Journal of the American Heart Association

ORIGINAL RESEARCH

Using Machine Learning to Predict Outcomes Following Thoracic and Complex Endovascular Aortic Aneurysm Repair

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BACKGROUND: Thoracic endovascular aortic repair (TEVAR) and complex endovascular aneurysm repair (EVAR) are complex procedures that carry a significant risk of complications. While risk prediction tools can aid in clinical decision making, they remain limited. We developed machine learning algorithms to predict outcomes following TEVAR and complex EVAR.

METHODS: The Vascular Quality Initiative database was used to identify patients who underwent elective TEVAR and complex EVAR for noninfrarenal aortic aneurysms between 2012 and 2023. We extracted 172 features from the index hospitalization, including 93 preoperative (demographic/clinical), 46 intraoperative (procedural), and 33 postoperative (in-hospital course/complications) variables. The primary outcome was 1-year thoracoabdominal aortic aneurysm life-altering event, defined as new permanent dialysis, new permanent paralysis, stroke, or death. The data were split into training (70%) and test (30%) sets. We trained 6 machine learning models using preoperative features with 10-fold cross-validation. Model robustness was evaluated using calibration plots and Brier scores.

RESULTS: Overall, 10 738 patients underwent TEVAR or complex EVAR, with 1485 (13.8%) experiencing 1-year thoracoabdominal aortic aneurysm life-altering event. Extreme Gradient Boosting was the best preoperative prediction model, achieving an area under the receiver operating characteristic curve of 0.96 (95% CI, 0.95–0.97), compared with 0.70 (95% CI, 0.68–0.72) for logistic regression. The Extreme Gradient Boosting model maintained excellent performance at the intra- and postoperative stages, with areas under the receiver operating characteristic curves of 0.97 (95% CI, 0.96–0.98) and 0.98 (95% CI, 0.97–0.99), respectively. Calibration plots indicated good agreement between predicted/observed event probabilities, with Brier scores of 0.09 (preoperative), 0.08 (intraoperative), and 0.05 (postoperative).

CONCLUSIONS: Machine learning models can accurately predict 1-year outcomes following TEVAR and complex EVAR, performing better than logistic regression.

Key Words: complex endovascular aneurysm repair (EVAR) ■ machine learning ■ outcome ■ prediction ■ thoracic endovascular aortic repair (TEVAR) ■ thoracoabdominal aortic aneurysm life-altering event (TALE)

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This manuscript was sent to Shaan Khurshid, MD, MPH, Assistant Editor, for review by expert referees, editorial decision, and final disposition.

This work was presented at the Society for Vascular Surgery Annual Meeting, June 19–22, 2024, in Chicago, IL.

Supplemental Material is available at https://www.ahajournals.org/doi/suppl/10.1161/JAHA.124.039221

For Sources of Funding and Disclosures, see page 16.

JAHA is available at: www.ahajournals.org/journal/jaha

CLINICAL PERSPECTIVE

What Is New?

- Using data from 10 738 patients who underwent thoracic endovascular aortic repair or complex endovascular aneurysm repair in the Vascular Quality Initiative database, we developed robust machine learning models that accurately predict 1-year postoperative outcomes.
- Our machine learning models achieved an area under the receiver operating characteristic curve of 0.96 for predicting the primary outcome of 1-year thoracoabdominal aortic aneurysm life-altering events using preoperative data, performing better than logistic regression (area under the receiver operating characteristic curve, 0.70).

What Are the Clinical Implications?

- The machine learning tools developed through this study have potential for important utility in guiding risk-mitigation strategies for patients being considered for thoracic endovascular aortic repair or complex endovascular aneurysm repair to improve outcomes.

Nonstandard Abbreviations and Acronyms

EVAR	endovascular aneurysm repair
ML	machine learning
SVS	Society for Vascular Surgery
TAAA	thoracoabdominal aortic aneurysm
TALE	thoracoabdominal aortic aneurysm life-altering event
TEVAR	thoracic endovascular aortic repair
VQI	Vascular Quality Initiative
XGBoost	Extreme Gradient Boosting

Thoracic endovascular aortic repair (TEVAR) and complex endovascular aneurysm repair (EVAR) are increasingly common treatment options for noninfrarenal abdominal aortic aneurysms (AAAs).[1,2] These procedures are anatomically and technically challenging, generally requiring treatment of aortic branch vessels.[3] Patel et al evaluated the risk of complications following TEVAR and complex EVAR in the Vascular Quality Initiative (VQI) database from 2011 to 2022, demonstrating 1-year postprocedural thoracoabdominal aortic aneurysm life-altering event (TALE; composite of death, dialysis, paralysis, or stroke) rates of up to 14%.[4] Although TALE was originally used to describe life-altering events after repair of thoracoabdominal aortic aneurysms (TAAAs) by Rocha and colleagues,[5] this composite outcome has been demonstrated to be useful in assessing outcomes following TEVAR and complex EVAR regardless of the location and extent of aortic repair.[4] Given the significant death/morbidity rates associated with these procedures, careful preoperative risk assessment is critical when considering patients for aortic intervention, as recommended by the Society for Vascular Surgery (SVS) and European Society for Vascular Surgery guidelines.[6,7]

Currently, there are no widely used tools to support prediction of complications following TEVAR and complex EVAR. Most risk prediction models are limited to the treatment of infrarenal AAA.[8] For example, the SVS VQI Cardiac Risk Index is limited to predicting in-hospital myocardial infarction after infrarenal EVAR and open AAA repair and does not include TEVAR or complex EVAR.[9] Other tools, such as the National Surgical Quality Improvement Program online surgical risk calculator, rely on modeling techniques that require manual input of clinical variables, which can be challenging in busy medical environments.[10] Consequently, there is an important need for the development of more effective and user-friendly risk prediction tools for patients being considered for TEVAR and complex EVAR.

Machine learning (ML) is a rapidly advancing technology that enables computers to learn from large data sets and make accurate predictions.[11] This progress is fueled by the surge in electronic data and enhanced computational power.[12] For instance, Bonde and colleagues utilized National Surgical Quality Improvement Program data to develop ML algorithms that predict perioperative complications across a diverse data set of >2900 unique procedures, including abdominal, thoracic, neurologic, and extremity interventions.[13] Given the heterogeneity of this data set, more accurate predictions may be achieved by creating ML algorithms tailored specifically for patients undergoing TEVAR and complex EVAR using the VQI database, a dedicated vascular registry containing highly granular and procedure-specific variables.[14] We previously described VQI-based ML algorithms for predicting outcomes following infrarenal EVAR[15] and open AAA repair,[16] demonstrating superior performance compared with traditional statistical methods like logistic regression. The development of an ML-based risk prediction algorithm for TEVAR and complex EVAR would complement these existing algorithms and expand clinical guidance for patients being considered for advanced aortic interventions. In this study, we used VQI data to develop ML algorithms aimed at predicting 1-year TALE following TEVAR and complex EVAR at the pre-, intra-, and postoperative stages.

METHODS

Code Availability Statement

The complete code used for model development and evaluation in this project is publicly available on GitHub: https://github.com/benli12345/TEVAR-ML-VQI.

Data Availability Statement

The data used for this study come from the VQI Database, which is maintained by the Society for Vascular Surgery Patient Safety Organization. Access and use of the data requires approval through an application process available at https://www.vqi.org/data-analysis/.

Study Approval

The SVS Patient Safety Organization Research Advisory Council approved this project and supplied the anonymized data set. Patient consent was not required since the data were sourced from an anonymized registry.

