

Original Article

Construction and verification of an early warning model for hypothermia in emergency trauma patients based on the random forest method

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Received January 24, 2026; Accepted May 9, 2026; Epub June 15, 2026; Published June 30, 2026

Abstract: Objective: To construct an early warning model for hypothermia in emergency trauma patients using Random Forest (RF) and compare its predictive performance with Logistic regression. Methods: A total of 400 trauma patients were included. Hypothermia was defined as any temperature < 36.0 °C within 3 hours after admission. Patients were randomly divided into training and test sets (7:3). Based on the data of the modeling set, the least absolute shrinkage and selection operator (LASSO) regression was used to identify the characteristic variables of hypothermia in patients. Logistic regression model and RF model are constructed based on the identified characteristic variables. Results: Among 400 patients, 92 (23.00%) developed hypothermia. The LASSO regression identified six non-zero coefficient indicators, including RTS score, ISS, SI index, ambient temperature at the time of injury, wet clothing, and shock upon entering the room. Based on these, a Logistic regression model and a RF model were constructed. The RF model achieved an AUC of 0.985 (95% CI: 0.972-0.997) in the training set and 0.956 (95% CI: 0.921-0.990) in the test set; the Logistic model achieved 0.963 (95% CI: 0.939-0.988) and 0.956 (95% CI: 0.923-0.989), respectively. Calibration curves demonstrated good agreement between predicted and observed outcomes. DCA revealed that the RF model provided higher standardized net benefit across a wider range of threshold probabilities. Conclusion: The RF-based early warning model demonstrates high predictive efficacy for hypothermia in emergency trauma patients and outperforms traditional Logistic regression, supporting early identification and preventive intervention.

Keywords: Emergency trauma, hypothermia, random forest, machine learning, early warning model, risk factors

Introduction

Trauma remains a leading cause of death and disability worldwide [1]. Statistics indicate that over 5 million deaths occur annually due to trauma, making it the primary cause of mortality among individuals under 45 years of age in China [2], thereby imposing a substantial burden on public health systems. Trauma management involves multiple critical phases, with temperature control being a pivotal element throughout the entire care continuum [3]. Hypothermia is a frequent complication in trauma patients, with reported incidence rates ranging from 20% to 66% [4]. In the pathophysiology of trauma, hypothermia, acidosis, and coagulopathy constitute the lethal “triad of

death” [5]. These three conditions mutually exacerbate one another, creating a vicious cycle that significantly elevates patient mortality [6]. Studies have demonstrated that when the core temperature of trauma patients drops below 35 °C, mortality increases by 3- to 5-fold compared to normothermic patients; notably, mortality approaches 100% when temperature falls below 32 °C [7]. Consequently, the American College of Surgeons’ Advanced Trauma Life Support (ATLS) curriculum identifies the maintenance of normothermia as a core objective in the early resuscitation of trauma patients [8].

The mechanisms underlying trauma-induced hypothermia are complex, encompassing not

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only trauma-related dysfunction of the thermoregulatory center and reduced heat production secondary to hemorrhagic shock but also iatrogenic factors such as prehospital environmental exposure, fluid resuscitation, and transport conditions [9]. Existing literature suggests that the Injury Severity Score (ISS), Glasgow Coma Scale (GCS), ambient temperature at the time of injury, wet clothing status, prehospital fluid volume, and admission lactate levels are primary determinants of hypothermia onset [10]. However, these factors exhibit intricate interactions and non-linear relationships that are difficult to fully capture using traditional analytical methods [11]. Early identification of high-risk populations and the implementation of preventive interventions are crucial for improving prognosis [12].

In current clinical practice, risk assessment for hypothermia largely relies on the subjective experience of healthcare providers, lacking objective quantitative tools [13]. Although some trauma centers employ scoring systems based on risk factors, their predictive efficacy remains limited [14]. Traditional risk prediction models are predominantly constructed using Logistic Regression. While these models offer interpretability, they often fail to adequately capture the non-linear relationships and complex interactions inherent in clinical variables [15]. The rapid advancement of machine learning technologies has provided novel methodologies for constructing clinical prediction models [16]. Random Forest (RF), a representative ensemble learning algorithm, constructs multiple decision trees and integrates their outputs. It offers distinct advantages, including the ability to handle high-dimensional data, automatically capture non-linear relationships, resist overfitting, and evaluate variable importance [17]. Previous studies have confirmed that RF outperforms traditional regression models in predicting clinical outcomes such as perioperative hypothermia [18] and nosocomial infections [19]. Nevertheless, there is currently a paucity of systematic research focusing on early warning models for hypothermia specifically within the emergency trauma population. Therefore, this study aims to construct an early warning model for hypothermia in emergency trauma patients based on the RF algorithm, evaluate its predictive performance, and provide robust decision support for early clinical identification and intervention.

Materials and methods

General materials

The emergency trauma patients who were treated in The Second Affiliated Hospital of Guizhou University of Traditional Chinese Medicine from January 2022 to December 2024 were selected as the research subjects. Inclusion criteria: (1) Emergency patients with trauma; (2) Patients aged ≥ 18 ; (3) Patients with complete clinical data. Exclusion criteria: (1) Patients who died or developed hypothermia before admission; (2) Patients with hypoglycemia, malnutrition, adrenal dysfunction, and vitamin B1 deficiency who are prone to hypothermia; (3) Patients with hypothermia caused by chronic heart disease and wasting diseases; (4) Patients with heat-regulating center (hypothalamus) injury and craniocerebral injury receiving treatment for mild hypothermia; (5) Length of emergency room stay < 3 h. This study was approved by the Ethics Committee of The Second Affiliated Hospital of Guizhou University of Traditional Chinese Medicine.

