconomic backgrounds.

The Model

The response variable for the model is readmissions. In total, 5,396 patients were readmitted, while 71,142 were not. This leads to a readmission rate of 7.05%. Because the response variable is binary (readmitted/not readmitted), the study team chose to fit a logistic regression model for the purposes of this study.

Methods

Notation

Let P be the probability that the patient is readmitted within 30 days after discharge.

(1-P): probability that the patient is not readmitted within 30 days after discharge.

Table 1. Data Summary

N = *76,538*						
Variable	*Factors*	*Year 2010* (n = *15,516*)	*Year 2011* (n = *15,072*)	*Year 2012* (n = *15,566*)	*Year 2013* (n = *15,176*)	*Year 2014* (n = *14,937*)
Race	White	.71	.70	.71	.71	.94
	Hispanic	.23	.24	.23	.24	
	Asian	.02	.02	.02	.02	.02
	Black	.02	.02	.02	.02	.02
	Other	.02	.02	.02	.02	.02
DRG	Medical	.48	.48	.51	.51	.53
	Surgical	.46	.46	.43	.42	.40
	Ungrouped	.06	.06	.06	.07	.07
Admitted from Type	Emergency	.40	.40	.42	.46	.45
	Pre Admit	.40	.38	.37	.34	.33
	Observation	.14	.15	.15	.15	.16
	Other	.06	.07	.06	.05	.06
Readmission	Yes	.072	.074	.075	.068	.064
	No	.928	.926	.925	.932	.936
Age	Min	15	15	15	15	15
	Mean	57.89	57.75	57.74	57.92	57.84
	Max	104	110	111	112	106
LACE Score	Min	1	1	1	1	1
	Mean	5.60	5.78	5.65	6.01	6.30
	Max	19	19	17	19	19
CDPS Risk Score	Min	.14	.14	.14	.14	.14
	Mean	3.008	3.095	3.207	3.359	3.538
	Max	29.00	22.14	20.44	29.85	25.87
Length of Stay	Min	0	0	0	0	0
	Median	3	3	3	3	3
	Mean	3.820	4.154	4.309	3.977	4.029
	Max	79	239	143	98	122

CDPS, Chronic Illness and Disability Payment System; DRG, Diagnosis-Related Group; LACE, length of stay, acuity of admission, comorbidity, and emergency department visits in the previous 6 months.

log: natural logarithm.

odds: the ratio of the number of ways something can occur to the number of ways it cannot occur (ie, P/(1-P))

logit: denotes the log of the odds (ie, log (P/(1-P)))

Logistic regression

Logistic regression (logit model/logit regression) is a regression model in which the response variable is binary or multinomial, with several predictors. In this case there is a binary response (readmitted/not readmitted).

- The response variable is Y and X is the (vector of) predictor variables. Y = 1 implies a readmission and Y = 0 implies no readmission. (Y|X) follows a Bernoulli distribution with (Y = 1|X) occurring with unknown probability P, and (Y = 0|X) occurring with unknown probability (1-P).
- The predicted value for the response variable must be either 0 or 1, according to the logistic distribution function.

The model is an example of a generalized linear model, in which the link function component is the logit function.

The goal is to predict the probability that a patient is readmitted to the hospital within 30 days after discharge based on available characteristics such as age, sex, length of stay during primary admission, diagnoses, source of admission (eg, emergency department, scheduled admission), and number of emergency visits, among others. Logistic regression links the binary outcomes of readmission status with a combination of the linear predictors.

The statistical model of logistic regression may be represented as follows:

$$P = \frac{e^{(\beta + \alpha_1 X_1 + \ldots \alpha_n X_n)}}{1 + e^{(\beta + \alpha_1 X_1 + \ldots \alpha_n X_n)}}$$

Alpha and beta are estimated using maximum likelihood based on iteration methods such as Fisher Scoring and Newton-Raphson methods.

