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Prehospital prediction of severe injury in road traffic injuries: A multicenter cross-sectional study

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ABSTRACT

Background: To develop and validate a risk stratification model of severe injury (SI) and death to identify and prioritize road traffic injury (RTI) patients for transportation to an appropriate trauma center (TC).
Methods: A 2-phase multicenter-cross-sectional study with prospective data collection was collaboratively conducted using 9 dispatch centers (DC) across Thailand. Among the 9 included DC, 7 and 2 DCs were used for development and validation, respectively. RTI patients who were treated and transported to hospitals by advanced life support (ALS) response units were enrolled. Multiple logistic regression was used to derive risk prediction score of death in 48 h and SI (new injury severity score $\geq$ 16). Calibration/discrimination performances were explored.
Results: A total of 5359 and 2097 RTIs were used for development and external validation, respectively. Seven and 9 predictors among demographic data, mechanism of injury, physic data, EMS operation, and prehospital managements were significant predictors of death and SI, respectively. Risk prediction models fitted well with the developed data (O/E ratios of 1.00 (IQR: 0.69, 1.01) and 0.99 (IQR: 0.95, 1.05) for death and SI, respectively); and the C statistics of 0.966 (0.961, 0.972) and 0.913 (0.905, 0.922). The risk scores were further stratified as low, moderate and high risk. The derive models did not fit well with external data but they were improved after recalibrating the intercepts. However, the model was externally good/excellent discriminated with C statistics from 0.896 (0.871, 0.922) to 0.981 (0.971, 0.991).
Conclusion: Risk prediction models of death and SI were developed with good calibration and excellent discrimination. The model should be useful for ALS response units in proper allocation of patients.

Introduction

Road traffic injury (RTI) is the most common event for emergency medical services [1], accounting for approximately 23% of injury related deaths worldwide [2]. In Thailand, RTI was responsible for half of all injuries (49.4%), and accounted for 64.3% of injury related deaths in 2005 [3]. Despite the implementation of several programs (e.g., traffic law enforcement, traffic calming intervention, etcetera.) the high mortality rate remains [4].

An emergency medical service (EMS) system has been set up and integrated into existing health care systems to minimize morbidity and mortality by providing pre-hospital treatments and transportation to the most appropriate hospital [5]. Current evidence indicates that severely injured patients should be transferred to a high-level rather than low-level trauma center (TC) [6], but there are few such centers in Thailand and other developing countries.

Currently, EMS system in Thailand is developing and there is no standardized triage tool implemented for identifying severity of RTI patients. Knowing their severity of injuries (SI) would aid to properly prioritize and thus lead to allocate treatment management and appropriately transfer of RTI victims to hospitals. Several risk prediction scores have been developed to classify severity of

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injured victims in general trauma patients, (e.g., revised trauma score (RTS) trauma injury severity score (TRISS), and the field triage decision scheme) mainly considering physiologic factors (i.e., systolic blood pressure (SBP), respiratory rate (RR) and Glasgow coma scale (GCS)) [7–10]. The field triage decision scheme was firstly recommended by the American College of Surgeons Committee on Trauma (ACS-COT) in 1999 [7] and later revised in 2006 considering vital signs, anatomical involvement, mechanism of injury and special circumstances in order, which mainly aimed to prioritize high risk of severe trauma patients. However, it was low to fair in discriminating high risk from low risk RTI patients (C statistic 0.55 to 0.65) [11]. Although some risk prediction models for RTI patients exist, their diagnostic accuracies varied greatly [12–15]. Given the high incidence of RTI, a risk prediction score should be able to stratify a patient's severity and prioritize them properly.

We conducted a multi-center cross-sectional study, which aimed to develop a risk stratification model of severe injury (SI) and death to identify and prioritize RTI patients for transportation to an appropriate trauma center (TC). This study was approved by the ethics committee of the Faculty of Medicine Ramathibodi Hospital, Mahidol University and applied waiver of informed consent due to urgent situation.

Methods

Study design and setting

The study design was a multi-center cross-sectional study with prospective data collection, which composed of development and validation phases following suggestions for risk prediction model developments by Moons et al [16,17]. We enrolled RTI subjects under provincial dispatch centers (DC) during July 2015 to February 2017.

The EMS system in Thailand consists of basic and advanced life support units (BLS, ALS), which are provided by non-government foundations and provincial/regional hospitals, respectively, under regulations of provincial DCs and the National Institute of Emergency Medicine. All EMS personnel must be certified before practicing under regulation of the National Institute of Emergency Medicine. All traffic victims have to be treated and transported by ALS units, except minor injury (e.g., pure laceration wound or mild head injury) which can be looked after by the BLS teams.

