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Research article

Development and validation of a clinical nomogram for predicting in-hospital mortality in patients with traumatic brain injury prehospital: A retrospective study

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ABSTRACT

Objective: Traumatic brain injury (TBI) is among the leading causes of death and disability globally. Identifying and assessing the risk of in-hospital mortality in traumatic brain injury patients at an early stage is challenging. This study aimed to develop a model for predicting in-hospital mortality in TBI patients using prehospital data from China.

Methods: We retrospectively included traumatic brain injury patients who sustained injuries due to external forces and were treated by pre-hospital emergency medical services (EMS) at a tertiary hospital. Data from the pre-hospital emergency database were analyzed, including demographics, trauma mechanisms, comorbidities, vital signs, clinical symptoms, and trauma scores. Eligible patients were randomly divided into a training set (241 cases) and a validation set (104 cases) at a 7:3 ratio. Least absolute shrinkage and selection operator (LASSO) and multivariate logistic regression were employed to identify independent risk factors. Analyzed the discrimination, calibration, and net benefit of the nomogram across both groups.

Results: 17.40 % (42/241) of TBI patients died in the hospital in the training set, while 18.30 % (19/104) in the validation set. After analysis, chest trauma (odds ratio [OR] = 4.556, 95 % confidence interval [CI] = 1.861–11.152, P = 0.001), vomiting (OR = 2.944, 95%CI = 1.194–7.258, P = 0.019), systolic blood pressure (OR = 0.939, 95%CI = 0.913–0.966, $P < 0.001$), SpO_2 (OR = 0.778, 95%CI = 0.688–0.881, $P < 0.001$), and heart rate (OR = 1.046, 95%CI = 1.015–1.078, P = 0.003) were identified as independent risk factors for in-hospital mortality in TBI patients. The nomogram based on the five factors demonstrated well-predictive power, with an area under the curve (AUC) of 0.881 in the training set and 0.866 in the validation set. The calibration curve and decision curve analysis showed that the predictive model exhibited good consistency and covered a wide range of threshold probabilities in both sets.

Conclusion: The nomogram based on prehospital data demonstrated well-predictive performance for in-hospital mortality in TBI patients, helping prehospital emergency physicians identify and assess severe TBI patients earlier, thereby improving the efficiency of prehospital emergency care.

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1. Background

Traumatic brain injury (TBI) is among the leading causes of death and disability globally, with particularly high prevalence in Southeast Asia and the Western Pacific regions. Annually, there are over 60 million new cases of TBI worldwide from various causes [1–3]. Whether caused by traffic accidents or sports injuries, traumatic brain injury has become the leading cause of death among young and middle-aged patients [4,5]. Despite significant improvements in TBI patient outcomes over the past two decades, China continues to face a higher incidence of TBI than most other countries, highlighting the severity of this public health issue [3]. Assessing and predicting in-hospital mortality associated with TBI is crucial, as it aids in efficiently allocating healthcare resources and sets realistic expectations for patients and their families. Moreover, accurate outcome predictions strengthen public health strategies, supporting preventive measures and ultimately reducing the burden of TBI on healthcare systems.

At present, emergency medical staff can use the Injury Severity Score (ISS) and Revised Trauma Score (RTS) to assess the severity of TBI in hospitalized patients [6–8]. While these scores possess some predictive capabilities, there remains a need for a simpler, faster, and more accessible scoring system in prehospital emergency care. Such a predictive tool would enable prehospital emergency medical personnel to assess the severity of TBI patient's condition more effectively [9,10]. In patients with TBI, various factors may contribute to in-hospital mortality, including age, heart rate, blood pressure, complications, cranial computed tomography findings, and others [11]. However, the assessment of the prognosis for TBI patients based on prehospital data remains unclear.

The nomogram serves as a visualization tool that displays the weights of variables in a model, enabling the calculation of outcome probabilities by incorporating diverse prognostic and determinant variables [12,13]. Therefore, we aimed to develop a novel nomogram using easily accessible prehospital data to facilitate the early identification and assessment of the severity of TBI patients.

2. Methods

2.1. Study design and patients

This study retrospectively included TBI patients who were transported by ambulance to the Second Affiliated Hospital of Wannan Medical College between January 2020 and August 2023. The study was approved by the Ethics Committee of the Second Affiliated Hospital of Wannan Medical College (No. WYEFYLS2023095), and the requirement for patient informed consent was waived.

