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Article

Development and Temporal Validation of an Interpretable Perioperative Nomogram for Prolonged Mechanical Ventilation in Older Adults Undergoing Cardiac Surgery

Shukun Wang[1], Junzhe Wang[1], Chenguang Pan[1], Nanyang Shi[1], Tianbo Xie[1], Wen Chen[1], Zhibing Qiu[1,*], Xin Chen[1,*]

[1]Department of Thoracic and Cardiovascular Surgery, Nanjing First Hospital, Nanjing Medical University, 210006 Nanjing, Jiangsu, China
*Correspondence: qiuzhibing2009@163.com (Zhibing Qiu); stevecx@njmu.edu.cn (Xin Chen)

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Abstract

Background: Prolonged mechanical ventilation (PMV) after cardiac surgery reflects delayed early recovery and is associated with increased perioperative resource use. Older adults are especially vulnerable, yet practical models that jointly capture preoperative reserve and intraoperative burden remain limited. **Methods:** We performed a single-center retrospective cohort study of 1632 consecutive patients aged ≥60 years who underwent cardiac surgery at Nanjing First Hospital between 25 January 2022 and 8 March 2024. PMV was defined as postoperative mechanical ventilation lasting more than 24 h. Patients treated in 2022 formed the development cohort and were stratified by PMV status into a training set and an internal validation set at a 7:3 ratio. Patients treated from 1 January 2023 to 8 March 2024 comprised the temporal validation cohort. Candidate predictors available before or during surgery were entered into least absolute shrinkage and selection operator (LASSO) regression with 10-fold cross-validation. Predictors with non-zero LASSO coefficients were then refitted in a multiple logistic regression model and presented as a nomogram. Model performance was evaluated using receiver operating characteristic curves, calibration curves, Brier scores, Hosmer–Lemeshow testing, and decision curve analysis. **Results:** Among 1632 eligible patients, 346 (21.2%) developed PMV. The training, internal validation, and temporal validation sets included 484, 208, and 940 patients, with PMV incidences of 22.3%, 22.6%, and 20.3%, respectively. LASSO retained six predictors: age, preoperative creatinine, preoperative left ventricular ejection fraction, European System for Cardiac Operative Risk Evaluation II (EuroSCORE II) score, operation time, and non-valve surgery. In the final logistic model, older age, higher creatinine, higher EuroSCORE II score, and longer operation time were associated with an increased risk of PMV. In contrast, higher preoperative left ventricular ejection fraction was associated with decreased risk. The nomogram showed good discrimination in the training, internal validation, and temporal validation cohorts, with areas under the curve of 0.873 (95% confidence interval [CI], 0.835–0.911), 0.893 (95% CI, 0.844–0.942), and 0.878 (95% CI, 0.849–0.906), respectively. The corresponding Brier scores were 0.100, 0.115, and 0.098. **Conclusions:** This LASSO-derived perioperative nomogram estimates PMV risk in older adults undergoing cardiac surgery by integrating baseline vulnerability, cardio–renal reserve, and operative burden. The model is interpretable, relies on routinely available variables, and may facilitate preoperative counseling, end-of-surgery risk updating, intensive care unit resource planning, and postoperative extubation strategy. Multicenter prospective validation is needed before widespread implementation.

Keywords: prolonged mechanical ventilation; cardiac surgery; older adults; least absolute shrinkage and selection operator; nomogram; prediction model; temporal validation

1. Introduction

Prolonged mechanical ventilation (PMV) after cardiac surgery is more than a respiratory endpoint. It is a clinically important marker of delayed recovery and perioperative risk, reflecting the combined influence of patient vulnerability, cardiopulmonary reserve, surgical complexity, systemic inflammation, and haemodynamic instability [1,2,3,4]. Among older adults, even a moderate physiological insult can result in delayed weaning, longer intensive care use, greater exposure to ventilation-related complications, and higher perioperative mortality [5,6]. A practical tool that estimates PMV risk before surgery or immediately after the procedure may therefore improve risk communication and help clinicians allocate critical-care resources more rationally.

Contemporary cardiac surgery, and the management of postoperative respiratory recovery, cannot be separated from the development of cardiopulmonary bypass (CPB). Modern CPB evolved from early concepts of cardiopulmonary physiology and the ancient notion of pneuma as a life-sustaining breath or vital principle into the heart-lung machine, which temporarily replaces cardiac and pulmonary function during complex operations. This historical path illustrates why ventilation after cardiac surgery is embedded in broader cardiopulmonary support rather than being a purely pulmonary phenomenon [7].

Several models have been proposed to identify patients at high risk of prolonged ventilation after cardiac surgery, including studies in general adult cardiac-surgery cohorts and in procedure-specific populations such as coro-

nary artery bypass grafting (CABG), robot-assisted CABG, redo valve surgery, redo aortic arch surgery, and valve surgery [5,8,9,10,11,12,13,14,15,16]. Across these settings, age, cardiac function, renal function, chronic pulmonary disease, emergency surgery, and operative complexity have repeatedly emerged as relevant factors. Perioperative datasets, however, pose specific modelling challenges: candidate variables are often numerous, clinically correlated, and measured at different stages of care. Selection based only on univariable significance can retain redundant predictors and increase overfitting, whereas fully automated algorithms may sacrifice clinical interpretability [17].

The least absolute shrinkage and selection operator (LASSO) is useful in this context because it shrinks regression coefficients and selects a smaller predictor set while allowing correlated candidate variables to be considered together [18]. A nomogram can then translate the multivariable model into a point-based risk tool that is easier to review at the bedside than a regression equation [17]. Discrimination alone, however, is not enough for a credible prediction model; calibration, clinical utility, and transparent reporting also need to be examined [19,20,21,22,23].

In this study, we developed and temporally validated an interpretable LASSO-derived perioperative nomogram for PMV in older adults undergoing cardiac surgery. Candidate predictors were deliberately restricted to variables available before or during surgery, and postoperative complications were excluded from model development to reduce temporal leakage and maintain clinical usability.

2. Materials and Methods

2.1 Study Design and Population

This single-center retrospective cohort study used data from consecutive patients who underwent cardiac surgery at Nanjing First Hospital between 25 January 2022 and 8 March 2024. Eligible patients were aged 60 years or older, had undergone cardiac surgery, and had a complete PMV endpoint. Exclusion criteria were age <60 years, absence of a complete PMV endpoint, and unavailable essential preoperative or intraoperative variables required for model construction. Emergency surgery, redo surgery, previous percutaneous coronary intervention (PCI), and postoperative reintubation were not exclusion criteria. In total, 1632 patients met the study criteria.

True multicentre validation was not possible because the source dataset did not include a multicentre identifier. We therefore adopted a temporal validation strategy. Patients treated in 2022 constituted the development cohort and were randomly divided into a training set and an internal validation set at a 7:3 ratio, stratified by PMV status. Patients treated from 1 January 2023 to 8 March 2024 constituted the temporal validation cohort.

2.2 Outcome Definition

The primary outcome was PMV, defined as postoperative mechanical ventilation lasting more than 24 h. This threshold is widely used in cardiac-surgery literature and identifies patients with delayed early postoperative respiratory recovery and increased critical-care needs [9,10,11,24].

2.3 Candidate Predictors and Preprocessing

Candidate variables were selected on the principle that predictor information had to be available before the outcome occurred. Demographic characteristics, comorbidities, preoperative laboratory tests, cardiac function including left ventricular ejection fraction (LVEF), European System for Cardiac Operative Risk Evaluation II (EuroSCORE II) score, and intraoperative information were considered as candidates. EuroSCORE II was analysed as a score rather than as a percentage.