Because prehospital care and the EMS information system in Thailand have been recently developed, we purposively selected 9 DCs across the country based on following three criteria: high density of RTI cases treated by the ALS response unit, an emergency physician (EP) as medical director, and having an EMS information system. Among 9 DCs, 7 DCs (i.e., Saraburi, Ayutthaya, Chiang Mai, Nakhon Ratchasima, Khon Kaen, Nakhom Si Thammarat, and Chonburi) were used to develop and internally validate the risk prediction model whereas two DCs (i.e., Ubonratchathani and Trang) were selected to externally validate the risk model. This study followed transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD) [18].

Selection of participants

Subjects were eligible if they were aged 15 years or older, experienced a RTI, and were transported to hospital by ALS response unit in the studied DCs. Patients were excluded if they had at least one sign of irreversible death (i.e., decapitation, incineration, separation, or destruction of heart or brain, rigor mortis, and lividity), declined EMS treatment or transportation to hospital, or could not be assessed for eligibility due to an unsafe accident scene.

Outcomes

The primary outcome was death within 48 h of the RTI occurrence. The secondary outcome was SI, defined as a new injury severity score (NISS) $\geq$ 16. [19,20,13,11,12,14] For individual subjects, NISS was assessed using an abbreviated injury scale (AIS), according to AIS 2005 (update 2008) dictionary [21], for all injury related diagnoses. NISS was then estimated by the sum of squares of the first three highest AIS diagnoses.

Methods of measurement

Predictors were classified into 7 domains as follows:

- Demographic data included age (year), sex, body mass index (BMI). Age was categorized based on field triage decision scheme [7].
- The crash characteristics data included types of road user (pedestrian/bicyclist or motorcyclist/4, or more wheels vehicles), and total number of victims.
- EMS operation domain included response time, on scene time, transportation time, distance from the EMS base to scene and scene to destination hospital, and out of hospital management (i.e., intravenous fluid administration, airway management). Response time, on scene time, and transportation time were defined as the time since EMS was requested to the time at scene arrival, time since the response unit arrival to departure from the scene, and departure to receiving hospital, respectively. Response time was also categorized into $\leq$ 8 min or longer [5]. Out of hospital management referred to receiving any intravenous fluid administration or airway management (not receiving/ clear airway/ assisted ventilation) before hospital arrival.
- Mechanism of injury consisted of presence of burn, blunt, and penetrating injuries.
- Physiological data were results of the first physical examinations at scene, i.e., SBP, RR (breaths/minute), and GCS. These variables were also categorized based on RTS [10].
- Environmental domain included time (day/ night) and location of incidence (highway/non-highway).
- Risk behavior domain included alcohol consumption before the accident.

EMS personnel (paramedics/ pre-hospital nurse/ doctors) in study provinces were trained about variable definition and data collection processes before fieldwork. All predictors were prospectively collected at scene during pre-hospital management, except EMS operation and physiological factors which were recorded by EMS operation forms according to EMS system in Thailand and subsequently extracted to case record form. Death and trauma related diagnosis were extracted from medical record. Predictors and outcomes were collected by trained EMS personnel. All data were checked and enquired for completeness, correctness, and inconsistency before data entry. The two databases were validated and rechecked before final analysis.

Sample size estimation

The pooled prevalence of SI was 12.5% (95% CI: 10.8%–14.3%) from our literature review [19,20,11,14]. A sample size was calculated based on estimating this proportion with setting 5% type one error, adjusting for design effect of clustering and 10% missing data; which indicated 5111 subjects were required for the derivation phase and an additional 1022 subjects were enrolled for the external validation. Therefore, 6133 subjects were required for this study.

Data analysis

Multiple imputation

Multiple imputation (MI) with chained equations was used to impute missing data [22]. Logistic regression and interval regressions with 40 imputations were used to predict binary and continuous variables, respectively. Complete data of predictors (e.g., age, sex, mean arterial pressure (MAP), GCS, PR) and outcome (i.e., NISS and death in 48 h) were used to predict missing data for weight, height, and RR. These predictors plus types of road users, time of incidence, total number of victims, burn, penetration, and blunt injury were used to predict alcohol consumption. Performance of the MI was explored and assessed using relative variance increase (RVI) and fraction of missing information (FMI). The largest FMI of missing variable was used to suggest the adequate number of imputations according to the rule of thumb, i.e., FMI x100. For instance, if FMI was 0.39, number of imputations was at least 39.

