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Calibration and validation of the pediatric resuscitation and trauma outcome model among injured children in Rwanda☆,☆☆

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ABSTRACT

Background: Trauma is a leading cause of mortality in low- and middle-income countries. The Pediatric Resuscitation and Trauma Outcomes (PRESTO) model uses six low-tech variables available at point of care in resource-limited environments to predict in-hospital mortality of injured children. This model was never calibrated and validated in a low-income country. We aimed to calibrate the model's coefficients and compare its performance against the Revised Trauma Score (RTS) and Kampala Trauma Score (KTS) using data from a low-income country.
Study design: Data from 2011 to 2015 in the prospectively-maintained Rwanda Injury Registry were reviewed after ethical approval was obtained. Patients were included for analysis if they were referred or admitted for traumatic injury, were younger than 15 years and if hospital outcomes were recorded. The variables in the PRESTO model include age, hypotension, heart rate, neurological status, oxygen saturation and airway intervention. The outcome of interest was in-hospital death. After calibration, Receiver-Operating-Characteristic curves were constructed to compare the area-under-curve (AUC) of PRESTO, RTS, and KTS with imputation of missing data. Comparisons of the relative AUC's were performed using Delong's test after bootstrapping in the full cohort and in a subset of patients <5 years-old.
Results: There were 113 in-hospital deaths out of 1695 included patients (6.7%). The AUC for the PRESTO model was 0.90 (95% CI [0.82–0.91]), higher than for RTS (0.77, 95% CI [0.80–0.97], $p < 0.01$) but not statistically different from KTS (0.89, 95% CI [0.72–0.82], $p = 0.856$). In the under-five cohort, the PRESTO model AUC was 0.84 (95% CI [0.75–0.92]), significantly higher than RTS (0.73 95% CI [0.64–0.81], $p < 0.01$) and KTS (0.58, 95% CI [0.50–0.66], $p < 0.01$).
Conclusion: PRESTO appears to be the superior benchmarking tool for pediatric patients in a low- and middle-income country context. The PRESTO score outperforms the KTS in children <5 years of age. Further validation of the PRESTO model is needed from other low- and middle-income settings.
Level of evidence: Level III: case–control (prognostic) study.

Remarkable improvements in childhood mortality from infectious disease have been observed globally over the past 15 years, but the injury burden has yet to be addressed [1]. Ninety-five percent of all childhood deaths occur in low- and middle-income countries (LMIC), and injury-related deaths now surpass those owing to human immunodeficiency virus (HIV), malaria and tuberculosis combined [2–6]. It is estimated that trauma remains a leading cause of death and disability for children living in these settings [7,8]. It is estimated that approximately one million children die each year as a result of injury and violence. Moreover, tens of millions of children sustain nonlethal injuries

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resulting in long-term disability [9]. The burden of childhood injury represents a significant public health problem and weighs heaviest on the world's lowest-income populations [10].

Trauma performance benchmarking and quality improvement require standardized metrics for risk-adjustment according to severity of patient injury as well as availability of human and material resources. Modern and effective trauma systems rely heavily on data from trauma registries to facilitate injury surveillance, clinical research, benchmarking of outcome rates, quality improvement, resource allocation, and tracking changes in trauma system performance over time [11]. Registries have enabled the reorganization of trauma delivery into more efficient regional systems of trauma care and have played a critical role in the dramatic improvements in trauma mortality observed in many high-income countries [12].

The proliferation of trauma registries in LMICs is well documented [13]. As trauma registries develop in LMICs, the models used to estimate and compare patient injury severity should be adapted to the current resource limitations of these settings [14]. Furthermore, pediatric trauma patients have distinct physiology and normative values compared with their adult counterparts and therefore require appropriately adapted severity indicators [15].

Multiple trauma severity indicators have been developed based on anatomic, physiologic, and combinations of different variables [15]. The Pediatric Resuscitation and Trauma Outcomes (PRESTO) model was developed using the American College of Surgeons (ACS) National Trauma Data Bank. It uses six low-tech variables available at point of care in virtually all environments to predict in-hospital mortality of injured children [16]. In order to use PRESTO in the LMIC setting, however, the model coefficients need to be calibrated to reflect trauma mortality rates in this environment.

