Cai *et al.*
European Journal of Medical Research (2025) 30:277
https://doi.org/10.1186/s40001-025-02510-w

European Journal of Medical Research

RESEARCH

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Interpretable prognostic modeling for long-term survival of Type A aortic dissection patients using support vector machine algorithm

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Abstract

Objectives This study aims to develop a reliable and interpretable predictive model for long-term survival in Type A aortic dissection (TAAD) patients, utilizing machine learning (ML) algorithms.

Methods We retrospectively reviewed the clinical data of patients diagnosed with TAAD who underwent open surgical repair at the First Affiliated Hospital of Chongqing Medical University, from September 2017 to December 2020, and at the Chongqing University Central Hospital between October 2019 and April 2020. Cases with less than 20% missing data were imputed using random forest algorithms. To identify significant prognostic factors, we performed LASSO (Least Absolute Shrinkage and Selection Operator) Cox regression analysis, including preoperative blood markers, previous medical history and intraoperative condition. Based on the advantages of the model and the characteristics of the data set, we subsequently developed a machine learning-based prognostic model using Support Vector Machine (SVM) and evaluated its performance across key metrics. To further explain the decision-making process of the SVM model, we employed SHapley Additive exPlanation (SHAP) values for model interpretation.

Results A total of 171 patients with TAAD were included in model training and internal test groups; 73 patients with TAAD were included in external test group. Through LASSO Cox regression, univariate analysis, and clinical relevance assessment, seven feature variables were selected for modeling. Performance evaluation revealed that the SVM model showed excellent performance in both the training and test sets, with no significant overfitting, indicating strong clinical applicability. In the training set, the model achieved an AUC of 0.9137 (95% CI 0.9081–0.9203) and in the internal and external testing set, 0.8533 (95% CI 0.8503–0.8624) and 0.8770 (95% CI 0.8698–0.8982), respectively. The accuracy values were 0.8366, 0.8481 and 0.8030; precision values were 0.8696, 0.8374 and 0.8235; recall values were 0.8421, 0.7933 and 0.7651; F1 scores were 0.8290, 0.8148 and 0.7928; Brier scores were 0.1213, 0.1417 and 0.1323; average precision (AP) values were 0.9019, 0.8789 and 0.8548, respectively. SHAP analysis revealed that longer operation time, extended cardiopulmonary bypass (CPB) duration, prolonged aortic cross-clamp (ACC) time, advanced age, higher plasma transfusion volume, elevated serum creatinine and increased white blood cell (WBC) count significantly contributed to higher model predictions.

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Conclusions This study developed an interpretable predictive model based on the SVM algorithm to assess long-term survival in TAAD patients. The model demonstrated accuracy, precision, and robustness in identifying high-risk patients, providing reliable evidence for clinicians.

Keywords Type A aortic dissection, Machine learning, Long-term survival, Predictive model, Support vector machine (SVM)

Introduction

Aortic dissection is a life-threatening condition with an increasing incidence worldwide [1]. According to the Stanford classification system, Type A aortic dissection (TAAD) involves the ascending aorta and may extend to the aortic arch and descending aorta. Unlike Type B aortic dissection, TAAD has well-defined emergency indications for surgical repair [2]. Early studies indicate that the mortality rate for TAAD increases by 1–2% per hour during the first 48 h [3]. Despite advancements in surgical techniques and life support systems, the prognosis for TAAD patients remains poor due to the time-critical nature of the condition and a high risk of complications in the early stages. Recent data reveal that in-hospital and 30-day mortality rates for TAAD surgery exceed 20%, underscoring the urgent need for improved prognostic strategies [4, 5]. Therefore, identifying high-risk patients is crucial for optimizing prognosis management and guiding clinical decisions.

Perioperative conditions, such as cardiopulmonary bypass (CPB) duration, and specific biomarkers, including C-reactive protein (CRP) levels, have been identified as significant prognostic factors. For instance, Zhu et al. reported that prolonged CPB time was significantly associated with an increased risk of postoperative complications in TAAD patients, including central nervous system events, spinal cord ischemia, and myocardial ischemia or infarction[6]. Similarly, Tang et al. demonstrated that elevated preoperative CRP levels independently predict in-hospital mortality, renal dysfunction, and stroke in TAAD patients [7]. Moreover, the Systemic Immune-Inflammation Index (SII), which combines neutrophil, lymphocyte, and platelet counts, has shown promise in predicting postoperative complications and 3-year survival [8, 9]. Subsequent studies have reported several additional prognostic indicators in TAAD patients, including uric acid, D-dimer, fibrinogen, and the neutrophil-to-lymphocyte ratio [10–13]. Despite their statistical significance, these indicators are not widely implemented in clinical practice, primarily due to their limited ability to account for the complexity of TAAD prognosis in real-world settings.

The limited clinical application of these indicators may stem from their narrow focus, which fails to account for the multi-organ impact of TAAD, including the heart, kidneys, respiratory system, and coagulation system—key factors essential for survival. Consequently, prognosis assessments based solely on such indicators may be potentially inaccurate. Moreover, an exclusive focus on significantly abnormal markers may overlook the interrelationships between variables, leading to missing key information and underestimating the prognostic value of certain factors. Most of the prognostic indicators identified in previous studies have primarily been used for preoperative risk stratification to guide surgical timing. Unlike other acute or malignant conditions, early surgical intervention is critical to mitigate risks of aortic rupture and mortality [14]. Preoperative assessments alone are insufficient for comprehensive prognostic management. Therefore, models that incorporate intraoperative variables alongside clinical factors are essential to improve risk stratification and guide individualized decision-making.

Traditional regression methods, such as logistic regression and Cox regression, provide valuable insights but struggle to manage high-dimensional data and complex interactions, potentially overlooking critical prognostic factors [15, 16]. In contrast, machine learning (ML) techniques excel in identifying complex patterns within data sets, offering advantages in model optimization and predictive accuracy [17]. ML has demonstrated significant potential in healthcare, particularly in predicting health outcomes and disease progression in cardiovascular conditions [17–20]. However, the application of ML to TAAD prognosis research, especially for long-term survival prediction, remains underexplored.

To improve the accuracy of prognostic prediction for long term outcomes in TAAD patients, we conducted a retrospective study using data from two centers. This study aims to develop and validate a comprehensive ML model that incorporates a range of preoperative, intraoperative, and clinical variables to enhance prognostic assessment in TAAD patients. Considering the characteristics of the data set and the strengths of the algorithm, we have selected the SVM machine learning approach to develop the predictive model. By utilizing SHapley Additive exPlanations (SHAP)-based visualization, the model aims to identify key prognostic factors, providing interpretable insights to clinicians. We hypothesize that incorporating machine learning methods and multiple factors will enhance risk stratification, enable more personalized

treatment strategies, optimize perioperative management, and ultimately improve patient outcomes.

Materials and methods

Study design and participants

This retrospective cohort study aims to address the challenge of improving the accuracy of prognostic prediction for long-term survival. It was conducted to analyze the clinical outcomes of patients with Stanford TAAD who underwent surgical repair at the Department of Thoracic and Cardiovascular Surgery, First Affiliated Hospital of Chongqing Medical University, from September 2017 to December 2020, and at the Chongqing University Central Hospital between October 2019 and April 2020. Due to the relatively low incidence of TAAD, this study consecutively included eligible cases to ensure data integrity and minimize selection bias, adhering to predefined inclusion and exclusion criteria. The inclusion criteria for this study were as follows: (1) patients diagnosed with Stanford TAAD following aortic computed tomography angiography (CTA); (2) patients who underwent surgical repair; and (3) patients aged 18 years or older. The exclusion criteria included: (1) patients with more than 20% absence of clinical or laboratory data; (2) patients with preoperative comorbidities, such as malignant tumors, hematological disorders, infections, systemic inflammatory diseases, or undergoing treatments that could influence biomarker levels and survival; (3) patients who died directly or indirectly from causes other than TAAD; and (4) patients with chronic-phase TAAD.

The determination of the minimum sample size considered multiple factors. Initially, we estimated that no more than 10 features would be included in the model to maintain practical applicability. Following the widely accepted rule of thumb that at least 10 samples are needed per predictor variable, we set a preliminary minimum sample size of 100. Previous studies reported a sample size of 59 cases for deep learning model, which typically require larger data sets, and 188 cases for ML model predicting postoperative complications in TAAD patients [21, 22]. Given the SVM algorithm's adaptability to small data sets and its ability to generalize well without large sample sizes, we concluded that a minimum of 200 cases would be appropriate.

