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RESEARCH ARTICLE

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Development and validation of a prediction model for in-hospital mortality in patients with sepsis

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Abstract

Background: Sepsis, a life-threatening condition marked by organ dysfunction due to a dysregulated host response to infection, involves complex physiological and biochemical abnormalities.

Aim: To develop a multivariate model to predict 4-, 6-, and 8-week mortality risks in intensive care units (ICUs).

Study Design: A retrospective cohort of 2389 sepsis patients was analysed using data captured by a clinical decision support system. Patients were randomly allocated into training ($n = 1673$) and validation ($n = 716$) sets at a 7:3 ratio. Least Absolute Shrinkage and Selection Operator (LASSO) regression identified variables incorporated into a multivariate Cox proportional hazards regression model to construct a prognostic nomogram. The area under the receiver operating characteristic curve (AUROC) assessed model accuracy, while performance was evaluated for discrimination, calibration and clinical utility.

Results: A risk score was developed based on 11 independent predictors from 35 initial factors. Key predictors included minimum Acute Physiology and Chronic Health Evaluation II (APACHE II) score as having the greatest impact on prognosis, followed by days of mechanical ventilation, number of vasopressors, maximum and minimum Sequential Organ Failure Assessment (SOFA) scores, infection sources, Gram-positive or Gram-negative bacteria and malignancy. The nomogram demonstrated superior discriminative ability, with AUROC values of 0.882 (95% confidence interval [CI], 0.855–0.909) and 0.851 (95% CI, 0.804–0.899) at 4 weeks; 0.836 (95% CI, 0.798–0.874) and 0.820 (95% CI, 0.761–0.878) at 6 weeks; and 0.843 (95% CI, 0.800–0.887) and 0.794 (95% CI, 0.720–0.867) at 8 weeks for training and validation sets, respectively.

Conclusion: A validated nomogram and web-based calculator were developed to predict in-hospital mortality in ICU sepsis patients. Targeting identified risk factors may improve outcomes for critically ill patients.

Wen Shi and Mengqi Xie contributed equally to this work.

Relevance to Clinical Practice: The developed prediction model and nomogram offer a tool for assessing in-hospital mortality risk in ICU patients with sepsis, potentially aiding in nursing decisions and resource allocation.

KEYWORDS
ICUs, nomogram, prediction of prognosis, sepsis

1 | INTRODUCTION

Sepsis is a complex syndrome triggered by infection, characterized by dysregulated host immune responses that lead to multi-organ dysfunction, which can become life-threatening if not treated promptly.[1] As a major global public health challenge, sepsis affects millions of patients annually, with its incidence and mortality rates varying significantly across different regions.[2,3] For example, in the United States, sepsis is the leading cause of in-hospital deaths and incurs an annual cost of over $24 billion. Despite advanced diagnostic technologies and standardized treatment guidelines, its mortality rate remains high.[4,5] However, in low- and middle-income countries, the incidence and mortality rates of sepsis are even more severe due to limited medical resources, delayed diagnosis, restricted treatment options and inadequate nursing systems.[6] In intensive care units (ICUs), the mortality rate of sepsis can reach as high as 41.9% or more, depending on the severity of the patient's condition, the timeliness of treatment and the availability of medical resources.[5] Sepsis not only places a significant burden on patients but also imposes considerable strain on global public health resources, underscoring the urgent need for effective measures to address this challenge.[7]

Despite significant advances in the diagnosis and treatment of sepsis over the past few decades, early mortality prediction remains a key challenge.[8] Research based on biomarkers offers potential for prediction, but the sensitivity and specificity of individual biomarkers are insufficient to support routine clinical application. For example, studies have shown that the mortality of sepsis patients may be influenced by multiple pathophysiological mechanisms, which are difficult to fully capture with a single indicator.[9] Existing scoring systems, such as the Sequential Organ Failure Assessment (SOFA) score and the Acute Physiology and Chronic Health Evaluation (APACHE II) score, are widely used to assess the severity and prognosis of sepsis. However, these scores have certain limitations in terms of sensitivity, specificity and data applicability, making them inadequate for individualized prediction and clinical application,[10,11] and there is even a possibility of underestimating some patients with clinical sepsis.[12] Additionally, although numerous predictive models developed using open databases, such as the MIMIC database, provide rich resources for research, the data predominantly originate from health care systems in high-income countries. Consequently, variable selection is biased towards medical practices in resource-rich settings, leading to suboptimal external validation performance and limited clinical applicability in low- and middle-income countries.[13]

What is known about the topic

- Sepsis is a global health issue with a high mortality rate in intensive care units (ICUs), posing a significant threat to patient health.
- Most predictive models are based on ICU data from high-income countries, lacking validation from low- and middle-income countries and fail to address the practical needs of resource-limited settings.
- Current models lack intuitive and simple tools, limiting their practical application in critical care nursing.

What this paper adds

- In response to the needs of developing countries, a new sepsis mortality prediction model was developed and validated using local ICU data.
- The model integrates key variables from nursing practice, aiding nurses in more accurately assessing patient conditions and optimizing resource allocation.
- An online calculator based on the model was developed to provide critical care nurses with a simple and easy-to-use tool, enhancing nursing efficiency and improving patient outcomes.

Based on the aforementioned background, this study aims to develop a multivariable predictive model for sepsis mortality risk, incorporating the SOFA and APACHE II scores along with other clinical variables. A nomogram will be constructed using local datasets to provide an early assessment tool for short-term mortality risk in sepsis patients, supporting clinical decision-making and guiding interventions for high-risk patients.

2 | METHODS

2.1 | Data source and study design

This retrospective study was conducted across 10 intensive care units (ICUs) located in two campuses of Ruijin Hospital, affiliated with Shanghai Jiao Tong University School of Medicine. The main campus includes the ICUs of Respiratory, Emergency, Cardiology (1 and 2), Cardiac Surgery, and Surgical (1 and 2), while the North campus