Validation

The logistic regression model was built using 80% of the data set. The remaining 20% of the data set is used for internal validation. Like other classification methodologies, in order to test how accurate the logistic regression created is, the confusion matrix was examined to compare true positive rate (TPR), false negative rate (FNR), positive predicted value, and C statistic. A new cutoff value was altered in order to compromise the trade-off between TPR and FNR, given that the data set is highly imbalanced.

Table 2. Results

Variable	*Coefficient*	*Odds ratio*	*95% Confidence interval*
Intercept	–3.130	0.044	(0.032, 0.059)
Sex Male (vs. Female)	0.079	1.072	(0.885, 1.145)
Race Black (vs. Asian)	0.198	1.219	(0.885, 1.686)
Race Hispanic (vs. Asian)	0.299	1.348	(1.054,1.749)
Race White (vs. Asian)	0.101	1.106	(0.873,1.423)
Race Other (vs. Asian)	–0.410	0.664	(0.409, 1.047)
Admission From ED (vs. No ED Admission)	**0.420**	**1.522**	**(1.403, 1.653)**
DRG Surgical (vs. DRG Medical)	**-0.761**	**0.467**	**(0.429, 0.508)**
DRG Ungroup (vs. DRG Medical)	0.128	1.137	(1.021, 1.263)
LACE Low (vs. LACE High)	**-1.157**	**0.314**	**(0.270, 0.365)**
LACE Moderate (vs. LACE High)	–0.240	0.786	(0.723, 0.855)
Age (at 65)	0.003	1.208	(1.211, 1.211)
CDPS Risk Score	**0.101**	**1.107**	**(1.096, 1.118)**
Length of Stay	0.014	1.014	(1.009, 1.019)
ED Visits in 2010	0.069	1.072	(1.050, 1.093)
ED Visits in 2011	0.093	1.098	(1.073, 1.123)
ED Visits in 2012	0.106	1.112	(1.090, 1.135)
ED Visits in 2013	0.081	1.085	(1.061, 1.108)
ED Visits in 2014	0.075	1.078	(1.057, 1.100)

Bolded variables indicate those that are significant at an α value of .05.

CDPS, Chronic Illness and Disability Payment System; DRG, Diagnosis-Related Group; ED, emergency department; LACE, length of stay, acuity of admission, comorbidity, and emergency department visits in the previous 6 months.

Results

Table 2 indicates the variables with the most significance in predicting readmissions. Significant variables are admissions from the emergency department, a primary admission for a surgical procedure (the coefficient of this variable is negative, implying that the comparator variable, medical admission, is the more risky), a high LACE score (as one would expect) in addition to a CDPS risk score. Thus the model confirms that LACE, while significant, does not capture the full effect of risk because of other non–LACE predictors. The model confirms for hospitals the importance of collecting the additional information at patient admission.

The output of the model is the probability of being readmitted. There are different ways to determine whether or not a patient is likely to be readmitted. One method is to determine a priori a ''cutoff value.'' This cutoff value is a probability such that it represents a threshold value for the likelihood of being readmitted; if the patient is more likely to be readmitted than the cutoff value, the patient will be classified as likely to be readmitted. Table 3 shows the optimal cutoff values for 2 logistic regression models the study team created plus the prespecified threshold in the LACE model. The optimal cutoff values are chosen in such a way that they produce equivalent rates in sensitivity and specificity. Sensitivity is the metric that indicates the model's ability to correctly detect readmissions while specificity indicates the ability to correctly detect non–readmissions.

Both of the logistic models have significantly higher sensitivity values than LACE, which suggests that the study team's models do a better job of finding readmissions. In return, the team reduces the models' predictive power at predicting non–readmissions as the specificity rates in both models are smaller than LACE's. This serves the purpose of imposing a higher penalty on models for making a classification error on the readmission class. In other words, the goal is to have the models focus more attention on readmission cases instead of focusing primarily on non–readmission cases. Overall, AUC values of 0.78 on the general population model and 0.71 on the second model (Medicare population) imply a moderate level of prediction taking into account all possible cutoff values in the (0,1) interval.