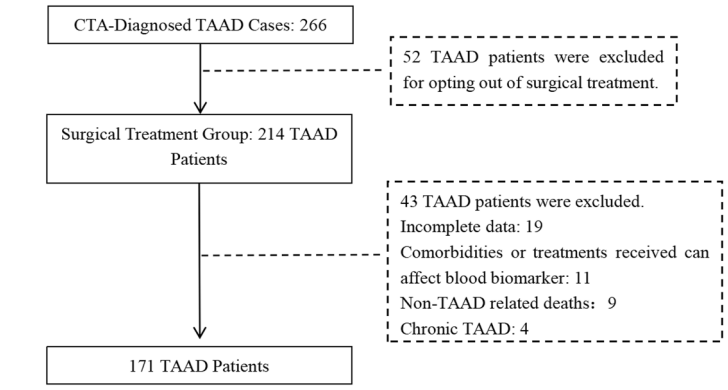
Ultimately, 244 TAAD patients were included in the study, as illustrated in Fig. 1. Of 266 CTA-diagnosed TAAD cases, 171 were included in the training and internal test sets after excluding those who declined surgery ($n = 52$), had incomplete data ($n = 19$), had comorbidities or treatments affecting blood biomarkers ($n = 11$), had chronic phase ($n = 4$) or died from non-TAAD-related causes ($n = 9$) (Fig. 1A). The external test set comprised 73 patients from 91 CTA-diagnosed cases after excluding those who refused surgery ($n = 5$), had incomplete data ($n = 8$), received treatments affecting blood biomarkers ($n = 3$), or died from non-TAAD-related causes ($n = 2$) (Fig. 1B).

The study was approved by the Independent Ethics Committee of the First Affiliated Hospital of Chongqing Medical University (approval number: 2024 - 583- 01; approval date: 01.02.2024), and the study was conducted in compliance with the ethical standards of the World Medical Association Declaration of Helsinki. Informed consents were obtained from all the participants. This study adhered to the STROBE guidelines for cohort studies, ensuring the reliability of the data handling and analysis (Table S3). The statistical analysis followed established practices for survival analysis and machine learning model validation, as outlined in previous studies.

To ensure the objectivity of the analysis and minimize bias, this study employed both data extraction blinding and statistical analysis blinding. During data collection, patient records were de-identified to ensure confidentiality, and the data extraction team was blinded to the clinical outcomes, including survival status, and treatment details. For statistical analysis, an independent team conducted the analysis without knowledge of other clinical details unrelated to the outcome. Prior to analysis, all variables were coded to obscure their identities. This coding process involved assigning numerical or alphanumeric identifiers to each variable, ensuring that the data analysis team was unaware of the exact nature of the variables. The clinical outcome (survival status) was, however, a key outcome variable used in the analysis, and thus, the statistical team was aware of these outcomes during model development. This approach maintained blinding while ensuring that the model development process was based exclusively on the anonymized, encoded data.

Data collection

Demographic characteristics, clinical symptoms, and hemodynamic profiles at admission—including gender, age, smoking history, hypertension (HTN), diabetes mellitus (DM), cardiovascular disease (CVD), blood pressure, and heart rate and intraoperative details such as blood loss, operation time, cardiopulmonary bypass time (CPB), aortic cross-clamp time (ACC), red blood cell transfusion volume, and plasma transfusion volume were retrospectively reviewed and extracted from electronic medical records. Blood indicators were assessed within 24 h of hospital admission and prior to surgery. The biomarkers measured included red blood cell (RBC) count, creatinine, absolute neutrophil count (ANC), white blood cell (WBC) count, hemoglobin (Hb), platelet count, absolute lymphocyte count (ALC), monocyte count, serum albumin, uric acid, urea nitrogen, alanine



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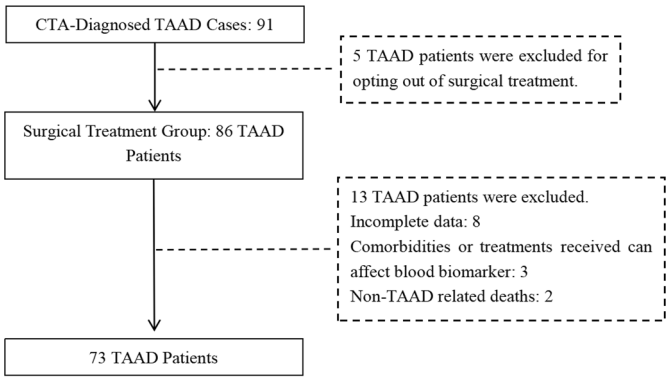

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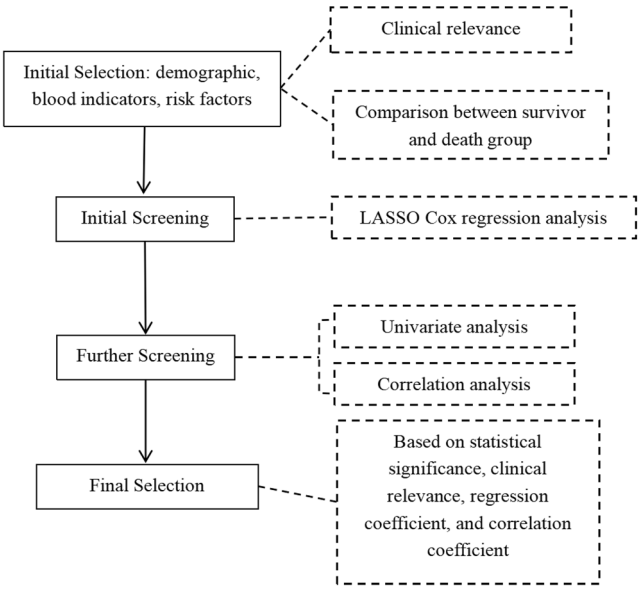


C

Fig. 1 Workflow for patient inclusion: training set and internal test set (**A**), workflow for patient inclusion: external test set (**B**), feature variable selection (**C**). Notes: Non-TAAD-related deaths (9 cases) in Fig. 1 A included trauma (4), cancer (1), psychologically-related suicide (2) and community-acquired pneumonia (3); non-TAAD-related deaths (two cases) in Fig. 1B included cancer (1) and trauma (1)

aminotransferase (ALT), aspartate aminotransferase (AST), cardiac troponin T (cTnT), myoglobin, fibrinogen, and D-dimer, etc. A composite metric, the Systemic Immune-Inflammation Index (SII), was calculated using the following formula: platelet count × neutrophil count/lymphocyte count.

Follow-up and treatments

All patients included in this study underwent surgical repair. The primary outcome variables were survival status and Aortic Survival (AS). Survival status indicated whether the patient was alive or deceased at the time of the follow-up. AS was defined as the time from surgery to an aortic-related death, including mortality due to aortic dissection, its complications (e.g., surgical complications, aneurysm rupture, thrombosis), or reintervention-related causes. Both AS and survival status were used as key variables to assess patient survival condition. For patients included for model training and internal test, follow-up started 3 months after discharge and concluded on August 20, 2024. Telephone follow-ups, conducted by trained interviewers, were performed at 3, 6, and 12 months after discharge, and subsequently every 6 months to support post-discharge care. The maximum AS observed was 2445 days, with a median AS of 1190 days. A retrospective follow-up of the patients' survival status was conducted for those included in the external test, with data collected up to February 7, 2025. The maximum observed AS was 1930 days, with a median AS of 784 days.

Data preprocessing and feature variable selection

For features with a missing data rate below 20%, random forest imputation was applied consistently to both survivors and mortalities, as per guidelines by Ou et al. [23]. Patients in this study were randomized into an 80% training set and a 20% internal test set, based on simple randomization using a computer-generated random number list, with the allocation ratio adapted from the study by Cao et al. [24]. To reduce the risk of overfitting, feature selection was conducted using LASSO Cox regression analysis. Features were excluded based on regression results and clinical relevance, yielding an initial model with 16 features, including 2 categorical and 14 continuous variables. Subsequently, univariate analysis and correlation analysis were performed on the preliminarily selected variables. Features were finalized for inclusion in the machine learning model based on statistical significance, clinical relevance, correlation coefficients and LASSO Cox regression coefficients (Fig. 1C). To address data imbalance, data normalization was performed first, followed by the application of the Synthetic Minority Over-sampling Technique (SMOTE) to the training set, following the methods reported by Dablain et al. [25]. A sensitivity analysis was conducted to evaluate the impact of SMOTE method on the model's predictive performance, thus verifying the robustness of oversampling approach.

