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Article

Development and Validation of a Predictive Model for Prolonged Mechanical Ventilation After Heart Valve Surgery

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Abstract

Background: Prolonged mechanical ventilation (PMV) is a common and serious complication after heart valve surgery, associated with increased morbidity, mortality, and healthcare resource utilization. Although several predictive models exist, many are limited by population homogeneity or lack of intraoperative variables. This study aimed to develop and validate a practical predictive model for PMV risk stratification to facilitate early intervention and optimize resource allocation. **Methods**: This was a retrospective study of adult patients who underwent elective heart valve surgery between January 2013 and January 2023. Patients from Center A were randomly assigned to a training cohort (n = 349) or an internal validation cohort (n = 149, with a 7:3 ratio). PMV was defined as mechanical ventilation lasting more than 48 hours postoperatively. Preoperative, intraoperative, and early postoperative variables were analyzed. Univariate and multivariate logistic regression analyses were used to identify independent predictors in the training cohort. A predictive nomogram was subsequently developed. Model performance was evaluated using discrimination (area under the receiver operating characteristic (AUROC) curve), calibration (calibration plots, Hosmer–Lemeshow test), and clinical utility (decision curve analysis (DCA) and clinical impact curve (CIC)). **Results**: Data were analyzed from 498 patients (training: n = 349; internal validation: n = 149). The incidence of PMV was 32.7% in the training cohort. Multivariate analysis identified six independent predictors: age (per 1-year increase), body mass index (per 1 kg/m^2 increase), chronic obstructive pulmonary disease severity (per 1-grade increase), forced expiratory volume in 1 s (per 1% increase), left ventricular ejection fraction (per 1% increase), and cardiopulmonary bypass time (per 10 minute increase). The nomogram demonstrated strong discrimination, with area under the curve (AUC) values of 0.847 (95% confidence interval (CI), 0.798–0.882) in training and 0.891 (95% CI, 0.858–0.927) in internal validation. Calibration was good across cohorts (Hosmer–Lemeshow $p > 0.05$). The DCA and CIC indicated that the model provided meaningful clinical benefit compared with treating all or no patients when the predicted probability threshold ranged from 40% to 100%. **Conclusion**: PMV was associated with higher in-hospital mortality, increased healthcare resource utilization, and reduced long-term survival. The proposed predictive model may aid in optimizing perioperative management, thereby improving outcomes and reducing costs.

Keywords: prolonged mechanical ventilation; heart valve surgery; predictive model; risk stratification; nomogram

1. Introduction

Prolonged mechanical ventilation (PMV), defined as postoperative ventilatory support lasting more than 24 hours, remains a significant complication following heart valve surgery [1]. Contemporary studies report PMV incidence rates as high as 22%, with associated mortality exceeding 40% among affected patients [2–6]. PMV markedly increases the risk of ventilator-associated pneumonia, prolongs intensive care unit (ICU) stays, and escalates healthcare costs, posing considerable clinical and economic burdens [7,8].

Early identification of patients at high risk for PMV can optimize perioperative management through targeted resource allocation, closer monitoring, and timely preemptive strategies [9]. Although several predictive models have been proposed, their clinical applicability remains limited [10,11]. Many were derived from relatively homogeneous populations or relied on complex variables with limited feasibility in routine care [12,13]. Additionally, intraoperative factors—important determinants of postoperative respiratory outcomes—have not been comprehensively integrated into most existing risk models.

To address these limitations, we developed and internally validated a novel risk-prediction model specifically for patients undergoing valve surgery. Using a contemporary, heterogeneous cohort from a tertiary cardiac center, we incorporated both preoperative characteristics and intraoperative variables. The model emphasizes clinically

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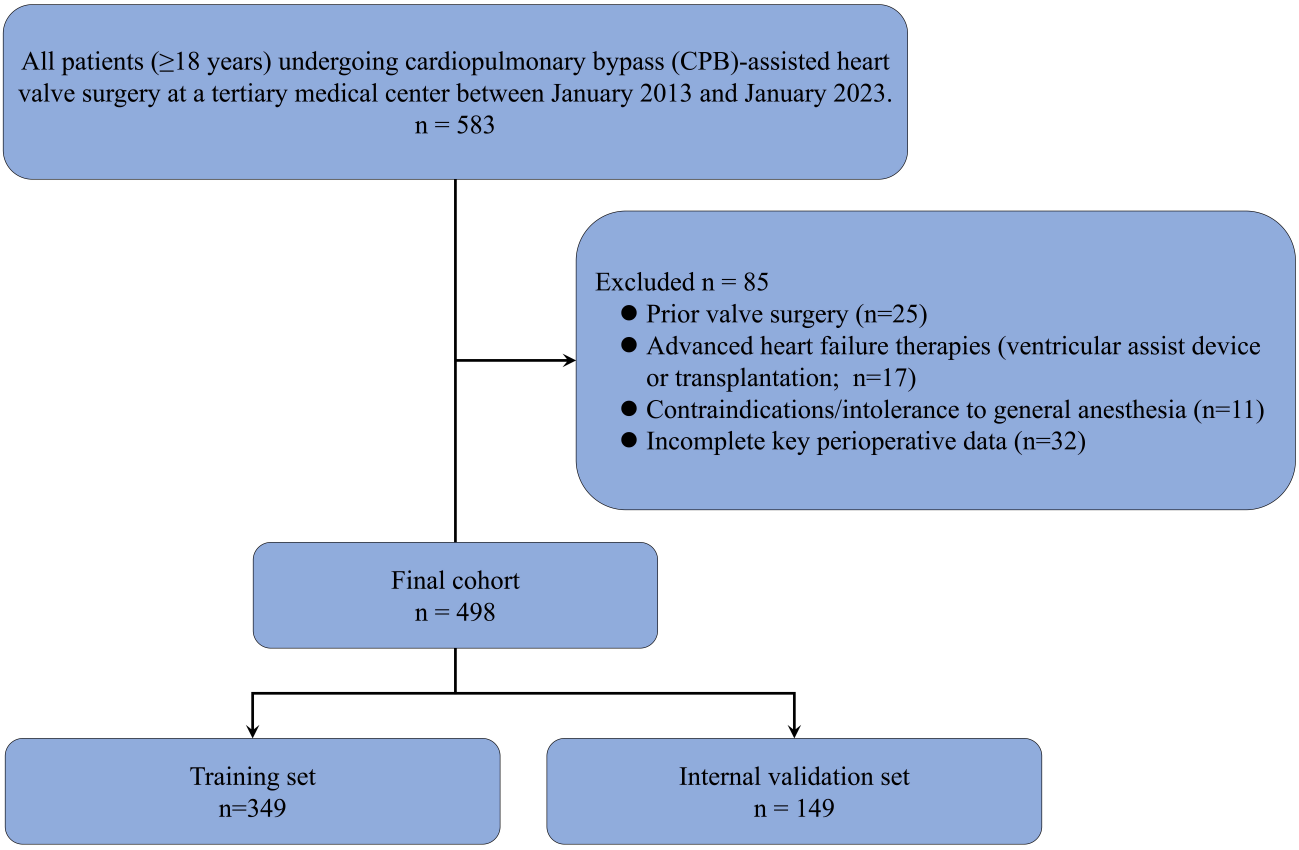