Design

This was an ML-based prognostic study with findings reported according to the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis + Artificial Intelligence statement.[17]

Data Set

The VQI database is a clinical registry managed by the SVS Patient Safety Organization, aimed at enhancing vascular care (www.vqi.org).[14] Vascular surgeons, interventionalists, and other specialists from >1000 academic and community hospitals across the United States, Canada, and Singapore contribute demographic, clinical, and outcomes data on consecutive eligible patients on vascular care. These data include information from their initial procedure and extends up to about 1 year of follow-up.[18] Routine audits are conducted to compare submitted data with hospital claims to ensure accuracy.[19]

Patient Cohort

All patients who underwent TEVAR and complex EVAR for noninfrarenal aortic aneurysms from March 1, 2012, to October 3, 2023, in the VQI database were included. TEVAR included repair of the descending thoracic aorta without any renal or visceral vessel incorporation (proximal aortic zones 2–5 and distal aortic zones 2–5) and arch repair (proximal aortic zones 0–1 and distal aortic zones 0–1).[4] Complex EVAR included repair of juxtarenal, pararenal, and suprarenal AAAs and extent IV TAAAs with at least 1 scallop, fenestration, branch, or parallel grafting (chimney, snorkel, periscope, or sandwich techniques) into a renal or visceral artery (proximal aortic zones 6–8 and distal aortic zones 9–11) and extent I to III TAAAs (proximal aortic zones 2–5 and distal aortic zones 6–11).[4] Patients who underwent repair for nonaneurysmal pathology (ie, dissection, penetrating aortic ulcer, intramural hematoma, aortic thrombus, or trauma), presented with ruptured or symptomatic aneurysm, required conversion to open repair, or had no reporting of the proximal or distal landing zones or symptom status were excluded. The reason for these exclusion criteria was to establish a cohort of patients undergoing elective TEVAR and complex EVAR for aneurysmal pathology. TEVAR and complex EVAR were combined because VQI provides a single registry for these procedures. To maximize sample size and event rates critical for robust ML model training, these procedures were combined for model development. Although this approach may increase heterogeneity of the cohort, model performance specific to TEVAR and complex EVAR was investigated separately through subgroup analyses to determine clinical utility on the basis of procedure type.

Features

Predictive features used in the ML models were categorized into pre-, intra-, and postoperative variables. To leverage the strengths of ML in managing numerous input features, all available VQI variables were used to enhance predictive performance. Preoperative features (n=92) included demographics, comorbidities, previous procedures, functional status, investigations (hemoglobin, creatinine, cardiac stress test results, ejection fraction), medications, and anatomy including maximum aortic diameter, aneurysm type, procedure type, proximal/distal landing zones, repair technique, device type, and planned treatment of branch vessels. Intraoperative features (n=46) included type of anesthesia, access details, adjunctive procedures, completion endoleaks, estimated blood loss, intraoperative transfusion of packed red blood cells and crystalloids, contrast volume, fluoroscopy time, and procedure time. Postoperative features (n=33) included in-hospital characteristics: time to extubation, need for vasopressor support, spinal drain insertion, access site complications, myocardial infarction, dysrhythmia, congestive heart failure exacerbation, respiratory complication, arm or leg ischemia, leg compartment syndrome, bowel ischemia, length of stay in the intensive care unit and hospital, discharge medications, and nonhome discharge. A complete list of features and their definitions can be found in Tables S1 through S3.

Outcomes

The primary outcome was 1-year postprocedural TALE (composite of new permanent dialysis, new

permanent paralysis, stroke, or death). New permanent dialysis was defined as the need for dialysis at 1-year of follow-up in a patient who was not dialysis dependent before repair.[4] New permanent paralysis was defined as a lack of palpable muscle contraction in at least 1 lower extremity at 1 year of follow-up in a patient who did not have paralysis before repair.[4] Stroke was defined as any new motor or sensory loss, speech abnormality, or other neurologic deficits related to the right or left cerebral hemisphere lasting ≥24 hours.[4] Death was defined as all-cause death.[4] This primary outcome was chosen because it is a composite of major complications that have a significant impact on patients' lives following TEVAR and complex EVAR and recently described by multiple groups for its relevance to these specific procedures.[4,5] Secondary outcomes were individual components of the primary outcome. These definitions were based on the VQI data dictionary.[14]

Model Development

We trained 6 different ML models to predict primary and secondary outcomes: Extreme Gradient Boosting (XGBoost), random forest, Naïve Bayes classifier, radial basis function support vector machine, multilayer perceptron artificial neural network, and logistic regression. These models were chosen on the basis of their established efficacy in predicting postoperative outcomes using structured data.[20–22] Logistic regression was included as the baseline comparator to evaluate relative model performance because it is the most commonly applied statistical technique in traditional risk prediction tools.[23]

The data were randomly divided into training (70%) and testing (30%) sets, with the testing data reserved exclusively for model evaluation to ensure an unbiased assessment. To identify the optimal hyperparameters for the models, we applied 10-fold cross-validation and grid search to the training data.[24,25] Given that 10-fold cross-validation was applied to the training data, a separate validation data set was not required, as 10% of the training data were iteratively used for model validation.[24] Model optimization was performed only using the 70% training data with 10-fold cross-validation. Specifically, the cross-validation procedure was used to facilitate model training and hyperparameter tuning within the 70% partition.[26] The remaining 30% of test set data was not used for model training nor hyperparameter optimization and was reserved only for model evaluation. Given that 70% of the data was used for model training and 30% of the data was used for model evaluation, all 100% of the data was used in determining the final model. Initial analysis showed that the primary outcome occurred in 1485 of 10 738 patients (13.8%) in our cohort. To improve class balance, Random Over-Sample Examples was applied to training data.[27] Random Over-Sample Examples uses a smoothed bootstrapping technique to create new samples from the feature space surrounding the minority class, a well-established method for enhancing predictive modeling of rare events.[27] The models were evaluated on the test set and ranked on the basis of the primary discriminatory metric: the area under the receiver operating characteristic curve (AUROC). We focused on preoperative predictions, as they offer the greatest potential for mitigating adverse events by guiding decisions on whether to proceed with intervention.[28] The best-performing model was XGBoost, optimized with the following hyperparameters: number of rounds=250, maximum tree depth=3, learning rate=0.2, γ=0, column sample by tree=0.7, minimum child weight=1, and subsample=1. The process for selecting these hyperparameters is detailed in Table S4.

After determining the best-performing ML model at the preoperative stage, we continued training the algorithm with intra- and postoperative data. This method involved incorporating different sets of features at each phase of the perioperative course. At the preoperative stage, only preoperative characteristics were used. During the intraoperative stage, both pre- and intraoperative features were included. At the postoperative stage, the model used all pre-, intra-, and postoperative features. This approach enables clinicians to assess a patient's risk at various stages of the perioperative process, providing valuable insights to inform decision making before, during, and after intervention. This model training method has been previously used, particularly for developing prediction tools for long-term outcomes.[29,30]

Statistical Analysis

Pre-, intra-, and postoperative features were summarized as means±SDs or medians (interquartile ranges) for continuous variables and as numbers (percentages) for categorical variables. Differences between patients with and without 1-year TALE were analyzed using independent *t* tests for continuous variables and χ^2 tests for categorical variables. To address multiple comparisons, we applied the Bonferroni correction to determine statistical significance. The primary evaluation metric for the model was AUROC (95% CI), which measures discriminatory ability by considering both sensitivity and specificity.[31] Secondary performance metrics included accuracy, sensitivity, specificity, positive predictive value, and negative predictive value. Risk thresholds were determined by calculating Youden's index, which optimizes the sensitivity and specificity of a model.[32] To evaluate model robustness, we plotted calibration curves and calculated Brier scores,

which assess the agreement between predicted and observed event probabilities.[33] In the final model, feature importance was assessed by ranking the top 10 predictors on the basis of variable importance scores (gain), which indicate the relative contribution of each covariate to the overall prediction.[34] Feature selection was not performed to generate a more parsimonious model because the goal was to maximize the predictive performance of a model that could provide automated predictions with many clinically relevant input features. To evaluate potential model bias, we assessed predictive performance across various demographic and clinical subgroups, including age, sex, race, ethnicity, rurality, median Area Deprivation Index percentile, procedure type, repair type, and prior aortic interventions. For both training and test sets, missing data were <5%, so we used a complete-case analysis approach, considering only nonmissing covariates for each patient. This method is appropriate for data sets with minimal missing data (<5%) and accurately reflects the nature of real-world data, which often include missing information.[35,36] The models were developed with consideration of real-world performance as a priority. Specifically, no data cleaning was performed, which reflects the often variable and incomplete nature of real-world clinical data.[35,36] Patients lost to follow-up were censored. All analyses were performed using R version 4.3.1 (R Foundation for Statistical Computing, Vienna, Austria).[37]