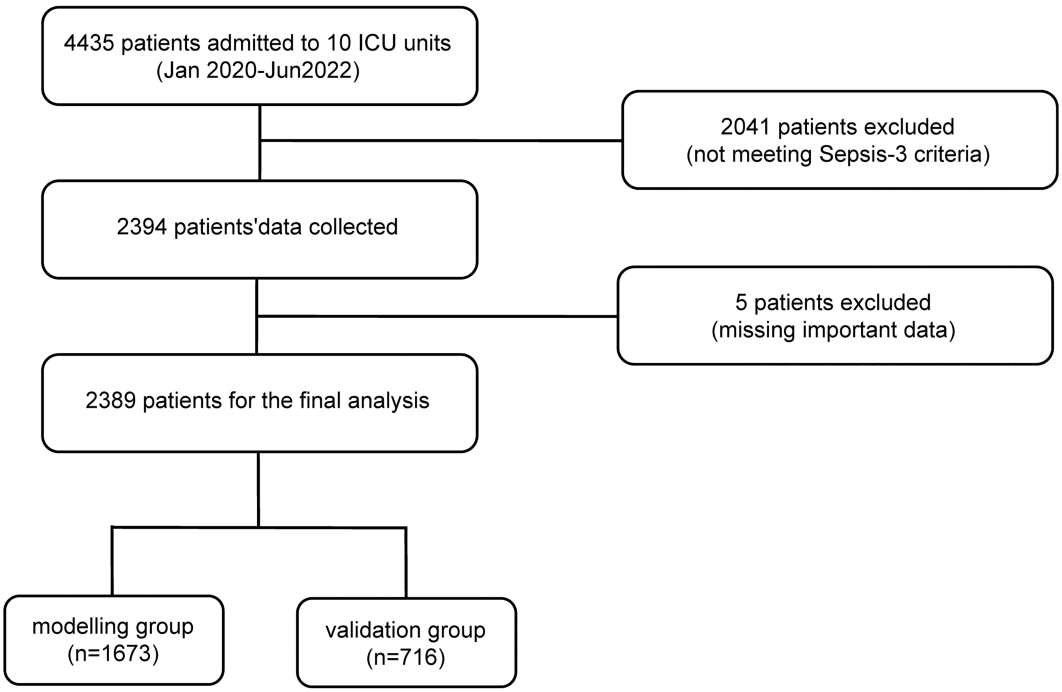

FIGURE 1 Study design.

houses ICUs for Emergency 2, Cardiology 3 North and Surgery 3 North ICUs.

To effectively capture electronic patient information during hospitalization, this study utilized a Clinical Decision Support System (CDSS), version V3.0, jointly developed by Beijing Huimei Cloud Technology Co., Ltd. The system interfaces with the hospital's information system and uses Structured Query Language (SQL) queries to extract patient data from electronic medical records. The data undergoes rigorous cleaning and preprocessing to ensure accuracy and integrity. The system, in conjunction with continuous clinical feedback and iterative optimization, accurately screens for suspected infection cases and automatically calculates the SOFA and APACHE II scores, aiding in the diagnosis of sepsis. Additionally, the system employs standardized data extraction logic to ensure that all patients' clinical features are extracted and processed consistently, effectively controlling selection bias.

This study included 4435 sepsis patients aged 18 years or older who were admitted to the aforementioned 10 ICUs between 1 January 2020 and 30 June 2022. The inclusion criteria were as follows: (1) age ≥18 years; (2) patients met the Sepsis-3 criteria,[1] and were diagnosed with sepsis; (3) complete clinical data, including relevant laboratory test results and vital sign records. Patients not meeting the criteria were excluded. Using the CDSS system to screen patients with suspected infections, 2389 study subjects were ultimately identified after excluding 2041 patients who did not meet the Sepsis-3 criteria and five patients with missing critical data (Figure 1).

The follow-up initiation time was determined based on 75% of the patients' actual survival time (approximately 4 weeks), after which the follow-up period was extended to 6 and 8 weeks. For patients who died or were discharged within 4 weeks, complete inpatient data were retained for analysis. All patient data were randomly divided into a training set ($n = 1673$) and a validation set ($n = 716$) in a 7:3 ratio. The training set was used to develop the prediction model, while the validation set was used to evaluate its performance.

2.2 | Ethical considerations

This study was conducted in accordance with the ethical principles of the Declaration of Helsinki and was approved by the Ethics Committee of Ruijin Hospital (approval number: 2022-59, approval date: 19 July 2022). The study reporting adhered to the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD) guidelines.[14]

2.3 | Data collection

The study collected clinical data of patients from the hospital's electronic database through the CDSS, including basic information, medical history, laboratory test results, severity indicators and discharge status. Based on clinical relevance, the study selected the following risk factors as candidate predictors: (1) Demographic characteristics: age, gender, body mass index (BMI); (2) Chronic underlying diseases: hypertension, diabetes, cardiovascular diseases, cerebrovascular diseases, chronic obstructive pulmonary disease, chronic kidney disease, malignancies, haematologic diseases and autoimmune disorders; (3) Infection status: infection sites and pathogen classification (Gram-negative bacteria, Gram-positive bacteria and fungi); (4) Laboratory assessments: maximum values of lactate, procalcitonin, fibrin degradation products (FDP) and D-dimer within 4 weeks; (5) SOFA and APACHE II scores: the statistical range includes SOFA scores on days

TABLE 1 Patient characteristics of the training set and validation set.

Characteristics	Total ($n = 2389$)	Training set ($n = 1673$)	Validation set ($n = 716$)	*p* value	Statistic
Age, M (IQR) (years)	68 (52, 79)	68 (52, 79)	68.5 (52.8, 80)	.501	588 530.5
Gender, *n* (*n*%)				.268	1.228
Male	1547 (64.8)	1071 (64.0)	476 (66.5)		
Female	842 (35.2)	602 (36.0)	240 (33.5)		
BMI, M (IQR)	23.31 (20.45, 26.12)	23.15 (20.45, 26.12)	23.39 (20.45, 26.19)	.554	589 803
Comorbidities, *n* (*n*%)					
Hypertension				.805	0.061
No	1217 (50.9)	849 (50.7)	368 (51.4)		
Yes	1172 (49.1)	824 (49.3)	348 (48.6)		
Diabetes				.637	0.222
No	1623 (67.9)	1142 (68.3)	481 (67.2)		
Yes	766 (32.1)	531 (31.7)	235 (32.8)		
Cardiovascular disease				.620	0.246
No	2180 (91.3)	1523 (91.0)	657 (91.8)		
Yes	209 (8.7)	150 (9.0)	59 (8.2)		
Cerebrovascular disease				.306	1.046
No	2089 (87.4)	1471 (87.9)	618 (86.3)		
Yes	300 (12.6)	202 (12.2)	98 (13.7)		
COPD				.952	0.004
No	2215 (92.7)	1552 (92.8)	663 (92.6)		
Yes	174 (7.3)	121 (7.2)	53 (7.4)		
Chronic kidney disease				.660	0.193
No	2154 (90.2)	1505 (90.0)	649 (90.6)		
Yes	235 (9.8)	168 (10.0)	67 (9.4)		
Autoimmune disease				.169	1.892
No	2297 (96.1)	1615 (96.5)	682 (95.3)		
Yes	92 (3.9)	58 (3.5)	34 (4.7)		
Haematological disease				.178	1.814
No	2298 (96.2)	1603 (95.8)	695 (97.1)		
Yes	91 (3.8)	70 (4.2)	21 (2.9)		
Malignancy				.406	0.69
No	2120 (88.7)	1491 (89.1)	629 (87.8)		
Yes	269 (11.3)	182 (10.9)	87 (12.2)		
Sources of infection, *n* (*n*%)				.072	8.596
Respiratory tract	1152 (48.2)	792 (47.3)	360 (50.3)		
Abdomen	409 (17.1)	282 (16.9)	127 (17.7)		
Digestive tract	255 (10.7)	171 (10.2)	84 (11.7)		
Urinary tract	139 (5.8)	107 (6.4)	32 (4.5)		
Others	434 (18.2)	321 (19.2)	113 (15.8)		
Pathogenic microorganisms, *n* (*n*%)					
Gram-negative bacterium				.052	3.767
No	1686 (70.6)	1201 (71.8)	485 (67.7)		
Yes	703 (29.4)	472 (28.2)	231 (32.3)		
Gram-positive bacterium				.198	1.658
No	2012 (84.2)	1420 (84.9)	592 (82.7)		
Yes	377 (15.8)	253 (15.1)	124 (17.3)		