Fig. 1. Flowchart of patient enrollment and cohort allocation. A schematic overview of inclusion and exclusion criteria and cohort stratification. A total of 583 patients who underwent CPB-assisted heart valve surgery between January 2013 and January 2023. After applying exclusion criteria (n = 85), 498 patients were included and randomly assigned to the training cohort (n = 349) or internal validation cohort (n = 149).

accessible predictors to ensure practical application, while internal validation using separate training and testing cohorts methodological robustness. This tool aims to support individualized risk stratification, improve perioperative decision-making, and guide efficient resource utilization.

2. Materials and Methods

2.1 Study Population

This retrospective cohort study included adult patients (≥18 years) who underwent cardiopulmonary bypass (CPB)-assisted heart valve surgery at a tertiary medical center between January 2013 and January 2023. Data were extracted from electronic perioperative clinical databases, imaging archives, and surgical repositories. Patient demographics, clinical characteristics, and perioperative variables were systematically collected from electronic health records. Anesthesia documentation was independently verified by two reviewers blinded to postoperative outcomes, using de-identified records prior to PMV adjudication. Inclusion criteria were: (1) primary valvular disease requiring surgical intervention; (2) age ≥18 years (no upper age limit); (3) ASA physical status I–III. Exclusion criteria included prior valve surgery, advanced heart failure therapy (ventricular assist device or transplantation), contraindications or intolerance to general anesthesia, and incomplete key perioperative data. Concurrent radiofrequency ablation for atrial fibrillation was permitted. After exclusions (n = 85), 498 patients were included in the final cohort (Fig. 1). Ethics approval was granted by the Institutional Review Board (IRB) of Zhangzhou Affiliated Hospital of Fujian Medical University (Approval No. 2025LWB257), which waived the requirement for informed consent due to the retrospective study design. Standardized protocols were used to ensure a comprehensive capture of demographic characteristics, anesthetic management, and postoperative outcomes, particularly ventilation duration and weaning parameters.

2.2 Surgical Techniques and Postoperative Critical Care Management

All heart valve procedures were performed under CPB by the center's surgical team, typically composed of 3 to 4 members, including chief physicians, attending surgeons, and residents. CPB was established via femoral arterial and venous cannulation. Valve interventions (aortic, mi-

tral, tricuspid, or multiple) involved either replacement or repair, with mitral and tricuspid repairs performed whenever anatomically feasible. Concomitant atrial fibrillation ablation and prosthesis selection (mechanical vs. bioprosthetic) were guided by preoperative and intraoperative findings, as well as patient-specific factors such as age, comorbidities, and preferences. Intraoperative efforts focused on minimizing CPB duration and ensuring meticulous hemostasis. Transesophageal echocardiography was routinely employed to assess valve function and confirm procedural success. Postoperatively, patients were transferred to the ICU for continuous hemodynamic monitoring, fluid management, and inotropic support as needed. Multimodal analgesia—combining opioids, non-opioid agents, and regional techniques such as epidural or paravertebral blocks—was prioritized to promote early mobilization and facilitate timely extubation. Standardized ICU protocols guided the management of prolonged ventilation, including daily weaning assessments and prevention of complications (e.g., ventilator-associated pneumonia). Clinical guidelines informed the detection and management of postoperative complications, including bleeding, infection, and arrhythmias. Patients were closely monitored for respiratory distress, hemodynamic instability, and other factors potentially contributing to prolonged ventilation.

2.3 Definition of Key Variables

PMV was defined as invasive mechanical ventilation lasting more than 48 h after surgery. This included patients who remained continuously intubated for >48 h, as well as those who were extubated but subsequently reintubated, with a cumulative ventilation duration exceeding 48 h. Total mechanical ventilation time, measured from the end of surgery to final successful extubation, was also analyzed as a secondary outcome. Arterial partial pressure of oxygen (PaO_2) was assessed using the first arterial blood gas sample obtained within 10 minutes of ICU admission. Pain intensity was measured preoperatively and postoperatively using the visual analog scale (VAS) [14], scored from 0 (no pain) to 10 (worst imaginable pain). All measurements adhered to standardized perioperative assessment protocols, and data were recorded by trained clinical personnel.

2.4 Statistical Analysis

The study cohort comprised 498 patients from the Zhangzhou Affiliated Hospital of Fujian Medical University. Patients were randomly assigned to a training cohort (70%) and an internal validation cohort (30%). Comparative analyses between patients requiring PMV and those not requiring PMV (non-PMV) were performed using Fisher's exact test or the χ^2 test for categorical variables and the Wilcoxon rank-sum test for non-normally distributed continuous variables. Significant predictors identified via multivariate logistic regression in the training cohort were used to construct a postoperative PMV prediction nomogram. Model discrimination was assessed using the area under the receiver operating characteristic (ROC) curve (AUC). Calibration, defined as the agreement between predicted and observed outcomes, was evaluated using the Hosmer–Lemeshow goodness-of-fit test. Clinical utility was quantified using decision curve analysis (DCA) and clinical impact curves (CIC), which estimate net benefit across a range of predicted probability thresholds. Continuous measures are presented as mean ± standard deviation if normally distributed and as median with interquartile range (median [IQR]) if non-normally distributed. Categorical variables are summarized as frequencies and percentages. Normality was tested using the Shapiro–Wilk test. A two-tailed p-value < 0.05 was considered statistically significant. All analyses were performed using R (version 4.4.0, Boston, MA, USA) and SPSS (version 26.0, IBM SPSS statistics, Chicago, IL, USA).

