


BMJ Open Prediction of preoperative in-hospital mortality rate in patients with acute aortic dissection by machine learning: a two-centre, retrospective cohort study

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ABSTRACT

Objectives To conduct a comprehensive analysis of demographic information, medical history, and blood pressure (BP) and heart rate (HR) variability during hospitalisation so as to establish a predictive model for preoperative in-hospital mortality of patients with acute aortic dissection (AD) by using machine learning techniques.

Design Retrospective cohort study.

Setting Data were collected from the electronic records and the databases of Shanghai Ninth People's Hospital Affiliated to Shanghai Jiao Tong University School of Medicine and the First Affiliated Hospital of Anhui Medical University between 2004 and 2018.

Participants 380 inpatients diagnosed with acute AD were included in the study.

Primary outcome Preoperative in-hospital mortality rate.

Results A total of 55 patients (14.47%) died in the hospital before surgery. The results of the areas under the receiver operating characteristic curves, decision curve analysis and calibration curves indicated that the eXtreme Gradient Boosting (XGBoost) model had the highest accuracy and robustness. According to the SHapley Additive exPlanations analysis of the XGBoost model, Stanford type A, maximum aortic diameter >5.5 cm, high variability in HR, high variability in diastolic BP and involvement of the aortic arch had the greatest impact on the occurrence of in-hospital deaths before surgery. Moreover, the predictive model can accurately predict the preoperative in-hospital mortality rate at the individual level.

Conclusion In the current study, we successfully constructed machine learning models to predict the preoperative in-hospital mortality of patients with acute AD, which can help identify high-risk patients and optimise the clinical decision-making. Further applications in clinical practice require the validation of these models using a large-sample, prospective database.

Trial registration number ChiCTR1900025818.

INTRODUCTION

Aortic dissection (AD) is an aortic catastrophe instigated by a tear of the aortic intima, which causes blood to flow forward into the false lumen, thus leading to unstable

STRENGTHS AND LIMITATIONS OF THIS STUDY

- ⇒ This study constructed a predictive model with machine learning algorithm for risk measurement and stratification in patients with acute aortic dissection.
- ⇒ This study investigated the association between variability of haemodynamic features (ie, blood pressure and heart rate) and in-hospital mortality in patients with acute aortic dissection.
- ⇒ The areas under the receiver operating characteristic curves were used to evaluate discrimination of the predictive models.
- ⇒ The calibration curves and decision curve analysis were applied to assess calibration and clinical utility of the machine learning models, respectively.
- ⇒ The sample size of the current study was relatively small, which may introduce some bias.

haemodynamics, vital organ malperfusion and aortic rupture.^{1–3} According to the time course, AD can be divided into acute, subacute and chronic AD, where acute AD is characterised by rapid progression and extreme danger. Previous studies have reported that the mortality rate in patients with untreated acute AD increases by 1%–2% per hour immediately after symptom onset.^{4,5} While several factors such as increasing age, hypotension, kidney failure and branch vessel involvement are well known to be associated with poor outcomes of AD,^{6–8} the mechanisms of its progression have not yet been fully understood. Hence, analysing the prognostic risk factors for AD is of crucial importance for helping to predict its development, measure its progress and improve its management.

Although comprehensive treatment for acute AD has substantially improved over the past two decades, the in-hospital mortality rates are still relatively high, reaching up to 22% for type A AD and 13% for type B AD.^{4,9} Accordingly, there is a pressing need to determine how to identify high-risk

patients with AD immediately following their admission. Some researchers used multivariable logistic regression models to analyse the demographic features, medical history, laboratory test results and imaging data to predict the in-hospital death of patients with acute AD.^{6–8 10 11} Although logistic regression offers some insight into the relationship between mortality risk and patient demographic and clinical characteristics, this approach is limited due to the presumption of a linear relationship between variables and outcomes. As a result, the existing prediction models may not be suitable for clinical application, and an alternative and efficient approach is required for the development of a precise prediction model. In recent years, machine learning methods have become extremely popular in medical prognosis prediction due to their data-driven nature and minimal assumptions regarding the input variables and their relationship to the outcome.^{12 13} Several research teams applied machine learning to predict preoperative acute ischaemic stroke and mortality of patients with AD; yet, their prediction models did not include the variance of blood pressure (BP) and heart rate (HR),^{14–16} which are crucial indicators for the management of AD.^{5 17 18} In this paper, we adopted the machine learning techniques to comprehensively analyse the demographic information, medical history and variation of BP and HR during hospitalisation and establish a prediction model for preoperative in-hospital mortality of patients with acute AD.

