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Development and External Validation of a Prediction Model for Postoperative Pulmonary Complications in Mechanically Ventilated Surgical Patients Using MIMIC-IV and eICU

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Abstract

Background: Postoperative pulmonary complications (PPC) substantially affect surgical outcomes. We aimed to develop and externally validate a risk prediction model for postoperative pulmonary complications in mechanically ventilated surgical patients using public critical care databases.

Methods: The development cohort was derived from the Medical Information Mart for Intensive Care (MIMIC)-IV, including adults with documented surgery who received invasive mechanical ventilation within 24 h of intensive care unit admission; external validation used the eICU Collaborative Research Database. The primary outcome was a narrow composite of atelectasis, pneumonia, or aspiration pneumonitis. Multiple imputation and least absolute shrinkage and selection operator (LASSO) regression were used; internal validation used 10-fold cross-validation (50 repeats), and external

validation assessed discrimination and calibration.

Results: The development cohort comprised 18379 patients with 4650 PPC events (25.3%); the external cohort comprised 2778 patients with 549 events (19.8%). The final model included 16 predictors, with an area under the receiver operating characteristic curve (AUC) of 0.731 in development and 0.729 on internal cross-validation. External validation yielded an AUC of 0.680 (95% confidence interval 0.655-0.706) and a Brier score of 0.147. Adding vital signs and ventilator parameters to a base clinical model improved the AUC from 0.667 to 0.731.

Conclusion: The model showed moderate discrimination and was externally validated in an independent database (AUC 0.680). Its structure was transportable, but absolute risk required recalibration in the external cohort; the model is therefore better suited to risk stratification than to individual absolute-risk prediction.

Keywords: Postoperative pulmonary complications (PPC); Prediction model; Mechanical ventilation; Intensive care unit (ICU); MIMIC-IV; eICU; External validation.

1. Background

PPC, namely atelectasis, pneumonia, respiratory failure, and aspiration pneumonitis, remain a leading cause of morbidity and mortality after surgery, with reported incidences ranging from 5% to 33% depending on the surgical population and the definition used[1,2]. Even mild PPC have been associated with increased early postoperative mortality, higher overall morbidity, greater intensive care use and prolonged hospital stay[3].

PPC are not confined to thoracic procedures. General anaesthesia and mechanical ventilation themselves promote atelectasis and lung injury, so every patient who is ventilated is exposed[4-7]. Those who remain ventilated and require intensive care after surgery sit at the upper end of this risk. In a recent cohort of 495 critically ill surgical patients who needed intraoperative ventilation and postoperative ICU care, one in five developed a PPC[8].

Risk scores for the preoperative setting are well established. The Assess Respiratory Risk in Surgical Patients in Catalonia (ARISCAT) score was derived from a large population-based surgical cohort and combines patient characteristics with surgical factors[9]; the Local Assessment of Ventilatory Management During General Anesthesia for Surgery (LAS VEGAS) score was built from an international observational study of intraoperative ventilation[10]. Registry-based tools such as National Surgical Quality Improvement Program (NSQIP)-derived models have been developed mainly for general surgical populations[11-15]. All of them were designed to be used before or during the operation, and they depend largely on preoperative and demographic variables. Their performance outside that setting is modest. In a recent evaluation of 495 critically ill surgical patients, LAS VEGAS, ARISCAT and Chinese Brief Predictive Risk Index (CHI-BPRI) reached AUCs of only 0.63, 0.60 and 0.55, none reaching 0.70[8]. External validation in an independent cohort is also uncommon[11]. Models that actually use them are still scarce: most ICU prediction work has targeted mortality, acute kidney injury or weaning rather than PPC, and few models have been tested in a second, independent database[16-18].

Mechanical ventilation can itself injure the lung: ventilator-induced lung injury reflects the interaction between the mechanical energy delivered and the regional mechanical properties of the lung. Positive End-Expiratory Pressure (PEEP), Tidal Volume/Predicted Body Weight (VT/PBW), Plateau Pressure (Pplat), Driving Pressure (ΔP) and the PaO_2/FiO_2 (P/F) ratio describe the mechanical load applied to the lung, and each has been linked to lung injury and to PPC[19-22]. Trials of individualised PEEP and of driving-pressure-guided ventilation suggest that these variables are not only markers of severity but potentially modifiable. Mechanical power has been proposed as a single metric combining tidal volume, airway pressures, respiratory rate and inspiratory flow; in a cohort of more than 33000 non-cardiothoracic surgical patients, intraoperative mechanical power was independently associated with PPC[23]. It remains unclear how much predictive information routinely recorded ventilator parameters add beyond demographic and comorbidity variables in a surgical ICU population.

We therefore developed and externally validated a model to predict PPC in surgical patients receiving invasive mechanical ventilation in the ICU, using only variables available in the first 24 hours. The model was developed in MIMIC-IV, validated in the independent multi-centre eICU-CRD database, and reported according to the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) recommendations.

2. Methods

2.1 Study design and data sources

This was a retrospective prediction model development and external validation study. The development cohort was derived from the MIMIC-IV. External validation was performed using the eICU-CRD. The study was conducted and reported in accordance with the TRIPOD statement.

Upon successfully passing the Collaborative Institutional Training Initiative (CITI) assessment (certificate ID: 60273273), the author, Xiaona An, obtained authorization to use the database and then performed the data extraction. Because the dataset was de-identified, the requirement for obtaining informed consent was exempted.

2.2 Study population

Inclusion criteria were: (i) age ≥18 years; (ii) documented surgery (surgical service record services.curr_service containing SURG, or procedure codes (International Classification of Diseases (ICD)-9 01–86 / ICD-10-PCS starting with 0); (iii) invasive mechanical ventilation started within 24 h of ICU admission (identified in MIMIC-IV by procedureevents.Itemid = 225792, and in eICU by airwaytype of Oral or Nasal ETT with respcarestatusoffset <=1440 min); and (iv) first ICU stay per patient. Patients aged <18 years, without a surgical record, with a non-first ICU stay, or without invasive ventilation within 24 h were excluded (Figure 1).

The cohort was built by stepwise filtering (adult ICU admissions, documented surgery, first stay, invasive ventilation within 24 h), yielding 18379 patients in the development cohort. The same eligibility criteria were applied to the eICU-CRD cohort where possible.

2.3 Outcome definition

The outcome was a narrow PPC composite based on ICD diagnosis codes recorded during the hospitalisation: atelectasis (518.0/J98.11/J98.19), pneumonia (ICD-9 480–486; ICD-10 J12–J18), or aspiration pneumonitis (507/J69), a subset of EPCO definitions for pulmonary complications. Any positive component was classified as PPC. Diagnosis codes were not restricted to a specific postoperative window.

2.4 Predictors

First-24-hour demographics, comorbidities, vital signs, ventilator parameters, laboratory values, and vasopressors were considered. Vital signs and ventilator parameters were extracted from chartevents (window: intime - 24 h to time_zero + 24 h). Aggregation was as follows: mean for Positive End-Expiratory Pressure (PEEP) (220339), Fraction of Inspired Oxygen (FiO_2) (223835), tidal volume (VT) (224684), plateau pressure (Pplat) (224696), heart rate (HR) (220045), minimum for mean arterial pressure (MAP) (220052), peripheral oxygen saturation (SpO_2) (220277) and maximum for respiratory rate (RR) (220210).

Derived variables included: driving pressure (ΔP) = plateau pressure − PEEP; tidal volume per kg predicted body weight (VT/PBW) (PBW: 50 + 0.91 × (height − 152.4) for men; 45.5 + 0.91 × (height − 152.4) for women); and P/F ratio = PaO_2 (50821) / FiO_2. FiO_2 values >1 were divided by 100 to convert percentages to fractions.

Continuous predictors were truncated to prespecified physiological ranges to reduce the influence of outliers, and the full list of truncation ranges is provided in Additional file 1: Table S1.

2.5 Missing data

Multiple imputation by chained equations (MICE, m = 5) was used. Variables with >50% missingness (temperature, albumin) were excluded. The imputed dataset was used for all subsequent LASSO, logistic, and validation analyses. The eICU external validation cohort was imputed separately, without borrowing the imputation model from the development cohort.

2.6 Model development

LASSO variable selection was performed (family = binomial, 5-fold cross-validation, selection-direction = both), using the lambda.1se rule (the most parsimonious model whose cross-validation error is within one standard error of the minimum). Because lambda.1se coefficients are shrunk, an unpenalised logistic regression was refitted on the selected variables, and its coefficients and odds ratios are reported. Calibration was assessed with calibration plots and the Hosmer-Lemeshow (H-L) test, and clinical usefulness with decision curve analysis.

2.7 Model validation

Internal validation used 10-fold cross-validation repeated 50 times. External validation used a frozen model: coefficients, intercept, and variable set were fixed to the development cohort results, and the eICU data were used only to compute predicted probabilities and assess performance, with no refitting.