Collection of clinical data

The research variables were developed by the study team through reviewing relevant literature and consulting with emergency trauma treatment experts and emergency department medical staff. The variables include: gender, age, body temperature, respiratory rate, heart rate (HR), Systolic blood pressure, diastolic blood pressure, oxygen saturation (SpO_2), PH, type of injury, Glasgow coma scale (GCS) score, Revised trauma score (RTS), Injury severity score (ISS), Shock index (SI), nighttime injury (yes/no), ambient temperature at the time of injury, response time (time from call to ambulance arrival at the scene), transport time (time from scene to hospital arrival), presence of wet clothing (yes/no), prehospital fluid resuscitation (yes/no), prehospital endotracheal intubation (yes/no), and shock on admission (yes/no).

Outcome variables

The occurrence of hypothermia in emergency patients with trauma was the outcome variable in this study. An infrared ear thermometer (Bruan ThermoScan PRO 6000) was used to measure the body temperature of trauma patients. From the time the patients entered

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the emergency room, the temperature was measured every 30 minutes for 3 hours or more. Patients were included in the hypothermia group if any temperature measurement during the observation period was $< 36.0^{\circ}\text{C}$, and the remaining patients were included in the normothermia group. The diagnostic threshold of 36.0°C for hypothermia aligns with the guidelines of the American College of Surgeons' Advanced Trauma Life Support (ATLS) course.

Statistical analysis

Data analysis was performed using SPSS version 29.0 (IBM Corp., Armonk, NY, USA). Continuous variables conforming to a normal distribution were expressed as mean \pm standard deviation (SD) and compared using the independent samples t-test. Non-normally distributed continuous variables were presented as median with interquartile range [M (P25, P75)] and compared using the Mann-Whitney U test (rank-sum test). Categorical variables were expressed as frequencies and percentages (%) and compared using the Chi-square (χ^2) test. The study population was randomly split into a training set and a validation set at a ratio of 7:3. All analyses were performed only in the training set, and the validation set was only used for model performance evaluation. LASSO regression was used to select the features of all clinical related variables in the training set, and a multivariate logistic regression prediction model was constructed on this basis. R4.2.1 software was used to construct a random forest model. Based on the six feature variables identified by the LASSO regression sieve as input features, the random forest algorithm used the Sklearn machine learning toolkit to set the same prior probability for all categories. The Gini coefficient was used to split the nodes, the optimal number of trees was determined by the minimum misclassification cost, and the importance of each variable was sorted. The discrimination, calibration and clinical net benefit of the Logistic regression model and random forest model were evaluated by receiver operating characteristic curve (ROC), calibration curve and decision curve analysis (DCA). All statistical tests were two-tailed, with a significance level set at $\alpha = 0.05$. Model construction and validation were executed using the rms and caret packages in R.

Results

Baseline clinical characteristics of emergency trauma patients

Among the 400 enrolled emergency trauma patients, 293 were male and 107 were female. The age ranged from 16 to 89 years, with a mean of 53.41 ± 17.13 years. Regarding the mechanism of injury, 384 patients sustained blunt trauma, while 16 suffered from penetrating head injuries. Overall, 92 patients (23.00%) developed hypothermia, whereas 308 (77.00%) remained normothermic. The study population was randomly stratified into a training set ($n = 285$) and a validation set ($n = 115$) at a 7:3 ratio. Hypothermia occurred in 64 cases (22.46%) in the training set and 28 cases (20.87%) in the validation set. Statistical analysis revealed no significant difference in the incidence of hypothermia or baseline characteristics between the two sets ($P > 0.05$, **Table 1**).

Characteristic variable identification

Based on the data of the modeling set, the patient's hypothermia was used as the dependent variable, and the indicators in **Table 1** were used as independent variables. The 10-fold cross-validation in the LASSO regression model was used to determine the optimal penalty coefficient λ . The line was drawn at λ and $\lambda + \text{SE}$, and 6 non-0 indicators of LASSO regression coefficient were finally identified at $\lambda + \text{SE}$, which were RTS score, ISS, SI index, ambient temperature at the time of injury, wet clothes, and shock when entering the room (**Figure 1; Table 2**).

Construction of the logistic risk prediction model

Based on the six characteristic variables identified by LASSO regression, a prediction model for hypothermia in emergency trauma patients was constructed: $\text{Logit}(P) = -5.909 - 0.574 \times (\text{RTS score}) + 0.691 \times (\text{ISS}) + 4.257 \times (\text{SI index}) - 0.095 \times (\text{ambient temperature at the time of injury}) + 1.130 \times (\text{wet clothing})$. The Logistic regression model nomogram for hypothermia in emergency trauma patients was plotted (**Figure 2**). According to the risk factors in the nomogram, corresponding scores were obtained; after summing up the scores, the pre-

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Table 1. Clinical data of emergency trauma patients