TABLE 1 (Continued)

Characteristics	Total ($n = 2389$)	Training set ($n = 1673$)	Validation set ($n = 716$)	*p* value	Statistic
Fungus				.946	0.005
No	2082 (87.1)	1457 (87.1)	625 (87.3)		
Yes	307 (12.9)	216 (12.9)	91 (12.7)		
Laboratory parameters, M (IQR)					
Lactate.max (mmol/L)	2.928 (2.14)	2.9 (2.09)	3.036 (2.24)	.199	579 089
Procalcitonin.max (ng/mL)	1.18 (6.20)	1.14 (6.27)	1.285 (5.96)	.908	600 725
FDP.max (mg/L)	17.8 (27.30)	17.39 (27.00)	19.05 (28.40)	.244	580 937.5
D-dimer.max (mg/L)	5.02 (8.99)	4.66 (8.98)	5.67 (9.22)	.182	578 305
Treatment interventions, *n* (*n*%), M (IQR)					
Mechanical ventilation				.461	0.542
No	1652 (69.2)	1165 (69.6)	487 (68.0)		
Yes	737 (30.8)	508 (30.4)	229 (32.0)		
Mechanical ventilation (day)	0 (0, 1)	0 (0, 1)	0 (0, 1)	.349	587 186
CRRT				.180	1.799
No	2332 (97.6)	1628 (97.3)	704 (98.3)		
Yes	57 (2.4)	45 (2.7)	12 (1.7)		
No. vasopressors	0 (0, 1)	0 (0, 1)	0 (0, 2)	.435	588 335.5
Scoring system, M (Q1, Q3)					
SOFA-d1	2 (0, 4)	2 (0, 4)	2 (0, 4)	.298	583 107
SOFA-d2	3 (2, 5)	3 (2, 5)	3 (2, 5)	.775	594 578.5
SOFA-d3	2 (1, 4)	2 (1, 4)	2 (1, 4)	.857	601 699.5
SOFA-d7	2 (0.7, 3)	2 (0.67, 3)	2 (0.74, 3.84)	.495	588 448
SOFAmin	0 (0, 1)	0 (0, 1)	0 (0, 1)	.136	580 227.5
SOFAmax	4 (3, 6)	4 (3, 6)	4 (3, 6)	.918	597 362.5
APACHEIImin	5 (3, 6)	5 (3, 6)	5 (3, 6)	.381	585 647.5
APACHEIImax	16 (11, 22)	16 (11, 22)	16 (11, 23)	.167	577 581.5
Outcome, *n* (*n*%), M (IQR)					
In-hospital mortality	526 (22.02)	361 (21.6)	165 (23.0)	.460	0.546
Survival time (weeks)	2.6 (1.6, 4.1)	2.6 (1.6, 4.1)	2.6 (1.6, 4.3)	.607	590 999.5

Abbreviations: APACHE II, Acute Physiology and Chronic Health Evaluation II; BMI, body mass index; COPD, chronic obstructive pulmonary disease; CRRT, continuous renal replacement therapy; IQR, interquartile range; SOFA, Sequential Organ Failure Assessment.

1, 2, 3 and 7 after admission, as well as peak and nadir SOFA scores and APACHE II scores within 4 weeks; (6) Treatment interventions: including the use of vasopressors, mechanical ventilation, continuous renal replacement therapy (CRRT) and other interventions, as well as the cumulative number of days on mechanical ventilation; (7) Outcomes: survival status at 4, 6 and 8 weeks post-admission. All data were collected within 4 weeks of admission, and for patients who died or were discharged within 4 weeks, relevant data were collected throughout their hospitalization.

2.4 | Statistical analysis

To address missing data, this study employed the missForest algorithm, implemented through the randomForest package in R software (v4.2.3). Variables with more than 20% missing data were excluded. For the remaining missing data, imputation was evaluated using cross-validation and residual analysis to ensure the accuracy and completeness of the dataset. In the statistical analysis, normally distributed continuous variables were presented as mean (standard deviation), while skewed variables were reported as median (interquartile range). For continuous variables, *t*-tests were used to compare differences between two groups. Categorical data were presented as frequencies and percentages, with group comparisons performed using the χ^2 test.

In terms of variable selection, to ensure sufficient representation for each predictor, the study adhered to the principle of at least 10 septic patients per candidate predictor, ensuring a minimum of 10 events per variable (EPV).[15,16] Ultimately, 35 variables