Postoperative laboratory values, intensive care unit (ICU) stay, postoperative complications, length of hospital stay, cost, in-hospital death, 30-day death, and postoperative echocardiographic reassessment were retained in the supplementary variable inventory but were not used for model development, because their inclusion could introduce temporal leakage. Direct identifiers, date fields, and non-analytic reason fields were removed from the supplementary table before manuscript preparation.

Before model fitting, we examined missingness. The PMV endpoint was complete in the final analytic cohort. For LASSO screening, missing continuous candidate predictors were imputed with the median value from the training set, whereas missing categorical values were retained as an explicit missing category when applicable. For the final six-predictor model, missing continuous predictors were imputed with the corresponding training-set median. Binary variables originally recorded as 1/blank in the source spreadsheet were treated analytically as 1 for yes and 0 for no when blank or missing. Postoperative variables were excluded from the primary perioperative prediction model, but not from clinical consideration.

Postoperative haemodynamic status, vasoactive or inotropic support, and postoperative arrhythmias are important determinants of delayed extubation and PMV. They were not entered into the primary model, however, because the model was intended for preoperative assessment and end-of-surgery risk updating. Since the PMV endpoint is determined during the postoperative ICU course, variables measured after ICU admission may occur after the outcome process has begun or may represent downstream mediators. Treating such variables as baseline predictors could cause temporal leakage and overestimate model performance. They are better addressed in future dynamic postoperative models rather than in the present perioperative model.

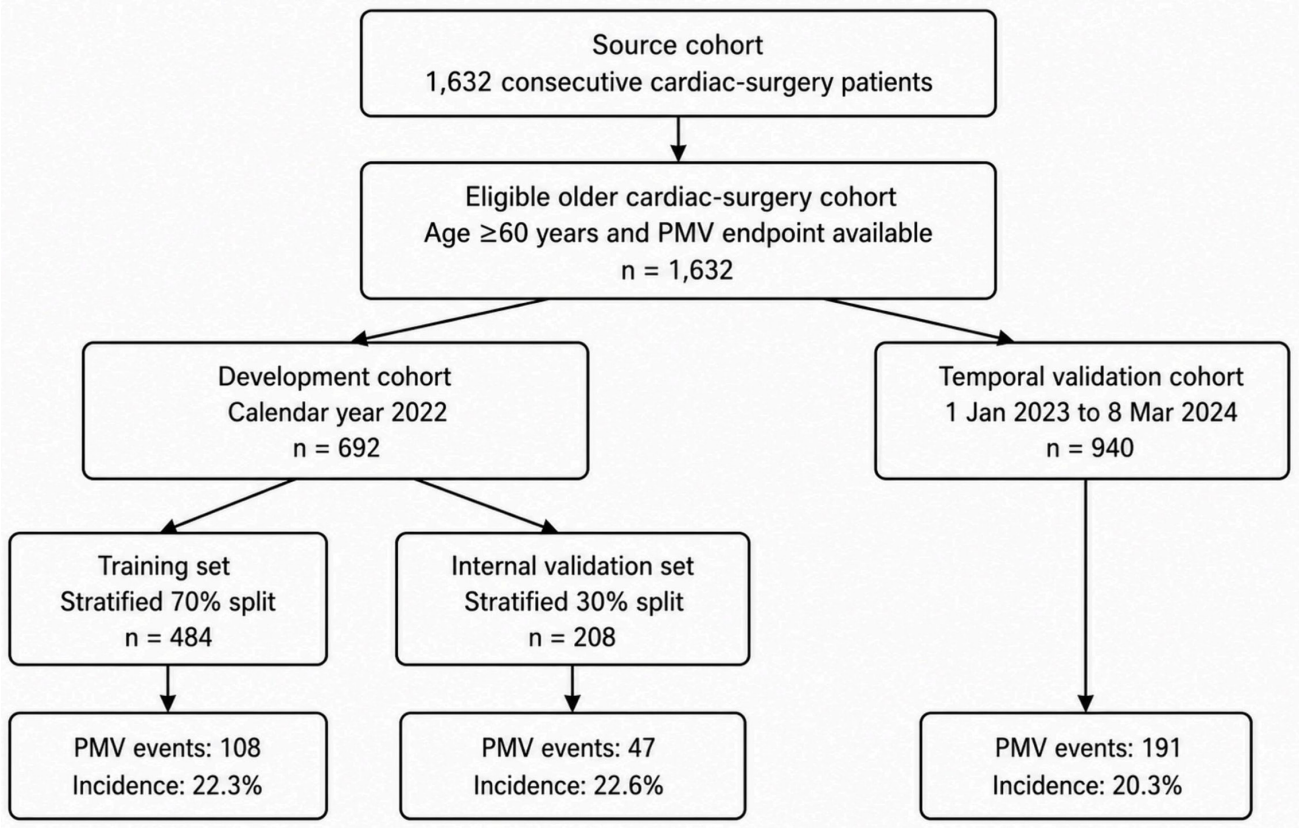

Fig. 1. Cohort assembly and temporal validation design. PMV, prolonged mechanical ventilation.

2.4 Statistical Analysis

Continuous variables were summarized as mean ± standard deviation (SD) when approximately normally distributed and as median (interquartile range [IQR]) otherwise. Categorical variables were summarized as n (%). Table entries were labelled as n (%), mean ± SD, or median (IQR), as applicable. Comparisons across the training, internal validation, and temporal validation sets used one-way analysis of variance or the Kruskal-Wallis test for continuous variables, and the chi-square test or Fisher's exact test for categorical variables, as appropriate. Within the training set, patients with and without PMV were compared using the Student *t*-test or Mann-Whitney U test for continuous variables and the chi-square test or Fisher's exact test for categorical variables.

All eligible preoperative and intraoperative candidate predictors were screened by LASSO logistic regression with 10-fold cross-validation, using binomial deviance as the optimization criterion. Predictors with non-zero coefficients were refitted in a multiple logistic regression model. Odds ratios (ORs), 95% confidence intervals (CIs), and *p*-values were reported. Discrimination was assessed using receiver operating characteristic curves and the area under the curve (AUC) with 95% CIs. Sensitivity and specificity were reported with 95% CIs calculated by the exact binomial method. Calibration was evaluated using calibration curves, Brier scores, and Hosmer-Lemeshow tests. Clinical utility was assessed by decision curve analysis. Statistical test results were cross-validated using Stata software. All tests were two-sided, and $p < 0.05$ was considered statistically significant.

2.5 Model Development

All candidate predictors available before or during surgery were entered into a LASSO logistic regression model in the training set. Continuous variables were analysed on the appropriate numeric scale, and categorical variables were dummy-coded when required. Ten-fold cross-validation was used to select the penalty parameter lambda. Predictors with non-zero coefficients were then entered into a multiple logistic regression model, and ORs, 95% CIs, and *p*-values were reported.

The final model was converted into a nomogram for bedside estimation of individual PMV risk. The original valve-surgery variable had a negative coefficient in the multivariable model; to align the nomogram with risk-score direction, it was re-expressed as non-valve surgery. This variable should be read as a predictive coding term rather than as a causal effect.

2.6 Model Validation and Clinical Utility

Discrimination was evaluated using receiver operating characteristic curves and the AUC, with 95% CIs. Calibration was examined with calibration curves, Brier scores,

Table 1. Cohort assembly and dataset division.