2.8 Incremental value

Incremental value was assessed using the net reclassification improvement (NRI) and integrated discrimination improvement (IDI). Categorical NRI was calculated using

prespecified risk categories (<10%, 10–20%, >20%), whereas continuous NRI and IDI were calculated on the continuous predicted probability scale. Confidence intervals were estimated by 500 bootstrap resamples, and *P* values were two-sided. The Youden-optimal cut-off of predicted risk and the corresponding diagnostic performance (sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and likelihood ratios), together with all cut-off values used in this study, were summarised in Additional file 1: Table S2.

2.9 Statistical software and sensitivity analysis

All primary analyses were performed using Free-Statistics 2.6 (Free-Statistics, China). Bootstrap sensitivity analyses were performed in R 4.2.2 using the glm function. For the acute respiratory distress syndrome (ARDS) coefficient, 1000 bootstrap resamples were drawn with replacement (each of the same size as the development cohort), and the full 16-predictor model was refitted in each resample. We reported the median odds ratio (OR), the 2.5th and 97.5th percentiles, and the proportion of resamples with OR < 1. The same bootstrap procedure was applied to the coefficients for sepsis and chronic obstructive pulmonary disease (COPD) to assess the stability of their ORs. Discrimination with and without ARDS was compared across 300 bootstrap resamples. The random seed was fixed at 20260916 for reproducibility.

3. Results

3.1 Baseline characteristics

The development cohort comprised 18379 patients, among whom 4650 experienced PPC events (25.3%). Baseline demographic, clinical, and laboratory characteristics are

177 summarized in Table 1.

178 **3.2 Model development**

179 The LASSO cross-validation curve and coefficient path are shown in Figure 2 and
180 Figure 3. The nomogram derived from the final model is shown in Figure 4. LASSO
181 selected 16 predictors. Their coefficients, odds ratios, 95% CIs, and *P* values are
182 reported in Table 2.

183 **3.3 Internal validation**

184 In the development cohort, the model achieved an AUC of 0.731 (Figure 5), a Dxy of
185 0.461, and a Brier score of 0.164. The H-L test yielded $P = 0.101$, suggesting acceptable
186 calibration (Table 3). In 10-fold cross-validation repeated 50 times, the mean AUC was
187 0.729 (SD 0.013), with a calibration slope of 0.993 and an intercept of −0.008,
188 indicating no substantial overfitting. The distribution of discrimination and calibration
189 indices across the 50 repeats is shown in Figure 6; development calibration and decision
190 curve analysis are shown in Figure 7 and Figure 8.

191 **3.4 External validation**

192 The external eICU cohort included 2778 patients, with 549 PPC events (19.8%). The
193 external AUC was 0.680 (95% CI 0.655–0.706), and the Brier score was 0.147 (Table
194 3). External calibration was poor: the calibration slope was 0.70 (95% CI 0.60–0.81),
195 the intercept 0.07 (−0.03 to 0.17), and the H-L $P < 0.001$. External Receiver operating
196 characteristic (ROC) and calibration curves are shown in Figure 9 and Figure 10.

197 **3.5 Incremental value of ventilator parameters**

198 The base model (demographics and comorbidities, 8 variables) had an AUC of 0.667.

Adding vital signs and ventilator parameters (16 variables) increased the AUC to 0.731 (ΔAUC = 0.064). The incremental value was further supported by NRI and IDI. The categorical NRI was 0.225 (95% CI 0.206–0.245, $P < 0.001$), the continuous NRI was 0.498 (95% CI 0.465–0.530, $P < 0.001$), and the IDI was 0.059 (95% CI 0.055–0.063, $P < 0.001$) (Table 4). These results indicate that vital signs and ventilator parameters provided significant incremental predictive value for PPC beyond demographic and comorbidity variables.

3.6 Sensitivity analysis (ARDS)

ARDS was uncommon (191/18379, 1.04%), and its coefficient was estimated with limited precision (OR 1.426, 95% CI 1.030-1.975). In 1000 bootstrap resamples the OR exceeded 1 in 98.3% of replicates (median 1.429, 2.5th-97.5th 1.019-2.070), indicating a robust direction but an unstable magnitude; by contrast, sepsis and COPD retained ORs well above 1 in every resample (2.5th percentiles 2.140 and 1.476, respectively). Removing ARDS did not materially change discrimination (AUC 0.7307 vs 0.7305; delta AUC = +0.0002; bootstrap 95% CI -0.00002 to +0.00088), indicating that the overall model is insensitive to its inclusion. See Additional file 2: Table S3, Figure S1 and Note S1.

4. Discussion

4.1 Main findings

We developed and externally validated a model that predicts PPC in surgical patients requiring mechanical ventilation, using variables available in the first 24 hours of ICU stay. LASSO retained 16 predictors; the model reached an AUC of 0.731 in the

development cohort and 0.729 (SD 0.013) on repeated 10-fold cross-validation, with a calibration slope of 0.993. In the independent eICU-CRD cohort the AUC was 0.680 and the Brier score was 0.147.

Ventilator parameters, including PEEP, FiO_2, VT, Pplat, and P/F ratio, were significantly associated with PPC. Sepsis (OR 2.43), COPD (OR 1.67), and ARDS (OR 1.43) were the strongest independent predictors, while elective admission was protective (OR 0.39). Incremental analysis showed that adding vital signs and ventilator parameters increased the AUC from 0.667 to 0.731, with categorical NRI 0.225, continuous NRI 0.498, and IDI 0.059 (all $P < 0.001$), supporting the independent incremental value of ICU ventilator parameters beyond demographics and comorbidities.

4.2 Comparison with existing models

PPC prediction models have predominantly focused on general surgical populations. Commonly used tools such as ARISCAT and LAS VEGAS incorporate preoperative and intraoperative variables, but ICU-specific models integrating ventilator parameters remain scarce. In a comparable ICU mechanically ventilated surgical population, the AUCs of ARISCAT[9], LAS VEGAS[10], and CHI-BPRI were 0.60, 0.63, and 0.55[8], respectively, all below 0.70. Our model achieved a development AUC of 0.731 and an external AUC of 0.680, indicating better discrimination than these scores.

The difference from comorbidity-based scores is likely to lie in the ventilator data: PEEP, VT/PBW, Pplat, ΔP, and the P/F ratio directly describe the mechanical stress applied to the lung, whereas comorbidity-based scores capture only host

susceptibility[20]. This is consistent with the physiological rationale that mechanical ventilation characteristics directly influence lung injury and postoperative pulmonary outcomes. Whether this translates into better clinical decisions remains untested, and the comparison is indirect because those scores were not refitted in our cohort.

4.3 Incremental value of ventilator parameters

The NRI and IDI results indicate that the ventilator variables carry information that demographic and comorbidity variables do not[24]. The categorical NRI of 0.225 represents a net gain in reclassification across the prespecified risk strata (<10%, 10-20%, >20%) rather than a fixed number of patients moved; the continuous NRI (0.498) and IDI (0.059) describe the same improvement on the probability scale. These findings suggest that ventilator parameters are not merely proxies for disease severity but capture distinct pathophysiological information relevant to PPC risk. This fits the physiological argument that ventilation itself contributes to lung injury[4,20]. In practice, it means that data already recorded in the ICU can refine risk estimates, which may help target lung-protective ventilation and decide how closely a patient is watched after surgery[20]. However, the gain is modest, and the model does not indicate which ventilator settings should be changed.

4.4 External validation and calibration

Discrimination fell from 0.731 to 0.680 in eICU-CRD, the sort of drop expected when a model is transported to another database. Case-mix, ICU organisation, and documentation differ between MIMIC-IV and eICU-CRD, and the event rate was lower (19.8% vs 25.3%). Discrimination was not the main problem; absolute risk was. The

calibration slope in eICU was 0.70 (95% CI 0.60–0.81) with an intercept of 0.07 (−0.03 to 0.17) and a H-L $P < 0.001$, meaning predicted risks were too extreme at both ends of the range. This pattern of transferable discrimination with non-transferable calibration is common in cross-database external validation and reflects the absence of intraoperative data in eICU, differences in variable definitions and documentation granularity, and differences in case mix and intensity of care between the two databases. After logistic recalibration, the H-L P was 0.471 and the Brier score 0.146, while discrimination was unchanged (AUC 0.679); under 5-fold cross-validation the recalibrated model gave a H-L P of 0.251. The ranking of patients therefore appears transportable, but the probabilities attached to that ranking do not. Until the model is recalibrated locally, it should be used to stratify and to flag patients, not to quote an individual's absolute risk.

4.5 Sensitivity analysis for ARDS

ARDS was recorded in only 1.04% of the development cohort (191/18379), and its coefficient was correspondingly imprecise (OR 1.426, 95% CI 1.030 to 1.975). The direction was stable: the OR exceeded 1 in 98.3% of 1000 bootstrap resamples, but the magnitude was not (median 1.429; 2.5th to 97.5th percentiles 1.019 to 2.070). Removing ARDS changed discrimination by +0.0002 (AUC 0.7307 vs 0.7305; bootstrap 95% CI −0.00002 to +0.00088), indicating that the overall model is insensitive to its inclusion. Part of the difficulty is definitional: ARDS is itself defined through the P/F ratio and PEEP, both already in the model, so the coefficient should not be read as an independent effect. Sepsis and COPD stayed well above 1 in every

resample (2.5th percentiles 2.140 and 1.476, respectively). See Additional file 2: Table S3, Figure S1 and Note S1.