Project	Training set (n = 285)	Validation set (n = 115)	t/ χ^2	P
Sex			0.193	0.660
Male	207 (72.63)	86 (74.78)		
Female	78 (27.37)	29 (25.22)		
Age (years)	53.20±16.59	54.92±19.73	0.889	0.374
GCS (points)	12.25±3.87	11.80±3.70	1.067	0.287
RTS (points)	11.06±1.75	11.10±1.36	0.246	0.806
Systolic blood pressure (mmHg)	132.49±29.94	132.96±29.72	0.142	0.887
Diastolic blood pressure (mmHg)	80.33±15.05	79.97±17.77	0.210	0.887
HR (beats/minute)	87.93±20.32	85.27±19.55	1.199	0.231
SpO ₂ (%)	97.08±4.46	96.89±4.50	0.385	0.700
PH	7.28±0.14	7.30±0.13	1.291	0.197
ISS (points)	13.27±3.83	13.38±3.90	0.264	0.792
SI	0.65±0.22	0.64±0.21	0.346	0.729
Ambient temperature at time of injury (°C)	25.32±6.40	25.30±5.95	0.029	0.977
Ambulance arrival time (min)	47.38±12.43	48.83±13.71	1.025	0.306
Time taken by ambulance to reach hospital (min)	51.11±16.60	52.70±16.62	0.867	0.386
Nature of injury			0.623	0.430
Penetrating injury	10 (3.51)	6 (5.22)		
Thornton contusion	275 (96.49)	109 (94.78)		
Injured at night			0.004	0.951
Yes	118 (41.40)	48 (41.74)		
No	167 (58.60)	67 (58.26)		
Wet clothing			0.452	0.501
Yes	71 (24.91)	25 (21.74)		
No	214 (75.09)	90 (78.26)		
Pre-hospital infusion			0.666	0.414
Yes	244 (85.61)	102 (88.70)		
No	41 (14.39)	13 (11.30)		
Pre-hospital tracheal intubation			0.023	0.879
Yes	87 (30.53)	36 (31.30)		
No	198 (69.47)	79 (68.70)		
Shock on admission			23.296	< 0.001
Yes	79 (27.82)	30 (26.09)		
No	206 (72.28)	85 (73.91)		

Note: HR, Heart Rate; SpO₂, Peripheral Capillary Oxygen Saturation/Oxygen Saturation; pH, Potential of Hydrogen/Hydrogen Ion Concentration; RTS, Revised Trauma Score; ISS, Injury Severity Score; SI, Shock Index.

dicted probability corresponding to the total score was the probability of hypothermia in emergency trauma patients.

Construction of the RF prediction model

Based on the six characteristic variables screened by LASSO regression, the RF model was established by running the code with R software. At each node of the forest, the num-

ber of preselected variables is set to the square root of the total number of variables, the random seed number is set to 12345. When ntree = 200 and mtry = 2, the error tends to stabilize and becomes the optimal model. The dynamic relationship between the random forest prediction error and the number of random trees is shown in **Figure 3A**. Based on the average reduction in the Gini index, the variables for predicting the occurrence of hypothermia in

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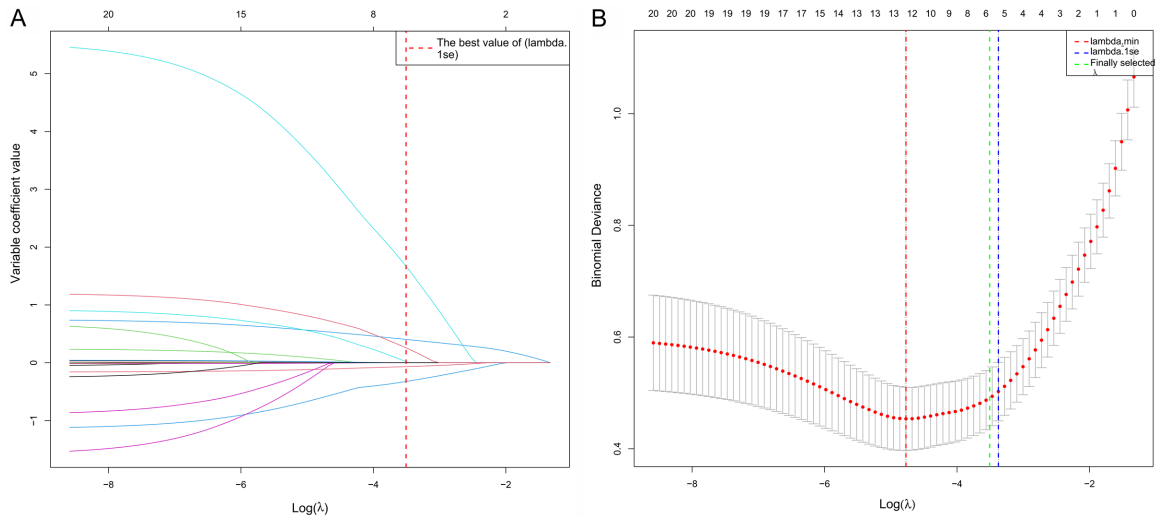


Figure 1. Variable screening based on LASSO regression analysis. A. Dynamic graph of variable screening in LASSO regression analysis; B. Ten-fold cross-validation graph of LASSO regression analysis. LASSO, least absolute shrinkage and selection operator.

Table 2. Variable screening in LASSO regression analysis

Factor	β
RTS (points)	-0.324
ISS (points)	0.404
SI	1.670
Ambient temperature at time of injury ($^{\circ}\text{C}$)	-0.068
Wet clothing	0.018
Shock on admission	0.258

Note: RTS, Revised Trauma Score; ISS, Injury Severity Score; SI, Shock Index.

emergency trauma patients are ranked by importance, from largest to smallest: ISS score (40.55 points) > RTS score (11.64 points) > Ambient temperature at the time of injury (9.67 points) > SI (9.57 points) > The clothes are damp (1.95 points) > Fainting upon entering the room (1.04 points), as shown in **Figure 3B**.