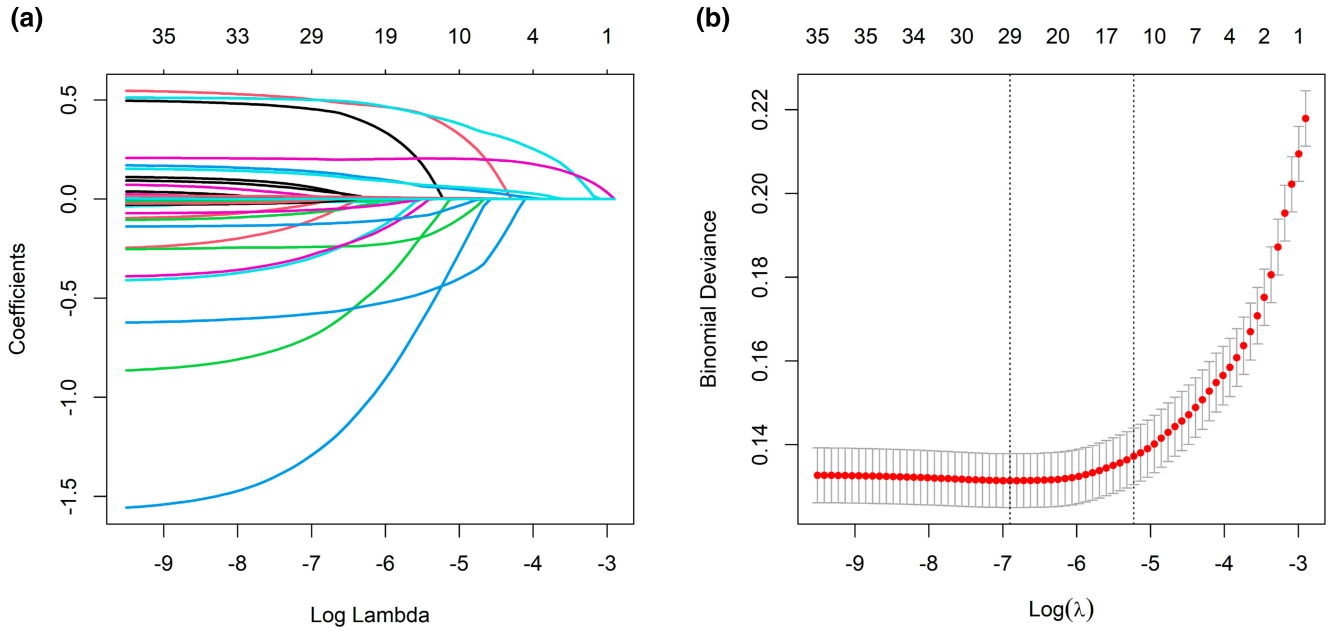

FIGURE 2 Feature selection utilizing the Least Absolute Shrinkage and Selection Operator (LASSO) Binary Logistic Regression Model. (a) Profiles of LASSO coefficients for the 32 baseline features. (b) Selection of tuning parameter (λ) in the LASSO model via tenfold cross-validation employing minimum criteria.

TABLE 2 Multivariate Cox proportional hazards regression model for predicting in-hospital mortality in patients with sepsis.

Variables	HR	95% CI	*p* value
Sources of infection			
Respiratory tract			
Abdomen	0.827	0.545–1.257	.374
Digestive tract	0.431	0.256–0.726	.002
Urinary tract	0.182	0.074–0.445	<.001
Others	0.634	0.482–0.834	.001
Haematological disease	1.287	0.794–2.088	.306
Malignancy	1.648	1.259–2.158	<.001
Gram-negative bacterium	0.616	0.481–0.788	<.001
Gram-positive bacterium	0.533	0.396–0.718	<.001
Mechanical ventilation (day)	0.737	0.651–0.835	<.001
No. vasopressors	1.680	1.531–1.843	<.001
SOFAmin	1.109	1.038–1.185	.002
SOFAmax	1.101	1.055–1.149	<.001
APACHEIImin	1.215	1.174–1.258	<.001
Lactate.max	1.008	0.991–1.026	.340

Abbreviations: APACHE II, Acute Physiology and Chronic Health Evaluation II; CI, confidence interval; HR, hazard ratio; SOFA, Sequential Organ Failure Assessment.

were selected as candidate predictors. To perform variable selection, the Least Absolute Shrinkage and Selection Operator (LASSO) regression was used. Specifically, the optimal λ value (λ_{min}) was determined through tenfold cross-validation to prevent overfitting and ensure model robustness. LASSO regression applies an L1 penalty to the regression coefficients, forcing insignificant variables' coefficients towards zero, thereby retaining only the most influential variables for model prediction. The selected variables were subsequently incorporated into a multivariate Cox proportional hazards regression model to assess their predictive ability for mortality risk in septic patients. To validate the proportional hazards assumption, the Schoenfeld residuals were tested. These steps laid the foundation for the subsequent development of the nomogram.

The nomogram development process began with a random allocation of samples into a training set and a validation set at a 7:3 ratio. An initial nomogram to predict in-hospital mortality among sepsis patients was constructed using the training set, and an interactive, web-based risk calculator was developed (https://lotus-247.shinyapps.io/DynNomapp/). The performance of the nomogram was evaluated in two stages: preliminary quantification within the training cohort, followed by independent validation in the validation cohort, focusing on discrimination, calibration and clinical utility. Discrimination was assessed by generating the receiver operating characteristic (ROC) curve and calculating the area under the curve (AUC), which reflects the model's ability to distinguish between survivors and non-survivors. Calibration was evaluated by plotting a calibration curve to examine the concordance between predicted probabilities and observed outcomes. Decision curve analysis (DCA) was employed to assess the net benefit of the model at various prediction thresholds, thereby evaluating its clinical applicability. All analyses were performed using R software (v4.2.3, http://www.r-project.org/), with statistical significance defined as a *p*-value <.05.

