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Risk factors and predictive models for post-operative moderate-to-severe mitral regurgitation following transcatheter aortic valve replacement: a machine learning approach

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Abstract

Background Post-operative moderate-to-severe mitral regurgitation (MR) following transcatheter aortic valve replacement (TAVR) is associated with poor outcomes, yet the factors contributing to this complication are not well understood. This study aimed to identify risk factors and develop predictive models for post-operative MR following TAVR using machine learning (ML) techniques to enhance early detection and intervention.

Methods We retrospectively analyzed data from patients who underwent TAVR at our center between August 2014 and August 2023. Patients were classified into post-operative and nonpost-operative MR groups based on postprocedural MR severity. Various ML models were evaluated for predictive performance using metrics such as accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve (AUC). Shapley Additive Explanation (SHAP) values were used to interpret predictive patterns and develop a clinically relevant model.

Results Among the evaluated models, the random forest model exhibited the highest predictive performance for post-operative moderate-to-severe MR after TAVR. Key predictors, which were confirmed by the SHAP analysis as important in the predictive framework, included echocardiographic parameters, blood test results, patient age, and body mass index.

Conclusions ML models show promise in predicting post-operative moderate-to-severe MR after TAVR by integrating clinical indicators to enhance predictive accuracy.

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Clinical trial number Not applicable.

Keywords Aortic stenosis (AS), Machine learning, Mitral regurgitation (MR), Transcatheter aortic valve replacement (TAVR), Predictive model

Introduction

In recent years, aortic stenosis (AS) represents the most common valvular disorder among older adults, characterized by increased peak transvalvular flow velocity and elevated pressure gradients across the valve [1], impacting nearly 5% of individuals aged 75 years or older. Once symptoms develop due to AS, mortality rates rise sharply [2]. Patients with severe disease who remain untreated face a five-year survival rate of roughly 50%, with an approximate yearly death rate of 25% [3].Transcatheter aortic valve replacement (TAVR) has emerged as a safe and effective treatment for severe AS and has been widely adopted in clinical practice [4, 5]. Patients with severe AS often exhibit varying degrees of mitral regurgitation (MR) [6], with the prevalence of moderate-to-severe MR in this population reported to range from 30–40% [7–9].

For patients with concurrent AS and MR, TAVR has been shown to significantly alleviate MR in most cases, with studies suggesting that 50–70% of patients experience improvement following TAVR [8]. However, about 30% of patients continue to experience moderate-to-severe MR postoperatively [7, 10]. Post-operative moderate-to-severe MR after TAVR is strongly associated with increased mortality and is an independent risk factor that adversely affects the prognosis of older adults with TAVR [8, 10]. Despite its clinical significance, the factors contributing to post-operative moderate-to-severe MR post-TAVR remain poorly understood, and effective predictive models to guide clinical practice are lacking.

The increasing application of machine learning (ML) algorithms in medicine has revolutionized data analysis methods. ML excels at analyzing many variables with nonlinear and complex relationships without requiring prior assumptions about the input variables or their interactions with the output [11]. Recent studies have demonstrated that ML algorithms outperform traditional logistic regression (LR) models in predictive accuracy [12–14].

In this study, we aimed to retrospectively analyze and compare the predictive capabilities of various ML algorithms with those of traditional methods to identify and validate independent predictors of post-operative moderate-to-severe MR following TAVR. Additionally, we developed a Mitral Regurgitation Prediction Model (MRPM) to evaluate the risk of post-operative moderate-to-severe MR post-TAVR. The MRPM is designed to facilitate early identification and intervention for high-risk patients, thereby improving long-term outcomes and supporting physicians in making informed decisions. These findings demonstrate the potential of ML-driven approaches as valuable tools for optimizing patient outcomes and guiding clinical decision-making in TAVR management.

Materials and methods

Study design and subjects

This single-center retrospective cohort study analyzed the records of patients who underwent TAVR at Zhongshan Hospital of Fudan University between August 2014 and August 2023. Comprehensive preoperative and postoperative data—including echocardiography, computed tomography findings, and intraoperative transesophageal echocardiography—were meticulously recorded. This study was approved by the Ethics Committee of Zhongshan Hospital, Fudan University (Approval No.: B2020-039), and all patients provided signed an informed consent form.

Patient selection

Exclusion criteria included the following: (1) diagnosis of pure aortic regurgitation, (2) absence of preoperative or postoperative imaging data, (3) history of mitral valve repair, or (4) perioperative mortality.

MR severity was evaluated postoperatively using echocardiography and classified as follows: No MR, Mild MR (I+), Mild-to-Moderate MR (II+), Moderate-to-Severe MR (III+), Severe MR (IV+).

Patients classified as III+ or IV+ were collectively defined as having moderate-to-severe MR or higher. Based on these classifications, patients were divided into two groups: "moderate-or-greater MR" and "control." Statistical analyses were conducted to compare demographic characteristics and perioperative variables between the groups.

Statistical analyses

Continuous variables following a normal distribution are expressed as mean ± standard deviation (SD), while non-normally distributed variables are reported as median values with interquartile ranges (25th–75th percentile). Categorical variables are presented as percentages. The risk of significant MR post-TAVR was assessed by analyzing the relationships between candidate predictors and this outcome using both univariate and multivariate regression analyses. For univariate analysis, independent sample t-tests or chi-square tests were employed, while multivariate analysis involved LR with stepwise selection. Statistical significance was set at $p < 0.05$. All statistical analyses were conducted using R software (The R Project for Statistical Computing) or SPSS Version 25.0 (IBM Corp.).

Construction of machine learning models

The dataset was randomly partitioned into training and testing sets in a 7:3 ratio. Missing data were addressed using multiple and median imputation techniques to minimize the risk of extreme or biased results. Six ML models were developed using the training set: random forest (RF), gradient boosting decision tree, LR, support vector machine, decision tree (DT), and XGBoost. Model performance was evaluated using extensive metrics, including accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve (AUC).