Because the data set is imbalanced with about 7% of the population of patients experiencing readmission events, logistic regression yields a bias toward the majority class (non–readmission). A method to adjust for this disadvantage is to manually select the cutoff value based on the model goal. In the present case the optimal cutoff value was chosen to achieve equivalent rates of sensitivity and specificity. Because the purpose is to target and focus on readmission events, cutoff values are selected to produce higher sensitivity and lower specificity. In addition, as with other typical regression methods, the study team presumes the logistic regression meets all the required assumptions.

Table 3 shows statistical results for a specific cutoff value; however, the effectiveness of the model throughout the range of predicted values, as well as the use of the model

Table 3. Model Comparisons

Criterion	*LACE*	*General model*	*Age 65+ and penalty conditions model*
Cutoff Values	HIGH	0.086	0.124
Sensitivity	0.430	0.700	0.660
Specificity	0.880	0.700	0.660
PPV	0.170	0.150	0.210
AUC	N/A	0.780	0.710

AUC, area under the curve; LACE, length of stay, acuity of admission, comorbidity, and emergency department visits in the previous 6 months; PPV, positive predictive value.

for practical case management purposes, can be demonstrated by combining cost with data. Table 4 shows predicted and actual values in the 20% hold-back data for each decile of the All Patient and Medicare populations. For example, the top decile of Medicare patients contains the 666 patients with the highest predicted likelihood of readmission. This decile is predicted to experience 154.4 readmissions based on the model; in reality, the cohort experienced slightly more readmissions (157). This number represents one third of all readmissions, identified within just 10% of the population, implying that the model is reasonably efficient at stratifying patients for case management.

Table 4 applies the final logistic regression model readmission rates based on the 13 independent variables seen in Table 1 to generate expected readmissions by decile. (See Supplementary Data for the complete model.) As Table 4 shows, the models are able to predict with reasonable accuracy the risk stratum for each patient. This analysis is useful for operational purposes, as will be discussed in the next section.

Practical application

The final model combines variables such as age, risk score, and admission source (eg, emergency department, planned). All variables are either present on admission or can be calculated by an algorithm from admitting data (risk score), making the model relatively straightforward to operationalize in a modern electronic health record (EHR) system.

One of the purposes of a readmission predictive model is to identify patients who require more intense intervention to prevent a readmission. The analysis in Table 4 is helpful in developing an ''opportunity'' approach to intervention planning, as discussed in Duncan.[12]

Assume that a program is to be designed to address the highest-risk decile of Medicare patients. In Table 4, the number of patients in this decile is 666, but this number represents 2% of all Medicare patients admitted over the 5-year period of the study, implying that annual Medicare admissions are approximately 666 for the top 10% of all Medicare patients. The further assumption is that all 666 patients are assigned to nurse case managers, and that the case manager follows the patient for 10 days following discharge. The average Medicare length of stay is 5.5 days, so in total, patients are managed for 15.5 days, or 10,323 total days of care. Assuming a nurse caseload of 50 patients and a 200-day work year, 1 full-time equivalent nurse could handle the highest risk decile in the course of the year. Further, assuming that the cost of a nurse with a full caseload is $100,000 annually, management of the top decile of patients could be achieved at a cost of approximately $150 per patient, or $100,000 in total.

The potential savings from the intervention are more complicated to estimate. Table 4 shows that within the top decile of Medicare patients, 157 readmissions occurred. Assuming that the intervention successfully avoids 15% of these readmissions and that Medicare would have reimbursed $10,500 per readmission,[13] Medicare reimbursement is reduced by $0.15 \times 157 \times \$10{,}500$, or $247,275. However, the loss to the hospital is not full Medicare reimbursement but only the margin (reimbursement minus cost). Assuming a 10% margin, the hospital loses $24,728 in unreimbursed margin, in addition to program costs of $100,000.

