Identifying Patients at Increased Risk for Unplanned Readmission

Elizabeth H. Bradley, PhD, Olga Yakusheva, PhD,† Leora I. Horwitz, MD,‡§ Heather Sipsma, PhD,‖ and Jason Fletcher, PhD**

Background: Reducing readmissions is a national priority, but many hospitals lack practical tools to identify patients at increased risk of unplanned readmission.

Objective: To estimate the association between a composite measure of patient condition at discharge, the Rothman Index (RI), and unplanned readmission within 30 days of discharge.

Subjects: Adult medical and surgical patients in a major teaching hospital in 2011.

Measures: The RI is a composite measure updated regularly from the electronic medical record based on changes in vital signs, nursing assessments, Braden score, cardiac rhythms, and laboratory test results. We developed 4 categories of RI and tested its association with readmission within 30 days, using logistic regression, adjusted for patient age, sex, insurance status, service assignment (medical or surgical), and primary discharge diagnosis.

Results: Sixteen percent of the sample patients ($N = 2730$) had an unplanned readmission within 30 days of discharge. The risk of readmission for a patient in the highest risk category ($RI < 70$) was >1 in 5 while the risk of readmission for patients in the lowest risk category was about 1 in 10. In multivariable analysis, patients with an $RI < 70$ (the highest risk category) or 70–79 (medium risk category) had 2.65 (95% confidence interval, 1.72–4.07) and 2.40 (95% confidence interval, 1.57–3.67) times higher odds of unplanned readmission, respectively, compared with patients in the lowest risk category.

Conclusion: Clinicians can use the RI to help target hospital programs and supports to patients at highest risk of readmission.

Key Words: quality, readmissions, hospital care

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Reducing unnecessary readmissions has become a national priority.[1,2] Nearly 1 in 5 Medicare beneficiaries who are discharged from the hospital are readmitted within 30 days of the first admission. Hospitals and clinicians are particularly interested in finding ways to reduce readmissions as the Centers for Medicare & Medicaid Services (CMS) has begun penalizing hospitals with higher readmission rates.[1] Although the field is still developing, several studies have examined the effectiveness and costs of various practices to reduce readmissions, with mixed results.[3,4] If they can be anticipated, readmissions may be prevented in ways that both reduce unnecessary health care costs and improve patients' experience.

A variety of approaches have been used to try to reduce readmissions,[5–8] all of which are fairly resource intensive. Because of their resource-intensive nature, the cost effectiveness of these approaches depends on being able to identify and target high-risk patients; however, prospectively identifying patients at elevated risk of readmission has been challenging. Many tools exist[9,10] for early identification but many are disease specific. Furthermore, previous approaches have not included information from nursing assessments in the estimation of risk of readmission and have focused largely on data available at the time of admission, rather than incorporating subsequent updates to patients' clinical condition. To address the problem of readmissions, we need a risk prediction approach that works in real-time across many conditions and does not require intensive manual data collection outside regular clinical care processes. Practical approaches will accurately discriminate among patients who are at significantly elevated risk for readmission and will be easily interpreted by hospital clinicians.

In this study, we sought to examine the association between unplanned readmission within 30 days of discharge

From the *Department of Health Policy and Management, Yale School of Public Health, New Haven, CT; †College of Business, Marquette University, Milwaukee, WI; ‡Section of General Internal Medicine, Department of Medicine, Yale School of Medicine; §Center for Outcomes Research and Evaluation, Yale-New Haven Hospital, New Haven, CT; and ‖College of Nursing, University of Illinois at Chicago, Chicago, IL.

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Reprints: Elizabeth H. Bradley, PhD, Department of Health Policy and Management, Yale School of Public Health, 60 College Street, New Haven, CT 06520. E-mail: elizabeth.bradley@yale.edu.

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and a composite measure of the patient's condition, the Rothman Index (RI), which accounted for nursing assessment data and was automatically generated from the hospital's electronic medical record (EMR). We hypothesized that poor patient condition on the day of discharge as well as worsening condition in the last 48 hours of the hospitalization would be significantly associated with unplanned 30-day readmission. Findings from this study can inform practical efforts to reduce readmissions by identifying patients that might be targeted for interventions to mitigate risks of readmission.

