ORIGINAL ARTICLE

Rothman Index as a Predictor of 30-Day Hospital Readmission

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Introduction: The Centers for Medicare and Medicaid services financially penalize hospitals for elevated 30-day readmission rates. Identifying patients at high risk for short-term readmission would allow health systems to strategically allocate resources to this vulnerable population. The objective of this study was to determine whether there was a difference in mean Rothman Index value for patients readmitted to the hospital within 30 days of index stay versus patients not readmitted in order to evaluate the Rothman Index's utility as a predictive tool.

Materials and Methods: Data from 100 subjects from a single academic medical center, with a balanced number of readmit (n=50, mean age 68.9 years, 54% female) and non-readmits (n=50, 46% female, mean age 70.9 years), was collected.

Results: Non-readmits demonstrated significantly higher mean Rothman Index values (70.94 ± 1.3) compared to patients readmitted within 30 days (mean Rothman Index of 61.68 ± 1.6) at (P< .001; 95% CI, 5.10 to 13.41). Age (95% CI, -0.052 to 0.006; P= .12), gender (95% CI, -0.949 to 0.948; P= .99) and primary discharge diagnosis from index stay (P= 0.31) were not predictive of readmission; only the Rothman Index was (95% CI, -0.136 to -0.039; P<.001).The coefficient of the Rothman Index was -0.088, indicating that for each 1 point increase in Rothman Index, a patient's odds of readmission within 30 days declined by 8.8% (95% CI, -0.136 to -0.039; P< .001).

Conclusions: The Rothman Index can be utilized as a predictive tool to identify patients at high risk of unplanned 30-day hospital readmission, thereby allowing health systems to strategically allocate outside hospital resources.

INTRODUCTION

Hospital readmission rates within 30 days of discharge from initial stay are reported in 1 out of every 5 Medicare beneficiaries in the United States (1). It is estimated that 90% of these readmissions are unplanned.[2] In addition to increasing patient morbidity and mortality, this poses an estimated annual cost of $12-17.4 billion dollars to our nation due to penalties imposed by federal organizations (2). The consequences of unplanned hospital readmission are severe enough to warrant national policy intervention. Under the

Affordable Care Act, Congress implemented the Hospital Readmission Reduction Program in 2010, which allows the Center for Medicare and Medicaid Services to financially penalize hospitals with elevated readmission rates of Medicare patients (3).

Less than ideal patient outcomes leading to short-term readmission are commonly attributed to the following factors: lack of a reliable clinical indicator to identify patients at high risk for readmission, poor discharge instructions and patient education on self-management, and untimely or non-existent follow-up with primary care physicians (4). Thus, implementation of a clinical indicator capable of alerting physicians of patients who are at high risk for short-term readmission would potentially reduce post-discharge mortality as well as reduce annual health care costs. There are many predictive models to assess hospital readmission risk for physicians and care coordinators to utilize - some available online for no-cost, such as the LACE score, and others embedded into their respective EMRs.

The Rothman Index (RI), a commercially developed software program (PeraHealth), utilizes an algorithm to compute a numerical score ranging from -6 to 100 that is reflective of patient general health status. A score of 100 is considered to be reflective of optimal health, while lower scores are associated with poorer clinical outcomes (5). Although the manufacturer does not reveal all of the inputs or the weighting of the individual inputs - vital signs, routine blood laboratory tests, nursing assessment scores, cardiac rhythms, and a Braden Scale score are listed as components (**Table 1**) (6). The Rothman Index is recalculated automatically whenever new data is entered into the EMR, thereby tracking changes in patient condition, which are displayed on a color-coded graph that facilitates trend interpretation (5).

Table 1: Inputs of Rothman Index. This table displays the components incorporated into the composite Rothman Index score – the algorithm is proprietary, thus specific details of how each category is scored is unknown.

Vital Signs
Blood Test Results
Nursing Assessment Scores
Cardiac Rhythm Interpretation
Braden Scale Score

The Rothman Index has been proposed as a useful tool for identifying patients with impending clinical deterioration and for flagging patients with an elevated likelihood of readmission. A 2013 publication reported that investigators found the Rothman Index to be strongly associated with unplanned 30-day hospital readmission, which held true across various diagnoses and medical specialties (6). A study conducted at the Yale University School of Medicine found a decreasing Rothman Index score to be strongly associated with readmission to the surgical intensive care unit within 48 hours (5). A separate study found the Rothman Index to be reflective of changing physiological state indicative of postoperative complications in a cohort of patients who had undergone colorectal procedures (7).

