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Rothman Index variability predicts clinical deterioration and rapid response activation

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ABSTRACT

Background: The overall utility of the Rothman Index (RI), a global measure of inpatient acuity, for surgical patients is unclear. We evaluate whether RI variability can predict rapid response team (RRT) activation in surgical patients.
Methods: Surgical patients who underwent RRT activation from 2013 to 2015 were matched to four control cases. RI variability was gauged by maximum minus minimum RI (MMRI) and RI standard deviation (RISD) within a 24-h period before RRT. The primary outcome measured was RRT activation, and our secondary outcome was in-hospital mortality.
Results: Two hundred seventeen (217) patients underwent RRT. RISD (odds ratio, OR, 1.31, 95% confidence interval, CI, 1.23–1.38, $P < 0.001$; area under receiver operating characteristic, AUROC, curve 0.74, 95% CI 0.70–0.77) and MMRI (OR 1.10, 95% CI 1.08–1.12, $P < 0.001$; AUROC 0.76, 95% CI 0.72–0.79) predicted increased likelihood of RRT.
Conclusions: RISD is predictive of RRT.

1. Introduction

The Institute for Healthcare Improvement's call for significant reduction in hospital mortality during the "100,000 Lives Campaign" motivated the rapid, nationwide adoption of rapid response teams (RRT) or medical emergency response systems. The goal of RRT activation is to quickly mobilize a skilled, predetermined team of first responders to address potential clinical deterioration prior to cardiac arrest. Despite significant attention to outcome following RRT activation, its effect on reducing patient cardiac arrest and unexpected patient mortality is mixed.[1–5] Although there has been near universal adoption of RRT, criteria for activation are not well defined, and there is significant site-to-site practice variation in both pediatric and adult hospitals.[6,7]

In order to aid the identification of general ward patients experiencing physiologic decline, several early warning scores have been developed.[8–12] Their promise lies in their potential to highlight patients in need of additional monitoring and deliver increased resources in a timely fashion, prior to decompensation. The downsides of many early warning systems, and physiologic assessment scores in general, are that they are mostly based on expert opinion, can overweigh the importance of vital signs, were developed and validated to predict specific endpoints (cardiac arrest), or apply only in ICU settings (e.g. Sequential Organ Failure Assessment Score). The recent mandate for electronic medical records (EMR) resulted in an abundance of patient data offering great potential to identify patients on the verge of deterioration. One such measure is the Rothman Index.

The Rothman Index (RI) is a gauge of inpatient acuity incorporating twenty-six data points (Table 1) readily accessible from EMR, including vital signs, lab values, cardiac rhythm, and nursing assessments.[13–15] It is a partially heuristic model defined by the excess contribution of each variable to the risk of one-year mortality. In the original model derivation, variables from among ~500 laboratory values and ~6500 EMR flowsheet inputs were considered if they directly reflected current inpatient condition, were regularly collected on all patients, and could be expected to change over the course of an inpatient stay—i.e., the values that would highlight a patient's most up-to-the-minute clinical status. To this end, the model ultimately included the most frequently collected variables with the highest degree of correlation. Laboratory values are treated on a continuous basis, nursing assessments are

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Table 1
Components of the Rothman Index.[15]

Vital Signs[6]	Temperature Diastolic blood pressure Systolic blood pressure Blood oxygen saturation Respiration rate Heart rate
Laboratory tests[7]	Creatinine Sodium Chloride Potassium Blood urea nitrogen (BUN) White blood cell count (WBC) Hemoglobin
Cardiac Rhythm[1]	Choose *one* of: asystole, sinus rhythm, sinus bradycardia, sinus tachycardia, atrial fibrillation, atrial flutter, heart block, junctional rhythm, paced, ventricular fibrillation, ventricular tachycardia
Nursing assessments[12]	Cardiac Respiratory Gastrointestinal Genitourinary Neurological Skin Safety Peripheral Vascular Food/Nutrition Psychosocial Musculoskeletal Braden score

considered on a pass/fail basis, and cardiac rhythms are treated categorically based on each rhythm's contribution to excess mortality. A maximum score of 100 indicates variables consistent with no excess risk, and the score is reduced proportionate to increasing risk. The model was derived from inpatient data at a large regional medical center and validated against separate inpatient data from the same institution and other large teaching institutions.[15]