METHODS

RI

Our main objective was to evaluate the RI as a tool for identifying individual patients who may be at elevated risk of readmission. RI[11–13] is calculated and updated multiple times on a daily basis, using data from the hospital EMR and novel, privately developed software adopted by the study site and clinically validated among diverse patient populations and with multiple hospitals. The RI ranged from −6 to 99, with lower scores indicating poorer condition. The RI is computed from 26 medical measures including vital signs (temperature, blood pressure, heart, blood oxygen saturation, and respiratory rate), nursing assessments (cardiac, respiratory, gastrointestinal, genitourinary, neurological, skin and tissue, safety and fall risk, peripheral vascular, food and nutrition, psychosocial, musculoskeletal), Braden Scale[14] (a score used to assess the likelihood of skin breakdown), the most recent cardiac rhythm entered in the EMR (eg, asystole, sinus rhythm, sinus bradycardia, sinus tachycardia, atrial fibrillation, atrial flutter, heart block, junctional rhythm, paced, ventricular fibrillation, and ventricular tachycardia), and results of laboratory tests (serum creatinine, blood urea nitrogen, chloride, sodium, potassium, hemoglobin, white blood cell count). See the Technical Appendix (Supplemental Digital Content, http://links.lww.com/MLR/A529) for a detailed, technical description of how the RI is calculated. At the time when the study was conducted, the RI was not visible to physicians and therefore could not influence admitting, observation, or discharge decisions.

Procedure

To assess the ability of the RI to identify individual patients at elevated risk of 30-day readmission, we examined data on all adult medical or surgical discharges from a 966-bed, teaching hospital during a 5-month period in 2011. We collected data on readmissions to the same hospital for these patients within 30 days of discharge and used multivariable logistic regression to determine the statistical association between patients' RI and their likelihood of readmission within 30 days. Using a derivation dataset, which was randomly generated as half of the full dataset, we examined the frequency of readmission for each RI decile. On the basis of the pattern that emerged, we determined 4 categories of risk that fit the data best and were deemed potentially useful in clinical practice. We then tested these cut-points in the other half of the full dataset, also called the validation dataset, to ensure that the cut-points could be extrapolated for clinical utility in a second dataset; this process has been used by researchers in other studies in the field.[15–18]

Sample

We obtained clinical data from the hospital's EMR (Sunrise Clinical Manager; Allscripts, Chicago, IL) and patient activity database for all adult discharges for which the attending physician was assigned to the medicine or surgery service ($n = 12,844$). We excluded encounters that were readmissions within 30 days of a previous discharge ($n = 2574$), yielding a total of 10,270 discharges. We then excluded patients who were admitted for observation only ($n = 501$), patients with length of stay of <48 hours ($n = 3243$), and patients who died during the hospital stay ($n = 189$), yielding a sample of 6337 eligible inpatient discharges. From this sample, 535 additional patients were eliminated because of missing clinical data, for a sample of 5802 patients, or 92% of all eligible inpatient discharges. The 535 patients with missing data did not differ significantly ($P > 0.50$) from the 5802 patients with complete data in terms of sex or length of stay, although they were younger ($P = 0.02$) and more likely to have private insurance than Medicare ($P < 0.001$). Having RI missing was not associated with 30-day readmission ($P = 0.62$). We excluded from the analysis the 291 patients whose health condition at discharge made up the lowest 5% based on the measure of patient condition ($RI < 42$) to avoid competing risk of mortality concerns. This resulted in an analytic sample of 5511 inpatient discharges.

Measures

Outcome

Our outcome was a binary variable indicating whether or not the patient was readmitted for inpatient care within 30 days of previous discharge. Because we focused on unplanned readmissions, we excluded planned readmissions using the procedure applied by the CMS.[19] Hence, readmissions for specific types of care (eg, rehabilitation, maintenance chemotherapy) and nonacute readmissions for a scheduled procedure were not considered unplanned readmissions, consistent with the approach used by CMS. Although we could not account for readmissions to another hospital, data provided to Yale-New Haven Hospital by CMS[20] indicate that 85% of readmissions of Medicare fee-for-service patients during 2011, the study period, occurred back to Yale-New Haven Hospital.