Comparison of the prediction effect of RF model and Logistic regression model

The ROC curve results of the Logistic Regression Model showed that the ACU of the GBM model in the training set was 0.963 (95% CI: 0.939-988), with sensitivity and specificity of 90.60% and 92.80% respectively; in the validation set, the AUC was 0.956 (95% CI: 0.923-0.989), with sensitivity and specificity of 100.00% and 81.60% (as shown in **Figure 4**).

The calibration curve results showed that the predicted probabilities of the GBM model in the training set and validation set were in good consistency with the actual incidence rates (as shown in **Figure 5**). The ROC curve results of the RF model showed that the ACU of the model in the training set was 0.985 (95% CI: 0.972-0.997), with sensitivity and specificity of 95.30% and 94.60%; in the validation set, the AUC was 0.956 (95% CI: 0.921-0.990), with sensitivity and specificity of 100.00% and 80.50%; as shown in **Figure 6**). The calibration curve results showed that the predicted probabilities of the RF model in the training set and validation set were in good consistency with the actual incidence rates (as shown in **Figure 7**). The Delong test results showed that there was no statistically significant difference in the prediction efficacy of the two models between the training set and validation set ($P > 0.05$).

Comparison of clinical applicability of RF algorithm model and logistic regression model at different threshold probabilities

The DCA results showed that within the lower threshold range, the standardized net benefit of both the Logistic regression model and the Random Forest (RF) model was significantly higher than the two extreme strategies of “all intervention” and “no intervention at all” (All and None), indicating that both models have clinical application value. When the threshold

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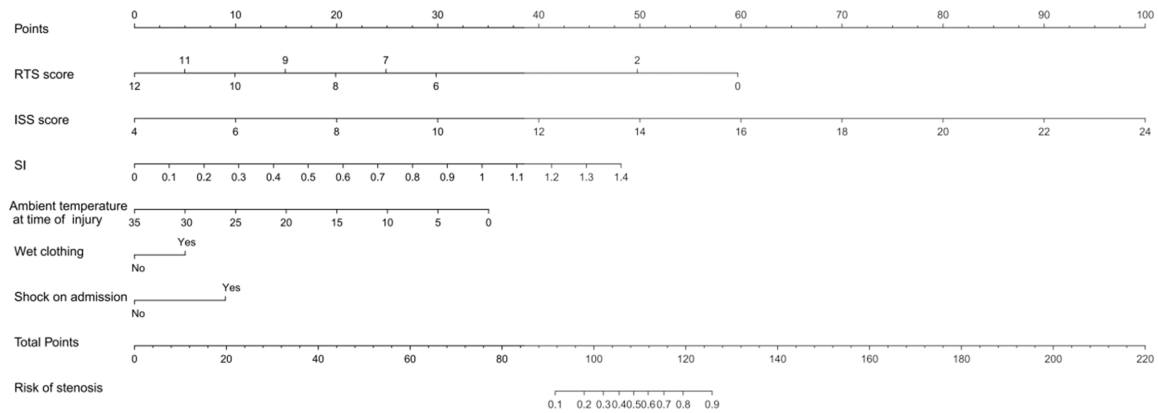


Figure 2. Construction of the risk prediction model using logistic regression analysis.

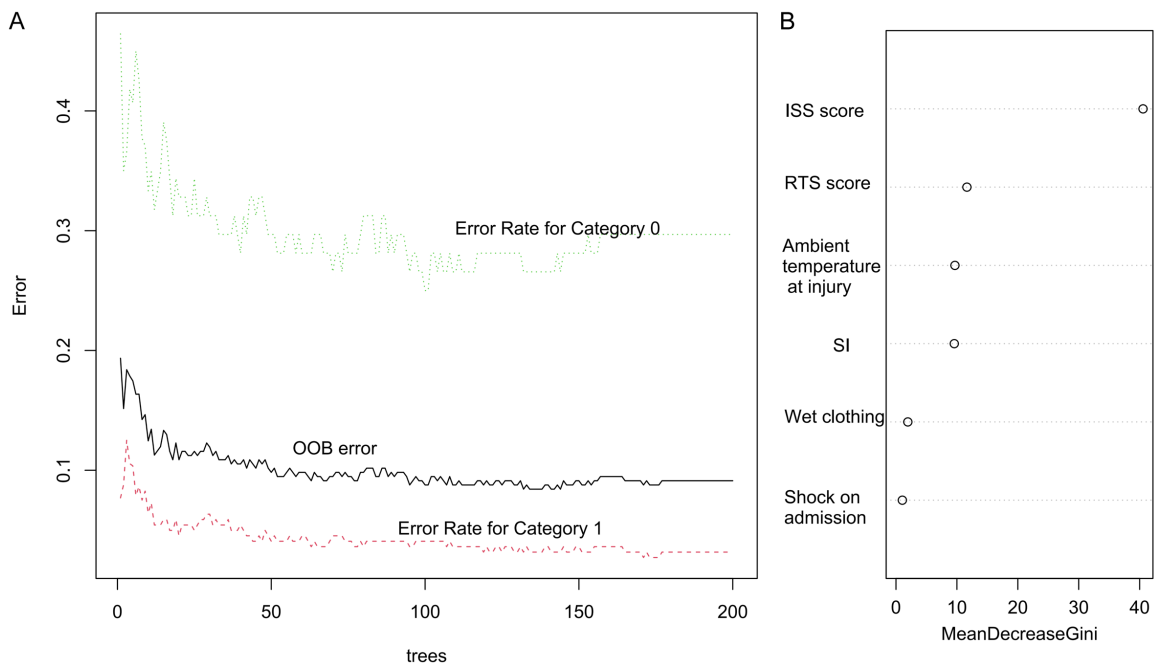


Figure 3. RF model establishment. A. Dynamic relationship between RF model prediction error and the number of random trees; B. Ranking of RF model variables based on Mean Decrease Gini importance. RF, random forest.

was further increased, the net benefit of the “all intervention” strategy dropped below 0, while both models still maintained a positive standardized net benefit; among them, the net benefit curve of the RF model was overall higher and more stable. Within the commonly used core threshold range in clinical practice, its standardized net benefit was always higher than that of the Logistic regression model, suggesting that the RF model has better clinical applicability and decision-making value (as shown in **Figures 8 and 9**).