The inclusion criteria for patients were as follows: (1) age≥18 years; (2) the injury of the brain was caused by the external force [14]; (3) treated by the prehospital emergency medical physicians; The exclusion criteria were: (1) patients died out-of-hospital; (2) secondary transport; (3) incomplete prehospital emergency data; (4) loss to follow-up. Finally, 345 patients were randomly divided into a training set (n = 241) and a validation set (n = 104) in a 7:3 ratio, as illustrated in Fig. 1.

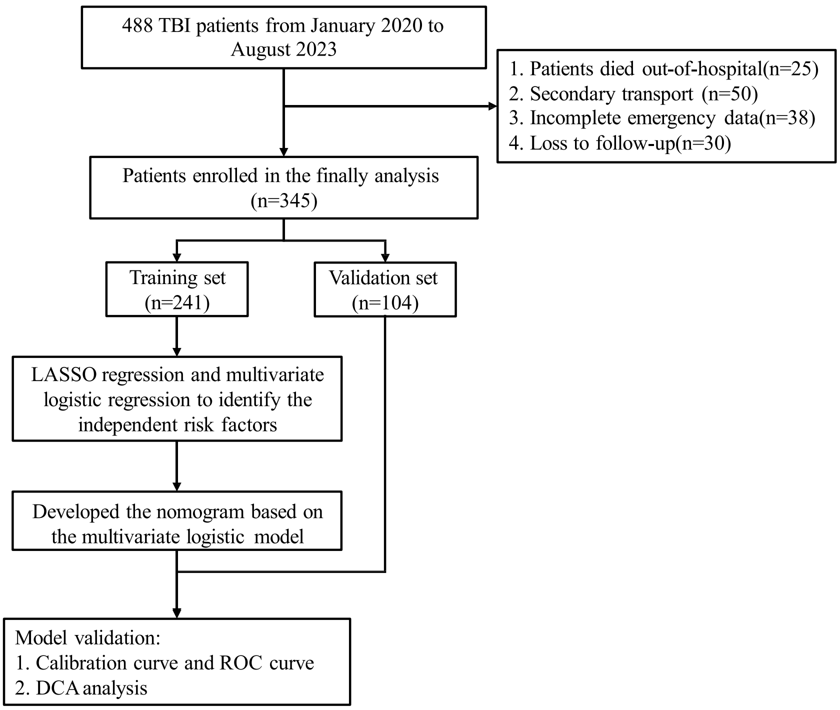

Fig. 1. Flow chart of the study. TBI, traumatic brain injury; LASSO, least absolute shrinkage and selection operator; ROC, receiver operator characteristic; DCA, decision curve analysis.

2.2. Data collection

All clinical variables in this study were collected from electronic records of Wuhu Emergency Medical Center, including demographics (age, gender, job status, pre-hospital time), past medical history (hypertension, diabetes), traumatic mechanism (falls, road traffic accidents), comorbidities (chest trauma, abdominal trauma, limb fracture), prehospital treatment (intravenous fluids, airway management, oxygen supply, hemorrhage control), prehospital vital parameters, prehospital clinical symptoms (headache, vomiting), prehospital trauma score (prehospital index score, modified early warning score). TBI-related death was defined as the death of a patient during hospitalization, directly or indirectly attributable to traumatic brain injury [15,16].

2.3. Sample size

For multivariate logistic analysis, the sample size was estimated using the events per variable (EPV) method, requiring 10 samples per independent variable [17]. The study anticipated the inclusion of at least 5 variables in the predictive model construction, with a TBI-related mortality of approximately 25 % [18,19]. Therefore, a minimum of 200 patients were necessary to participate in the final analysis of this study.

2.4. Data analysis

Variables that were normally distributed were summarized as mean ± standard deviation, whereas those with a non-normal distribution were represented as median (interquartile range). Categorical variables were described using frequencies (%). Appropriate statistical comparisons between the training and validation sets were made using the chi-square test, Student's t-test, and Mann-Whitney *U* test. For all variables, missing values were under 10 %, and the multiple imputation technique was applied to handle the gaps in the data.

The least absolute shrinkage and selection operator (LASSO) regression method, along with multivariate logistic regression

Table 1
Characteristics of TBI patients in the training set and validation set.