Independent Variables

In addition to the RI, we gathered data on the patient's sex, age, and primary payer from the EMR classified as: (1) Medicaid including managed Medicaid; (2) Medicare including managed Medicare; (3) Blue Cross or commercial including managed care commercial; and (4) "other," which included self-pay, grant funded, and other insurance. We ascertained the service (medical vs. surgical) based on attending physician, and the patient's primary discharge diagnosis based on the diagnosis groups as defined by the

Agency for Healthcare Research and Quality Clinical Classification Software.[21]

Data Analysis

Using a statistical software, we generated a random sample of approximately half the discharges (N = 2781) and used it as the derivation set to explore the categorization of our primary independent variable, patient condition. We used the remaining discharges (N = 2730) as the validation set to conduct the analysis. The derivation and validation samples were not statistically different in any of the variables assessed with the exception of patient condition, measured by the RI described below, at admission, which was 1 point higher in the derivation sample (72.6 vs. 71.6, $P = 0.04$). A detailed comparison table is included in Appendix Table A, http://links.lww.com/MLR/A529. We also repeated the analysis for subgroups by age, Medicare status, service assignment (medical vs. surgical), and primary discharge diagnosis (of acute myocardial infarction, heart failure, and pneumonia).

We used the derivation dataset to determine cut-points based on the risk of readmission across the range of RI values at discharge. We ranked discharges in the derivation dataset according to their discharge RI and divided them into 10 equal size groups based on deciles. We combined the decile groups that did not differ significantly ($P > 0.10$) in observed unplanned readmission rates into risk categories and rounded the cut-off values for ease of interpretation in clinical practice. This analysis using the derivation dataset suggested the existence of 4 categories including high risk (RI < 70), medium risk (RI = 70–79), low risk (RI = 80–89), and lowest risk (RI ≥ 90).

We modeled the likelihood of readmission as a function of RI using the validation sample (N = 2730) and both unadjusted analysis and multivariable logistic regression analysis. Our final multivariable regression model included covariates hypothesized, based on previous literature,[22–25] to be associated with readmission to determine the independent association between the RI at discharge and risk of readmission. We assessed the Variance Inflation Factor, which evaluates the presence of collinearity,[26] and it was 1.52 and 8.22 for the unadjusted and adjusted models, respectively, suggesting no substantial concern of multicollinearity. We adjusted SEs to account for clustering[27] for patients who had additional admissions but not within 30 days of discharge, using the Huber-White variance estimator.

We reported a C-statistic as well as the sensitivity, specificity, positive predictive value, and negative predictive value for each of 4 RI cut-points to measure the ability of the RI categories to discriminate between discharges that were followed by an unplanned readmission within 30 days of discharge and those that were not. We compared the observed and predicted readmission rates and calculated the 95% confidence interval for the observed rate using exact methods[28] for the deciles of discharge RI groups. We examined the calibration of our model using the Hosmer-Lemeshow goodness-of-fit test.[29] We also examined RI as a continuous variable, but the categorical variable explained more of the variance in readmission, and we believed it to be more clinically useful.

To test our hypothesis about changes in RI and readmission, we calculated changes in RI category in the last 48 hours as a 3-level variable indicating no change in RI category, a change in RI category indicating poorer patient condition, or a change in RI category indicating improved patient condition. All analyses were conducted with both SAS 9.3 (Carey, NC) and STATA 11 (College Station, TX). All research procedures were reviewed and approved by the Institutional Review Board at the Yale School of Medicine.

RESULTS

Characteristics of the Sample

The mean age of the patients in the validation sample (N = 2730) was 60 years, with two thirds medical patients and one third surgical patients (Table 1). The mean RI score at discharge was 77, with 28% having a score <70, 23% scoring 70–79, 31% scoring 80–89, and 19% scoring ≥ 90. The RI decreases with age (mean RI: 83 for those 18–45 y, 80 for those 45–65 y, and 72 for those 65 y and older). Mean RI for patients with Medicaid was 81, with Blue Cross or commercial insurance was 83, with Medicare was 73, and other insurance or self-pay was 82. The category of patient condition worsened in the last 48 hours for 10% of the discharges, did not change for 59% of the discharges, and improved in approximately 31% of discharges.

Unplanned Readmission and Patient Condition at Discharge

The relationship between RI decile and readmission is shown in Figure 1, which reflects the full sample (N = 5511). Overall, 16% of patients had an unplanned readmission within 30 days of discharge, and this was significantly more common for medical compared with surgical patients (18% and 14%, respectively, $P = 0.009$). Patient condition at the time of discharge varied substantially and was strongly related to readmission, with 21% of patients in the highest risk category compared with 10% of patients in the lowest risk category being readmitted within 30 days of discharge (Table 1). Patient age, sex, and insurance type were not associated with readmission.