4.6 Limitations

This study has several limitations. The outcome relied on ICD codes and covers only a subset of the EPCO definitions[25], so some PPC events were probably missed; the codes were not restricted to a postoperative window, which may have captured complications unrelated to surgery. No intraoperative anaesthesia record was available, so the model cannot describe the contribution of anaesthetic management. Variable definitions and granularity differ between MIMIC-IV and eICU-CRD, and harmonisation cannot remove all of that difference. Missing data were handled by MICE (m = 5), and the effect of imputation was not examined in detail. ARDS was rare and its definition overlaps with variables already in the model. External calibration was poor (calibration slope 0.70, H-L $P < 0.001$), so local recalibration is needed before individual risk is quoted. Finally, the retrospective design rules out causal interpretation, and the model is a stratification aid rather than a diagnostic test.

4.7 Implications and future directions

The model uses data already collected in routine ICU care, which is what makes it practical. Prospective validation in other ICUs, ideally outside the United States, is the next step, together with recalibration to local event rates. Adding ventilator-derived features such as mechanical power or the stress index may improve performance, although the gain from the variables already included was modest and further additions should be tested rather than assumed. Comparing the model with ARISCAT or LAS

VEGAS in the same prospective cohort, and asking whether acting on it changes outcomes, would say more about clinical value than further retrospective work.

5. Conclusions

We developed a PPC prediction model from public critical care databases and externally validated it in an independent cohort (AUC 0.680). The model's structure was transportable, but absolute-risk calibration in the external cohort was poor. Local recalibration is therefore needed before the model can be used to predict individual absolute risk; at present, it is better suited to perioperative risk stratification and case finding.

6. List of abbreviations

ΔP: Driving pressure

ARDS: Acute respiratory distress syndrome

ARISCAT: Assess Respiratory Risk in Surgical Patients in Catalonia

AUC: Area under the receiver operating characteristic curve

CHI-BPRI: Chinese Brief Predictive Risk Index

CI: Confidence interval

COPD: Chronic obstructive pulmonary disease

DCA: Decision curve analysis

Dxy: Somers' Dxy rank correlation

eICU-CRD: eICU Collaborative Research Database

EPCO: European Perioperative Clinical Outcome

FiO_2: Fraction of inspired oxygen

HR: Heart rate

H-L: Hosmer-Lemeshow

ICD: International Classification of Diseases

ICU: Intensive care unit

IDI: Integrated discrimination improvement

LAS VEGAS: Local Assessment of Ventilatory Management During General Anesthesia for Surgery

LASSO: Least absolute shrinkage and selection operator

LR: Likelihood ratio

MAP: Mean arterial pressure

MICE: Multiple imputation by chained equations

MIMIC-IV: Medical Information Mart for Intensive Care IV

NPV: Negative predictive value

NRI: Net reclassification improvement

NSQIP: National Surgical Quality Improvement Program

OR: Odds ratio

PaO_2: Arterial partial pressure of oxygen

P/F: PaO_2/FiO_2 ratio

PBW: Predicted body weight

PEEP: Positive end-expiratory pressure

PPC: Postoperative pulmonary complications

Pplat: Plateau pressure

PPV: Positive predictive value

ROC: Receiver operating characteristic

RR: Respiratory rate

SD: Standard deviation

SpO_2: Peripheral oxygen saturation

TRIPOD: Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis

VT: Tidal volume

VT/PBW: Tidal volume per predicted body weight

7. Declarations

7.1 Ethics approval and consent to participate

MIMIC-IV and the eICU-CRD are publicly available, de-identified databases. MIMIC-IV was collected under approval of the Institutional Review Boards of Beth Israel Deaconess Medical Center (BIDMC) and the Massachusetts Institute of Technology (MIT). The author (Xiaona An) obtained access to both databases through PhysioNet after completing the Collaborative Institutional Training Initiative (CITI) "Data or Specimens Only Research" course (certification no. 60273273) and signing a data use agreement. Because all data were de-identified, the requirement for written informed consent was waived, and no additional institutional review board approval was required for this secondary analysis.

7.2 Consent for publication

Not applicable.

7.3 Availability of data and materials

The MIMIC-IV and eICU-CRD databases used in this study are available on PhysioNet and require credentialed access and a signed data use agreement (MIMIC-IV: *https://physionet.org/content/mimiciv/;* and eICU-CRD: *https://physionet.org/content/eicu-crd/*). Owing to the terms of the data use agreements, the authors cannot share the raw data directly. The analysis code, variable definitions and statistical scripts are available from the corresponding author on reasonable request.

7.4 Competing interests

The authors declare that they have no competing interests.

7.5 Funding

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7.6 Authors' contributions

XA designed the study, curated and analysed the data, acquired funding, and drafted the manuscript. LS and LZ contributed to data curation and validation. LQ contributed to data resources and investigation. WG conceived and supervised the study and revised the manuscript. All authors read and approved the final manuscript.

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Figure legends

Figure 1. Flowchart of cohort selection

Figure 2. LASSO cross-validation curve.

Figure 3. LASSO coefficient shrinkage paths.

Figure 4. Nomogram for predicting postoperative pulmonary complications.

Figure 5. Receiver operating characteristic (ROC) curve in the development cohort.

Figure 6. Distribution of internal cross-validation performance indices.

Figure 7. Calibration curve in the development cohort.

Figure 8. Decision curve analysis.

Figure 9. Receiver operating characteristic (ROC) curve in the external validation cohort.

Figure 10. Calibration curve in the external validation cohort.

Table 1. Baseline characteristics of the study participants.

Variables	PPC			
	All participants (n = 18379)	NO (n = 13729)	Yes (n = 4650)	*P*-value
Gender, n (%)				0.007
Male	11453 (62.3)	8633 (62.9)	2820 (60.6)	
Female	6926 (37.7)	5096 (37.1)	1830 (39.4)	
Age (year)	63.4 ± 15.9	63.7 ± 15.7	62.8 ± 16.7	0.002
BMI (kg/m²)	29.7 ± 7.7	29.7 ± 7.4	29.6 ± 8.7	0.357
HR (beats/min)	84.6 ± 14.6	84.0 ± 13.8	86.5 ± 16.4	< 0.001
MAP (mmHg)	57.6 ± 14.6	57.7 ± 13.9	57.2 ± 16.6	0.029
RR (breaths/min)	27.4 ± 6.3	27.1 ± 6.1	28.2 ± 6.6	< 0.001
SpO_2 (%)	92.3 ± 6.7	92.5 ± 6.6	91.8 ± 7.1	< 0.001
Creatinine (mg/dL)	0.9 (0.7, 1.2)	0.9 (0.7, 1.1)	0.9 (0.7, 1.4)	< 0.001
HGB (g/dL)	10.1 ± 1.9	10.1 ± 1.9	10.2 ± 2.1	0.011
WBC(*10^9/L)	15.1 ± 8.0	15.1 ± 7.6	15.2 ± 9.0	0.479
FiO_2	0.5 ± 0.1	0.5 ± 0.1	0.5 ± 0.1	< 0.001
VT/PBW (mL/kg PBW)	7.4 ± 1.4	7.5 ± 1.4	7.2 ± 1.4	< 0.001
Pplat (cmH_2O)	18.0 ± 4.4	17.6 ± 4.2	19.1 ± 4.8	< 0.001
ΔP (cmH_2O)	12.0 ± 3.5	11.9 ± 3.5	12.3 ± 3.6	< 0.001
P/F (mmHg)	304.8 ± 142.8	321.5 ± 141.4	255.5 ± 135.4	< 0.001
PEEP (cmH_2O)	6.0 ± 2.4	5.7 ± 2.0	6.8 ± 3.1	< 0.001
COPD n (%)	1375 (7.5)	891 (6.5)	484 (10.4)	< 0.001
ARDS, n (%)	191 (1.0)	91 (0.7)	100 (2.2)	< 0.001
Sepsis, n (%)	1229 (6.3)	557 (3.8)	672 (13.4)	< 0.001
CKD, n (%)	2943 (16.0)	2087 (15.2)	856 (18.4)	< 0.001
DM, n (%)	5327 (29.0)	3998 (29.1)	1329 (28.6)	0.483
CHF, n (%)	4125 (22.4)	2841 (20.7)	1284 (27.6)	< 0.001
Admission Type, n (%)				< 0.001
Elective	4637 (25.2)	4148 (30.2)	489 (10.5)	
Non-elective	13742 (74.8)	9581 (69.8)	4161 (89.5)	
Vaso, n (%)	10804 (58.8)	8233 (60)	2571 (55.3)	< 0.001

Abbreviations: Data are presented as mean±SD, medians [interquartile ranges] or numbers (percentages). BMI, Body Mass Index; HR, heart rate; MAP, mean arterial pressure; RR, Respiratory Rate; SpO_2, oxygenated hemoglobin saturation; HGB, hemoglobin; WBC, white blood cell; FiO_2, Fraction of Inspired Oxygen; VT/PBW, Tidal Volume/Predicted Body Weight; Pplat, Plateau Pressure; ΔP, Driving Pressure; P/F, PaO_2/FiO_2 ratio; PEEP, Positive End-Expiratory Pressure; COPD, Chronic Obstructive Pulmonary Disease; ARDS, Acute Respiratory Distress Syndrome; CKD, Chronic Kidney Disease; DM, Diabetes Mellitus; CHF, Congestive Heart Failure; Vaso, Vasopressor Use; PPC, Postoperative Pulmonary Complications.

