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CLINICAL STUDY

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Development and validation of a nomogram for predicting acute kidney injury in elderly patients in intensive care unit

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ABSTRACT

Background: This study aimed to develop and validate a nomogram for predicting acute kidney injury (AKI) in elderly patients in the intensive care unit (ICU).

Methods: Population data regarding elderly patients in ICU were derived from the Medical Information Mart for Intensive Care IV database from 2008 to 2019. The nomogram model was constructed from the training set using LASSO regression and logistic regression analysis, and the performance of the model was evaluated by decision curve analysis, calibration curve, and receiver operating characteristic (ROC) curve.

Results: According to inclusion and exclusion criteria, 14,373 elderly ICU patients were studied, of which 10,061 (70%) were assigned to the training set, and 4,312 (30%) were allocated to the validation set. Multivariate logistic analysis revealed that age, weight, myocardial infarction, congestive heart failure, dementia, diabetes, paraplegia, cancer, sepsis, body temperature, blood urea nitrogen, mechanical ventilation, urine volume, Sequential Organ Failure Assessment (SOFA) score, and Simplified Acute Physiology Score II (SAPS II) were independent risk factors for AKI in elderly ICU patients. The AUC values for the 15-factor nomogram were 0.812 (95% CI 0.802–0.822) and 0.802 (95% CI 0.787–0.818) in the training and validation sets, respectively. For clinical application, a simplified nomogram was constructed, which included age, weight, urine volume, SOFA score, and SAPS II, with the AUCs of 0.780 (95% CI 0.769–0.790) and 0.776 (95% CI 0.760–0.793), respectively. Calibration curve and decision curve analyses confirmed the models' high prediction accuracy and clinical value.

Conclusions: The nomogram developed in this study shows excellent predictive performance for AKI in elderly patients in the ICU.

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Acute kidney injury; intensive care unit; MIMIC-IV; nomogram; prediction model

Introduction

Acute kidney injury (AKI), a multidisciplinary and common clinical critical illness characterized by a short-term acute decline in kidney function due to multiple etiologies, has become a major global public health challenge, especially in the elderly patient population in the intensive care unit (ICU) [1]. Older ICU patients are at higher risk for AKI as age increases, with changes in physiological function, increasing comorbidities, and the complexity of critical illness [2,3]. The high incidence of AKI in this population is not only associated with a longer duration of hospitalization but also with increased mortality [4]. Therefore, timely identification and risk stratification of patients at risk of AKI is of great significance for early intervention and improvement of patient prognosis.

In the last decade, numerous studies have identified the potential risk factors for ICU patients with AKI, including age, sepsis, shock, and surgery [5]. In particular, the Sequential Organ Failure Assessment (SOFA) score and Simplified Acute Physiological Score II (SAPS II) have emerged as critical prognostic tools for assessing organ dysfunction and disease severity in critically ill patients [6–8]. In addition, urine volume has been recognized as an early sensitive indicator of renal impairment [9,10]. Although these studies provide a scientific basis for AKI risk prediction, most of them focus on

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other populations and pay insufficient attention to the prediction of AKI risk in elderly patients. Moreover, there is an unmet need to integrate these risk factors into a user-friendly forecasting model. Filling these gaps will be critical to improve risk stratification and guide prevention strategies.

Nomograms are considered a powerful tool for constructing simple and intuitive predictive models to quantify the perceived risk of clinical events [11]. Despite their broad application, the availability of nomograms tailored to forecast the risk of AKI in geriatric ICU populations is relatively scarce. To fill this gap, the aim of this study was to develop reliable nomograms for predicting the occurrence of AKI in older adults in the ICU.

