Evaluation of Electronic Medical Record Vital Sign Data Versus a Commercially Available Acuity Score in Predicting Need for Critical Intervention at a Tertiary Children's Hospital

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Objectives: Evaluate the ability of vital sign data versus a commercially available acuity score adapted for children (pediatric Rothman Index) to predict need for critical intervention in hospitalized pediatric patients to form the foundation for an automated early warning system.

Design: Retrospective review of electronic medical record data.

Setting: Academic children's hospital.

Patients: A total of 220 hospitalized children 6.7 ± 6.7 years old experiencing a cardiopulmonary arrest (condition A) and/or requiring urgent intervention with transfer (condition C) to the ICU between January 2006 and July 2011.

Interventions: None.

Measurements and Main Results: Physiologic data 24 hours preceding the event were extracted from the electronic medical record. Vital sign predictors were constructed using combinations of age-adjusted abnormalities in heart rate, systolic and diastolic blood pressures, respiratory rate, and peripheral oxygen saturation to predict impending deterioration. Sensitivity and specificity were determined for vital sign–based predictors by using 1:1 age-matched and sex-matched non-ICU control patients. Sensitivity and specificity for a model consisting of any two vital sign measurements simultaneously outside of age-adjusted normal ranges for condition A, condition C, and condition A or C were 64% and 54%, 57% and 53%, and 59% and 54%, respectively. The pediatric Rothman Index (added to the electronic medical record in April 2009) was evaluated in a subset of these patients ($n = 131$) and 16,138 hospitalized unmatched non-ICU control patients for the ability to predict condition A or C, and receiver operating characteristic curves were generated. Sensitivity and specificity for a pediatric Rothman Index cutoff of 40 for condition A, condition C, and condition A or C were 56% and 99%, 13% and 99%, and 28% and 99%, respectively.

Conclusions: A model consisting of simultaneous vital sign abnormalities and the pediatric Rothman Index predict condition A or C in the 24-hour period prior to the event. Vital sign only prediction models have higher sensitivity than the pediatric Rothman Index but are associated with a high false-positive rate. The high specificity of the pediatric Rothman Index merits prospective evaluation as an electronic adjunct to human-triggered early warning systems. (*Pediatr Crit Care Med* 2015; XX:00–00)

Key Words: cardiac arrest; early warning system; medical rapid response team; respiratory arrest; Rothman Index

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Clinical deterioration of hospitalized pediatric patients carries potentially devastating consequences when it occurs. Progress has been made in the early identification of clinical decompensation in pediatric patients for the purpose of activating medical emergency response teams (1–6) and it follows that early identification of at-risk patients would improve outcomes (7–9). In-hospital cardiopulmonary

arrest occurs in 0.1 to 20 of 1,000 children admitted to inpatient units and is associated with poor survival and significant morbidity (10, 11). Activation of medical critical response teams has been shown to mitigate clinical deterioration (1, 5, 6), and there are several early warning scores (EWS) in existence for the pediatric population (3, 12–16). Many institutions have adopted well-studied EWS such as the bedside pediatric EWS (PEWS) system to meet their unique institutional infrastructure and patient populations (17, 18). Although these scores have been shown to perform well with good adherence to proper scoring algorithms, a common barrier to implementation of many such scores is their reliance on repeated subjective assessments of the patient necessary to accurately compute the EWS, which could vary based on nursing resources and level of training, inpatient census, and/or location in the hospital. There have been attempts to minimize the number of subjective/caregiver assessment components of the scores such as the bedside PEWS (14, 15), but to date, a fully automated EWS free of a caregiver-intensive subjective component variables has not been described. In large pediatric hospitals such as our institution, with busy inpatient floors and high patient to caregiver ratios, there may be a role for a fully automated "hands-free" EWS. The goal of such a system would be to generate a score within the electronic medical record (EMR) that is refreshed every time pertinent data fields are repopulated, such as vital sign data from continuous bedside monitors.