METHODS

Study design

The medical records of 380 patients with acute AD at Shanghai Ninth People's Hospital Affiliated to Shanghai Jiao Tong University School of Medicine and the Vascular Department of the First Affiliated Hospital of Anhui Medical University between January 2004 and December 2018 were retrospectively reviewed. This study was registered on the Chinese Clinical Trial Registry (registration number: ChiCTR1900025818) prior to its commencement. The need for written patient informed consent was waived as this was a retrospective study, which did not affect the welfare and rights of the patients.

Data collection

The demographic information, clinical condition and haemodynamic features during hospitalisation (systolic blood pressure (SBP), diastolic blood pressure (DBP) and HR) were exhaustively reviewed and collected from electronic medical records and the database, for which the integrity of data was ensured. Patients with acute AD were diagnosed by CT angiography at admission. The exclusion criteria were the following: age <18 years, pregnancy, incomplete medical history, previous aortic or cardiac surgery and iatrogenic, inflammatory or traumatic AD. The BP data of the participants were collected before surgery. The BP during hospitalisation was measured by automated non-invasive BP monitors approximately every

15–30 min. We used the SD index to represent SBP variability (SBPV), DBP variability (DBPV) and HR variability (HRV) during hospitalisation.¹⁹

Variable definitions

The primary outcome was preoperative in-hospital mortality, which was defined as all-cause death before the patient underwent endovascular or open surgery. Complicated AD was defined as saccular aneurysm >20 mm, rapid aneurysmal enlargement, impending rupture or rupture, intractable chest or back pain under medical therapy and malperfusion syndrome.²⁰ A history of AD was defined as a new acute AD in patients with a history of AD. Concomitant aneurysm was defined as the maximum aortic diameter of the lesion site >5.5 cm. Onset-to-door time (ODT) was defined as the time interval between the onset of symptom and the time of admission.

Machine learning

Data were randomly divided without block randomisation or matching as follows: 80% into a training set and 20% into a testing set.²¹ We developed the prediction models using the following supervised learning methods: logistic regression, simple decision tree, random forest (RF), eXtreme Gradient Boosting (XGBoost) and support vector machine (SVM), all of which are popular and up-to-date methods for classification and regression analysis. The logistic regression model determines the regression coefficient by maximum likelihood estimation, and the associated nomograms were generated with the R package rms to enable prediction in practice. Then, we developed a simple decision tree using the Classification and Regression Tree algorithm. However, the simple decision tree is unstable and limited by the risk of overfitting, which prompted another two tree-based machine learning algorithms, RF and XGBoost, to be added to improve prediction. In particular, RF is a classifier that uses multiple decision trees to train samples and make a prediction, and XGBoost is a scalable tree boosting system that is more complicated, while provides state-of-the-art prediction.²² In addition, we implemented the hyperparameter optimisation, which selects the optimal set of parameters for a learning algorithm.²³ The SVM, an algorithm for binary classification of data points by supervised learning, which employs kernel tricks in order to solve non-linear problems in comparison to tree-based methods that generate hyper-rectangles in input space to solve problems, was also employed. Areas under the receiver operating characteristic curves (AUCs), decision curve analysis (DCA) and calibration curve were used for quantifying the predictive abilities of the five machine learning models. DCA uses net benefit as an indicator to evaluate the utility of predictive models for decision making.²⁴ The importance matrix plot was drawn using the R package ggplot2. SHapley Additive exPlanations (SHAP) method, a value explainable tool for tree-based models, was used to explain the outcomes of these

