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RESEARCH

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A risk prediction model for venous thromboembolism in hospitalized patients with thoracic trauma: a machine learning, national multicenter retrospective study

Kaibin Liu[1†], Di Qian[2†], Dongsheng Zhang[3†], Zhichao Jin[2], China Chest Injury Research Society (CCIRS), Yi Yang[4*] and Yanfang Zhao[2*]

Abstract

Background Early treatment and prevention are the keys to reducing the mortality of VTE in patients with thoracic trauma. This study aimed to develop and validate an automatic prediction model based on machine learning for VTE risk screening in patients with thoracic trauma.

Methods In this national multicenter retrospective study, the clinical data of chest trauma patients hospitalized in 33 hospitals in China from October 2020 to September 2021 were collected for model training and testing. The data of patients with thoracic trauma at Shanghai Sixth People's Hospital from October 2021 to September 2022 were included for further verification. The performance of the model was measured mainly by the area under the receiver operating characteristic curve (AUROC) and the mean accuracy (mAP), and the sensitivity, specificity, positive predictive value, and negative predictive value were also measured.

Results A total of 3116 patients were included in the training and validation of the model. External validation was performed in 408 patients. The random forest (RF) model was selected as the final model, with an AUROC of 0·879 (95% CI 0·856–0·902) in the test dataset. In the external validation, the AUROC was 0.83 (95% CI 0.794–0.866), the specificity was 0.756 (95% CI 0.713–0.799), the sensitivity was 0.821 (95% CI 0.692–0.923), the negative predictive value was 0.976 (95% CI 0.958–0.993), and the positive likelihood ratio was 3.364.

Conclusions This model can be used to quickly screen for the risk of VTE in patients with thoracic trauma. More than 90% of unnecessary VTE tests can be avoided, which can help clinicians target interventions to high-risk groups and ensure resource optimization. Although further validation and improvement are needed, this study has considerable clinical value.

Keywords Thoracic trauma, Venous thromboembolism, Rib fracture, Risk prediction model, Random forest, Machine learning

†Kaibin Liu, Di Qian and Dongsheng Zhang these authors contributed equally to this work.

*Correspondence:
Yi Yang
7250012312@shsmu.edu.cn
Yanfang Zhao
zhyf715@s126.com
Full list of author information is available at the end of the article

Introduction

Venous thromboembolism (VTE) includes pulmonary thromboembolism (PE) and deep venous thromboembolism (DVT). The incidence of VTE among hospitalized patients in the United States ranges from 10–40%, and up to 60% of surgical patients are at intermediate or high risk for VTE [1, 2]. The incidence of VTE ranges from 7 to 53%, depending on the type of disease, and survivors also have varying degrees of sequelae. [2–4] According to different reports, the mortality rate of DVT ranges from 2·6 to 19·6%, [2, 5] and the mortality rate of PE ranges from 5·2 to 19·6% [2, 6]. VTE is one of the most important fatal complications in trauma patients [7, 8], and it is one of the leading causes of death in trauma patients who survive beyond the first day [9]. The incidence of VTE in patients with trauma ranges from 11·8–65% [9]. The incidence of VTE can reach 40–80% in patients with severe or multiple traumas who do not receive thromboprophylaxis [7, 10]. It poses great clinical risk and financial burden to patients and medical institutions. [11]

Unlike the traditional view that PE is secondary to DVT in the past, PE and DVT in patients with thoracic trauma are independent clinical events [12, 13]. Therefore, identifying high-risk individuals before further examination to make personalized prevention, diagnosis, and treatment decisions is urgently needed by thoracic surgeons [14, 15]. In our previous literature search, we found that there was no targeted prediction model for VTE in patients with thoracic trauma, and there was a lack of efficient prediction methods. (eText1, eFig1).

Materials and methods

This study was approved by the Ethics Committee of the Third Hospital of Shijiazhuang (2021) Ethical Approval No. 047 and was reviewed by all participating institutions.

Subjects

The clinical data of 5774 patients with thoracic trauma treated at 33 tertiary or secondary medical institutions in China from October 2020 to September 2021 were collected. After screening according to the inclusion and exclusion criteria, 3116 patients were included in this study. In addition, we enrolled 474 patients with thoracic trauma in a single center at six hospitals in Shanghai from October 2021 to September 2022. Among these patients, 408 patients who met the inclusion criteria were used for external validation. All the participants provided written informed consent. The inclusion and exclusion criteria were as follows:

Inclusion criteria

(1) 25–80 years old, admitted within 3 days after chest trauma; (2) for patients with thoracic trauma combined with other injuries, the abbreviated injury score (AIS) was defined as AIS ≥ 3 for thoracic injury and AIS ≤ 3 for other injury sites independently.