The objectives of this study were therefore to calibrate the model's coefficients using data from Rwanda and to compare its prognostic performance against validated trauma scores.

1. Methods

1.1. Ethical approval

Ethical approval was obtained from the Human Investigation Committees of the University of Rwanda (No. 405/CMHS IRB/2017) and the McGill University Health Centre (#2018-3820).

1.2. Study setting

Rwanda has a population of 12.2 million people, including nearly 5 million under the age of 15 [17]. This low-income country in sub-Saharan Africa made significant strides in improving its health indicators in the postgenocide period after 1994 by prioritizing programs in line with the Millennium Development Goals [18]. Despite these efforts, a significant shortage of resources and specialized personnel for the management of acute conditions persists. A trauma registry was established in March 2011 through collaboration between the two university referral centers in Rwanda to collect data from injured patients [18,19]. This was initially implemented and funded through a National Institutes of Health Fogarty International Clinical Research Fellowship (R24 TW007988) and subsequently through support from the University of Virginia. The referral centers selected for registry implementation were the University Teaching Hospital-Kigali (UTH-K), a 520-bed hospital in the capital, Kigali, and the University Teaching Hospital-Butare (UTH-B), a 430-bed hospital in the university town of Butare, approximately 2 h south of the capital. Both sites are publicly funded, serve as training sites for students in the health professions at the University of Rwanda, and receive injury referrals from the nation's network of district hospitals and emergency response units [20]. Both hospitals care for pediatric as well as adult trauma victims. The trauma registry consisted of a 31-item, two-page form that collected data on all injured patients who were referred for treatment of their injury, died in the emergency department as a result of their injury, or were admitted to the hospital for treatment of their injuries. Patient demographics, prehospital care, initial physiology, early interventions, and disposition were recorded in the emergency department. Contents of the registry are shown in Appendix. 1**.** The initial registry was modeled after the Kampala Trauma Registry [21] but expanded to include both 2 week and 30-day mortality, disposition, and in-patient complications. Inpatient 30-day follow-up data were abstracted from patient charts. Data were collected in the emergency department 24 h a day, 7 days a week, by trained nurses who were assigned to the task on a per-shift basis. Inpatient data were collected initially by medical students and registrars, and then by a nurse manager for the registry. A trained data manager entered all data into a searchable, password-protected, Microsoft Access database. The Rwanda Injury Registry was suspended in 2015 owing to insufficient funding as well as a transition in training paradigms at the participating hospitals. The database was accessed from inception until interruption (2011–2015). Plans for a national trauma registry are currently being developed.

1.3. Patient selection and data collection

For the purposes of this analysis, patients were included if they were younger than 15 years and were referred or admitted to hospital for management of their injuries. Patients were excluded if they were older than 15 years, if they presented with minor injuries, were treated and sent home from the emergency department within 24 h of arrival, or if their hospital disposition information was incomplete.

1.4. Statistical analysis

Multiple imputations were performed for missing data, which were assumed to be missing not-at-random [22]. The number of imputations was determined based on the proportion of missing data, as previously described. In this case, $M = 20$ imputations were performed [23–25]. Patient characteristics were summarized using appropriate descriptive statistics. Differences between hospital survivors and those who died in-hospital were analyzed using the Chi-Squared test for nonparametric comparison of proportions and the Kruskal–Wallis Test for nonparametric comparison of medians. The PRESTO model was applied based on its previous derivation and validation [16], and its coefficients were calibrated using multivariable logistic regression analysis for the outcome of in-hospital death. The six variables in PRESTO include age, hypotension, pulse, oxygen saturation, neurological status classified using the Alert Verbal Painful Unresponsive (AVPU) system, and the need for invasive airway intervention [16]. Calibration was tested using the Hosmer–Lemeshow method, which measures goodness-of-fit, and tests the null hypothesis by assessing differences between observed and predicted outcomes within multiple subsets of the sample. The test yields a chi-squared value and associated p-value, which, if elevated, suggest no difference between observed and expected outcomes, thus indicating good model calibration [26]. Overfitting of the calibrated model was evaluated using bootstrap bias-correction as described and published by Harrell [27,28]. Calibration error was summarized as mean absolute calibration error.