Table 2. Final model coefficients and odds ratios

Variable	Coef	OR	95% CI	*P* value
Intercept	-1.091	-	-	0.003
Gender (Male)	-0.099	0.906	0.839–0.978	0.012
BMI	-0.023	0.977	0.972-0.983	<0.001
HR	0.003	1.003	1.001-1.005	0.015
RR	0.011	1.011	1.005-1.017	<0.001
SpO_2	0.013	1.013	1.007-1.019	<0.001
FiO_2	-1.681	0.186	0.129-0.268	<0.001
VT/PBW	-0.071	0.931	0.906-0.957	<0.001
Pplat	0.028	1.028	1.018-1.039	<0.001
P/F	-0.003	0.997	0.997-0.997	<0.001
PEEP	0.143	1.154	1.131-1.177	<0.001
COPD	0.514	1.672	1.475-1.895	<0.001
ARDS	0.355	1.426	1.030-1.975	0.032
Sepsis	0.886	2.425	2.123-2.771	<0.001
CHF	0.219	1.245	1.144-1.354	<0.001
Admission Type (Non-elective)	-0.936	0.392	0.353-0.436	<0.001
Vaso	-0.364	0.695	0.644-0.750	<0.001

Abbreviations: Coef, logistic regression coefficient; OR = exp (Coef); 95% CI = exp (Coef +/- 1.96 x SE). Continuous predictors were centred and truncated to physiological ranges before modelling.

OR, Odds Ratio; BMI, Body Mass Index; HR, heart rate; RR, Respiratory Rate; SpO2, oxygenated hemoglobin saturation; FiO2, Fraction of Inspired Oxygen; VT/PBW, Tidal Volume/Predicted Body Weight; Pplat, Plateau Pressure; P/F, PaO2/FiO2 ratio; PEEP, Positive End-Expiratory Pressure; COPD, Chronic Obstructive Pulmonary Disease; ARDS, Acute Respiratory Distress Syndrome; CHF, Congestive Heart Failure; Vaso, Vasopressor Use.

Table 3. Model performance (internal and external)

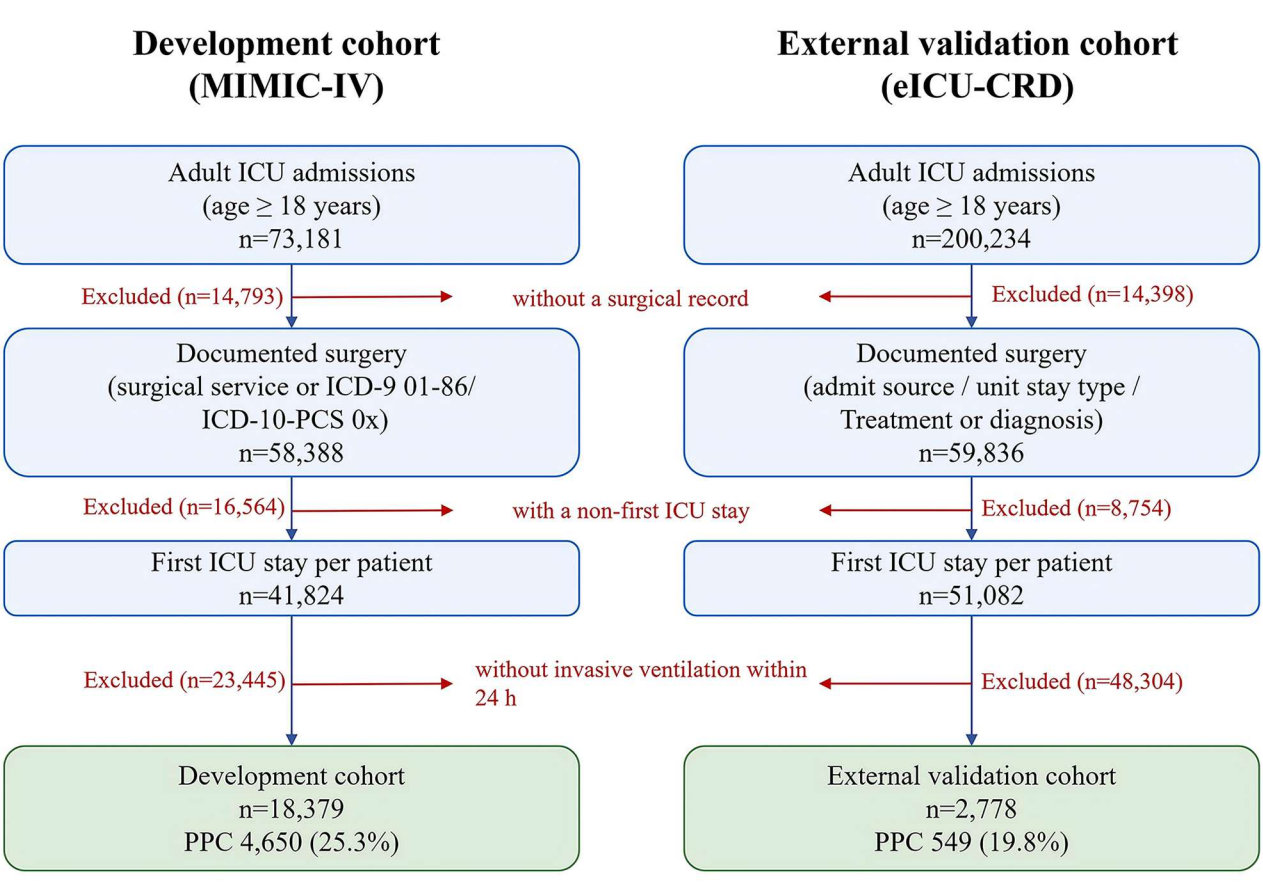
Metric	Development (MIMIC- IV)	External (eICU)
N	18,379	2,778
Event rate	25.30%	19.8%
AUC	0.731	0.680 (0.655-0.706)
Dxy	0.461	-
Base model AUC (8 variables)	0.667	-
Internal validation AUC	0.729 (SD 0.013)	-
Internal calibration slope	0.993	-
Internal calibration intercept	-0.008	-
Brier score	0.164	0.147
Calibration (H-L test *P*)	0.101	-