Exclusion criteria were as follows

(1) received preventive physical or chemical anticoagulation therapy before admission; (2) VTE occurred before admission; and (3) except for thoracic injury, the other injury sites had an independent AIS score > 3. (4) Incomplete case data. (5) Written informed consent was not provided.

Main prediction results and diagnostic methods

The primary outcome was in-hospital VTE, including DVT confirmed via deep vein ultrasonography and PE confirmed via CTPA [16]. DVT was routinely detected, and PE was selectively detected.

Development of machine learning models

The development process of the model is shown in Fig. 1, which is divided into the following steps:

Data collection and sorting

All the data were collected and managed via the designated chest trauma cloud database. All analyses were performed via R Studio (version 4.2.2) and Python (version 3.9.0).

A total of 25 clinical data and epidemiological characteristics of patients with thoracic trauma [14, 16–19], including sex, age, body mass index (BMI), number of broken ends of rib fractures, treatment methods, surgical treatment plans, underlying diseases, and complications, were recorded. (eTable 1).

Selection of related factors

The development of the machine learning model began with the Python-based BorutaShap algorithm (eMethod 1) for feature selection [20–22]. Only the influencing factors screened from the feature selection were included in the final machine learning model.

Sample size calculation and data segmentation

At present, there is no perfect sample size calculation rule for the training and validation of machine learning models [23, 24]. Generally, the research data are divided into a training set, test set, and external validation set = 3:1:1. In this study, the sample size calculation method of Riley et al. [25] was used to calculate the minimum sample size of the training set and the external validation set in three steps (eMethod 2; eFig2; eFig3).