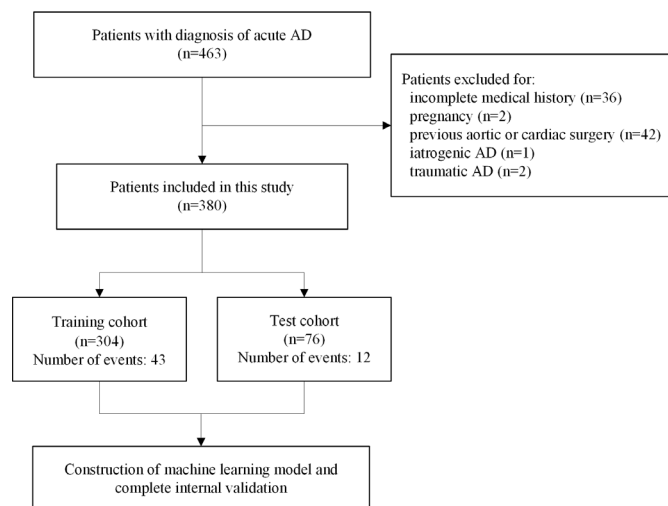


Figure 1 Flow diagram of patient selection. AD, aortic dissection.

models and provide accurate attribution values for each variable.²⁵

Statistical analysis

The sample size calculation was conducted using Stata software V.16. Assuming the overall preoperative in-hospital mortality was 15%, the sample size required to accurately assess the risk with 5% significance and 80% power was 196 individuals for the training cohort.²⁶ Categorical variables were expressed as numbers and percentages, and continuous variables were expressed as mean±SD. All statistical analyses were completed in R statistical software (V.4.1.3). Statistical differences of categorical variables were analysed by the χ^2 test or Fisher's exact test, and continuous variables were examined by two-tailed t-tests or Mann-Whitney U tests. A p value <0.05 was considered statistically significant.

Patient and public involvement

No patients or members of the public were involved in the design, conduct or reporting of this study. The study results were not disseminated to study participants.

RESULTS

Baseline characteristics

The medical records of 380 patients with acute AD from January 2004 to December 2018 were thoroughly reviewed (figure 1). The demographics and clinical variables are listed in table 1. Patients were randomly divided, and 80% were allocated to the training set and the remaining 20% to the test set. Among the patients, 132 (34.7%) were diagnosed with type A AD, and 248 (65.3%) had type B AD. Two-hundred and sixty-five (69.7%) patients suffered from hypertension. The variances of the haemodynamic features (SBPV, DBPV, HRV) are listed in table 1. There were no significant differences in the demographics and clinical variables between the two sets.

Prediction models' performance comparison

The preoperative in-hospital mortality rate was 14.47% (n=55) in the whole cohort. We used the machine learning methods with all the variables as input variables, including logistic regression, simple decision tree, RF, XGBoost and SVM, to predict preoperative in-hospital mortality; the AUCs are presented in figure 2. Among all the approaches, XGBoost exhibited the best prediction efficacy with an AUC of 0.926 (95% CI 0.855 to 0.997). The AUCs for logistic regression, simple decision tree, RF and SVM were all >0.8, while the simple decision tree exhibited the smallest AUC (0.815, 95% CI 0.688 to 0.942) due to its known instability. RF and XGBoost models appeared to outperform SVM based on AUCs, which is consistent with the evidence that decision trees are more suitable for categorical data and can handle collinearity better than SVMs.

The net benefit curves of DCA for the five models are shown in figure 3. Consistent with our analysis of AUC, the preferred model was the XGBoost model, whose net benefit was larger than the range of the other four models. The calibration curves are shown in figure 4. All calibration curves exhibited acceptable fit to the line y=x. Still, apart from the SVM model, the predicted mortality was lower than the actual mortality in the curves for the XGBoost, logistic regression, decision tree and RF models.

Decision tree and nomogram

Based on the demographics and clinical variables of the training set, a decision tree was applied to predict in-hospital mortality, and the patients were divided into different groups (online supplemental figure 1). The results indicated that for patients with type A AD, those with maximum aortic diameter >5.5 cm had the highest in-hospital mortality rate. In contrast, patients with uncomplicated AD with SBPV<6.6 and no aortic aneurysm had the lowest mortality rate. For patients with type B AD, HRV≥6.8 was an indicator of poor prognosis; however, HRV<6.8 and SBPV<13 were associated with decreased in-hospital mortality. Moreover, a nomogram based on the logistic regression analysis showed a scoring system for assessing the risks of in-hospital mortality using 23 selected variables (online supplemental figure 2).

