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Original Research

Prediction of Major Adverse Cardiac Events After Transcatheter Aortic Valve Implantation: A Machine Learning Approach with GRACE Score

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Abstract

Objectives: Predictive risk scores have a significant impact on patient selection and assessing the likelihood of complications following interventions in patients with severe aortic stenosis (AS). This study aims to explore the utility of machine learning (ML) techniques in predicting 30-day major adverse cardiac events (MACE) by analyzing parameters, including the Global Registry of Acute Coronary Events (GRACE) score.

Methods: This retrospective, multi-center, observational study enrolled 453 consecutive patients diagnosed with severe AS who underwent transcatheter aortic valve implantation (TAVI) from April 2020 to January 2023. The primary outcome was defined as a composition of MACE comprising periprocedural myocardial infarction (MI), cerebrovascular events (CVE), and all-cause mortality during the 1-month follow-up period after the procedure. Conventional binomial logistic regression and ML models were utilized and compared for prediction purposes.

Results: The study population had a mean age of 76.1, with 40.8% being male. The primary endpoint was observed in 7.5% of cases. Among the individual components of the primary endpoint, the rates of all-cause mortality, MI, and CVE were reported as 4.2%, 2.4%, and 1.9%, respectively. The ML-based Extreme Gradient Boosting (XGBoost) model with the GRACE score demonstrated superior discriminative performance in predicting the primary endpoint, compared to both the ML model without the GRACE score and the conventional regression model [Area Under the Curve (AUC)= 0.98 (0.91-0.99), AUC= 0,87 (0.80-0.98), AUC= 0.84 (0.79-0.96)].

Conclusion: ML techniques hold the potential to enhance outcomes in clinical practice, especially when utilized alongside established clinical tools such as the GRACE score.

Keywords: Decision tree, GRACE score, MACE, TAVI, XGBoost, VARC-3

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Degenerative aortic stenosis (AS) is the most prevalent valvular heart disease and carries an unfavourable prognosis if left untreated.[1] Transcatheter aortic valve implantation (TAVI) is a minimally invasive procedure employed for substituting a damaged aortic valve in patients over the age of 75 or in those who are high risk, or ineligible for surgical aortic valve replacement (sAVR).[2] Although TAVI has substantially enhanced the outcomes for patients at high risk, there remains a possibility of experiencing major adverse cardiac events (MACE), including myocardial infarction, stroke, and mortality, after the procedure.[3,4] However, the risk factors and preoperative surgical risk scores

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established for sAVR may not possess sufficient reliability in predicting early mortality following TAVI.[4] Hence, identifying patients with suitable perioperative risk profiles, for whom the potential benefits of invasive treatment outweigh those of conservative medical management alone, is of utmost importance.

Multiple novel risk scores tailored specifically for the TAVI procedure have been developed[5-7]; however, their applicability in independent cohorts remains limited.[8,9] Therefore, it is crucial to accurately estimate the risk of MACE in patients undergoing TAVI, not only to prioritize patient care but also to enhance clinical outcomes. The Global Registry of Acute Coronary Events (GRACE) score is a validated tool utilized for predicting the likelihood of poor prognosis in individuals with acute coronary syndrome (ACS). In this regard, this scheme incorporates a range of patient-specific factors including age, heart rate (HR), systolic blood pressure (SBP), serum creatinine level, presence of cardiac arrest upon presentation, Killip class, and elevated cardiac markers. Furthermore, clinicians widely employ the GRACE score as a guiding instrument in making treatment-related decisions for patients with ACS. This encompasses determining the appropriate treatment strategy, as well as the intensity of monitoring and follow-up required. Similarly, the score has undergone considerable research and validation across a wide range of clinical circumstances, making it a powerful tool for risk stratification and clinical decision-making in diverse disease entities.[10-12]

In the modern era, machine learning (ML) algorithms have been employed to analyze medical data and develop predictive models for diverse outcomes.[13,14] Various approaches for predicting heart disease have been developed using supervised ML algorithms.[15] Consequently, numerous research papers have been published, extensively investigating the performance of a wide array of models that leverage ML techniques.[16-17] In this context, our objective was to investigate the predictive capability of the GRACE score in determining 30-day all-cause mortality among patients with symptomatic severe AS who underwent TAVI.