Variables	Total (n = 345)	Training set (n = 241)	Validation set (n = 104)	t/z/ x^2	*P* value
Demographics					
Age, years (mean ± SD)	58.55 ± 15.38	58.32 ± 14.63	59.10 ± 16.44	−0.430	0.667
Female, n (%)	150 (43.50)	109 (45.20)	41 (39.40)	0.996	0.318
Job, employed, n (%)	187 (54.20)	131 (54.40)	56 (53.80)	0.008	0.930
Pre-hospital time, min	16.86 ± 4.05	16.61 ± 3.99	17.44 ± 4.14	−1.767	0.078
Past Medical History, n (%)					
Hypertension	90 (26.10)	62 (25.70)	28 (26.90)	0.054	0.816
Diabetes	83 (24.10)	53 (22.00)	30 (28.80)	1.868	0.172
Traumatic mechanism				0.994	0.608
Falls	81 (23.50)	56 (23.20)	25 (24.00)		
Road traffic accidents	185 (53.60)	133 (55.20)	52 (50.00)		
Others	79 (22.90)	52 (21.60)	27 (26.00)		
Comorbidities					
Chest trauma	79 (22.90)	54 (22.40)	25 (24.00)	0.110	0.741
Abdominal trauma	54 (15.70)	34 (14.10)	20 (19.20)	1.444	0.229
limb fracture	67 (19.40)	44 (18.30)	23 (22.10)	0.691	0.406
Prehospital treatment					
Intravenous fluids	164 (47.50)	119 (49.40)	45 (43.30)	1.087	0.297
Airway management	175 (50.70)	123 (51.00)	52 (50.00)	0.031	0.860
Oxygen supply	144 (41.70)	104 (43.20)	40 (38.50)	0.658	0.417
Hemorrhage control	172 (49.90)	116 (48.10)	56 (53.80)	0.949	0.330
Prehospital vital parameters					
SBP, mmHg, IQR	128.00 (116.00, 46.50)	125.00 (116.00, 145.00)	130.00 (113.25, 150.75)	−0.617	0.537
DBP, mmHg, IQR	76.00 (69.00, 85.50)	76.00 (68.50, 84.50)	77.00 (70.00, 89.50)	−1.034	0.301
Respiratory rate, min^{-1}, IQR	19.00 (18.00, 19.00)	19.00 (18.00, 19.00)	18.00 (18.00, 19.00)	−0.132	0.895
Heart rate, min^{-1}, IQR	92.00 (83.50, 101.00)	93.00 (85.00, 102.00)	90.00 (80.25, 100.00)	−1.473	0.141
SpO_2, %, IQR	93.00 (91.00, 96.00)	93.00 (90.50, 96.00)	94.00 (91.00, 96.00)	−0.979	0.328
GCS, score, IQR	8.00 (7.00, 10.00)	8.00 (7.00, 10,00)	8.00 (6.00, 11.00)	−0.206	0.837
Prehospital clinical symptoms					
Headache, n (%)	67 (19.40)	47 (19.50)	20 (19.20)	0.003	0.953
Vomiting, n (%)	72 (20.90)	50 (20.70)	22 (21.20)	0.007	0.932
Prehospital trauma score					
MEWS, score, IQR	3.00 (2.00,4.00)	3.00 (2.00, 4.00)	3.00 (2.00, 3.00)	−0.202	0.840
PHI, score, IQR	10.00 (6.00, 12.00)	10.00 (6.50, 12.00)	9.50 (6.00, 12.00)	−0.393	0.695
Outcomes					
TBI-related mortality	61 (17.70)	42 (17.40)	19 (18.30)	0.035	0.851

TBI, traumatic brain injury; SBP, systolic blood pressure; DBP, diastolic blood pressure; GCS, glasgow coma scale; IQR, interquartile range; MEWS, modified early warning score; PHI, prehospital index.

analysis, was used to identify independent risk factors associated with in-hospital mortality in TBI patients [20,21]. The ability of the nomogram to discriminate, calibrate, and offer clinical value was analyzed through receiver operating characteristic (ROC) curves, calibration plots, and decision curve analysis (DCA), respectively. Data analysis was carried out using SPSS 25.0 and R software version 4.3.1. A two-sided *P*-value of <0.05 was deemed statistically significant.