Model selection and performance evaluation

The support vector machine (SVM) stands out among machine learning models for its suitability in small-sample data sets, offering significant theoretical and algorithmic advantages. Based on statistical learning theory, SVM utilizes the Structural Risk Minimization (SRM) principle, which prioritizes minimizing generalization error over merely optimizing training error. This approach significantly enhances the model's ability to generalize, especially when working with small sample sizes. Unlike traditional models, such as neural networks, which depend on large data sets to approximate the target function, SVM can effectively predict unseen data by maximizing the margin between classes, even with limited sample sizes [26].

SVM is particularly effective in handling small sample, high-dimensional data sets, offering a robust solution to the "curse of dimensionality." By employing kernel functions, SVM maps the original feature space into a higher-dimensional space, enabling the identification of an optimal, linearly separable hyperplane without the need to explicitly compute the high-dimensional mappings [27]. In addition, when combined with LASSO Cox regression analysis, SVM incorporates regularization techniques to control model complexity and reduce the risk of overfitting. These features make SVM a widely adopted approach in various fields, including disease classification (e.g., early cancer diagnosis), survival analysis, and treatment recommendation [28–30].

Given the distinct advantages of Support Vector Machines (SVM), widespread application in medicine and bioinformatics, and the characteristics of the data set in this study, the SVM model was chosen for subsequent analysis. A tenfold cross-validation strategy was employed to ensure a comprehensive evaluation of model performance. The training data was divided into 10 subsets, with each iteration using 9 subsets for model training and the remaining subset for validation. This process was repeated 10 times, allowing each subset to serve as the validation set once. Key performance metrics used to evaluate the model's predictive and generalization ability included the area under the receiver operating characteristic curve (AUC), accuracy, precision, recall, F1 score, Brier score, and the area under the precision–recall curve (AP), consistent with the protocols outlined in previous studies by Goodswen and Cao et al. [24, 31].

To improve model interpretability, this study used the SHAP (SHapley Additive exPlanations) method, which quantifies each feature's contribution to the model's predictions. SHAP provides both global and local insights, identifying the most influential features by assigning precise attribution values to each variable [32].

Statistical analysis

This study included the demographic characteristics, risk factors, admission status, preoperative blood markers, and intraoperative conditions of TAAD patients. Continuous variables were presented as mean ± standard deviation (SD), with comparisons performed using the Student's t test or the Mann–Whitney U test, based on the results of normality tests. For continuous variables that did not exhibit a normal distribution, the Mann–Whitney U test was employed for comparison. Categorical variables were expressed as frequencies and percentages (%) and analyzed using either the Chi-square test or Fisher's exact test, depending on the size of the expected frequencies. The assumptions for the statistical tests were as follows: the Student's t test assumed that the samples were drawn from normally distributed populations with equal variances. The Mann–Whitney U test was used for non-normally distributed data, assuming that the distributions of the two independent samples were similar. The chi-square test assumed that the observed frequencies in each category were sufficiently large, typically with expected frequencies of at least 5 per cell. Fisher's exact test was applied when sample sizes were small or when expected frequencies were less than 5. Pearson's chi-squared test was used to evaluate correlations among variables, visualized through a heatmap. The model was constructed using the SVM algorithm, and performance was evaluated using AUC, accuracy, precision, recall, F1 score, Brier score, and AP. Survival outcomes for patients with TAAD were evaluated and visualized using the Kaplan–Meier method. Finally, the SHAP method was used for model interpretation. A two-tailed p value of <0.05 was considered statistically significant.

Data analysis was performed using SPSS 27.0 and Python 3.1. The Python libraries used were numpy (version 1.23.5), pandas (version 1.5.3), scikit-learn (version 1.2.2; including modules, such as model_selection, metrics, svm, ensemble, calibration, preprocessing, linear_model, exceptions, utils, and base), matplotlib (version 3.6.3), shap (version 0.41.0), imblearn (version 0.10.1), statsmodels (version 0.13.5), scipy (version 1.9.3). All libraries are open-source under respective licenses (e.g., MIT, BSD, etc.).

Results

Patient characteristics

A total of 171 TAAD patients were included in the study for model development and internal testing (Table S1), with 53 deaths observed during the follow-up period. The proportion of missing data for key variables ranged from 0% to 17.54%. Missing values were handled using random forest algorithms for patients with <20% missing data, while cases with >20% missing values were excluded from the analysis. The average age of the cohort was 48.82 ± 9.61 years, and the majority were male (136 cases, 79.53%). While only a small proportion of patients (6.43%, 11 cases) experienced concomitant shock, this group had a markedly higher mortality rate compared to those without shock (63.64% vs. 28.75%).

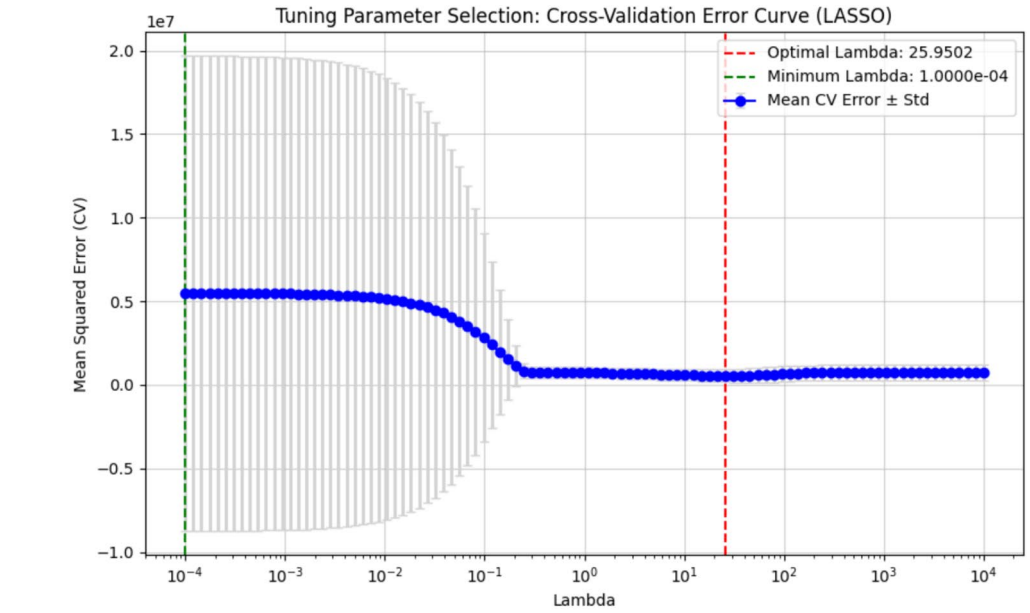
At admission, abdominal pain was reported in 9.94% of patients (17 cases) and was more prevalent in the outcome group, with 18.87% (10 cases) reporting this symptom. This observation suggests a potential association between abdominal pain and the severity of TAAD. In addition, patients with endpoint events had significantly shorter postoperative hospital stays compared to survivors (10.25 ± 9.65 vs. 23.50 ± 14.41). This likely reflects that patients with serve conditions are more prone to early mortality and fail to benefit from postoperative care.

171 TAAD patients from our center were randomly assigned to the training (137 patients, 80%) and internal test (34 patients, 20%) groups; 73 TAAD patients from the other center were assigned to the external test group. No significant differences were found between the training and test groups in terms of demographic data, risk factors, admission conditions, hospital stays, preoperative laboratory results, and intraoperative conditions (Table S2).

Feature variable selection

LASSO (Least Absolute Shrinkage and Selection Operator) Cox regression was used to preliminarily screen variables associated with long-term survival, yielding 16 perioperative characteristic variables. The optimal lambda value, determined through cross-validation, was 25.9502 (Fig. 2A, B). Based on these findings, univariate analysis was performed on perioperative characteristics between survivors and patients who experienced endpoint events in the training set (Table 1). To avoid information leakage from the test set, this analysis was limited to the training set. Variables with p values <0.05 were considered statistically significant.