Item	n	Definition
Source cohort	1632	Consecutive patients undergoing cardiac surgery at Nanjing First Hospital, 2022-01-25 to 2024-03-08
Eligible older cardiac-surgery cohort	1632	Age ≥60 years and PMV endpoint available
Development cohort	692	Calendar year 2022
Training set	484	Random 70% of the 2022 development cohort, stratified by PMV
Internal validation set	208	Random 30% of the 2022 development cohort, stratified by PMV
Temporal validation cohort	940	2023-01-01 to 2024-03-08

Abbreviations: PMV, prolonged mechanical ventilation.

Table 2. Prolonged mechanical ventilation (PMV) events in the overall cohort and validation datasets.

Cohort	n	PMV events	PMV incidence, %
All eligible cohort	1632	346	21.2
Training set	484	108	22.3
Internal validation set	208	47	22.6
Temporal validation cohort	940	191	20.3

Abbreviations: PMV, prolonged mechanical ventilation.

and Hosmer-Lemeshow tests. Clinical utility was evaluated by decision curve analysis, which compared the net benefit of the nomogram with treat-all and treat-none strategies [23].

3. Results

3.1 Cohort Assembly and Dataset Division

The final cohort included 1632 consecutive older adults who underwent cardiac surgery. PMV occurred in 346 patients, yielding an overall incidence of 21.2%. The training, internal validation, and temporal validation cohorts included 484, 208, and 940 patients, respectively; the corresponding PMV incidences were 22.3%, 22.6%, and 20.3%. The cohort assembly and temporal validation design are presented in Fig. 1. The cohort division is summarized in Table 1. PMV events and incidence rates across the study cohorts are presented in Table 2.

3.2 Baseline and Perioperative Characteristics

The three datasets were broadly comparable in age, sex, body mass index, major medical history, preoperative laboratory variables, cardiac function, and most operative characteristics. Emergency surgery, beta-blocker use within 24 h before surgery, nadir temperatures, infection, in-hospital death, and 30-day death differed across datasets. The clinical characteristics of the training, internal validation, and temporal validation sets are summarized in Table 3.

3.3 Characteristics Associated With PMV in the Training Set

In the training set, patients who developed PMV were older and had higher proportions of peripheral arterial disease and emergency surgery. They also had higher preoperative creatinine and EuroSCORE II scores, lower preoperative LVEF, and longer operation times. Taken together, these findings suggest that PMV in this population reflects baseline reserve, cardio-renal function, and operative burden rather than an isolated pulmonary event. Detailed comparisons between patients with and without PMV in the training set are presented in Table 4.

3.4 LASSO Variable Selection

All eligible preoperative and intraoperative candidate predictors were analysed by LASSO regression in the training set. With increasing penalization, the coefficients were progressively shrunk toward zero. Ten-fold cross-validation identified the optimal lambda. Six predictors retained non-zero coefficients: age, preoperative creatinine, preoperative LVEF, EuroSCORE II score, operation time, and non-valve surgery. The LASSO coefficient profiles and cross-validation process are illustrated in Fig. 2A,B, respectively.

3.5 Multiple Logistic Regression and Nomogram Construction

The six predictors selected by LASSO were entered into a multiple logistic regression model. Older age, higher preoperative creatinine, higher EuroSCORE II score, and longer operation time were associated with increased PMV risk. Higher preoperative LVEF was associated with lower PMV risk. Non-valve surgery was retained in the final model as a predictive coding term. The regression coefficients, odds ratios, 95% confidence intervals, and *p*-values for the final model are presented in Table 5.

The fitted prediction equation was: logit(PMV) = –8.025 + 0.084 × Age + 0.200 × Creatinine_10 – 0.087 × LVEF + 0.136 × EuroSCORE II score + 0.132 × Operation_time_10 + 0.759 × Non-valve surgery. Creatinine_10

Table 3. Clinical characteristics in the training, internal validation, and temporal validation sets.

Characteristics (format)	Training set	Internal validation set	Temporal validation set	*p* value
Demographics				
Age, yr (mean ± SD)	71.37 ± 4.48	70.83 ± 4.62	71.05 ± 4.52	0.275
Male (n (%))	293 (60.5)	123 (59.1)	574 (61.1)	0.874
BMI, kg/m^2 (mean ± SD)	23.83 ± 3.30	23.73 ± 3.45	23.92 ± 3.26	0.705
Medical history				
Smoking (n (%))	91 (18.8)	40 (19.2)	178 (18.9)	0.991
Diabetes (n (%))	145 (30.0)	55 (26.4)	280 (29.8)	0.601
Insulin-treated diabetes (n (%))	66 (13.6)	25 (12.0)	129 (13.7)	0.803
Hypertension (n (%))	314 (64.9)	129 (62.0)	578 (61.5)	0.451
Peripheral arterial disease (n (%))	13 (2.7)	7 (3.4)	31 (3.3)	0.802
Chronic lung disease (n (%))	18 (3.7)	5 (2.4)	24 (2.6)	0.418
Carotid artery stenosis (n (%))	31 (6.4)	22 (10.6)	56 (6.0)	0.052
Previous cerebrovascular accident (n (%))	66 (13.6)	31 (14.9)	124 (13.2)	0.806
Atrial fibrillation (n (%))	117 (24.2)	41 (19.7)	215 (22.9)	0.440
Previous PCI (n (%))	34 (7.0)	17 (8.2)	86 (9.1)	0.389
Laboratory and cardiac function				
Creatinine, μmol/L (median (IQR))	77.45 (60.58, 92.53)	77.70 (62.68, 92.43)	75.95 (62.90, 93.62)	0.843
Total bilirubin, μmol/L (median (IQR))	11.00 (7.80, 15.12)	10.75 (7.38, 14.83)	10.20 (7.50, 14.00)	0.110
Hemoglobin, g/L (median (IQR))	128.00 (117.00, 139.00)	127.00 (117.00, 139.00)	128.00 (116.00, 138.00)	0.768
Preoperative LVEF, % (median (IQR))	61.50 (53.25, 63.90)	60.90 (51.73, 63.73)	61.00 (54.88, 64.00)	0.896
EuroSCORE II score (median (IQR))	2.82 (0.77, 5.29)	2.65 (0.70, 5.13)	2.54 (0.76, 4.89)	0.374
Preoperative medication				
Beta-blocker within 24 h before surgery (n (%))	223 (46.1)	99 (47.6)	335 (35.6)	<0.001
Surgical information				
Redo surgery (n (%))	13 (2.7)	3 (1.4)	20 (2.1)	0.575
Emergency surgery (n (%))	26 (5.4)	16 (7.7)	29 (3.1)	0.005
Operation time, min (median (IQR))	259.00 (223.00, 305.25)	259.50 (219.00, 299.75)	260.00 (225.00, 308.00)	0.649
Cardiopulmonary bypass (n (%))	443 (91.5)	195 (93.8)	874 (93.0)	0.494
Aortic cross-clamp time, min (median (IQR))	75.00 (55.00, 102.25)	76.00 (58.00, 100.75)	76.00 (55.00, 103.00)	0.782
CPB time, min (median (IQR))	109.50 (84.75, 137.25)	114.00 (92.00, 138.25)	110.00 (86.00, 138.00)	0.482
Nadir nasopharyngeal temperature, °C (median (IQR))	32.80 (32.40, 33.10)	32.80 (32.30, 33.10)	32.90 (32.70, 33.20)	<0.001
Nadir bladder temperature, °C (median (IQR))	33.60 (33.10, 34.00)	33.65 (33.10, 34.02)	33.40 (33.00, 33.80)	<0.001
CABG (n (%))	294 (60.7)	131 (63.0)	589 (62.7)	0.752
Valve surgery (n (%))	271 (56.0)	111 (53.4)	523 (55.6)	0.804
Combined surgery (n (%))	81 (16.7)	34 (16.3)	172 (18.3)	0.673
Isolated CABG (n (%))	213 (44.0)	97 (46.6)	417 (44.4)	0.804
Isolated valve surgery (n (%))	190 (39.3)	77 (37.0)	351 (37.3)	0.752
Use of internal mammary artery (n (%))	250 (51.7)	108 (51.9)	469 (49.9)	0.762
Postoperative outcomes				
First ICU stay, days (median (IQR))	1.00 (1.00, 2.00)	1.00 (1.00, 2.00)	1.00 (1.00, 2.00)	<0.001
Postoperative reintubation (n (%))	14 (2.9)	6 (2.9)	42 (4.5)	0.257
Acute kidney injury (n (%))	30 (6.2)	11 (5.3)	45 (4.8)	0.529
Low cardiac output syndrome (n (%))	21 (4.3)	11 (5.3)	43 (4.6)	0.860
Infection (n (%))	79 (16.3)	32 (15.4)	239 (25.4)	<0.001
In-hospital death (n (%))	8 (1.7)	9 (4.3)	39 (4.1)	0.037
30-day death (n (%))	8 (1.7)	9 (4.3)	45 (4.8)	0.012
Length of hospital stay, days (median (IQR))	18.00 (15.00, 21.00)	18.00 (15.00, 21.00)	18.00 (15.00, 23.00)	0.156