Despite these encouraging results, the Rothman Index has yet to be extensively studied and evaluated. One objective of this study is to expand the Rothman Index knowledge base and its potential clinical functions. Our research hypothesis states lower Rothman Index values will be observed in patients readmitted within 30 days of index hospital stay compared to patients not readmitted within this time interval.

MATERIALS & METHODS

Data Collection

A list of patients discharged from the Penn State Milton S. Hershey Medical Center in Hershey, Pennsylvania was obtained from an Institutional Review Board approved eighteen month period (Chart Review and/or Analysis of Existing Restricted Data Set Study, # 00006019, January 2016-June 2017). A sample size calculation at a $P < .05$ and power = 0.8 determined that a 100 patient sample size was needed to detect a 40% reduction in readmissions. As such, data from 100 patients, hospitalized under the care of the Family and Community Medicine or the Internal Medicine services, was analyzed for this study. The study protocol incorporated a balanced number of readmit (n=50) and non-readmit patients (n=50). Subjects were included regardless of whether they were under "observation" or "admission" status.

Date of initial discharge, the service managing the patient's care, Rothman Index value at the time of discharge of index hospital stay, primary medical diagnosis, and demographic information were accessed from the EMR. Patient charts were audited for dates of hospital readmission. This study did not limit patient inclusion by age or gender. Gender data was recorded by patient self-identification. Race/ethnicity was not available for data collection. Patients who did not have a primary care physician in the Penn State Health network were excluded. Patients with planned 30-day hospital readmissions, and those discharged to hospice care following index hospital stay were also excluded.

Data Analysis

The data set was grouped into six diagnostic categories according to the primary medical diagnosis that appeared on each study patient's index hospital discharge summary. The following legend was used to group the disease etiologies: 1 = infectious disease, 2 = gastrointestinal, 3 = pulmonary, 4 = renal, 5 = cardiovascular, 6 = other. The "other" category included multiple disease etiologies such as hematology, musculoskeletal, endocrine, and alcohol and drug toxicity, with individual sample sizes too small to be statistically significant when analyzed alone.

Statistical analysis of the data was accomplished by use of the Minitab software program (Version 18, Minitab, LLC). Analyses performed on the data included two-sample T-tests, binary logistic regression, and a one-way Analysis of Variance (ANOVA).

RESULTS

Univariate

Of 100 total subjects, 50 readmits (mean age 68.9 years, 54% female) and 50 non-readmits (mean age 70.9 years, 46% female) were analyzed. T-test indicated no significant difference in average age of patients in the readmission vs. non readmission group (95% CI, -4.43 to 9.23; P= .47). Two of the readmits were designated as "observation" status during their index stay, while 8 of the non-readmits held this designation. T-test yielded a p-value of 0.05, which approached statistical significance among the groups.

A correlation analysis was also performed on the data examining patient age and Rothman Index value. This analysis yielded a Pearson correlation coefficient of -0.215 and a p-value of .03, which suggests a negative, weak linear correlation between patient age and Rothman Index that is significant.

Average Rothman Index value at the time of discharge of index hospitalization in the readmitted group was 61.68 ± 1.6 and 70.94 ± 1.3 in the non-readmitted group (**Figure 1**). Two-sample T-test revealed P< .001; 95% CI, 5.10 to 13.41. This result supported the initial study hypothesis.