3. Results

3.1. Patient characteristics in the two sets

A total of 345 patients were included in this study, comprising 150 females and 195 males. The average age was 58.55 ± 15.38 years, and the prehospital time was 16.86 ± 4.05 min. The mortality of TBI patients in the training set was 17.40 % (42/241), while 18.30 % (19/104) was in the validation set. No statistically significant differences were observed in the distribution of demographic characteristics between the two groups (Table 1).

3.2. Independent risk factors for TBI-related death

From the 22 variables included in the LASSO regression model (at a ∼4:1 ratio), 6 potential predictors were identified, including chest trauma, vomiting, heart rate, SpO_2, Glasgow coma scale (GCS), and systolic blood pressure (Fig. 2A and B). After multivariable analysis, 5 independent risk factors were selected to build the nomogram (Table 2), including chest trauma (OR = 4.556, 95 % CI: 1.861–11.152, $P = 0.001$), vomiting (OR = 2.944, 95 % CI: 1.194–7.258, $P = 0.019$), systolic blood pressure (OR = 0.939, 95 % CI: 0.913–0.966, $P < 0.001$), SpO_2(OR=0.778,95%CI: 0.688-0.881,P<0.001), and heart rate (OR = 1.046, 95 % CI: 1.015–1.078, $P = 0.003$).

3.3. Development of the predictive model

The predictive nomogram was developed using the five optimal predictive variables, as shown in Fig. 3. First, assigned a score (0–100) to each independent factor based on the nomogram, and then aggregated the initial scores into the total points. Then, the probabilities for TBI-related death were obtained at the bottom of the nomogram. For example, a TBI patient presented with vomiting (52 points), complicated by chest trauma (55 points), with prehospital vital parameters including systolic blood pressure 122 mmHg (50 points), SpO_2 89 % (53 points), and heart rate 95 beats per minute (45 points). According to the nomogram, a total score of 255 corresponds to an estimated in-hospital mortality probability of approximately 77.70 %.

3.4. Assessment and performance of nomogram

The calibration curves revealed a good fit between the predicted probability of TBI-related mortality and the actual observations in both the training set (Fig. 4A) and validation set (Fig. 4B), as confirmed by 1000 bootstrap resamples. ROC curve analysis of the nomogram revealed an AUC of 0.881 (95 % CI: 0.831–0.931, $P < 0.001$), which was superior to the MEWS (0.770, 95 % CI: 0.691–0.849, $P < 0.001$), GCS score (0.694, 95 % CI: 0.603–0.784, $P < 0.001$), and PHI score (0.740, 95 % CI: 0.668–0.812, $P < 0.001$) in the training set (Fig. 5A). Additionally, the AUC of the nomogram in the validation set (Fig. 5B) also demonstrated superior predictive performance compared to MEWS, GCS score, and PHI score.

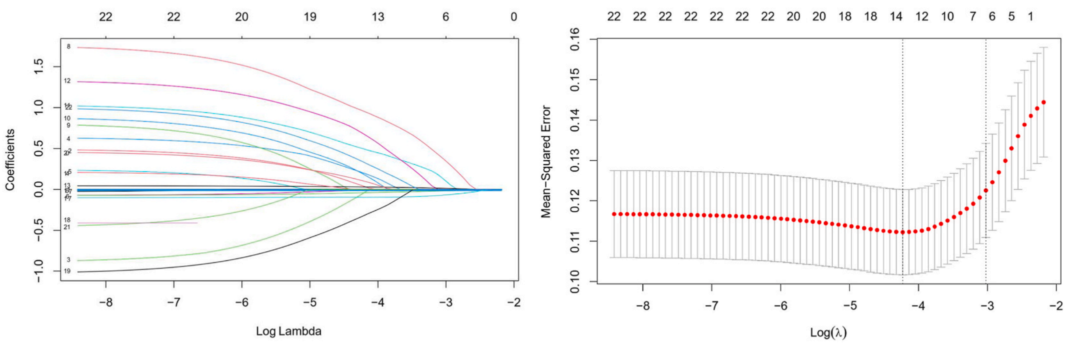

Fig. 2. Clinical variables were selected using the Least Absolute Shrinkage and Selection Operator (LASSO) regression model. A. The optimal parameter (λ) was obtained by using 10-fold cross-validation via the minimum criteria. Dashed lines were drawn vertically at the optimal values by using the minimum criteria (lambda. min = 0.0145) and the 1-SE of the minimum criteria (lambda.1se = 0.0488). B. LASSO coefficient profiles of the 22 features and a coefficient profile plot were drawn against the log (lambda) sequence. 6 variables with nonzero coefficients were selected based on the optimal lambda.