Our hospital's medical emergency response team currently uses a caregiver-triggered system that relies on evaluation of the patient and both subjective (e.g., neurological status) and objective (e.g., vital sign) criteria. We hypothesized that models can be generated from data elements routinely populated in the EMR that can predict acute deterioration culminating in cardiopulmonary arrest (condition A) and/or the need for urgent intervention requiring transfer (condition C) to the PICU. We further hypothesized that supplementing objective vital sign data with subjective data would improve predictive power. To this end, we used the pediatric Rothman Index (pRI), a generalized acuity score validated in hospitalized adult patients, that is composed of variables including vital signs, nursing assessment of multiple systems including neurological evaluation, and laboratory tests (17), implemented in our hospital and included in our EMR since April 2009.

MATERIALS AND METHODS

This study was approved by the institutional review board of the University of Pittsburgh. EMR (Cerner 2007.19.01; Cerner Corporation, Kansas City, MO) data were reviewed for patients where the PICU medical emergency response team was activated for 1) the need for immediate cardiopulmonary resuscitation (CPR) including bag-mask ventilation and/or chest compressions (condition A), or 2) clinical concerns for imminent deterioration warranting immediate intervention and/or transfer to the PICU (condition C), at the Children's Hospital of Pittsburgh between June 2006 and November 2011 ($n = 412$). Activation of the PICU medical emergency response team is logged into a database capturing all events for quality improvement purposes. This database includes patients in the PICU and cardiac ICU (CICU) with unexpected cardiopulmonary arrest where the bedside nurse triggers an alarm summoning the PICU team (condition A) and when a non-PICU service (e.g., general pediatric, neurological, transplant surgery, or extracorporeal membrane oxygenation perfusion team) is summoned urgently for a PICU patient (condition C). Only patients with at least 24 hours of physiologic data recorded in the EMR prior to the acute event were included in the analysis ($n = 220$). Patient age, sex, location at time of acute event, and event mortality were recorded. All physiologic variables of interest, such as temperature (T), heart rate (HR), systolic blood pressure (SBP), diastolic blood pressure (DBP), respiratory rate (RR), and peripheral oxygen saturation (Spo_2), populating the EMR within the 24-hour pre-event period were extracted. The same physiologic variables were extracted in 220 age-matched and sex-matched hospitalized non-ICU (neonatal ICU, PICU, and CICU) control patients who had at least 24 hours of inpatient data recorded.

Vital Sign Only–Based Predictors

We first determined the prevalence of T, HR, SBP, DBP, RR, and Spo_2 falling outside of predefined normal ranges (**Supplemental Table 1**, Supplemental Digital Content 1, http://links.lww.com/PCC/A165). The variables for age-adjusted normal ranges of physiologic variables HR, SBP, DBP, and RR were initially based on age-specific normal ranges as described in *Nelson Textbook of Pediatrics* (18). These age-adjusted normal ranges were then modified to reflect thresholds that would trigger a condition A and/or C upon evaluation by caregivers based on our hospital's guidelines. For Spo_2, a value less than 90% was considered abnormal. Binary data (normal or abnormal) for each vital sign were generated to use as predictors.

The first series of predictors simply identified those study patients who had a pre-event occurrence of one, two, three, four, or five abnormal physiologic variables assigned binary values (normal or abnormal) at any time during the 24-hour observation period. The second series of predictors refined the algorithms by evaluating two-variable combinations of abnormal physiologic variables (excluding T) occurring simultaneously at any point during the observation period. Additional analyses included simultaneous abnormalities in three to five physiologic variables recorded at a single time point, as well as at two consecutive time points. Lead time or the average time from alert detection to the acute event was determined for each analysis.

Evaluation of the pRI

The Rothman Index (PeraHealth, Charlotte, NC) is a generalized acuity score validated in hospitalized adult patients for the prediction of mortality and hospital readmission (19). The pRI has been age adjusted and modified for pediatric patients and is composed of variables including vital signs (T, HR, SBP, DBP, RR, and Spo_2), nursing assessment of multiple systems