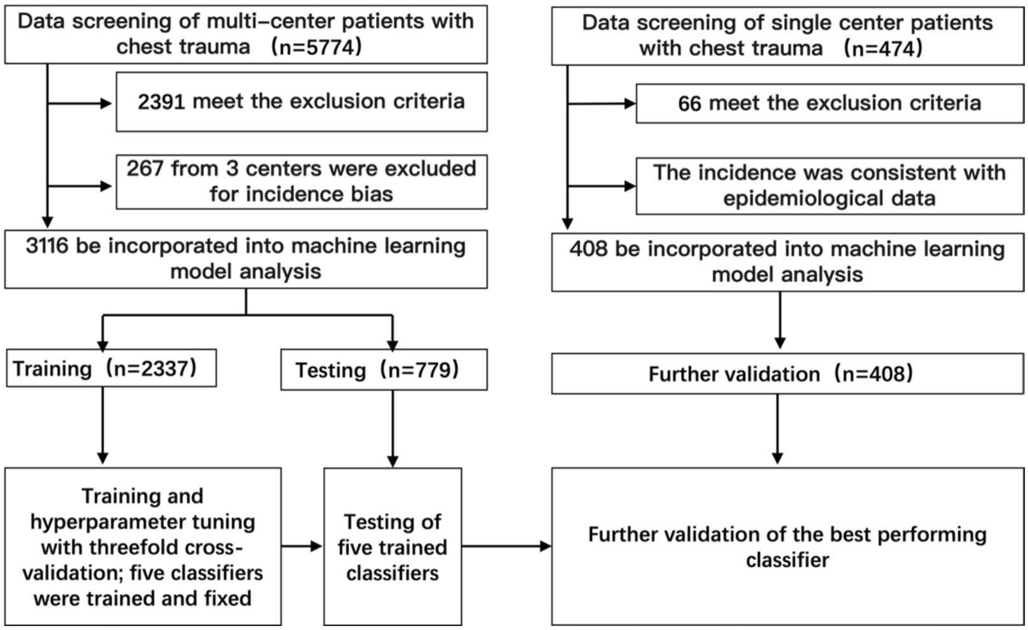

Fig. 1 Flowchart of the study and data analyses

Model training and verification

Five machine learning models were trained [26, 27]: logistic regression (LR) [28, 29], random forest (RF) [30], support vector machine (SVM) [31], multilayer perceptron (MLP) [32], and gradient boosting machine (GBM) [33]. The synthetic minority oversampling technique (SMOTE) was used to address imbalanced data in the training set [34]. The test set was used to validate the five models to further screen out the best-performing machine learning model. To ensure the fairness of the comparison, algorithms that had advantages in some training processes received corresponding weakening adjustments. The logistic regression model was trained on the basis of the Akaike information criterion and reverse feature method. To adjust the hyperparameters of the RF, SVM, MLP, and GBM models, we defined a hyperparameter space for each model and performed a grid search and triple cross-validation in the training set. The hyperparameters that yielded the highest area under the receiver operating characteristic curve (AUROC) for each model during validation were selected and fixed for subsequent model testing. The outcome measures included the AUROC for each model and the mean accuracy (mAP) of the model, as well as the sensitivity, specificity, positive predictive values, and negative predictive values. The mAP was defined as the average precision over all the recall rates and was equal to the area under the precision–recall curve in the current study. The bootstrap method was used to calculate the 95% confidence interval (CI) and compare the AUROC and average accuracy curves. The best-performing model was subjected to operation-point analysis with the highest Youden index as the operating point of the ROC curve. The AgrestiCoull method was used to calculate 95% confidence intervals (CIs) for the sensitivity, specificity, and positive and negative predictive values [35]. Differences in sensitivity and specificity were analyzed via McNemar's chi-square test, and differences in predictive values were analyzed via generalized score statistics [36]. The Shapley additive explanatory value (SHAP value) is used to measure the contribution of each feature to the model output. [37]The output probabilities were calibrated via the Platt scale, and a calibration curve was drawn. To assess the net clinical benefit of different thresholds, we performed a decision curve analysis. [38, 39]As the actual risk of VTE in the screened population was low, the use of the polygenic risk score (PRS) instead of the actual risk of VTE is more conducive to further analysis [40]. The PRS reflects the estimated actual risk via the following formula:

$$\text{Estimated actualrisk} = \frac{\exp(6\cdot37\times PRS-6\cdot41)}{1+\exp(6\cdot37\times PRS-6\cdot41)}$$

Finally, an external validation set was used to validate the performance of the optimal prediction model. In the above procedures, all tests were two-sided, and p values less than 0 · 05 were considered to indicate significant differences.

Construction of the visual web program

The research team constructed a visualization procedure (eMethod 3; eFig. 4; eFig. 5) for the model on the basis of the gap value and PRS of the model.

Results

Selection of the main prediction results

Among the 3116 patients with thoracic trauma included in the analysis, there were 190 cases of VTE, with an incidence of approximately 6 · 1%, including 183 cases of DVT and 17 cases of PE, seven of which were found to have PE without DVT. There were 37 VTE cases in the external validation set of 408 cases, with an incidence of 9·1%, including 41 cases of DVT and three cases of PE, of which two cases of PE were detected without DVT. Because the sample size and incidence of PE cases were much lower than those of DVT cases, VTE was used as the only main prediction result.

Feature selection

Twelve related factors were selected: age, BMI, number of broken ends of rib fracture, rib fracture surgery, multiple traumas, lower limb fracture, tracheal intubation, blood transfusion, D-D 24 h, PT 24 h, Plt 24 h, and Hb 24 h.

Machine learning model training and screening

Segmentation of data

The study population was divided into a training group (before) and a test group (after), with June 30, 2021, as the cutoff. A ratio of 3:1 was used to divide the 2337 samples before June 30, 2021, into the training set and 779 samples after June 30, 2021, into the test set. The sample size of the training set used in this study was significantly larger than the minimum calculated sample size (eMethod 2; eFig 2). eTable 2 shows the baseline data after variable screening and grouping.

Machine learning model training performance

All the models performed well in the training set, and the performances of all the parameters of the training and test sets are shown in Table 1.