RESULTS

Patients, Events, and Follow-Up

From an initial cohort of 18 265 patients who underwent TEVAR and complex EVAR for aneurysmal disease in the VQI database between 2012 and 2023, a total of 7527 patients were excluded for the following reasons: ruptured aneurysm (n=746), symptomatic aneurysm (n=2763), conversion to open repair required (n=170), or no reporting of proximal or distal landing zone (n=3793) or symptom status (n=55). The final analysis included 10 738 patients (mean age, 72.6±9.2 years; 3363 [31.3%] women) who underwent the following elective procedures: complex EVAR for juxtarenal, pararenal, and suprarenal AAA and extent IV TAAA (4512 [42.0%]), TEVAR for descending thoracic aortic aneurysm (3014 [28.1%]), extent I to III TAAA repair (2702 [25.2%]), and arch repair (510 [4.7%]). Repair techniques included fenestrated EVAR (8511 [79.3%]), physician modified endograft (1588 [14.8%]), and parallel grafting (639 [6.0%]). Overall, 1485 (13.8%) experienced 1-year TALE. The secondary outcomes occurred in the following distribution: new permanent dialysis (n=198 [1.8%]), new permanent paralysis (n=107 [1.0%]), stroke (n=197 [1.8%]), and death (n=1198 [11.2%]). Mean follow-up was 15.2±1.2 months. Table S5 summarizes the pre-, intra-, and postoperative characteristics of the training (n=7517 [70%]) and test set data (n=3221 [30%]) for the cohort. The event rate for 1-year TALE was the same in both groups: training data (n=1040 [13.8%]) and testing data (n=445 [13.8%]).

Preoperative Characteristics

Compared with patients who did not experience a primary outcome, those who developed 1-year TALE were older and more frequently women, Black individuals, or Asian individuals. They were more likely to be covered by Medicare and to have been transferred from another hospital or rehabilitation unit to the intervention center. Additionally, these patients were more likely to have hypertension, coronary artery disease, congestive heart failure, a history of stroke, and chronic obstructive pulmonary disease, and were more likely to be classified as American Society of Anesthesiologists class ≥4. A greater proportion of patients with an event had previous procedures including open and endovascular aortic interventions, carotid endarterectomy or stent, and bypass and endovascular interventions for peripheral artery disease. Functionally, patients with 1-year TALE were more likely to live in nursing homes and require assisted care. They also had a higher mean creatinine and were more likely to have an ejection fraction <50%, yet less likely to receive acetylsalicylic acid and angiotensin-converting enzyme inhibitors or angiotensin II receptor blockers preoperatively. Anatomically, patients with an outcome had a higher mean maximum aortic diameter and were more likely to have saccular aneurysms and planned proximal landing zones proximal to aortic zone 4 and undergo extent I to III TAAA or arch repair, parallel grafting, and branch treatment of the innominate, left common carotid, left subclavian, celiac, and superior mesenteric arteries (Table 1).

Intraoperative Characteristics

Patients with 1-year TALE were less likely to have antibiotics given within 1 hour of intervention and stopped within 24 hours of intervention and more likely to require iliac, arm/neck, and open femoral access and intraoperative intravascular ultrasound or transthoracic echocardiogram. They were also more likely to have an injury to the access artery and type Ia, Ib, and indeterminant completion endoleaks and less likely to have successful technical deployment of the aortic device(s). Patients with an event had a higher median estimated blood loss, mean number of units of packed red blood cells transfused intraoperatively, median volume of crystalloids administered intraoperatively, median volume of contrast given, median fluoroscopy time, and median procedure time (Table 2).

Table 1. Preoperative Demographic and Clinical Characteristics of Patients Undergoing Thoracic and Complex Endovascular Aortic Aneurysm Repair With and Without 1-Year TALE

	Absence of 1-y TALE (n=9253)	Presence of 1-y TALE (n=1485)	*P* value
Demographics			
Age, y, mean±SD	72.3±9.3	74.2±8.6	<0.001
Female	2815 (30.4)	548 (36.9)	<0.001
BMI, kg/m^2, mean±SD	27.8±5.7	26.3±6.1	<0.001
Race			
American Indian or Alaskan Native	23 (0.2)	4 (0.3)	0.02
Asian	224 (2.4)	49 (3.3)	
Black	885 (9.6)	168 (11.3)	
Native Hawaiian or other Pacific Islander	10 (0.1)	4 (0.3)	
White	7526 (81.3)	1174 (79.1)	
>1 race	33 (0.4)	1 (0.07)	
Unknown/other	552 (6.0)	85 (5.7)	
Hispanic ethnicity	350 (3.8)	43 (2.9)	0.11
Insurance status			
Medicare	4752 (51.4)	873 (58.8)	<0.001
Medicaid	283 (3.1)	45 (3.0)	
Commercial	2392 (25.9)	321 (21.6)	
Military/Veterans Affairs	346 (3.7)	50 (3.4)	
Non-US insurance	367 (4.0)	72 (4.9)	
Self-pay (uninsured)	63 (0.7)	2 (0.1)	
Unknown/other	1050 (11.3)	122 (8.2)	
Rural residence	279 (3.0)	49 (3.3)	0.61
Area deprivation index percentile, median (IQR)	52 (30–70)	52 (32–73)	0.78
Transfer status			
From another hospital	229 (2.5)	74 (5.0)	<0.001
From rehabilitation unit	3 (0.03)	6 (0.4)	
Comorbidities			
Smoking status			
Never	1436 (15.5)	213 (14.3)	0.32
Prior	5062 (54.7)	806 (54.3)	
Current	2755 (29.8)	466 (31.4)	
Hypertension	8191 (88.5)	1354 (91.2)	<0.001
Diabetes	1665 (18.0)	268 (18.0)	0.41
Coronary artery disease	2357 (25.5)	414 (27.9)	0.02
Congestive heart failure	1369 (14.8)	322 (21.7)	<0.001
Previous stroke	1105 (11.9)	239 (16.1)	<0.001
Chronic obstructive pulmonary disease			
Not treated	926 (10.0)	163 (11.0)	<0.001
On medications	1979 (21.4)	422 (28.4)	
On home oxygen	504 (5.5)	139 (9.4)	
Connective tissue disease	247 (2.7)	42 (2.8)	0.73
ASA class			
1	13 (0.1)	0	<0.001
2	202 (2.2)	10 (0.7)	
3	5283 (57.1)	670 (45.1)	
4	3731 (40.3)	802 (54.0)	
5	7 (0.08)	0	
Not reported	17 (0.02)	3 (0.2)	

(*Continued*)

Table 1. Continued

	Absence of 1-y TALE (n=9253)	Presence of 1-y TALE (n=1485)	*P* value
Previous procedures			
Aortic intervention	2499 (27.0)	488 (32.8)	<0.001
Open	1176 (12.7)	220 (14.8)	
Endovascular	1089 (11.8)	219 (14.7)	
Both	234 (2.5)	49 (3.3)	
Open ascending/arch repair	791 (8.6)	115 (7.7)	0.32
Open descending thoracic aortic repair	198 (2.1)	33 (2.2)	0.92
Open suprarenal aortic repair	89 (1.0)	26 (1.8)	0.009
Open infrarenal aortic repair	514 (5.6)	125 (8.4)	<0.001
Endovascular ascending/arch repair	162 (1.8)	32 (2.2)	0.33
Endovascular descending thoracic aortic repair	489 (5.3)	86 (5.8)	0.46
Endovascular suprarenal aortic repair	116 (1.3)	26 (1.8)	0.15
Endovascular infrarenal aortic repair	739 (8.0)	168 (11.3)	<0.001
Coronary artery bypass graft	1428 (15.5)	238 (16.1)	0.70
Percutaneous coronary intervention	1863 (20.2)	318 (21.4)	0.27
Carotid endarterectomy or stent	375 (4.1)	86 (5.8)	0.01
Bypass for peripheral artery disease	560 (6.1)	111 (7.5)	0.04
Endovascular intervention for peripheral artery disease	583 (6.3)	148 (10.0)	<0.001
Major amputation	42 (0.5)	13 (0.9)	0.11
Functional status			
Living status			
Home	9188 (99.3)	1447 (97.4)	<0.001
Nursing home	55 (0.6)	36 (2.4)	
Homeless	10 (0.1)	2 (0.1)	
Functional status			
Full	5821 (62.9)	730 (49.2)	<0.001
Light work	2142 (23.1)	388 (26.1)	
Self-care	1135 (12.3)	280 (18.9)	
Assisted care	148 (1.6)	81 (5.5)	
Bed bound	7 (0.08)	6 (0.4)	
Investigations			
Hemoglobin, g/L, mean±SD	130.0 (22.5)	122.0 (21.2)	<0.001
Creatinine, umol/L, mean±SD	100.0 (56.1)	113.0 (62.7)	<0.001
Cardiac stress test			
Not done	5518 (59.6)	875 (58.9)	0.29
Normal	2976 (32.2)	471 (31.7)	
Positive for ischemia	350 (3.8)	71 (4.8)	
Positive for infarction	310 (3.4)	47 (3.2)	
Positive for ischemia and infarction	99 (1.1)	21 (1.4)	
Ejection fraction			
<30%	172 (1.9)	53 (3.6)	<0.001
30%–50%	1050 (11.3)	224 (15.1)	
>50%	5256 (56.8)	867 (58.4)	
Not done	2188 (23.6)	251 (16.9)	
Unknown	587 (6.3)	90 (6.1)	
Medications			
Acetylsalicylic acid	6116 (66.1)	944 (63.6)	0.04
$P2Y_{12}$ antagonist	1364 (14.7)	228 (15.4)	0.07
Statin	6811 (73.6)	1079 (72.7)	0.48
β blocker	5998 (64.8)	1036 (69.8)	<0.001