Among them, shock demonstrated minimal contribution in the LASSO Cox regression and was, therefore, excluded from the final analysis. Similarly, abdominal pain was excluded from the model due to its



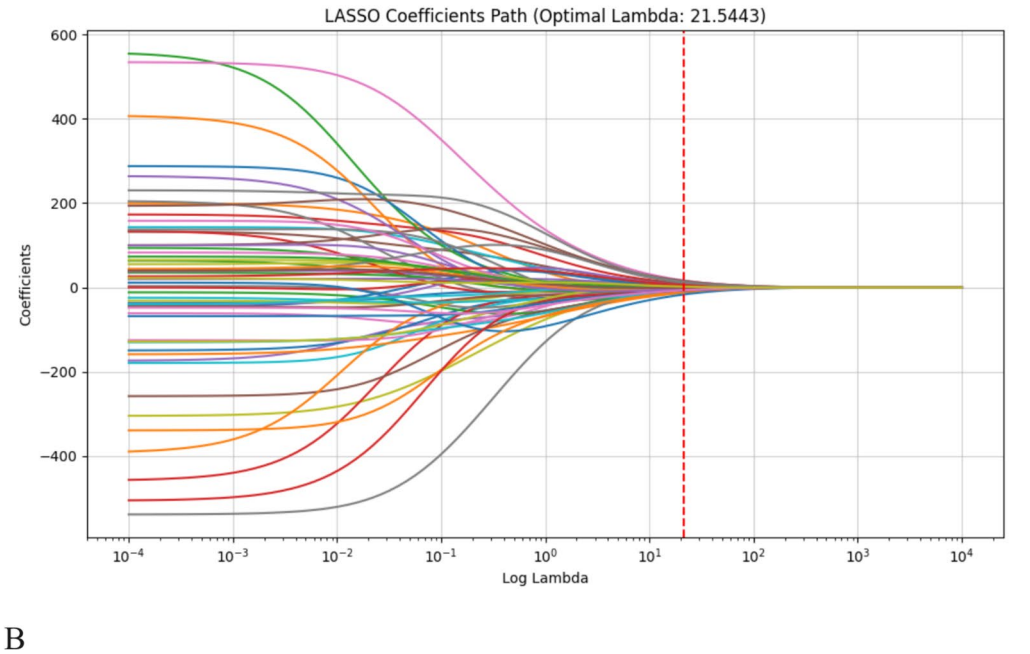


Fig. 2 Feature variable selection based on the LASSO COX regression analysis. **A** Tuning parameter selection cross-validation error curve. (LASSO, least absolute shrinkage and selection operator); **B** plot of the LASSO coefficient profiles

low reporting rate, lack of specificity, and limited clinical relevance. Although postoperative hospital stay (POHS) was significantly longer in survivors compared to those who experienced endpoint events (22.79 ± 14.79 vs. 12.29 ± 10.65 days, $p < 0.001$), likely reflecting underlying disease severity and early postoperative mortality in high-risk patients. Despite its statistical significance and substantial regression coefficient, POHS was excluded from model development to avoid selection bias and reverse causation.

In the training group, the difference in ACC time between survivor and mortality group was not statistically significant ($p = 0.057$, Table 1). However, ACC demonstrated a relatively high regression coefficient in the

Table 1 Comparison of perioperative conditions: variables selected through LASSO cox regression for initial screening in the training set

Variables	No. of outcomes (%)	No. of survivors (%)	*p* value
Shock			0.007
No	32 (84.21%)	95 (95.96%)	
Yes	6 (15.79%)	4 (4.04%)	
Abdominal pain			0.043
No	31 (81.58%)	92 (92.93%)	
Yes	7 (18.42%)	7 (7.07%)	
Age	50.97 ± 8.32	48.52 ± 9.86	0.176
POHS (days)	12.29 ± 10.65	22.79 ± 14.79	< 0.001
ICUHS (days)	11.53 ± 10.56	12.54 ± 8.53	0.563
WBC ($\times 10^9$/L)	13.85 ± 5.15	11.45 ± 4.06	0.012
AST (IU/L)	111.66 ± 326.96	39.51 ± 68.72	0.187
Creatinine (μmol/L)	111.87 ± 52.3	85.8 ± 34.5	0.006
Fibrinogen (g/L)	3.16 ± 2.09	3.07 ± 1.67	0.801
BNP (pg/mL)	992.75 ± 1194.83	971.16 ± 1546.08	0.931
SII	3696.2 ± 6274.47	2339.37 ± 2290.6	0.065
Operation time (min)	624.29 ± 177.61	524.05 ± 113.71	0.002
Intraoperative bleeding (ml)	947.58 ± 1158.87	582.65 ± 471.87	0.067
Transfusion of SRBC (U)	4.13 ± 3.51	3.35 ± 2.96	0.226
Transfusion of Plasma (ml)	948.46 ± 424.49	749.3 ± 375.54	0.014
CPB time (min)	308.16 ± 86.55	264.76 ± 63.88	0.007
ACC time (min)	172.62 ± 31.57	158.92 ± 50.50	0.057

POHS postoperative hospital stay, *ICUHS* intensive care unit hospital stay, *WBC* white blood cell count, *AST* aspartate aminotransferase, *BNP* B-type natriuretic peptide, *SII* Systemic Immune-Inflammation Index, *SRBC* suspended red blood cells, *CPB* cardiopulmonary bypass, *ACC* aortic cross-clamp

LASSO Cox regression model, suggesting potential prognostic relevance. As an important indicator of surgical complexity and the intensity of cardiopulmonary bypass support, ACC indirectly reflects the duration of intraoperative tissue ischemia–reperfusion. This prolonged ischemia–reperfusion process has a profound impact on postoperative recovery of organ function, the risk of complications, and long-term survival in TAAD patients. Therefore, we decided to include ACC in further analysis. Similarly, although age did not reach statistical significance ($p = 0.176$) and CPB duration exhibited a relatively small coefficient in the LASSO Cox regression analysis, both variables were retained in the model due to their well-established clinical relevance. Age represents a fundamental demographic factor, while CPB duration has been consistently associated with postoperative prognosis in TAAD patients undergoing surgical repair.

Correlation among selected variables included in the model

After further screening, seven variables were selected for model training based on the results of LASSO Cox regression analysis, univariate analysis, and clinical relevance. These variables included plasma transfusion, creatinine, operation time, age, WBC, ACC and CPB.

Pearson's Chi-square test was used to assess variable associations, while the heatmap visualized the Pearson correlation coefficients among variables, illustrating the strength and direction of these relationships. The heatmap presented Pearson's correlation coefficients among variables, providing a visual depiction of the strength and direction of these correlations. The color gradient, ranging from dark grey to dark red, represented the spectrum from weak to strong correlations. Each cell in the heatmap was labeled with a Pearson's correlation coefficient, quantifying the linear relationship between two variables. A coefficient of 1 indicated a perfect positive correlation, − 1 signified a perfect negative correlation, and 0 reflects no correlation. Asterisks were used to denote statistical significance, with a single asterisk (*) representing a p value of less than 0.05.

Pearson's Chi-squared test demonstrated significant correlations between creatinine and transfusion of plasma, WBC, operation time ($p < 0.001$, $p < 0.001$ and $p = 0.016$, respectively). The corresponding Pearson correlation coefficients were 0.34, 0.35, and 0.17, indicating weak to moderate correlations (Fig. 3). Conversely, no significant correlations were observed between operation time and either age or transfusion of plasma ($p > 0.05$). Although a strong correlation was observed between