The discrimination of PRESTO was then compared to the Revised Trauma Score (RTS) and the Kampala Trauma Score (KTS), which were chosen as comparators in this study for two reasons. Firstly, these are two commonly used and well-described injury severity scores that can be computed using data variables available within our registry. Secondly, both have been shown to perform well in low-resource settings by virtue of their simplicity and user-friendliness [21,29,30]. In fact, the KTS was designed specifically to address the limitations of LMIC environments and is reported to have validity in children as well as adult patients [21]. Receiver-operating characteristic (ROC) curves were constructed for each model and then each area-under-curve (AUC) was compared using Delong's test with 2000 bootstrapping

Table 1
Baseline patient characteristics of children who survived their injury and those who died in hospital.

Variable	Survivors (n = 1582)		In-Hospital Death (n = 113)		p-value
	N (%)	Median (IQR)	*N* (%)	Median (IQR)	
Female	506 (32%)	-	46 (41%)	-	0.071
Age	-	7 (4–11)	-	6 (3–8)	0.945
Site		-		-	<0.01
CHUK	795 (50%)		102 (90%)		
CHUB	787 (50%)		11 (10%)		
Insurance		-		-	0.715
Military	16 (1%)		1 (1%)		
Mutuelle	1292 (87%)		90 (86%)		
None	35 (2%)		5 (5%)		
NUR	2 (0%)		0 (0%)		
Private	7 (0%)		0 (0%)		
Private or other	60 (4%)		5 (5%)		
RAMA	68 (5%)		3 (3%)		
Transfer origin		-		-	<0.01
DH	1212 (80%)		80 (73%)		
Home	107 (7%)		4 (4%)		
Referral Hospital	27 (2%)		7 (6%)		
Scene of Accident	169 (11%)		18 (17%)		
Initial O_2 saturation	-	98 (97–100)	-	96 (91–99)	<0.01
Initial systolic blood pressure	-	115 (105–125)	-	110 (96–121)	<0.01
Initial diastolic blood pressure	-	66 (60–73)	-	65 (58–74)	<0.01
Initial respiratory rate	-	22 (20–24)	-	24 (22–26)	<0.01
Initial pulse rate	-	100 (84–120)	-	110 (86–132)	<0.01
Initial AVPU neurologic status		-		-	<0.01
Alert	1363 (86%)		44 (39%)		
Responsive to verbal stimuli	100 (6%)		12 (11%)		
Responsive to painful stimuli	97 (6%)		31 (27%)		
Unresponsive	22 (1%)		26 (23%)		
Initial Glasgow Coma Scale	-	15 (15–15)	-	11 (6–15)	<0.01
Invasive airway intervention	2 (0%)	-	58 (51%)	-	<0.01
Hypotensive on arrival	41 (3%)	-	16 (14%)	-	<0.01
Number of serious injuries		-		-	<0.01
None	94 (6%)		6 (5%)		
One	1400 (88%)		85 (75%)		
More than one	88 (6%)		22 (20%)		
HIV status		-		-	<0.01
Known negative	671 (44%)		33 (30%)		
Known positive	9 (1%)		0 (0%)		
Unknown	831 (55%)		76 (70%)		
Diagnostic peritoneal lavage	1 (0%)	-	0 (0%)	-	1.000
FAST ultrasound	18 (1%)	-	1 (1%)	-	1.000
Formal ultrasound	26 (2%)	-	5 (4%)	-	0.077
Chest x-ray	102 (6%)	-	18 (16%)	-	<0.01
Pelvis x-ray	73 (5%)	-	13 (12%)	-	0.002
Extremity x-ray	910 (58%)	-	20 (18%)	-	<0.01
Spine x-ray	66 (4%)	-	9 (8%)	-	0.097
CT body	2 (0%)	-	0 (0%)	-	1.000
CT head	239 (15%)	-	50 (44%)	-	<0.01
Skull x-ray	151 (9%)	-	17 (15%)	-	0.084
Mode of arrival		-		-	0.293
Ambulance	1088 (72%)		77 (73%)		
Foot	51 (3%)		2 (2%)		
Motorcycle	17 (1%)		0 (0%)		
Other	5 (0%)		0 (0%)		
Police	6 (0%)		0 (0%)		
Private vehicle	294 (20%)		19 (18%)		
SAMU	43 (3%)		7 (7%)		
Mechanism of Injury		-		-	<0.01
Bite (incl. human)	10 (1%)		1 (1%)		
Blunt force	113 (7%)		5 (4%)		
Burn	211 (13%)		28 (25%)		
Choking (incl. hanging)	1 (0%)		0 (0%)		
Fall	803 (51%)		23 (21%)		
Gunshot	2 (0%)		0 (0%)		
Landmine	9 (1%)		0 (0%)		
Other	11 (1%)		1 (1%)		
Road traffic accident	385 (25%)		53 (48%)		
Stab	26 (2%)		0 (0%)		
Injury Location		-		-	0.026
Farm	97 (6%)		1 (1%)		
Home	808 (52%)		51 (46%)		
Industry	6 (0%)		0 (0%)		
Other	18 (11%)		1 (1%)		
Public space	11 (1%)		0 (0%)		