Feature importance was assessed using the RF model, while Shapley Additive Explanation (SHAP) values were applied to interpret the contributions of individual features to postoperative MR prediction. A SHAP summary plot was generated to highlight the top 20 features influencing the model, providing valuable insights into their clinical relevance.

Results

A total of 987 patients were included in the study. Preoperatively, 247 patients (25%) presented with moderate-to-severe MR, while 132 patients (14%) exhibited moderate-or-greater MR on echocardiography, postoperatively (Fig. 1). Among these, 28 patients (21.2%) experienced progression from moderate to moderate-or-greater MR. Demographic and perioperative variables for patients with moderate-or-greater MR and those without are summarized in Table 1.

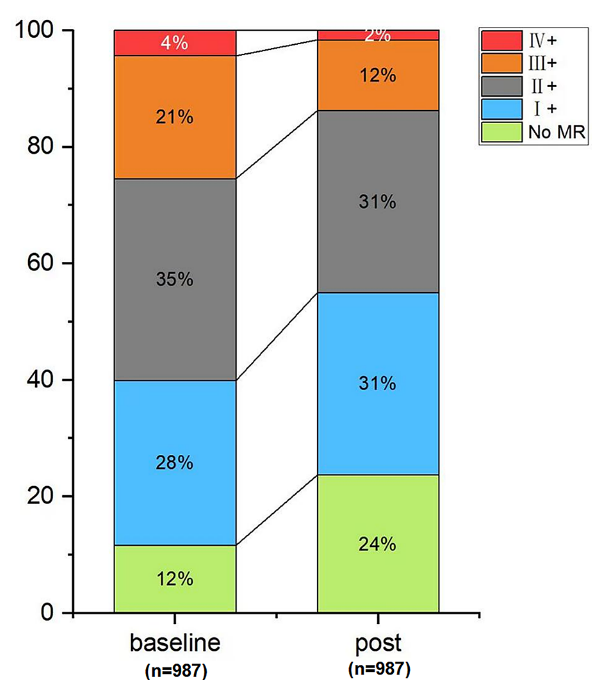

Fig. 1 Percentage of patients with different regurgitation grades preoperatively and postoperatively

LR analysis identified several independent predictors for moderate-or-greater MR, including a history of percutaneous coronary intervention, hypertension, peripheral vascular disease, past medical history, hyperuricemia, baseline severity of aortic regurgitation, MR severity, and mitral valve leaflet thickening (Table 2)

Subsequently, patients were randomly divided into a training set (70%) and a test set (30%), with their characteristics summarized in Supplementary Table 1. No significant differences were observed between the two sets for any analyzed variables. Six predictive models were developed using the training set (Table 3; Fig. 2). Among these, the RF model exhibited the highest predictive performance, achieving an AUC of 0.91 (95% CI: 0.89–0.93). Conversely, the DT model demonstrated the lowest performance, with an AUC of 0.64 (95% CI: 0.61–0.67). The AUC, accuracy, precision, recall, and F1 score for all models are presented in Table 3.

The importance matrix for the RF model is shown in Fig. 3, highlighting the 10 most critical predictors of postoperative MR. These predictors included moderate-to-severe MR, left ventricular ejection fraction (LVEF), left atrial dimension (LAD), mitral valve leaflet thickening, troponin T (TnT), maximum aortic valve velocity, body mass index (BMI), left ventricular end-diastolic diameter (LVEDD), aortic valve orifice area, and effective orifice area.

Additionally, a summary SHAP plot (Fig. 4) was generated for the RF model to highlight the influence of the top 20 most important features on prediction outcomes. The magnitude of SHAP values was positively correlated with predictive likelihood, meaning that higher SHAP values indicated an increased probability of postoperative MR. Figure 5 further ranks the mean SHAP values for each feature, showing their contribution to outcome predictions for each patient.

SHAP analysis also provided insights into how individual predictors contribute to the occurrence of postoperative MR in each patient (Fig. 6). The SHAP value heatmap (Fig. 6A) shows the impact of the individual predictors on model performance. Figure 6B illustrates the distribution and trends of SHAP values for various predictors across the entire population. Finally, Fig. 6C comprehensively illustrates how SHAP values quantify the influence of predictors on postoperative MR severity in a specific patient.

Discussion

In this retrospective study, we compared ML algorithms with traditional analytical methods to predict the risk of moderate-to-severe postoperative MR following TAVR