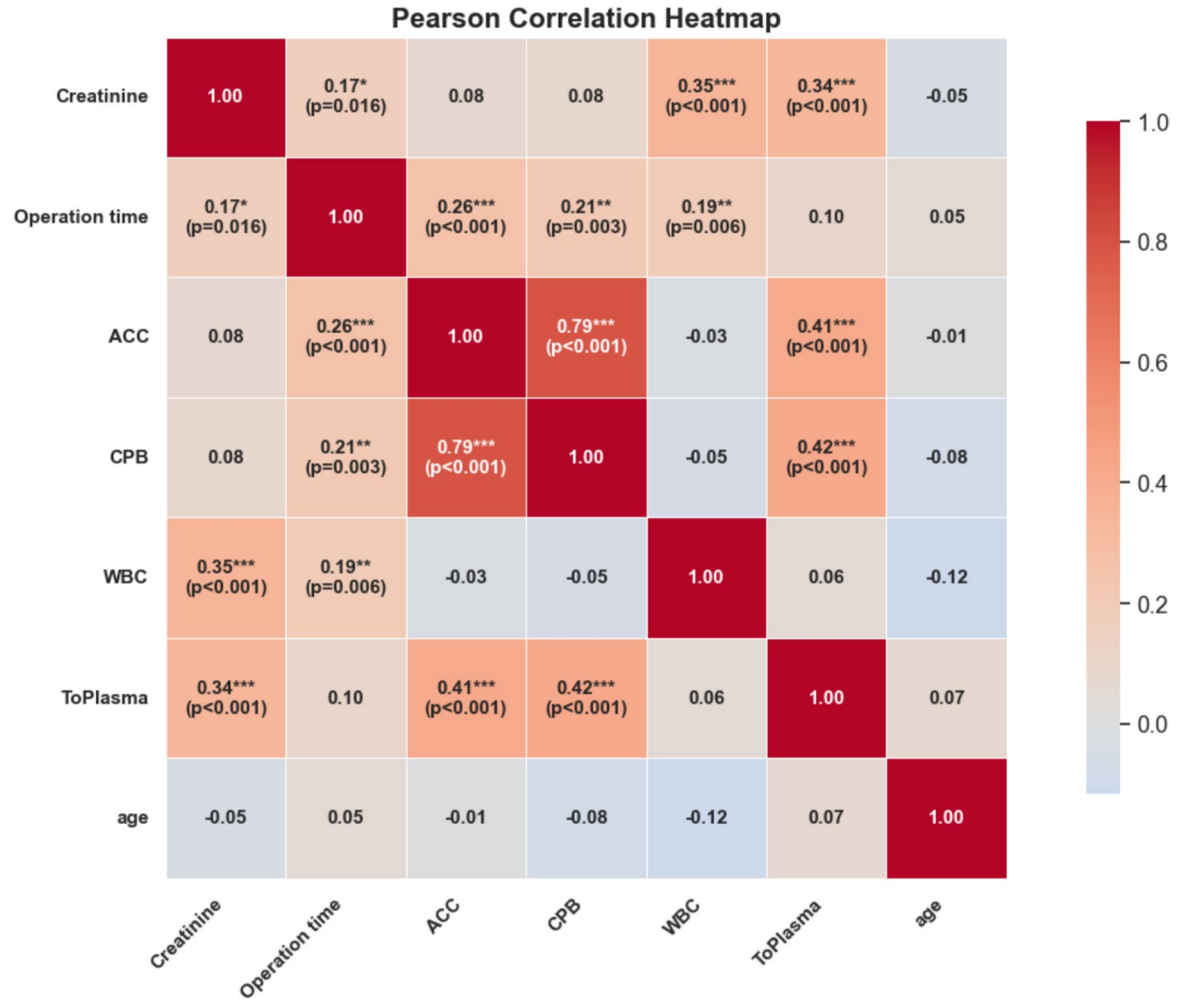


Fig. 3 Correlation heatmap of variables in the model. CPB Cardiopulmonary bypass, ToPlasma transfusion of plasma. WBC White blood cell count, ACC Aortic cross-clamp. '*' denotes $p < 0.05$, '**' denotes $p < 0.01$, '***' denotes $p < 0.001$

CPB and ACC (Pearson correlation coefficient: 0.79, $p < 0.001$), each variable reflects distinct intraoperative risks in the surgical management of TAAD. ACC time primarily represents the duration of direct aortic occlusion, which is closely associated with myocardial ischemia, distal organ hypoperfusion, and the extent of aortic repair. In contrast, CPB time encompasses the entire period of extracorporeal circulation and reflects systemic exposure to non-physiological perfusion, inflammation, and coagulation disturbances. Therefore, both variables were retained in the model for their complementary prognostic value. For the remaining variables, the correlation strengths were generally weak or lacked statistical significance (Fig. 3).

The performance of the SVM model

After selecting the feature variables, the SMOTE method was applied to the training set to address data imbalance. Sensitivity analysis demonstrated that SMOTE substantially improved the predictive performance (mean AUC increased from 0.8270 to 0.9343), along with reduced variability, confirming the robustness and suitability of SMOTE in addressing data imbalance. Subsequently, the SVM algorithm was implemented, and model generalization was enhanced using tenfold cross-validation, with final validation performed on the both internal and external test sets. The model demonstrated excellent performance, achieving AUC values exceeding 0.85 for the training and test sets, indicating strong discriminatory ability (Table 2, Fig. 4A and S2 A). Specifically, the training set achieved an AUC of 0.9137 (95% CI 0.9081–0.9203), while the internal test set achieved an AUC of 0.8533 (95% CI 0.8503–0.8624), and the external test set achieved an AUC of 0.8770 (95% CI 0.8698–0.8982). The slightly lower AUC for the test sets suggests some performance

Table 2 Performance of the SVM model between training set and test set

Metrics	SVM (training set)	SVM (internal test set)	SVM (external test set)
AUC	0.9137	0.8533	0.8770
95% CI	(0.9081–0.9203)	(0.8503–0.8624)	(0.8698–0.8982)
Accuracy	0.8366	0.8481	0.8030
Precision	0.8696	0.8374	0.8235
Recall	0.8421	0.7933	0.7651
F1 score	0.8290	0.8148	0.7928
Brier score	0.1213	0.1417	0.1323
AP	0.9019	0.8789	0.8548

AUC area under the curve, *SVM* support vector machine, *CI* confidence interval, *AP* average precision

decline, but the difference remains within a reasonable range, with no significant signs of overfitting.

The model demonstrated consistent accuracy across both the training and test sets, with internal test set achieving slightly higher accuracy (training set: 0.8366, internal test set: 0.8481, external test set: 0.8030). Notably, the internal test set achieved a precision comparable to that of the external test set (0.8374 vs. 0.8235), and slightly lower than the training set (0.8696), highlighting the model' s robustness and reliability in predicting survival among TAAD patients (Table 2, Fig. 4C, D, S2D). The precision–recall curves demonstrated similar shapes across data sets, with the training set achieving an AP of 0.9019. Slightly lower AP values were observed in the internal and external test sets (0.8789 and 0.8548, respectively), further supporting the model's consistent performance and generalizability (Fig. 4B and S2B). The Brier Scores for the training and test sets were notably low, at 0.1213, 0.1417 and 0.1323, respectively, indicating well-calibrated probabilistic predictions. Performance metrics, including accuracy, precision, AUC, AP, Brier Score, and F1 Score showed comparable results among the training, internal and external test sets, demonstrating the model' s robustness, reliability, and practical value in clinical applications (Fig. S1).

Furthermore, risk scores were calculated for all 244 patients with TAAD using the SVM model. Based on the median risk score (0.2029), patients were divided into high-risk and low-risk groups. Survival analysis demonstrated that patients in the low-risk group had significantly better long-term survival outcomes compared to those in the high-risk group ($p < 0.001$, Fig. 5). These findings further highlight the clinical applicability of the predictive model.

SHAP interpretation and feature importance visualization

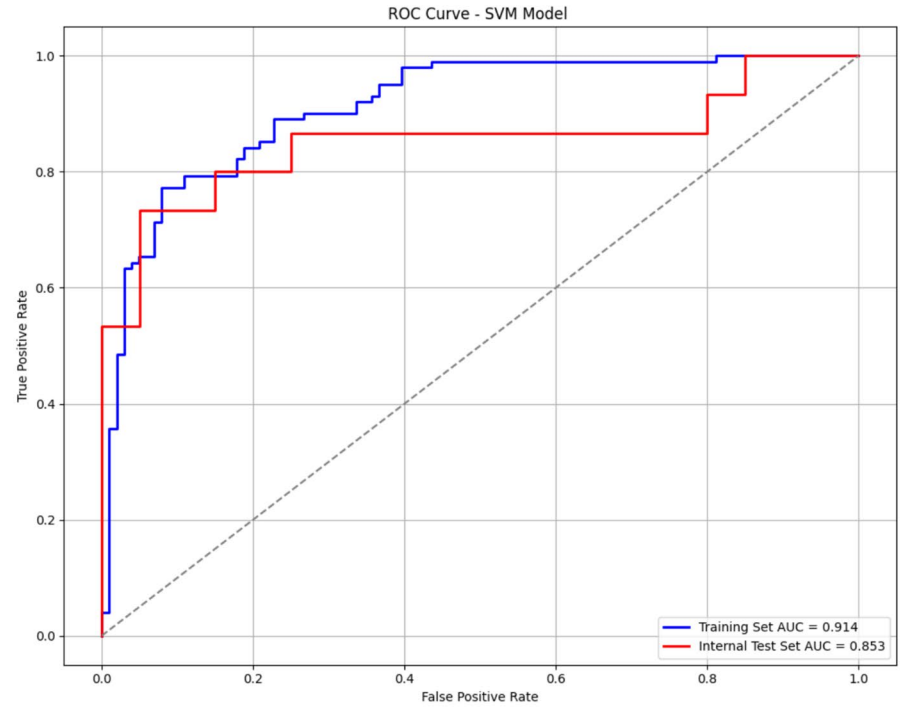
The SHAP method was employed to interpret the SVM model's predictions and evaluate its clinical relevance. By quantifying the contribution of each feature, SHAP values provided insights into their impact on the model's outputs. Feature importance analysis identified operation time as the most critical predictor of long-term survival in TAAD patients, highlighting the significant impact of intraoperative duration on postoperative outcomes and overall prognosis (Fig. 6A). Furthermore, the SHAP summary plot revealed that higher plasma transfusion volume, creatinine levels, age, WBC count, ACC time, and CPB time positively contributed to the model's predicted risk, indicating their significant roles in influencing survival outcomes (Fig. 6B).