Table 1 *(continued)*

Variable	Survivors (n = 1582)		In-Hospital Death (n = 113)		p-value
	N (%)	Median (IQR)	*N* (%)	Median (IQR)	
River/lake/pool	3 (0%)		0 (0%)		
Road	515 (33%)		54 (49%)		
School	76 (5%)		1 (1%)		
Sports/recreation	22 (1%)		1 (1%)		
Unknown	7 (0%)		1 (1%)		
Activity at time of injury		-		-	<0.01
Cooking	28 (2%)		0 (0%)		
Education	7 (0%)		2 (2%)		
Fighting	20 (1%)		1 (1%)		
Playing	618 (40%)		34 (31%)		
Sport	22 (1%)		1 (1%)		
Travel	523 (34%)		49 (45%)		
Unknown	158 (10%)		18 (17%)		
Work	168 (11%)		4 (4%)		
Intent		-		-	0.337
Intentional	31 (2%)		2 (2%)		
Undetermined	3 (0%)		1 (1%)		
Unintentional	1517 (98%)		108 (97%)		
Site of anatomic injury		-		-	
Head	364 (23%)		69 (61%)		<0.01
Face and Neck	14 (1%)		0 (0%)		0.641
Spine	26 (2%)		2 (2%)		1.000
Upper extremity (open)	64 (4%)		1 (1%)		0.151
Upper extremity (closed)	376 (24%)		8 (7%)		<0.01
Lower extremity (open)	123 (8%)		3 (3%)		0.069
Lower extremity (closed)	447 (28%)		6 (5%)		<0.01
Burn	182 (12%)		28 (25%)		<0.01
Intraabdominal injury	42 (3%)		8 (7%)		0.016
Chest trauma	32 (2%)		8 (7%)		<0.01
Pelvis	16 (1%)		3 (3%)		0.254
Other	40 (3%)		3 (3%)		1.000