External verification

Data from 408 patients with chest trauma who met the inclusion criteria were included in an external validation set to further verify the performance of the RF prediction model (Table 2). Compared with the test dataset, the RF model also had similar AUROCs (0·83, 95% CI

Table 1 Prediction performance of the machine learning models in the training and testing sets

Model	LR	RF	SVM	MLP	GBM
Train_auc	0.798	0.997	1	0.757	0.843
Test_auc	0.815	0.879	0.739	0.728	0.838
auc_ci	(0.788,0.842)	(0.856,0.902)	(0.708,0.77)	(0.697,0.759)	(0.812,0.864)
Specificity	0.734	0.687	0.589	0.684	0.899
Specificity_ci	(0.702,0.766)	(0.653,0.721)	(0.553,0.624)	(0.65,0.718)	(0.877,0.92)
Sensitivity	0.8	0.956	0.822	0.756	0.644
Sensitivity_ci	(0.689,0.911)	(0.889,1.0)	(0.711,0.933)	(0.622,0.867)	(0.511,0.778)
F1	0.261	0.27	0.193	0.219	0.392
Youden Index	0.534	0.642	0.411	0.439	0.544
MCC	0.273	0.314	0.193	0.216	0.374
Kappa	0.182	0.19	0.101	0.133	0.339
npv	0.984	0.996	0.982	0.979	0.976
npv_ci	(0.973,0.993)	(0.99,1.0)	(0.968,0.993)	(0.965,0.99)	(0.964,0.987)
ppv	0.156	0.158	0.109	0.128	0.282
Ppv_ci	(0.113,0.203)	(0.117,0.201)	(0.077,0.145)	(0.09,0.169)	(0.194,0.369)
plr	3.011	3.049	1.998	2.39	6.392
nlr	0.272	0.065	0.302	0.357	0.395
mAP	0.597	0.717	0.636	0.565	0.64

RF (0·879, 95% CI 0·856–0·902) had the best curve performance. In terms of the negative predictive rate and mAP, the RF (npv = 0·996 95% CI 0·99–1·0, mAP = 0·717) also achieves the best performance. The ROC curve (Fig. 2. A), precision–recall curve (Fig. 2. B), calibration curve (Fig. 2. C), and DCA decision curve (Fig. 2. D) for all the candidate models in the test set are shown in Fig. 2. On the basis of these results, RF was selected as the final model for subsequent external validation

Table 2 Comparison of the results of the test set with those of the external verification set

RF	Test set	External verification set
Test_auc	0.879	0.83
auc_ci	(0.856,0.902)	(0.794,0.866)
Specificity	0.687	0.756
Specificity_ci	(0.653,0.721)	(0.713,0.799)
Sensitivity	0.956	0.821
Sensitivity_ci	(0.889,1.0)	(0.692,0.923)
F1	0.27	0.398
Youden Index	0.642	0.577
MCC	0.314	0.37
Kappa	0.19	0.295
npv	0.996	0.976
npv_ci	(0.99,1.0)	(0.958,0.993)
ppv	0.158	0.262
Ppv_ci	(0.117,0.201)	(0.189,0.344)
plr	3.049	3.364
nlr	0.065	0.237
mAP	0.717	0.688

0·794–0·866) and mAPs (0·688) in the external validation dataset.

We analyzed the relative influence of the 12 features on the model output according to the mean absolute SHAP values (Fig. 3A). In addition, to further clarify the influence of different features on the model output, we plotted the prediction plots of negative and positive correlations (Fig. 3B).

Discussion

This study has the advantages of being a multicenter study with a large sample size and can better reflect the incidence of VTE in patients with thoracic trauma during hospitalization in most parts of China. The use of machine learning algorithms can ensure the rigor of research to the greatest extent possible and improve the accuracy and generalizability of prediction models. [26, 27]

In this model, the excluded features had little influence on the final prediction results, and if they were included together, the model would overfit [27]. Brain trauma, spinal fracture, pelvic fracture, abdominal injury, upper limb fracture, and surgery in other departments are known risk factors for VTE [18, 41], but they did not have a significant influence in this study. Only patients with simple thoracic trauma and severe thoracic trauma (independent AIS score ≥ 3) and patients with mild trauma (independent AIS score ≤ 3) were included in this study. Therefore, injuries to other parts of the body with minor injuries and surgeries had an insufficient influence on the final prediction results of the model and were not included in this model. Among the 12 features included in the model, the influence of different features on the final prediction results is shown in Fig. 3. Lower limb fracture, Hb24h, age, BMI, and the number of broken ends of the rib fracture had the highest correlation with the final prediction result. Tracheal intubation, PT24h, blood transfusion, D-D24h, multiple traumas, Plt24h, and rib surgery were also strongly correlated with the final prediction.