Derivation phase

Simple logistic regression was used to screen predictors of death and SI. Variables with a p value less than or equal to 0.1 were simultaneously considered in a multivariable logit model using forward selection. Likelihood ratio test were used to select only significant variables in the final model. Model performance was assessed as follows: Calibration was assessed using Hosmer-Lemeshow goodness of fit (HL-GOF) test by equally dividing predicted probability into 10, 30, 45, 65 and 110 groups where appropriate [23,24]. In addition, observed (O) and expected (E) numbers, and O/E ratio along with its interquartile range (IQR) were estimated. The O/E ratio close to 1 indicated the predicted values close to observed values. A calibration plot was constructed by plotting O values on X-axis and E values on and Y-axis. Finally, discrimination was assessed using receive operating characteristic (ROC) curve analysis; and a concordance statistic (C statistic) was estimated.

All coefficients in the final model were used to construct a risk prediction score. The score cutoff was then calibrated based on its distribution and ROC analysis. Diagnostic parameters of moderate and high-risk groups compared to the rest (i.e., sensitivity, specificity, positive predictive value (PPV), positive likelihood ratio (LR^+) were then estimated.

Internal validation

A bootstrap with 1000 repetitions was used to assess internal performances. For the calibration coefficient, Somers' D rank correlations of derived model (D_{orig}) and each set of bootstrapping (D_{boot}) were estimated [25]. Then, optimism (O_c) was calculated by D_{orig}- D_{boot}. Finally, the bootstrap corrected calibration coefficient was estimated by D_{orig}- Mean O_c. For discrimination, C statistic of the derived model was subtracted by C statistic of each bootstrapping (C_{boot}); and the bootstrapping corrected discrimination coefficient was then estimated.

External validation

The risk prediction score from the development phase (called M0) was calculated in the validation data, along with estimated probability of outcome occurrence. Calibration and discrimination performance were explored as previously mentioned. If the risk prediction model did not fit well with the external data, model recalibration was performed by recalibrating the intercept with/without the updated model where appropriate [26]. Model revision by recalibration of the intercept (Called M1) [16], and its performance was then re-explored. The scores were categorized into low, moderate and high risk groups, based on the cut off points of derivative phase. Diagnostic parameters of moderate and high-risk groups compared to the rest (i.e., sensitivity, specificity,

Table 1
Predictors of death: A multiple logistic regression.

Predictors	Coefficients	95%CI	SE	*P*	OR	95%CI
Intercept	−6.620	−7.280, -5.960	1.34	<0.001	0.001	1.01, 1.02
Age	0.018	0.011, 0.026	0.00	<0.001	1.01	1.01, 1.02
Blunt injury						
Yes	0.835	0.524, 1.147	0.15	<0.001	2.30	1.68, 3.15
No	0				1	
RR 4 groups						
<6	1.032	0.582, 1.483	0.22	<0.001	2.80	1.79, 4.40
6-9	1.021	0.380, 1.662	0.32	0.002	2.77	1.46, 5.27
>29	1.051	0.509, 1.592	0.27	<0.001	2.86	1.66, 4.91
10-29	0				1	
SBP 4 groups						
<50	2.251	1.809, 2.694	0.22	<0.001	9.50	6.10, 14.80
50-75	1.661	1.103, 2.220	0.28	<0.001	5.26	3.01, 9.20
76-89	1.234	0.728, 1.740	0.25	<0.001	3.43	2.07, 5.70
>89	0				1	
GCS 5 groups						
3	2.602	2.028, 3.175	0.29	<0.001	13.40	7.60, 23.90
4-5	2.614	1.939, 3.289	0.34	<0.001	13.60	6.95, 26.8
6-8	1.539	0.967, 2.111	0.29	<0.001	4.66	2.63, 8.26
9-12	1.336	0.754, 1.919	0.29	<0.001	3.80	2.12, 6.81
13-15	0				1	
Airway management						
Assisted ventilation	1.217	0.474, 1.960	0.37	0.001	3.37	1.60, 7.10
Open/clear airway	0.419	−0.25, 1.092	0.34	0.223	1.52	0.77, 2.98
No supplement	0				1	
IV fluid administration						
YES	0.611	0.082, 1.141	0.27	0.024	1.84	1.08, 3.13
No	0				1	

CI: confidence interval; GCS: Glasgow coma scale; IV: intravenous; OR: odds ratio; P: p value; RR: respiratory rate; SBP: systolic blood pressure; SE: standard error.

positive predictive value (PPV), positive likelihood ratio (LR^+) were then estimated.