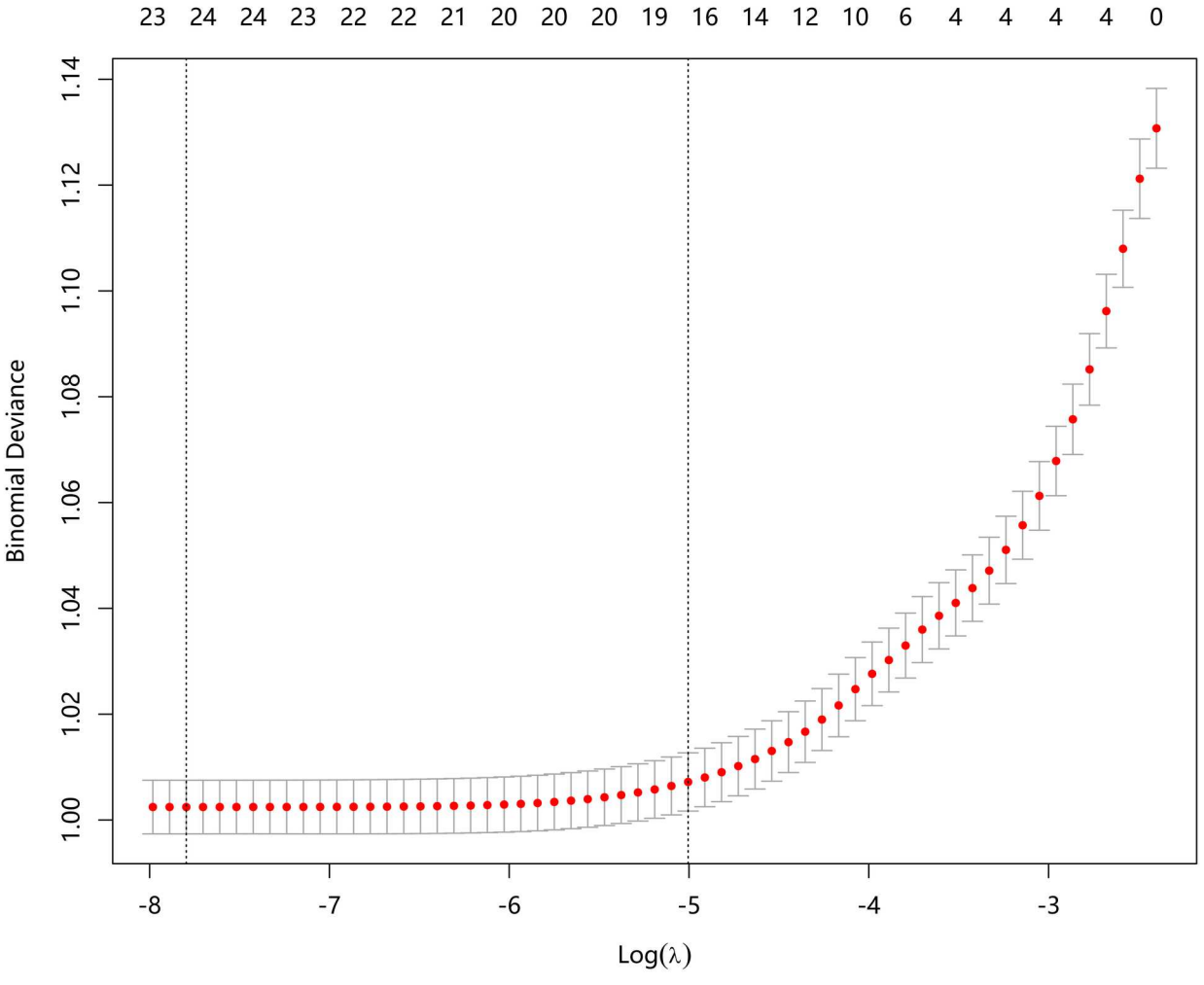
Note: AUC, area under the receiver operating characteristic curve; Dxy, Somers' Dxy rank correlation; SD, standard deviation; H-L, Hosmer-Lemeshow test. Internal validation was performed by 10-fold cross-validation repeated 50 times, and values are means across repeats. External validation used the eICU-CRD cohort (n = 2,778). The base model included demographic and comorbidity variables only (8 predictors); the extended model additionally included vital signs and ventilator parameters (16 predictors).

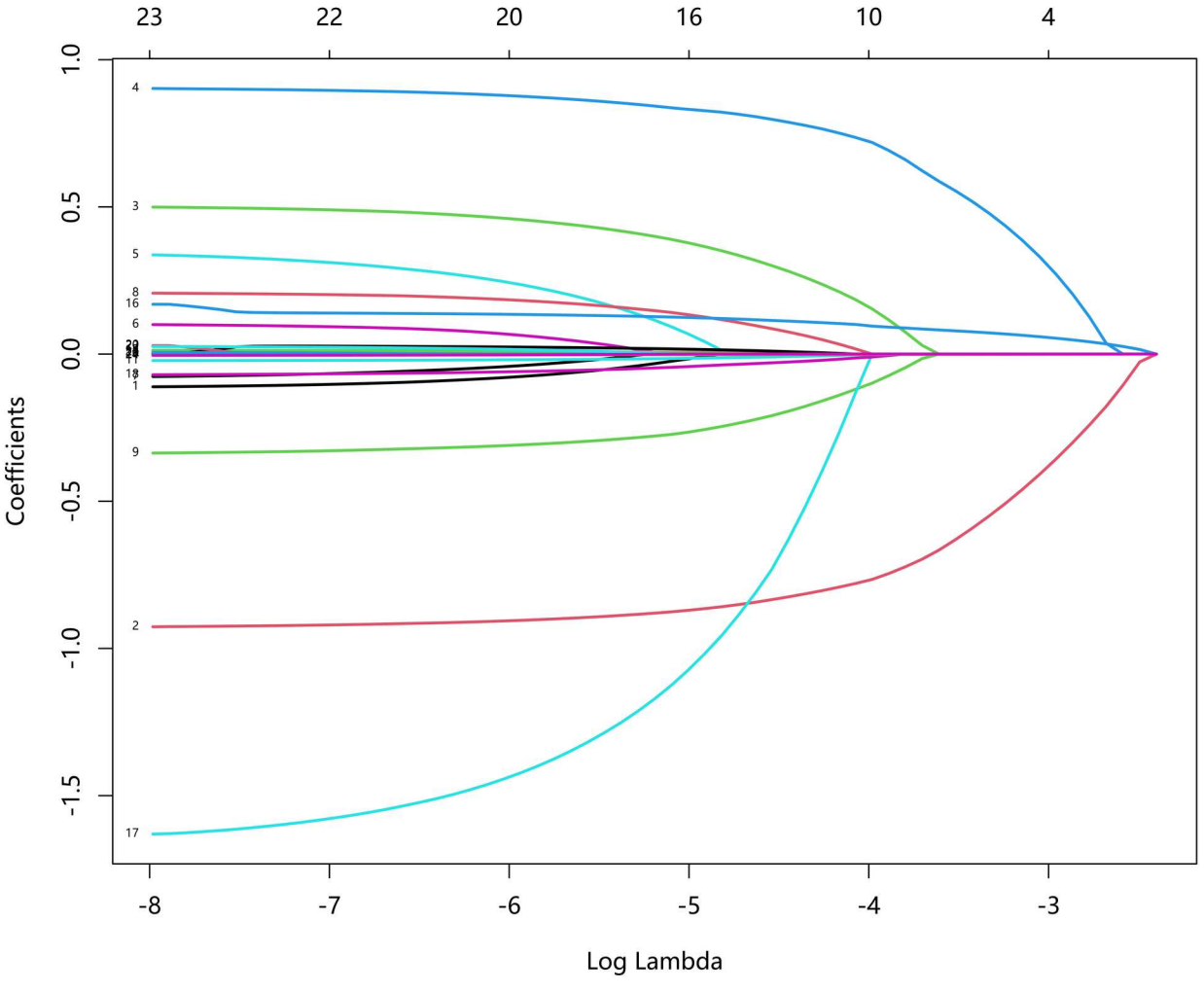
Table 4. Ventilator Parameters for PPC Prediction: Extended vs Base Model

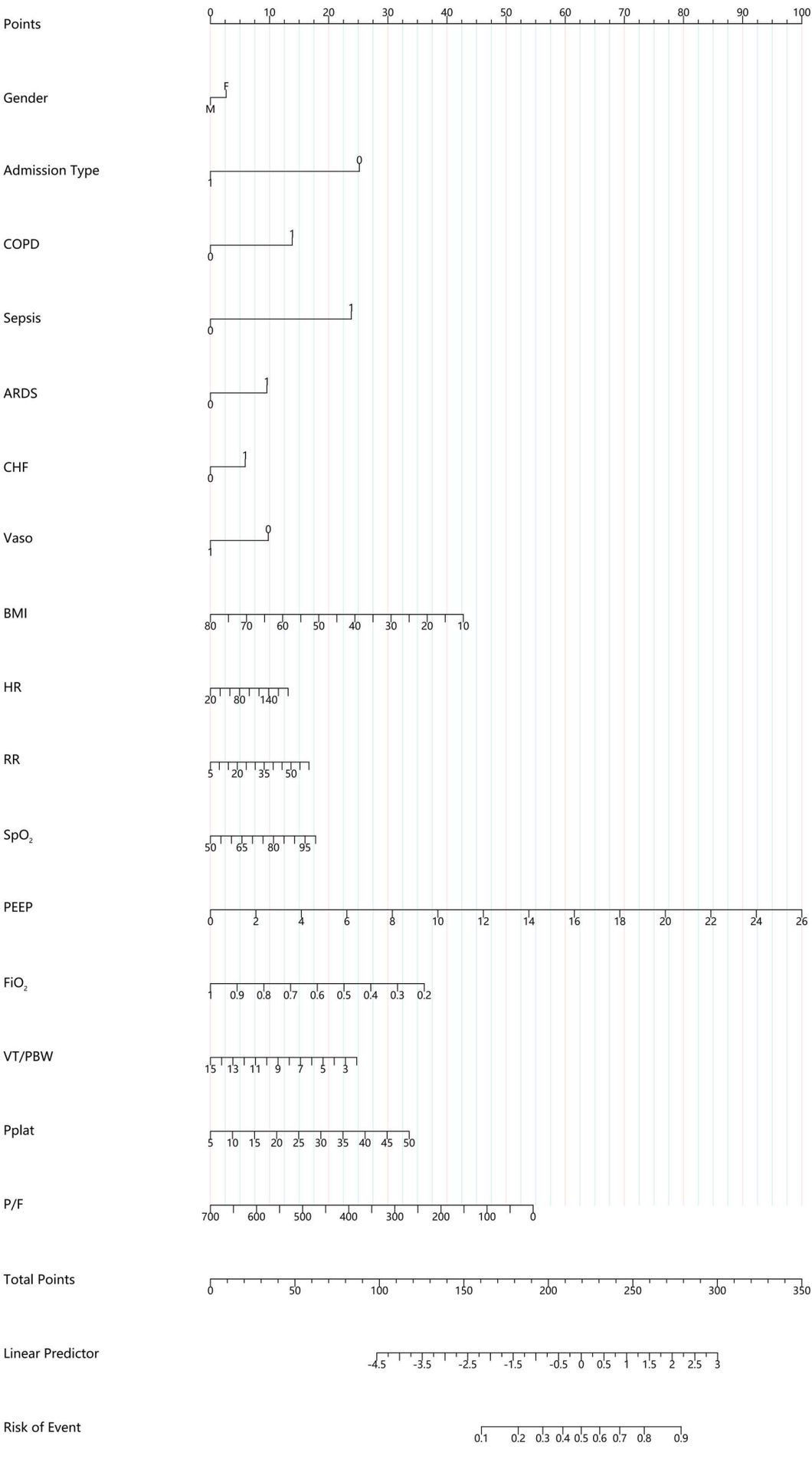
Metric	Base model (8 variables)	Extended model (16 variables)	Incremental value (95% CI)	*P* value
AUC	0.667	0.731	ΔAUC = 0.064	-
NRI (categorical)	-	-	0.225 (0.206-0.245)	<0.001
NRI (continuous)	-	-	0.498 (0.465-0.530)	<0.001
IDI	-	-	0.059 (0.055-0.063)	<0.001