Methods

Database introduction

The Medical Information Mart for Intensive Care (MIMIC-IV) database is a publicly available biomedical dataset that records the clinical data of patients in the ICU at Beth Israel Deaconess Medical Center between 2008 and 2019[12]. It covers multi-dimensional information such as patient demographics, vital signs, laboratory results, and treatment options, providing researchers with a platform for in-depth analysis of ICU patient care and outcomes. With its data comprehensiveness and openness, MIMIC-IV facilitates collaborative research on a global scale. Because it does not contain any identifying information and is not directly relevant to clinical decision-making, the statement of individual patient consent and ethical informed consent is not necessary, and we are eligible to apply for access to the database after passing the required assessment.

Study population

Patients in the MIMIC-IV database who met the following criteria were included in this study: (1) patients aged 65 and older in the present study; (2) initial admission to the ICU; (3) stay in the ICU for more than 24 h. Only the first admission was considered for patients with multiple ICU admissions. Patients under the age of 65 and those who spent less than 24 h in the ICU were excluded.

Data collection

This study focused on the incidence of AKI in elderly ICU patients during hospitalization. To improve the clinical applicability of the model, we screened 46 easily accessible clinical variables based on clinical expertise. These variables included demographic characteristics (sex, age, weight, and ethnicity), multiple complications (myocardial infarction, congestive heart failure, peripheral vascular disease, cerebrovascular disease, dementia, chronic lung disease, rheumatic disease, peptic ulcer disease, liver disease, diabetes, paraplegia, kidney disease, cancer, acquired immune deficiency syndrome, and sepsis), and vital signs (heart rate, mean blood pressure, respiratory rate, body temperature, peripheral blood oxygen saturation) and laboratory examination indicators (hematocrit, hemoglobin, platelet, white blood cell count, anion gap, bicarbonate, blood urea nitrogen, calcium, chloride, creatinine, glucose, sodium, potassium, international normalized ratio, prothrombin time, partial thromboplastin time). For patients with repeat admissions, only the data from the first admission were considered. For multiple tests, the first test was selected within 24 h after admission. In addition, we recorded urine output during the first 24 h after ICU admission and the receipt of concurrent treatments, including mechanical ventilation, vasopressors, and renal replacement therapy. SOFA score and SAPS II were assessed as a measure of disease severity within the first 24 h after admission. The SOFA score is used to assess the degree of dysfunction in six major organ systems, including the respiratory, cardiovascular, liver, coagulation, central nervous system, and kidneys, with scores for each system ranging from 0 to 4, with higher scores indicating more severe dysfunction. The SAPS II is a clinical scoring system for predicting in-hospital mortality in ICU patients. It assesses the severity of illness by considering the patient's physiological parameters, chronic health status, and acute physiological variables. Both scoring systems are well recognized for evaluating the severity of illness in critically ill patients, and they are essential tools to guide treatment decisions in both research and clinical practice.

Outcome

The outcome of our investigation was the occurrence of AKI among elderly patients during their ICU stay. For the diagnosis of AKI, we adhered to the criteria set forth by the 2012 Kidney Disease [13]: Improving Global Outcomes (KDIGO) guidelines: a creatinine increase of at least 0.3 mg/dL within 48 h, or an increase to at least 1.5 times the baseline value within the past 7 days, with the baseline creatinine defined as the lowest creatinine level measured within the 7 days prior to each episode of AKI, or a urine output of less than 0.5 mL/kg/h for at least 6 consecutive hours.

Statistical analysis

In the application of the MIMIC-IV database, we faced the common problem of missing data. The analysis included only variables with less than 20% missing data in order to reduce the potential risk of bias. Using the 'mice' package in R software, we performed multiple imputations on missing data to ensure data integrity.

We randomly assigned patients in a 7:3 ratio to the training cohort and the validation cohort to ensure that outcome events were evenly distributed in the two cohorts. For the continuous variables in this study, we chose to describe these variables by median and interquartile range, considering that they usually show non-normal distribution, and used the Mann-Whitney U test to evaluate the differences between different groups. Categorical variables were reported as frequencies and percentages and were compared between

groups with the use of the chi-square test or Fisher's exact test, depending on the distribution of data.