(including cardiac, respiratory, gastrointestinal, genitourinary, neurological, nutrition, safety, musculoskeletal, peripheral vascular, skin, psychosocial, and the Braden [Q] scale), laboratory tests (creatinine, sodium, chloride, potassium, blood urea nitrogen, white blood cell count, and hemoglobin), and cardiac rhythm, with lower scores reflecting instability (17). The pRI was implemented in our hospital and included in our EMR since April 2009. Continuous vital sign data can be imported, and the pRI recalculated at intervals of up to every 4 minutes. In the subset of patients with condition A or C between April 2009 and July 2011 ($n = 131$), all pRI data were extracted for the 24-hour pre-event observation period. During this time period, the pRI was not used in clinical decision making or to determine whether the medical emergency response team should be activated. Since a major objective of implementing an additional trigger to the hospital's EWS is to avoid unnecessary alerts (false positives), we used a large control set consisting of pRI data from 16,138 hospitalized non-ICU control patients admitted to Children's Hospital of Pittsburgh in 2013. Changes in pRI over time up to the event were determined for condition A and C cases.

Statistical Methods

To determine the capacity of various combinations of vital sign abnormalities to identify patients requiring CPR (condition A) and those with clinical concerns for imminent deterioration warranting immediate intervention and transfer to the PICU (condition C), patients experiencing a condition A or C ("cases") were matched 1-to-1 with control patients not requiring CPR or ICU transfer. Optimal Mahalanobis matching was performed on the basis of age and sex (20). To initially restrict the number of possible combinations, all two-variable combinations of abnormal physiologic variables were treated as binary predictors, for example, if a patient registered abnormal HR and abnormal SBP at the same time at any point during the observation period, then that patient would have an "yes" for the HR + SBP combination. These combinations were tested for significant associations as cases versus controls using the paired McNemar test. Within the same matched dataset, sensitivity and specificity for determining case versus control were also calculated. To quantify the uncertainty of these sensitivity and specificity estimates, bootstrapped 95% CIs were calculated by repeatedly resampling the dataset by pairs and extracting the appropriate quantiles of the sensitivity and specificity values across the resampled datasets. R version 3.0.0 (The R Foundation for Statistical Computing, Institute for Statistics and Mathematics, Vienna, Austria) was used for data management, and Stata version 13 (StataCorp., College Station, TX) was used for statistical analysis.

To determine the sensitivity and specificity of the pRI in identifying patients where a condition A or condition C was triggered, the 131 cases where pRI data were available were compared with 16,138 unmatched controls. All 24-hour pre-event pRI values for each of the cases and all data within a 24-hour epoch for each of the controls are included in the analysis. Receiver operating characteristic (ROC) curves were generated, and sensitivity and specificity for the ability to predict condition A and/or C were calculated at predetermined pRI cutoff values of 30, 40, and 50 (17, 19). Stata version 13 (StataCorp.) was used for statistical analysis.

RESULTS

Vital Sign Only–Based Predictors

Patient inclusion, demographic, and survival to discharge data are shown in **Table 1**. Of the total 412 patients in our cohort who experienced condition A or C, there were 220 patients with at least 24 hours of pre-event data in the EMR. The presence of HR above, RR above, SBP above, and DBP below age-adjusted normal ranges were the most commonly abnormal variables in the 24-hour period prior to either condition A or C in our study population (**Fig. 1**). For condition A, SBP (above or below), DBP (above or below), HR (above or below), and RR (above) alerts were detected in 50% of the cases at 16.2, 15.5, 15.0, and 14.3 hours pre-event, respectively. For condition C, SBP (above or below), DBP (above or below), HR (above or below), and RR (above) abnormalities were detected in 50% of the cases at 18.3, 17.0, 17.3, and 14.0 hours pre-event, respectively.

Based on these results, we then constructed more stringent predictors using combinations of two vital sign abnormalities occurring simultaneously at any point during the 24-hour observation period. For the condition A group alone (72 pairs), a predictor that identified any of the possible combinations of abnormalities (either above or below normal for age) in two out of five variables at a single time point achieved

TABLE 1. Demographic Data for Patient Cohorts

Group	Condition A	Condition C	Conditions A and C	Control
Total patients (January 2006 to July 2011)	90	322	412	
Patients with 24-hr pre-event data	72	148	220	220
Age (mo)	63.3 ± 79.6	88.2 ± 79.2	80.4 ± 80.2	79 ± 76.8
Male (%)	44 (58)	88 (59)	132 (60)	129 (59)
Non-PICU patients (%)	39 (54)	139 (94)	178 (80.9)	220 (100)
Survival to discharge (%)	55 (76)	145 (98)	200 (91)	220 (100)