Table 2
The risk factors associated with in-hospital mortality of TBI patients in the training set.

Variables	OR	95 % CI	*P*-value
Chest trauma	4.556	1.861–11.152	0.001
Vomiting	2.944	1.194–7.258	0.019
SBP, mmHg	0.939	0.913–0.966	<0.001
SpO_2, %	0.778	0.688–0.881	<0.001
Heart rate, min^{-1}	1.046	1.015–1.078	0.003

SBP, Systolic blood pressure; OR, Odds ratio; CI, confidence intervals.

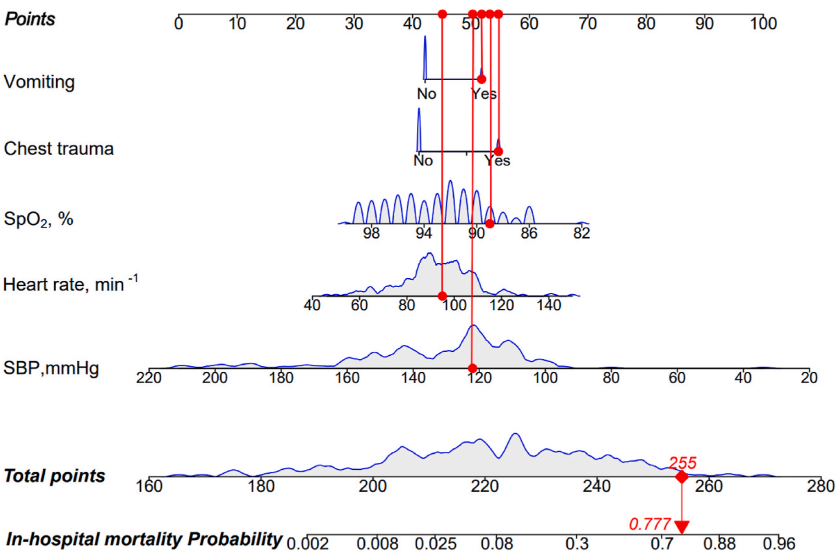

Fig. 3. The nomogram for predicting the risk of TBI-related mortality. SBP, systolic blood pressure. The grey aera below the blue lines represented the distribution of each sample in this study.

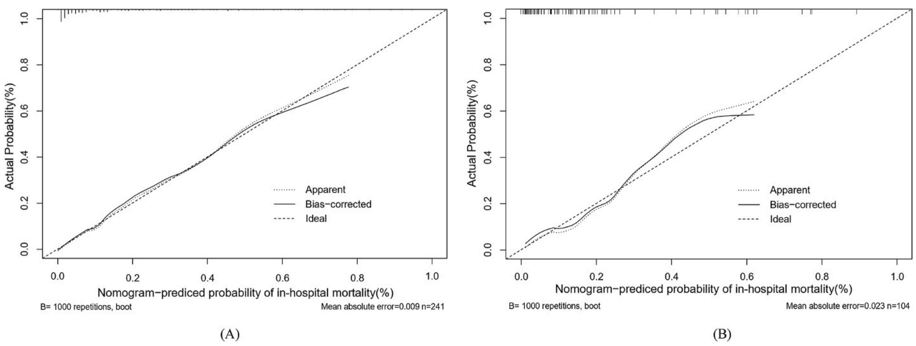

Fig. 4. Calibration curves of the nomogram. A. the nomogram in the training set (n = 241); B. the nomogram in the validation set (n = 104). The x-axis showed the nomogram-predicted probability of TBI-related death, and the y-axis represented the observed rate of TBI-related death. The dotted lines represented by the nomogram are closer to the diagonal grey lines representing a better prediction.

3.5. Clinical use of nomogram

The DCA curve demonstrated that the predictive model offered a greater net benefit over a wider range of threshold probabilities, spanning from 0.1 to 0.85 in the training set (Fig. 6A) and from 0.1 to 0.78 in the validation set (Fig. 6B).