Discussion

Post-traumatic hypothermia is not merely the result of environmental temperature exposure; it is a complex pathological process resulting from the combined effects of trauma, shock, iatrogenic factors, and the failure of the body's compensatory mechanisms. As one of the initiating factors of the “death triad”, hypothermia significantly increases the mortality and complication risks of trauma patients [20]. Shafi et al. [21] confirmed through analysis of a large

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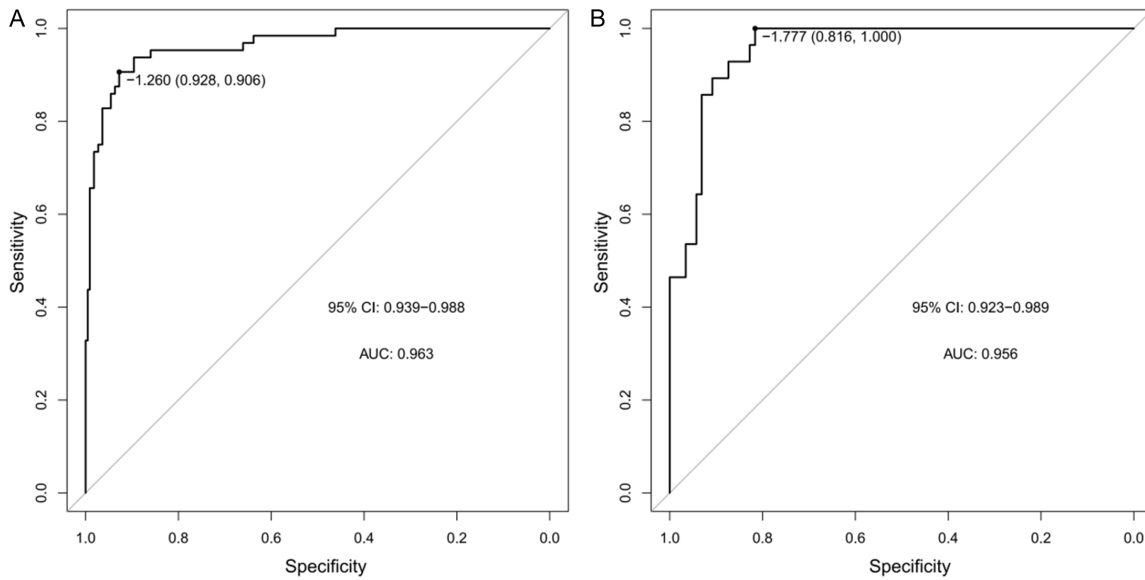


Figure 4. ROC curve of the Logistic regression model for predicting hypothermia in emergency trauma patients. A. Training set; B. Validation set. ROC, receiver operating characteristic curve.

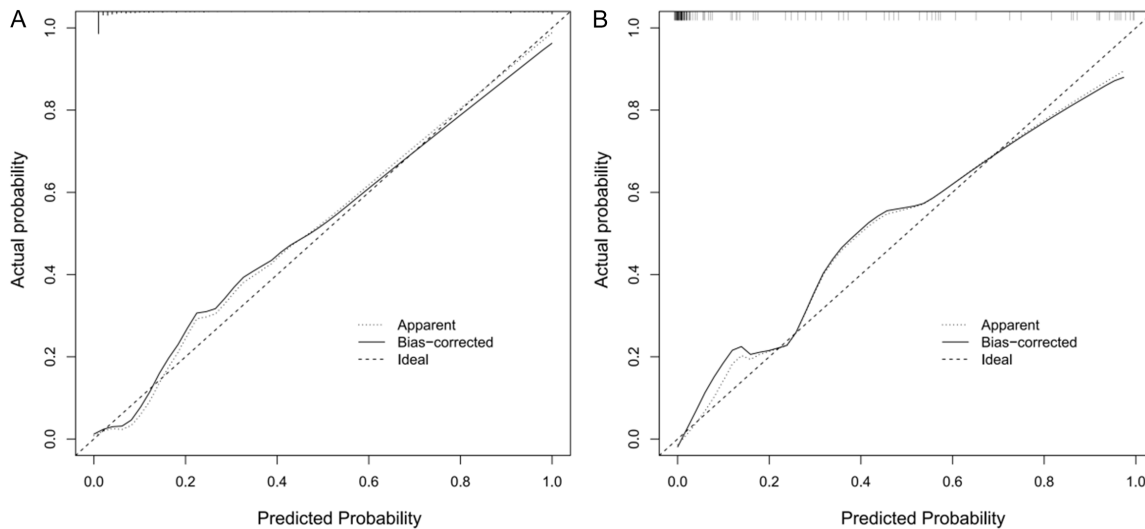


Figure 5. Calibration curve of the Logistic regression model for predicting hypothermia in emergency trauma patients. A. Training set; B. Validation set.

national trauma database that hypothermia is not only a marker of the severity of shock but also an independent risk factor for trauma patients' death. When the core body temperature is below 36.0°C, the mortality rate increases exponentially. Therefore, establishing a predictive model for the occurrence of hypothermia in emergency trauma patients can effectively identify high-risk individuals and provide clinical experience for early identification and intervention in the clinic.