Methods

Study Design and Population

This retrospective, multi-center, observational study included a cohort of 485 consecutive patients diagnosed with symptomatic severe AS who underwent TAVI within the period from April 2020 to January 2023. Individuals who met any of the following criteria were excluded from the study: acute coronary syndrome (n=5), active kidney infection, nephrotic syndrome, or chronic kidney disease undergoing regular hemodialysis therapy (n=4), hypertrophic cardiomyopathy (n=2), pulmonary embolism (n=2), presence of pacemaker rhythm (n=3), acute ischemic symptoms with carotid artery disease exhibiting a narrowing exceeding 50% (n=3), active bleeding or any hematologic disease (n=4), and those with missing data (n=9). After this step, the final analysis was performed on a total of 453 subjects. Demographic, laboratory, and clinical information were collected from the medical database of the hospital. Additionally, follow-up data were obtained through the national health registration system. This study was conducted in accordance with the principles outlined in the Declaration of Helsinki. The study protocol was approved by the Ethics Committee of Basaksehir Cam and Sakura City Hospital (Date: 22.03.2023, Decision number: 131).

Definitions and Risk Scores

The diagnosis of severe AS was established based on the criteria outlined in the 2017 guidelines for the management of valvular heart disease by the European Society of Cardiology (ESC) and the European Association for Cardio-Thoracic Surgery (EACTS).[18] The decision to perform the TAVI procedure was based on the assessment of high surgical risk by the cardiac team, which consisted of a cardiologist, cardiovascular surgeon, and anesthesiologist. Upon hospital admission, blood samples were obtained from all patients to measure baseline values of complete blood count (using Beckman Coulter LH 750, Fullerton, California, USA) and various biochemical parameters including albumin, glucose, and other relevant variables (utilizing Cobas C7001 Roche Diagnostic, Rotkreuz, Switzerland). Renal function was evaluated based on the estimated glomerular filtration rate (eGFR) using the formula validated in the Modification of Diet in Renal Disease Study.[19] Echocardiographic assessments were conducted by licensed physicians at the study clinic following the recommendations of the American Society of Echocardiography[20], utilizing a Hitachi ultrasound cardiovascular system (Arietta 65, USA) equipped with a 2.5-3.5 MHz transducer. The measurement of left ventricular ejection fraction (LVEF) was performed using the modified biplane Simpson's method. The Society of Thoracic Surgeons Predicted Risk of Mortality (STS-PROM) and GRACE scores of the participants were calculated using the latest online versions available. The GRACE score incorporates eight parameters, including age, HR at presentation, SBP at admission, serum creatinine level at presentation, Killip score, presence of ST-segment depression on the initial electrocardiogram, elevated levels of initial serum cardiac biomarkers, and occurrence of cardiac arrest upon admission. Specific points are assigned to each variable based on pre-established criteria, and the cumulative points obtained are utilized to calculate the GRACE score. This score provides an estimation of the probability of death from admission to 6 months.[11]

Outcomes

The primary endpoint was defined as the composition of MACE within 30 days after the procedure, or beyond if the patient had not been discharged, in accordance with the classification criteria recommended by the Valvular Academic Research Consortium 3 (VARC-3). The components of MACE included periprocedural myocardial infarction (MI), cerebrovascular events (CVE), and periprocedural all-cause mortality. MACE was assessed and determined by an independent clinical events committee. Neurological outcomes were assessed using the Neurologic Academic Research Consortium (NeuroARC) classification, which takes into account symptoms and specific neurological imaging findings related to cardiovascular interventions, as recommended by VARC-3. The study included symptomatic cases of permanent NeuroARC Type 1 events (Ischemic and Hemorrhagic stroke, hypoxic-ischemic injury), Type 2 events (Covert CNS infarction or hemorrhage), and Type 3a events (Transient focal neurological signs or symptoms). The modified VARC-3 classification, which incorporates elements of the 4th Universal MI, Society for Cardiovascular Angiography and Interventions (SCAI), and Academic Research Consortium 2 (ARC-2) definitions, was utilized for identifying and categorizing MI events. All MI events were documented based on this criterion. Periprocedural death was defined according to two criteria: death within the first month following the procedure or death occurring more than one month after the procedure but while the patient was still hospitalized.[21]

Statistical Analysis

The normality of continuous variables was assessed using Shapiro-Wilk's test. Descriptive statistics such as mean (standard deviation) and median (interquartile range - IQR25th-75th) were used to summarize numerical variables. Percentages and absolute numbers were used to present discrete data. For comparisons of continuous data, an unpaired t-test or Mann-Whitney U test was employed, depending on the normality assumption. For comparisons of discrete data, a Chi-Square test or Fisher's Exact test was used, as appropriate. In this study, both conventional binomial logistic regression and ML models were developed to predict MACE in the study sample. The ML algorithm employed was extreme gradient boosting (XGBoost), a decision tree-based model. The XGBoost algorithm was initially introduced by Chen et al.[22] with the aim of enhancing the performance and efficiency of gradient-boosted decision trees (DT). This algorithm employs a series of iterative training steps on the dataset to combine weak predictors and generate robust predictors. In the sequential modeling process of XGBoost, each decision tree relies on the outcomes of the previous trees to construct an improved predictor. The XGBoost algorithm includes a regularization term which helps prevent overfitting during the modeling process. Moreover, the algorithm provides a measure of the percentage improvement for each variable in DT.