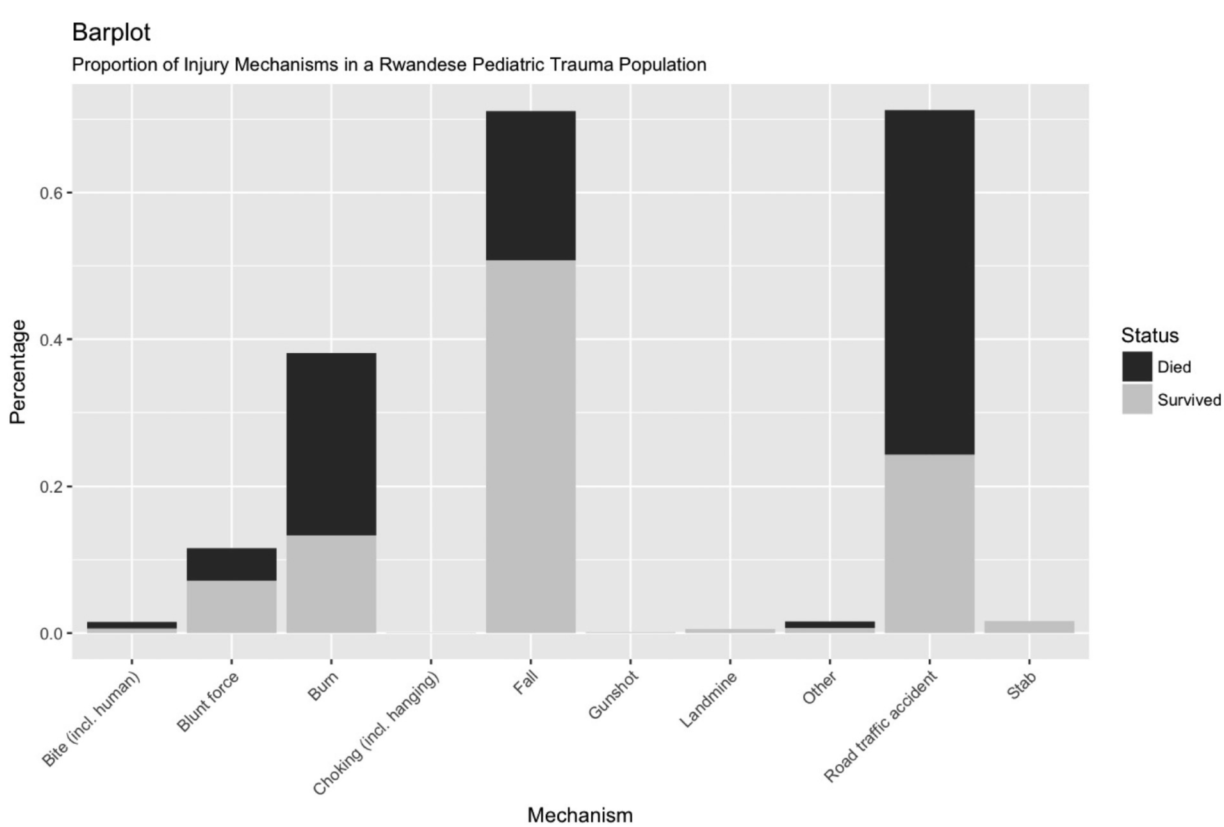

Fig. 1. Mechanism of injury among Rwandese pediatric trauma patients who survived and those who did not.

Table 2
Calibrated model coefficients.

Variable	Name	Coefficient	OR (95% Confidence Interval)
Intercept	β_0	4.66	106.63 (0.22–3.05e+04)
Age	β_1		
Infant		0 (Ref.)	0 (Ref).
Toddler		−0.30	0.74 (0.18–3.39)
Preschool		0.24	1.27 (0.36–5.42)
Child		−0.97	0.38 (0.11–1.54)
Preteen		−0.90	0.41 (0.08–2.21)
Hypotension (TRUE if SBP < (70 + (2 × Age in years))	β_2	0.75	2.11 (0.55–6.31)
Heart Rate (beats per minute)	β_3	0.00	1.00 (0.99–1.01)
Neurologic status	β_4		
Alert		0 (Ref.)	0 (Ref.)
Responsive to Verbal Stimuli		1.17	3.22 (1.41–6.66)
Responsive to Painful Stimuli		0.85	2.33 (0.96–5.10)
Unresponsive		−0.02	0.97 (0.12–4.79)
Oxygenation (percentage)	β_5	−0.08	0.92 (0.87–0.98)
Airway Intervention	β_6	6.29	542.21 (123.08–4.61e+03)
Variable for the interaction between Age and Heart Rate	β_7		
Infant * Heart Rate		0 (Ref.)	0 (Ref.)
Toddler * Heart Rate		0.00	1.0 (0.99–1.01)
Preschool * Heart Rate		0.00	1.0 (0.99–1.01)
Child * Heart Rate		0.00	1.0 (0.99–1.01)
Preteen * Heart Rate		0.00	1.0 (0.99–1.01)

iterations [31]. Ninety-five percent confidence intervals (95% CI) were reported. We examined differences in the AUC for the full cohort and those under 5 years old. This cutoff was chosen a priori based on the KTS cutoff values in the age variable. Statistical significance was set at $p < 0.05$. Given the high proportion of missing data, a sensitivity analysis was performed using only complete cases to ensure that the multiple imputation procedure had not significantly altered the statistical inferences [32] All statistical analyses were performed using R version 3.4.3 [33] (Auckland, New Zealand).

2. Results

2.1. Missing data

Missing data ranged from 0 to 30% per variable. The highest proportion of missing data was in the oxygen saturation category. The mean percentage of missing data was 11% in the dataset. We therefore elected to estimate missing data based on $M = 20$ imputations.