All analyses were performed using STATA version 15.0 (Stata Corp, College Station, Texas, USA), based on mi estimation commands. P value less than 0.05 was considered as statistically significant.

Results

Characteristics of study subjects

A total of 7456 subjects were enrolled, 5359 and 2097 subjects for derivation and external validation, respectively. Among 5359 subjects, mean age (SD) was 35.1 (16.0) years, 3824 subjects (71.4%) were male, and 4380 (81.7%) subjects rode 2–3 wheel vehicles. A total of 1472 (27.5%; 95% CI: 26.3%, 28.7%) subjects were classified as SI and 696 (13.0%; 95% CI: 12.1%, 13.9%) died within 48 h. The characteristics of subjects are described by province in Supplemental Table 1.

Main results

Imputation

There were 13 (0.17%), 28 (0.37%), 40 (0.53%), and 922 (12.36%) observations where data for RR, height, weight, and alcohol consumption were missing respectively. These data were therefore imputed with estimated FMI and RVI of 0.001 to 0.3968 and 0.001 to 0.3226, respectively. Alcohol consumption contributed the largest FMI (0.3968) and RVI (0.3226) (see Supplemental Table 2).

Prehospital prediction of death in 48 h

Development phase

Of 20 potential predictors, 17 were candidates in the multivariable analysis but only 16 (80%) were included because direction of daytime effect was counter-intuitive which might be due to survival bias (see Supplemental Table 3). Finally, 7 were kept including age, physical examination (i.e., SBP, RR, and GCS), blunt injury and EMS operation, i.e., IV fluid administration, and airway managements (Table 1). The risk prediction score was calculated following the equation described in Supplemental Figure 1.

The C statistic of this model was 0.966 (95% CI: 0.961, 0.972) indicating excellent performance in discriminating death from survival in RTI subjects. The HL-GOF test revealed the model fitted well with the data (Chi-square = 24.43, df = 28, P = 0.66) with O/E ratio of 1.00 (IQR: 0.69, 1.01), see Table 2 and Supplemental Table 4. The calibration plot indicated that the observed and predicted values were very close, see Supplemental Figure 2.

The risk scoring scheme was constructed, which ranged from -6.319 to 3.635 with a median of -4.723. The score was then categorized into <-4.282, -4.282 to -2.212, and >-2.212 for low, moderate, and high risk groups with the corresponding PPV of 0.3%, 4.5%, and 53.6%, respectively. LR + of moderate and high risk group were 3.2 and 7.7 compared to the rest group (see Table 3).

A 1000-replication bootstrap yielded calibration and discrimination biases of -0.00127 (95% CI: -0.00162, 0.00092) and -0.00066 (95% CI: -0.00084, -0.00049) indicating good calibration and discrimination (see Supplemental Table 5).

External validation

Ubonratchathani. There were 1104 subjects recruited from Ubonratchathani DC. Death rate was 8.3%, which was lower than in the development data. In addition, the distribution of predictors were different, with a higher proportion of SBP > 90 mmHg (90.6% vs 86.8%), RR 10–29 breaths/minute (92.7% vs 88%), GCS 13–15 (78.1% vs 69.2%), and airway management (59.1% vs 56.4%), whereas blunt injury (37.6% vs 62.3%) and IV fluid administration (42.1% vs 47.6%) were lower (see Supplemental Table 6). All predictors were significantly associated with death without change in the direction of association (see Supplemental Table 7).

The risk prediction score was calculated using the equation from the derivation phase, with a median of -5.063 (range: -6.338, 3.521). HL-GOF test indicated good calibration (Chi-square = 3.45, df = 8, P = 0.90). The estimated O/E was 1.00 with a wide range IQR of 0.57, 1.01, see Table 2. However, calibration plot showed deviation from the perfect line (see Supplemental Figure 3). Therefore, recalibration of the intercept was performed and

Table 2
Model performance for predicting death and SI in RTI subjects.