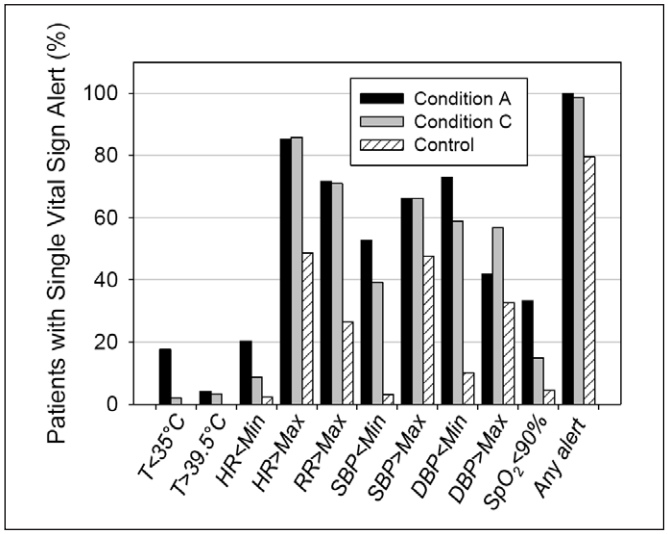

Figure 1. Prevalence of individual vital sign abnormalities during a 24-hr observation period for patients with cardiopulmonary arrest (condition A; *black bar*) or requiring urgent intervention and transfer to the ICU (condition C; *gray bar*) versus control patients (*cross-hatched bar*). DBP = diastolic blood pressure, HR = heart rate, RR = respiratory rate, SBP = systolic blood pressure, Spo_2 = peripheral oxygen saturation, T = temperature.

statistical significance (**Table 2**; $p = 0.026$; McNemar test), with a sensitivity of 63.9% (95% CI, 52.8–75.0%) and a specificity of 54.2% (95% CI, 43.1–65.3%), and provided an average lead time of 13.6 hours. Various two vital sign combinations had a range of observed sensitivity from 5.6% to 37.5% (DBP + Spo_2 and DBP + SBP, respectively) and specificity from 70.8% to 100% (DBP + SBP and SBP + Spo_2, respectively).

For the condition C group alone (148 pairs), a predictor that identified any of the possible combinations of abnormalities (either above or below normal for age) in two out of five variables at a single time point did not achieve statistical significance (**Table 3**; $p = 0.091$; McNemar test), with a sensitivity of 56.8% (95% CI, 48.6–64.2%) and a specificity of 53.4% (95% CI, 45.3–61.5%), and provided an average lead time of 13.1 hours. Various two vital sign combinations had a range of observed sensitivity from 2.0% to 39.2% (DBP + Spo_2 and DBP + SBP, respectively) and specificity from 76.4% to 99.3% (DBP + SBP and SBP or DBP + Spo_2, respectively).

For the condition A and C populations analyzed together, a predictor identifying a combination of abnormalities (either above or below normal for age) in any two of five variables at a single time point achieved statistical significance (**Table 4**; $p = 0.006$; McNemar test), with a sensitivity of 59.1% (95% CI, 52.7–65.5%) and a specificity of 53.6% (95% CI, 46.8–60.5%), and provided an average lead time of 13.4 hours. Various two vital sign combinations had a range of observed sensitivity from 3.2% to 38.6% (DBP + Spo_2 and DBP + SBP, respectively) and specificity from 74.5% to 99.5% (DBP + SBP and SBP or DBP + Spo_2, respectively).