This study, based on the clinical data of 400 emergency trauma patients, used the random forest algorithm to construct an early warning model for hypothermia. The incidence of hypothermia was 23.00%, which is consistent with the literature reports [22]. In this study, six predictive variables (RTS score, ISS score, SI index, ambient temperature at the time of injury, wet clothes, shock at the time of admission) identified based on LASSO regression were independent risk factors for hypothermia in emergency

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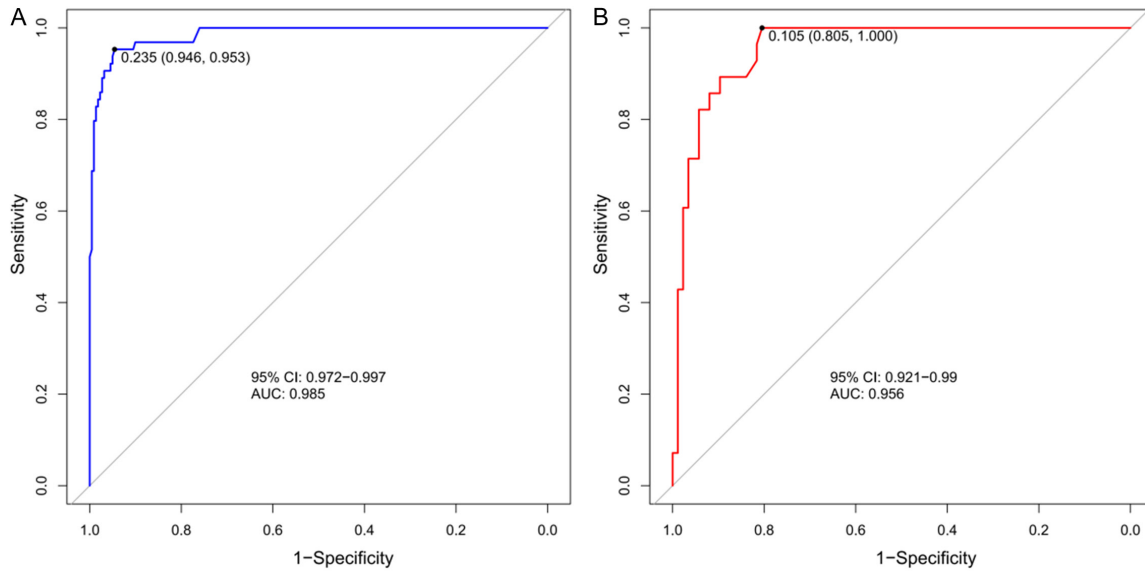


Figure 6. ROC curve of the RF model for predicting hypothermia in emergency trauma patients. A. Training set; B. Validation set. RF, random forest; ROC, receiver operating characteristic curve.

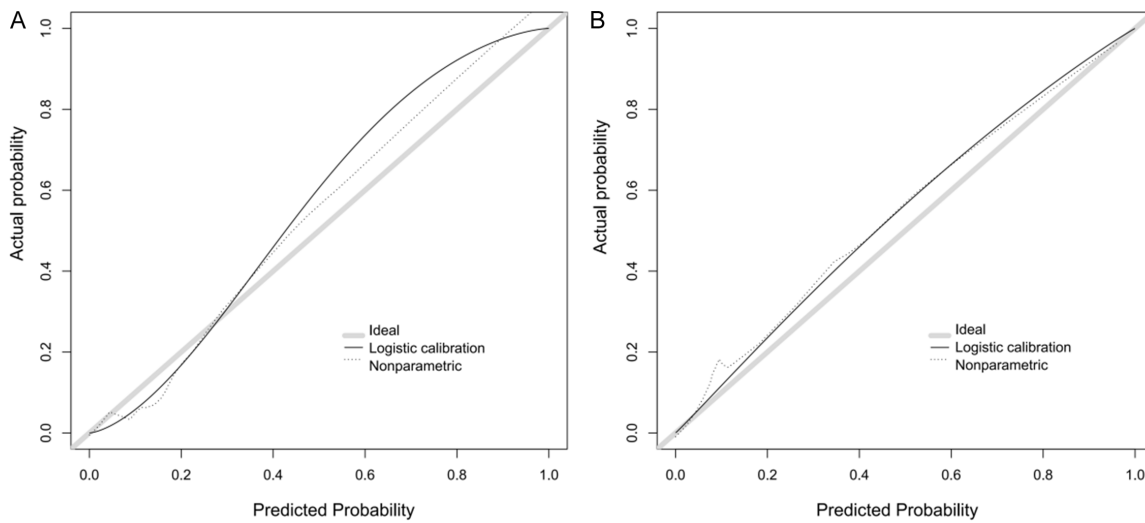


Figure 7. Calibration curve of the RF model for predicting hypothermia in emergency trauma patients. A. Training set; B. Validation set. RF, random forest.

trauma patients. A recent systematic review included 9 predictive model studies with sample sizes ranging from 91 to 732 cases, and the model AUC ranged from 0.704 to 0.990. The study pointed out that the severity of trauma, damp clothing, lack of insulation measures, fluid resuscitation, and environmental temperature were the most common predictive factors [23]. Akena et al. [24] conducted a prospective observational study showing that environmental temperature (AOR = 0.09) and warm clothing (AOR = 0.05) were significant protective fac-

tors for hypothermia, while age and injury site increased the risk. Feng et al. [12] also confirmed in a study of emergency trauma patients that the severity of trauma, body position, damp clothing, insulation measures during transfer, pre-hospital fluid resuscitation, and modified GCS score were independent influencing factors for hypothermia. Weuster et al. [4] analyzed 15,230 multiple trauma patients from the German trauma registry and found that the incidence of hypothermia at admission (< 36.0°C) was as high as 33.3%, and the inci-