Final prediction model

The importance matrix plot for the XGBoost method is shown in figure 5, which revealed that the top five most important variables contributing to the model were type of AD, DBPV, concomitant aortic aneurysm, HRV and ODT. A SHAP method was applied to determine the impact of relevant risk factors on prognostic prediction for in-hospital mortality (figure 6). This plot depicts how high and low features' values were in relation to SHAP values in the training data set. According to the prediction model, the higher the SHAP value of a feature, the more likely mortality is to occur. The results showed that type A AD, concomitant aortic aneurysm, high HRV, high DBPV and aortic arch involved had the greatest influence

Table 1 Physical and clinical characteristics of the included patients

Variables	All	Training cohort	Test cohort	P value
n	380	304	76	
Age (years)	56.7±13.2	57.0±13.3	55.6±12.8	0.192
Male, n (%)	307 (80.8)	246 (80.9)	61 (80.3)	0.448
ODT (days)	1.7±2.5	1.8±2.6	1.3±2.0	0.090
Time of admission (hours)	14:03	14:10	13:32	0.228
Symptom, n (%)				0.086
None	15 (3.9)	10 (3.3)	5 (6.6)	
Pain	336 (88.4)	268 (88.2)	68 (89.5)	
Shock	8 (2.1)	7 (2.3)	1 (1.3)	
Others	21 (5.5)	19 (6.3)	2 (2.6)	
Marfan syndrome, n (%)	18 (4.7)	16 (5.3)	2 (2.6)	0.168
COPD, n (%)	21 (5.5)	15 (4.9)	6 (7.9)	0.157
Hypertension, n (%)	265 (69.7)	214 (70.4)	51 (67.1)	0.289
Diabetes mellitus, n (%)	16 (4.2)	14 (4.6)	2 (2.6)	0.222
History of AD, n (%)	16 (4.2)	13 (4.3)	3 (3.9)	0.449
Cardiac diseases, n (%)	53 (13.9)	45 (14.8)	8 (10.5)	0.169
Renal insufficiency, n (%)	23 (6.1)	20 (6.6)	3 (3.9)	0.195
PAD, n (%)	13 (3.4)	9 (3.0)	4 (5.3)	0.162
MAD≥5.5 cm, n (%)	66 (17.4)	50 (16.4)	16 (21.1)	0.172
Type of AD, n (%)				0.167
Stanford type A	132 (34.7)	102 (33.6)	30 (39.5)	
Stanford type B	248 (65.3)	202 (66.4)	46 (60.5)	
Range of AD, n (%)				
Aortic arch	142 (37.4)	110 (36.2)	32 (42.1)	0.171
Abdominal aorta	224 (58.9)	179 (58.9)	45 (59.2)	0.479
Complicated AD, n (%)	70 (18.4)	59 (19.4)	11 (14.5)	0.161
Pericardial effusion, n (%)	36 (9.5)	28 (9.2)	8 (10.5)	0.363
Pleural effusion, n (%)	91 (23.9)	68 (22.4)	23 (30.3)	0.075
SBPV (mm Hg)	8.6±4.5	8.6±4.5	8.6±4.4	0.493
DBPV (mm Hg)	5.6±2.9	5.6±3.1	5.3±2.0	0.210
HRV (bpm)	6.2±4.4	6.1±3.4	6.4±7.0	0.308
Mortality, n (%)	55 (14.5)	43 (14.1)	12 (15.8)	0.716

Data are presented as n (%) or mean (SD).

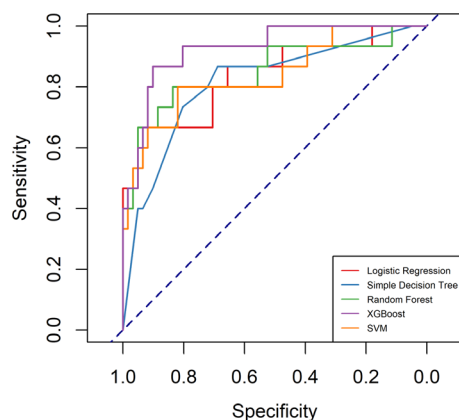
AD, aortic dissection; COPD, chronic obstructive pulmonary disease; DBPV, diastolic blood pressure variability; HRV, heart rate variability; MAD, maximum aortic diameter; ODT, onset-to-door time; PAD, peripheral arterial disease; SBPV, systolic blood pressure variability.

on the occurrence of preoperative in-hospital death. Moreover, we applied the XGBoost model to predict the preoperative in-hospital mortality rate at the individual level, and the results revealed a consistency between the predicted values and actual outcomes (figure 7).