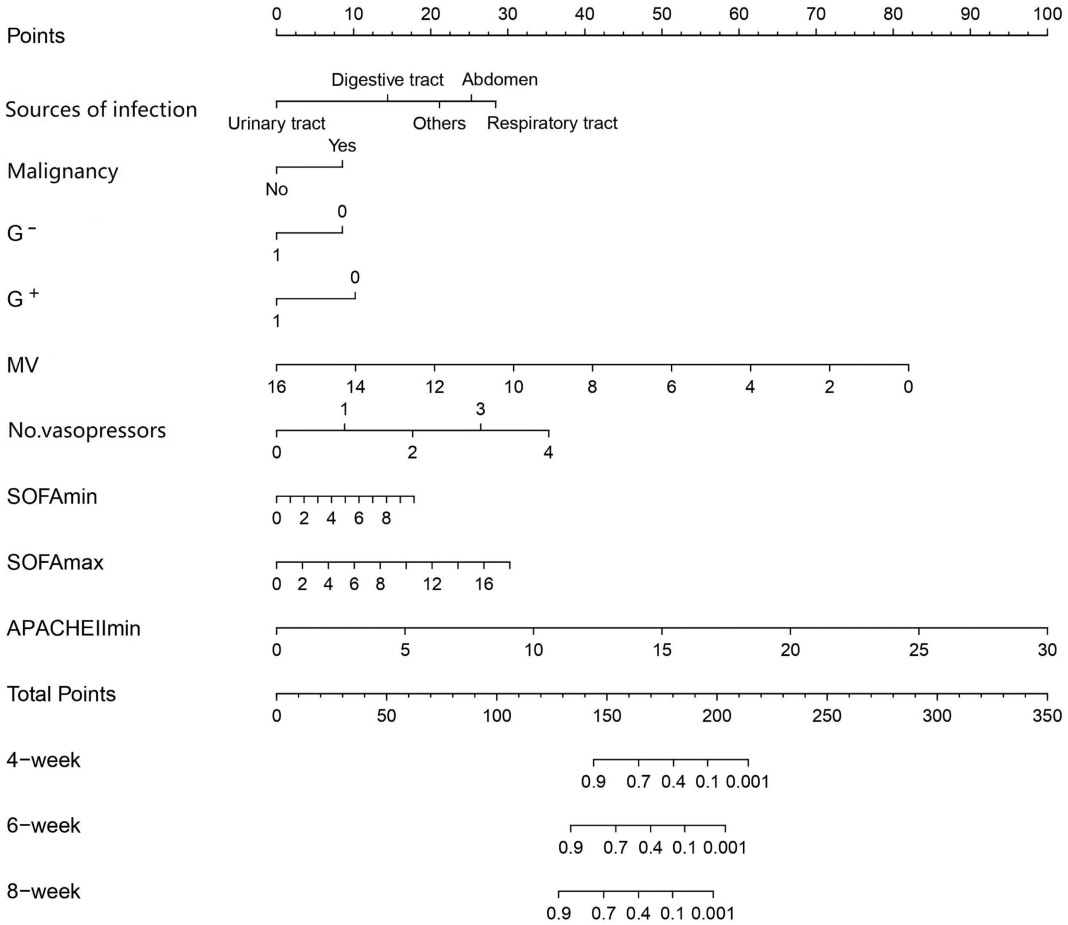

FIGURE 3 Nomogram for predicting 4-, 6- and 8-week hospital survival in sepsis patients. Individual variable scores are plotted along their respective axes, and the total score is calculated by summing these values. The total score is then mapped to the survival probability axis to estimate the likelihood of survival at specific time points. MV, mechanical ventilation.

3 | RESULTS

3.1 | Patient characteristics

A total of 2389 patients participated in the study, with 1673 allocated to model development and 716 for validation. Table 1 presents the demographic and clinical characteristics of all participants. No disparities emerged between the two sets regarding age, gender, BMI, comorbidities, infection sources, pathogenic microorganisms, laboratory parameters, treatment interventions, scoring systems and outcomes.

3.2 | Predictor selection

Clinical relevant information was screened using the CDSS, adhering to the principle of at least 10 sepsis patients per predictor (EPV). LASSO regression analysis was performed on 35 candidate predictors (Figure 2), resulting in the identification of 15 significant predictors. These variables included: source of infection (respiratory tract, abdomen, digestive tract, urinary tract, other), blood system diseases or malignancy comorbidities, presence of Gram-negative and Gram-positive bacteria, maximum lactate levels, maximum and minimum SOFA scores, minimum APACHE II score, days of mechanical ventilation and the number of vasopressors used within 4 weeks.

After incorporating these 15 variables into the multivariate Cox proportional hazards regression model, we identified 11 independent predictors of in-hospital mortality (Table 2). These predictors include digestive tract infection (hazard ratio [HR], 0.431; 95% confidence interval [CI], 0.256–0.726; $p = .002$), urinary tract infection (HR, 0.182; 95% CI, 0.074–0.445; $p < .001$), other infections (HR, 0.634; 95% CI, 0.482–0.834; $p = .001$), malignancy (HR, 1.648; 95% CI, 1.259–2.158; $p < .001$), Gram-negative bacterium (HR, 0.616; 95% CI, 0.481–0.788; $p < .001$), Gram-positive bacterium (HR, 0.533; 95% CI, 0.396–0.718; $p < .001$), days of mechanical ventilation (HR, 0.737; 95% CI, 0.651–0.835; $p < .001$), vasopressor use (HR, 1.680; 95% CI, 1.531–1.843; $p < .001$), minimum SOFA score (HR, 1.109; 95% CI, 1.038–1.185; $p = .002$), maximum SOFA score (HR, 1.101; 95% CI, 1.055–1.149; $p < .001$) and minimum APACHE II score (HR, 1.215; 95% CI, 1.174–1.258; $p < .001$).

3.3 | Nomogram and web-based calculator

To facilitate clinical application and evaluation, a prognostic nomogram was developed based on the variables identified in

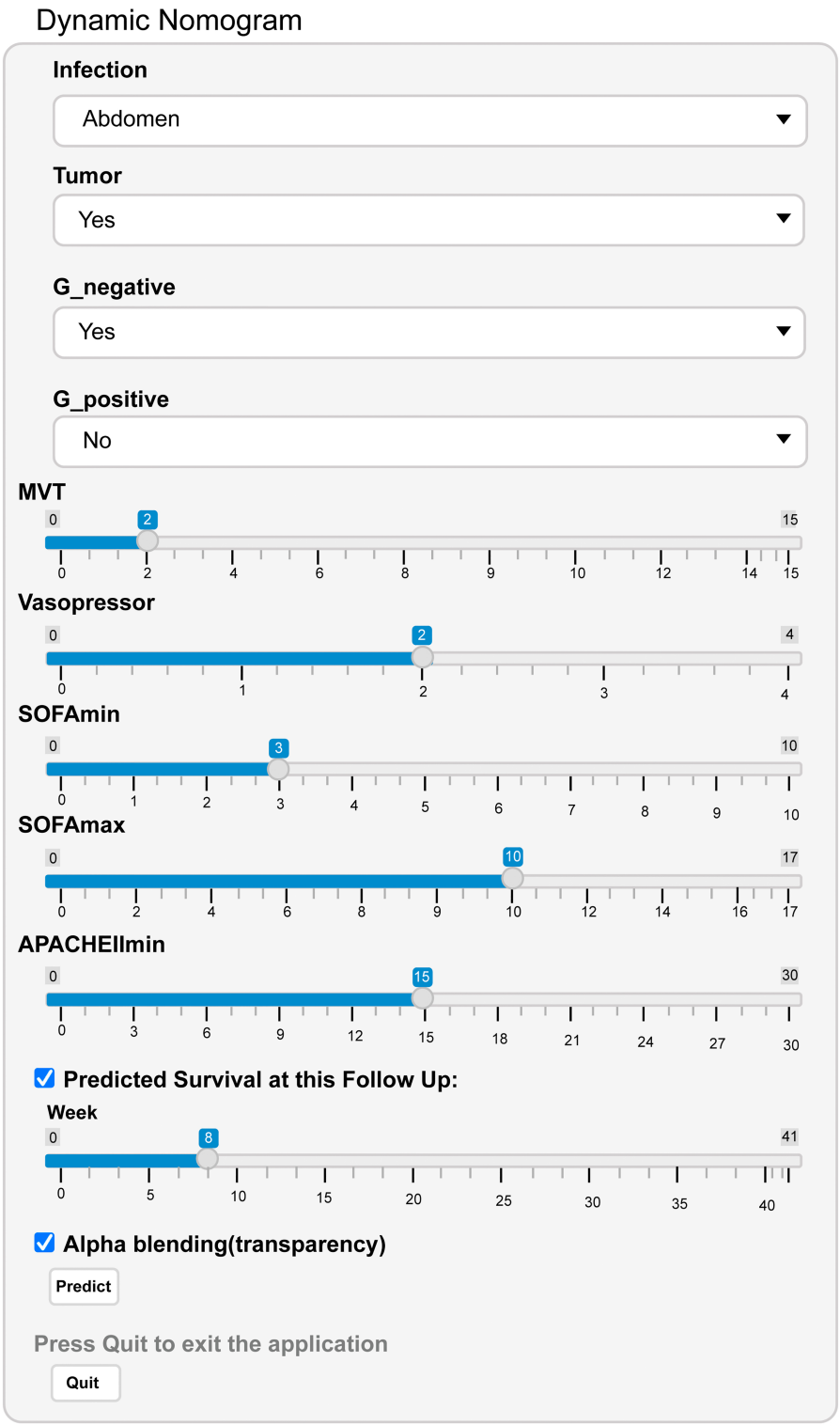

FIGURE 4 Online web-based calculator for predicting survival at 4, 6 and 8 weeks in hospitalized patients with sepsis.