Predictors	Phases	Provinces	Model	Calibration				Discrimination
				HL Chi^2	df	P	O/E (IQR)	C statistic (95% CI)
Death	Derivation			24.43	28	0.66	1.00 (0.69, 1.01)	0.966 (0.961, 0.972)
	External Validation	Ubonratchathani	M_0	3.45	8	0.90	1.00 (0.57, 1.01)	0.981 (0.971, 0.991)
			M_1	3.50	8	0.89	0.99 (0.31, 1.01)	0.981 (0.971, 0.991)
		Trang	M_0	4.48	8	0.81	1.00 (0.89, 1.09)	0.947 (0.922, 0.973)
			M_1	5.71	8	0.68	1.00 (0.97, 1.36)	0.947 (0.922, 0.973)
SI	Derivation			13.8	28	0.09	0.99 (0.95, 1.05)	0.913 (0.905, 0.922)
	External Validation	Ubonratchathani	M_0	28.7	8	<0.001	1.00 (0.71, 1.03)	0.909 (0.885, 0.932)
			M_1	7.2	8	0.51	1.00 (0.95, 1.05)	0.909 (0.885, 0.932)
		Trang	M_0	21.0	8	0.007	0.99 (0.78, 1.04)	0.896 (0.871, 0.922)
			M_1	7.5	6	0.28	1 (0.94, 1.04)	0.896 (0.871, 0.922)

C statistic: concordance statistic; df: degree of freedom; P: p value; O/E: observed over expected value; HL Chi^2: Hosmer-Lemeshow Chi^2; RTI: road traffic injury; SI: severe injury.

Table 3
Diagnostic performance of moderate and high risk compared with low risk groups of derived and external validated models for predicting death and SI.

Outcomes	Phases	Provinces	Model	Risk groups	Death	Alive	%PPV	%Sens (95% CI)	%Spec (95% CI)	LR+ (95% CI)
Death	Derivation			Low	9	3207	0.3			
				Moderate	42	898	4.5	98.7 (97.6, 99.4)	68.8 (67.4, 70.1)	3.2 (3.0, 3.3)
				High	645	558	53.6	92.7 (90.5, 94.5)	88.0 (87.1, 89.0)	7.7 (7.1, 8.4)
	External validation	Ubonratchathani	M0	Low	1	769	0.1			
				Moderate	5	153	3.2	98.9 (94.1, 100)	76.0 (73.2, 78.6)	4.1 (3.7, 4.6)
				High	86	90	48.9	93.4 (86.2, 97.5)	91.1 (89.2, 92.8)	10.5 (8.6, 12.9)
			M1	Low	1	767	0.1			
				Moderate	5	155	3.1	98.9 (94.1, 100)	75.8 (73.0, 78.4)	4.1 (3.7, 4.6)
				High	86	90	48.9	93.5 (86.3, 97.6)	91.1 (89.1, 92.8)	10.5 (8.6, 12.9)
		Trang	M0	Low	3	684	0.4			
				Moderate	9	163	5.2	95.3 (86.9, 99.0)	73.6 (70.7, 76.4)	3.6 (3.2, 4.1)
				High	52	82	38.8	81.3 (69.5, 89.9)	91.2 (89.2, 92.9)	9.2 (7.3 11.7)
			M1	Low	5	773	0.6			
				Moderate	8	101	7.3	92.2 (82.7, 97.4)	83.2 (80.6, 85.6)	5.5 (4.7, 6.4)
				High	51	55	48.1	79.7 (67.8, 88.7)	94.1 (92.4, 95.5)	13.5 (10.1, 17.9)
Outcome	Phases	Provinces	Model	Risk groups	SI	Non-SI	%PPV	%Sens (95% CI)	%Spec (95% CI)	LR+ (95% CI)
SI	Derivation			Low	144	2949	4.7			
				Moderate	231	562	29.1	90.2 (88.6, 91.7)	75.9 (74.5, 77.2)	3.7 (3.5, 4.0)
				High	1097	376	74.5	74.5 (72.2, 76.7)	90.3 (89.4, 91.2)	7.7 (7.0, 8.5)
	External validation	Ubonratchathani	M0	Low	24	704	3.3			
				Moderate	26	131	16.6	87.1 (81.4, 91.6)	76.7 (73.8, 79.4)	3.7 (3.3, 4.3)
				High	136	83	62.1	73.1 (66.1, 79.3)	91 (88.9, 92.7)	8.1 (6.5, 10.1)
			M1	Low	31	773	3.9			
				Moderate	30	93	24.4	83.3 (77.2, 88.4)	84.2 (81.7, 86.5)	5.3 (4.5, 6.2)
				High	125	52	70.6	67.2 (60.0, 73.9)	94.3 (92.6, 95.7)	11.9 (8.9, 15.7)
		Trang	M0	Low	23	621	3.6			
				Moderate	42	144	22.6	86.9 (81, 91.5)	76 (72.9, 78.9)	3.6 (3.2, 4.2)
				High	111	52	68.1	63.1 (55.5, 70.2)	93.6 (91.7, 95.2)	9.9 (7.4, 13.2)
			M1	Low	33	661	4.8			
				Moderate	38	110	25.7	81.3 (74.7, 86.7)	80.9 (78.0, 83.5)	4.3 (3.6, 5.0)
				High	105	46	69.5	59.7 (52.0, 67.0)	94.4 (92.6, 95.8)	10.6 (7.8, 14.4)