Lower extremity fracture, age, BMI, tracheal intubation, PT24h, D-D24h, and multiple traumas were positively correlated with VTE. Hb24h and Plt24h levels were negatively correlated with the occurrence of VTE, and blood transfusion was positively correlated with the occurrence of VTE. These results are consistent with previous findings (eText 2). [7, 18, 41–44]

The number of broken ends of rib fractures had a considerable influence on the final prediction results. In addition to the common risk factors for trauma, patients with thoracic trauma have their own characteristics [11, 14, 45]. Rib fracture, hemopneumothorax, pulmonary contusion directly caused by trauma, pneumonia, acute respiratory distress syndrome (ARDS), and respiratory failure indirectly caused by trauma are all risk factors for VTE, which may be caused by fractures, chest strap fixation, and prolonged bed rest [8, 41, 46, 47]. Patients with chest trauma, especially those with multiple rib fractures or flail chests, have limited breathing, poor sputum excretion, and an increased risk of respiratory infections. [46–48]

In the screening process of the machine learning models, the RF model showed obvious advantages over the other machine learning models in terms of the ROC curve, P-R curve, calibration curve, and DCA curve (Fig. 2). The highest AUC (0.879) and mAP (0.44) indicated that the RF model had the highest accuracy [27]. As shown in the calibration curve, the RF model had the highest degree of calibration. In the DCA curve, the RF model also showed the greatest net benefit, indicating that the RF model has the highest clinical value while meeting the actual needs of clinical decision-making [38]. When the incidence is low, the RF model has greater accuracy and clinical value. The overall incidence of VTE in this study (6·1%) was low and consistent with the incidence of VTE observed in clinical practice. [1, 2]

Trauma patients, especially those with multiple injuries, are critically ill and have poor underlying conditions [49]. Unnecessary examinations and transportation often result in unnecessary economic burdens and clinical risks to patients. In this study, a machine learning model was used to automatically generate an objective PRS score by inputting easily available hospitalization data and epidemiological information of hospitalized patients, which