Data are presented as indicated in the first column: n (%), mean ± SD, or median (IQR). Abbreviations: BMI, body mass index; CABG, coronary artery bypass grafting; CPB, cardiopulmonary bypass; EuroSCORE II, European System for Cardiac Operative Risk Evaluation II; ICU, intensive care unit; LVEF, left ventricular ejection fraction; PCI, percutaneous coronary intervention; SD, standard deviation; IQR, interquartile range.

Table 4. Characteristics of patients with and without prolonged mechanical ventilation (PMV) in the training set.

Characteristics (format)	Non-PMV	PMV	*p* value
Demographics			
Age, yr (mean ± SD)	71.06 ± 4.34	72.44 ± 4.81	0.008
Male (n (%))	227 (60.4)	66 (61.1)	0.890
BMI, kg/m^2 (mean ± SD)	23.89 ± 3.26	23.62 ± 3.42	0.475
Medical history			
Smoking (n (%))	66 (17.6)	25 (23.1)	0.241
Diabetes (n (%))	111 (29.5)	34 (31.5)	0.785
Insulin-treated diabetes (n (%))	52 (13.8)	14 (13.0)	0.942
Hypertension (n (%))	246 (65.4)	68 (63.0)	0.720
Peripheral arterial disease (n (%))	6 (1.6)	7 (6.5)	0.015
Chronic lung disease (n (%))	12 (3.2)	6 (5.6)	0.392
Carotid artery stenosis (n (%))	21 (5.6)	10 (9.3)	0.249
Previous cerebrovascular accident (n (%))	52 (13.8)	14 (13.0)	0.942
Atrial fibrillation (n (%))	91 (24.2)	26 (24.1)	1.000
Previous PCI (n (%))	27 (7.2)	7 (6.5)	0.970
Laboratory and cardiac function			
Creatinine, μmol/L (median (IQR))	73.50 (58.35, 89.17)	89.05 (74.00, 117.48)	<0.001
Total bilirubin, μmol/L (median (IQR))	10.80 (7.80, 14.60)	11.80 (7.57, 16.62)	0.347
Hemoglobin, g/L (median (IQR))	128.00 (117.00, 140.00)	128.00 (118.00, 136.25)	0.626
Preoperative LVEF, % (median (IQR))	62.40 (57.85, 64.20)	50.75 (39.02, 60.82)	<0.001
EuroSCORE II score (median (IQR))	2.36 (0.31, 4.38)	6.12 (2.90, 8.94)	<0.001
Preoperative medication			
Beta-blocker within 24 h before surgery (n (%))	179 (47.6)	44 (40.7)	0.249
Surgical information			
Redo surgery (n (%))	10 (2.7)	3 (2.8)	1.000
Emergency surgery (n (%))	9 (2.4)	17 (15.7)	<0.001
Operation time, min (median (IQR))	251.50 (218.00, 292.25)	307.50 (252.00, 350.25)	<0.001
Cardiopulmonary bypass (n (%))	342 (91.0)	101 (93.5)	0.518
Aortic cross-clamp time, min (median (IQR))	76.00 (55.00, 104.00)	70.00 (54.75, 97.25)	0.410
CPB time, min (median (IQR))	109.00 (84.75, 138.00)	110.50 (84.50, 135.50)	0.979
Nadir nasopharyngeal temperature, °C (median (IQR))	32.80 (32.40, 33.10)	32.80 (32.40, 33.00)	0.707
Nadir bladder temperature, °C (median (IQR))	33.60 (33.10, 34.00)	33.65 (33.10, 34.10)	0.798
CABG (n (%))	222 (59.0)	72 (66.7)	0.187
Valve surgery (n (%))	215 (57.2)	56 (51.9)	0.382
Combined surgery (n (%))	61 (16.2)	20 (18.5)	0.677
Isolated CABG (n (%))	161 (42.8)	52 (48.1)	0.382
Isolated valve surgery (n (%))	154 (41.0)	36 (33.3)	0.187
Use of internal mammary artery (n (%))	190 (50.5)	60 (55.6)	0.417
Postoperative outcomes			
First ICU stay, days (median (IQR))	1.00 (1.00, 2.00)	1.00 (1.00, 2.00)	0.561
Postoperative reintubation (n (%))	12 (3.2)	2 (1.9)	0.745
Acute kidney injury (n (%))	20 (5.3)	10 (9.3)	0.204
Low cardiac output syndrome (n (%))	17 (4.5)	4 (3.7)	1.000
Infection (n (%))	63 (16.8)	16 (14.8)	0.739
In-hospital death (n (%))	7 (1.9)	1 (0.9)	0.691
30-day death (n (%))	7 (1.9)	1 (0.9)	0.691
Length of hospital stay, days (median (IQR))	18.00 (15.00, 21.00)	18.00 (15.00, 20.00)	0.501

Data are presented as indicated in the first column: n (%), mean ± SD, or median (IQR). Abbreviations: BMI, body mass index; CABG, coronary artery bypass grafting; CPB, cardiopulmonary bypass; EuroSCORE II, European System for Cardiac Operative Risk Evaluation II; ICU, intensive care unit; LVEF, left ventricular ejection fraction; PCI, percutaneous coronary intervention; PMV, prolonged mechanical ventilation.

Table 5. Multiple logistic regression of least absolute shrinkage and selection operator (LASSO)-selected predictors for prolonged mechanical ventilation (PMV) in the training set.