RI is updated continually throughout the day whenever new patient data is recorded and contributes to RI calculation for up to forty-eight hours after collection. While the excess risk functions for input variables were developed using one-year mortality data, RI itself was not modeled to predict this particular end point. Instead, evidence supports its prediction of other outcomes including discharge disposition, twenty-four hour mortality, and thirty-day readmission.[15,16] It has also been shown to correlate with other physiologic scores (MEWS, APACHE III), while improving accuracy in identifying patients at risk for imminent cardiopulmonary arrest.[15,17] Others report decreased mortality when RI is employed as the continuous monitoring platform of choice.[18] Nevertheless, these studies include internal medicine patients and little is reported on the utility of RI in surgical patients.

There is some evidence to support RI's utility in managing surgical inpatients. RI can stratify patients after colorectal surgery for risk of post-operative complications, including sepsis.[19] RI may also play a role in the management of surgical intensive care unit (SICU) patients, as patients with declining RI at SICU discharge are at increased risk of readmission within forty-eight hours.[20] Less is known about the use of RI in managing surgical floor patients. Specifically, the correlation of RI with surgical floor patient acuity and its ability to predict RRT activation is unknown. This study aims to fill that knowledge gap and identify the degree to which change in RI values over the course of twenty-four hours can forecast RRT activation. Such knowledge may potentially facilitate improved recognition and triage of surgical floor patients at risk for deterioration for transfer to a higher level of care.

2. Methods

2.1. Rothman Index calculation

The Rothman Index (PeraHealth, Charlotte, NC) is a proprietary, third-party algorithm that is fully automated and embedded within existing commercial electronic medical records. Twenty-six variables, twelve of which are nursing assessments, including vital signs and laboratory values are tabulated and continuously updated as new values become available. A composite score is rendered and color bars are graphically displayed to demonstrate a patient's overall physiologic condition.

2.2. RRT activation

Hospital wide RRT activation policy endorses widely accepted trigger criteria (such as deterioration of vital signs, mental status changes, airway compromise) for which providers are expected to activate RRT. Response teams consists of a physician, experienced critical care nurse, and respiratory therapist.[21]

2.3. Patient dataset

Cases consisted of 217 consecutive post-operative patient encounters with RRT activations and at least three consecutive Rothman Index readings over the period from 2013 through 2015. Each case was matched to four different controls from the same hospital floor with at least three Rothman Index readings within the same twenty-four-hour time interval. Case matching in this manner is previously described.[22] Patients were excluded if they had previously experienced RRT activation during that admission or if they did not meet entry criteria. Data was retrospectively retrieved from the electronic medical record database. This study was approved by the Yale Human Investigation Committee and the Yale Human Research Protection Program. Written informed consent was not required for reviewing retrospective de-identified patient data.

2.4. Observations and outcomes

Our primary observation was change in the Rothman Index within a given twenty-four-hour interval. Change in Rothman Index was assessed as Rothman Index standard deviation (RISD) and maximum-minus-minimum Rothman Index (MMRI). Our primary outcome was documented activation of the rapid response team (RRT) code during hospitalization. Our secondary outcome was in-hospital mortality and disposition at discharge (independence or not). Rothman Index was not used to make clinical decisions.

2.5. Statistical methods

Variables were expressed as means with standard deviations, medians with interquartile ranges or percentages, and compared respectively using χ^2 tests, Mann-Whitney rank sum tests, or two-sample T-tests after checking for equal variance and using Welch's approximation for degrees of freedom.[23] Association between change in Rothman Index and outcome (RRT or in-hospital mortality) was assessed using conditional logistic regression with ward as the matched variable. This was done to minimize the effect of nursing and specific ward practice differences. Multivariable analysis was also performed adjusting for possible confounders. Predictive accuracy was assessed using areas under the receiver operating characteristic curve (AUROC). Standard errors were calculated by the DeLong method.[24] Sensitivity and specificity were assessed by 2×2 table analysis after AUROC. P values < 0.05 two-tailed were considered statistically significant. Statistical analyses were performed using STATA 14/IC software package (StataCorp LP, College Station, Texas).

3. Results

Two hundred seventeen (217) cases of rapid response team code activation (RRT) and 868 ward-matched controls were included in this study. Their baseline characteristics are summarized in Table 2. Gender and age differed significantly between cases and controls, and were causally linked to both RRT and the Rothman Index (RI); therefore, they were adjusted for as possible confounders in subsequent analyses. There was no difference in race or payer status.