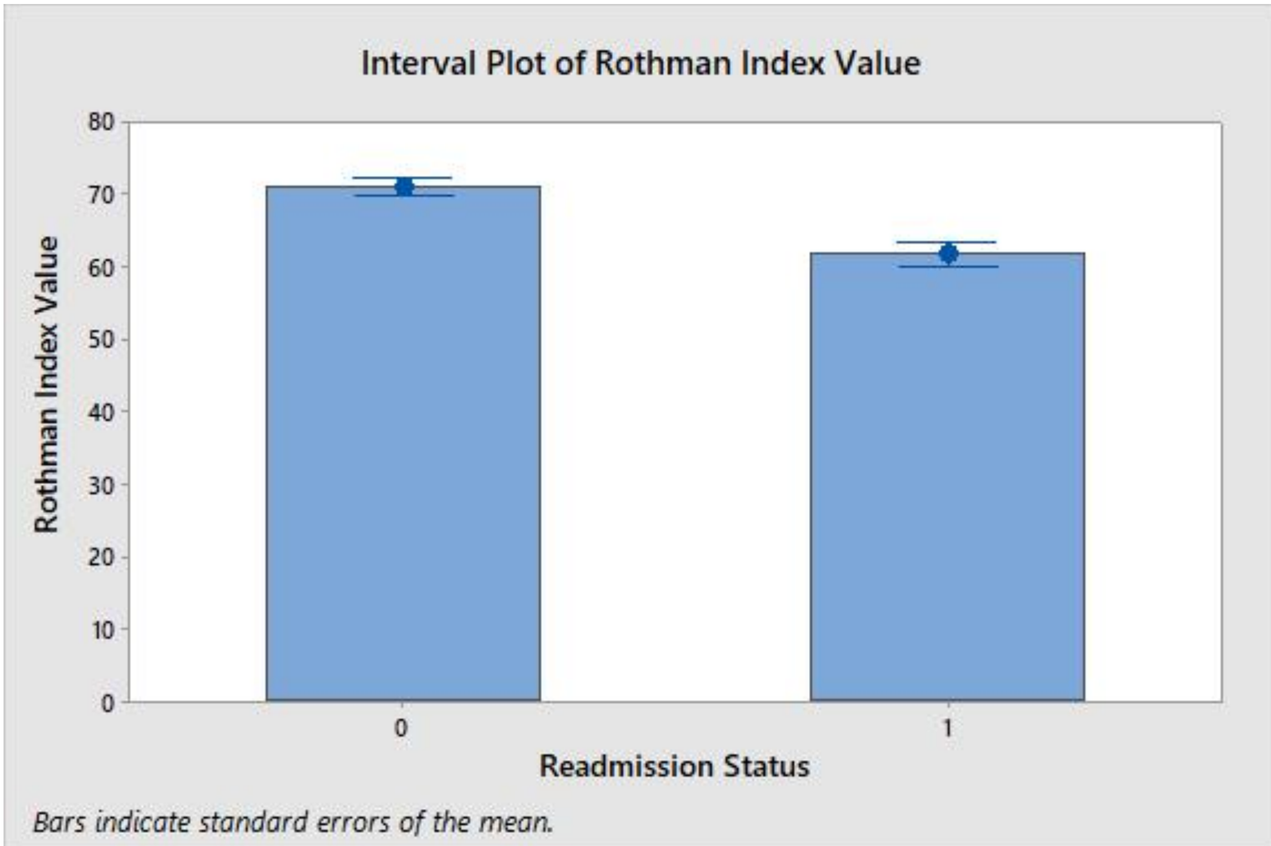

Figure 1. Interval Plot of Rothman Index Value Between Study Groups. This figure displays the interval plot of mean Rothman Index values for each of the study groups where '0' represents patients not readmitted to the hospital within 30 days of index stay and '1' denotes patients readmitted within 30 days of index stay. T-test validates a significant difference between the groups at P < 0.001.

Study groups were examined by gender to determine if patient gender influences the Rothman Index value as it varies with readmission status (**Table 2**). Within the readmits, mean Rothman Index value did not significantly vary by patient gender. The same is true of non-readmits.

The concordance statistic (C-statistic) for the Rothman Index is 0.73, indicating it is a strong discriminator for 30-day hospital readmission.

Table 2. Results of Two-Sample T –Test of the Average Rothman Index Value By Gender Among Readmitted and Non-Readmitted Patients. This table displays the results of a two-sample T-test comparing the average Rothman Index between males and females in the readmission and non-readmission group. 'S.E.M.' is standard error of the mean and '95% CI' is 95% confidence interval.

	Non-Readmitted Males (n=23)	Non-Readmitted Females (n=27)	Readmitted Males (n=27)	Readmitted Females (n=23)
Average Rothman Index	71.3	70.5	63.3	60.3
S.E.M.	1.8	1.9	2.6	2.0
P value	0.76		0.37	
95% CI	(-4.55, 6.41)		(-3.74, 9.65)	

Multivariable

For the binary logistic regression analysis, 'readmission status' represented the dependent variable, and 'Rothman Index value,' 'age,' 'gender,' and 'primary discharge diagnosis category,' represented the independent variables. 'Rothman Index value' and 'age' were used as continuous variables, while 'gender' and 'discharge diagnosis category' were considered to be categorical variables. The 'discharge diagnosis category' was comprised of 6 levels (see methods section for legend).

To assess the fit of the binary logistic regression model, variance inflation factors (VIFs) were derived to examine the degree of multicollinearity in the model given the potentially related nature of the independent variables.[8] All VIFs were less than 2. Additionally, there were no influential observations using Cook's distance as a measure, with all values < 0.25.