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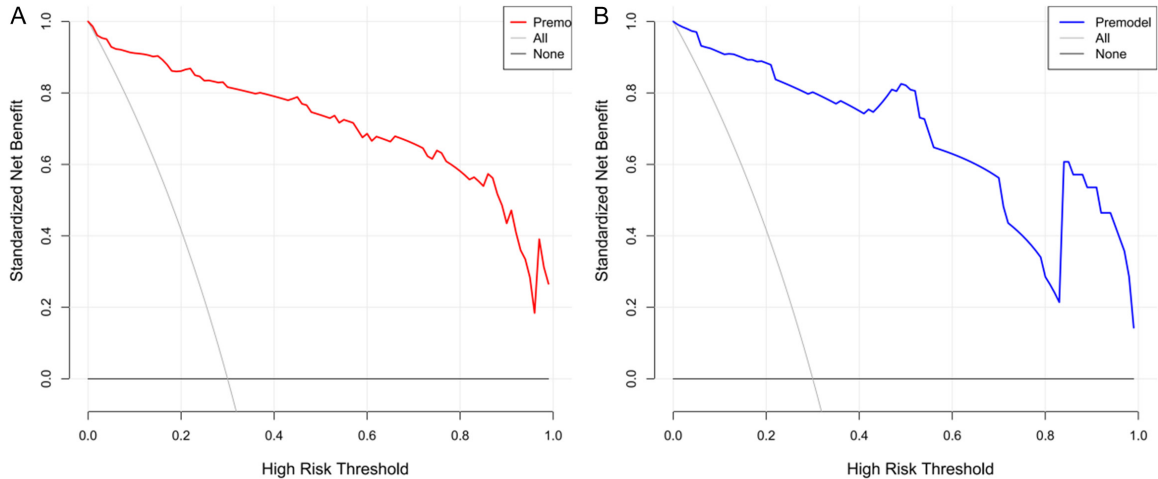


Figure 8. DCA curve of Logistic regression model for predicting hypothermia in emergency trauma patients. A. Training set; B. Validation set. DCA, decision curve analysis.

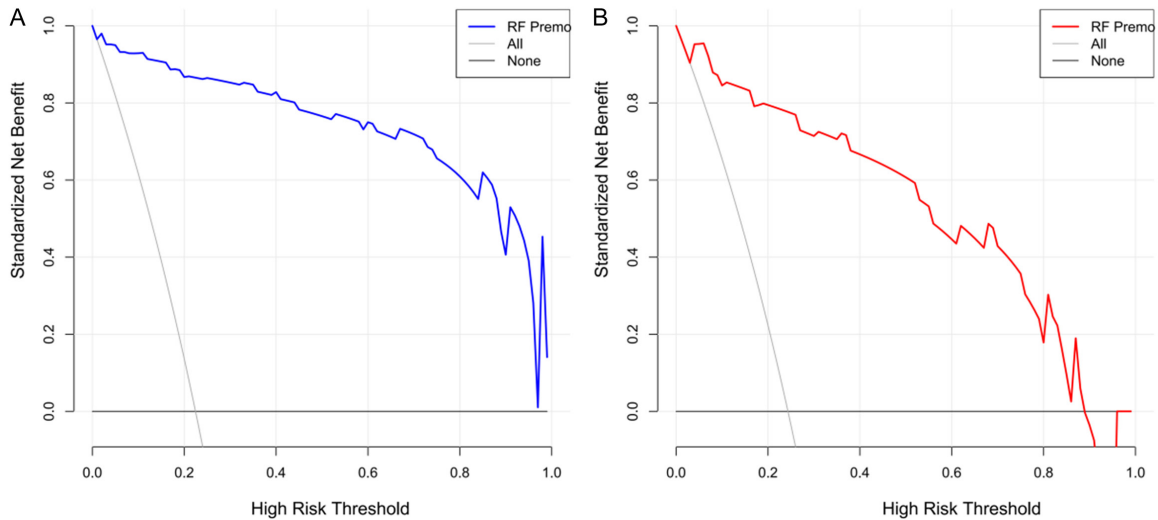


Figure 9. DCA curve of the RF algorithm model for predicting hypothermia in emergency trauma patients. A. Training set; B. Validation set. DCA, decision curve analysis.

dence of sepsis, multiple organ failure, and mortality in hypothermia patients were significantly increased, with the mortality rate gradually increasing as the body temperature decreased. The importance of the variable of ISS score in the random forest ranking was the first, suggesting that the severity of injury anatomy has the most critical impact on hypothermia. Lapostolle et al. [25] showed that the RTS score is the most important risk factor for hypothermia in trauma patients, and the RTS score of patients with hypothermia was a full 10 points [13]. Perlman et al. [26] proposed a management guideline for hypothermia in

severely injured patients, systematically elaborating the reinforcing mechanism between hemorrhagic shock and hypothermia: shock leads to insufficient tissue perfusion and reduced heat production, while hypothermia further aggravates coagulation dysfunction by inhibiting thrombin activity and platelet function, forming a vicious cycle of the “death triad”; this guideline emphasizes that the SI index, as an early identification indicator of shock, is of great value for warning hypothermia. van Veelen et al. [27] published a review further stating that damp clothing is the most easily overlooked but crucial controllable factor in the

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pre-hospital stage, and damp clothing accelerates heat loss through conduction and convection, timely changing dry clothing or covering with a thermal blanket can significantly reduce heat loss; at the same time, patients with shock at admission often have a decreased level of consciousness, the hypothalamic temperature regulation center is inhibited by trauma stimulation, resulting in impaired vascular vasoconstriction and shivering thermogenesis mechanisms, which emphasizes the crucial role of early hemodynamic resuscitation in maintaining body temperature homeostasis.