A separate sensitivity analysis was carried out using clustered logistic regression to predict condition A or C using each of the dichotomous vital sign abnormalities while adjusting for the number of vital sign measurements per subject taken over the observation period. The number of within-subject measurements did not substantially affect the significance, sensitivity, or specificity of the predictors (not shown). Other predictors generated identifying the possible combinations of abnormalities relative to age-adjusted normal ranges for two, three, four, or five variables over the entire 24-hour pre-event period did not achieve clinically meaningful sensitivity and specificity (not shown). Refinement of predictors by categorizing and analyzing abnormalities in variables as above, below, or above or below similarly did not significantly improve sensitivity or specificity (not shown).

pRI-Based Prediction of Condition A and C

For the condition A group alone, the pRI ranged from −39.5 to 90.6 with a median (interquartile range [IQR]) of 37.2

TABLE 2. Two-Variable Simultaneous Vital Sign Abnormalities Used to Predict Condition A

Two-Variable Combination	Cases Correctly Identified	McNemar Test, *p*	Observed Sensitivity (%)	Sensitivity Bootstrapped (95% CI)	Observed Specificity (%)	Specificity Bootstrapped (95% CI)
DBP and SBP	27	0.327	37.5	26.4–48.6	70.8	59.7–80.6
DBP and HR	16	0.052	22.2	12.5–31.9	90.3	83.3–95.8
DBP and RR	13	0.169	18.1	9.7–26.4	91.7	84.7–97.2
DBP and Spo_2	4	0.134	5.6	1.4–11.1	100.0	100.0–100.0
SBP and HR	18	0.211	25.0	15.3–34.7	84.7	76.4–93.1
SBP and RR	18	0.441	25.0	15.3–34.7	81.9	72.2–90.3
SBP and Spo_2	12	0.001	16.7	8.3–25.0	100.0	100.0–100.0
HR and RR	18	0.081	25.0	15.3–34.7	87.5	79.2–94.4
HR and Spo_2	11	0.004	15.3	8.3–23.6	98.6	95.8–100.0
RR and Spo_2	12	0.039	16.7	8.3–26.4	95.8	90.3–100.0
Any two	46	0.026	63.9	52.8–75.0	54.2	43.1–65.3

DBP = diastolic blood pressure, SBP = systolic blood pressure, HR = heart rate, RR = respiratory rate, Spo_2 = peripheral oxygen saturation.

TABLE 3. Two-Variable Simultaneous Vital Sign Abnormalities Used to Predict Condition C

Two-Variable Combination	Cases Correctly Identified	McNemar Test, *p*	Observed Sensitivity (%)	Sensitivity Bootstrapped (95% CI)	Observed Specificity (%)	Specificity Bootstrapped (95% CI)
DBP and SBP	58	0.007	39.2	31.8–47.3	76.4	69.6–83.1
DBP and HR	32	0.193	21.6	15.5–28.4	85.1	79.7–90.5
DBP and RR	17	0.029	11.5	6.8–16.9	95.9	92.6–98.7
DBP and Spo_2	3	0.617	2.0	0.0–4.7	99.3	98.0–100.0
SBP and HR	35	0.332	23.6	16.9–31.1	81.8	75.7–87.8
SBP and RR	18	0.078	12.2	7.4–17.6	94.6	90.5–98.0
SBP and Spo_2	5	0.221	3.4	0.7–6.8	99.3	98.0–100.0
HR and RR	19	1.000	12.8	8.1–18.2	87.8	82.4–92.6
HR and Spo_2	7	0.128	4.7	1.4–8.8	98.6	96.6–100.0
RR and Spo_2	4	1.000	2.7	0.7–5.4	98.0	95.3–100.0
Any two	84	0.091	56.8	48.6–64.2	53.4	45.3–61.5

DBP = diastolic blood pressure, SBP = systolic blood pressure, HR = heart rate, RR = respiratory rate, Spo_2 = peripheral oxygen saturation.