3. Results

3.1 Baseline Characteristics of Study Population

This study included 498 adult patients (≥18 years) who underwent CPB-assisted heart valve surgery at a tertiary medical center between January 2013 and January 2023. The cohort was randomly assigned to either the training set (n = 349, 70%) or the internal validation set (n = 149, 30%). PMV, defined as ventilation lasting >48 h, was required in 162 patients (32.5%), with comparable incidences observed in the training (114 patients, 32.7%) and validation (48 patients, 32.2%) cohorts (Tables 1,2). In the training set, significant differences (all $p < 0.05$, two-tailed) were observed between the PMV group (n = 114) and the non-PMV group (n = 235) across multiple baseline characteristics. These included demographic variables (age, sex distribution, BMI, current smoking status), comorbidities (COPD severity, pulmonary hypertension, atrial fibrillation), functional status (New York Heart Association [NYHA] class, left ventricular ejection fraction [LVEF]), respiratory function (predicted forced expiratory volume in 1 second [FEV1%]), surgical parameters (surgery type, operative time, CPB time), oxygenation status (PaO_2/FiO_2 ratio), and clinical outcomes (intra-aortic balloon pump use, extracorporeal membrane oxygenation [ECMO], tracheostomy, reintubation, 30-day mortality, and overall mortality) (Table 1).

3.2 Independent Predictors and Predictive Model Development

Univariate analysis identified 13 factors significantly associated with PMV (all $p < 0.05$) (Table 3). These included demographic variables (age, male sex, BMI), respiratory status (current smoking, COPD severity grade, FEV1%, pulmonary hypertension), cardiac function (NYHA class III/IV, LVEF%, atrial fibrillation), and procedural metrics (surgery type, operative time, CPB time). Six variables retained independent predictors of PMV in

Table 1. General characteristics of training set.

Variable	Non-PMV (n = 235)		PMV (n = 114)		*p* value
	N, mean or median	%, σ or IQR	N, mean or median	%, σ or IQR	
Preoperative Characteristics					
Age, years	55.1	5.9	68.1	4.3	<0.001
Male, n (%)	114	48.5%	69	60.5%	0.040
BMI, kg/m^2	24.9	1.9	28.9	1.6	<0.001
Current smoker, n (%)	58	24.7%	43	37.7%	0.016
COPD severity, n (%)					<0.001
None	192	81.7%	70	61.4%	
Mild	28	11.9%	17	14.9%	
Moderate	12	5.1%	20	17.5%	
Severe	3	1.3%	7	6.1%	
FEV1% predicted	74.7	8.5	56.0	9.0	<0.001
NYHA class, n (%)					<0.001
I/II	148	63.0%	39	34.2%	
III/IV	87	37.0%	75	65.8%	
LVEF, %	54.4	5.8	39.3	6.1	<0.001
Serum albumin, g/L	36.7	3.0	37.3	3.0	0.101
eGFR, mL/min/1.73 m^2	70.3	17.1	68.0	17.1	0.245
Hemoglobin, g/dL	11.9	1.2	12.0	1.1	0.900
Pulmonary hypertension, n (%)	77	32.8%	58	50.9%	0.002
Diabetes, n (%)	49	20.9%	23	20.2%	0.884
Hypertension, n (%)	100	42.6%	42	36.8%	0.353
CAD, n (%)	41	17.4%	20	17.5%	0.982
Previous MI, n (%)	20	8.5%	14	12.3%	0.336
Stroke, n (%)	26	11.1%	14	12.3%	0.724
Liver dysfunction, n (%)	11	4.7%	10	8.8%	0.152
PVD, n (%)	34	14.5%	14	12.3%	0.623
Cancer, n (%)	12	5.1%	9	7.9%	0.340
Atrial fibrillation, n (%)	73	31.1%	60	52.6%	<0.001
Endocarditis, n (%)	12	5.1%	12	10.5%	0.072
Intraoperative Characteristics					
Surgery type, n (%)					<0.001
MVR	142	60.4%	50	43.9%	
MVP	36	15.3%	9	7.9%	
MVR + TVP	36	15.3%	34.00	29.8%	
AVR + MVR	9	3.8%	8.00	7.0%	
AVR + MVR + TVP	3	1.3%	8.00	7.0%	
MVP + TVP	9	3.8%	5.00	4.4%	
Operative time, min	201.6	29.7	237.9	37.0	<0.001
CPB time, min	119.1	17.7	154.1	20.2	<0.001
Aortic cross-clamp time, min	89.0	17.2	90.9	17.4	0.333
Blood transfusion, units	3	1–5	4	2–5	0.109
Crystalloid infusion, mL	2745.9	435.0	2798.5	428.5	0.288
Lowest SpO_2, %	93.8	2.3	93.73	2.4	0.880
Mean PEEP, cmH_2O	3.4	0.9	3.5	0.8	0.291
Pleural adhesion, n (%)	27	11.5%	21	18.4%	0.097
AF ablation, n (%)	52	22.1%	30	26.3%	0.420
Postoperative Characteristics					
PaO_2/FiO_2 ratio	270.7	29.4	165.7	29.4	<0.001
Peak airway pressure, cmH_2O	18.8	2.7	19.1	2.8	0.467
Plateau airway pressure, cmH_2O	15.1	2.3	17.1	4.8	0.078
VIS score	12	8–15	28	21–35	<0.001
Temperature, °C	36.5	0.7	36.4	0.9	0.312

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Table 1. Continued.