4. Discussion

Using data available during prehospital care, we developed and validated a prognostic model to predict in-hospital mortality for TBI patients. Traumatic brain injury is a condition associated with high mortality and disability rates [22], significantly increasing

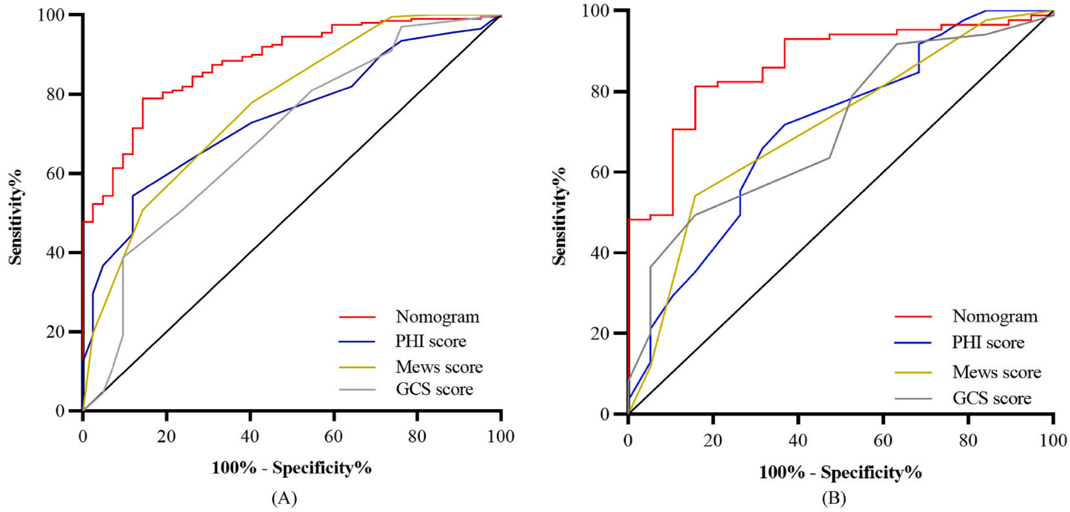

Fig. 5. The receiver operating characteristic (ROC) of the nomogram. A. ROC in the training set; B. ROC in the validation set. PHI, prehospital index; MEWS, modified early warning score; GCS, glasgow coma scale.

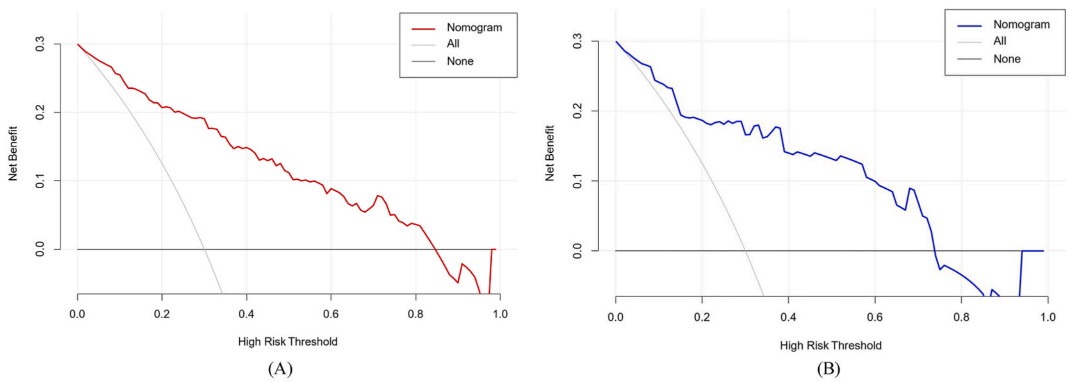

Fig. 6. The decision curves analyses (DCA) of the nomogram. A. The DCA curve in the training set; B. The DCA curve in the validation set. The x-axis showed the threshold probability, and the y-axis showed the net benefit. The red line and blue line represented the net benefit of nomogram in the training set and validation set, respectively.

annual healthcare expenditures due to its high mortality rate [23]. Early identification and assessment of TBI patients is crucial for emergency physicians to enable timely interventions, mitigate adverse outcomes, and improve survival rates.

The predictive nomogram was developed using five factors: chest trauma, vomiting, systolic blood pressure, SpO_2, and heart rate, which have been previously identified as correlated with mortality among TBI patients [24]. Identifying the severity of TBI typically requires inquiries about the cause of injury and medical imaging, which are not readily available during the study period. However, the risk factors included in this nomogram are objective and easily obtainable in prehospital settings, enhancing its practicality and convenience for prehospital emergency physicians.