CI: confidence interval; LR+: likelihood ratio positive; Non-SI: non -severe injury; PPV: positive predictive value; Sens: sensitivity; SI: severe injury; Spec: specificity.

indicated M_1 was better in calibration plot (see Supplemental Figure 4). The C statistic was 0.981 (95% CI: 0.971, 0.991), see Table 2. According to M0, the PPV of low, moderate and high risk groups were 0.1%, 3.2% and 48.9%, whereas those of M1 were 0.1%, 3.1% and 48.9%, respectively (see Table 3).

Trang. Among 993 subjects recruited from Trang DC, 6.3% of subjects died, which was lower than in the development data. Subjects were older (mean age 37 vs 35.5 years), had a higher SBP > 90 mmHg (92.9% vs 86.8%), RR 10–29 breaths/minute (93.8% vs 88%), and GCS 13–15 (80.7% vs 69.2%), but had a lower proportion with blunt injury (37.6% vs 62.3%), IV fluid administration (42.1% vs 47.6%), and airway management (54.8% vs 56.4%) (see Supplemental Table 6). All predictors were significantly associated with death, except age (see Supplemental Table 7). The median risk score was -4.931 (range: -6.319, 3.388). HL-GOF test indicated good calibration (Chi-square = 4.88, df = 8, P = 0.81). The estimated O/E was 1.00 with a wide range IQR of 0.89, 1.09. Calibration plot indicating deviation of predicted value from observed value (see Supplemental Figure 3). Therefore, recalibration of the intercept was performed and indicated M_1 was better in calibration plot (see Supplemental Figure 5). The C statistic was 0.947 (95% CI: 0.922, 0.973), see Table 2. According to M0, the PPV of low, moderate and high risk groups were 0.4%, 5.2% and 38.8%, whereas those of M1 were 0.6%, 7.3% and 48.1%, respectively (see Table 3).

Prehospital prediction of SI

The NISS cut-off threshold was calibrated by dividing into minor (1–3), moderate (4–8), serious (9–15), severe (16–24), and

Table 4
Predictors associated with SI: Multiple logistic regression.

Predictors	Coefficients	(95%CI)	SE	*P*	OR	(95%CI)
Intercept	−3.934	−4.201, -3.677	0.131	<0.001	0.02	(0.02, 0.03)
Age						
>55 years	0.351	0.105, 0.597	0.125	0.005	1.42	(1.11, 1.82)
≤ 55 years	0				1	
SBP						
>50	0.701	0.245, 1.156	0.232	0.003	2.02	1.28, 3.18
50-75	0.790	0.24, 1.339	0.281	0.005	2.20	1.27, 3.82
76-89	0.581	0.152, 1.009	0.219	0.008	1.79	1.17, 2.74
>89	0				1	
RR						
<10	0.208	−0.223, 0.638	0.220	0.34	1.23	0.81, 1.89
>29	0.646	0.175, 1.115	0.240	0.007	1.91	1.20, 3.05
10-29	0				1	
GCS						
3	2.250	1.867, 2.633	0.195	<0.001	9.49	6.47, 13.91
4-5	2.553	1.988, 3.117	0.288	<0.001	12.84	7.30, 22.58
6-8	1.476	1.162, 1.789	0.160	<0.001	4.37	3.20, 6.00
9-12	1.137	0.858, 1.414	0.142	<0.001	3.12	2.36, 4.12
13-15	0				1	
Blunt injury						
Yes	0.699	0.512, 0.884	0.095	<0.001	2.01	1.67, 2.42
No	0				1	
Type of road user						
Pedestrian	0.780	0.263, 1.296	0.264	0.003	2.18	1.30, 3.66
4 or more wheels	0.079	−0.15, 0.307	0.117	0.50	1.08	0.86, 1.37
Bicycle or motorcycle	0				1	
Response time ≤ 8 minutes						
>8	0.189	0.011, 0.365	0.090	0.04	1.21	1.01, 1.45
≤8	0				1	
Airway management						
Assisted ventilation	1.219	0.844, 1.594	0.191	<0.001	3.38	2.33 4.93
Open/clear airway	0.671	0.403, 0.939	0.137	<0.001	1.96	1.50, 2.56
No supplement	0				1	
IV fluid administration						
YES	1.213	0.971, 1.455	0.124	<0.001	3.37	2.64, 4.39
No	0				1	

CI: confidence interval; GCS: Glasgow coma scale; IV: intravenous; OR: odds ratio; P: p value; RR: respiratory rate; SBP: systolic blood pressure; SE: standard error.

critical (25–75) injury and their diagnostic performances were described, see Supplemental Table 8.