Variable	Non-PMV (n = 235)		PMV (n = 114)		*p* value
	N, mean or median	%, σ or IQR	N, mean or median	%, σ or IQR	
RASS score	–2	–3 to –1	–2	–3 to –1	0.156
Pain score (0–10)	4	3–5	3	2–5	0.546
Chest tube drainage, mL	494	396–616	502	395–603	0.819
Respiratory inflammation, n (%)					0.196
None	138	58.7%	60	52.6%	
Mild	66	28.1%	32	28.1%	
Moderate	22	9.4%	16	14.0%	
Severe	9	3.8%	6	5.3%	
Pulmonary edema, n (%)	31	13.2%	18	15.8%	0.515
Atelectasis, n (%)	53	22.6%	35	30.7%	0.115
Pneumothorax, n (%)	12	5.1%	4	3.5%	0.595
IABP, n (%)	0	0.0%	15	13.2%	<0.001
ECMO, n (%)	0	0.0%	9	7.9%	<0.001
Tracheostomy, n (%)	4	1.7%	30	26.3%	<0.001
Reintubation, n (%)	7	3.0%	45	39.5%	<0.001
30-day mortality, n (%)	9	3.8%	32	28.1%	<0.001
Overall mortality, n (%)	4	1.7%	45	39.5%	<0.001

PMV, prolonged mechanical ventilation (>48 hours); BMI, body mass index; COPD, chronic obstructive pulmonary disease; FEV1, forced expiratory volume in 1 second; NYHA, New York Heart Association; LVEF, left ventricular ejection fraction; eGFR, estimated glomerular filtration rate; CAD, coronary artery disease; MI, myocardial infarction; PVD, peripheral vascular disease; MVR, mitral valve replacement; MVP, mitral valve plasty; TVP, tricuspid valve plasty; AVR, aortic valve replacement; CPB, cardiopulmonary bypass; PEEP, positive end-expiratory pressure; AF, atrial fibrillation; VIS, vasoactive-inotropic score; RASS, Richmond Agitation Sedation Scale; IABP, Intra-aortic balloon pump; ECMO, extracorporeal membrane oxygenation.

multivariate logistic regression: age (per 1-year increase), BMI (per 1 kg/m^2 increase), COPD severity (per 1-grade increase), FEV1% (per 1% increase), LVEF% (per 1% decrease), and CPB time (per 10-minute increase). A predictive nomogram incorporating these factors was developed to estimate individualized PMV risk (Fig. 2). Each variable was assigned a weighted score proportional to its regression coefficient. The total score corresponds to the patient-specific probability of requiring PMV >48 h, facilitating preoperative risk stratification.

3.3 Model Validation and Performance Metrics

The predictive model for PMV demonstrated strong calibration performance. In the derivation cohort, the mean absolute error between predicted and observed probabilities was 0.011 (Fig. 3). The model also showed robust discriminatory ability, with an AUC of 0.847 (95% CI: 0.798–0.882) during initial testing (Fig. 4). Internal validation confirmed the model's stability. The mean absolute error was 0.019 (Fig. 3), and the AUC remained high at 0.891 (95% CI: 0.858–0.927) (Fig. 4).

3.4 Clinical Utility and Decision Threshold Optimization

DCA was used to quantitatively assess the clinical utility of the PMV prediction model. As shown in Fig. 5, the model demonstrated superior net benefit compared with the strategies of treating all or no patients across a wide range of clinically relevant threshold probabilities. This suggests that applying the model to guide clinical decisions—such as targeted ICU resource allocation or early preventive measures for high-risk individuals—offers greater clinical value than indiscriminate or absent intervention.

Further assessment using a clinical impact curve revealed that, at thresholds below 40%, the number of false-positive classifications (i.e., patients identified as high-risk who did not experience PMV) increased disproportionately relative to true positives (Fig. 5). This underscores the need for careful threshold selection to balance the benefits of intervention with the risk of overtreatment. Calibration-guided threshold analysis identified a predicted risk probability of 0.40 as the optimal cutoff. At this threshold, true-positive identification was maximized while maintaining an acceptable false-positive rate, supporting its use for targeted postoperative respiratory monitoring. Overall, both DCA and the clinical impact curve confirmed that predicted probability thresholds between 40% and 100% yielded a meaningful clinical benefit. Within this range, the model achieved an optimal trade-off between minimizing false negatives and avoiding false positives. These findings support the model's utility in enhancing perioperative decision-making and ICU resource allocation for patients undergoing valve surgery.

Table 2. General characteristics of internal validation set.

Variable	Non-PMV (n = 101)		PMV (n = 48)		*p* value
	N, mean or median	%, σ or IQR	N, mean or median	%, σ or IQR	
Preoperative characteristics					
Age, years	54.8	5.9	67.3	4.2	<0.001
Male, n (%)	60	59.4%	35	72.9%	<0.001
BMI, kg/m^2	24.8	1.7	29.3	1.6	<0.001
Current smoker, n (%)	18	17.8%	16	33.3%	0.039
COPD severity, n (%)					<0.001
None	82	81.2%	29	60.4%	
Mild	13	12.9%	6	12.5%	
Moderate	5	5.0%	10	20.8%	
Severe	1	1.0%	3	6.3%	
FEV1% predicted	74.6	8.5	66.9	14.9	<0.001
NYHA class, n (%)					0.002
I/II	64	63.4%	17	35.4%	
III/IV	37	36.6%	31	64.6%	
LVEF, %	54.1	5.9	49.2	9.5	<0.001
Serum albumin, g/L	36.9	2.9	37.0	3.0	0.730
eGFR, mL/min/1.73 m^2	70.2	16.5	69.3	17.4	0.643
Hemoglobin, g/dL	13.4	1.8	11.8	2.5	<0.001
Pulmonary hypertension, n (%)	25	24.8%	24	50.0%	0.003
Diabetes, n (%)	19	18.8%	12	25.0%	0.395
Hypertension, n (%)	42	41.6%	30	62.5%	0.017
CAD, n (%)	19	18.8%	9	18.8%	0.862
Previous MI, n (%)	7	6.9%	7	14.6%	0.145
Stroke, n (%)	10	9.9%	3	6.4%	0.550
Liver dysfunction, n (%)	3	3.0%	4	8.3%	0.213
PVD, n (%)	18	17.8%	8	16.7%	0.284
Cancer, n (%)	3	3.0%	0	0%	0.551
Atrial fibrillation, n (%)	35	34.7%	19	39.6%	0.557
Endocarditis, n (%)	7	6.9%	4	8.3%	0.755
Intraoperative Characteristics					
Surgery type, n (%)					0.008
MVR	62	61.4%	20	41.7%	
MVP	15	14.9%	4	8.3%	
MVR + TVP	15	14.9%	15	31.3%	
AVR + MVR	3	3.0%	4	8.3%	
AVR + MVR + TVP	1	1.0%	4	8.3%	
MVP + TVP	5	5.0%	1	2.1%	
Operative time, min	197.5	27.8	241.6	33.5	<0.001
CPB time, min	118.7	16.9	146.6	18.9	<0.001
Aortic cross-clamp time, min	89.9	16.4	87.4	15.2	0.372
Blood transfusion, units	3	1–5	3	1–6	0.676
Crystalloid infusion, mL	2808.4	430.4	2713.6	439.4	0.214
Lowest SpO_2, %	94.4	2.3	93.8	2.3	0.123
Mean PEEP, cmH_2O	3.5	0.9	3.6	0.9	0.218
Pleural adhesion, n (%)	12	11.9%	13	27.1%	0.018
AF ablation, n (%)	25	24.8%	13	27.1%	0.841
Postoperative characteristics					
PaO_2/FiO_2 ratio	273.9	27.8	169.3	28.4	<0.001
Peak airway pressure, cmH_2O	16.8	2.8	16.8	2.7	0.995
Plateau airway pressure, cmH_2O	13.9	2.4	15.1	2.2	0.556
VIS score	12	9–17	27	23–35	<0.001
Temperature, °C	36.3	0.5	36.4	0.3	0.118