(*Continued*)

Table 1. Continued

	Absence of 1-y TALE (n=9253)	Presence of 1-y TALE (n=1485)	*P* value
ACE-I/ARB	4396 (47.5)	654 (44.0)	0.03
Anticoagulant	1378 (14.9)	229 (15.4)	0.96
Anatomic characteristics			
Maximum aortic diameter, cm, mean±SD	6.0 (1.1)	6.3 (1.3)	<0.001
Aneurysm type			
Degenerative, fusiform	6776 (73.2)	1002 (67.5)	<0.001
Degenerative, saccular	1395 (15.1)	277 (18.7)	
Anastomotic	114 (1.2)	19 (1.3)	
Intercostal or visceral patch	32 (0.3)	5 (0.3)	
Not reported	936 (10.1)	182 (12.3)	
Procedure type			
Complex EVAR for juxtarenal, pararenal, and suprarenal AAA and extent IV TAAA	4023 (43.5)	489 (32.9)	<0.001
TEVAR for descending thoracic aortic aneurysm	2608 (28.2)	406 (27.3)	
Extent I–III TAAA repair	2235 (24.2)	467 (31.4)	
Arch repair	387 (4.2)	123 (8.3)	
Proximal landing zone			
0	203 (2.2)	55 (3.7)	<0.001
1	184 (2.0)	68 (4.6)	
2	1024 (11.1)	187 (12.6)	
3	1386 (15.0)	263 (17.7)	
4	1042 (11.3)	199 (13.4)	
5	1391 (15.0)	224 (15.1)	
6	808 (8.7)	113 (7.6)	
7	1833 (19.8)	221 (14.9)	
8	1382 (14.9)	155 (10.4)	
Distal landing zone			
0	9 (0.1)	1 (0.07)	<0.001
1	4 (0.04)	0	
2	16 (0.2)	9 (0.6)	
3	159 (1.7)	24 (1.6)	
4	692 (7.5)	134 (9.0)	
5	2072 (22.4)	351 (23.6)	
6	258 (2.8)	76 (5.1)	
7	111 (1.2)	20 (1.4)	
8	169 (1.8)	41 (2.8)	
9	2086 (22.5)	315 (21.2)	
10	3549 (38.4)	488 (32.9)	
11	128 (1.4)	26 (1.8)	
Repair technique			
Fenestrated EVAR	7355 (79.5)	1156 (77.8)	<0.001
Physician modified endograft	1396 (15.1)	192 (12.9)	
Parallel grafting*	502 (5.4)	137 (9.2)	
Device type			
Off-the-shelf	5447 (58.9)	954 (64.2)	<0.001
Custom designed by manufacturer	2410 (26.0)	339 (22.8)	
Physician modified	1396 (15.1)	192 (12.9)	
Aortic branches treated†			
Innominate	279 (3.0)	74 (5.0)	<0.001
Left common carotid	487 (5.3)	147 (9.9)	<0.001

(*Continued*)

Table 1. Continued

	Absence of 1-y TALE (n=9253)	Presence of 1-y TALE (n=1485)	*P* value
Left subclavian	1505 (16.3)	328 (22.1)	<0.001
Celiac	3574 (38.6)	711 (47.9)	<0.001
Superior mesenteric	5142 (55.6)	877 (59.1)	0.01
Right renal	6156 (66.5)	977 (65.8)	0.60
Left renal	6156 (66.5)	977 (65.8)	0.60
Right common iliac	4178 (45.2)	618 (41.6)	0.01
Left common iliac	3748 (40.5)	546 (36.8)	0.007

Values are reported as n (%) unless otherwise indicated. AAA indicates abdominal aortic aneurysm; ACE-I, angiotensin converting enzyme inhibitor; ARB, angiotensin II receptor blocker; ASA, American Society of Anesthesiologists; BMI, body mass index; EVAR, endovascular aneurysm repair; IQR, interquartile range; TAAA, thoracoabdominal aortic aneurysm; TALE, thoracoabdominal aortic aneurysm life-altering event; and TEVAR, thoracic endovascular aortic repair.

Other race indicates a patient's self-reported race other than the following: American Indian or Alaskan Native, Asian, Black, Native Hawaiian or other Pacific Islander, or White.

*Parallel grafting includes chimney, snorkel, periscope, and sandwich configurations.

†Branch treatment includes coverage, occlusion (ie, coil/plug), stent, stent-graft, chimney, scallop, fenestration, fenestration branch, side-arm branch, surgical bypass, thromboembolectomy, or iliac device.

Postoperative Characteristics

A greater proportion of patients with 1-year TALE were extubated >12 hours after intervention, required vasopressor support, and had a spinal drain inserted. They were also more likely to experience in-hospital complications such as access site hematoma, occlusion, and infection, myocardial infarction, dysrhythmia, congestive heart failure exacerbation, respiratory complication, arm ischemia, leg ischemia, leg compartment syndrome, and bowel ischemia. Patients with an event had a longer median length of stay in the intensive care unit and total hospital length of stay and were more likely to have a nonhome discharge. Despite these complications, they were less likely to receive acetylsalicylic acid, $P2Y_{12}$ antagonists, statins, angiotensin-converting enzyme inhibitors/angiotensin II receptor blockers, and β blockers at discharge (Table 3).

Model Performance

Among the 6 ML models evaluated at the preoperative stage using test set data, XGBoost demonstrated the best performance in predicting 1-year TALE, with an AUROC of 0.96 (95% CI, 0.95–0.97). In comparison, the AUROCs for the other models were as follows: random forest (0.95 [95% CI, 0.94–0.96]), Naïve Bayes (0.88 [95% CI, 0.87–0.90]), radial basis function support vector machine (0.84 [95% CI, 0.83–0.86]), multilayer perceptron artificial neural network (0.80 [95% CI, 0.78–0.82]), and logistic regression (0.70 [95% CI, 0.68–0.72]). The secondary performance metrics for XGBoost were the following: accuracy, 0.89 (95% CI, 0.88–0.90); sensitivity, 0.89; specificity, 0.89; positive predictive value, 0.90; and negative predictive value, 0.89. A summary of model performance results is provided in Table 4.

We further refined the XGBoost model by incorporating intra- and postoperative data. This addition marginally enhanced performance, achieving AUROCs of 0.97 (95% CI, 0.96–0.98) for intraoperative data and 0.98 (95% CI, 0.97–0.99) for postoperative data. The ROC curves are shown in Figure 1. Calibration plots in Figure 2A through 2C illustrate good agreement between predicted and observed event probabilities, with Brier scores of 0.09 for preoperative, 0.08 for intraoperative, and 0.05 for postoperative data. XGBoost also predicted individual components of the primary outcome with AUROC ranges of 0.94 to 0.96 (preoperative), 0.95 to 0.97 (intraoperative), and 0.97 to 0.98 (postoperative) (Table 5).