Table 1 Patient demographics and baseline characteristics

Characteristic	MR post		p-value
	Control (N = 855)	moderate-or-greater MR(N = 132)	
Age	74.2 ± 8.3	76.5 ± 8.7	0.026
Gender	365 (42.7%)	61 (46.2%)	0.447
Height	162.9 ± 8	162.8 ± 8.6	0.875
Weight	62.4 ± 11.1	60.6 ± 11.2	0.081
BMI	23.4 ± 3.4	22.8 ± 3.9	0.103
BSA	1.5 ± 1.7	1.6 ± 1.7	0.134
AVA	0.86 ± 0.52	0.80 ± 0.45	0.213
PASP	139 (16.1%)	55 (41.5%)	< 0.001
Hb	125.1 ± 19.2	119.5 ± 20.7	0.004
TnT	0.05 ± 0.02	0.07 ± 0.02	0.424
BAV	419 (49.0%)	47 (35.6%)	0.004
LVEF	59.8 ± 10.6	51.5 ± 13.8	< 0.001
LAD	42.9 ± 6.4	47.4 ± 6.9	< 0.001
LVEDD	49.9 ± 7.5	54.3 ± 9.4	< 0.001
BAV Type	212 (24.8%)	20 (15.2%)	0.015
Creatinine	102.2 ± 98.7	127.6 ± 12.4	0.029
Creatinine clearance	67.2 ± 18.5	61.1 ± 21.5	0.002
PCI	75 (8.8%)	20 (15.2%)	0.012
Diabetes	178 (20.8%)	21 (18.9%)	0.117
NYHA	737 (86.1%)	123 (93%)	< 0.001
AVB	66 (7.7%)	11 (8.3%)	0.229
LBBB	16 (1.9%)	1 (0.8%)	0.810
RBBB	43 (5%)	6 (4.5%)	> 0.999
CAD	603 (70.5%)	98 (74.2%)	0.381
MI	11 (1.3%)	6 (4.5%)	0.018
CABG	8 (0.9%)	4 (3.0%)	0.064
AF	146 (17.1%)	43 (32.6%)	< 0.001
PMM	16 (1.9%)	11 (8.3%)	< 0.001
COPD	44 (5.1%)	11 (8.3%)	0.137
Cancer	38 (4.4%)	10 (7.6%)	0.120
Stroke	45 (5.3%)	10 (7.6%)	0.281
HF	412 (48.2%)	101 (76.5%)	< 0.001
Aspirin	386 (45.1%)	67 (50.8%)	0.229
Smoker	77 (9.0%)	14 (10.6%)	0.554
Syncope	48 (5.6%)	13 (9.8%)	0.060
Warfarin	27 (3.2%)	10 (7.6%)	0.023
Hypertension	517 (60.5%)	69 (52.3%)	0.074
Carotiddisease	97 (11.3%)	19 (14.4%)	0.311
Periphdisease	45 (5.3%)	23 (17.4%)	< 0.001
Hyperuricaemia	8 (0.9%)	6 (4.5%)	0.006
Surgery history	67 (7.8%)	8 (6.1%)	0.474
Aortic orifice area	474.3 ± 95.1	480.8 ± 109.9	0.551
Pulmonary infection	21 (2.5%)	0 (0.0%)	0.098
Maximum aortic valve velocity	4.4 ± 0.9	4.2 ± 1	0.220
Mean pressure gradient	81.5 ± 31.6	76.4 ± 31.7	0.087
Moderate to severe AR	257 (29.9%)	50 (37.8%)	0.021
Mitral valve calcification	94 (11.0%)	25 (18.9%)	0.009
Mitral valve leaflet adhesion	16 (1.9%)	7 (5.3%)	0.025
Mitral valve leaflet thickening	38 (4.4%)	33 (25.0%)	< 0.001
Aortic annulus diameter	22.5 ± 2.3	22.7 ± 2.7	0.306
Aortic annulus circumference	80.1 ± 7.8	80.2 ± 10.3	0.907

Table 1 (continued)

Characteristic	MR post		p-value
	Control (N = 855)	moderate-or-greater MR(N = 132)	
Effective aortic orifice area	84.9 ± 64.8	85.4 ± 67.1	0.954
Calcification of the aortic valve	706 (82.6%)	109 (82.6%)	> 0.999
Right coronary artery hight	15.2 ± 3.5	15.5 ± 3.8	0.447
Left coronary artery hight	14.3 ± 5.3	14 ± 3.3	0.556
Autoimmune diseases	13 (1.5%)	3 (2.3%)	0.462
P2Y12 receptor antagonists	428 (50.1%)	73 (55.3%)	0.262
Xall factor antagonist	190 (22.2%)	34 (25.8%)	0.367

using 60 preoperative noninvasive parameters. Among the evaluated models, the RF algorithm demonstrated the highest AUC in classifying patients in the training set.

Hernandez-Suarez et al. [15] were among the first to use ML techniques to predict in-hospital mortality risk postsurgery. Building on this, subsequent ML models have been developed to predict long-term mortality, postoperative pacemaker implantation, and short-term heart failure readmissions, yielding satisfactory results [16–20]. For example, Pollari et al. [21] reported significantly high predictive accuracy using an RF model, with a negative predictive value of 96%, a positive predictive value of 92%, and an overall accuracy of 96% in predicting 1-year mortality risk for patients with TAVR. Our study integrated the top 10 predictors identified from the RF importance matrix and the SHAP model. We found that echocardiographic parameters, blood test results, and patient-specific metrics (e.g., BMI and weight) were crucial for predicting post-operative moderate-to-severe MR.

Notably, most echocardiographic parameters routinely assessed in TAVR evaluations—including MR, mitral valve leaflet thickening, LVEF, LAD, LVEDD, PASP, aortic orifice area, and maximum aortic valve velocity—were significant contributors to the predictive model, with the first four being particularly influential. Unlike traditional models, which often rely on a limited range of echocardiographic features, the SHAP-based ML model incorporates a broader set of parameters, capturing more nuanced clinical insights. This likely reflects the ability of the model to mitigate collinearity, which can otherwise obscure the contribution of important features.

In addition to echocardiographic parameters, our findings highlight the predictive value of blood markers (e.g., TnT and creatinine), BMI, and weight. These factors underscore the relevance of cardiac injury and overall patient health in assessing postoperative MR risk.

The absolute degree of postoperative MR, rather than its trend of improvement, is a superior indicator of long-term prognosis. Even with some improvement, residual high-grade MR often signifies underlying issues, such as left ventricular remodeling impairment or intrinsic mitral valve dysfunction [22–25]. Notably, Mauri et al. [26] developed an MR reduction score using MR grades and mitral valve characteristics to predict MR ≤II+, achieving an AUC of 0.816 (95% CI: 0.731–0.902). In our study, which incorporated a broader range of clinical indicators beyond echocardiographic features, the RF model achieved superior predictive performance, with an AUC of 0.91 (95% CI: 0.89–0.93).

As TAVR indications expand, the number of treated patients continues to increase. However, only approximately half of patients with preoperative high-grade MR experience significant postoperative improvements [27]. Studies suggest that staged MR treatment can improve long-term survival; however, many patients do not undergo subsequent mitral valve interventions. This could be due to insufficient clinical evidence or challenges related to patient awareness and long-term management.