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Table 2. Continued.

Variable	Non-PMV (n = 101)		PMV (n = 48)		*p* value
	N, mean or median	%, σ or IQR	N, mean or median	%, σ or IQR	
RASS score	–2	–2 to –1	–2	–2 to –1	0.370
Pain score (0–10)	3	2–5	3	2–4	0.705
Chest tube drainage, mL	486	403–576	516	391–600	0.504
Respiratory inflammation, n (%)					0.002
None	65	64.4%	21	43.8%	
Mild	26	25.7%	15	31.3%	
Moderate	9	8.9%	9	18.8%	
Severe	1	1.0%	3	6.3%	
Pulmonary edema, n (%)	18	17.8%	3	6.3%	0.077
Atelectasis, n (%)	19	18.8%	9	18.8%	0.993
Pneumothorax, n (%)	4	4.0%	1	2.0%	0.552
IABP, n (%)	0	0.0%	7	14.6%	<0.001
ECMO, n (%)	0	0.0%	2	4.2%	<0.001
Tracheostomy, n (%)	1	1.0%	18	37.5%	<0.001
Reintubation, n (%)	6	5.9%	26	54.2%	<0.001
30-day mortality, n (%)	1	1.0%	12	25.0%	<0.001
Overall mortality, n (%)	4	4.0%	20	41.7%	<0.001

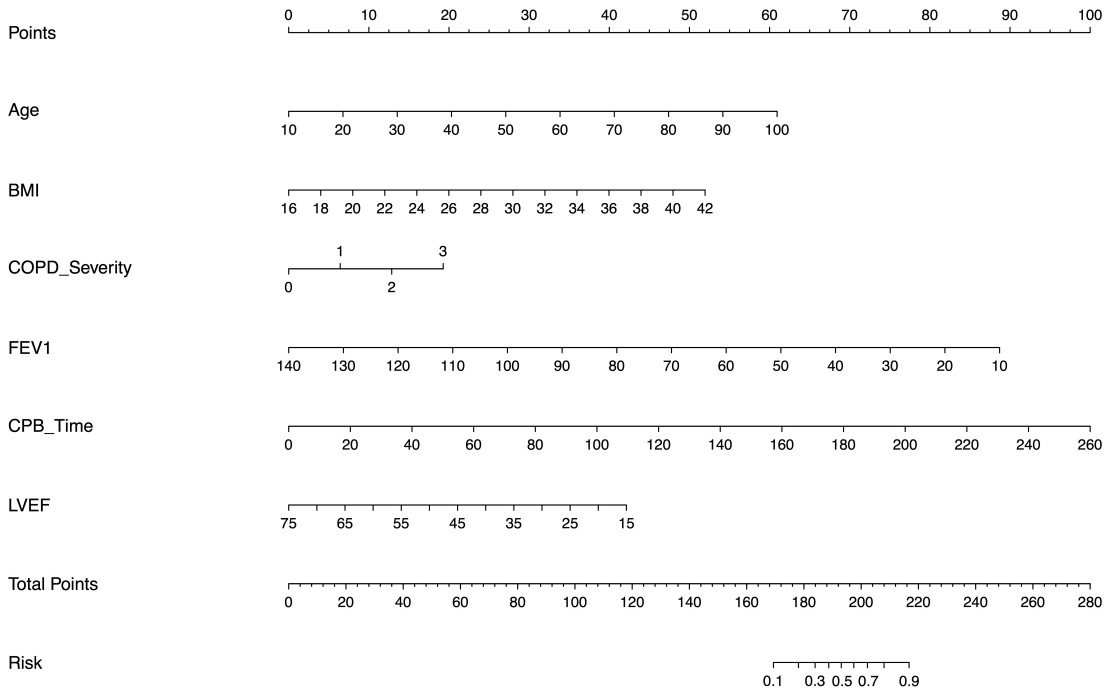

Fig. 2. Multivariable nomogram for predicting postoperative mechanical ventilation risk. The visual scoring tool incorporates six independent predictors: age (per 1-year increase), body mass index (BMI; per 1 kg/m^2 increase), chronic obstructive pulmonary disease (COPD) severity (per 1-grade increase), predicted forced expiratory volume in 1 second (FEV1%; per 1% increase), left ventricular ejection fraction (LVEF%; per 1% decrease), and cardiopulmonary bypass (CPB) time (per 10-minute increase). The total score points correspond to the patient-specific probability of requiring mechanical ventilation for >48 h postoperatively.

4. Discussion

4.1 Key Findings and Clinical Implications

This study developed and internally validated a predictive nomogram incorporating six readily available clinical variables—age, BMI, COPD severity, FEV1%, LVEF%, and CPB time—to stratify the risk of PMV (>48 h) following heart valve surgery. The model demonstrated robust discrimination (AUC 0.847–0.891) and calibration across both the training and validation cohorts. DCA confirmed a clinically meaningful net benefit at the 40% risk

Table 3. Logistic regression analysis of PMV.