The top 10 predictors of 1-year TALE in the final XGBoost model included 7 preoperative features (proximal landing zone, functional status, procedure type [arch repair and extent I–III TAAA repair], chronic obstructive pulmonary disease, previous stroke, congestive heart failure, and prior aortic intervention), 1 intraoperative feature (total procedure time), and 2 postoperative features (nonhome discharge and acetylsalicylic acid on discharge) (Figure 3).

Subgroup Analysis

Model performance remained robust across various demographic and clinical subgroups, including age, sex, race, ethnicity, rurality, median Area Deprivation Index percentile, procedure type, repair type, and prior aortic interventions. AUROCs ranged from 0.95 to 0.97, with no significant differences observed between majority and minority groups (Figures S1 through S9).

Table 2. Intraoperative Characteristics of Patients Undergoing Thoracic and Complex Endovascular Aortic Aneurysm Repair With and Without 1-Year TALE

	Absence of 1-y TALE (n=9253)	Presence of 1-y TALE (n=1485)	*P* value
Anesthesia			
Local	132 (1.4)	25 (1.7)	0.44
Regional	49 (0.5)	11 (0.7)	
General	9072 (98.0)	1449 (97.6)	
Antibiotics given within 1 h of intervention	8693 (93.9)	1391 (93.7)	0.05
Antibiotics stopped within 24 h of intervention	8455 (91.4)	1313 (88.4)	<0.001
Right-sided access			
None	822 (8.9)	152 (10.2)	<0.001
Percutaneous femoral	6372 (68.9)	905 (60.9)	
Open femoral	1999 (21.6)	403 (27.1)	
Iliac	60 (0.6)	25 (1.7)	
Left-sided access			
None	1971 (21.3)	381 (25.7)	<0.001
Percutaneous femoral	5762 (62.3)	798 (53.7)	
Open femoral	1475 (15.9)	294 (19.8)	
Iliac	45 (0.5)	12 (0.8)	
Arm or neck access			
None	7057 (76.3)	971 (65.4)	<0.001
For branch treatment	1350 (14.6)	328 (22.1)	
For femoral–brachial wire	399 (4.3)	78 (5.3)	
For both	447 (4.8)	108 (7.3)	
Arm or neck access location			
None	7057 (76.3)	971 (65.4)	<0.001
Right arm	228 (2.5)	46 (3.1)	
Left arm	1018 (11.0)	200 (13.5)	
Right axillary	180 (2.0)	56 (3.8)	
Left axillary	538 (5.8)	144 (9.7)	
Right carotid	12 (0.1)	3 (0.2)	
Left carotid	137 (1.5)	27 (1.8)	
Multiple	83 (0.9)	38 (2.6)	
Intravascular ultrasound or transthoracic echocardiogram			
None	6814 (73.6)	1028 (69.2)	<0.001
Intravascular ultrasound	2070 (22.4)	366 (24.6)	
Transthoracic echocardiogram	201 (2.2)	61 (4.1)	
Both	168 (1.8)	30 (2.0)	
Injury to access artery*	444 (4.8)	148 (10.0)	<0.001
Technical success of aortic device deployment†	8901 (96.2)	1411 (95.0)	0.04
Completion endoleak			
Type Ia	279 (3.0)	61 (4.1)	0.03
Type Ib	151 (1.6)	37 (2.5)	0.03
Type Ic‡	63 (0.7)	17 (1.1)	0.08
Type II	1008 (10.9)	127 (8.6)	0.007
Type III	248 (2.7)	32 (2.2)	0.28
Type IV	110 (1.2)	16 (1.1)	0.81
Indeterminate	292 (3.2)	67 (4.5)	0.009
Estimated blood loss, mL, median (IQR)	150 (50–300)	250 (100–500)	<0.001
Intraoperative transfusion of packed red blood cells, units, mean±SD	0.3±0.1	1.6±0.4	<0.001
Intraoperative administration of crystalloids, mL, median (IQR)	1843 (1250–2500)	2000 (1300–3000)	<0.001
Total contrast volume, mL, median (IQR)	107 (72–150)	112 (75–164)	<0.001
Total fluoroscopy time, min, median (IQR)	41.0 (20.8–68.0)	42,2 (21.5–77.8)	<0.001
Total procedure time, min, median (IQR)	185 (120–260)	226 (135–320)	<0.001

Values are reported as n (%) unless otherwise indicated. IQR indicates interquartile range; and TALE, thoracoabdominal aortic aneurysm life-altering event.

*Includes dissection, thromboembolism, pseudoaneurysm, and stenosis.

†Successful delivery to intended implantation site with absence of device deformations (kinks, stent eversion, maldeployment, or misaligned deployment) and inadvertent covering of aortic branch vessels followed by successful withdrawal of delivery system.

‡Type 1c endoleak at a fenestration, branch end point, or branch occluding plug/coil.

DISCUSSION

Summary of Findings

We used data from a large clinical registry (VQI) consisting of 10 738 patients who underwent elective TEVAR or complex EVAR for noninfrarenal aortic aneurysms to develop ML models that accurately predict 1-year postprocedural TALE with AUROC's exceeding 0.90. Several key findings emerged from our study. First, patients who develop adverse events following TEVAR or complex EVAR are a high-risk population with predictive features at the pre-, intra-, and postoperative stages. ML modeling enabled us to evaluate the cumulative impact of these factors on the risk of complications. Second, we assessed 6 ML models and found that XGBoost achieved the best performance. This algorithm demonstrated excellent discrimination and calibration throughout the pre-, intra-, and postoperative stages and maintained robust predictive performance across various demographic and clinical subpopulations. Third, while intra- and postoperative factors contributed to long-term risk, most of the top 10 predictors for 1-year TALE were preoperative features. This underscores the potential for our risk prediction

Table 3. Postoperative In-Hospital Characteristics and Complications of Patients Undergoing Thoracic and Complex Endovascular Aortic Aneurysm Repair With and Without 1-Year TALE

	Absence of 1-y TALE (n=9253)	Presence of 1-y TALE (n=1485)	*P* value
Time to extubation after intervention, h			
In operating room	8323 (89.9)	1093 (73.6)	<0.001
<12	408 (4.4)	95 (6.4)	
12–24	208 (2.3)	87 (5.9)	
>24	105 (1.1)	161 (10.8)	
Not reported	209 (2.3)	49 (3.3)	
Need for vasopressor support	1523 (16.5)	588 (39.6)	<0.001
Total packed red blood cells transfused during admission, units, mean±SD	0.6±0.2	3.2±0.6	<0.001
Spinal drain			
None	7013 (75.8)	952 (64.1)	<0.001
Inserted preoperatively	2097 (22.7)	454 (30.6)	
Inserted postoperatively (prophylactic)	103 (1.1)	26 (1.8)	
Inserted postoperatively for spinal cord ischemia	40 (0.4)	53 (3.6)	
Access site hematoma	246 (2.7)	81 (5.5)	<0.001
Access site occlusion	63 (0.7)	24 (1.6)	<0.001
Access site infection	18 (0.2)	14 (0.9)	<0.001
Myocardial infarction	58 (0.6)	65 (4.4)	<0.001
Dysrhythmia	382 (4.1)	248 (16.7)	<0.001
Congestive heart failure exacerbation	83 (0.9)	66 (4.4)	<0.001
Respiratory complication			
None	9047 (97.8)	1199 (80.7)	<0.001
Pneumonia	74 (0.8)	35 (2.4)	
Reintubation	111 (1.2)	196 (13.2)	
Both	21 (0.2)	55 (3.7)	
Arm ischemia	26 (0.3)	13 (0.9)	0.005
Leg ischemia	92 (1.0)	77 (5.2)	<0.001
Leg compartment syndrome	42 (0.5)	27 (1.8)	<0.001
Bowel ischemia	53 (0.6)	110 (7.4)	<0.001
Length of stay in intensive care unit, d, median (IQR)	1 (0–3)	3 (1–6)	<0.001
Total hospital length of stay, d, median (IQR)	3 (2–6)	6 (3–13)	<0.001
Discharge medications			
Acetylsalicylic acid	7805 (84.4)	976 (65.7)	<0.001
$P2Y_{12}$ antagonist	3939 (42.6)	463 (31.2)	<0.001
Statin	7396 (79.9)	932 (62.8)	<0.001
ACE-I/ARB	3839 (41.5)	414 (27.9)	<0.001
β blocker	5963 (64.4)	815 (54.9)	<0.001
Anticoagulant	1648 (17.8)	253 (17.0)	0.11
Nonhome discharge	867 (9.4)	706 (47.5)	<0.001

Values are reported as n (%) unless otherwise indicated. ACE-I indicates angiotensin-converting enzyme inhibitor; ARB, angiotensin II receptor blocker; IQR, interquartile range; and TALE, thoracoabdominal aortic aneurysm life-altering event.

tool to enhance patient selection and optimize preoperative care. Overall, these models may offer valuable support for clinical decision making throughout the perioperative period, facilitating individualized risk assessment and management.