A total of eight variables, namely age, NT-proBNP, BMI, LVEF, hemoglobin, creatinine, STS-PROM score, and GRACE score, were utilized to predict the occurrence of MACE in patients. The remaining parameters were set to their default values. The XGBoost model employed had a maximum tree depth of six and employed logistic regression as the task for binary classification, with the output provided as a probability. The training process involved 70 rounds, with the selection of the round yielding the lowest test Root Mean Squared Error (RMSE). All samples were internally validated and calibration plots were generated using the val.prob.ci.2 functions in R. The best model from each iteration was recorded and compared to evaluate the robustness and validity of each important feature. Data analysis was performed using R version 4.22, with the "rms," "XGBOOST," "pROC," and "rpart" packages (R Foundation, Vienna, Austria).

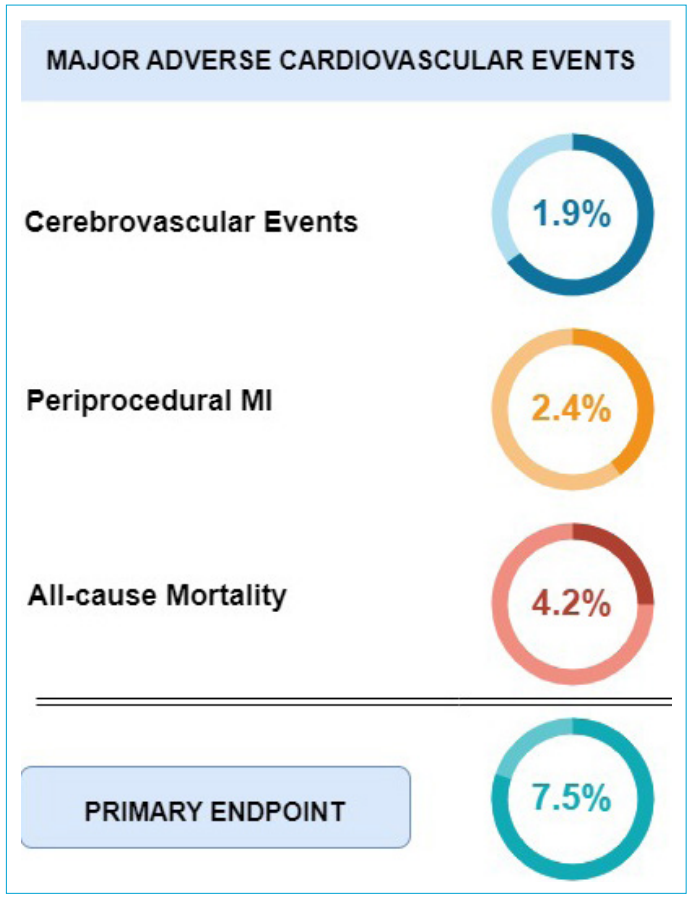

Figure 1. The distribution of individual parameters of major adverse cardiovascular events constituting the primary endpoint.

Results

The study population included a total of 453 participants, with a mean age of 76.1 (6.6) years, and 185 (40.8%) of them were male. The primary endpoint, occurring within one month, was observed in 34 individuals, resulting in an event rate of 7.5%. Among the individual components of the primary endpoint, all-cause mortality, periprocedural MI and CVE rates were reported in 17 (4.2%), 11 (2.4%), and 9 (1.9%) participants, respectively (Fig. 1). Additionally, the need for a permanent pacemaker after the procedure was found to be 63 (13.8%). Baseline characteristics of the overall population were compared between the MACE and non-MACE groups, as presented in Table 1. The prevalence of chronic obstructive pulmonary disease was found to be significantly higher in the high-MACE group compared to the non-MACE group. However, there were no significant differences in terms of male gender, diabetes mellitus, hypertension, hyperlipidemia, and smoking status between the two groups. The MACE group exhibited significantly higher levels of Log (NT-proBNP) and creatinine compared to the non-MACE group (p<0.001 for both). Furthermore, no significant association was observed between MACE and variables such as before TAVI aortic valve area, aortic valve mean gradient, severe aortic valve regurgitation, and the type of valve utilized during the TAVI procedure (self-expandable device or balloon-expandable device). However, the MACE group exhibited a significantly lower LVEF compared to the non-MACE group (45 vs. 55%, p<0.001).