Variable	Coefficient	OR	95% CI	*p*-value
Intercept	–8.025	--	--	--
Age, per year	0.084	1.09	1.02–1.16	0.008
Preoperative creatinine, per 10 μmol/L	0.200	1.22	1.13–1.32	<0.001
Preoperative LVEF, per 1%	–0.087	0.92	0.89–0.94	<0.001
EuroSCORE II score, per point	0.136	1.15	1.08–1.21	<0.001
Operation time, per 10 min	0.132	1.14	1.09–1.20	<0.001
Non-valve surgery	0.759	2.13	1.19–3.85	0.011

Abbreviations: CI, confidence interval; EuroSCORE II, European System for Cardiac Operative Risk Evaluation II; LASSO, least absolute shrinkage and selection operator; LVEF, left ventricular ejection fraction; OR, odds ratio; PMV, prolonged mechanical ventilation.

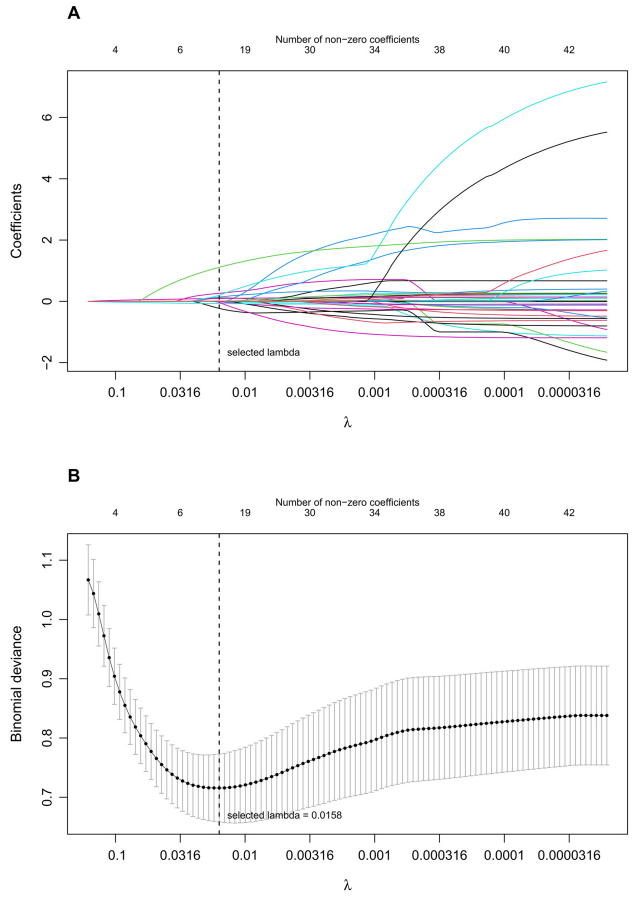

Fig. 2. LASSO variable selection and optimal penalty parameter determination. (A) Least absolute shrinkage and selection operator (LASSO) coefficient profiles of all candidate perioperative variables. The dashed vertical line indicates the selected optimal lambda. (B) Ten-fold cross-validation for optimal lambda selection in the LASSO model. The dashed vertical line indicates the selected optimal lambda.

denotes preoperative creatinine divided by 10 μmol/L, Operation_time_10 denotes operation time divided by 10 min, and Non-valve surgery was coded as 1 for non-valve surgery and 0 otherwise. The predicted probability was calculated as p = exp(logit) / [1 + exp(logit)]. The final prediction tool was visualized as a nomogram (Fig. 3).

The procedural term should not be interpreted as evidence that CABG itself is a causal risk factor. CABG, isolated CABG, valve surgery, and combined surgery were included in the candidate variable set and described in the preceding descriptive analyses; in the training set, none of these categories differed significantly between the PMV and non-PMV groups. The retained "non-valve surgery" term is a re-coded representation of the original valve-surgery variable with a negative coefficient and was kept only for prediction. Clinically, combined CABG and valve surgery often indicates greater operative complexity; in the present model, that complexity is probably captured mainly by operation time and EuroSCORE II score.

3.6 Model Performance and Clinical Utility

The nomogram showed good discrimination in all datasets. AUCs were 0.873 (95% CI, 0.835–0.911) in the training set, 0.893 (95% CI, 0.844–0.942) in the internal validation set, and 0.878 (95% CI, 0.849–0.906) in the temporal validation set. The corresponding Brier scores were 0.100, 0.115, and 0.098. Model performance metrics for the training, internal validation, and temporal validation sets are summarized in Table 6. In the temporal validation cohort, the Hosmer-Lemeshow p-value was 0.102, supporting acceptable calibration over time. In the smaller internal validation set, the Hosmer-Lemeshow p-value was 0.026, suggesting sensitivity to local miscalibration; calibration curves should therefore be interpreted alongside the global performance measures. Receiver operating characteristic curves are shown in Fig. 4, calibration curves are shown in Fig. 5, and decision curve analysis is shown in Fig. 6.

4. Discussion

In this retrospective cohort of older adults undergoing cardiac surgery, we developed and temporally validated an interpretable LASSO-derived nomogram for PMV. The

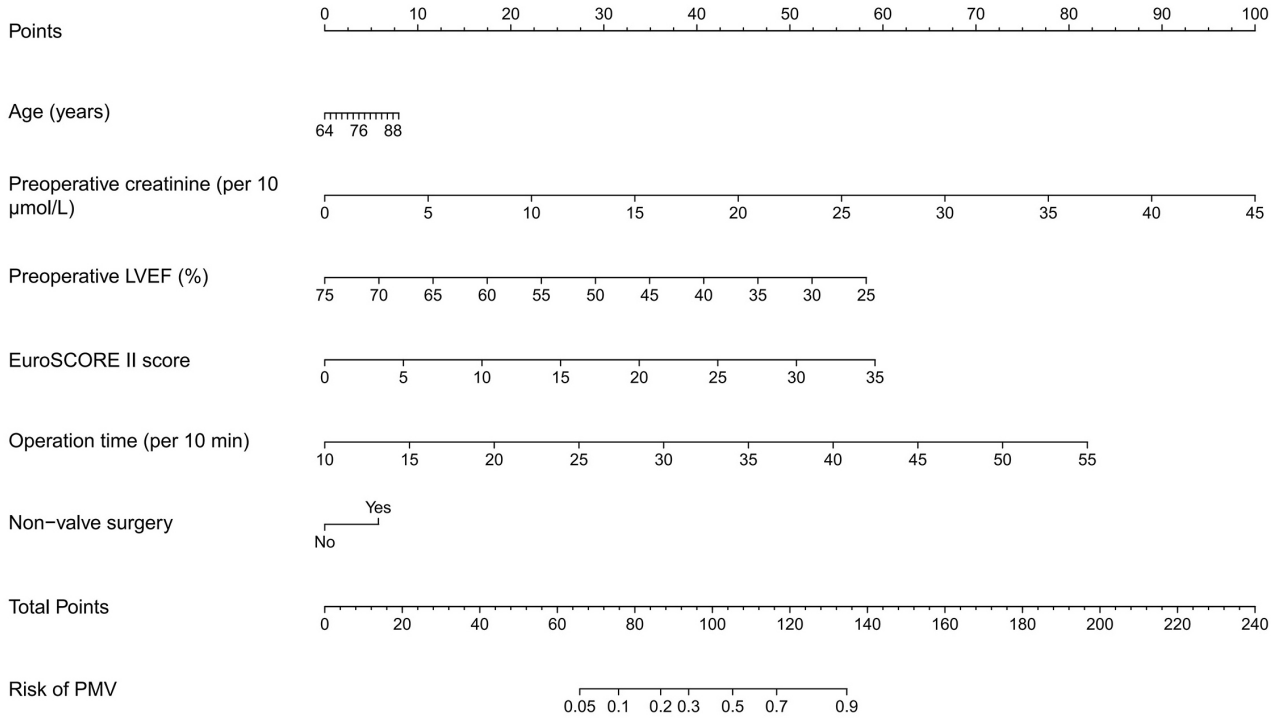

Fig. 3. Nomogram derived from the training cohort for predicting prolonged mechanical ventilation (PMV). The nomogram assigns points to each predictor and converts total points into the predicted probability of PMV. LVEF, left ventricular ejection fraction; EuroSCORE II, European System for Cardiac Operative Risk Evaluation II.