the multivariate Cox proportional hazards regression analysis (Figure 3). The nomogram highlights that the minimum APACHE II score has the most significant impact on prognosis, followed by days of mechanical ventilation, number of vasopressor doses, maximum SOFA score, source of infection, minimum SOFA score, Gram-positive bacterium, Gram-negative bacterium and malignancy. Each variable's category is assigned a corresponding score on the scale, and the cumulative score is associated with the probability of survival at 4, 6 and 8 weeks during hospitalization.

Based on this prognostic nomogram, an online calculator was developed, allowing clinicians to input the values of the 11 predictive variables and automatically calculate the survival probability and its 95% CI for septic patients at 4, 6 and 8 weeks (Figure 4). The

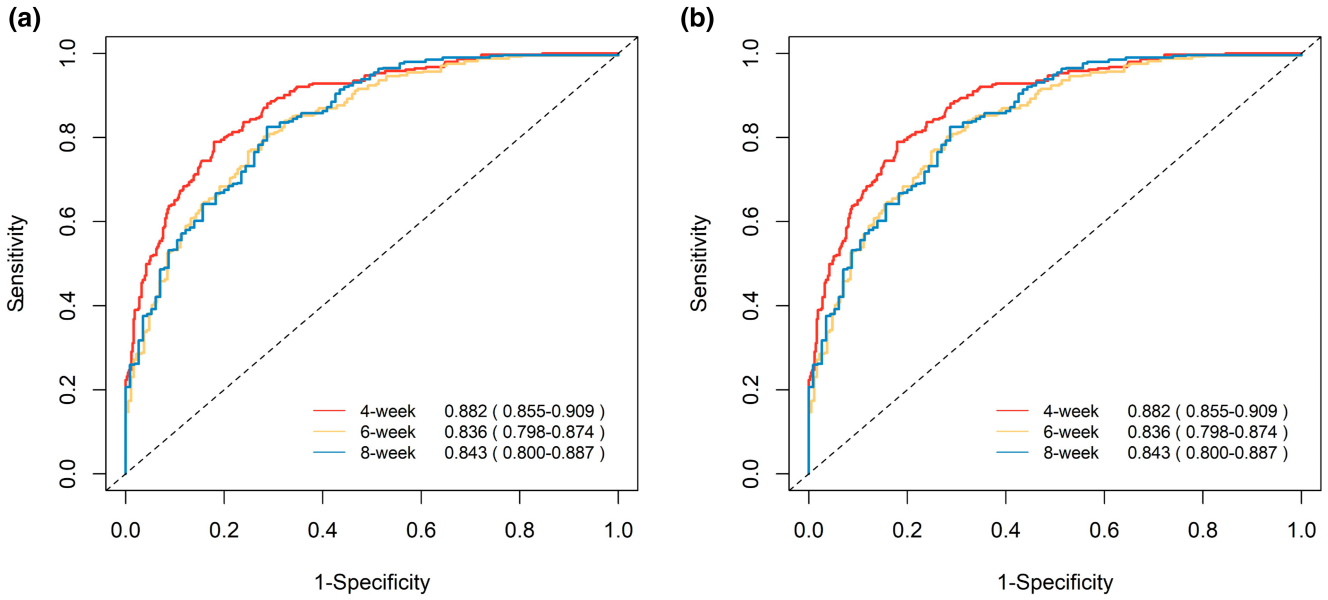

FIGURE 5 Receiver operating characteristic (ROC) curve for the nomogram. (a) Training set; (b) validation set.

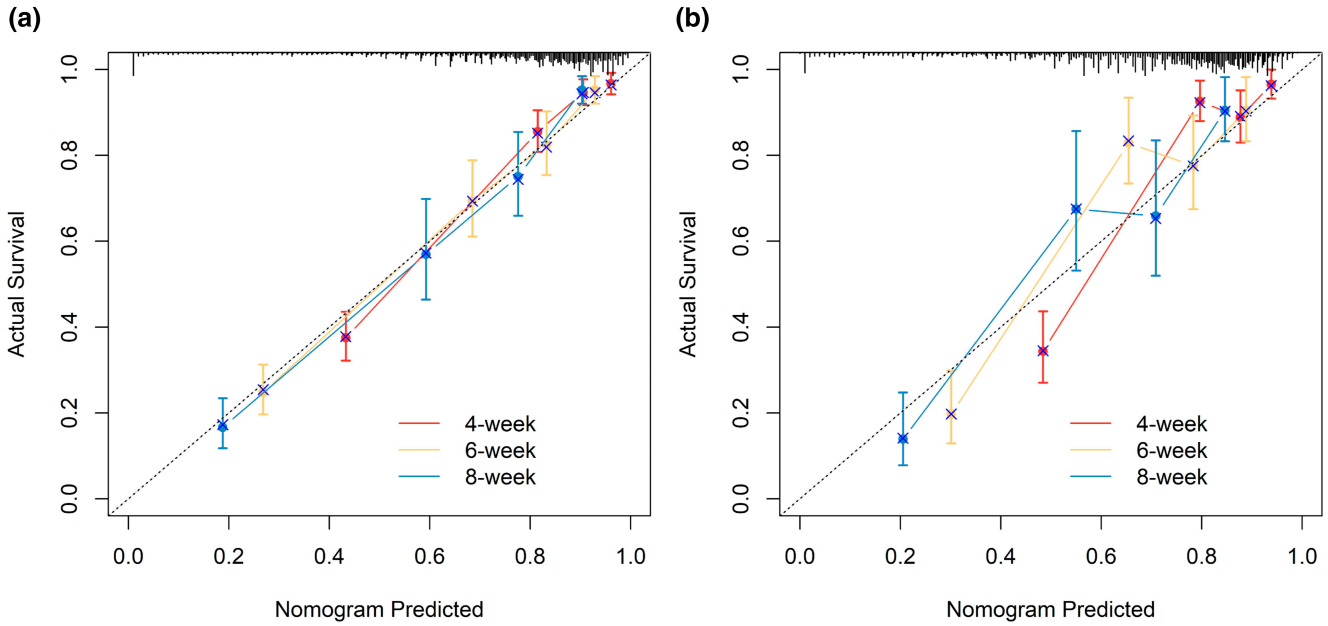

FIGURE 6 Calibration curves demonstrating alignment between predicted and observed outcomes for the nomogram. (a) Training set; (b) validation set.

calculator is available via the following link: https://lotus-247.shinyapps.io/DynNomapp/.