In our study, chest trauma was an independent factor associated with poor prognosis in TBI patients. One possible explanation for this finding could be that patients with one or more associated complications were more likely to experience severe traumatic brain injury compared to those without such complications [24]. Chest trauma can lead to a series of injuries, including rib fractures, flail chest, and pneumothorax, which may cause breathing difficulties or even respiratory arrest, ultimately resulting in death [25]. Vomiting is a clinical manifestation of elevated intracranial pressure, often accompanied by symptoms such as headache, papilledema, and nausea in the early phases. As intracranial pressure increases, TBI patients are more likely to develop coma, pupillary changes, and abnormal respiration, eventually leading to cardiopulmonary arrest [26]. Therefore, early vomiting symptoms in TBI patients warrant close monitoring and attention. Furthermore, lower systolic blood pressure and SpO_2 were independent predictors of poor outcomes in TBI patients in our study. Lower systolic blood pressure and SpO_2 lead to hypotension, hypoxia, and high heart rate, which further leads to secondary injury due to insufficient cerebral perfusion pressure [4]. Moreover, perfusion insufficiency and hypoxia exacerbate cerebral inflammation, increase neuronal death and lesion size, adversely affect the blood-brain barrier integrity, contribute to edema formation, and result in a poorer functional outcome [27,28].

Although the GCS score demonstrated satisfactory predictive ability for in-hospital mortality in TBI patients, the AUC of nomogram increased from 0.881 to 0.884 after incorporating the GCS score, with no significant difference. GCS was a pivotal indicator of the severity of consciousness disorder in patients, with abundant research demonstrating its significant correlation with adverse outcomes [29–31]. As the GCS score decreases, indicating a more severe brain injury, the risk of complications and poorer prognosis increases [32]. According to the ROC analysis in our study, the nomogram demonstrated higher predictive accuracy for mortality in TBI patients compared to the GCS score, likely due to the inclusion of factors such as vomiting and hypotension. Furthermore, the overall evaluation efficiency of the nomogram surpassed that of the GCS score.

The nomogram notably enhanced predictive efficacy, surpassing that of MEWS and PHI scores. Prehospital emergency medical physicians quickly assessed the patient's condition through the following steps: (1) Determine the score associated with each risk factor in the first step; (2) The scores of each predictive factor were added together to obtain the total score; (3) The predicted probability was calculated based on the'Total Points' axis. Physicians can formulate targeted treatment plans and also assist in communicating the patient's condition to their family and in assessing the overall situation.

A higher risk of mortality suggests the need for intensive care, as such cases may swiftly become fatal and require prioritized treatment. Conversely, patients with a lower risk of mortality can be managed with less urgency, allowing for a balanced distribution of medical resources. This predictive nomogram facilitates the optimal estimation of individualized disease-related risks, thereby streamlining decisions regarding patient management.

However, this study has some limitations. First, it was possible that parts of independent variables influencing the mortality of TBI might not have been included. Second, this study did not differentiate the severity of injury among TBI patients, and the management strategies and prognosis may vary for patients with different severity levels of injury [33,34]. In addition, the constructed predictive model lacked comparison with existing prognostic tools for TBI, including the GCS score, Glasgow outcome scale, and Marshall CT classification. Therefore, we hoped that the multi-center prospective study would be conducted in the future to include more risk factors and consider different subtypes to obtain more comprehensive research results.

5. Conclusion

The five-variable risk prediction nomogram, constructed using chest trauma, vomiting, systolic blood pressure, SpO_2, and heart rate, demonstrated well-predictive performance for in-hospital mortality in TBI patients. Prehospital emergency physicians can use this tool for the early assessment of TBI patients and the identification of critically ill patients.

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Data Availability statement

Further data and materials can be obtained from the corresponding author for research purposes only.

CRediT authorship contribution statement

Bing Wang: Writing – original draft, Visualization, Data curation. **Yanping Liu:** Writing – original draft, Methodology, Data curation. **Jingjing Xing:** Visualization, Methodology, Formal analysis, Data curation. **Hailong Zhang:** Project administration, Investigation, Data curation. **Sheng Ye:** Writing – review & editing, Visualization, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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None.

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