Additionally, TAVR-induced structural changes to the mitral valve may reduce the effectiveness of MR interventions and limit MR improvement [28]. This highlights the need to explore early intervention strategies, concurrent mitral valve procedures, and surgical alternatives for patients unlikely to experience postoperative MR improvement. Enhancing preoperative assessments, intraoperative decision-making, and postoperative management for patients with multivalvular diseases is imperative.

Although detailed imaging of mitral annulus characteristics and calcification levels is valuable for predicting postoperative MR outcomes [29], such comprehensive evaluations are often impractical in high-volume TAVR centers. Baseline high-grade MR remains a critical preoperative indicator; however, approximately 20% of postoperative high-grade MR cases result from the exacerbation of baseline low-grade MR. To address this, preliminary screening of patients with high-risk post-operative MR is essential. Our model leverages simple and accessible preoperative indicators to provide robust predictive performance, offering a practical tool for identifying high-risk patients with MR and guiding further clinical evaluation and management strategies.

Table 2 Univariate and multivariate analysis of influencing factors (Logistic regression)

Characteristic	Univariable			Multivariable		
	OR	95% CI	*p*-value	OR	95% CI	*p*-value
Age	1.03	1.00, 1.06	0.019	0.99	0.96, 1.03	0.749
Gender	1.15	0.80, 1.67	0.447			
Height	1.00	1.00, 1.00	0.874			
Weight	1.00	1.00, 1.00	0.078	1.00	1.00, 1.00	0.564
BMI	1.00	1.00, 1.00	0.069	1.00	1.00, 1.00	0.990
BSA	0.99	0.98, 1.00	0.143			
CAD	1.20	0.79, 1.83	0.382			
MI	3.65	1.33, 10.05	0.012	0.76	0.14, 4.06	0.744
PCI	1.76	1.03, 3.03	0.040	2.49	1.09, 5.69	0.030
CABG	3.31	0.98, 11.15	0.053	2.95	0.48, 17.93	0.241
Diabetes	1.49	0.49, 4.51	0.482			
Hypertension	0.72	0.50, 1.03	0.075	0.52	0.31, 0.90	0.019
Smoker	1.20	0.66, 2.19	0.555			
Carotiddisease	1.31	0.77, 2.23	0.313			
Periphdisease	3.80	2.21, 6.52	< 0.001	2.53	1.11, 5.79	0.028
AF	2.35	1.56, 3.52	< 0.001	1.12	0.61, 2.07	0.713
PMM	4.77	2.16, 10.51	< 0.001	3.99	1.24, 12.84	0.020
COPD	1.68	0.84, 3.33	0.141			
Pulmonary infection	0.00	0.00, Inf	0.978			
Cancer	1.76	0.86, 3.63	0.124			
Stroke	1.48	0.72, 3.00	0.284			
Autoimmune diseases	1.51	0.42, 5.36	0.527			
Hyperuricaemia	5.04	1.72, 14.77	0.003	5.12	1.10, 23.90	0.038
Surgery history	0.76	0.36, 1.62	0.475			
Syncope	1.84	0.97, 3.49	0.064	0.56	0.21, 1.51	0.255
HF	3.50	2.29, 5.35	< 0.001	1.59	0.83, 3.06	0.160
NYHA ≥ III	1.01	1.01, 1.01	< 0.001	1.00	1.00, 1.01	0.663
Aspirin	1.25	0.87, 1.81	0.229			
P2Y12 receptor antagonists	1.23	0.85, 1.78	0.263			
Warfarin	2.51	1.19, 5.32	0.016	1.62	0.55, 4.81	0.380
XaII factor antagonist	1.21	0.80, 1.85	0.367			
AVB	0.83	0.37, 1.86	0.652			
LBBB	0.49	0.06, 3.80	0.497			
RBBB	0.99	0.41, 2.39	0.985			
Creatinine	1.00	1.00, 1.00	0.013	1.00	1.00, 1.00	0.235
Creatinine clearance	1.00	1.00, 1.00	< 0.001	1.00	1.00, 1.00	0.191
Hb	1.00	1.00, 1.00	0.003	1.00	1.00, 1.00	0.205
TnT	1.00	1.00, 1.01	0.559			
LVEF	0.95	0.93, 0.96	< 0.001	0.99	0.97, 1.02	0.726
LAD	1.00	1.00, 1.00	< 0.001	1.00	1.00, 1.00	0.871
LVEDD	1.00	1.00, 1.00	< 0.001	1.00	1.00, 1.00	0.517
Maximum aortic valve velocity	1.00	1.00, 1.00	0.205			
Mean pressure gradient	1.00	1.00, 1.00	0.085	1.00	1.00, 1.00	0.793
Moderate to severe AR	1.00	1.00, 1.00	0.024	1.00	0.99, 1.00	0.043
Moderate to severe MR	1.02	1.02, 1.03	< 0.001	1.03	1.02, 1.03	< 0.001
Mitral valve calcification	1.89	1.16, 3.07	0.010	0.90	0.44, 1.86	0.785
Mitral valve leaflet adhesion	2.94	1.18, 7.28	0.020	0.63	0.17, 2.32	0.487
Mitral valve leaflet thickening	7.17	4.30, 11.95	< 0.001	4.44	2.02, 9.79	< 0.001
PASP	1.01	1.00, 1.01	< 0.001	1.00	1.00, 1.00	0.222
Aortic systolic blood pressure	1.00	1.00, 1.00	0.637			
Annulus diameter	1.00	1.00, 1.00	0.232			
Aortic annulus circumference	1.00	1.00, 1.00	0.886			

Table 2 (continued)