Development phase

Of 20 potential predictors, 9 were kept in the final model of SI (NISS ≥ 16 vs <16) (see Table 4) and prediction score was calculated following the equation in Supplemental Figure 6. The C statistic was 0.913 (95% CI: 0.905, 0.922), indicating excellent discrimination. The calibration plot showed no deviation from the reference line (see Supplemental Figure 6 and 7) with a corresponding HL-GOF test (Chi-square = 13.8, df = 8, $P =$ 0.09), O/E of 0.99 (IQR: 0.95, 1.05), see Table 2 and Supplemental Table 4.

The median risk score was 2.296 (range: -3.933, 3.488). This was then categorized into low, moderate, and high risk groups and their diagnostic accuracy was then estimated, see Table 3. The PPV for these corresponding groups were 4.7%, 29.1%, and 74.5%, respectively.

A 1000-replication bootstrap yielded calibration and discrimination biases of 0.0009 (95% CI: -0.0239, 0.0281) and 0.0004 (95% CI: -0.0005, 0.00002), respectively (see Supplemental Table 9).

External validation

Ubonratchathani. Compared with derivation data, the prevalence of SI was lower (16.9% vs 27.5%). The distribution of predictors were compared by SI groups (see Supplemental Table 10) and all, except age > 55 years and response time ≤ 8 min, were significantly associated with SI (see Supplemental Table 11).

The calibration plot showed deviation from a perfect-fitted line (see Supplemental Figure 8), corresponding to HL-GOF (Chi-square = 28.7, df = 8, $P <$ .001), O/E ratio (O/E 1.00; IQR: 0.71, 1.03), see Table 2. Recalibration of the intercept was performed and indicated M_1 fitted well with the data (Chi-square = 7.2, df = 8, $P <$ .51) with O/E ratio 1.00 (95% CI: 0.95, 1.05), and an improved calibration test/plot, see Supplemental Figure 9. According to M0, the PPV of low, moderate and high risk groups were 3.3%, 16.6% and 62.1%, whereas those of M1 were 3.9%, 24.4% and 70.6%, respectively (see Table 3).

Trang. Compared with development data, the prevalence of SI was lower (17.7% vs 27.5%) and all, except type of road user and response time of ≤ 8 min, were significantly associated with SI (see Supplemental Table 10 and 11). Although discrimination was good (C statistic = 0.896; 95% CI: 0.871, 0.922, see Table 2), calibration plot showed poor fit (see Supplemental Figure 8) corresponding to HL-GOF (Chi-square = 21, df = 8, $P =$ 0.007) with O/E 0.99 (IQR: 0.78, 1.04). Recalibration of the intercept indicated M_1 had a better O/E ratio (1.00; 95% CI: 0.94, 1.04) and fitted well in Trang (Chi-square = 7.5, df = 6, $P =$ 0.28). In addition, there was improvement of the calibration plot (see Supplemental Figure 10). According to M0, the PPV of low, moderate and high risk groups were 3.6%, 22.6% and 68.1%, whereas those of M1 were 4.8%, 25.7% and 69.5%, respectively (see Table 3).

Discussion

We have derived and validated risk prediction scores for death and SI for RTI patients treated by ALS response units. The scores allow subjects to be classified into low, moderate and high risks of

SI and death during prehospital operations and may lead to improved allocation of patients to an appropriate hospital. The results yielded 10 predictors of death and SI including age, blunt injury, RR, SBP, GCS, incidence time, type of road users, response time of $\leq$ 8 min, prehospital airway management, and IV fluid administration. The risk score performed fairly in validation.

Cut off point of NISS

Our results found that NISS and ISS were not much different for predicting early death (i.e., 25 vs 20), which was similar to previous studies [27], but the NISS performed better when death within 30 days was considered [28,29]. This might be explained by the fact that subjects who died within 24–48 h were more likely to have major injuries distributed in different body regions and thus experience multi-organ system failure sooner.

Predictors, model performance and comparison to previous risk prediction scores

Prevalences of SI and death in this study were higher than previous reports [19,20,11,14]. These might be due to the fact that we considered only patients being treated by an ALS, which might bias to vector to moderate to severe victims according to the DC protocol. In addition, previous studies [20,11,5,14] were conducted in developed countries where road quality and traffic rules compliance are better than in Thailand.