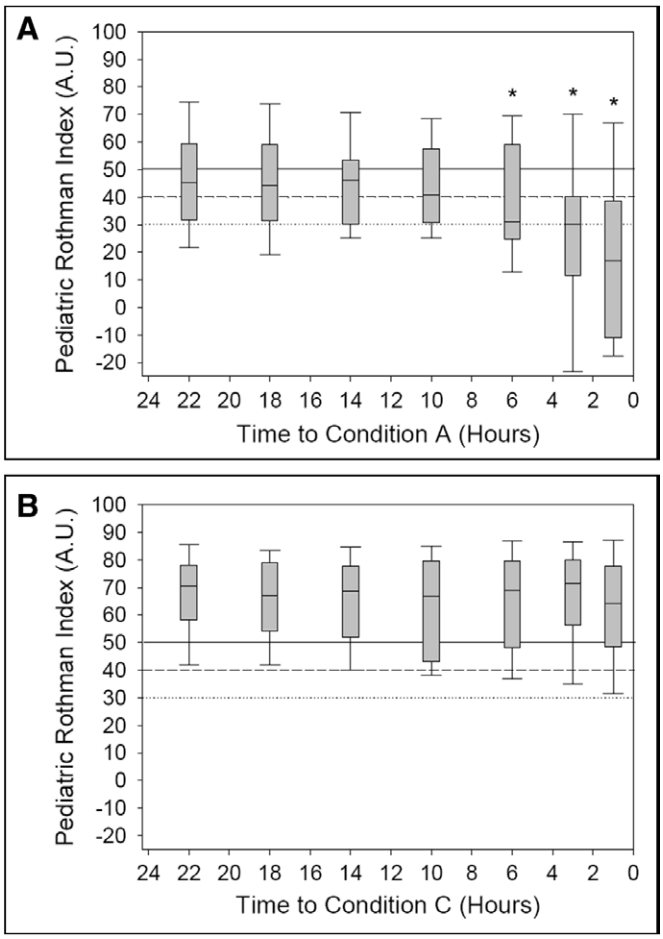

Figure 2. *Box and whisker plots* showing the pediatric Rothman Index (pRI; arbitrary units [A.U.]) score over time intervals of 24 to 20 hr, < 20 to 16 hr, < 16 to 12 hr, < 12 to 8 hr, < 8 to 4 hr, < 4 to 2 hr, and < 2 to 0 hr for patients with (**A**) cardiopulmonary arrest (condition A) or (**B**) requirement for urgent intervention and/or transfer to the ICU (condition C). Median and 25–75th percentiles (*boxes*) and 10–90th percentiles (*whiskers*) displayed, along with reference *lines* for pRI cutoffs used for statistical analysis. $^*p < 0.05$ versus 24- to 20-hr epoch, analysis of variance on ranks with Dunn post hoc test.

(25.9–55.9) for the 24-hour observation period. For the condition C group alone, the pRI ranged from −0.8 to 98.3 with a median (IQR) of 67.9 (50.4–78.8) for the 24-hour observation period. The median, IQR, and 10–90th percentile pRI within time epochs before event are shown in **Figure 2**. For condition A, the pRI decreased over time with a median pRI of 31.1, 30.1, and 17.0 within the 8 to 4, 4 to 2, and 2 to 0 hour pre-event epochs, respectively (all $p < 0.05$ vs 24- to 20-hour epoch). A pRI alert cutoff of 30, 40, and 50 was met in 50% of the condition A patients at 0, 0.1, and 13.6 hours, respectively. For condition C, the pRI did not change over time although lower pRI values were observed at epochs closer to the event ($p = 0.07$). A pRI alert cutoff of 30, 40, and 50 was not detected in 50% of the condition C patients at any time prior to the event.

Sensitivity, specificity, and likelihood ratio (LR) calculations using cutoff values of 30, 40, and 50 for prediction of condition A, condition C, and condition A or C are shown in **Table 5**. All 24-hour pre-event pRI values for each of the condition A ($n = 29$) and condition C ($n = 102$) cases (combined $n = 131$; 1,714 data points) and all pRI values within a 24-hour epoch for each of the controls ($n = 16{,}138$; 501,544 data points) were included in the analysis. ROC curves for prediction of condition A, condition C, and condition A or C are shown in **Supplemental Figure 1** (Supplemental Digital Content 2, http://links.lww.com/PCC/A166, which illustrates ROC curves for the pRI for detection of condition A [*A*], condition C [*B*], or condition A or C [*C*]; area under the curve [AUC]: condition A = 0.95, condition C = 0.84, and condition A or C = 0.80), generating AUC of 0.95, 0.84, and 0.80, respectively. For condition A alone, sensitivity ranged from 38% to 69% for pRI cutoff values of 30 to 50, respectively, and specificity ranged from 99.6% to 97.6%, respectively. For condition C alone, sensitivity ranged from 6% to 26% for pRI cutoff values of 30 to 50, respectively, and specificity ranged from 99.7% to 98.2%, respectively. For condition A and C combined, sensitivity ranged from 17% to 41%