First, the change in RI as a predictor of RRT was assessed. RI variability was quantified as RI standard deviation (RISD) and maximum-minus-minimum RI (MMRI) over a given 24-h window. RISD and MMRI were both associated with RRT activation after adjusting for gender and age ($P < 0.05$, Table 3). Agreement between RRT and RISD or MMRI was quantified using areas under the receiver operating characteristic curve (AUROC). RISD predicted RRT with AUROC of 0.74, 95% confidence interval (CI) (0.70, 0.77). Likewise, MMRI predicted RRT with AUROC of 0.76, 95% CI (0.72, 0.79). There was no significant difference in AUROC between RISD and MMRI ($P = 0.428$ Fig. 1 and Table 3).

Using AUROC, we further evaluated specificity and sensitivity for prediction of RRT at various cutoffs for RISD and MMRI. We selected a cutoff of 3.0 for RISD and a cutoff of 8 for MMRI to maximize sensitivity. At these cutoffs, RISD predicted RRT with a sensitivity of 91.7% but specificity of 39.9%. Likewise, MMRI predicted RRT with a sensitivity of 92.2 but specificity of 37.3% (Table 4). Consistent with our analysis, for this dataset the RISD cutoff (3.0) would have predicted 93% of RRT patients, whereas the MMRI cutoff (8) would have predicted 92% of RRT patients. Additionally, RISD captured 5 of the 17 (29%) patients missed by MMRI, whereas MMRI captured 4 of 16 (25%) patients missed by RISD. This indicates that sensitivity might be increased by a consideration of both values simultaneously, although this would come at the cost of decreased specificity.

In this study RRT cases had higher rates in-hospital mortality compared to controls (adjusted odds ratio 17.4, $P = 0.008$, Table 5). Given the ability of RISD and MMRI to predict RRT, we next determined whether MMRI could predict in-hospital mortality. MMRI and RISD were not significant predictors of in-hospital mortality (adjusted odds ratios of 1.06, $P = 0.36$, and 1.03, $P = 0.21$, respectively, Table 5).

4. Discussion

Although there is some evidence that RI is correlated to postoperative complications and unplanned readmissions to the surgical intensive care unit,[19,20] the precise role of RI in the management of surgical floor patients remains ill defined. Additionally, since RI was developed as a continuous, global indicator of patient physiology, it is potentially a reasonable marker of deterioration, and more specifically an early warning mechanism prior to overt decompensation. The specific goal for this study was to understand how fluctuation of RI over a twenty-four-hour period could predict RRT activation. The most at-risk patients could then be targeted for closer monitoring or other specific interventions including RRT activation and transfer to a higher level of care. Over- and under-activation of RRT is not well studied, but clearly hospital resources are necessary for a multidisciplinary team approach to emergency response on the ward. RRT is one important measure to minimize failure-to-rescue scenarios; the tradeoff is often high false positive rates as is the case when using our proposed RSID and MMRI cutoffs (Table 4).[25] If RI variability can predict RRT activation, there exists potential to improve outcomes by delivering care more efficiently and to reduce costs by devoting resources to those with the greatest likely need. These are important subjects of future study.

If RRT activation coarsely reflects the degree of inpatient acuity and decompensation, it may not be surprising that patients who underwent RRT activation are generally older, more likely to die in the hospital, or more likely to require additional post-discharge services as demonstrated in this study. Not surprisingly, in-hospital mortality and non-independence at discharge are worse for study patients who required RRT, even when adjusted for age and gender.

RISD and MMRI predicted RRT activation with similar degrees of accuracy. Although previous early warning systems were developed to predict cardiac arrest, not rapid response or medical emergency team activation, RISD and MMRI behaved similarly in terms of demonstrating substantially higher negative predictive values (Table 4).[17] In our sensitivity and specificity analysis, cutoffs of 8 (MMRI) and 3.0 (RISD) were required in order to maximize sensitivity. The rationale for maximizing sensitivity is to mitigate the potential of missing patients who would otherwise require rapid response activation. While median MMRI values were grossly different between cases and controls (19.7 vs. 10.9), this highlights the necessity of evaluating the patient's entire clinical picture when interpreting RI trends for any individual patient. It is unclear the degree to which more standardized RRT activation criteria would affect the data.