3.4 | Internal validation of the nomogram

The performance of the model was evaluated using ROC curve analysis. At 4 weeks, the area under the receiver operating characteristic curve (AUROC) for the training and validation sets was 0.882 (95% CI, 0.855–0.909) and 0.851 (95% CI, 0.804–0.899), respectively. At 6 weeks, the AUC values were 0.836 (95% CI, 0.798–0.874) for the training set and 0.820 (95% CI, 0.761–0.878) for the validation set. At 8 weeks, the AUC values were 0.843 (95% CI, 0.800–0.887) for the training set and 0.794 (95% CI, 0.720–0.867) for the validation set, indicating strong predictive ability (Figure 5).

The nomogram effectively predicted the survival of septic patients at 4, 6 and 8 weeks during hospitalization. The unadjusted C-index for the training group was 0.872 (95% CI, 0.853–0.891), and for the validation group, it was 0.839 (95% CI, 0.804–0.874).

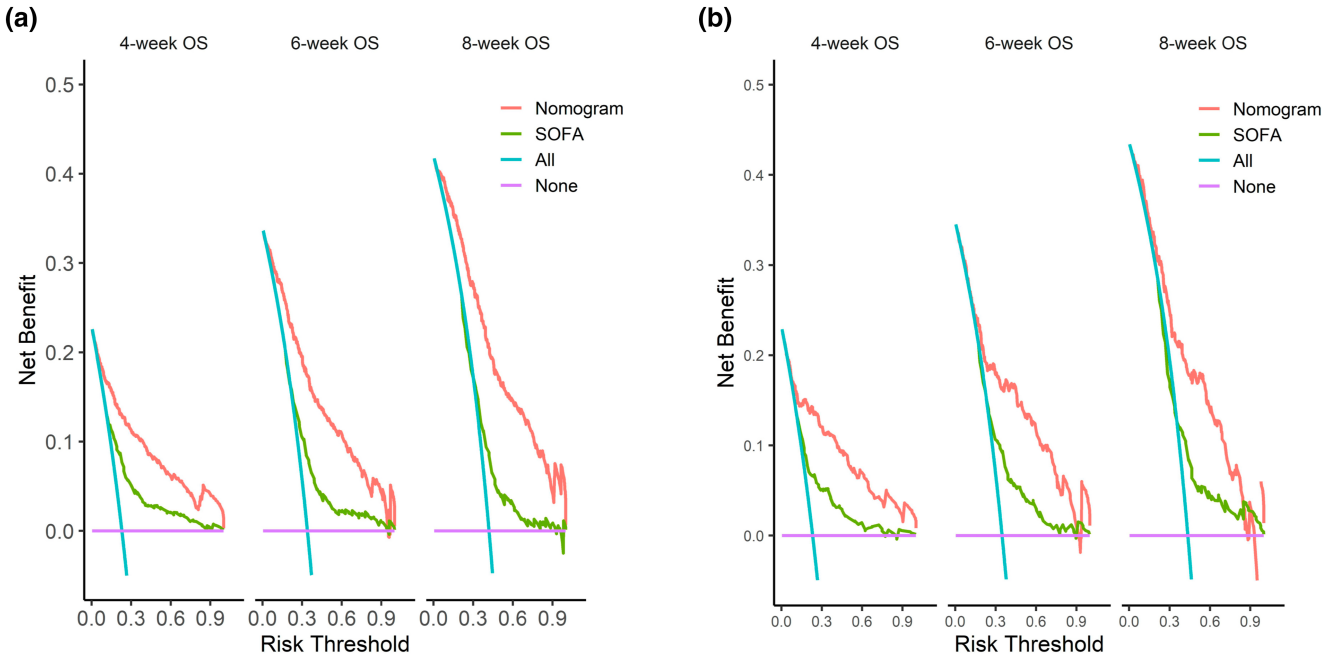

FIGURE 7 Decision curve analysis of the nomogram in contrast to the Sequential Organ Failure Assessment (SOFA) scoring system. (a) Training set; (b) validation set.

Calibration refers to the agreement between observed and predicted outcomes. To assess the calibration of our prediction model, we used the Hosmer–Lemeshow test and calibration plots. Calibration curves for both the training and validation datasets were generated using the bootstrap method (Figure 6). Notably, the significant line and bias-corrected line showed only minor deviation from the ideal line, indicating that the predicted probabilities were highly consistent with the observed outcomes.

3.5 | Clinical practicability

To assess the clinical utility of the nomogram, we generated a DCA curve and compared it with other clinical severity scoring systems. In the training set, clinical interventions guided by the nomogram showed higher net benefit within the threshold probability range of 0.1 to 0.9 (Figure 7a). In the validation set, the nomogram demonstrated higher net benefit in predicting 4-, 6-, and 8-week mortality of septic patients compared to the SOFA score system (Figure 7b).

To evaluate the risk stratification capability of the nomogram, all patients were categorized into high-risk, medium-risk and low-risk groups based on the optimal risk cut-off point. Kaplan–Meier survival curves for these risk groups, as shown in Figure 8, revealed significant differences in survival ($p < .001$).

4 | DISCUSSION

Sepsis is a severe infection associated with high mortality and a significant economic burden.[17] Although timely interventions can mitigate disease progression, predicting patient outcomes remains a clinical challenge. Therefore, the development of accurate predictive models to identify high-risk patients and forecast mortality is crucial. In this study, we developed and validated a multivariate prediction model for in-hospital mortality in ICU sepsis patients, incorporating multiple clinical variables. Our model demonstrated reliable discriminatory and predictive abilities, with the potential to assist clinicians and critical care nurses in the early identification of high-risk patients and the optimization of treatment and care strategies.