TABLE 4. Two-Variable Simultaneous Vital Sign Abnormalities Used to Predict Either Condition A or C

Two-Variable Combination	Cases Correctly Identified	McNemar Test, *p*	Observed Sensitivity (%)	Sensitivity Bootstrapped (95% CI)	Observed Specificity (%)	Specificity Bootstrapped (95% CI)
DBP and SBP	85	0.004	38.6	32.3–45.0	74.5	68.2–80.0
DBP and HR	48	0.026	21.8	16.4–27.7	86.8	82.3–90.9
DBP and RR	30	0.007	13.6	9.1–18.2	94.5	91.4–97.3
DBP and Spo_2	7	0.077	3.2	0.9–5.9	99.5	98.6–100.0
SBP and HR	53	0.106	24.1	18.6–30.0	82.7	77.7–87.7
SBP and RR	36	0.054	16.4	11.8–21.4	90.5	86.4–94.1
SBP and Spo_2	17	<0.001	7.7	4.5–11.4	99.5	98.6–100.0
HR and RR	37	0.229	16.8	11.8–21.8	87.7	83.2–91.8
HR and Spo_2	18	0.001	8.2	4.5–11.8	98.6	96.8–100.0
RR and Spo_2	16	0.055	7.3	4.1–10.9	97.3	95.0–99.1
Any two	130	0.006	59.1	52.7–65.5	53.6	46.8–60.5

DBP = diastolic blood pressure, SBP = systolic blood pressure, HR = heart rate, RR = respiratory rate, Spo_2 = peripheral oxygen saturation.

TABLE 5. Performance of the Pediatric Rothman Index for Prediction of Condition A, Condition C, and Condition A or C

	Condition A			Condition C			Condition A or C		
Variables	pRI < 50	pRI < 40	pRI < 30	pRI < 50	pRI < 40	pRI < 30	pRI < 50	pRI < 40	pRI < 30
Sensitivity (%)	69	56	38	26	13	6	41	28	17
Specificity (%)	97.6	98.9	99.6	98.2	99.3	99.7	96.6	98.5	99.4
LR+	28.8	50.9	95.0	14.4	18.6	20.0	12.1	18.7	28.3
LR−	0.3	0.4	0.6	0.8	0.9	0.9	0.6	0.7	0.8
Receiver operating characteristics area under the curve			0.95			0.84			0.80

pRI = pediatric Rothman Index, LR+ = positive likelihood ratio, LR− = negative likelihood ratio.

for pRI cutoff values of 30 to 50, respectively, and specificity ranged from 99.4% to 96.6%, respectively. While the specificity of the pRI is high, caution is in order in terms of post-test probability for prediction of condition A, given prevalence of the event and negative LRs achieved (Table 5).

DISCUSSION

Here we report the prevalence of vital sign abnormalities in hospitalized pediatric patients 24 hours before cardiopulmonary arrest (condition A) or need for urgent intervention and/or transfer to the PICU (condition C). Single and combinations of vital sign abnormalities are frequently detected within the 24-hour pre-event period in this patient population; however, they are also prevalent in matched control patients as well. As such, simple combination of vital sign predictors using binary inputs (normal or abnormal) results in performance characteristics (poor specificity) that would make implementation as an electronic trigger for the medical emergency response team impractical.

We subsequently evaluated the performance characteristics of the pRI, which also incorporates nursing assessment of multiple systems and laboratory tests in addition to standard vital signs (17) and is refreshed as new data are populated, including physiologic data from continuous bedside monitors. The pRI predicted occurrence of condition A or C in a reasonably stringent manner at all tested thresholds, with specificity ranging from 96.6% to 99.4% and positive LR of 12.1 to 28.3 (Table 5). Setting the pRI threshold to less than 40 for detection of condition A alone would yield relatively few false-positive signals while generating a positive LR of 51 (sensitivity 56% and specificity 99%). While the sensitivity of the pRI is insufficient to serve as the sole indicator of patient

deterioration, these performance characteristics are favorable in terms of using the pRI as an electronically surveyed adjunct alert, complementing our standard healthcare provider trigger for the medical emergency response team. This would be similar to using electronic adverse event identification to complement self-reported events (21).