Comparison With Existing Literature

Bertges et al developed the VQI Cardiac Risk Index to predict in-hospital myocardial infarction in patients undergoing major vascular procedures including infrarenal EVAR, open AAA repair, lower-extremity bypass, and carotid endarterectomy.[9] Using logistic regression, their model achieved an AUROC of 0.75.[9] Importantly, TEVAR and complex EVAR were not included in their model.[9] More recently, Naazie et al developed a logistic regression model using VQI data from 2014 to 2020 consisting of 2141 patients who underwent TEVAR, achieving an AUROC of 0.75 for predicting the 30-day mortality rate.[38] Applying ML techniques to a more up-to-date cohort exclusively composed of patients undergoing TEVAR and complex EVAR, we achieved better performance with AUROCs >0.90 for predicting 1-year TALE, a longer-term and more clinically relevant procedure-specific outcome.

Bonde et al (2021) developed ML models using a cohort of National Surgical Quality Improvement Program patients undergoing >2900 different procedures to predict perioperative complications, achieving AUROCs of 0.85 to 0.88.[13] Given that patients undergoing TEVAR and complex EVAR represent a unique population generally with vascular comorbidities, the applicability of general risk prediction tools to these patients may be limited.[39] By developing ML algorithms specific to patients undergoing TEVAR and complex EVAR, we achieved AUROCs >0.90. Therefore, there is value in building procedure-specific ML models, which

Table 4. Model Performance on Test Set Data for Predicting 1-Year TALE Following Thoracic and Complex Endovascular Aortic Aneurysm Repair Using Preoperative Features

	AUROC (95% CI)	Accuracy (95% CI)	Sensitivity	Specificity	PPV	NPV
XGBoost	0.96 (0.95–0.97)	0.89 (0.88–0.90)	0.89	0.89	0.90	0.89
Random forest	0.95 (0.94–0.96)	0.88 (0.87–0.89)	0.89	0.87	0.87	0.89
Naïve Bayes	0.88 (0.87–0.90)	0.84 (0.83–0.85)	0.84	0.83	0.84	0.84
RBF SVM	0.84 (0.83–0.86)	0.76 (0.75–0.78)	0.76	0.77	0.78	0.74
MLP ANN	0.80 (0.78–0.82)	0.73 (0.72–0.74)	0.72	0.75	0.69	0.76
Logistic regression	0.70 (0.68–0.72)	0.64 (0.62–0.65)	0.60	0.72	0.84	0.62

AUROC indicates area under the receiver operating characteristic curve; MLP ANN, multilayer perceptron artificial neural network; NPV, negative predictive value; PPV, positive predictive value; RBF SVM, radial basis function support vector machine; and XGBoost, Extreme Gradient Boosting.

can increase accuracy and clinical applicability. This TEVAR and complex EVAR risk prediction model complements our previously described ML algorithms for predicting outcomes following infrarenal EVAR[15] and open AAA repair.[16]

Patel et al performed multivariable logistic regression to assess risk factors for 1-year TALE following TEVAR and complex EVAR.[4] They showed that older age, female sex, cardiovascular comorbidities, aortic diameter, proximal landing zone, and contrast volume were independent predictors of poor outcomes following TEVAR and complex EVAR.[4] They also demonstrated that 1-year TALE occurred more frequently in patients undergoing arch repairs and extent I to III TAAA repairs.[4] We showed similar findings, with the most important preoperative predictors of 1-year TALE in the XGBoost model being proximal landing zone, functional status, procedure type (arch repairs and extent I–III TAAA repairs), and cardiovascular comorbidities.

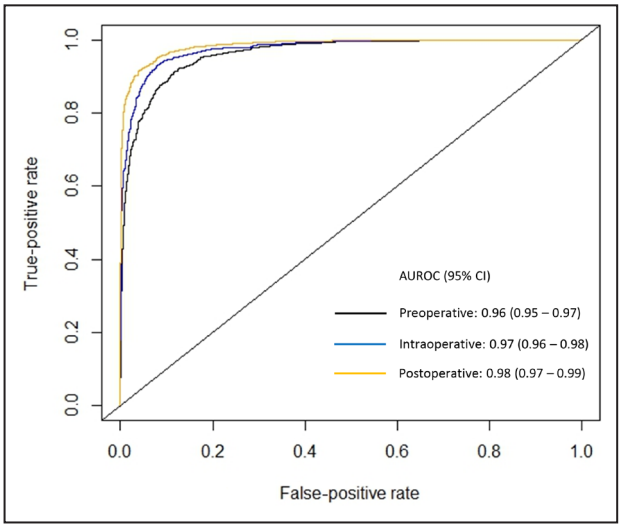

Figure 1. Receiver operating characteristic curve for predicting 1-y thoracoabdominal aortic aneurysm life-altering event following thoracic and complex endovascular aortic aneurysm repair using Extreme Gradient Boosting models at the pre-, intra-, and postoperative stages.
AUROC indicates area under the receiver operating characteristic curve.

Explanation of Findings

Several factors explain our findings. First, patients who experience complications after TEVAR and complex EVAR have multiple risk factors, which is supported by existing literature.[40] The SVS and European Society for Vascular Surgery guidelines emphasize the importance of thorough perioperative risk assessment and preoperative optimization for patients being considered for aortic interventions.[6,7] In particular, there is a strong recommendation for smoking cessation at least 2 weeks before aneurysm repair,[6] yet >30% of patients in our cohort were current smokers at the time of intervention. Despite having more cardiovascular comorbidities, patients who developed 1-year TALE were less likely to receive risk reduction medications preoperatively and at discharge. Therefore, there are important opportunities to improve care for patients being considered for TEVAR and complex EVAR by understanding their surgical risk and medically optimizing them before intervention. Second, anatomic complexity was an important risk factor for poor outcomes following TEVAR and EVAR. The most important predictor of 1-year TALE was proximal landing zone. Furthermore, patients who underwent arch repairs and extent I to III TAAA repairs, had a prior open or endovascular aortic intervention, a larger maximum aortic diameter, or a saccular aneurysm, or required branch treatment of the great vessels (innominate, left common carotid, or left subclavian arteries) were more likely to have complications. These findings may be related to increased risk of paralysis from increased aortic coverage from extent I to III TAAA repairs,[41] stroke from aortic arch manipulation from arch repair or branch treatment of the great vessels,[42] dialysis from increased contrast use and procedure time,[43] or death from procedural complexity and associated complications.[44] Given that anatomic complexity has a significant impact on outcomes, it is important for these high-risk patients to be