DISCUSSION

In the current retrospective study, we applied multiple machine learning models on demographic information, medical history and BP and HR features to predict preoperative in-hospital mortality in patients with acute

AD. Among all the tested models, the XGBoost model exhibited the best performance. A simple decision tree was used to divide the patients into different risk groups based on their clinical characteristics, and a nomogram was created to provide a scoring system for assessing the risks of in-hospital death. The importance matrix plot and SHAP summary plot of the XGBoost model revealed that Stanford classification, concomitant aortic aneurysm, BP variability (BPV) and HRV were the most critical factors for predicting in-hospital mortality rate. In addition, the XGBoost model can accurately predict the



Model	AUC in the test set (95% CI)
Logistic regression	0.837 (0.707-0.968)
Simple decision tree	0.815 (0.688-0.942)
Random forest (RF)	0.849 (0.716-0.983)
eXtreme Gradient Boosting (XGBoost)	0.926 (0.855-0.997)
Support vector machine (SVM)	0.840 (0.713-0.968)

Figure 2 Comparison of areas under the receiver operating characteristic curves (AUCs) among different machine learning models. XGBoost yielded the best prediction accuracy.

preoperative in-hospital mortality rate at the individual level.

The risk measurement and stratification are of great importance to lower the high mortality rates of acute AD, which were reported to be as high as 27.4%.²⁷ Yet, how to identify high-risk patients with acute AD remains a major question in clinical practice. Mehta *et al* applied a logistic regression model to evaluate patients with type A AD enrolled in the International Registry of Acute Aortic Dissection and found that age ≥ 70 years, abrupt onset of chest pain, hypotension, kidney failure, pulse deficit and abnormal ECG were the predictors of in-hospital death.⁶

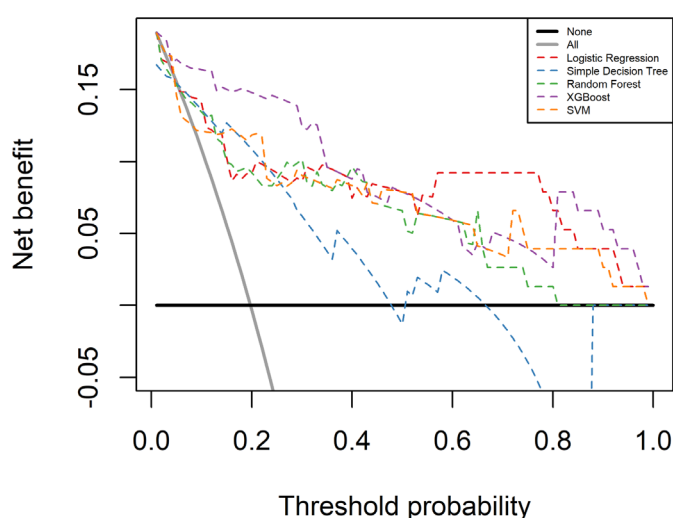


Figure 3 Decision curve analysis (DCA) of the five prediction models. The net benefit curves for these prognostic models are shown. X-axis indicates the threshold probability for mortality and y-axis indicates the net benefit. SVM, support vector machine; XGBoost, eXtreme Gradient Boosting.

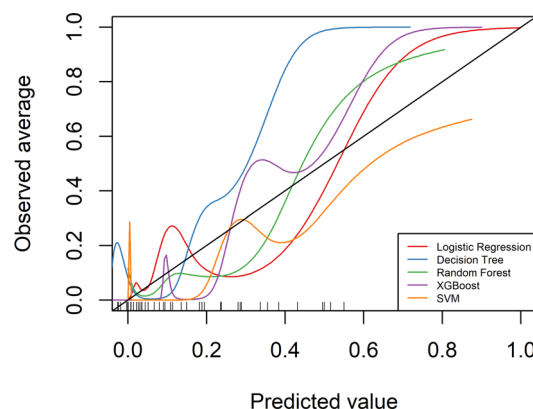


Figure 4 Calibration curves of the machine learning models illustrate how well the predicted probabilities match the actual in-hospital mortality in patients with acute aortic dissection. SVM, support vector machine; XGBoost, eXtreme Gradient Boosting.