The results of the binary logistic regression are listed below (**Table 3**). The multivariable analysis in **Table 3** demonstrates that only Rothman Index value is a statistically significant predictor of hospital readmission status (95% CI, -0.136 to -0.039; P<.001). Patient age (95% CI, -0.052 to 0.006; P= .12), gender (95% CI, -0.949 to 0.948; P= .99), and discharge diagnosis category (P= .31) were not significant predictors of readmission. Confidence intervals pertain to the logistic regression coefficients. In **Table 3**, categorical variables are broken down into 'levels,' where level one is assumed, as this is a comparative analysis. Male gender is assumed as level one; likewise, discharge diagnosis category 1 is assumed as level one.

A review of the statistical data in **Table 3** indicates discharge diagnosis category cannot be used as a significant predictor of 30-day hospital readmission status.

Table 3. Binary Logistic Regression Data of Rothman Index Value, Age, Gender and Discharge Diagnosis Category as Predictors of Readmission Status. This table displays the p-values and confidence intervals for Rothman Index value, age, gender, and discharge diagnosis category as predictors of hospital readmission status. A baseline, or 'assumed' patient would be a male with an assigned discharge diagnosis category of '1.'

			Gender	Discharge Diagnosis Category				
	Rothman Index Value	Age	Female	2	3	4	5	6
P value	< 0.001	0.12	0.99	0.98	0.88	0.15	0.13	0.65
95% CI	(-0.13, -0.03)	(-0.052, 0.01)	(-0.94, 0.94)	(-1.41, 1.38)	(-1.32, 1.53)	(-0.65, 4.06)	(-0.42, 3.32)	(-1.6, 1.0)

The coefficient of the Rothman Index value was -0.088, which denotes the estimated change in the odds for the event in reference, 30-day hospital readmission. For every increase in the Rothman Index by a value of 1, the odds of a patient being readmitted to the hospital within 30 days of index stay decreases by 8.8 percent (95% CI, -0.136 to -0.039; P< .001).

Figure 2 indicates the probability of being readmitted to the hospital within 30 days decreases as the Rothman Index value increases. When the Rothman Index value is 40 or less, the probability of being readmitted within 30 days exceeds 85%. When Rothman Index values are high (80 or greater) the probability of readmission approaches 10%.

A one-way analysis of variance (ANOVA) was performed on the data set to determine whether the mean readmission rate was different for groups of patients based upon their unique discharge diagnosis categories. At a significance level of $\alpha = 0.05$, the mean 30-day hospital readmission rate was not significantly different among the six discharge diagnosis categories as determined by a one-way ANOVA, $F(5, 94) = 2.19$, $P = .06$.

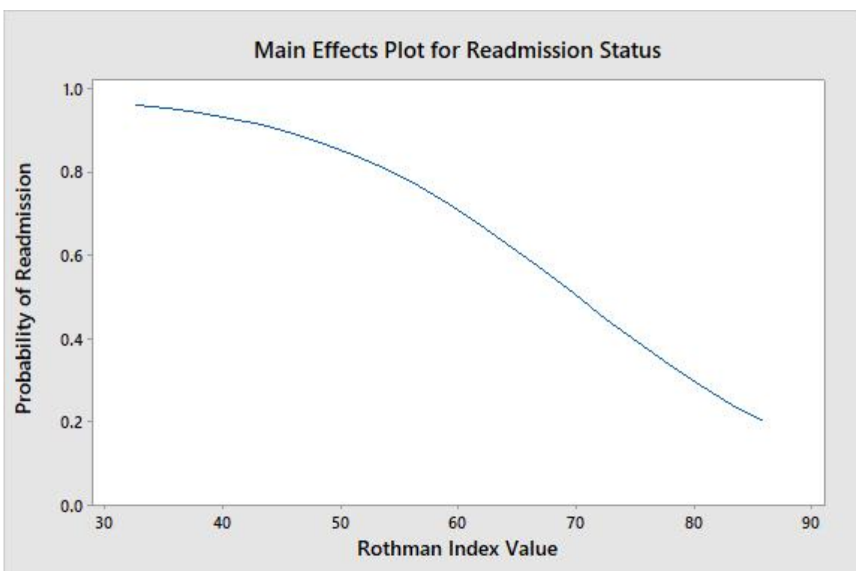

Figure 2. Fitted Line Plot of Binary Logistic Regression Analysis of Readmission Status by Rothman Index value. This figure displays the fitted line plot of the continuous variable 'Rothman Index Value' as a predictor of the probability of 30-day hospital readmission occurring, denoted by 'Probability of Readmission,' on the y-axis. A value of 1.0 on the y-axis would suggest 100% probability of 30-day readmission.