In terms of model performance and methodology, Random Forest, as a classifier based on decision tree ensemble, constructs multiple decision trees through the Bagging idea and the feature subspace idea, and makes category judgments through the combined voting results. Compared to a single decision tree, it has better noise resistance and is less prone to overfitting, significantly improving generalization ability [28]. Its advantages lie in the ability to automatically explore the variables that contribute significantly to classification and output the feature importance ranking, which is applicable to a wide range of scenarios. The Random Forest model in this study ranks the importance of feature variables, and the results show that the variables influencing the occurrence of hypothermia in emergency trauma patients are in the following order: ISS score > RTS score > ambient temperature at the time of injury > SI index > damp clothing > shock upon entering the room. This ranking is highly consistent with the independent risk factors identified by multivariate Logistic regression, further verifying the core position of these factors. In terms of predictive efficacy, the AUC of the Random Forest model in the training set is 0.985 (95% CI: 0.972-0.997), and in the test set is 0.956 (95% CI: 0.921-0.990); the Logistic regression model in the training set is 0.963 (95% CI: 0.939-0.988), and in the test set is 0.956 (95% CI: 0.923-0.989). The AUC of the test set for both models is exactly the same, indicating that although the Random Forest model has better fitting in the training set, its generalization ability is on par with Logistic regression. The calibration curve shows good consistency between predicted probabilities and actual incidence rates. The decision curve analysis indicates that both models have clinical application

value, but the Random Forest model has a higher standardized net benefit and better stability in each threshold interval, suggesting that it may have advantages in clinical decision support. This finding is consistent with the application results of machine learning models in other fields of emergency medicine. Okada et al. [29] showed in a multicenter study on accidental hypothermia patients that the C-statistic of the Random Forest model for predicting in-hospital mortality was 0.794, which was comparable to the traditional SOFA score (0.787), but the decision curve analysis indicated that machine learning models could achieve higher clinical net benefits. Long et al. in a study on the prediction of intraoperative hypothermia in total joint replacement patients, used Random Forest feature selection combined with decision tree modeling, and the model's AUC reached 0.810 [30]. In the validation set, the GBM and RF models achieved specificities of 81.60% and 80.50%, respectively, with false positive rates of approximately 18%-20%. Potential reasons include: ① Some normothermic patients may be in a state of compensated thermoregulation, with physiological features resembling mild hypothermia; ② Tympanic temperature measurement may be affected by peripheral circulatory status in trauma patients, leading to falsely low readings; ③ The model only incorporates single temperature measurement at admission, lacking dynamic trends. Future studies integrating continuous temperature monitoring and core temperature measurements (e.g., esophageal temperature) may help reduce false positives.

This study does have certain limitations. (1) The single-center retrospective design may have selection bias, with a relatively limited sample size (400 cases), and the hypothermia group only had 92 cases, which may affect the model's stability. Systematic reviews pointed out that existing prediction models generally have a higher risk of bias, related to sample selection, indicator measurement, and research design deficiencies [31]. (2) Some potential predictive variables (such as pre-hospital fluid resuscitation volume, analgesic drug use) could not be included due to missing data, possibly missing important information. (3) The warning window of the model is at the time of admission, and it fails to achieve dynamic real-time warning, while Zhang et al. [32]'s study

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has proved that dynamic models based on observation windows have higher clinical application value. (4) The model has not undergone multi-center external validation, and its generalization ability needs to be further evaluated. In addition, the Random Forest algorithm itself has limitations in realizing the visualization of the entire forest and may overfit when dealing with certain noisy datasets. Therefore, in clinical applications, attention should be paid to the continuous screening of variables and model updates. (5) Limitations of the variable selection approach: LASSO regression assumes linear relationships between predictors and the outcome, which may not fully capture complex non-linear interactions or higher-order effects among variables. Future studies could apply non-linear machine learning algorithms (e.g., random forest, XGBoost, or neural networks) without linear pre-selection to better detect complex patterns and interactions. (6) Tympanic temperature measurement was used in this study, which, while convenient and non-invasive, may not accurately reflect core body temperature. In trauma patients with shock, peripheral vasoconstriction can affect the accuracy of tympanic readings, potentially introducing measurement bias. Future studies should consider using core temperature measurements such as esophageal or bladder temperature to improve precision.

In conclusion, RTS score, ISS score, SI index, environmental temperature, damp clothing, and shock upon entering the room are risk factors for hypothermia in emergency trauma patients. The RF algorithm based on these risk factors and the early warning model for hypothermia in emergency trauma patients constructed by this algorithm have higher predictive efficacy and are superior to the traditional Logistic regression model. This model can assist emergency medical staff in early identification of high-risk patients with hypothermia, providing decision support for guiding preventive warming measures.

Acknowledgements

This work was supported by the Special Project for Scientific and Technological Research of Traditional Chinese Medicine and Ethnic Medicine, Guizhou Provincial Administration of Traditional Chinese Medicine (QZYY-2023-008) and Inheritance Studio of Famous Vete-

ran TCM Physician Shi Enjun (Qianzhongyiyao-han (2024) No. 38).

Disclosure of conflict of interest

None.

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