To validate the model's interpretability, decision curves were used to illustrate individualized predictions of long-term survival. The gray vertical line at 0 on the horizontal axis represented the model's baseline. Figure 7A visualizes the decision-making process for TAAD survivors, while Fig. 7B illustrates it for patients with endpoint events.

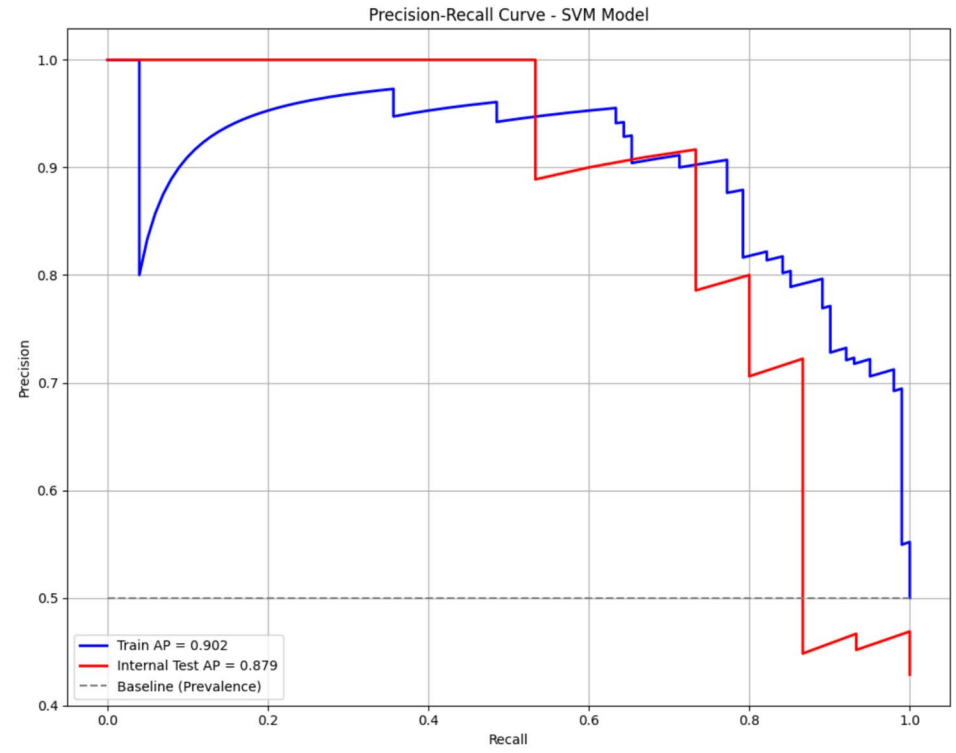
Discussion

In this retrospective study, we developed an SVM-based machine learning model to predict long-term survival in TAAD patients. The model demonstrated strong performance across training, internal test, and external test data sets. Based on the risk scores calculated from the predictive model, patients in low-risk group had significantly better survival outcomes than those in high-risk group. SHAP summary plots identified several key predictors of long-term survival, including operation time, CPB time, ACC time and age. We further interpreted the individual decision-making process of the model using SHAP decision plots, offering deeper insights into the model's predictions. By providing a comprehensive evaluation of perioperative factors, the model contributes to enhancing patient care quality and improve long-term survival outcomes.

TAAD is a life-threatening vascular emergency for which surgical repair remains the primary treatment. However, its prognostic management poses significant

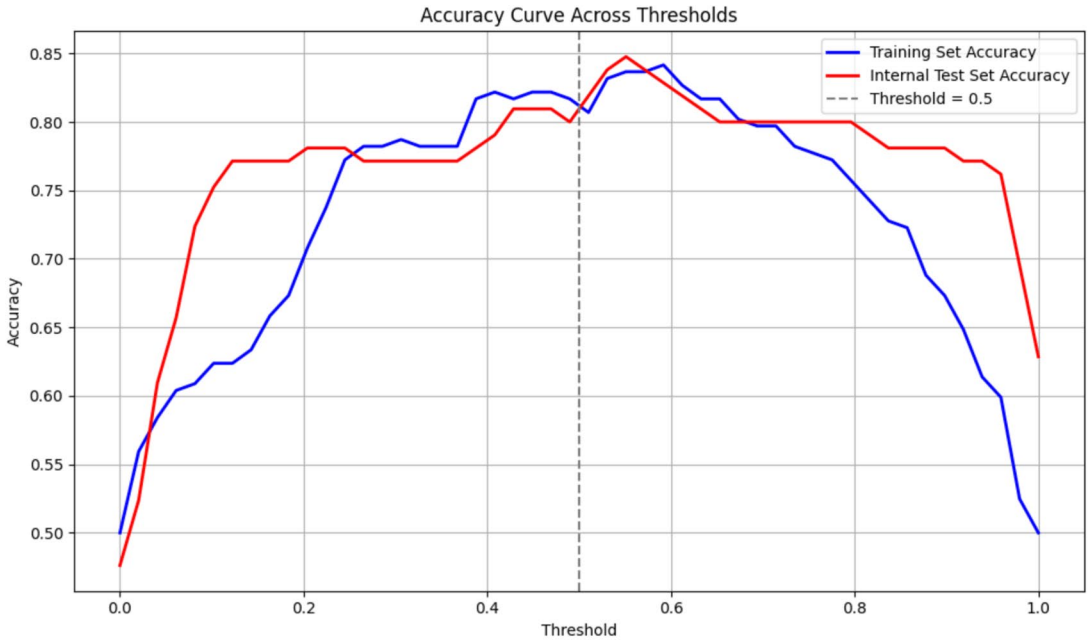


A



B

Fig. 4 Comprehensive performance evaluation of the SVM model. **A** ROC curve with AUC values for the training and internal test sets; **B** PR curve with AP values for the training and internal test sets; **C** accuracy curve illustrating the performance across different thresholds for the training and internal test sets; **D** precision curve showing the precision at various thresholds for the training and internal test sets. SVM Support vector machine, ROC Receiver operating characteristic



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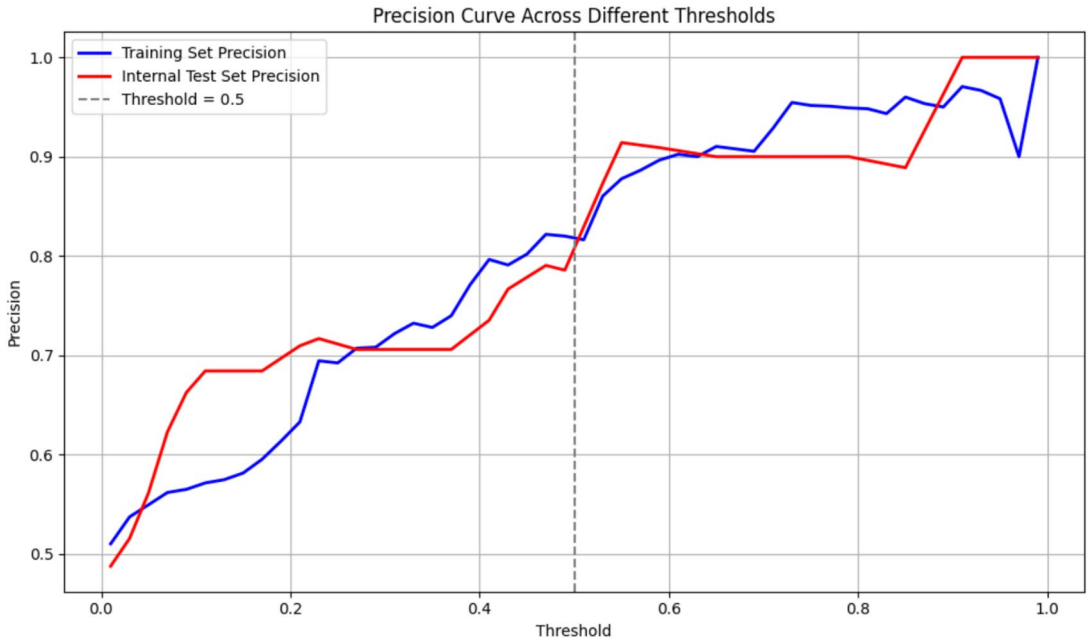


D

Fig. 4 continued

challenges, particularly in mortality risk. Several prognostic indicators have been identified in previous studies to support risk stratification. For instance, Zhang et al. identified systolic blood pressure at admission, NT-proBNP, and white blood cell count as independent factors affecting in-hospital mortality among TAAD patients [33]. Similarly, numerous studies have highlighted preoperative indicators such as fibrinogen, BUN, NLR, PLR, D-dimer, UA, and CRP as prognostic markers for both short-term and long-term survival in TAAD patients [10–12, 34–36]. However, the factors affecting patient survival are varied, and a single preoperative indicator