Despite the demonstrated association between RI variability and RRT activation, it is somewhat surprising that neither RISD nor MMRI was associated with in-hospital mortality. This may be due, in part, to the rare nature of mortality in our study cohort (three control patients and eight RRT patients) making elucidation of such an association more challenging.

Rapid response team is a common resource nationwide, yet the literature does not establish a set of common criteria for its activation. The definition of clinical deterioration is similarly ill-defined and depends on the covert, potentially late signs of impending decompensation such as blood pressure and respiratory compromise.[26] Much of literature suggests that RRT is a valuable resource, potentially reducing hospital stay, on-ward cardiac arrest, and facilitating timely transfer to the intensive care unit. Studies involving early warning systems and emergency response teams have generally been low quality and difficult to generalize.[27] Early warning score, developed in response to the Institute for Healthcare Improvement's call to save 100,000 lives, is a bedside assessment which establishes criteria for RRT activation largely based on vital sign derangements and is labor intensive for the bedside nurse. Ultimately, studies evaluating outcomes based on EWS have contradictory results.[28]

Table 2
Baseline patient characteristics comparing cases and controls. P values from χ^2 tests comparing means, from Mann-Whitney rank sum tests comparing medians or from two-sample T-tests comparing ratios. *P values < 0.05 two-tailed considered statistically significant. IQR = inter-quartile range, SD = standard deviation, MMRI = maximum minus minimum Rothman Index, RISD = Rothman Index standard deviation.

Patient characteristics	Cases	Controls	P value
Number of patients	217	868	–
RISD, median (IQR)	6.1 (3.9)	3.7 (3.6)	<0.001*
MMRI, median (IQR)	19.7 (14)	10.9 (11.7)	<0.001*
Female, %	52.5	42.3	0.007*
Admit Age, mean (SD)	63.1 (16.5)	59.0 (17.1)	0.002*
Independent at discharge, %	22.0	44.1	<0.001*
In-hospital mortality, %	3.7	0.3	<0.001*

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Table 3
Prediction of rapid response team (RRT) code activation using change in Rothman Index over a 24-h interval. Odds ratios from univariable or multivariable conditional logistic regression adjusting for age and gender. P values < 0.05 considered statistically significant. RISD = Rothman Index standard deviation, MMRI = maximum minus minimum Rothman Index, OR = odds ratio, Std Err = standard error, AUROC = areas under the receiver operating characteristic curve.

Variable	OR	95% CI	Std Err	P Value	Adj OR	Adj 95% CI	Adj Std Err	Adj P Value	AUROC	95% CI	Std Err	P value
RISD	1.31	1.24, 1.38	0.04	<0.001	1.31	1.23, 1.38	0.04	<0.001	0.74	0.70, 0.77	0.02	0.428
MMRI	1.10	1.08, 1.12	0.01	<0.001	1.10	1.08, 1.12	0.01	<0.001	0.76	0.72, 0.79	0.02	1.00

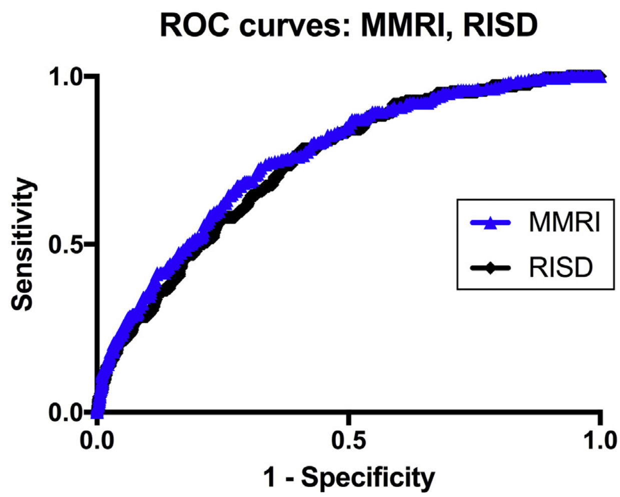

Fig. 1. AUROC for prediction of RRT using RISD and MMRI. RRT = rapid response team, RISD = Rothman Index standard deviation, MMRI = maximum minus minimum Rothman Index, AUROC = area under the receiver operating characteristic curve.