2.2. Descriptive statistics

Out of 11,275 total patients in the registry, 1695 were included in the study sample. Among excluded patients, 8686 were excluded on the basis of age, 675 were excluded for minor injuries not requiring

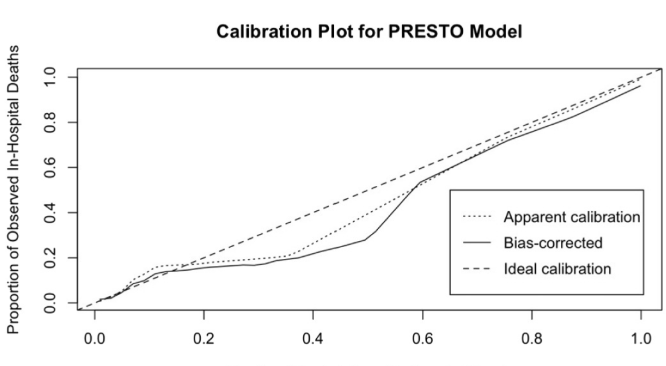

Fig. 2. Plot showing expected probability versus observed in-hospital deaths using PRESTO[a] model after apparent and bias-corrected calibration. [a]PRESTO = Pediatric Resuscitation and Trauma Outcome.

admission and 219 were excluded for incomplete outcome information. Baseline patient characteristics are shown in Table 1. The proportion of in-hospital mortality was 7% (113/1695). Leading injury mechanisms were falls, road traffic accidents and burns. Fatality was highest among road traffic accident and burn victims (Fig. 1). There was a statistically significant difference in the distribution of injury mechanisms among survivors and nonsurvivors ($p < 0.01$).

2.3. Calibration

Calibrated model coefficients are provided in Table 2. The Hosmer–Lemeshow test for calibration of the PRESTO model yielded a chi-squared value of 5.5 and a p-value of 0.71, indicating no significant difference between the predicted and observed outcomes. The calibration curve has been plotted in Fig. 2, yielding a mean absolute calibration error of 0.04.

2.4. Comparison to Kampala Trauma Score and Revised Trauma Score

ROC curves for each model are shown in Fig. 3A for the full cohort, and in Fig. 3B for the subset of patients younger than 5 years old.

In the full cohort, the AUC for PRESTO was excellent at 0.90 (95% CI [0.82–0.91]). This significantly outperformed the RTS (AUC = 0.77, 95% CI [0.80–0.97], $p < 0.01$) but was not statistically different from KTS (AUC = 0.89, 95% CI [0.72–0.82], $p = 0.856$).

In patients younger than 5 years-old, the AUC for PRESTO remained excellent at 0.84 (95% CI [0.75–0.92]), which was significantly better than RTS (AUC = 0.73 95% CI [0.64–0.81], $p < 0.01$) and KTS (AUC = 0.58, 95% CI [0.50–0.66], $p < 0.01$).

2.5. Sensitivity analysis

A similar analysis of cases without missing data yielded an AUC for PRESTO of 0.787 (95% CI [0.736–0.839], which was significantly higher than that of RTS (AUC = 0.735, 95% CI [0.663–0.809], $p < 0.01$) and of KTS (AUC = 0.683, 95% CI [0.604–0.763], $p < 0.01$).

3. Discussion

The trauma registry in Rwanda serves as a regionally-developed hospital-based repository for important injury data, which has been shown to provide valuable and actionable information about the burden