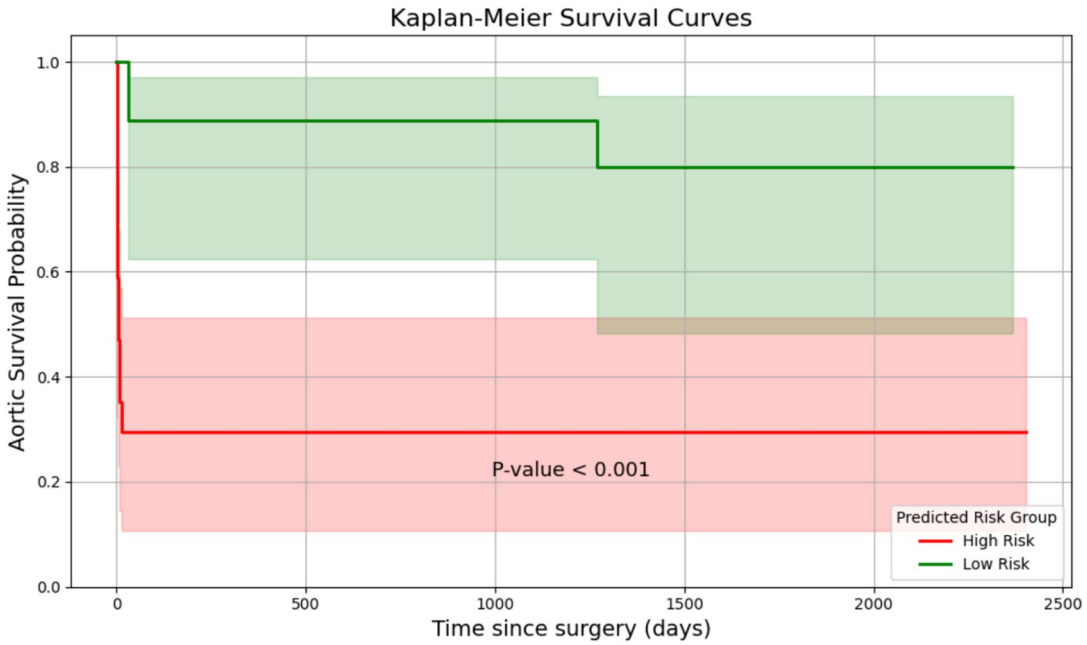


Fig. 5 Kaplan–Meier survival curves of aortic survival stratified by risk value in 244 TAAD patients (with log-rank test). AS Aortic survival

often fails to capture the complexity of a patient's condition. Consequently, these indicators have not been widely adopted in clinical practice. In addition, traditional Cox and logistic regression methods, although commonly used to identify prognostic indicators, have inherent limitations. These methods face challenges in handling complex data and exhibit limited generalizability, which reduces their predictive accuracy and clinical utility [37, 38].

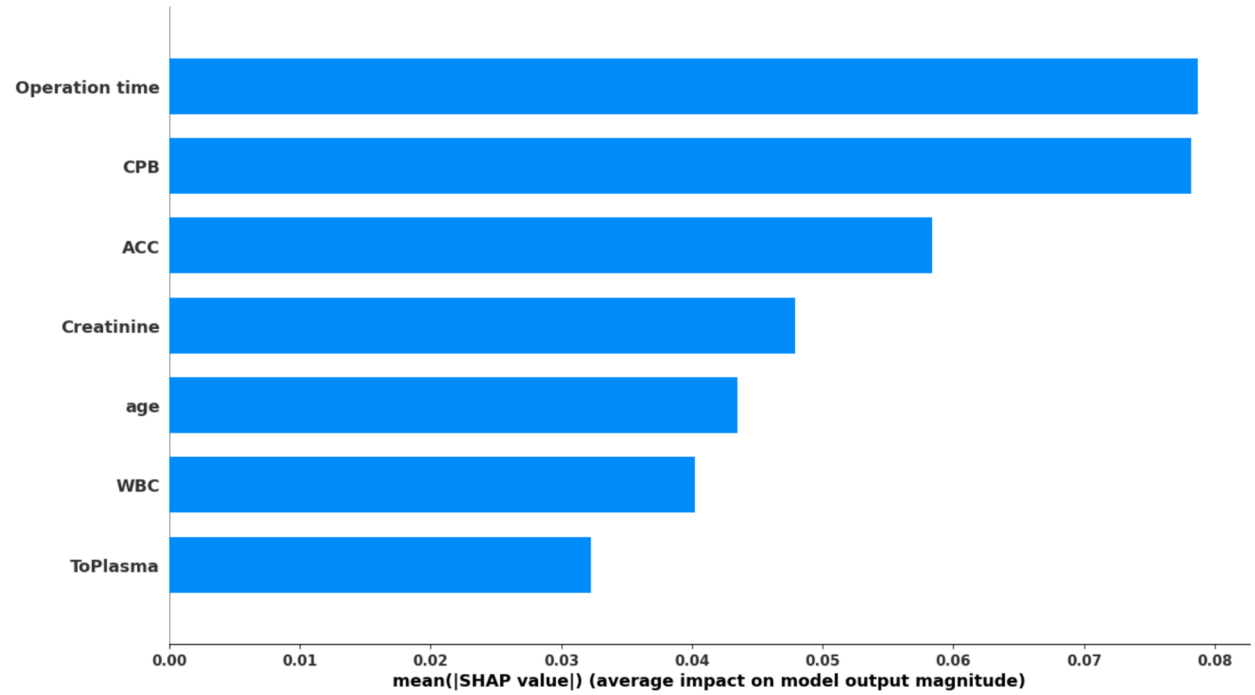
ML methods have gained interest for TAAD prognosis evaluation, but research is still in its early stages. Zhang et al. developed a Treebag model to predict 1-year mortality in TAAD patients, using 51 clinical characteristics, including blood markers at admission [39]. Nevertheless, exclusively relying on preoperative indicators may overlook the critical impact of intraoperative factors on survival outcomes in patients with TAAD. Moreover, most recent ML studies have primarily focused on short-term mortality and postoperative complications, while long-term survival prediction in TAAD patients remains unexplored [40–42].

In this study, we employed an interpretable machine learning approach to explore the relationship between multiple clinical variables and long-term survival in patients with TAAD. In addition to preoperative indicators, we specifically incorporated key intraoperative factors—such as operation time, CPB, and ACC—to enhance the assessment of survival outcomes. Based on SVM algorithm, the SHAP method was applied to interpret feature importance and its relationship with long-term mortality. SHAP decision plots were used to further illustrate the model's decision-making process.

Our findings identified operation time, CPB, and ACC as the most significant predictors of long-term prognosis in patients with TAAD. These surgical time-related parameters not only reflected the complexity of the surgical procedure but also indicated the overall physiological burden experienced during the operation. Prolonged durations were associated with organ ischemia, systemic inflammatory responses, and cardiopulmonary stress, all of which contributed to an increased risk of postoperative organ dysfunction and delayed recovery, ultimately compromising long-term survival outcomes [43, 44].

Other important predictors included age, plasma transfusion volume, creatinine, and WBC count. Severe TAAD cases or prolonged operation time were often associated with increased blood product requirements, which in turn were linked to poorer outcomes [45]. Elevated WBC count, along with advanced age and higher creatinine levels, reflected the patients' overall condition, preoperative immune and inflammatory status as well as renal function—all of which were associated with worse prognosis in TAAD patients [14, 46].