Table 4
Sensitivity and specificity analysis after AUROC for predicting RRT using change in Rothman Index. AUROC = area under the receiver operating characteristic curve, RRT = rapid response team, RISD = Rothman Index standard deviation, MMRI = maximum minus minimum Rothman Index, NPV = negative predictive value, PPV = positive predictive value.

	RISD	MMRI
Cutoff	3.0	8
Sensitivity %	91.7	92.2
Specificity %	39.9	37.3
NPV %	95.1	95.0
PPV %	27.7	26.9
LR+	1.53	1.46

There are several limitations to this study. Data garnered were retrospective in nature; however, RI's were prospectively calculated based on real-time information. We used randomly selected case controls in a 4:1 (control: case) ratio as representative of the overall nursing and ward conditions. Given that multiple surgical services are represented in this study (Trauma and Emergency General Surgery, Colorectal Surgery, Minimally Invasive/Bariatric Surgery, Surgical Oncology, Neurosurgery, Urology and Otolaryngology), the case controls may not represent patients who did not sustain RRT. We selected a 4:1 ratio to optimize case control matching which is reported by other authors.[29] Because RRT was such a rare event and the surgical characteristics (surgery, surgeon, pathology) so different, it was impractical to specifically case match controls. To capture all patients who sustained RRT in the study period, the sampling pool was necessarily broad. Additionally, it was necessary to randomly select for controls to minimize introduction of bias. While these patients were representative of patients in similar clinical settings (same cohort of nurses and ancillary staff), they were not selected based on care team membership, disease process, or surgical procedure. There were gender and age differences between control and case groups; however, these differences were incorporated into the multivariate analysis as possible confounders. Additionally, because RI is heavily dependent on nursing input, the nursing ward and clinical shifts were deemed more relevant independent variables. We attempted to control for differences in nursing staff and wards by limiting the controls to patients on the same ward around the same time periods patients who suffered RRT activation. Because the algorithm is proprietary, we are uncertain about the precise weighting of nursing assessment which involves some subjectivity versus objective data such as laboratory values. There is evidence to support that subjective nursing input is crucial in RRT activation.[30] The data were collected at a single, large tertiary care facility in the Northeast United States, and therefore may not be reflective of institutions of different sizes or in different regions. While RI was not actively integrated into the algorithms for any treatment teams covering the respective surgical floors under study, treatment teams were also not blinded to any patient RI values. Finally, patients transferred to the SICU or surgical step-down unit without RRT activation were not analyzed in this study.

Optimizing criteria for RRT activation remains elusive, but additional tools such as RI may facilitate identification of surgical patients at risk of cardiopulmonary compromise. Despite the large amount of data required for its implementation, its potential advantage is automation and ease of access. Perhaps the most useful application of RI variability is to alert providers that the patient may need additional monitoring due to impending RRT, rather than activation of RRT based on this study. A comparison of Rothman Index to traditional criteria for RRT activation in a prospective fashion may elucidate if RI is superior to current practices in detecting patient deterioration.

Table 5
Prediction of in-hospital mortality using change in Rothman Index over a 24-h interval. Odds ratios from univariable or multivariable conditional logistic regression adjusting for age and gender. P values < 0.05 considered statistically significant. RRT = rapid response team, RISD = Rothman Index standard deviation, MMRI = maximum minus minimum Rothman Index, OR = odds ratio, Std Err = standard error, AUROC = areas under the receiver operating characteristic curve.

Variable	OR	95% CI	Std Err	P Value	Adj OR	Adj 95% CI	Adj Std Err	Adj P Value
RRT	10.67	2.83, 40.21	7.22	<0.001	17.36	2.09, 144.36	18.76	0.008
RISD	1.03	0.92,1.16	0.06	0.57	1.06	0.93, 1.21	0.07	0.36
MMRI	1.02	0.98, 1.07	0.02	0.28	1.03	0.98, 1.08	0.02	0.212

5. Conclusion

RI variability predicted likelihood of rapid response activation. While RISD and MMRI predicted RRT, no variability measure predicted in-hospital mortality. Our data indicate that changes in RI may be used as a marker of clinical deterioration and impending RRT. There is potential for the use of RI variability as standard criteria for RRT activation but will need to be the subject of future study. Further validation of this work is necessary, both in terms of expanding this retrospective analysis to other sites within our system and carrying out prospective studies to determine if activation of RRT based on RI variability criteria result in decreased in hospital mortality and on-ward cardiac arrest.

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