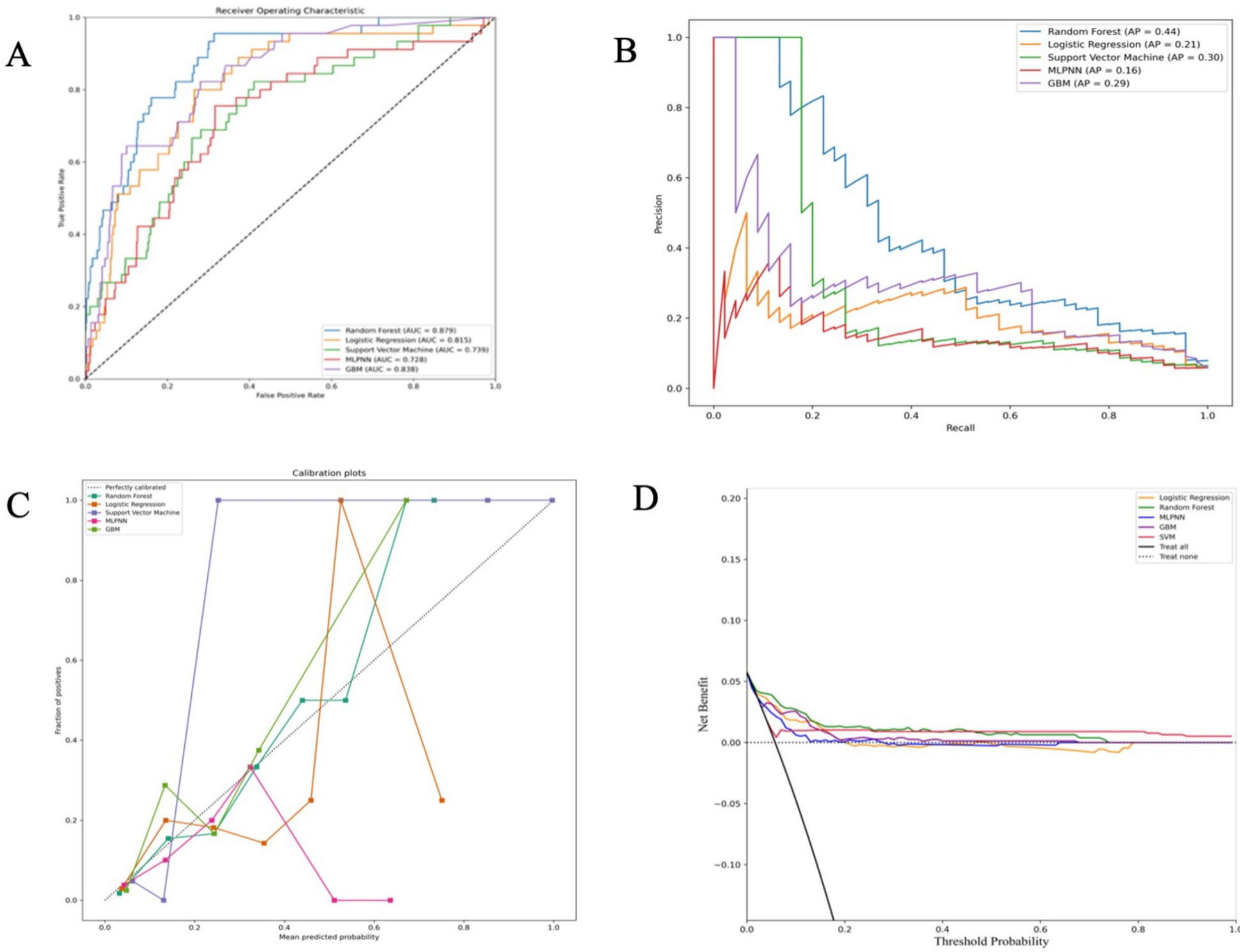

Fig. 2 Receiver operating characteristic curve (**A**), precision–recall curve (**B**), calibration curve (**C**), and decision curve (**D**)

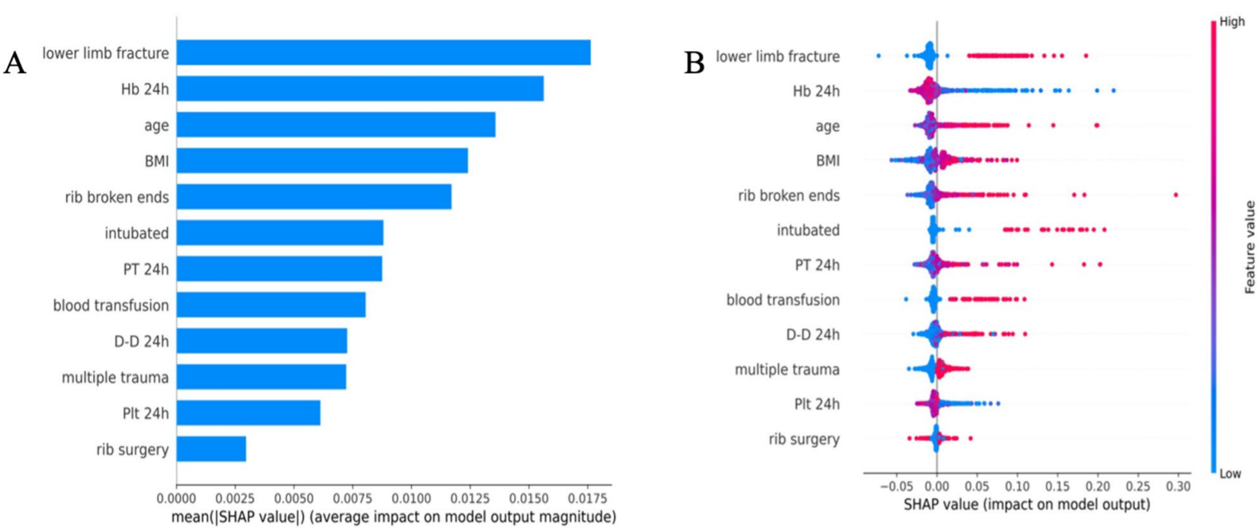

Fig. 3 Mean SHAP value (**A**), SHAP value (**B**)

effectively removed subjective factors in clinical VTE screening. The negative predictive value was 0.976 (95% CI 0.958–0.993). This means that approximately 97·6% of patients with thoracic trauma can avoid unnecessary transport and invasive tests when the model is used to predict the probability of VTE.