Despite these contributions, this study has several limitations. First, although the SVM model demonstrated good generalization across two-center data sets, the limited sample size and potential selection bias highlight the need for larger-scale studies to validate these findings. Second, although the study incorporated a range of preoperative and intraoperative variables, imaging-based



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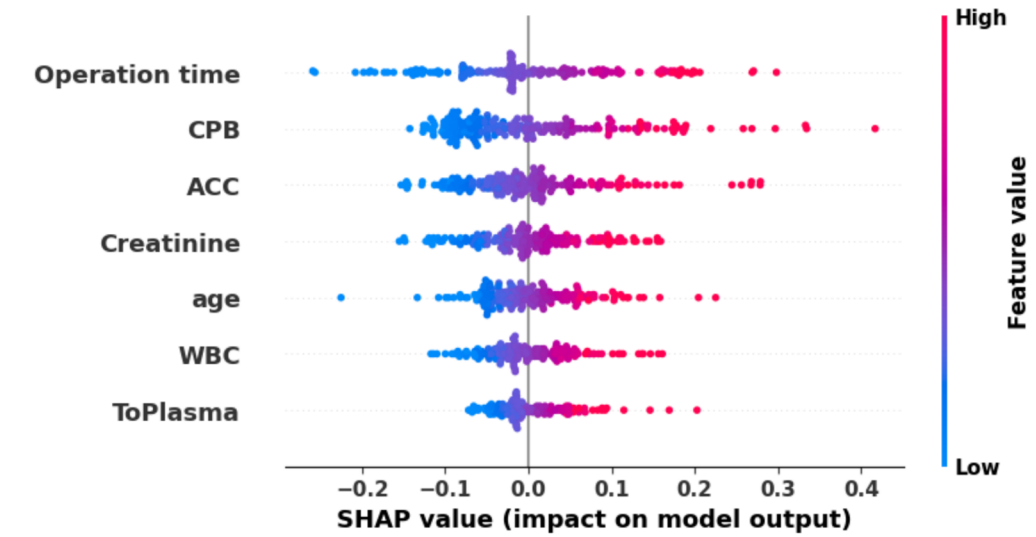

B

Fig. 6 SHAP analysis of SVM model. **A** Ranking feature importance based on the absolute mean values of SHAp values; **B** scatter plot of feature distributions using the SHAP analysis. WBC White blood cell count, ToPlasma transfusion of plasma, CPB Cardiopulmonary bypass, ACC Aortic cross-clamp

indicators that directly reflect the severity of TAAD were not included due to limited access to such data. This may have restricted the model's ability to fully capture disease complexity and improve predictive accuracy.

Conclusion

This study is the first to develop and validate a machine learning-based prognostic model for long-term survival in TAAD patients. The model demonstrated strong

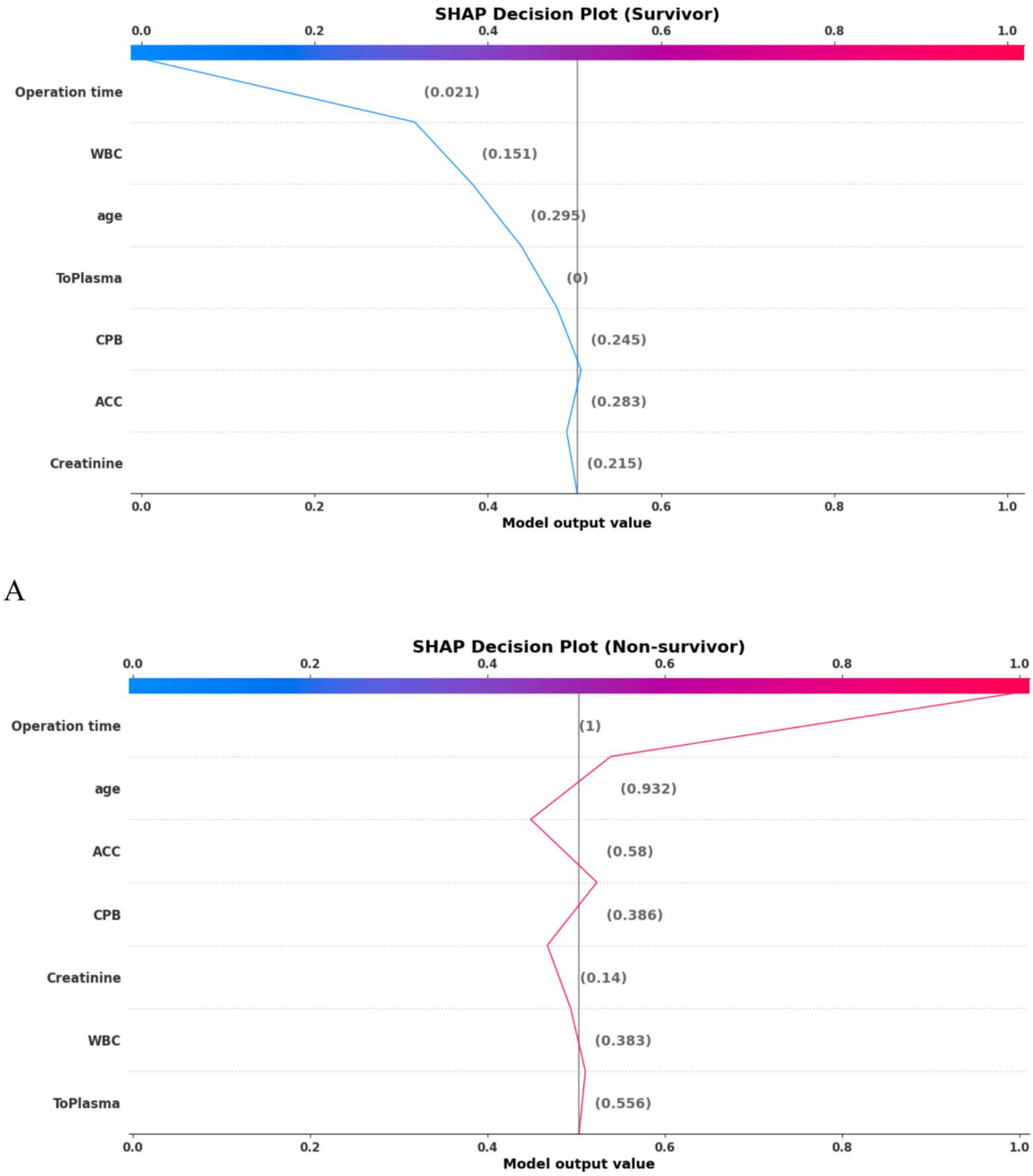

Fig. 7 SVM model SHAP decision plot. **A** Individual decision-making processes in the survivor group; **B** individual decision-making processes in the outcome group. WBC White blood cell count, ToPlasma transfusion of plasma, CPB Cardiopulmonary bypass, ACC Aortic cross-clamp

predictive performance among training, internal test and external test groups, supporting its clinical potential. It offers clinicians a tool for assessing long-term outcomes in TAAD patients.

Abbreviations

TAAD	Type A aortic dissection
ML	Machine learning
AS	Aortic survival
SVM	Support vector machine
SHAP	SHapley Additive exPlanations
LASSO	Least absolute shrinkage and selection operator
Cox	Cox regression model
CTA	Computed tomography angiography
CPB	Cardiopulmonary bypass

ACC	Aortic cross-clamp
RBC	Red blood cell
WBC	White blood cell
Hb	Hemoglobin
Plt	Platelet
ANC	Absolute neutrophil count
ALC	Absolute lymphocyte count
ALB	Albumin
ALT	Alanine aminotransferase
AST	Aspartate aminotransferase
BUN	Blood–urea–nitrogen
LDH	Lactate dehydrogenase
FDP	Fibrin/fibrinogen degradation products
CK-MB	Creatine kinase-muscle/brain
BNP	B-type natriuretic peptide
cTnT	Cardiac troponin T
SII	Systemic Immune-Inflammation Index
SRBC	Suspended red blood cells
POHS	Postoperative hospital stay
ICUHS	Intensive care unit hospital stay
AUC	Area under the curve
AP	Average precision
CI	Confidence interval
PR	Precision-recall
DCA	Decision curve analysis
NT-proBNP	N-terminal pro-B-type natriuretic peptide
NLR	Neutrophil-to-lymphocyte ratio
PLR	Platelet-to-lymphocyte ratio
ECG	Electrocardiogram

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40001-025-02510-w.

Additional file 1

Additional file 2

Acknowledgements
None.

Author contributions
HC was responsible for analysing data, drafting manuscripts. YS was responsible for making critical revisions and data collection. XYL, CYL and HYR were responsible for patient follow-up and related clinicopathological data collection. HMS and CZ were responsible for technical support for data analysis, article grammar proofreading. In addition, CZ provided substantial support in refining the study design and model development, and contributed to the acquisition of funding. QCW were responsible for the conception, design, and review of selected topics. This manuscript was read and approved by all credited authors. All authors read and approved the final manuscript.

Funding
This work was supported by grants from National Natural Science Foundation of China (82270506), and Project of innovation team for Graduate Teaching (CYYY-YJSJXCX- 202318).

Availability of data and materials
The datasets used in this study are available on request from the corresponding author.

Declarations

Ethics approval and consent to participate
This study was approved by the ethics committee of Chongqing Medical University (2024 - 583 - 01) and followed the ethical standards of the Helsinki Declaration. Informed consent was obtained from all the participants. All patients provided written informed consent.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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Received: 8 January 2025 Accepted: 25 March 2025
Published online: 15 April 2025

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