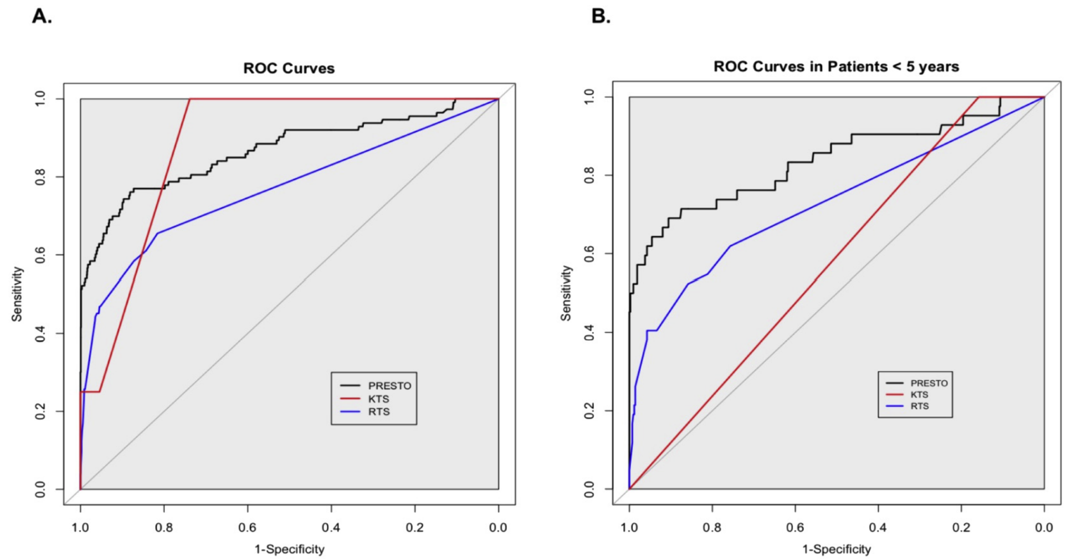

Fig. 3. Receiver operating characteristic curves of PRESTO[a], KTS[b] and RTS[c] in (A) the full study cohort and (B) a subgroup of patients younger than 5 years. [b]PRESTO = Pediatric Resuscitation and Trauma Outcome. [c]KTS = Kampala Trauma Score. [d]RTS = Revised Trauma Score.

of trauma-related disability and death in this country [18,19,34]. Previous reports have already shed a light on the primary demographic factors and injury mechanisms contributing to avertable mortality in injured children in Rwanda [34]. Despite significant improvements made in population health and economic development since 1994, a significant need for surgical care among children under 15 years old remains unmet. The findings published by the Surgeons OverSeas Assessment of Surgical Need (SOSAS) emphasized the need for further development of injury surveillance mechanisms and overall surgical capacity to address the significant burden of trauma on children, one of the most vulnerable subsets of Rwandese society [35].

Few trauma scores have been specifically validated in children. Furthermore, many trauma scores rely on investigations requiring material or human resources that are not consistently available in low resource environments [15]. Instead of relying on anatomic data derived from advanced imaging and laboratory data obtained through expensive tests, we have shown that the PRESTO model, a simple pediatric trauma score adapted to low-resource settings, can predict in-hospital death based on bedside variables available upon initial patient assessment and resuscitation. The calibrated model coefficients presented in this study can be used in the PRESTO model's mathematical equation to estimate the predicted probability of in-hospital death in the LMIC context. The formula and the manner in which the regression coefficients in Table 2 can be used are recapitulated below. They differ from the coefficients included in the original development paper since this was done using North-American data [16]. If desired, the PRESTO model can be used in high-income countries using the previously published coefficients; however, the ultimate goal for PRESTO was to be useful in the LMIC context.

$$P_{(PRESTO)} = Predicted\ probability\ of\ in-hospital\ death$$

$$P_{(PRESTO)} = \frac{1}{1+e^{b}}$$

$$b = \beta_0 + \beta_1.Age + \beta_2.Hypotension + \beta_3.Heart\ Rate + \beta_4.AVPU$$