Notably, although rib fracture surgery was positively associated with VTE in this study, it had a relatively weak effect. Figure 3(B) shows that not undergoing rib surgery had little effect on the occurrence of VTE, but the patient population that underwent surgery had both positive and negative effects. This may be due to the large differences in the degree of rib fracture in the patients with thoracic trauma included in this study and the different indications for rib surgery at each center. Recent studies have shown that rib surgery may have a protective effect on pulmonary complications and VTE in patients with severe rib fractures [47, 48, 50]. Studies have also reported that the incidence of VTE in patients who undergo surgery as soon as possible may be lower than that in delayed surgery patients [16]. This study could not determine whether rib surgery had a protective effect on VTE in patients at this time, which requires more targeted and standardized research.

This study had several limitations. First, the incidence of VTE in patients with thoracic trauma in this study was lower than that reported in other studies [51]. Because of the differences in physicians' clinical experience and because many asymptomatic PE cases occur without significant clinical manifestations, data from many patients with PE were not included in the study [12, 52]. In addition, only patients admitted within three days after trauma were included in this study. In a study of patients with acute trauma, up to 62% of VTE cases were reported after hospital discharge.8 This study also had problems such as insufficient sample size, imperfect inclusion and exclusion criteria, incomplete long-term follow-up, insufficient data homogeneity, and an insufficient external validation set. Further multicenter studies with larger sample sizes and improved internal and external consistency are needed. In addition, the fully automated clinical screening model developed in this study will require further regulatory review and approval to evaluate its performance, potential risks, and benefits for broad clinical applications.

In conclusion, we developed and tested a machine learning model to predict the probability of VTE in patients with thoracic trauma during the perioperative period. This convenient and automated screening method showed comparable diagnostic performance and prevented 97·6% of unnecessary lower-extremity vascular ultrasound or CTPA screening. The results of our study have the advantages of noninvasive examination, convenience, and high efficiency, which can significantly improve the efficiency of VTE prevention and treatment in patients with thoracic trauma and pave the way for better optimization of medical resources.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s13017-025-00583-w.

Additional file 1.

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Additional Contributions: We thank the members of the CCIRS study group and patients who participated in the trial.

Author contributions

Kaibin Liu, Di qian, and Dongsheng Zhang had full access to all the data in the study and took responsibility for the integrity of the data and the accuracy of the data analysis. All the members of the CCIRS contributed equally to this study. Concept and design: All authors. Acquisition, analysis, or interpretation of data: All members of the CCIRS. Drafting of the manuscript: Kaibin Liu, Di Qian, Dongsheng Zhang, Zhichao Jin, Yi Yang, and Yanfang Zhao. Critical review of the manuscript for important intellectual content: Yi Yang and Yanfang Zhao, members of the CCIRS. Statistical analysis: Kaibin Liu, Di qian, Yanfang Zhao, Zhichao Jin. Obtained funding: All members of the China Chest Injury Research Society (CCIRS). Administrative, technical, or material support: Zhichao Jin, Yi Yang, Yanfang Zhao, and all members of the CCIRS. Supervision: All authors. Conflict of Interest Disclosures: None. Group Information: CCIRS members. Data Sharing Statement: See Supplement. The machine learning part of this study was performed via R Studio (version 4.2.2) and Python (version 3.9.0). Machine learning was used only for model training and validation. All the authors take responsibility for the integrity of the content generated.

Data availability

The data of this multicenter study were collected from 33 medical institutions in China. The data were analyzed through the self-developed cloud database of chest trauma patients. Considering the infringement of patients' privacy rights and the violation of national medical data confidentiality regulations, it is not convenient to share the original data to the world for the time being. The original data were obtained from the corresponding author when reasonable. In this study, Kaibin Liu, Di qian and Dongsheng Zhang have limited data sharing rights. They had full access to all of the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis. They can obtain the individual patient data of multi-center for data analysis, but cannot modify the data information or share the data through network channels.

Declarations

Informed consent

Written informed consent was obtained from the patient for publication of this case report and accompanying images. A copy of the written consent is available for review by the Editor-in-Chief of this journal upon request.

Competing interest

The authors declare no competing interests.

Author details

[1]Department of Thoracic Surgery, Shanghai Jiao Tong University School of Medicine Affiliated Sixth People's Hospital, Shanghai 200233, China. [2]Department of Health Statistics, Faculty of Health Service, Naval Medical University, 800 Xiangyin Road, Shanghai 200433, China. [3]Department of Cardiothoracic Surgery, Shijiazhuang Third Hospital, Shijiazhuang 050000, Hebei, China. [4]Department of Thoracic Surgery, Shanghai Sixth People's Hospital, 600 Yishan Road, Shanghai 200235, China.

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