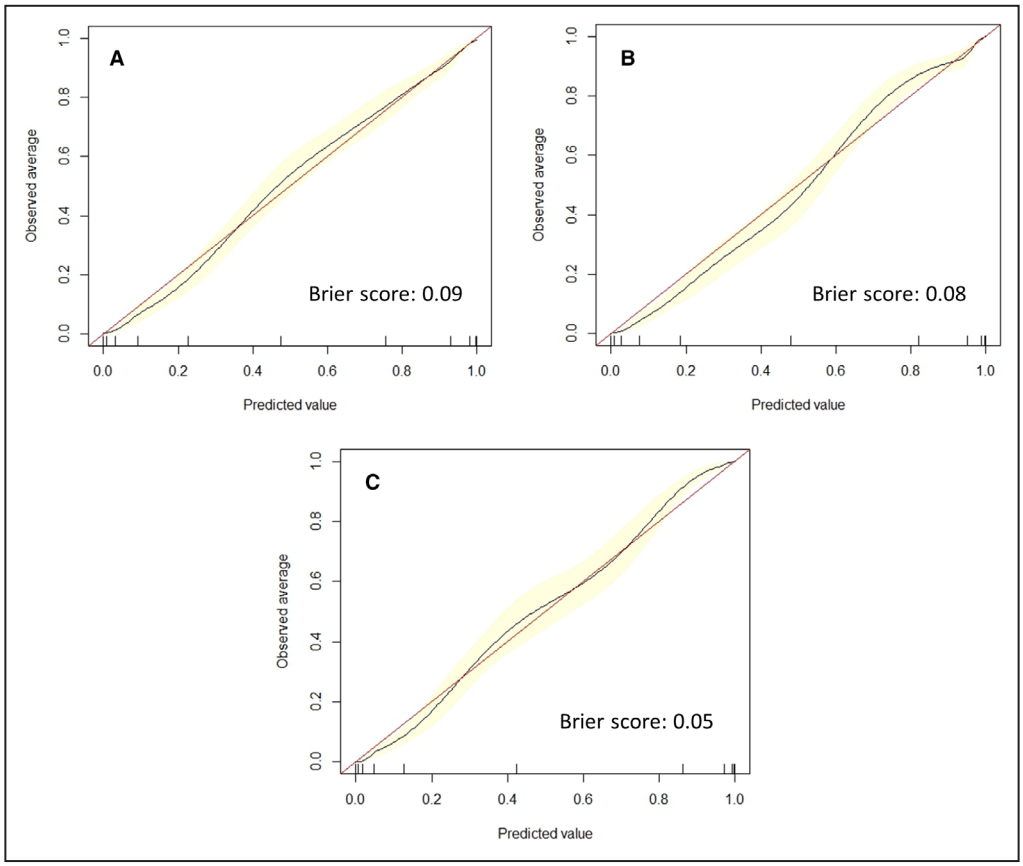

Figure 2. Calibration plots with Brier scores for predicting 1-y thoracoabdominal aortic aneurysm life-altering event following thoracic and complex endovascular aortic aneurysm repair using Extreme Gradient Boosting models at the (A) preoperative, (B) intraoperative, and (C) postoperative stages.

assessed by a multidisciplinary aortic team including vascular surgeons, cardiac surgeons, interventional radiologists, and other specialists to mitigate adverse events.[45] Third, our ML models outperformed existing tools likely due to their ability to model complex, nonlinear relationships between inputs and outputs.[46] Traditional logistic regression often struggles with these complexities, whereas advanced ML techniques excel in capturing intricate patterns often seen in health care data.[47] In particular, XGBoost offers distinct advantages including reduced overfitting and faster computation while maintaining precision.[48–50] Its effectiveness with structured data likely contributed to its superior performance compared with more complex algorithms like neural networks.[51] Fourth, our model's performance remained excellent across various demographic and clinical subgroups, addressing a common issue in ML models whereby bias against underrepresented populations can occur.[52] This robustness was likely due to the comprehensive capture of sociodemographic data by VQI, which helped mitigate potential biases in model predictions.[14]

Implications

Our ML models offer several ways to facilitate clinical decision making for patients being considered for TEVAR or complex EVAR. Preoperatively, for patients identified as high risk, a thorough evaluation of both modifiable and nonmodifiable risk factors is crucial.[53] Patients with significant nonmodifiable risks could be considered for another interventional approach or surveillance alone with a greater threshold for intervention.[54] Specifically, those with anatomically complex aneurysms may benefit from multidisciplinary vascular assessment by an aortic team to optimize patient selection and procedure planning.[45] In contrast, patients predicted to be at low risk might be suitable candidates for open surgical repair, which could offer better long-term durability.[55] Patients with modifiable risks, such as cardiovascular comorbidities, may benefit from further evaluation and optimization with appropriate referrals to medical specialists including cardiologists and internists.[56,57] Postoperatively, patients flagged as being at high risk for adverse events may be

Table 5. XGBoost Performance on Test Set Data for Predicting 1-Year Primary and Secondary Outcomes Following Thoracic and Complex Endovascular Aortic Aneurysm Repair at the Pre-, Intra-, and Postoperative Stages

	AUROC (95% CI)	Accuracy (95% CI)	Sensitivity	Specificity	PPV	NPV
TALE (primary outcome)*						
Preoperative	0.96 (0.95–0.97)	0.89 (0.88–0.90)	0.89	0.89	0.90	0.89
Intraoperative	0.97 (0.96–0.98)	0.92 (0.91–0.93)	0.92	0.92	0.92	0.92
Postoperative	0.98 (0.97–0.99)	0.94 (0.93–0.95)	0.93	0.94	0.95	0.93
New permanent dialysis						
Preoperative	0.95 (0.94–0.96)	0.87 (0.86–0.88)	0.88	0.86	0.87	0.87
Intraoperative	0.96 (0.95–0.97)	0.91 (0.90–0.92)	0.91	0.91	0.91	0.91
Postoperative	0.97 (0.96–0.98)	0.93 (0.92–0.94)	0.93	0.93	0.93	0.93
New permanent paralysis						
Preoperative	0.96 (0.95–0.97)	0.91 (0.90–0.92)	0.90	0.92	0.92	0.90
Intraoperative	0.97 (0.96–0.98)	0.93 (0.92–0.94)	0.91	0.94	0.94	0.91
Postoperative	0.98 (0.97–0.99)	0.94 (0.93–0.95)	0.92	0.94	0.94	0.94
Stroke						
Preoperative	0.94 (0.93–0.95)	0.87 (0.86–0.88)	0.87	0.87	0.87	0.87
Intraoperative	0.95 (0.94–0.96)	0.90 (0.89–0.91)	0.90	0.89	0.89	0.90
Postoperative	0.97 (0.96–0.98)	0.92 (0.91–0.93)	0.93	0.91	0.91	0.93
Death						
Preoperative	0.95 (0.94–0.96)	0.87 (0.86–0.88)	0.89	0.86	0.86	0.89
Intraoperative	0.96 (0.95–0.97)	0.89 (0.88–0.91)	0.90	0.89	0.89	0.90
Postoperative	0.98 (0.97–0.99)	0.93 (0.92–0.94)	0.93	0.92	0.92	0.93

AUROC indicates area under the receiver operating characteristic curve; NPV, negative predictive value; PPV, positive predictive value; TALE, thoracoabdominal aortic aneurysm life-altering event; and XGBoost, Extreme Gradient Boosting.

*TALE defined as a composite of new permanent dialysis, new permanent paralysis, stroke, or death.

closely monitored in the intensive care unit to provide timely intervention if complications arise.[58] Moreover, early involvement of allied health professionals can aid in optimizing discharge planning with consideration of early follow-up.[59] Importantly, it is critical to assess and potentially modify factors associated with nonhome discharge after endovascular interventions to improve patient outcomes and quality of life.[60] Figure 4 outlines a proposed clinical workflow demonstrating how our ML tool can support decision making at the pre-, intra-, and postoperative stages. By guiding perioperative decisions, our tool has the potential to reduce major complications and improve patient outcomes following TEVAR and complex EVAR.

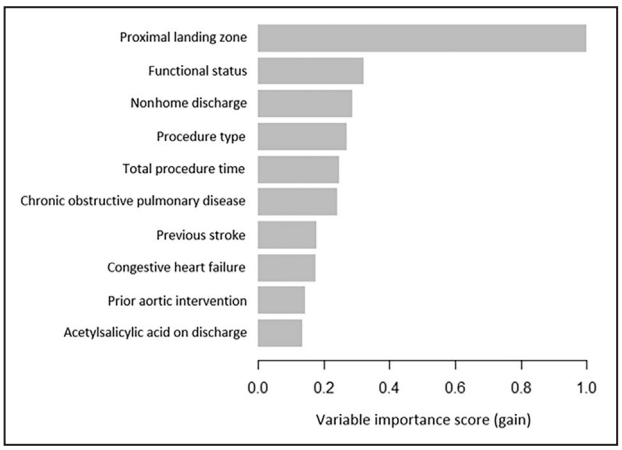

Figure 3. Variable importance scores (gain) for the top 10 predictors of 1-y thoracoabdominal aortic aneurysm life-altering event following thoracic and complex endovascular aortic aneurysm repair in the Extreme Gradient Boosting model at the postoperative stage.