Table 6. Model performance in the training, internal validation, and temporal validation sets.

Cohort	n	PMV events	PMV incidence, %	AUC (95% CI)	Brier score	Optimal threshold	Sensitivity (95% CI)	Specificity (95% CI)	HL *p* value
Training set	484	108	22.3	0.873 (0.835–0.911)	0.100	0.165	0.861 (0.781–0.920)	0.766 (0.720–0.808)	0.055
Internal validation set	208	47	22.6	0.893 (0.844–0.942)	0.115	0.136	0.872 (0.743–0.952)	0.739 (0.664–0.805)	0.026
Temporal validation set	940	191	20.3	0.878 (0.849–0.906)	0.098	0.249	0.770 (0.703–0.827)	0.841 (0.813–0.867)	0.102

Abbreviations: AUC, area under the receiver operating characteristic curve; CI, confidence interval; HL, Hosmer-Lemeshow; PMV, prolonged mechanical ventilation. Sensitivity and specificity 95% CIs were calculated using the exact binomial method.

model includes six routinely available perioperative variables: age, preoperative creatinine, preoperative LVEF, EuroSCORE II score, operation time, and non-valve surgery. Its main value lies not in algorithmic complexity, but in separating clinically meaningful risk domains: baseline vulnerability, cardio-renal reserve, and operative burden.

The retained predictors are clinically plausible and consistent with prior evidence. Age reflects reduced physiological reserve and lower tolerance of perioperative stress [5]. Creatinine captures renal reserve, which affects fluid balance, inflammatory response, and susceptibility to low perfusion during and after cardiac surgery [1,11,25]. Lower LVEF indicates impaired pump function and a greater likelihood of postoperative circulatory support, delayed recovery, and ventilator dependence [10,13]. EuroSCORE II summarises multiple baseline and procedural risk dimensions and remains widely used in cardiac-surgery risk assessment [26]. Operation time represents the cumulative burden of anaesthesia, surgical complexity, and tissue injury; previous studies in CABG, robot-assisted CABG, redo valve or aortic arch surgery, and valve surgery have likewise linked procedural burden and case complexity with delayed ventilatory recovery [12,13,14,15,16].

The model is intended to support two decision points. Before surgery, age, creatinine, LVEF, and EuroSCORE II can inform patient counselling, anaesthetic planning, and ICU resource allocation. At the end of surgery, operation time and procedural information can update risk estimates using data that are immediately available at handover. This structure is consistent with enhanced recovery principles, in which early extubation and structured perioperative pathways are tailored to patient risk rather than applied as uniform protocols [24].

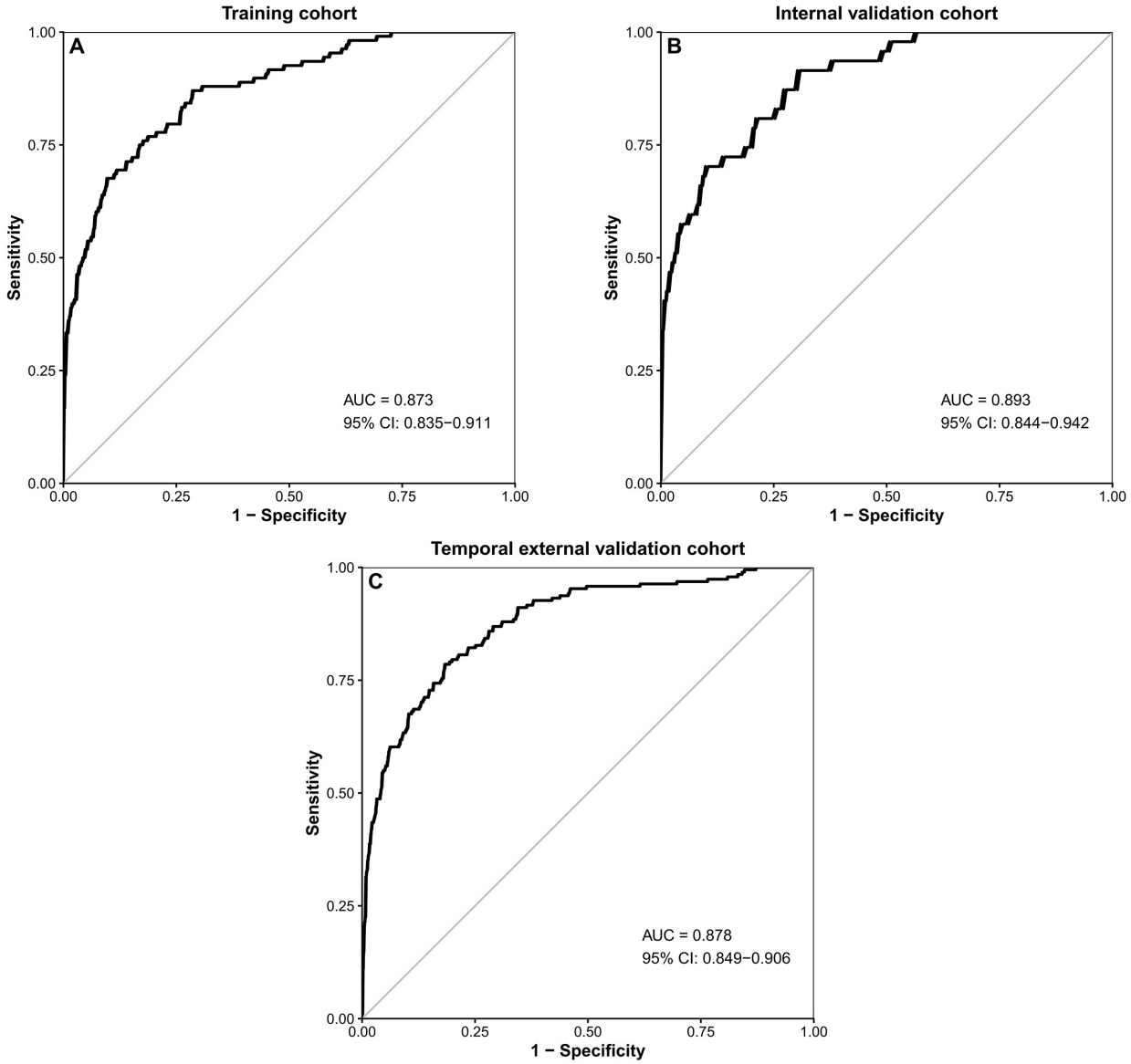

Fig. 4. Receiver operating characteristic curves of the prediction model. Receiver operating characteristic curves of the nomogram in the training cohort (A), internal validation cohort (B), and temporal validation cohort (C). AUC, area under the receiver operating characteristic curve; CI, confidence interval.