DISCUSSION

While the Rothman Index was originally designed to identify patients who were at high risk of clinical deterioration, our findings suggest it has value in identifying patients who are at an elevated risk of short-term readmission. When compared to patients who were not readmitted within 30 days of index stay (mean RI of 70.94 ± 1.3), the Rothman Index value at the end of index hospitalization was significantly lower (mean RI of 61.68 ± 1.6) in patients who returned within 30 days. This result also held true when the data were analyzed via binary logistic regression.

Univariate analysis indicated that patient age was not a significant determinant of readmission status, nor was patient age found to be a significant predictor of readmission status. Similarly, both univariate and multivariable analysis results indicated patient gender was not a determinant or predictor of 30-day unplanned hospital readmission status. When patients were divided into six categories based on the primary discharge diagnosis assigned at their index hospital stay, 30-day readmission rates did not significantly vary among these groups.

Upon comparison with the internationally used LACE score, the Rothman Index value has superior predictive capacity. The C-statistic for the LACE score is 0.58, which suggests it is a poor discriminator of 30-day readmission, while that of the Rothman Index is 0.73 (9).

One shortcoming of this analysis was unequal sample sizes in the discharge diagnosis categorical groups. This could explain the observed trend of a higher readmission rate among patients with renal disease compared to other disease etiologies, although this result was ultimately insignificant. Additionally, there were an unequal number of “observation” vs. “full admissions” in each group. The former would favor a less severe condition, and therefore a higher Rothman Index value, which introduces a potential confounding effect. However, it should be noted that the majority of both readmits (48/50) and non-readmits (42/50) were designated as full admissions during index stay.

The patient population was entirely obtained from one academic medical center, thus generalizability remains in question. The inclusion criterion specifying only patients with a primary care physician affiliated with the hospital health network is another potential limitation. By using only patients with a known primary care physician, it is possible the data set selected for patients with multiple chronic medical conditions, who therefore are more likely to have short-term readmission. Conversely, patients with primary care physicians are more likely to have access to outpatient follow-up.

Future research examining the influence of discharge diagnostic categories on Rothman Index and readmission status would benefit by larger, equal sample sizes among categorical groups. Additionally, future study could aim to examine timely follow-up with a primary care physician as a determinant of 30-day unplanned hospital readmission rates.

Binary logistic regression analysis revealed that an increase in Rothman Index value by 1 reduces a patient’s odds of being readmitted to the hospital within 30 days by 8.8%. Future analysis of the data may determine the inflection point at which the Rothman Index value corresponds to a change in readmission status. If a critical inflection value can be determined, this would give further utility for Rothman Index values being used by hospitalists to aid in the decision of determining when a patient is fit to be discharged. Identifying the patients who are at high risk of 30-day readmission is also advantageous to health systems, as resource allocation can be strategically directed towards this high-risk population.

Reducing unplanned 30-day hospital readmission rates could improve patient morbidity and mortality, and also allow for a reduction in the annual $12-17.4 billion dollars that short-term readmission costs the US health care system via Medicare and Medicare financial penalties (2). This value should be balanced with cost of the Rothman Index software, which varies according to the size of the purchasing institution (ie how many beds in the hospital) and the level of software package the institution chooses to purchase (ie the basic Rothman Index score calculator plus or minus a sepsis predictor, etc).

The findings of this study were consistent with those reported by Bradley et al, who found a strong association with Rothman Index value and 30-day unplanned readmission rates (6). The ability to predict the risk of readmission is of value to patients, providers and hospital administrators. Our study adds to the current literature base by reporting the coefficient of the Rothman Index, which indicates for every increase in a patient's Rothman Index score by 1, the odds of 30-day hospital readmission decrease by 8.8%.

Notes

Acknowledgements: I, Karissa Thal, am the corresponding author of this study. I agree to serve as the primary correspondent with the *AJHM* editorial office, to review the edited manuscript, and to serve as the decision maker regarding release of manuscript conclusions to the media, federal agencies, or both. I had full access to all data in the study and take responsibility for the integrity of data and the accuracy of data analysis. I pledge to properly investigate and address all questions pertaining to accuracy or integrity of any part of the work. Upon request by *AJHM* editorial staff, I will provide data upon which the results and conclusions of this manuscript were based. One additional contributor is listed below. She did not receive financial compensation for her contributions.

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