The XGBoost algorithm identified age as the most significant predictor of MACE, indicating its strong association with the outcome. On the other hand, in conventional regression analysis, the STS-PROM score was found to be the variable that accounted for the highest amount of variance in the MACE, followed by the GRACE score. To visually represent the results obtained from the XGBoost algorithm, an importance graph was generated to illustrate the global features of the model (Fig. 2a). Furthermore, Sinaplots were employed to depict the distribution of variable contributions to the prediction of the primary endpoint using SHAP (Shapley Additive Explanations) values for each variable across all observations. Each dot in Fig. 2b represents an individual observation.

The XGBoost model, incorporating the GRACE score, exhibited superior discriminative performance in predicting the primary endpoint, as evidenced by an Area Under the Curve (AUC) of 0.98 (95% Confidence Interval [CI], 0.91-0.99, p<0.001). In comparison, the ML model without the GRACE score achieved an AUC of 0.87 (95% CI, 0.80-0.98, p<0.001), while the conventional regression model yielded an AUC of 0.84 (95% CI, 0.79-0.96, p<0.001) (Fig. 3, Table 2). Upon comparing the predicted probabilities with the actual probabilities, it was observed that the XGBoost model exhibited a slight miscalibration. Notably, the predicted probabilities tended to be slightly lower than the actual probabilities, particularly in cases where the actual probability of the primary endpoint exceeded 30% (Fig. 4). The

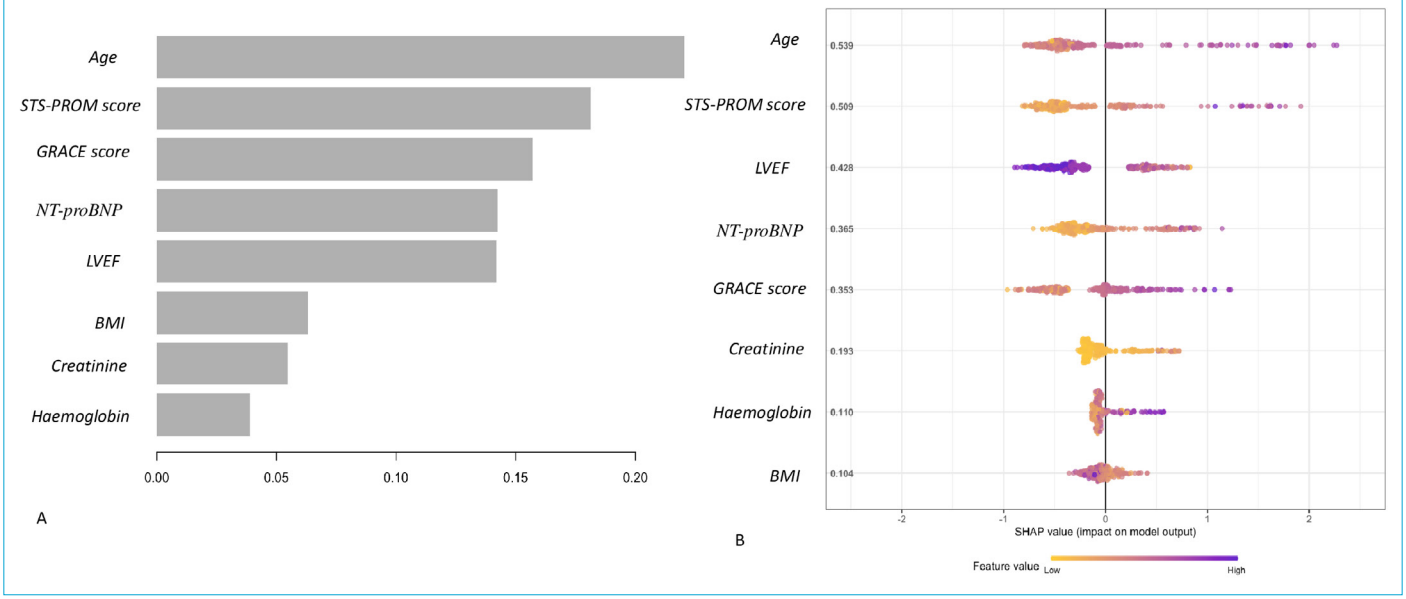

Figure 2 (a, b). Machine Learning-based XGBoost algorithm analysis. **(a)** Importance plot of variables of XGBoost algorithm. **(b)** Sinaplot visualization of differences in continuous variables.