Variable	Univariate		Multivariate	
	OR (95% CI)	*p* value	OR (95% CI)	*p* value
Preoperative characteristics				
Age (per 1-year increase)	1.90 (1.60–2.26)	<0.001	2.18 (1.32–3.61)	0.002
Male (vs female)	1.63 (1.03–2.56)	0.036		
BMI (per 1 kg/m^2 increase)	4.54 (3.11–6.63)	<0.001	2.05 (1.22–3.46)	0.007
Current smoker (vs non-smoker)	1.85 (1.14–2.99)	0.012		
COPD severity (per 1-grade increase)	1.57 (1.23–2.01)	<0.001	2.22 (1.28–3.84)	0.004
FEV1 (per 1% increase)	1.76 (1.10–1.81)	<0.001	3.05 (1.78–5.22)	<0.001
NYHA III/IV (vs I/II)	3.27 (2.08–5.23)	<0.001		
LVEF (per 1% increase)	1.56 (1.48–1.66)	<0.001	2.41 (1.40–4.15)	0.001
Serum albumin (per 1 g/L increase)	1.07 (0.99–1.45)	0.101		
eGFR (per 1 mL/min/1.73 m^2 increase)	0.99 (0.98–1.00)	0.112		
Hemoglobin (per 1 g/dL increase)	1.01 (0.83–1.23)	0.9		
Pulmonary hypertension (yes vs no)	2.23 (1.35–3.36)	<0.001		
Diabetes (yes vs no)	1.04 (0.60–1.82)	0.884		
Hypertension (yes vs no)	1.27 (0.80–2.01)	0.309		
CAD (yes vs no)	1.01 (0.56–1.81)	0.982		
Previous MI (yes vs no)	1.51 (0.73–3.10)	0.268		
Stroke (yes vs no)	1.13 (0.56–2.25)	0.738		
Liver dysfunction (yes vs no)	1.96 (0.81–4.76)	0.138		
PVD (yes vs no)	1.21 (0.62–2.35)	0.578		
Cancer (yes vs no)	0.63 (0.26–1.54)	0.308		
Atrial fibrillation (yes vs no)	2.47 (1.56–3.91)	<0.001		
Endocarditis (yes vs no)	2.19 (0.95–5.03)	0.066		
Surgery type	2.42 (1.47–4.00)	0.001		
Operation time (per 10-min increase)	1.04 (1.03–1.04)	<0.001		
CPB time (per 10-min increase)	1.10 (1.08–1.13)	<0.001	3.12 (1.85–5.26)	<0.001
Aortic cross-clamp time (per 10-min increase)	1.01 (0.99–1.02)	0.332		
Blood transfusion (per 1-unit increase)	1.09 (0.98–1.20)	0.109		
Crystalloid infusion (per 500-mL increase)	1.08 (0.98–1.19)	0.287		
Lowest SpO_2 (per 1% increase)	0.99 (0.90–1.09)	0.879		
Mean PEEP (per 1 cmH_2O increase)	1.15 (0.89–1.50)	0.29		
Pleural adhesion (yes vs no)	1.74 (0.94–3.24)	0.08		
AF ablation (yes vs no)	1.52 (0.2–2.51)	0.101		

threshold, which optimally balanced sensitivity and specificity for practical implementation. This threshold enables preemptive interventions for high-risk patients, including preoperative pulmonary optimization (e.g., inspiratory muscle training or bronchodilator therapy), ICU resource prioritization (e.g., allocation of advanced ventilators and respiratory therapists), and protocolized lung-protective ventilation strategies. The nomogram allows rapid bedside risk assessment using routinely collected variables, addressing the need for early identification of patients at increased risk for extended ventilatory support. Given the substantial morbidity and economic burden associated with PMV—as prior studies suggest hospital costs for affected patients may significantly exceed those of non-PMV patients [15]—timely identification and intervention may reduce complications such as ventilator-associated pneumonia and ICU length of stay.

4.2 Comparison With Prior Research and Methodological Advances

Our findings align with previously identified predictors for PMV [4,9,11,16,17], including advanced age, impaired cardiac function (reduced LVEF%), and prolonged CPB duration. These factors reflect established pathophysiologic mechanisms linking cardiopulmonary stress to postoperative ventilatory dependency [18]. However, our model improves upon prior approaches in several ways. First, unlike models such as the Intensive Care Unit Respiratory Support Score (ICURSS), which rely solely on static preoperative variables, or the Simplified Acute Physiology Score II (SAPS II), which focuses on ICU parameters [19,20], our nomogram incorporates intraoperative data (i.e., CPB duration), thereby improving temporal relevance to surgical insult. Second, the model is procedure-specific, targeting valve surgery rather than mixed cohorts domi-

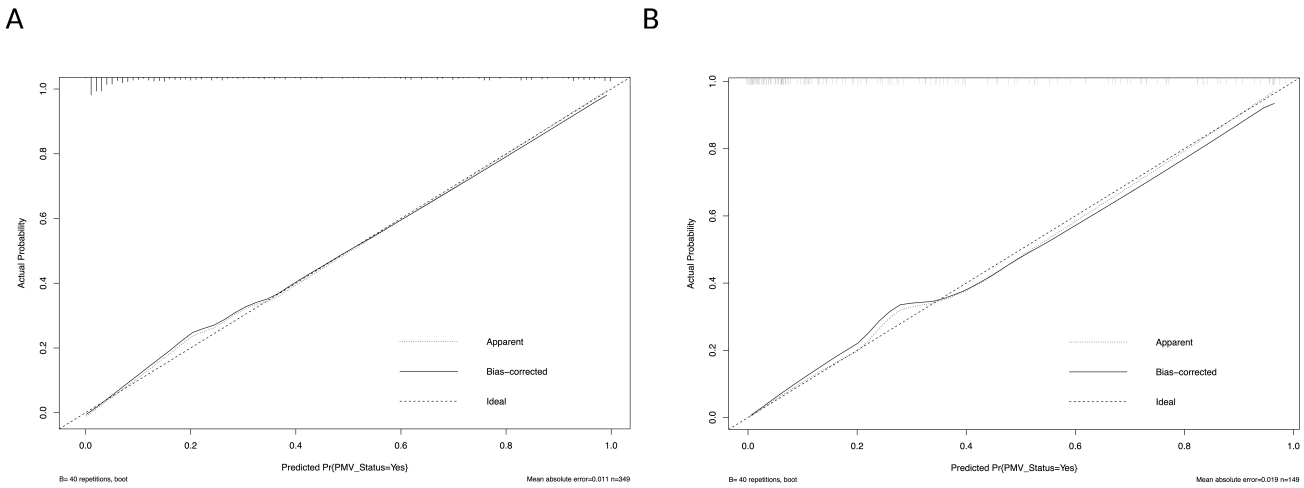

Fig. 3. Calibration curves of the prolonged mechanical ventilation (PMV) prediction model. (A) Calibration in the derivation cohort (training set, n = 349) showed strong agreement between predicted probabilities and observed PMV rates, with a mean absolute error (MAE) of 0.011. (B) Internal validation cohort (n = 149) demonstrated comparable calibration performance (MAE = 0.019). The dashed diagonal line represents ideal prediction accuracy. Both curves indicate minimal systematic bias, supporting the nomogram's reliability for clinical risk stratification. PMV was defined as mechanical ventilation lasting >48 hours postoperatively.