Characteristic	Univariable			Multivariable		
	OR	95% CI	*p*-value	OR	95% CI	*p*-value
AOA	1.00	1.00, 1.00	0.506			
EOA	1.00	1.00, 1.00	0.952			
BAV	0.58	0.39, 0.84	0.004	0.56	0.26, 1.19	0.132
BAV Type	0.54	0.33, 0.89	0.016	0.97	0.44, 2.13	0.938
Right coronary artery hight	1.00	1.00, 1.00	0.415			
Left coronary artery hight	1.00	1.00, 1.00	0.670			
Calcification of the aortic valve	1.00	0.62, 1.62	> 0.999			

Table 3 Training effectiveness of different machine learning models

	RF	GBDT	LR	DT	SVC	XGBoost
AUC	0.91	0.82	0.70	0.64	0.71	0.90
Accuracy	0.95	0.94	0.95	0.93	0.95	0.95
Precision	0.97	0.62	0.73	0.66	0.47	0.81
Recall	0.53	0.55	0.56	0.64	0.50	0.56
F1-score	0.55	0.57	0.59	0.65	0.49	0.59

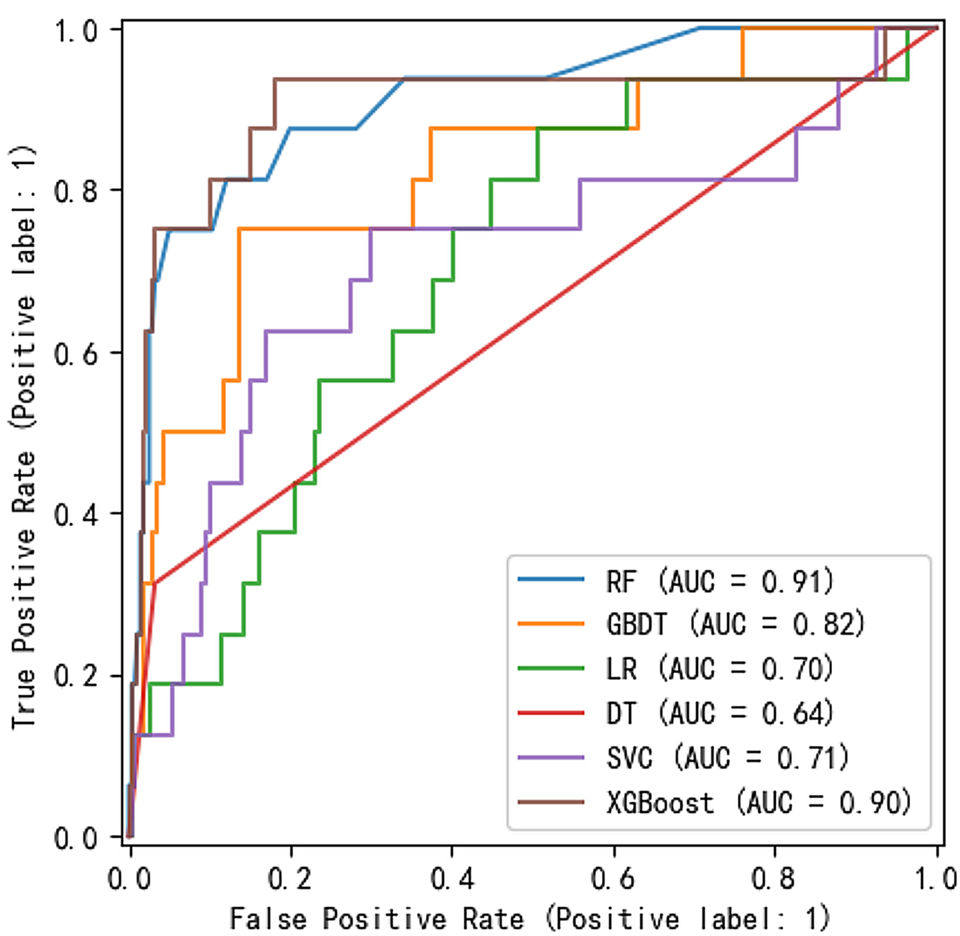

Fig. 2 ROC curves comparing the predictive effectiveness of multiple models on the training set