BMI: body mass index; GRACE score: Global Registry of Acute Coronary Events score; NTproBNP: N-terminal pro-b-type natriuretic peptide; LVEF: left ventricular ejection fraction; STS-PROM: Society of Thoracic Surgeons Predicted Risk of Mortality; XGBoost: The Extreme Gradient Boosting.

Table 1. Baseline characteristics of the study population

Variables	Overall (n=453)	MACE (-) (n=419)	MACE (+) (n=34)	p
Demographic features and risk factors				
Age; years, mean (SD)	76.1(6.6)	75.7 (6.2)	82.2 (8.0)	**<0.001**
Male; n (%)	185 (40.8)	170 (40.6)	15 (44.1)	0.686
DM; n (%)	192 (42.4)	178 (42.5)	14 (41.2)	0.516
HT; n (%)	349 (77)	324 (77.3)	25 (73.9)	0.373
HL; n (%)	77 (23.8)	70 (23.5)	7 (26.9)	0.425
Smoking; n (%)	106 (23.4)	98 (23.4)	8 (23.5)	0.564
CAD; n (%)	140 (30.9)	8 (23.5)	132 (31.5)	0.333
CKD; n (%)	80 (17.5)	74 (17.7)	6 (17.6)	0.495
COPD (severe II-III); n (%)	191 (42.1)	166 (36.9)	25 (73.6)	**<0.001**
History of CABG; n (%)	83 (18.3)	80 (19.1)	3 (8.8)	0.098
PAD; n (%)	48 (16.9)	45 (17.4)	3 (11.5)	0.327
CVE; n (%)	45 (9.9)	43 (10.3)	2 (5.9)	0.320
HR, beat/min; Median (IQR)	74 (65-82)	74 (65-83)	71 (63-76)	0.336
SBP, mmHg; Median (IQR)	130 (120-143)	131 (120-142)	133 (109-137)	0.110
DBP, mmHg; Median (IQR)	71 (61-80)	72 (66-80)	67 (60-70)	0.079
BMI; kg/m^2; Mean (SD)	27.3 (4.5)	27.1 (4.5)	27.0 (4.5)	0.924
Echocardiography and Electrocardiography findings				
LVEF, %; Median (IQR)	54 (50-65)	55 (50-65)	45 (35-50)	**<0.001**
Mean Gradient, mm Hg; Median (IQR)	46 (42-56)	46 (41-56)	47 (40-54)	0.278
Aortic Valve Area, m^2; Median (IQR)	0.7 (0.6-0.8)	0.7 (0.6-0.8)	0.7 (0.5-0.8)	0.811
Severe Aortic Regurgitation; n (%)	23 (5.1)	19 (4.5)	4 (11.8)	0.139
Atrial fibrillation; n (%)	124 (27.4)	113 (27.0)	11 (32.4)	0.310
Right Bundle Branch Block; n (%)	32 (7.1)	28 (6.7)	4 (11.8)	0.211
Left Bundle Branch Block; n (%)	64 (14.1)	62 (14.8)	2 (5.9)	0.113
Procedural feature				
Self-expandable Device; n (%)	345 (76.1)	317 (75.6)	28 (82.3)	0.378
Balloon-expandable Device; n (%)	108 (23.8)	102 (24.3)	6 (17.6)	0.371
Femoral Access; n (%)	443 (97.7)	410 (97.8)	33 (97.0)	0.995
Risk Scores				
STS-PROM score	6.1 (4.3-8.3)	5.9 (4.2-8.0)	10.2 (8.1-13.0)	**<0.001**
GRACE score	140 (131-151)	140 (129-149)	157 (147-170)	**<0.001**
Laboratory parameters				
Creatinine, mg/dl; median (IQR)	1.0 (0.6-1.2)	1.0 (0.7-1.2)	1.0 (0.8-1.3)	0.016
Sodium, mEq/L; mean (SD)	134.5 (3.7)	135.9 (4.1)	135 (4.5)	0.565
Potassium, mEq/L; mean (SD)	4.2 (0.6)	4.1 (0.5)	4.2 (0.4)	0.310
NT-proBNP, pg/ml; mean (SD)	235.5 (151)	225.7 (145.1)	356.7 (170.9)	**<0.001**
Hemoglobin, mg/dl; mean (SD)	11.2 (1.5)	11.3 (1.5)	10.9 (1.8)	0.129
Platelet count,10^3/dL; mean (SD)	222.7 (78.2)	223.2 (74.7)	216.7 (113.4)	0.643