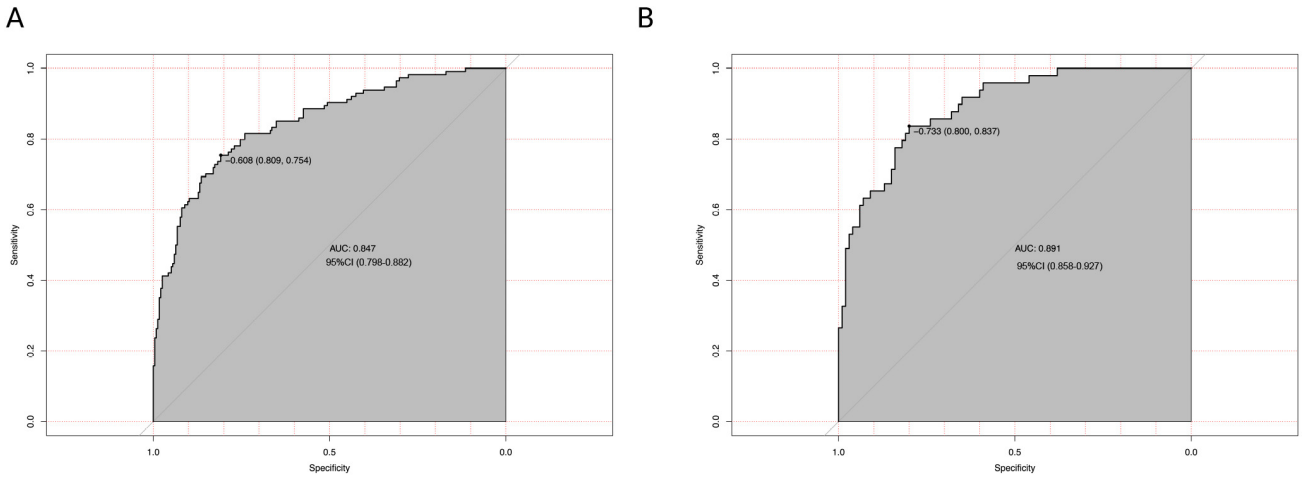

Fig. 4. Receiver operating characteristic (ROC) curves evaluating the discriminatory performance of the prediction model for prolonged mechanical ventilation (PMV). (A) In the derivation cohort (training set, n = 349), the model achieved an area under the curve (AUC) of 0.847 (95% CI: 0.798–0.882), indicating excellent discrimination between patients requiring PMV and those extubated within 48 hours. (B) In the internal validation cohort (n = 149), model performance remained high, with an AUC of 0.891 (95% CI: 0.858–0.927). The diagonal reference line indicates chance-level prediction. PMV was defined as mechanical ventilation lasting >48 hours following cardiac valve surgery.

nated by coronary artery bypass grafting [1,3,7,8], allowing greater sensitivity to the unique intraoperative and postoperative risks of valvular procedures. Third, the use of a >48-hour PMV definition aligns with contemporary critical care standards [9], offering a balance between overestimation (>24 hours) and delayed identification (>72 hours). Finally, the use of continuous variables (e.g., FEV1% instead of categorical COPD staging) allows more precise risk estimation. The empirically derived 40% cutoff further supports actionable, resource conscious-intervention planning.

4.3 Clinical Translation and Real-World Applicability

Beyond risk prediction, this model offers a platform for real-time, actionable clinical decision-making. Patients identified as high-risk (≥40% probability) can be prioritized for preoperative pulmonary rehabilitation, ICU bed allocation, and early implementation of postoperative interventions such as bronchoscopy readiness and secretion clearance protocols. These are not only clinically relevant but economically justified—Rajakaruna *et al.* [4] reported that PMV patients accrued 5.2-fold higher costs than