Offsetting the hospital's program costs and revenue and margin losses, however, are reduced CMS penalties. The size of the reduced penalty varies by hospital and depends on its readmission rate, relative to the comparable national readmission rate. The most recent year for which actual penalty results are available (2017) shows an average penalty of 0.74% of total Medicare reimbursement (among hospitals incurring a penalty).[4] Assuming that the hospital has 6660 Medicare admissions at an average reimbursement of $10,500 per admission, total Medicare reimbursement is equal to $69,930,000 and the penalty is $517,500. Therefore, although the hospital incurs costs for the program and loses reimbursement from avoided readmissions, assuming that the hospital experiences a penalty at the average national level, overall the hospital would be significantly better off implementing this program because of reduced penalties.

It is possible that expanding the program to a wider number of patients also may produce positive financial

Table 4. Prediction Breakdown by Decile for All Patients and Medicare Patient Models

	ALL PATIENTS				*MEDICARE PATIENTS*			
Decile (Risk group)	*Number in decile*	*Mean prediction within decile*	*Actual readmissions*	*Predicted readmissions*	*Number in decile*	*Mean prediction within decile*	*Actual readmissions*	*Predicted readmissions*
0–10 (*)	1611	0.0092	8.0	14.7	666	0.0092	6.0	6.1
10–20	1611	0.0112	11.0	18.1	666	0.0114	4.0	7.6
20–30	1611	0.0177	20.0	28.5	666	0.0185	15.0	12.3
30–40	1611	0.0248	48.0	39.9	666	0.0255	15.0	17.0
40–50	1611	0.0359	68.0	57.8	666	0.0364	22.0	24.2
50–60	1611	0.0569	94.0	91.7	666	0.0568	48.0	37.8
60–70	1611	0.0822	130.0	132.5	666	0.0821	60.0	54.7
70–80	1611	0.1025	164.0	165.1	666	0.1032	61.0	68.7
80–90	1611	0.1339	230.0	215.7	666	0.1366	98.0	91.0
90–100 (**)	1611	0.2351	360.0	378.7	666	0.2319	157.0	154.4
	16110		1133.0	1142.8	6660		486.0	473.9

* lowest risk group; ** highest risk group.

benefits; however, these benefits will depend on the specific penalty calculation of the hospital.

Discussion

Predictably, the CDPS Risk Score proved to be the most significant variable in the model, given that it is a severity measure. The highest risk patients were those admitted from the emergency department (1.522 times as likely to be readmitted), patients admitted for a medical DRG, and patients with multiple comorbidities (those patients with higher CDPS risk scores). These variables are either present on admission or can be calculated as part of an admission procedure in a modern EHR system, leading to an operationally feasible model.

In addition to simply identifying high-risk cases, the model also is useful for planning purposes. The study team has demonstrated the use in a hypothetical case of program planning for a hospital with 6660 admissions annually, Medicare revenue of $70 million, and a Medicare readmission penalty at the average national level (0.74%). Assuming that the hospital implements a program for the top decile of patients, the hospital can expect total program costs and reduced margin of $124,278, offset by reduced penalties of $517,500, or a nearly 4.15 return on investment.

Limitations

This model is developed for a specific hospital. Although the method can be generalized to other hospitals the specific variables and coefficients are likely to be different. In developing the model the study team makes certain assumptions such as the distribution of the residual terms and independence of the observations. The latter assumption is unlikely to be true because medical data contain multiple observations of the same individuals. The results from logistic models with incorrect independence assumptions could lead to an incorrect interpretation. Further work with more sophisticated methods is therefore required to address these issues. In the meantime, the model performs better than LACE and has clear applicability in a hospital setting.

Conclusion

A model for readmission that incorporates data from a specific hospital is likely to be more accurate than a general model, such as the LACE model. The study team has demonstrated not only that a more specific model, developed from specific hospital data, can be more accurate than a general model, but also that such a model can be extremely helpful in identifying patients for intervention. Further, such a model can provide useful input for planning a financially successful intervention program.

Author Disclosure Statement

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