Nevertheless, the robustness of this model is limited because of the relatively low AUC value (0.74). Using the same AD database, Tolenaar and colleagues analysed the clinical features of 1034 patients and developed a bedside risk prediction tool for in-hospital mortality.⁸ Their prediction tool based on multivariable logistic regression demonstrated that age, hypotension, periaortic haematoma, descending diameter ≥ 5.5 cm, mesenteric ischaemia, acute renal failure and limb ischaemia were associated with increased in-hospital death. Nevertheless, the methods that use the natural logarithm of ORs to calculate the model score may amplify or reduce the influence of certain factors. One single-centre retrospective cohort study used multiple machine learning algorithms to predict hospital-based mortality in patients with acute AD, revealing that treatment, type of acute

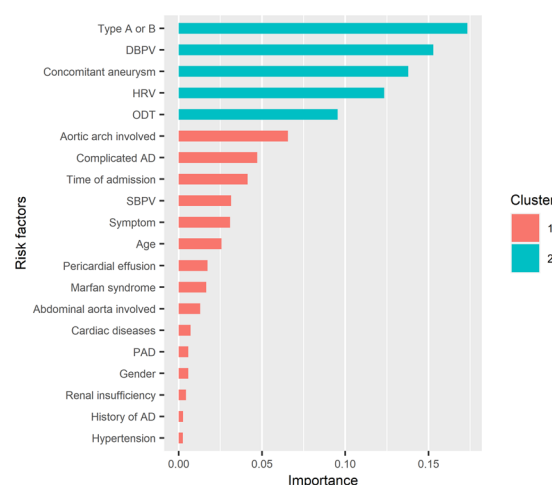


Figure 5 Importance matrix plot of the eXtreme Gradient Boosting (XGBoost) model. All variables were divided into two clusters according to their importance in the development of the final predictive model. AD, aortic dissection; DBPV, diastolic blood pressure variability; HRV, heart rate variability; ODT, onset-to-door time; PAD, peripheral arterial disease; SBPV, systolic blood pressure variability.

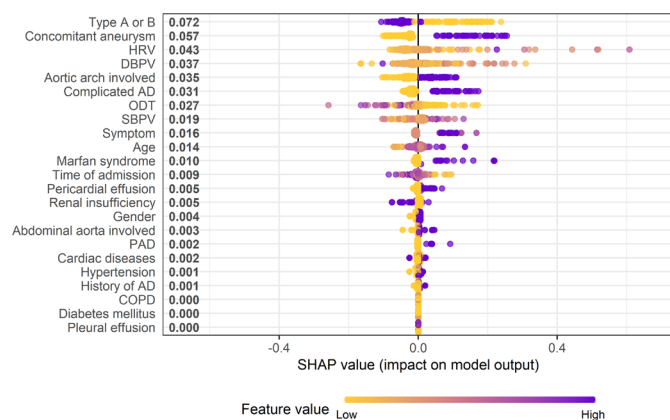


Figure 6 SHapley Additive exPlanations (SHAP) summary plot of the eXtreme Gradient Boosting (XGBoost) model. The higher the SHAP value of a feature, the higher the mortality rate of patients with AD. A dot was created according to the SHAP value of each patient. Dots were coloured according to the values of features. Purple represented higher feature values and yellow represented lower feature values. AD, aortic dissection; COPD, chronic obstructive pulmonary disease; DBPV, diastolic blood pressure variability; HRV, heart rate variability; ODT, onset-to-door time; PAD, peripheral arterial disease; SBPV, systolic blood pressure variability.