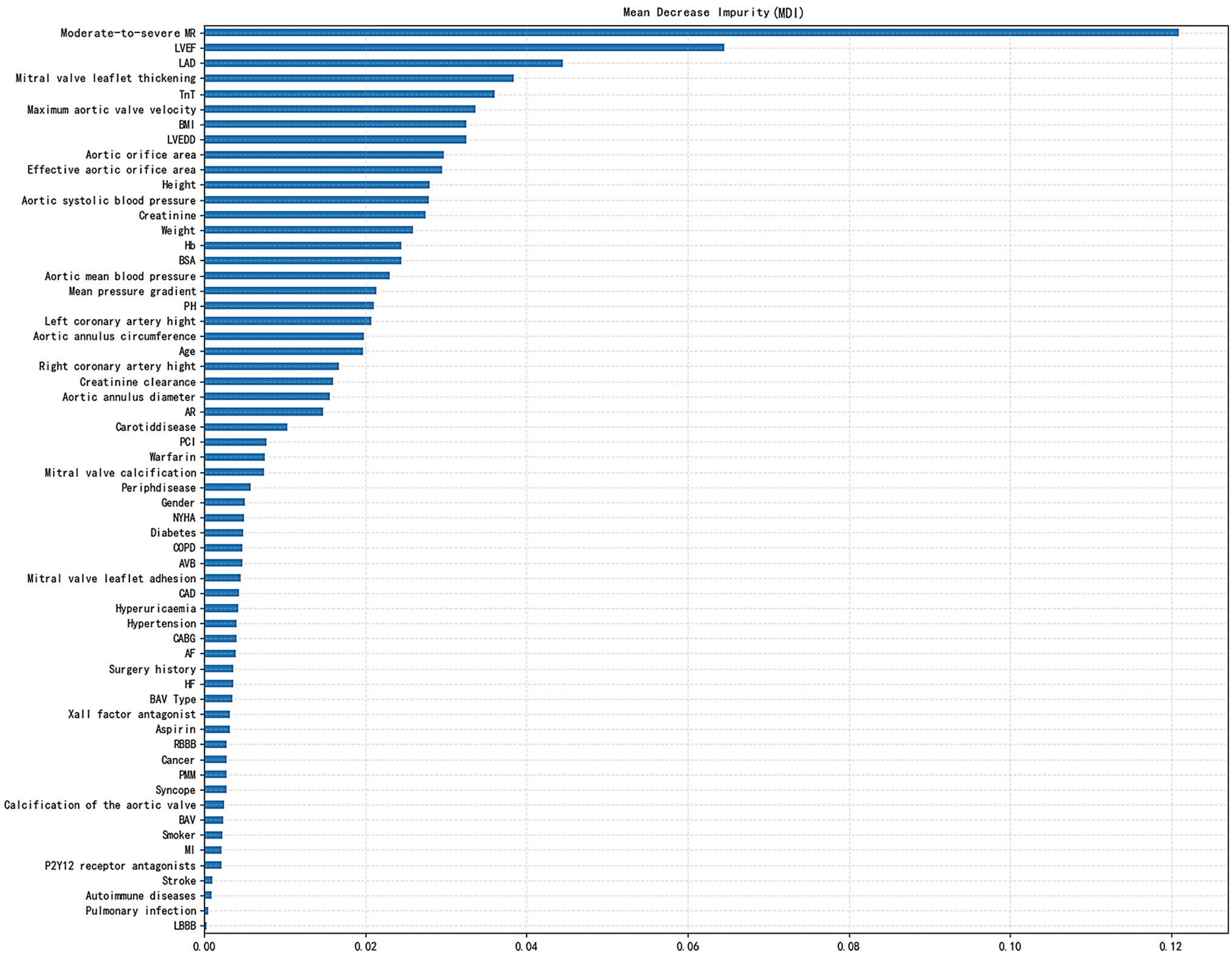

Fig. 3 The importance matrix of the RF method

Our findings demonstrate the robust predictive performance of LAD, which serves as a surrogate marker for mitral annular dilation and provides valuable insights into the etiology and potential improvement of MR. This highlights the utility of LAD in capturing critical aspects of mitral regurgitation pathology, even in the absence of comprehensive structural data on the mitral valve [19].

Conclusions

This study demonstrates that ML-driven approaches, combined with SHAP-based interpretability, can enhance the early identification of high-risk patients and facilitate more informed clinical decision-making in TAVR management. By leveraging readily available preoperative data, MRPM offers a practical tool to guide personalized treatment strategies and optimize outcomes for patients with concurrent aortic stenosis and MR.

Limitations

Our study had several limitations. First, as a single-center retrospective study, the relatively small sample size for ML modeling and the limited number of positive cases may have contributed to model overfitting. This could affect the generalizability of our findings to a broader patient population with similar clinical characteristics. Second, our patient classification relied solely on echocardiographic MR grading before discharge. Although this approach offers practical value for early decision-making and patient management, it may lead to misclassification in some cases, as MR severity can improve over time. The evolution of mitral regurgitation on follow-up echocardiography may offer prognostic insights. Future iterations will integrate these parameters to improve prediction accuracy. Our model builds on established evidence that discharge echocardiography predicts mortality, while minimizing attrition-related bias.

Finally, the current study lacks external validation, which may limit the generalizability and real-world