Values are given as numbers (n) and percentages (%), mean±standard deviation, or median (interquartile range 25th-75th percentiles). Independent Samples t-test or Mann-Whitney U-test was employed to calculate the p-value for continuous data, while the Chi-Square test or Fisher's exact test, as appropriate, was used for categorical variables. *p<0.05 was considered statistical significance. Abbreviations: BMI, body mass index; CAD, coronary artery disease; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease; CVE, cerebrovascular event; DBP, diastolic blood pressure, DM, diabetes mellitus; GRACE score, Global Registry of Acute Coronary Events score; HT, hypertension; HL, hyperlipidemia; HR, heart rate; IQR, inter-quantile range; NT-proBNP, N-terminal pro-b-type natriuretic peptide; LVEF, left ventricular ejection fraction; PAD, peripheral artery disease; SBP, systolic blood pressure, SD, standard deviation, STS-PROM, Society of Thoracic Surgeons Predicted Risk of Mortality.

performance of the model was further evaluated by calculating the test training error, which resulted in an average difference of 0.052 between the predicted values and the actual values. Even though the difference in the test training error of 0.052 is relatively small, it is crucial to take into account the miscalibration of the model when interpreting

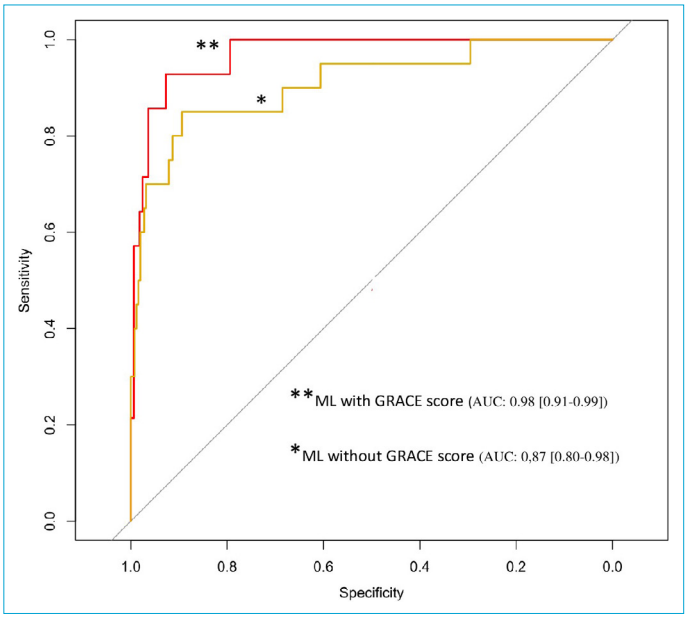

Figure 3. Comparison of receiver operating characteristics curve analyses for XGBoost and conventional logistic regression models.

AUC: Area Under the Curve; GRACE score: Global Registry of Acute Coronary Events score; ML: Machine learning; XGBoost: The Extreme Gradient Boosting.

its predictions, particularly in cases where the actual probability exceeds 30%.

The final DT model resulting from the recursive partitioning analysis aimed at predicting MACE among patients with AS who underwent TAVI generated a structure comprising five layers and eight nodes. Through the analysis, the GRACE score emerged as the most crucial discriminating factor, followed by STS-PROM, age, NT-proBNP, LVEF, and hemoglobin level (Fig. 5).

Discussion

This study highlights the significance of the ML-XGBoost algorithm, incorporating the GRACE score, in predicting the primary endpoint, which encompasses 30-day CVE, MI, and all-cause mortality among patients undergoing TAVI. Furthermore, this advantage was observed in both ML and conventional analyses, incorporating the GRACE score, which provides a more comprehensive assessment of hemodynamic status. To the best of our knowledge, this is the first study to establish the association between the GRACE score and short-term adverse outcomes in symptomatic severe AS patients undergoing TAVI, utilizing robust statistical methodologies.

Accurately predicting mortality following TAVI remains an unresolved challenge. Given the absence of a dedicated risk assessment tool, surgical risk scores have been extensively employed to stratify patient populations in

Table 2. Performances of conventional binomial logistic regression and machine learning models

	AUC	R squared
XGBoost	0.98 (0.91-0.99)	0.64
XGBoost (without GRACE score)	0.87 (0.80-0.98)	0.59
Logistic regression	0.84 (0.79-0.96)	0.49
Logistic regression (without GRACE score)	0.83 (0.75-0.96)	0.42

AUC: Area Under the Curve; GRACE score: Global Registry of Acute Coronary Events score; XGBoost: Extreme Gradient Boosting.