In the multivariable model adjusted for age, sex, insurance type, medical versus surgical service, and discharge diagnosis, lower RI scores at discharge remained strongly associated with increased odds of readmission (Table 2). Patients with a RI < 70 had 2.65 [95% confidence interval (CI), 1.72–4.07] times higher odds of readmission than those with RI scores of ≥ 90. Patients with RI scores of 70–79 had 2.40 (95% CI, 1.57–3.67) times higher odds of readmission than those with RI scores of ≥ 90. The overall test statistic for the RI is highly significant ($\chi^2 = 26.87$, $P < 0.001$).

The multivariable model was moderately discriminative (C-statistic = 0.73) and was well calibrated (Hosmer-Lemeshow goodness-of-fit statistic = 1574.96, $P = 0.68$). The predicted unplanned readmission rate was within the 95% CIs of the observed rates for all RI groups in the validation

TABLE 1. Characteristics of Patient Sample and Unadjusted Associations With Unplanned 30-Day Readmission (N = 2730)

	N (%)	Readmission (%)	Unadjusted *P**
Age (y)			0.958
18–44	563 (20.6)	93 (16.5)	
45–64	1023 (37.5)	166 (16.2)	
≥ 65	1144 (41.9)	191 (16.7)	
Mean (SD)	60.0 (18.56)	60.1 (18.70)	0.919
Sex			0.515
Male	1373 (50.3)	220 (16.0)	
Female	1357 (49.7)	230 (17.0)	
Insurance type†			0.190
Medicare	1348 (49.4)	241 (17.9)	
Medicaid	579 (21.2)	94 (16.2)	
Blue Cross/commercial	748 (27.4)	108 (14.4)	
Other/uninsured	55 (2.0)	7 (12.7)	
Service type‡			0.009
Medical	1846 (67.6)	328 (17.8)	
Surgical	884 (32.4)	122 (13.8)	
Rothman Index at discharge			< 0.001
Highest risk (< 70)	751 (27.5)	161 (21.4)	
Medium risk (70–79)	625 (22.9)	127 (20.3)	
Low risk (80–89)	846 (31.0)	111 (13.1)	
Lowest risk (≥ 90)	508 (18.6)	51 (10.0)	
Mean Rothman Index (SD)	77.3 (13.34)	73.8 (12.98)	< 0.001
Change in Rothman Index in last 48 h			0.527
Worsening	281 (10.3)	44 (15.7)	
No change	1609 (58.9)	276 (17.2)	
Improving	840 (30.8)	130 (15.5)	

**P*-values derived from χ^2 tests and independent *t* tests.
†Primary insurance only.
‡On the basis of the attending MD's department designation.

TABLE 2. Logistic Regression Models Examining Associations With Unplanned Readmission (N = 2730)

	Unadjusted OR (95% CI)	Adjusted† OR (95% CI)
Age (y)		
18–44	0.99 (0.75–1.29)	1.26 (0.85–1.85)
45–64	0.97 (0.77–1.21)	1.20 (0.87–1.64)
≥ 65	Reference	Reference
Sex		
Male	Reference	Reference
Female	1.07 (0.87–1.31)	1.09 (0.87–1.37)
Insurance type		
Medicare	1.49 (0.67–3.35)	1.51 (0.57–4.04)
Medicaid	1.33 (0.58–3.04)	1.36 (0.51–3.62)
Blue Cross/commercial	1.16 (0.51–2.63)	1.52 (0.58–4.03)
Other/uninsured	Reference	Reference
Service type		
Medical	1.35 (1.08–1.69)**	1.26 (0.88–1.82)
Surgical	Reference	Reference
Rothman index at discharge‡		
Highest risk (< 70)	2.45 (1.74–3.44)**§	2.65 (1.72–4.07)**§
Medium risk (70–79)	2.29 (1.61–3.25)**§	2.40 (1.57–3.67)**§
Low risk (80–89)	1.35 (0.95–1.94)	1.43 (0.95–2.14)
Lowest risk (≥ 90)	Reference	Reference

***P* < 0.01.
†Adjusted for covariates shown and discharge diagnosis.
‡The overall χ^2 statistic for the Rothman Index at discharge was 26.87, $P < 0.001$.
§Odds of readmission significantly different from odds of readmission for "80–89" category.
CI indicates confidence interval; OR, odds ratio.

cohort (Fig. 2). The C-statistic of the final model including a comprehensive set of diagnostic categories but excluding the RI was significantly worse when the RI was excluded (0.68 vs. 0.73, $P < 0.01$). In addition, the inclusion of RI to the full adjusted model significantly improves the model's fit (change in $-2\log L = 32.8$, 3 degrees of freedom; $P < 0.01$). The sensitivity, specificity, positive predictive value, and negative predictive value are shown in Table 3 for cut-points equal to 70, 80, and 90.