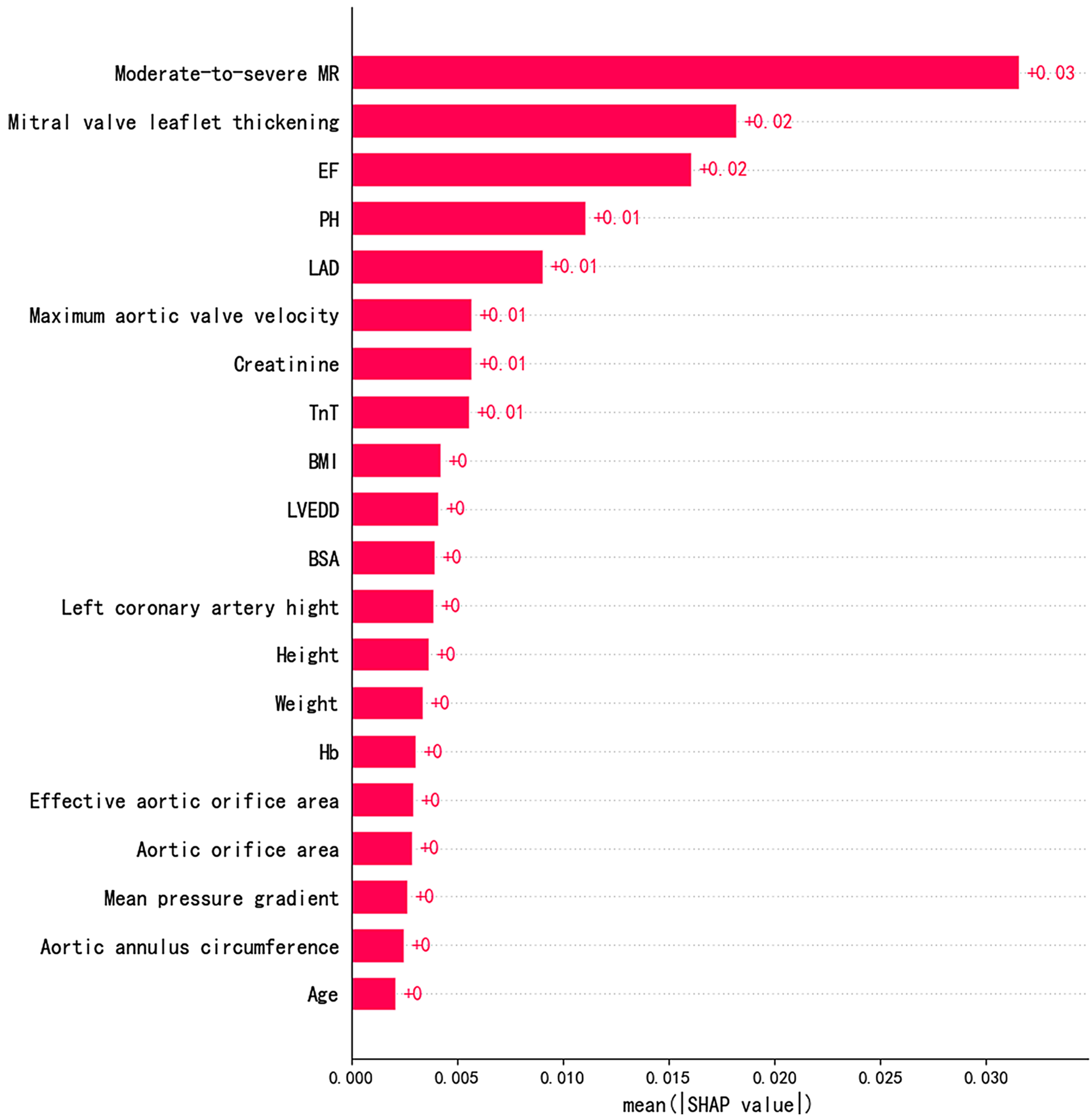

Fig. 4 SHAP plot for the RF model: illustrating the impact of the top 20 most significant features on prediction outcomes

performance of our findings. This important aspect requires further optimization and validation in future research.

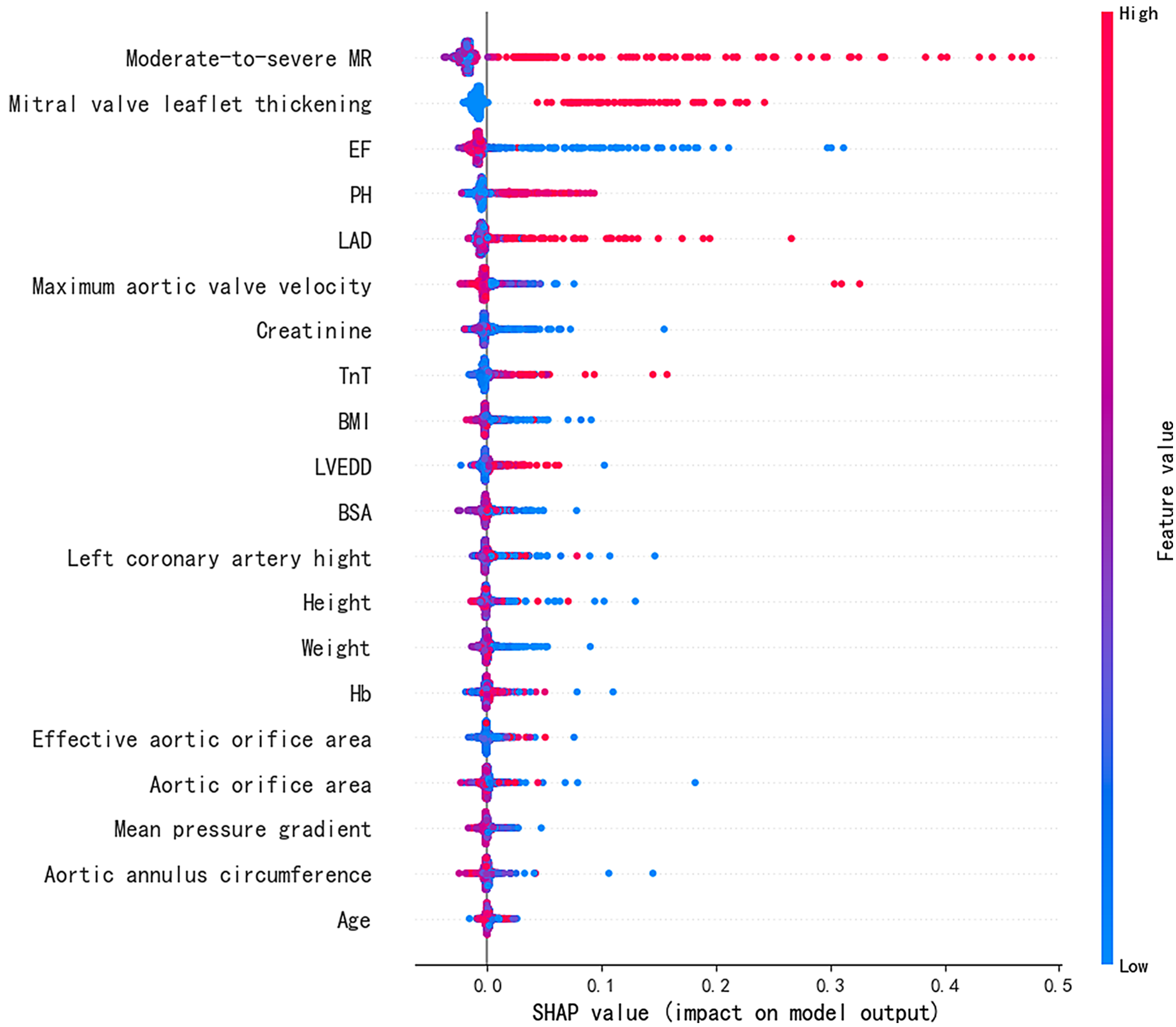

Fig. 5 Mean SHAP values ranking features by their contribution to patient outcome predictions