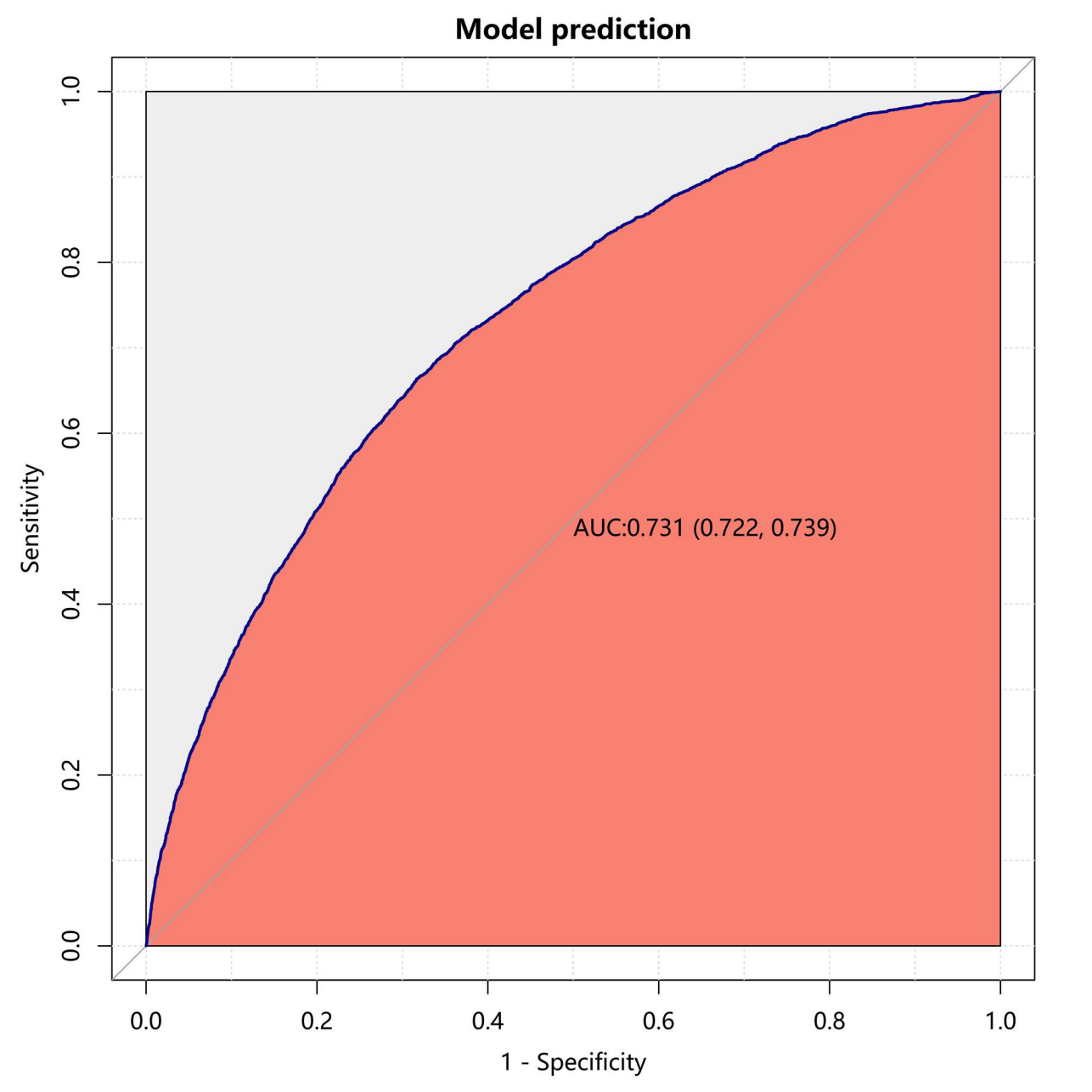
Note: NRI, net reclassification improvement; IDI, integrated discrimination improvement; CI, confidence interval. Categorical NRI was calculated using prespecified risk categories (<10%, 10-20%, >20%); continuous NRI and IDI were calculated on the continuous predicted probability scale. All values compare the extended model (16 predictors) with the base model (8 predictors); *P* values are from two-sided tests.

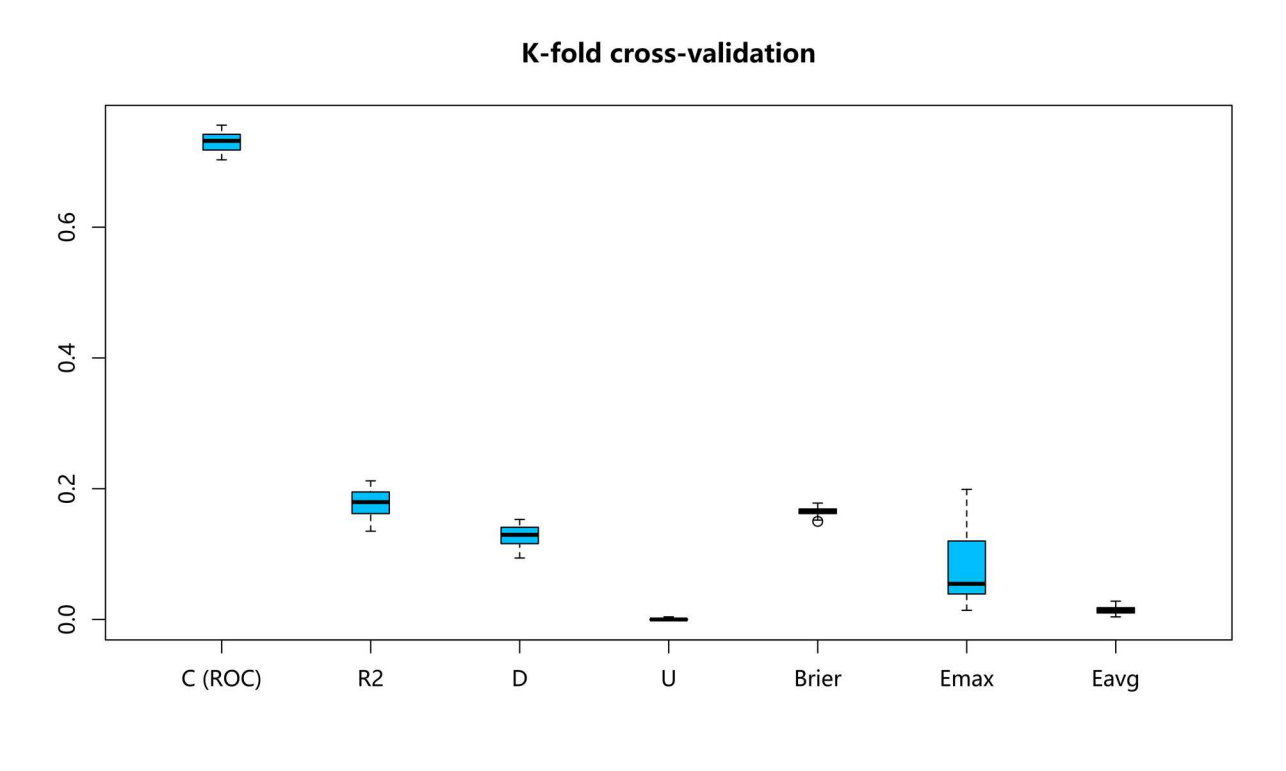

Development cohort
(MIMIC-IV)
External validation cohort
(eICU-CRD)
Adult ICU admissions
(age ≥ 18 years)
n=73,181
Adult ICU admissions
(age ≥ 18 years)
n=200,234
Excluded (n=14,793)
without a surgical record
Excluded (n=14,398)
Documented surgery
(surgical service or ICD-9 01-86/
ICD-10-PCS 0x)
n=58,388
Documented surgery
(admit source / unit stay type /
Treatment or diagnosis)
n=59,836
Excluded (n=16,564)
with a non-first ICU stay
Excluded (n=8,754)
First ICU stay per patient
n=41,824
First ICU stay per patient
n=51,082
Excluded (n=23,445)
without invasive ventilation within
24 h
Excluded (n=48,304)
Development cohort
n=18,379
PPC 4,650 (25.3%)
External validation cohort
n=2,778
PPC 549 (19.8%)