We did not find a significant association between the odds of readmission and the change in the RI score in the 48

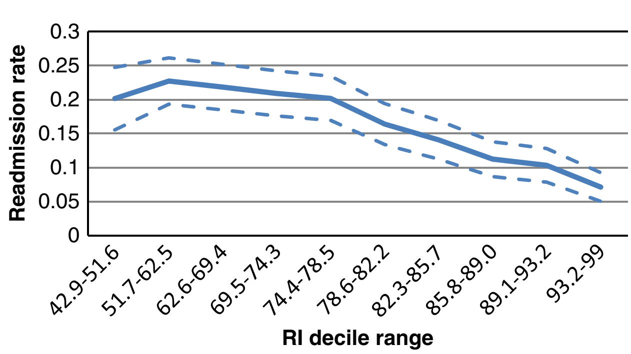

FIGURE 1. Observed unplanned readmission rate by Rothman Index (RI) decile in full sample (N = 5511). The solid line represents the observed readmission rate for each RI decile, and the dotted lines indicate the corresponding 95% confidence intervals for each decile. the *x*-axis shows the observed range of RI for each decile.

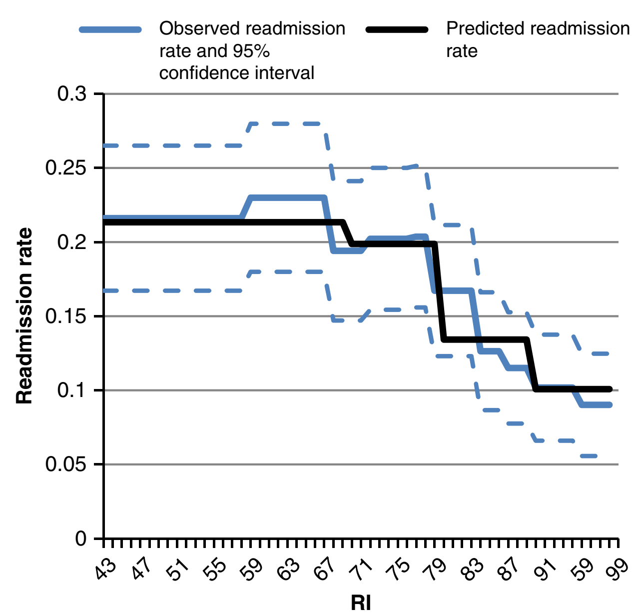

FIGURE 2. Observed and predicted unplanned readmission rates using Rothman Index (RI) in 4 categories, using validation dataset (N = 2730). Observed line is for RI deciles with confidence intervals for each decile; predicted line is for RI measured with 4 categories of risk. The *x*-axis shows the observed full range of RI.

TABLE 3. Sensitivity and Specificity of RI for Different Cut-Points*

	RI < 90	RI < 80	RI < 70
Sensitivity	0.89	0.64	0.36
Specificity	0.20	0.52	0.74
Positive predictive value	0.18	0.21	0.21
Negative predictive value	0.90	0.88	0.85

*Sensitivity is interpreted as the probability of accurately identifying patients who are readmitted, and specificity as the probability of accurately identifying patients who are not readmitted. Positive predictive value is interpreted as the probability of accurately identifying patients as at risk for readmission and negative predictive values as the probability of accurately identifying patients at risk for readmission.

RI indicates Rothman Index.

hours preceding discharge in either unadjusted or multivariable analysis. Because its removal did not significantly change the fit of the logistic regression model, the variable indicating the RI in the last 48 hours was dropped from the final model. In addition, we did not find significant differences in the associations of RI categories at discharge and readmission for subgroups according to age, sex, insurance type, service assignment, and primary discharge diagnosis. We examined the RI effects by relevant subgroups, including Medicare beneficiaries only, to avoid problems identified by researchers in interpreting interaction effects in nonlinear models.[30] The RI effects were similar across different subgroups, and interaction terms were nonsignificant ($P>0.10$).