$$+\beta_5.S_pO_2 + \beta_6.Airway\ Intervention + \beta_7.Age.Heart\ Rate$$

Certain features of the PRESTO model make it advantageous compared to KTS and RTS as a quality improvement tool. Effective quality improvement requires timely and accurate data collection, which is only achievable if the data required are readily available and unsusceptible to observational error. Arguably the KTS and RTS achieve some of these criteria. The KTS was first introduced as a novel model for prediction of mortality or hospital admission after trauma in Kampala, Uganda [21]. It was conceptualized as a simple and user-friendly score and its adoption has been widespread among trauma researchers, particularly in the developing world. It incorporates 5 variables, including age, systolic blood pressure, respiratory rate, neurologic status and a score for serious injury. Serious injury is defined as an injury requiring admission to hospital. The KTS validated to correlate with a composite outcome of hospital admission and death. Some limitations of its accuracy have been reported in the literature [36], and attempts have been made to modify it in order to improve its performance as a prognostic tool [37,38]. Some problematic features of this score include the subjectivity of the serious injury variable as well as the overlap between it and the composite response variable. The RTS is also a simple, physiologic scoring system, which incorporates the Glasgow Coma Scale (GCS), respiratory rate, and systolic blood pressure. A careful examination of the RTS and KTS may reveal why the PRESTO model has a better prognostic performance, especially among the younger children category. The constituent variables for KTS and RTS use physiologic cutoff values that are not relevant to young children. There is a normal variation in the blood pressure and respiratory rates of pediatric patients at various ages. For example, a systolic blood pressure below 90 mmHg may not be abnormal in an injured 3-year-old child. The accuracy of respiratory rate and GCS measurements has also been questioned in previous reports [15,39] Furthermore, in the KTS, age greater than 55 years and younger than 5 are given equivalent risk-weighting. Although simple and user-friendly, this categorization cannot be expected to yield high accuracy for prognostication among children. Finally, RTS and KTS were never expressly constructed to evaluate pediatric patients nor specifically validated in a pediatric population.

The following limitations of our study must be acknowledged. As with many hospital-based registries, information is lacking regarding the characteristics and outcomes of patients who never reached the hospital. Integration of this registry with a prehospital database would be very helpful to reduce this selection bias and provide a clearer picture of the Rwandese trauma system as a whole. This issue primarily limits our ability to make broad statements about the quality of prehospital trauma care or about the epidemiology of trauma in Rwanda as a whole. However, this limitation does not significantly impact the ability of any institution to use PRESTO for the purpose of tracking its performance in caring for the injured patients who *do* reach its emergency department by performing patient-level risk adjustment. The only caveat to this would be in a scenario where the eligible patient capture rate was low, and where the inclusion or exclusion of eligible patients was inadvertently biased by some unrecognized factors. Although attempts were made to track precise capture rates, this process relied on auditing emergency department admission logs, which were themselves too incomplete to precisely identify eligible patients. The data collected within the registry are susceptible to measurement or observation error. Periodic audits were performed by the research team to verify data completeness and accuracy. However, this process was dependent on chart review, which revealed data quality issues within archived medical records. The approved study protocol did not allow for broad review of all emergency department patient charts to determine eligibility for inclusion into the registry. The issue of data completeness and accuracy is not specific to Rwanda. Enhancing data acquisition and developing mechanisms to improve data quality in large trauma registries remain relevant to these efforts worldwide.

The Hosmer–Lemeshow test used has some drawbacks owing to the fact that it groups the sample into deciles of predicted probability, but some argue that the quantiles should be grouped differently, either proportionately to sample size, or in some other clinically relevant risk-intervals. It also suffers from poor power to detect miscalibration or overfitting in smaller sample sizes [23,24]. This is why we chose to also illustrate Harrell's bias-corrected method. We have not been able to identify proper reporting of calibration error summary statistics in the trauma literature. A recent systematic review analyzed the performance and validation of injury severity measures in low- and middle-income countries. This study revealed that an overwhelming majority of studies report only goodness-of-fit and validity measures such as the *c*-statistic, which is used to compare discrimination among several models [40]. The Hosmer–Lemeshow method of testing goodness-of-fit is occasionally reported, and has certain caveats as described above. It is therefore very difficult to compare the PRESTO model's mean absolute calibration error of 4% with other published models. The mean absolute calibration error must certainly be taken into account when interpreting the assessment of an institution's outcomes when caring for pediatric trauma patients. We acknowledge the value is reasonably high, especially when compared with reported calibration errors that are reported in physics or chemistry literature where precision instrument calibration is critical. Given that PRESTO is not a triaging tool or a diagnostic test for individual patient risk of in-hospital death, we would argue that this calibration error is not prohibitively detrimental for the intended use of the PRESTO model, which was developed for the purpose of quality improvement. Finally, we acknowledge that further validation of PRESTO is required in other LMICs to increase the external validity of the model.

4. Conclusion

PRESTO is the first injury severity model that has been developed and validated specifically for injured children in low-resource settings. This study shows that after calibration, the PRESTO model can be used for patient-level risk-adjustment in low-resource settings. Its ability to predict in-hospital death for injured children is superior to the RTS below age 15 and superior to the KTS below age 5 years.

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