The procedural variable requires a cautious interpretation. Although the final model retained non-valve surgery, this should not be read as evidence that CABG or non-valve surgery is biologically causal. In the training cohort, CABG, isolated CABG, valve surgery, and combined surgery were not significantly associated with PMV in univariable comparisons, and combined surgery was not selected by LASSO. The direction of the valve-surgery coding may reflect local case mix, collinearity among procedure categories, operation time, EuroSCORE II, and unmeasured perioperative management patterns. We therefore treat this term as a statistical coding term, while recognizing that combined CABG-valve operations are clinically complex and may carry higher complication rates in other cohorts.

Mental health disorders after cardiac surgery also deserve attention, beyond physiological and operative factors. Postoperative delirium is a common neuropsychiatric complication and has been linked to psychiatric vulnerability, inflammatory and cerebral susceptibility pathways, and adverse functional and cognitive consequences. Depression, anxiety, suicidality, and broader mental health disorders may further complicate recovery, particularly in patients receiving advanced cardiac therapies such as left ventricular assist devices; these conditions may also contribute to inequities in access, emergency presentation, prolonged hospitalization, readmission, and long-term outcomes. These variables were not available in our dataset and were therefore not included as candidate predictors. Future PMV models should consider validated preoperative

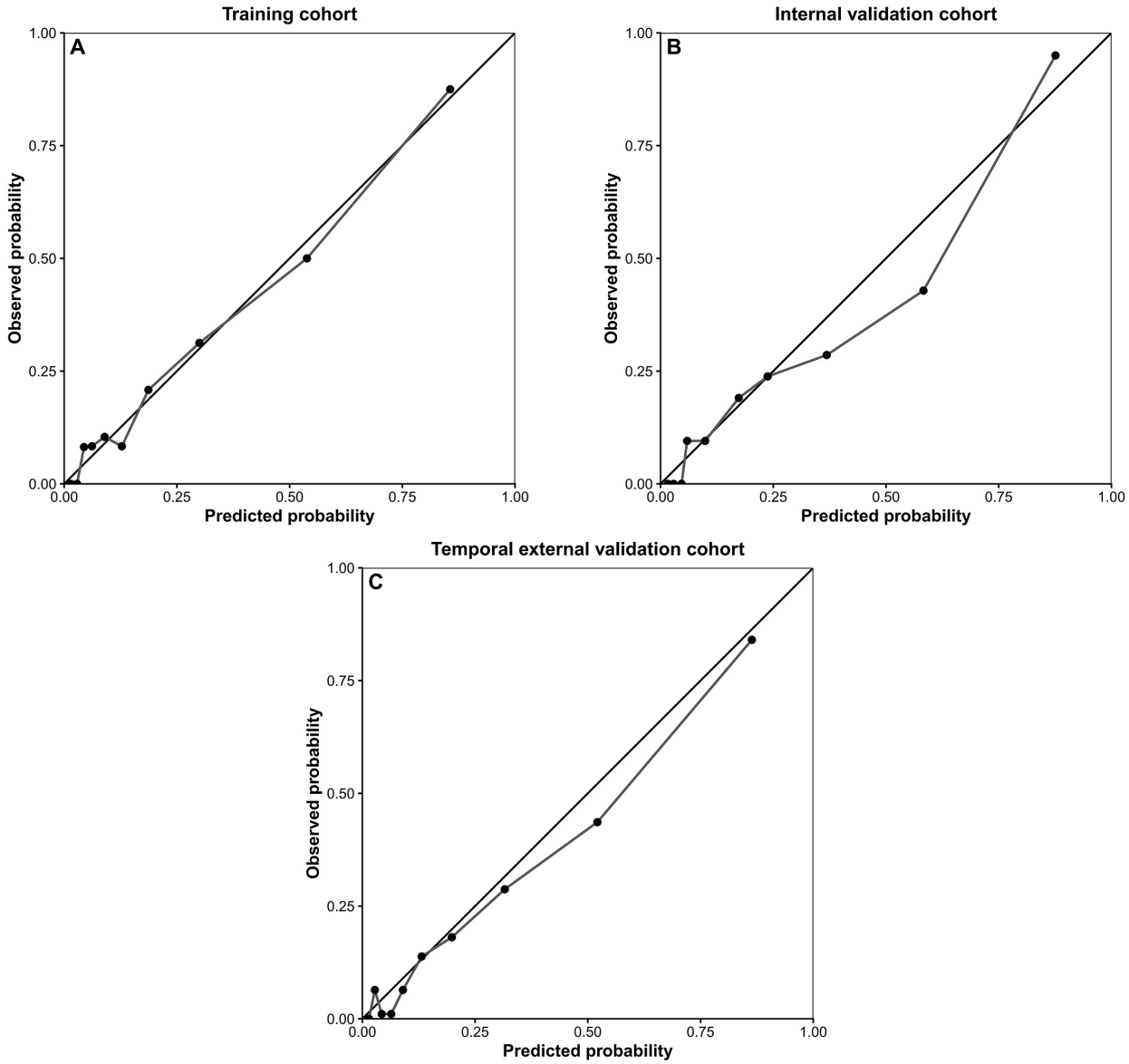

Fig. 5. Calibration curves of the prediction model. Calibration curves of the nomogram in the training cohort (A), internal validation cohort (B), and temporal validation cohort (C). The diagonal line represents perfect calibration.

mental health screening and postoperative neuropsychiatric assessment where feasible [27,28,29]. Recent nomogram work in elderly cardiac-surgery patients indicates that postoperative delirium can be predicted using routinely available perioperative variables, which supports the feasibility of adding neuropsychiatric vulnerability to staged perioperative risk assessment [30].

This broader context supports a patient-centered approach to cardiac surgery. Recent frameworks emphasize that psychosocial challenges, communication quality, shared decision-making, caregiver involvement, and evidence-based psychosocial interventions influence not only patient-reported outcomes, but also adherence, rehabilitation, pain, quality of life, and potentially healthcare utilization. For PMV prediction, a nomogram should be used as a communication and planning aid that complements, rather than replaces, individualized discussion of patients' values, psychological readiness, family support, and expected postoperative recovery trajectory [31].

Perioperative prediction models also intersect with the emerging concept of twin transformation in cardiothoracic surgery, namely the convergence of digital innovation and sustainability. Digital tools, artificial intelligence, big data, digital twins, telemedicine, and interoperable electronic records may improve risk stratification and follow-up. In parallel, sustainability-oriented practice encourages efficient resource use and a lower environmental burden. A routinely available PMV nomogram can be viewed as a small but practical part of this broader transition, because it supports targeted ICU planning and avoids indiscriminate resource allocation while remaining clinically transparent [32].