Specifically, among medical patients, the odds of readmission for the medium, high, and highest risk groups, compared with the low-risk group, were 1.50 ($P=0.12$), 2.41 ($P=<0.01$), and 2.78 ($P<0.01$), respectively. Among surgical patients, the odds of readmission for the medium, high, and highest risk groups, compared with the low-risk group, were 1.72 ($P=0.10$), 2.74 ($P<0.01$), 2.74 ($P<0.01$), respectively. The C-statistics for medical and surgical patients were 0.75 and 0.78, respectively. Among Medicare beneficiaries, the odds of readmission for the medium, high, and highest risk group, compared with the low-risk group, were 1.89 ($P=0.11$), 2.43 ($P<0.03$), 3.34 ($P<0.01$), respectively; the C-statistic is 0.75. Last, we repeated our analyses without excluding patients with less than 48 hour length of stays, and the results were largely unchanged.

DISCUSSION

We found that a composite measure of patient condition, the RI, using clinical data available in the EMR was strongly associated with unplanned readmission within 30 days of discharge. The association was strong and robust across diagnoses and specialties. Furthermore, because the RI[11,12] is recalculated automatically as clinical data (including nursing assessments) are entered into the EMR, the measure can be monitored easily, providing a potentially powerful tool for identifying patients at increased risk of readmission. Importantly, the clinical data added substantially to a model including variables from administrative data (age, sex, insurance type, service, and diagnosis), but was still automatically extracted and required no manual input.

Incorporating the RI into hospitals' EMRs is very manageable and has been accomplished at several institutions using different EMRs, including AllScripts, Epic, Cerner, and McKesson EMRs. As EMRs become more widespread and the availability of clinical data increases, indices derived from EMR-based data could have large-scale impact by helping clinicians anticipate and potentially prevent unplanned readmissions more effectively. Practically speaking, physicians considering whether to discharge a patient can have access to the latest updated values of RI from the EMR system. According to our findings, the risk of readmission for a patient in the highest risk category ($RI<70$) is >1 in 5, whereas the risk of readmission for patients in the lowest risk category is about 1 in 10. Our findings support possible inclusion of the RI in hospital discharge guidelines, with higher RI scores suggesting routine processes, whereas lower RI scores, particularly those <70, possibly triggering additional team communication and evaluation about the patient's appropriateness for discharge. In such cases, added support services might be engaged to ensure a smooth transition to home and postdischarge care.

Our hypothesis about the changes in the patient condition in the last 48 hours before discharge being associated with unplanned readmission was not upheld in the data. The 10% of patients whose condition worsened enough to move between risk categories in the last 48 hours were no more likely to be readmitted within 30 days than the patients whose risk category improved or stayed the same in the 48 hours before discharge. We also tested whether the change in the category of RI between admission and discharge was significantly associated with readmission, and it was not ($P=0.22$); however, these hypotheses would be useful to test again in additional samples and at other institutions.

Our hypothesis about the patient condition on the day of discharge was upheld, even after adjusting for diagnosis, service, age, sex, and insurance type. Although other risk assessment methods exist,[9] many are for specific disease groups, and none is updated on a real-time basis or is based on the patient's condition at discharge. As patient condition can change rapidly during hospitalization, real-time updates allow decision making to be tailored to patient risk up to the day of discharge.

Our findings should be interpreted in light of several limitations. First, the study was accomplished at only 1 hospital, and future studies would be helpful to corroborate these findings in other hospitals and settings as use of observation beds or other admitting practices may differ. Second, the sample size was relatively modest, possibly limiting the power to detect significant interaction effects, which might be nonetheless apparent in larger samples. Third, we lacked data on readmissions to other hospitals, which we estimate based on CMS data accounted for 15% of all readmissions. This omission could influence the C-statistic, although we cannot predict the direction. We have no reason to think the effect would be different for these patients; however, we could not test this empirically. Fourth, we did not have the data to directly compare our findings with other prediction models, although the C-statistic and other performance indicators suggest the RI has similar performance as existing risk prediction models.[8,9] Finally, we were unable to adjust for other important factors, including nonclinical factors, in readmission, such as socioeconomic and educational status of the patient, availability of family at home, social support more generally, and access to a primary care physician postdischarge. These factors may explain more of the odds of readmission; however, these data were not available in the EMR data we used.

In conclusion, we have documented a strong association between a measure of patient condition, the RI score, at the time of discharge and unplanned readmission within 30 days. The RI or similar indices can be embedded in the EMR and recalculated multiple times per day, thus providing a dynamic tool for assessing patient's condition. In addition, the meaningful cutpoints in the index can provide a practical way for clinicians to identify patients who might be at higher risk for unplanned readmission and intervene specifically for these patients to try to avert unplanned readmission. Automated integration of clinical data, including nursing data, into readmission risk prediction tools may be helpful in identifying patients at higher risks of unplanned readmissions.

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