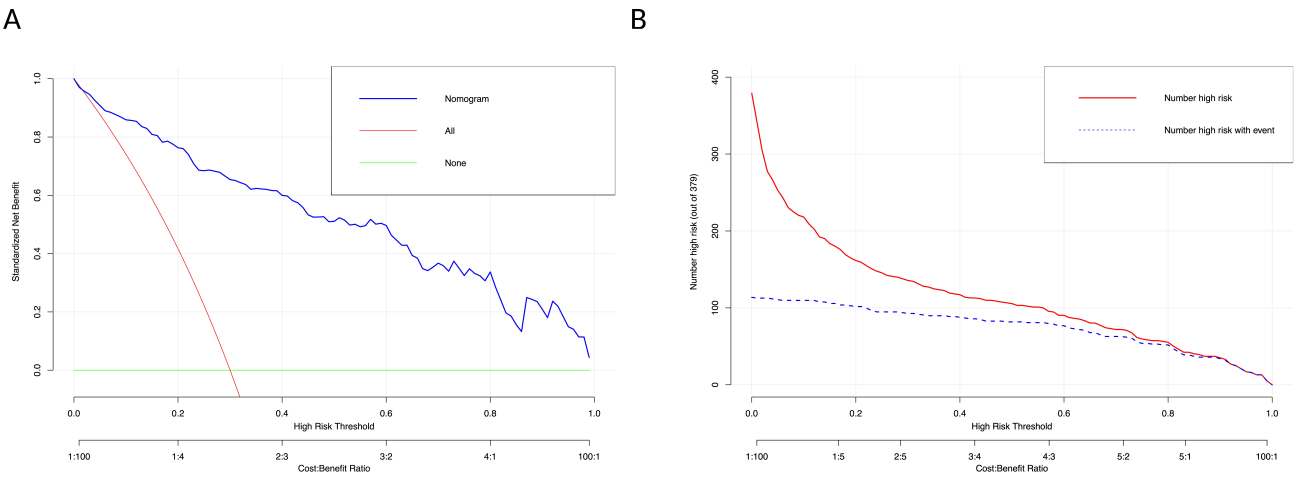

Fig. 5. Clinical utility of the prediction model for prolonged mechanical ventilation (PMV), assessed using decision curve analysis (DCA) and clinical impact curves (CIC). (A) DCA quantifies the net clinical benefit of the predictive nomogram (red curve) compared with treating all or no patients across a range of threshold probabilities (0–100%). The model shows superior clinical utility across nearly all thresholds range, with cost-benefit ratios indicated on the x-axis. (B) CIC evaluates the number of patients classified as high-risk (red curve) versus the number of actual PMV events (blue curve) at each threshold probability. Below the 40% threshold (dashed vertical line), high-risk classifications exceed observed PMV cases, indicating increased false positives. At the prespecified 40% cutoff, the model achieves optimal alignment between predicted and observed outcomes, maximizing true-positive identification while maintaining an acceptable false-positive rate. These findings support the model's application in targeted ICU resource allocation. PMV was defined as mechanical ventilation lasting >48 hours following cardiac surgery.

non-PMV patients ($14,286 vs. $2761 per case). Targeting high-intensity resources toward those most likely to benefit may mitigate overall expenditure. Although this was a single-center study, its cohort included heterogeneous surgical profiles: 38% of patients had atrial fibrillation, 32% underwent combined valve procedures, and repeat operations were included. This heterogeneity enhances the generalizability of the findings. Importantly, the model excludes postoperative variables (e.g., vasopressor requirements), enabling application at the point of surgical scheduling. While this limits adaptability to intraoperative complications, it enhances early planning value. Future prospective studies should evaluate whether model-guided interventions reduce PMV rates, ICU stays, and related costs. Integration into electronic health records could automate risk alerts, prompting intraoperative strategies such as bronchospasm prophylaxis or intensified recruitment maneuvers.

4.4 Limitations and Future Directions

This study has several limitations that merit consideration. Its retrospective, single-center design introduces potential selection bias and limits generalizability to centers with different surgical practices or case mixes. Although internal validation was rigorous, external verification in multicenter populations—particularly those with higher extracorporeal membrane oxygenation or urgent procedures—is needed. The exclusion of dynamic postoperative data (e.g., serial blood gases or sedation depth) limits the model's capacity for recalibration, which could be addressed in future iterations using machine learning algorithms. While the nomogram is simple and clinically accessible, its real-world impact depends on integration into hospital informatics systems for automated risk scoring. Future studies should assess whether model-based preoperative interventions (e.g., preoperative physiotherapy for high-risk patients) translate into reduced PMV incidence and better resource utilization. Despite these limitations, the current model provides a physiologically informed, clinically actionable tool for preoperative risk stratification and resource allocation in heart valve surgery.

5. Conclusions

This study developed and internally validated a predictive model for PMV (>48 hours) following heart valve surgery. Incorporating routine preoperative and intraoperative variables, the model demonstrated strong discrimination and calibration. DCA confirmed clinical utility, with a 40% risk threshold offering optimal sensitivity and specificity for real-world triage. This threshold enables early identification of high-risk patients while avoiding unnecessary interventions. Although based on a single-center cohort, the model's simplicity, predictive strength, and reliance on standard clinical parameters support its applicability. Implementation may improve ICU resource allocation and patient outcomes after heart valve surgery.

6. Summary Points

Prolonged mechanical ventilation (PMV >48 hours) remains a significant complication following heart valve surgery, associated with substantial morbidity, mortality, and resource burden. This study developed and internally validated a novel predictive model for PMV risk using comprehensive preoperative and intraoperative data from a tertiary center cohort. Decision curve analysis confirmed superior clinical utility compared to universal intervention strategies, with an optimized risk threshold ($\geq$40%) effectively balancing early intervention benefits against overtreatment risks. The validated tool facilitates early identification of high-risk patients, enabling targeted respiratory monitoring and preventive strategies to mitigate postoperative morbidity and optimize ICU resource allocation.

Availability of Data and Materials

The datasets supporting this study are included in the article. To preserve participant confidentiality, raw datasets containing identifiable information remain restricted. Deidentified data may be accessed by qualified researchers contingent upon ethical approval from their institution and authorization by our ethics committee. Requests must be submitted to the corresponding author, requiring submission of a methodologically sound proposal and institutional review board certification. Approved applicants will receive anonymized data in alignment with GDPR/regional data protection laws, contingent on executed data use agreements. Full compliance with institutional privacy protocols and collaborative governance frameworks is mandated for data utilization.

Author Contributions

YQW (First Author): Conceptualization, Methodology, Software, Investigation, Resources, Supervision, Formal Analysis, Validation Writing — Original Draft. QYZ, HDT, LC and LWC: Data Curation, Visualization, Funding Acquisition, Investigation, Writing — Original Draft and Writing — Review & Editing. XYC (Corresponding Author): Conceptualization, Funding Acquisition, Resources, Supervision, Writing — Review & Editing. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

All authors confirm accountability for study integrity, including thorough investigation of any data accuracy concerns. The protocol received ethical approval under the Declaration of Helsinki (2013 revision) and approved by the Institutional Review Board (IRB) of Zhangzhou Affiliated Hospital of Fujian Medical University (Approval No. 2025LWB257), which waived the requirement for informed consent due to the retrospective study design, with written informed consent obtained from participants for data publication and image usage. To ensure ethical rigor, explicit reconsent was secured from participants or legal proxies for secondary data utilization in this research. No conflicts of interest were reported by investigators. The study protocol posed no physical or psychological risks, as verified by an independent institutional review board. Methodological adherence to privacy standards and risk mitigation protocols was maintained throughout data collection and analysis.

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Conflict of Interest

No financial interests or institutional conflicts of interest were declared by the authors (Yueqiong Wang, Qiuyan Zhao, Huadong Tang, Ling Chen, Liangwan Chen and Xiaoyun Chen). The manuscript, including text, tables and figures, represents original work free from third-party intellectual property infringement. All visual and textual content has not been previously published or submitted elsewhere. Ethical standards for originality and attribution were rigorously maintained throughout the research and publication process.

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