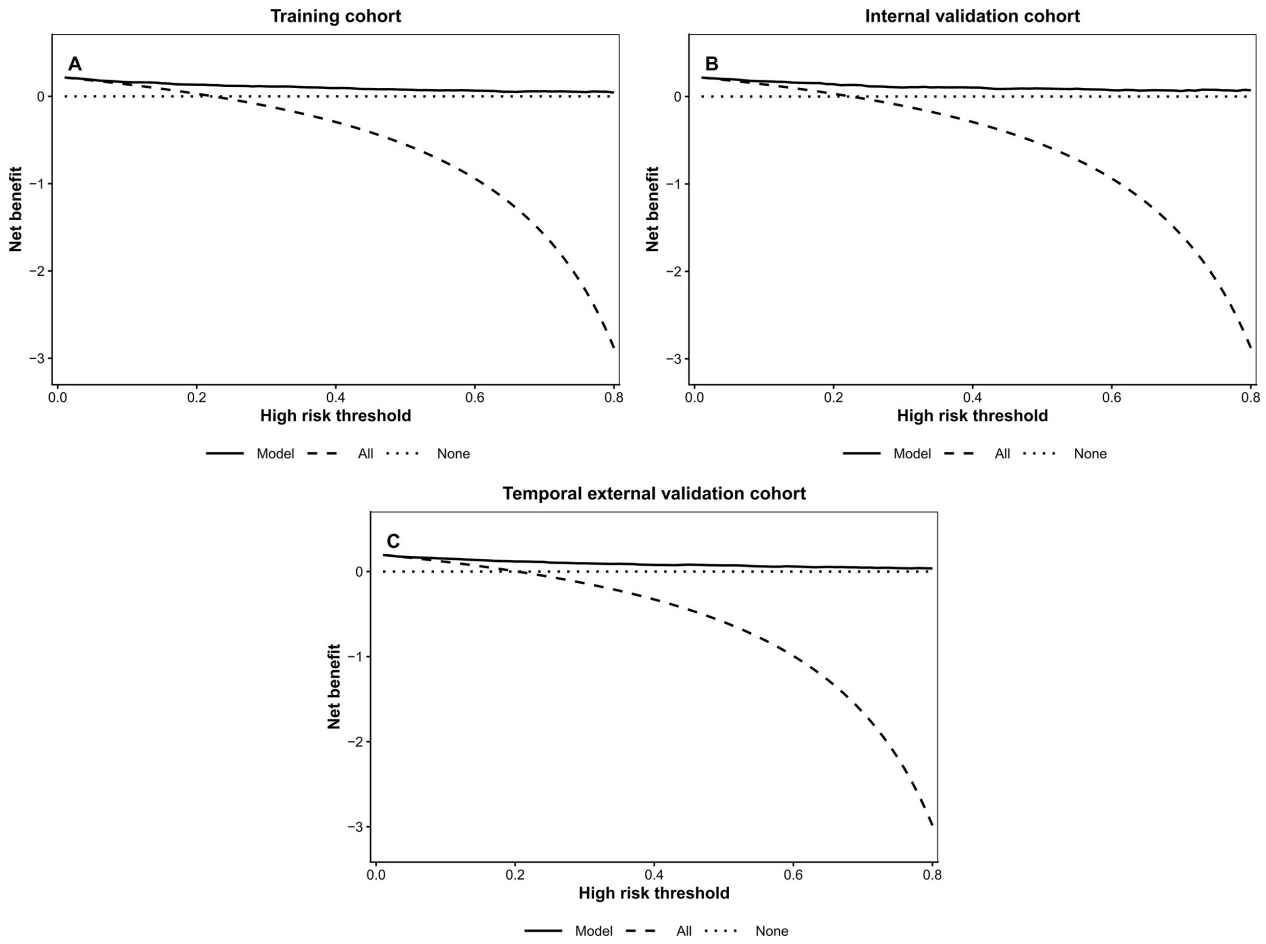

Fig. 6. Decision curve analysis of the prediction model. Decision curve analysis of the nomogram in the training cohort (A), internal validation cohort (B), and temporal validation cohort (C). The net benefit of the model is compared with treat-all and treat-none strategies.

A methodological clarification is important: postoperative variables were excluded only from the primary perioperative prediction model, not from clinical consideration. We agree that postoperative haemodynamic instability, vasoactive or inotropic support, and arrhythmias are important determinants of ventilator dependence after cardiac surgery. These variables are measured during the ICU course, however, and may arise after the outcome process has begun. Using them as predictors in a model intended for preoperative and end-of-surgery decision-making could introduce temporal leakage and inflate apparent performance. This nomogram should therefore be viewed as a perioperative risk-stratification tool rather than a dynamic postoperative extubation model [20,21].

Model evaluation was deliberately multidimensional. Although the AUCs showed good risk separation, discrimination alone does not confirm that predicted probabilities are accurate [19]. Calibration curves, Brier scores, and Hosmer-Lemeshow tests were therefore reported to assess probability accuracy [22]. Decision curve analysis further indicated potential clinical usefulness across a range of threshold probabilities by comparing net benefit with treat-all and treat-none strategies [23].

Compared with previous PMV prediction studies, this model places greater emphasis on temporal validation and transparent variable selection. Recent cardiac-surgery PMV scores have demonstrated the feasibility of training-validation frameworks [5,8,9], while procedure-specific studies suggest that risk structures may differ across CABG, robot-assisted CABG, redo valve surgery, redo aortic arch surgery, left ventricular assist device (LVAD) implantation, and valve-surgery cohorts [12,13,14,15,16,25]. The present study extends that work by focusing on older adults and by combining LASSO-based selection with a clinically interpretable logistic nomogram. Additional recent studies and reviews have broadened the PMV evidence base in large cardiac-surgery score development, cardiovascular-surgery cohorts, CABG-specific cohorts, aortic surgery cohorts, and narrative synthesis of PMV predictors [33,34,35,36,37].

5. Limitation

This study has several limitations. First, it was conducted at a single centre, and validation was temporal rather than multicentre. Second, the retrospective design remains

susceptible to residual confounding, measurement error, and local practice patterns in ventilation and extubation. Third, although the sample size and number of events were adequate for a parsimonious model, multicentre prospective studies should evaluate transportability, recalibration, and clinical impact before the nomogram is implemented as a decision-support tool [38,39]. Fourth, detailed postoperative haemodynamic variables, vasoactive-inotropic scores, and new-onset arrhythmias were not available with sufficient granularity to construct a dynamic postoperative model. Future prospective studies should develop staged models that update PMV risk after ICU admission using these variables.

6. Conclusions

We developed a LASSO-derived perioperative nomogram for predicting PMV in older adults undergoing cardiac surgery. The model combines patient vulnerability, cardiorenal reserve, and operative burden, and showed good discrimination and acceptable calibration in both internal and temporal validation. Because it relies on routinely available variables, the nomogram may support perioperative risk communication, end-of-surgery risk updating, and ICU resource planning. Prospective multicentre validation is required before broad clinical deployment. Future implementation should be embedded within patient-centered care pathways that address psychosocial vulnerability, postoperative mental health, digital integration, and sustainable perioperative resource use.

Availability of Data and Materials

The data analysed during the current study are available from the corresponding author upon reasonable request, subject to institutional data-sharing rules and patient privacy protection.

Author Contributions

SW designed the study framework, established the methodology, and developed the research protocol. JW performed the formal statistical analyses and generated the data visualizations. CP participated in the interpretation of the study data and findings, drafted the initial manuscript, and refined the text through iterative revisions to ensure logical flow and academic rigor. NS and TX were responsible for data collection and curation. WC supervised the overall research process, ensuring methodological quality, ethical compliance, and resource management. ZQ validated the analytical methods and independently cross-checked the key findings to ensure the robustness of the results. XC contributed to the study design and the interpretation of the data and clinical implications of the findings, and critically reviewed and revised the manuscript for important intellectual content. All authors contributed to editorial changes in the manuscript. 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

The study was approved by the Ethics Committee of Nanjing First Hospital (approval number: KY20220425-05) and was conducted in accordance with the Declaration of Helsinki. Because this retrospective analysis used de-identified clinical data, the ethics committee waived the requirement for informed consent.

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Conflicts of Interest

The authors declare no conflict of interest.

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