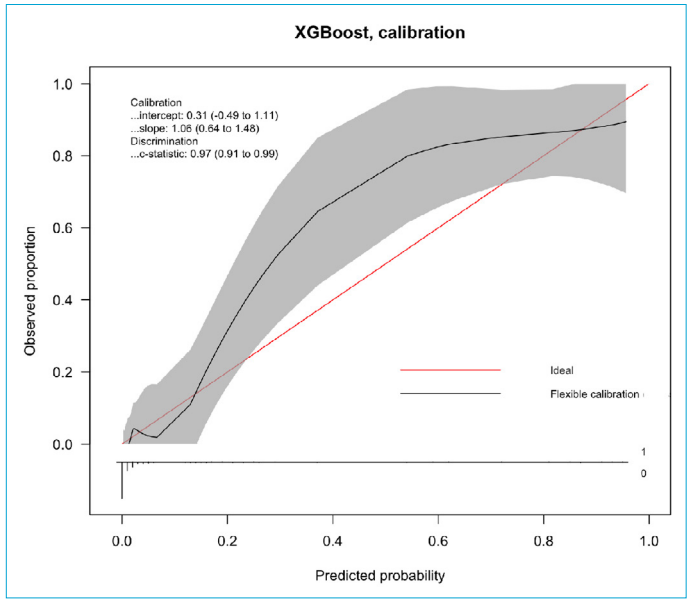

Figure 4. Calibration plot of XGBoost model.

XGBoost: The Extreme Gradient Boosting.

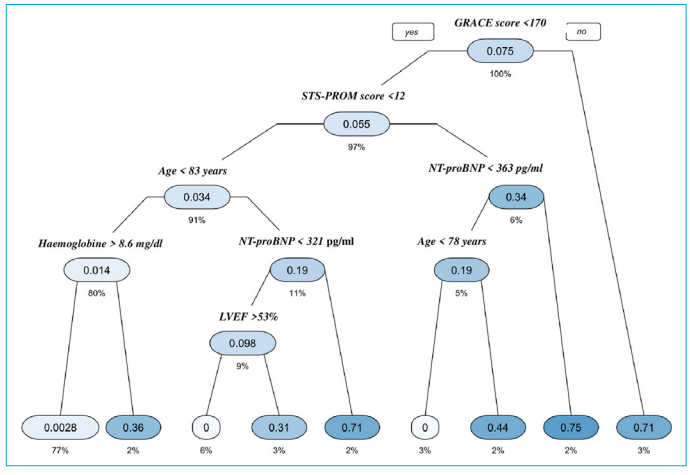

Figure 5. Decision tree model for improved prediction of the primary endpoint.

GRACE score: Global Registry of Acute Coronary Events score; NT-proBNP: N-terminal pro-b-type natriuretic peptide; LVEF: left ventricular ejection fraction; STS-PROM: Society of Thoracic Surgeons Predicted Risk of Mortalit.

randomized controlled clinical trials comparing sAVR with TAVI. These scores have also been suggested by European guidelines for evaluating surgical risk in individuals with severe AS.[18,23,24] However, there remains a need for a specific risk assessment tool that could reliably predict the poor outcome following TAVI. Furthermore, these existing risk assessment schemes do not adequately consider the presence of multiple comorbidities in TAVI patients. This limitation diminishes their ability to accurately predict outcomes and poses challenges in their application within this specific context. Previous studies have made attempts to develop various methods for early and long-term risk stratification following TAVI; however, their performance has been limited. These studies have primarily focused on high-risk patients within the target population and have included demographic characteristics, comorbidities, and certain laboratory values. Nevertheless, we have observed that these studies have not adequately included crucial parameters that reflect the hemodynamic and myocardial status of the patients.