Existing sepsis mortality prediction models are mostly based on data from high-income countries, which typically come from resource-rich health care systems where patients have access to advanced diagnostic and therapeutic methods.[18,19] In contrast, the data used in this study were sourced from an ICU in a hospital in a developing country, focusing on easily accessible traditional variables rather than advanced diagnostic technologies, thus reflecting the patient characteristics and medical practices in the local context. Specifically, we used a CDSS to identify 35 potential predictive variables and applied LASSO regression to identify 11 statistically significant key variables. We then used Cox regression analysis to further reveal the independent predictive relationship between these variables and in-hospital mortality. Among these, the minimum APACHE II score and duration of mechanical ventilation showed significant impact in the prognostic nomogram. Previous studies have shown that higher APACHE II scores are closely related to worse outcomes, with each increase of one unit significantly raising the risk of mortality.[20] Mechanical ventilation is a commonly used critical intervention for sepsis patients.[21] While it helps to sustain life in the short term, it is also associated with certain complications. Studies have shown that patients who can wean off mechanical ventilation early tend to have better prognoses.[22]

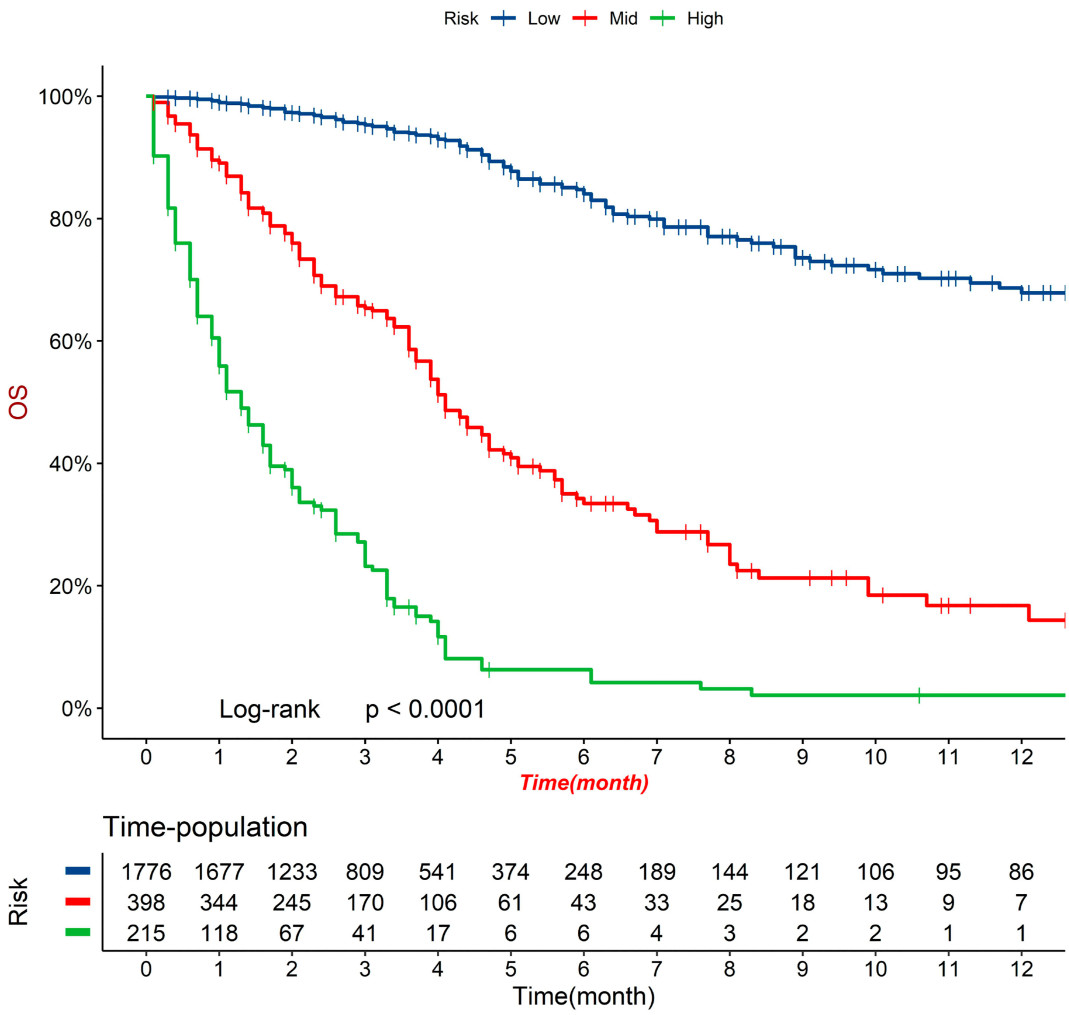

FIGURE 8 Kaplan–Meier survival curves stratified by the optimal cut-off of total points as per the proposed nomogram. Notably, the solid green, red and blue curves delineate cohorts categorized by the nomogram as high, middle and low risk, respectively, at distinct threshold probabilities.

5 | STRENGTHS AND LIMITATIONS

This study has several clinical implications. Firstly, the predictive model developed based on real local ICU data is more aligned with the clinical needs of middle- and low-income countries. By integrating key clinical variables, the model demonstrated good discriminatory ability in both the training and validation sets. Additionally, the accompanying online calculator provides a convenient decision-support tool for clinical nursing staff.

However, there are some limitations to this study. First, the data were sourced from a single centre, which may limit the model's generalizability. Future multicentre studies are needed to further validate its stability and applicability. Second, since the study employed a retrospective design, there may be missing data or measurement errors for some variables, which could impact the model's predictive accuracy. Future studies could incorporate larger-scale datasets and multidimensional information to further enhance the model's performance and clinical applicability.

6 | RELEVANCE AND IMPLICATIONS FOR CLINICAL PRACTICE

Our results further support the importance of these variables in prognostic evaluation for sepsis patients. Additionally, other key predictive factors identified in this study also play a crucial role in predicting mortality in sepsis patients. By integrating key clinical variables, nursing staff can make more efficient decisions. For example, for patients using vasopressors, nurses can closely monitor haemodynamic parameters and adjust care interventions as needed. For patients with prolonged mechanical ventilation, strengthening respiratory care can effectively prevent related complications.

7 | CONCLUSION

Based on the analysis and validation of the selected variables, we further developed a prognostic nomogram and an online calculator to

predict the survival probabilities of in-hospital patients at 4, 6 and 8 weeks. The model demonstrated superior discriminatory ability and net benefit in both the training and validation sets. Additionally, the online tool facilitates early detection of clinical deterioration and optimization of monitoring strategies. By providing individualized survival predictions, nurses can efficiently allocate resources, improving care quality and outcomes.

AUTHOR CONTRIBUTIONS

WS and MX spearheaded the research design, undertook data analysis, oversaw model development and validation and initiated the preliminary manuscript draft. QZ and YC were pivotal in orchestrating the acquisition and amalgamation of pertinent electronic medical history data from the hospital's patient pool. YC, EC, ZY and EM conceptualized and guided the research trajectory. EC and YC meticulously revised the manuscript. All authors collectively participated in manuscript refinement, review and the endorsement of the final version.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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