AD and ischaemia-modified albumin levels were three most significant aspects.¹⁴ However, the conclusion may not be generalised to patients just admitted to a hospital without any treatment, as a type of treatment is one of the major factors in the prediction models. The current study aimed to perform risk stratification and predict preoperative in-hospital mortality in patients with acute AD after admission. Due to the similar pathophysiological mechanism underlying both Stanford type A and type B AD, all patients with acute AD were included in the analysis and Stanford classification was considered as a variable. The XGBoost model included demographic information, medical history and variation of BP and HR during

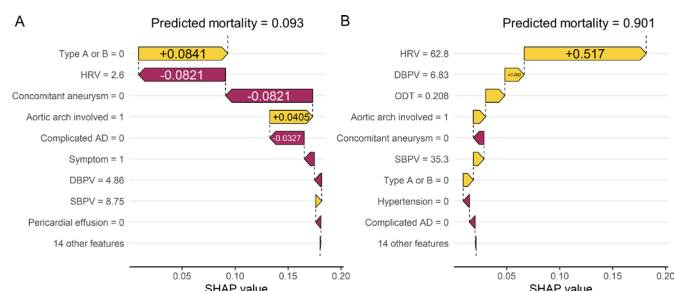


Figure 7 SHapley Additive exPlanations (SHAP) decision plot of the eXtreme Gradient Boosting (XGBoost) model for two selected extreme cases. (A) Prediction of in-hospital mortality for case 4 who survived during hospitalisation. (B) Prediction of in-hospital mortality for case 58 who died during hospitalisation. The contribution of each variable to the predicted mortality rate was shown in the corresponding pentagon-shaped arrow. AD, aortic dissection; DBPV, diastolic blood pressure variability; HRV, heart rate variability; ODT, onset-to-door time; SBPV, systolic blood pressure variability.

hospitalisation, exhibiting better prediction efficiency than previously reported.^{6 15 28 29} Besides, the AUCs of the other four models were all >0.8, which indicated that the combination of the included parameters was rather rational for the prediction of AD prognosis.

The DCA method, introduced in 2006, is a statistical method used for evaluating the accuracy of a prediction model, through the net benefit, which enables the comparison of performance between different models.²⁴ We therefore employed this vital validation tool to evaluate the utility of our predictive models in supporting clinical decisions, finding that the XGBoost model yielded the best performance with the highest overall net benefit. In particular, the XGBoost model outperformed other models in the range of threshold probability between 0 and 0.5, as well as between 0.8 and 1, while only the logistic regression showed a greater net benefit in the range of 0.5–0.8. The DCA results suggested that in the case of extremely high-risk patients, the XGBoost model had the highest predictive power, whereas we could use the nomograms (online supplemental figure 2) derived from the logistic regression to calculate the risk score as a supplementary tool to the risk stratification. Moreover, calibration curves were constructed to reflect the predicted values in each model versus the actual preoperative in-hospital deaths in the participants. As shown in figure 3, the calibration intercept of the XGBoost curve was equal to 0, indicating an excellent performance of the XGBoost model at the boundary point. Nevertheless, as the calibration intercepts of the other four models were all above 0, these models may overestimate the preoperative in-hospital death in patients with acute AD. Besides, according to the calibration slopes in the plot, good alignments between the predictive effects and the observed deaths were found in the XGBoost, logistic analysis and RF models. Consistent with the principles for validation of clinical prediction models,³⁰ our results implied that the XGBoost model had the greatest accuracy and robustness for timely prediction of death in patients with acute AD after hospital admission, while the nomogram based on the logistic regression model could be used as a supplementary predictive method.

BP and HR are the key factors affecting the development and progression of acute AD.³¹ The main primary objective of medication in AD treatment is to control the BP and HR, thus reducing the shear stress in the aorta.⁵ The BP measures included in the previous studies on prediction models were absolute values of BP following admission. Also, these studies mainly concluded that BP was not the key factor of AD prognosis or that merely the aggressively low absolute value would affect the outcome.^{6–8 10 11 32 33} However, many clinical studies have shown that rather than the absolute value of BP, the BPV could better reflect the impact of blood flow changes on the lesion site. Song *et al* demonstrated that high BPV was an independent risk factor for acute type B AD.³⁴ In their retrospective study, Zhang *et al* illustrated that high preoperative BPV was associated with increased aorta-related

death and decreased thrombosis ratio of false lumen after endovascular therapy.³⁵ Therefore, SBPV and DBPV were included in our prediction models for the risk measurement of acute AD. The results of the simple decision tree model revealed that $SBP \geq 6.6$ and $SBPV > 13.0$ were the independent predictors for preoperative in-hospital mortality of type A and type B AD, respectively. Moreover, XGBoost model exhibited that DBPV was associated with the preoperative in-hospital mortality, rather than SBPV, thus indicating that DBPV was an important factor for the progression of AD, and the clinician should pay more attention to the DBPV. More studies are urgently warranted to elucidate the pathophysiological mechanism through which DBPV influences AD progression.