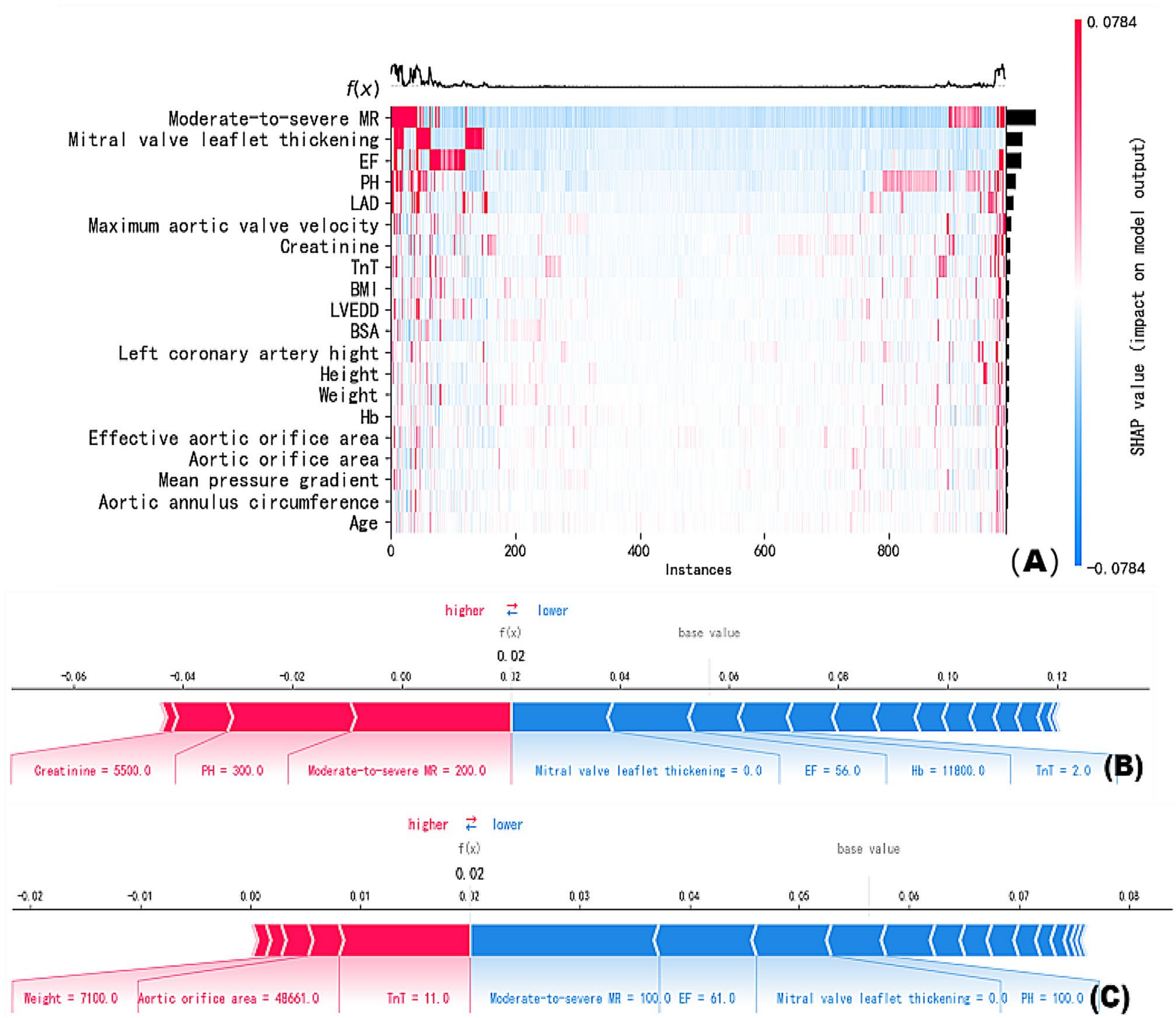

Fig. 6 SHAP Analysis of Model Feature Contributions (**A**) Summary plot of SHAP values for feature contributions across all instances. Features are ranked by importance, with "Moderate-to-severe MR," "Mitral valve leaflet thickening," and "EF" among the top contributors. Red indicates positive SHAP values (increasing predictions), while blue indicates negative values (decreasing predictions). (**B**, **C**) Patient-specific SHAP waterfall plots illustrating how individual features contribute to the final prediction. Red arrows represent positive contributions, and blue arrows represent negative contributions. Observed feature values for the respective patients are annotated

Abbreviations

MR	Mitral Regurgitation
TAVR	Transcatheter Aortic Valve Replacement
ML	Machine Learning
AS	Aortic Stenosis
LR	Logistic Regression
MRPM	Mitral Regurgitation Prediction Model
RF	Random Forest
DT	Decision Tree
SHAP	Shapley Additive Explanation
LVEF	Left Ventricular Ejection Fraction
LAD	Left Atrial Dimension
TnT	Troponin T
BMI	Body Mass Index
LVEDD	Left Ventricular End-Diastolic Diameter

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12872-025-04759-9.

Supplementary Material 1

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Author contributions

Ge Jun-bo Zhou Da-xin and Pan Wen-zhi presented the purpose of the study, the acquisition of funding. Miao Jia-xin and Zhao Jing-yan collected the research data. Fan Jia-jun and Lin Da-wei involved in statistical analysis. Zhang

Xiao-chun prepared figures. Fan Jia-ning and Li Zhenzhen wrote the main manuscript text and prepared figures. All authors reviewed the manuscript.

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Data availability
The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Declarations

Ethics approval and consent to participate
This study was approved by the Ethics Committee of Zhongshan Hospital, Fudan University (Approval No.: B2020-039),and all patients provided signed an informed consent form.

Consent for publication
Not applicable.

Informed consent
Informed consent was obtained from all subjects involved in the study.

Competing interests
The authors declare no competing interests.

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