The inclusion of the GRACE score, which involves parameters reflecting the hemodynamic and myocardial status such as age, heart rate, blood pressure, creatinine levels and ST-segment changes on electrocardiograms, may prove to be effective in predicting major cardiac events in patients undergoing TAVI. The GRACE score was initially developed in 2004 using data from the GRACE registry, which consisted of 17,142 patients across 94 hospitals and 14 countries. Its purpose was to aid in the classification of patients with ACS by predicting their 6-month mortality or probability of myocardial infarction.[25] This scheme differs from the scoring systems specifically developed to predict the prognosis of patients undergoing TAVI, as it integrates hemodynamic factors such as HR, SBP, troponin levels, and ST-segment changes. In severe symptomatic AS, there is an observed increase in myocardial stress due to progressive pressure overload, which subsequently leads to compensatory left ventricular hypertrophy. This progressive hypertrophy and accompanying diastolic dysfunction contribute to an elevation in left ventricular end-diastolic pressure. Increased end-diastolic pressure results in impaired perfusion flow within the coronary vasculature, leading to the compression of small intramyocardial arteries and impaired coronary reserve. This phenomenon disrupts the balance between myocardial oxygen demand and supply, which may trigger ischemia during physical exertion.[26,27] As a compensatory mechanism, an elevated HR may be observed both at rest and during physical exertion in patients with severe AS. A higher resting HR has been associated with an increased risk of adverse cardiovascular events, including cardiovascular death, the need for aortic valve replacement, and hospitalization due to heart failure.[28] Moreover, the reduced coronary oxygen supply resulting from tachycardia may lead to elevated troponin levels, indicating myocardial damage in individuals with AS. Elevated initial troponin levels may serve as an indicator of underlying heart damage, and numerous studies have demonstrated a poor prognosis in patients with high initial troponin levels.[29,30] For example, in a prospective study involving 1390 patients with severe symptomatic AS who underwent TAVI with various interventional approaches and device types, pre-procedure troponin levels were found to be associated with 30-day mortality and were identified as an independent predictor of 1-year mortality.[31] Furthermore, post-procedure troponin elevation was independently predictive of 1-year mortality, with a more pronounced effect observed in patients who had normal or nearly normal troponin levels before the procedure.[32] Electrocardiographic alterations, similar to troponin values, act as indicators of myocardial damage and remodeling in AS. The physiological and anatomical changes that occur in the left ventricle can lead to the development of arrhythmias, which further disrupt the hemodynamic balance. Impaired ventricular conduction and ST-segment deviation are commonly observed alongside ventricular enlargement and thickening. Patients with ST-segment deviation have been found to have increased early mortality rates and poorer pre- and post-TAVI prognosis.[32,33] These electrocardiographic changes reflect the significant impact of AS on the myocardium and highlight the importance of considering them in risk assessment and prognosis prediction.

In the present study, ML analysis using the XGBoost algorithm was implemented, demonstrating high accuracy in decision-making by taking into account some factors such as age, NT-proBNP, LVEF, hemoglobin, creatinine level, STS-PROM score and GRACE score. These variables have previously shown their predictive power in other studies.[34-36] The XGBoost algorithm has been proven to be a successful ML model for risk prediction across various clinical scenarios.[17,37,38] By leveraging these advanced analytical techniques and incorporating well-established prognostic factors, the study aimed to enhance the accuracy and precision of outcome prediction in the context of TAVI patients. Given the complexity of patients undergoing TAVI, ML algorithms offer the advantage of analyzing a substantial number of variables that may be interrelated. Despite the presence of these interrelationships among predictor variables, the validity of the model is not compromised. ML algorithms are capable of handling such complexity; capturing intricate patterns and interactions among variables, ultimately contributing to the robustness and accuracy of the predictive model. Therefore, the inclusion of multiple predictor variables in the model does not affect its validity but rather en-

hances its ability to capture the multifaceted nature of the TAVI patient population.[16,39] Recent studies have demonstrated the superior accuracy and robust predictive capabilities of ML models, particularly in the context of patient risk assessment and MACE prediction during the post-TAVI period.[4,17] Utilizing ML models, these investigations have revealed enhanced precision compared to traditional risk scoring methods. The incorporation of comprehensive datasets, including detailed patient profiles and procedural data, empowers ML algorithms to discern intricate patterns that contribute to more accurate risk ratios. This advancement not only showcases the potential of ML in revolutionizing risk prediction but also underscores its superiority over classical risk scores in the post-TAVI landscape, providing clinicians with valuable tools for more informed decision-making in cardiovascular care.[4,17,40] Our study findings too support current studies, and the XGBoost model that added the GRACE score demonstrated higher accuracy in short-term MACE prediction compared to the traditional regression model.

Limitation

Several significant limitations in this study warrant acknowledgment. Firstly, it is important to note that this is a retrospective, non-randomized study. Nevertheless, consecutive patient recruitment was employed to mitigate the impact of selection bias resulting from the absence of randomization. Although numerous clinical and laboratory parameters have been assessed for predicting MACE TAVI, certain factors, such as vulnerability and cognitive status, as emphasized in prior studies, were not evaluated. Moreover, the ML model with the GRACE score was not compared with prognostic risk schemes such as EuroSCORE-II, OBSERVANT score, France-2 risk score, and Core Valve score, which have demonstrated predictive capability in recent research. It is crucial to acknowledge that ML models rely on extensive datasets, and the accuracy of their predictions is closely tied to the breadth and depth of the data used for training. Consequently, when implementing ML models in clinical practice, meticulous attention must be paid to factors such as the quantity and diversity of data, as well as the presence of any biases.

Conclusion

The present study proposes that ML techniques hold promise for enhancing clinical outcomes, particularly when used in conjunction with existing tools such as the GRACE score. However, further research is required to validate these findings and assess the potential advantages and limitations associated with the integration of ML models into clinical practice.

Disclosures

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