Our findings indicated that RTIs commonly occurred in male, middle age, and motorcyclists/bicyclists, which was similar to previous global reports [30,2]. Type of road user was also a significant risk factor for both SI and death in RTI, but it was not considered in previous models. Three EMS operations (i.e., response time, prehospital IV administration, and airway management) were also significant predictors. Response time > 8 min was positively associated with SI, i.e, longer waiting time led to progression of injury such as expansion of intracranial hematoma, or tension pneumothorax. Receiving IV fluids, and airway management, due to poor conditions at scene, (i.e., lower RR, SBP, and GCS), were also significantly associated with increased odds of death and SI.

Discrimination performance of previous risk prediction scores varied because some included only physical examination [8–10,31,11] whereas some others included only crash characteristics [12–15]. However, this research simultaneously considered age, mechanism of injury, physical examination, crash characteristics, and additional EMS operations in the model. Including these important variables enabled the models to reach excellent discrimination for predicting death and SI [17]. Although our risk score only calibrated fairly with validation data, where death and SI were lower, recalibrating the intercept (M_1) improved calibration.

Our risk prediction scores should be useful for developing prehospital care in Thailand and other countries where numbers of TCs are limited. Applying our risk prediction scores is simple and straight forward. For instance, one traffic accident occurred on the highway road and was reported to DC at 10.00 a.m.. The ALS response unit arrived at scene 7 min later after being notified, finding two victims, i.e., male motorcyclist aged 35 years and female pedestrian aged 25 years. The first examination of motorcyclist reveals RR 8 breaths/minute, SBP 80 mmHg and GCS 8, blunt contusion on his right flank. He is urgently intubated, open venous with saline solution. Whereas, evaluation of female pedestrian reveals RR 20 breaths/minute, SBP 110 mmHg, and GCS 15, small abrasion on her shoulder and no need for further immediate treatment. The risk scores for death and SI of male motorcyclist are -0.286 and 1.364 indicating moderate risk for death and high risk for SI. As a result, the PPVs of this motorcyclist are 4.5% and 74.5% for death and SI. The risk scores of female pedestrian for death and SI are -5.162 and -2.455 with PPVs of 0.3% and 4.7%, indicating low risk of both death and SI. After receiving treatment management at scene, the motorcyclist should be prioritized to directly transport to a TC nearby, whereas the pedestrian should be initially sent to the nearest lower facilities hospital because of low risk.

Our study has a number of strengths. We complied with recommendations for the development of clinical prediction rules with adequate number of subjects. [32] The model has been internally and externally validated with good discrimination and calibration after recalibration of the model [26]. Predictors in the models are simple to measure and available in a routine prehospital practice. We recruited RTI subjects from various regions across the country, which reflected a wide coverage of RTI subjects. Our risk prediction models might be more readily applicable in the form of a mobile application given the widespread availability of mobile devices. Its impact on real practice should be further evaluated.

Limitations

There were some limitations in our study. Although data collection was standardized, prospectively corrected by well-trained personnel, and closely monitored; some missing data were unavoidable, in which 4 variables were missing which ranged from 0.17% to 12.36%. Therefore, we applied MI with chain equations to impute those missing values [22].

Apart from the concern of missing data, studied DCs were purposively selected based on availability of EP and a well-developed EMS information system. Results of our study might be less applicable to the DCs where their information system and service are less well organized and also patients were less severely injured. Thus, selection bias might be present. However, we attempted to include a representative sample of RTI subjects for the whole country by selection of subjects stratified by region (i.e., North, Northeast, East, Middle, and South). In addition, numbers of subjects for each center were proportional to the size of their RTI population treated by ALS unit/year. Given our strict inclusion criteria, applying our risk prediction scores may be limited in some settings that have following characteristics: EMS team leader consists of nurse/paramedic and/or EP; RTI subjects are not irreversible death; prehospital managements (e.g. assisting ventilation or IV fluid administration) should be standardized; death rate and severity of RTI subjects are similar to our setting, otherwise, external validation should be performed before applying.

Conclusions

In summary, our study has provided prehospital risk prediction scores of death and SI for RTI subjects. The models have fair calibration and excellent discrimination in development and internal validation. The risk score was categorized into low, moderate, and high risk groups. Threshold probabilities of 0.05 and 0.1 were suggested to treat subjects. Although, the model fit with external data was only fair, recalibration of original intercepts indicated improvement of calibration without changes of the discrimination power.

Conflict of interest statement

The authors have no conflict of interest.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.injury.2019.05.028.

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