The programming code for our ML models is publicly available on GitHub, enabling clinicians involved in the perioperative management of patients undergoing TEVAR and complex EVAR to access and use this tool. Our models can be integrated across the >1000 participating VQI centers, where the data required for our ML algorithms is routinely collected.[14] The number of VQI centers has significantly expanded from 400 in 2019 to >1000 in 2023.[14,61] Recently, the VQI recorded >1 million procedures.[62] This broad and growing network enhances the potential utility of our models. Additionally, because our predictors are commonly recorded in the routine care of patients with complex aortic aneurysms, our models have potential applicability beyond VQI sites.[63] To effectively deploy these prediction models in practice, careful consideration of implementation science principles is crucial.[64] A notable advantage

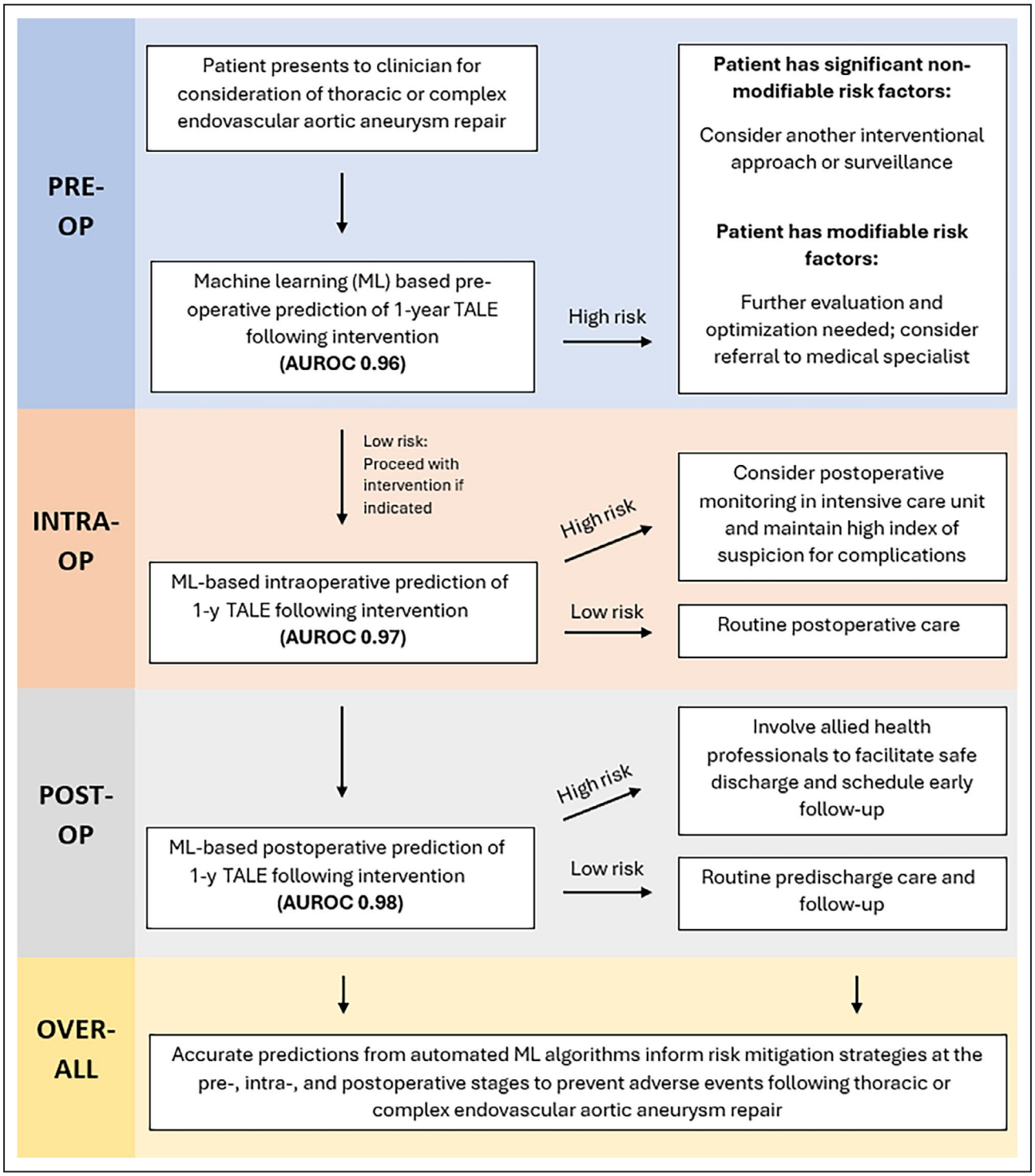

Figure 4. Clinical workflow for the use of machine learning algorithms to guide clinical decision-making at the pre-, intra-, and postoperative stages for patients being considered for thoracic or complex endovascular aortic aneurysm repair.
High risk defined as a model prediction positive for 1-y TALE. Low risk defined as a model prediction negative for 1-y TALE. The cutoffs for categorizing "high risk" and "low risk" were predicted probabilities of developing 1-y TALE of ≥50% and <50%, respectively. AUROC indicates area under the receiver operating characteristic curve; and TALE, thoracoabdominal aortic aneurysm life-altering event.

of our ML models is their capability to provide automated risk predictions, which enhances their feasibility in busy clinical settings compared with traditional risk predictors that often require manual input.[10] Specifically, our algorithms can automatically extract a patient's VQI data to generate risk predictions. Given

that our goal was to develop a highly accurate model that can automatically extract a large number of variables from VQI to make risk predictions, we opted not to reduce the number of input features through feature selection. For successful implementation, we recommend establishing and supporting data analytics teams at the institutional level. These teams can play a vital role in facilitating the deployment of our ML models and improving patient care.[65]

Limitations

Our study has several limitations. First, the models were developed using data from the VQI, a voluntary registry that predominantly includes information from North American centers. Lack of external validation is an important limitation, although this can be partly mitigated with a robust cross-validation strategy and clear separation of training and testing data to ensure that all model evaluations are performed on unseen data. Since test set data were used to compare the models, the optimal ML approach cannot be fully elucidated with the current analysis. Validation of the relative performance of the ML models in an external data set is warranted. With the development of the Vascular Verification Program through a partnership between the SVS and the American College of Surgeons, there may be opportunities to validate SVS VQI-derived models on American College of Surgeons National Surgical Quality Improvement Program data in the future.[66] Further research is needed to determine if these models can be generalized to settings outside of VQI institutions. Second, while we evaluated 6 different ML models on the basis of their established efficacy in predicting postoperative outcomes, other ML models could potentially offer different insights.[20] Although our chosen models performed well, it would be prudent to continuously explore and assess new ML techniques. Third, our models are limited to patients undergoing elective TEVAR and complex EVAR for aortic aneurysms. Emergent interventions for trauma and ruptured/symptomatic aneurysms were excluded given that these interventions are often indicated without the need for a risk prediction tool. Furthermore, treatment for nonaneurysmal pathologies including dissection, penetrating aortic ulcer, intramural hematoma, and aortic thrombus were excluded to reduce heterogeneity of our patient population. Future development of risk prediction tools for TEVAR and complex EVAR in nonaneurysmal pathologies may provide further guidance for these interventions.

CONCLUSIONS

We used a comprehensive vascular-specific clinical registry (VQI) to develop robust ML models that predict 1-year TALE following elective TEVAR and complex EVAR for noninfrarenal aortic aneurysms with excellent performance (AUROCs >0.90). Our models can be applied across the pre-, intra-, and postoperative stages to guide clinical decision making regarding strategies to mitigate the risk of major complications and improve outcomes. Importantly, these models demonstrated robustness across diverse demographic/clinical subpopulations and outperformed existing prediction tools and logistic regression, and therefore, have potential for important utility in the care of patients with noninfrarenal AAAs. Future prospective validation of our ML algorithms is needed to further establish their clinical utility.

ARTICLE INFORMATION

Received October 2, 2024; accepted January 28, 2025.

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Sources of Funding

This research was partially funded by the Canadian Institutes of Health Research, Ontario Ministry of Health, PSI Foundation, and University of Toronto Schwartz Reisman Institute for Technology and Society (Dr Li). The funding sources did not play a role in study design, collection, analysis, or interpretation of data, manuscript writing, creation of the manuscript, or the decision to submit the manuscript for publication.

Disclosures

None.

Supplemental Material

Tables S1–S5
Figures S1–S9

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