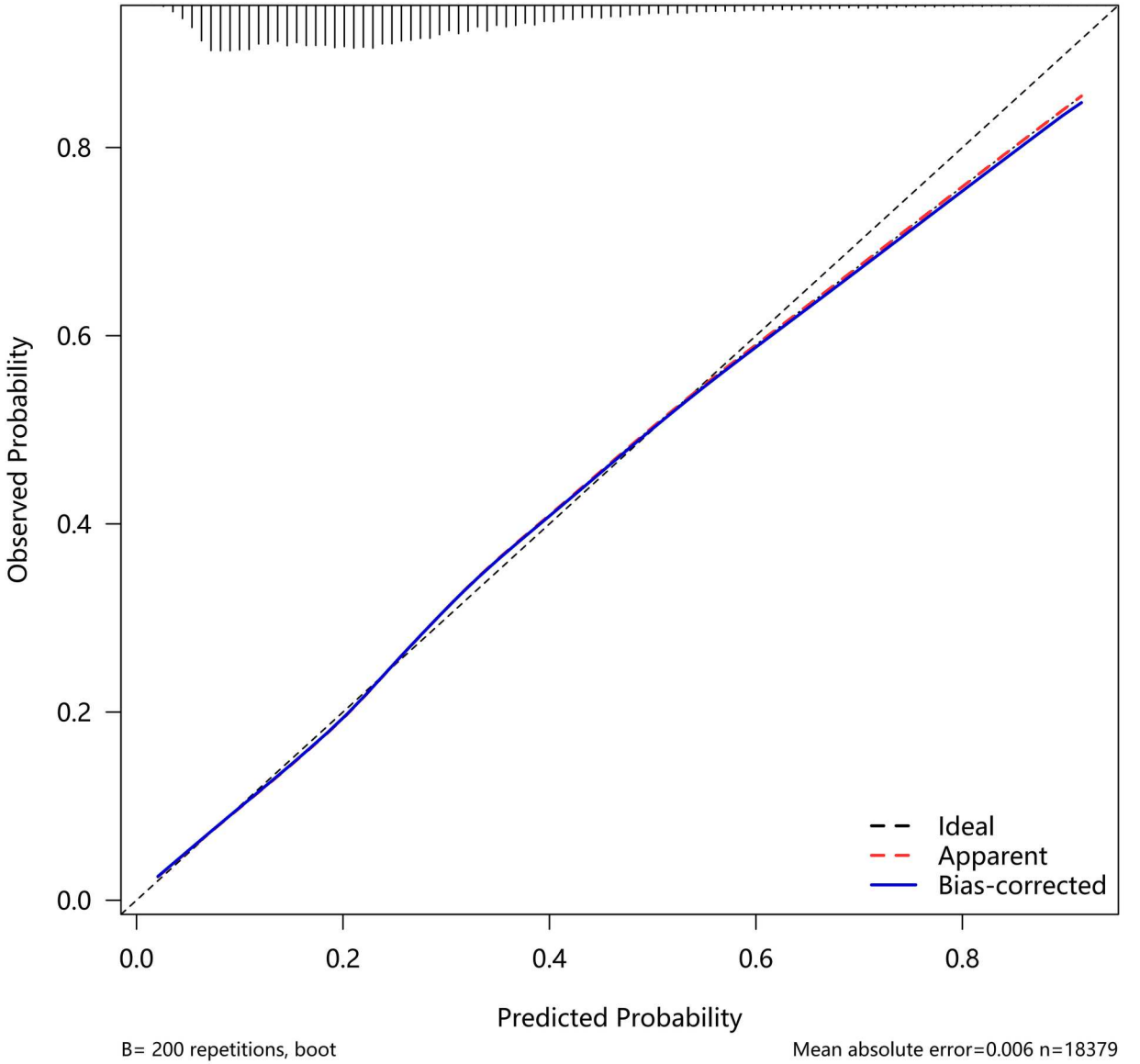

23 24 24 23 22 22 21 20 20 20 19 16 14 12 10 6 4 4 4 4 0
Binomial Deviance
1.00
1.02
1.04
1.06
1.08
1.10
1.12
1.14
-8
-7
-6
-5
-4
-3
Log(λ)

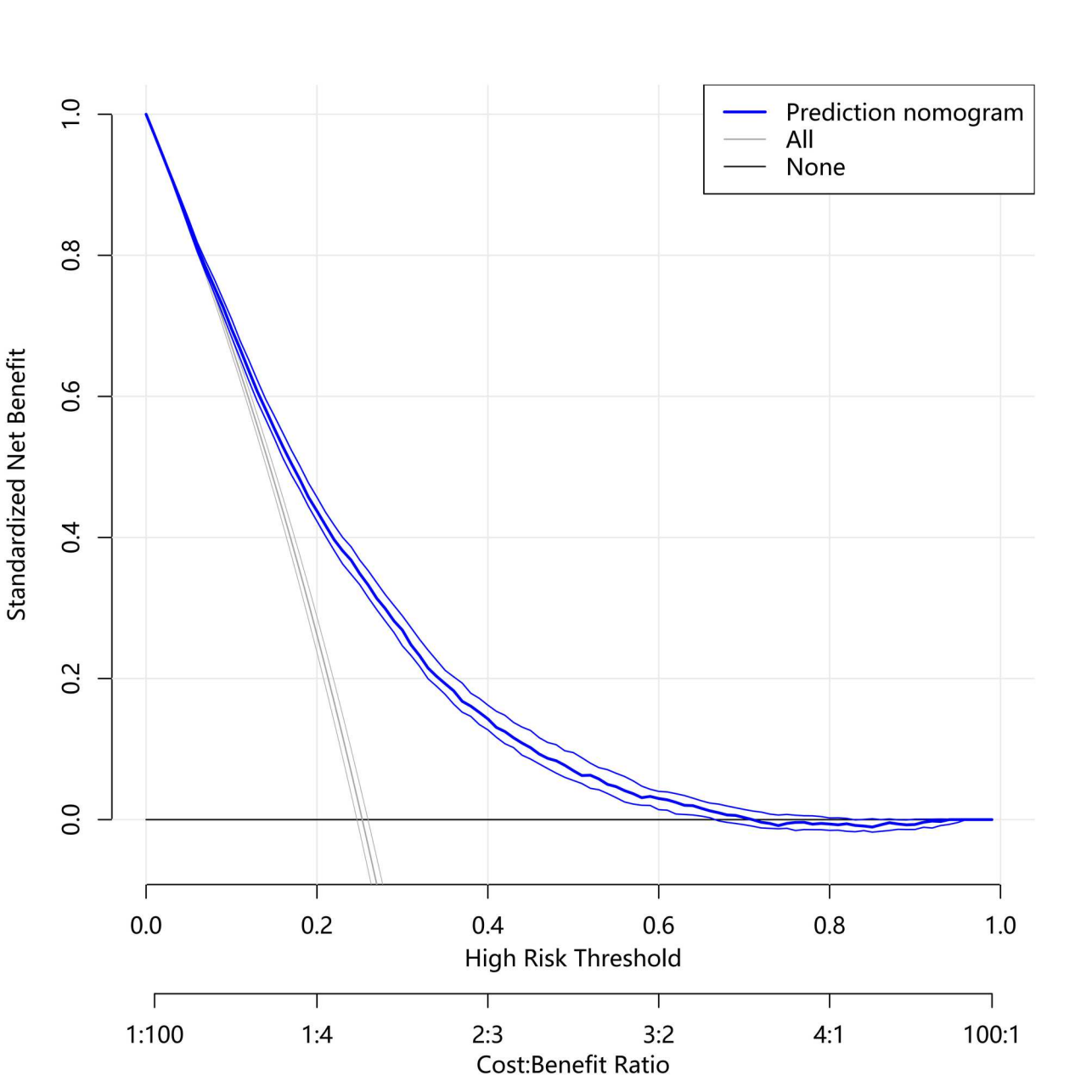

23
22
20
16
10
4
1.0
0.5
0.0
-0.5
-1.0
-1.5
Coefficients
4
3
5
8
16
6
1
9
2
17
-8
-7
-6
-5
-4
-3
Log Lambda