A single, age-adjusted vital sign abnormality within the 24-hour period preceding condition A or C was detected in every one of the cases; however, it was also detected in 80% of the age-matched and gender-matched controls. A binary predictor triggered when any two vital sign abnormalities are detected simultaneously during the 24-hour observation period occurred in 55% of the cases; however, it was also detected in 46% of controls. Increasing predictor stringency by testing combinations of vital sign abnormalities improved specificity at the expense of sensitivity, as expected. Two-variable predictors that included Spo_2 less than 90% plus SBP, DBP, or HR abnormalities all attained reasonable specificity (Tables 2–4) although Spo_2 abnormalities were detected in less than 13% of cases overall, in part because not all non-ICU patients are monitored with pulse oximetry, and Spo_2 as a predictor would be confounded in patients with cyanotic heart disease. This reduction in sensitivity would conceivably be less of a factor given that the current healthcare provider trigger remains in place although a more robust predictive model would clearly be desirable.

The pRI was implemented as part of our EMR in April 2009 and is refreshed as new data are populated, incorporating age-adjusted vital signs (T, HR, SBP, DBP, RR, and Spo_2), as well as nursing assessment of multiple systems, laboratory tests, and cardiac rhythm (17). The pRI predicted occurrence of condition A or C in a manner superior to the vital sign abnormality-based predictors and similar to other published bedside EWS. For example, in a multicenter study, the bedside PEWS was found to have an AUC of 0.87 for predicting cardiopulmonary arrest (14, 15), whereas the pRI had an AUC of 0.95 for predicting cardiopulmonary arrest (Supplemental Fig. 1, Supplemental Digital Content 2, http://links.lww.com/PCC/A166). ROC revealed that a pRI cutoff of 40 had a sensitivity of 28% and a specificity of 99% for prediction of both condition A or C (Table 5). The sensitivity of a pRI less than or equal to 40 for predicting condition A patients alone was higher at 56%, important given that the detection of these events is more critical compared with the condition C cohort. The performance characteristics using a pRI cutoff of less than or equal to 40 for condition A were similar to that reported for the bedside PEWS (14, 15). These performance values are based on individual data points, rather than patients, and thus would be independent of observation period. We believe that these performance characteristics favor the evaluation of the pRI as an electronic trigger to complement our standard healthcare provider trigger for our medical emergency response team, with course correction of pRI cutoff values based on interval evaluation of performance.

There are caveats given that these data represent a single center with limited sample size, particularly for the condition A patients, given its relatively low prevalence in our dataset. For this reason, we included both PICU and hospitalized non-PICU patients, an aspect that would be consistent with the objective of identifying EMR-based triggers applicable to all hospitalized pediatric patients. Vital signs are more frequently recorded in PICU patients relative to patients residing on the general inpatient wards. The varying frequency of monitoring and recording of physiologic data between subjects could confound our analysis, particularly when developing predictors (Tables 2–4), although we did not observe substantial differences in performance characteristics after adjusting for the number of measurements within subjects (not shown). For evaluation of the performance of the pRI, we used individual data points from 16,138 patients rather than a matched cohort and performed statistical analysis without adjustable variables, with the practical goal of determining the overall "alert burden" if this was incorporated into the hospital's medical emergency response team system. Finally, imprecise activation of the emergency response team is a potential limitation of the use of condition A and C as surrogates for clinical acuity and may confer a degree of reporting bias to our analysis. Planned prospective analysis of non-PICU patients using an independent outcome such as the recently defined critical deterioration metric (22, 23) should determine whether or not these concerns are valid.

In conclusion, a model consisting of simultaneous vital sign abnormalities and the pRI predicts activation of our hospital's medical emergency response team in the 24-hour period prior to the event. The high specificity of the pRI suggests that it may be a valuable electronic adjunct to human activated EWS; however, the relatively low sensitivity does not support its use as the sole alert. Future work includes development of weighted (vs binary) physiological models for retrospective analysis and in silico testing, as well as prospective analysis of the pRI as a complementary, EMR-based, "hands-free" trigger for activation of the medical emergency response team.

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