In the present study, the logistic regression, simple tree decision and XGBoost models showed that maximum aortic diameter > 5.5 cm was a critical predictive factor for the preoperative in-hospital death of acute AD, which was consistent with the previous studies. Early researchers found that the increase in aortic diameter was associated with higher incidence of aorta-related events in patients with AD.³⁶⁻³⁷ Besides, Ray *et al* revealed that patients with maximum ascending aortic diameter > 40.8 mm were at high risk for subsequent proximal and arch progression.³⁸ Some researchers demonstrated that the diameter of ascending aorta was an independent risk factor for the long-term prognosis of acute AD; yet, it could not be used as an indicator for evaluating the occurrence of AD.³⁹ According to the current guidelines, prophylactic interventions for AD are recommended for patients with an ascending aortic diameter above 5.5 cm.⁵⁻¹⁷ However, the cut-off value for intervention has been extensively debated.⁴⁰⁻⁴¹ A previous study of aortic diameter before AD showed that 98.8% of patients had an aortic diameter ≤ 5.5 cm and 84.8% of patients had an aortic diameter ≤ 4.0 cm, which suggested that the role of an aortic diameter > 5.5 cm as an indicator of AD might be over-rated.⁴² Researchers also found that 87.7% of patients had an aortic diameter < 4.5 cm when acute AD occurred.⁴³ Therefore, the threshold value of aortic diameter or other morphological parameters of aorta as an indication for surgical treatment needs to be further discussed in the future.

This study has several important limitations. The main limitation of the current study is the relatively small sample size and numbers of outcome events, which may increase the risk of overfitting in machine learning algorithms. Second, our model was applicable to patients with acute AD but may not be suitable for patients with chronic AD. Another limitation is that prognostic indicators other than preoperative in-hospital death, such as aortic-related events and neurological complications, have not been evaluated, which may be inadequate for a thorough evaluation of patients with acute AD. A further limitation of the study is that the retrospective nature of the present study could lead to selection bias and information bias, so our model should be validated in a prospective, large-sample database in the future. Finally, XGBoost algorithm has its

inherent limitations. The insufficient explainability may constrain application of XGBoost model in real-world clinical practice, and the risk of inflation of the importance of less important features should be noted.

CONCLUSIONS

Five predictive models for preoperative in-hospital mortality of patients with acute AD were successfully constructed in the current study, among which the XGBoost model exhibited the greatest prediction accuracy and net benefit. Our results demonstrated that variations of SBP, DBP and HR are crucial for risk measurement and stratification of acute AD. These models should be further validated for applications in clinical practice by using a large-sample, prospective database.

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Contributors Study conception and design: PQ, TC, XL. Acquisition of data: ZW, ZX, PQ. Analysis and interpretation of data: ZW, YL, ZX, PQ. Drafting of the manuscript: ZW, YL. Critical revision of the manuscript for important intellectual content: ZX, PQ, TC, XL. Statistical analysis: YL, KL, HL. Administrative, technical or material support: PQ, TC, XL. Supervision: PQ, TC, XL. Guarantor: XL.

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Competing interests YL was employed by Stoppingtime (Shanghai) BigData & Technology, Shanghai, China.

Patient and public involvement Patients and/or the public were not involved in the design, or conduct, or reporting, or dissemination plans of this research.

Patient consent for publication Not applicable.

Ethics approval The study protocol was reviewed and approved by the Medical Ethics Committee of Shanghai Ninth People's Hospital and registered on the Chinese Clinical Trial Registry (ChiCTR1900025818).

Provenance and peer review Not commissioned; externally peer reviewed.

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