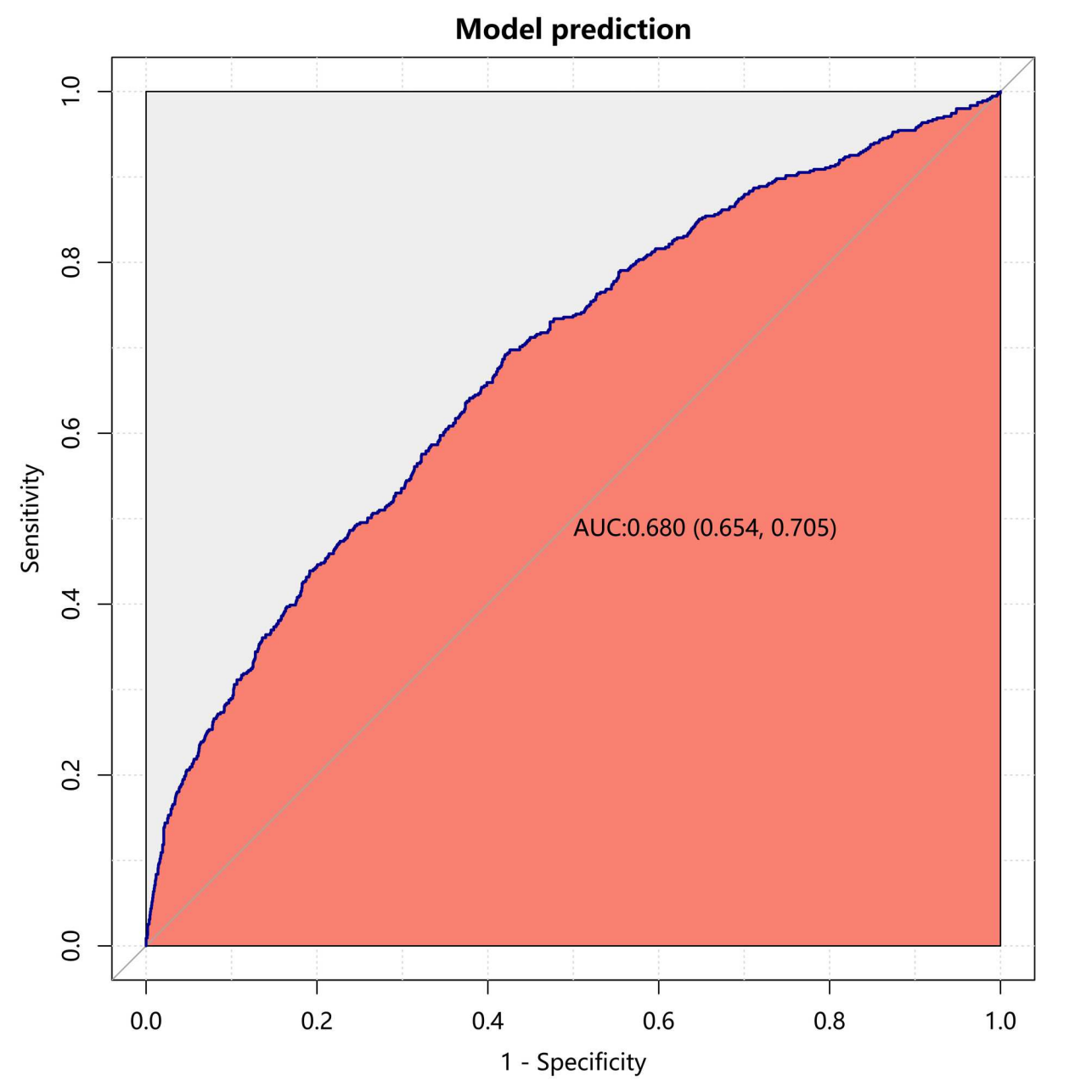

Points
0 10 20 30 40 50 60 70 80 90 100
Gender
F
M
Admission Type
0
1
COPD
1
0
Sepsis
1
0
ARDS
1
0
CHF
1
0
Vaso
0
1
BMI
80 70 60 50 40 30 20 10
HR
20 80 140
RR
5 20 35 50
SpO2
50 65 80 95
PEEP
0 2 4 6 8 10 12 14 16 18 20 22 24 26
FiO2
1 0.9 0.8 0.7 0.6 0.5 0.4 0.3 0.2
VT/PBW
15 13 11 9 7 5 3
Pplat
5 10 15 20 25 30 35 40 45 50
P/F
700 600 500 400 300 200 100 0
Total Points
0 50 100 150 200 250 300 350
Linear Predictor
-4.5 -3.5 -2.5 -1.5 -0.5 0 0.5 1 1.5 2 2.5 3
Risk of Event
0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9

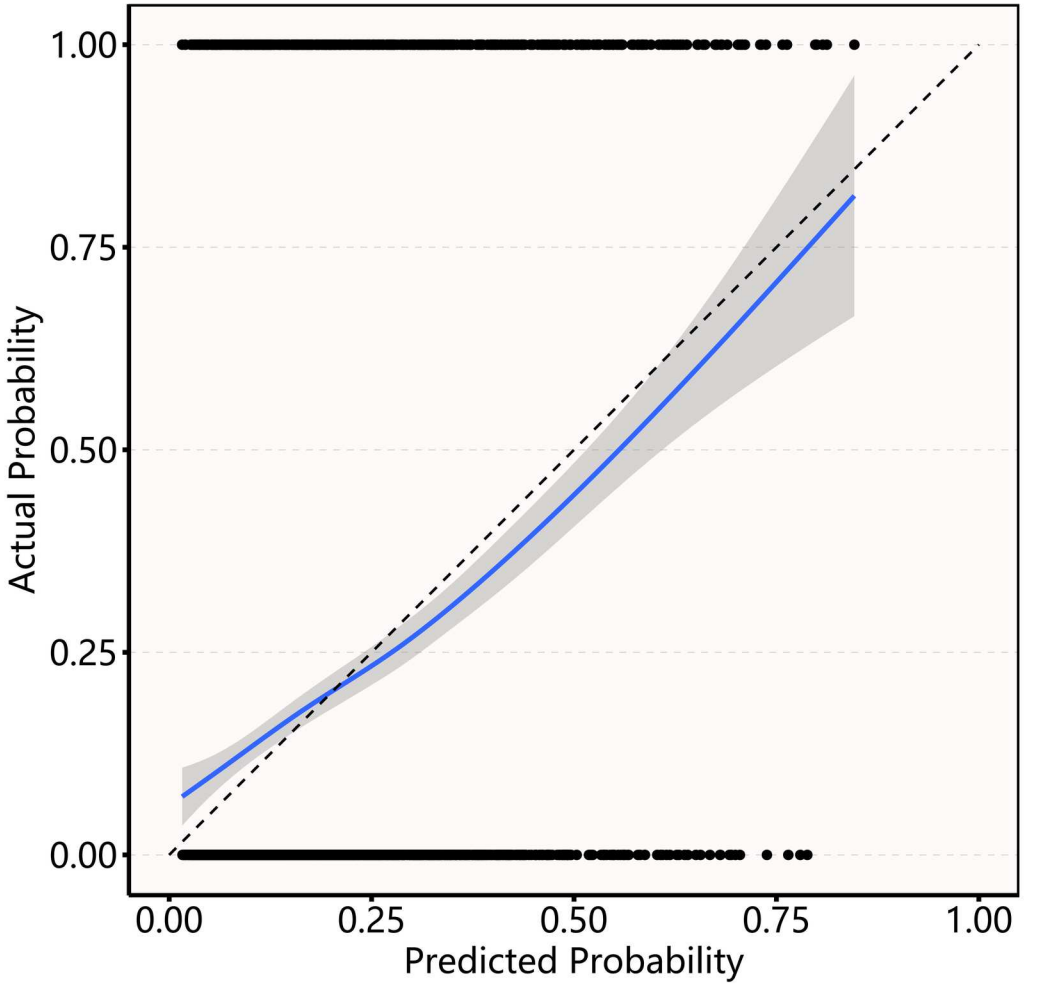

Model prediction
Sensitivity
1 - Specificity
0.0
0.2
0.4
0.6
0.8
1.0
AUC:0.731 (0.722, 0.739)


K-fold cross-validation
0.0
0.2
0.4
0.6
C (ROC)
R2
D
U
Brier
Emax
Eavg


Observed Probability
0.0
0.2
0.4
0.6
0.8
Predicted Probability
0.0
0.2
0.4
0.6
0.8
Ideal
Apparent
Bias-corrected
B= 200 repetitions, boot
Mean absolute error=0.006 n=18379


Prediction nomogram
All
None
Standardized Net Benefit
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
1.0
High Risk Threshold
1:100
1:4
2:3
3:2
4:1
100:1
Cost:Benefit Ratio


Model prediction
Sensitivity
1 - Specificity
0.0
0.2
0.4
0.6
0.8
1.0
AUC:0.680 (0.654, 0.705)


1.00
0.75
0.50
0.25
0.00
Actual Probability
0.00
0.25
0.50
0.75
1.00
Predicted Probability

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