By incorporating a penalty term into the loss function, LASSO regression can shrink some coefficients to zero, thereby achieving variable selection and regularization. This process enhances the model's prediction accuracy and improves its generalization ability. Using the LASSO regression analysis, our study identified variables with non-zero coefficients from the 46 variables in the training set. These variables were then further validated through stepwise backward logistic regression analysis, confirming those with statistical significance ($p < 0.05$) as independent risk factors. To simplify the model while ensuring prediction accuracy, we used the random forest (RF) method to select five key variables and constructed a simplified nomogram based on these variables. In addition, the predictive performance and clinical application of the model were further evaluated by calculating the area under the curve (AUC) and performing decision curve analysis (DCA).

All analyses were performed using R software (version 4.4.2). In statistical tests, a p value of less than 0.05 was considered statistically significant.

Results

Baseline characteristics

As shown in Figure S1, 14,373 geriatric ICU patients from the MIMIC-IV database were included in this study. Of these patients, 11,547 were diagnosed with AKI. The median age of AKI patients was 77.42 years, which was slightly higher than 76.06 years in the non-AKI group ($p < 0.001$), and the proportion of male patients in the AKI group (54.8%) was significantly higher than that in the non-AKI group (49.3%) ($p < 0.001$). The AKI group had a significantly higher incidence of complications than the non-AKI group, including myocardial infarction (24.7% vs. 16.0%, $p < 0.001$), congestive heart failure (42.3% vs. 25.9%, $p < 0.001$), and peripheral vascular disease (16.7% vs. 11.6%, $p < 0.001$). In addition, compared with the non-AKI group, the AKI group showed higher levels of creatinine, blood glucose, blood urea nitrogen, and other biochemical indicators while significantly lower urine volume. In terms of hematological examination, hemoglobin, hematocrit, and platelet count in the AKI group were lower than those in the non-AKI group ($p < 0.001$). Table 1 shows detailed information on the baseline characteristics of the AKI and non-AKI groups, including key parameters such as demographic characteristics, vital signs, and laboratory findings. We also created baseline tables for different stages of AKI according to the detailed information of AKI staging in the 2012 KDIGO guideline [13] (Table S1). The number of patients with AKI stage 2 was the highest, reaching 5571, followed by AKI stage 3 (3808) and AKI stage 1 (2168). This indicates that in this study, the incidence of moderate-to-severe AKI (AKI stage 2 and AKI stage 3) was relatively high (Table S2).

Screening of predictor variables

Patients were randomly assigned to a training set (10,061 patients) and a validation set (4312 patients). In the training set of this study, LASSO regression analysis was used to identify significant variables associated with the development of AKI (Figure 1a). By selecting lambda.1se (0.009309) of the lambda value as the regularization parameter, 15 variables with non-zero coefficients were identified as predictors (Figure 1b). Subsequently, stepwise logistic regression analysis was used to validate the variables selected by LASSO analysis further. Age, weight, myocardial infarction, congestive heart failure, dementia, diabetes, paraplegia, cancer, sepsis, body temperature, blood urea nitrogen, mechanical ventilation, urine output, SOFA score, and SAPS II were independent risk factors for AKI (Table 2).

Construction and validation of a nomogram

The results of multivariate logistic regression were applied to construct a nomogram of AKI in elderly patients in the ICU, and scores were assigned to the screened variables according to their regression coefficients (Figure 2a). Based on testing in the training and validation cohorts, the nomogram showed excellent discrimination power, with AUC values of 0.812 (95% CI 0.802–0.822) and 0.802 (95% CI 0.787–0.818), respectively (Figure 3a and 3b). In addition, the model calibration curve analysis showed a high degree of agreement between the predicted probabilities and the actual observed probabilities, which provided strong evidence for the accuracy and reliability of the model (Figure 4a and 4b). The clinical utility of the nomogram was further confirmed by DCA, which showed additional benefits from using the nomogram for treatment decisions at all risk levels (Figure 5a and 5b). To further validate the predictive performance of the nomogram across different patient groups, we conducted validations in the training and validation cohorts for different genders and common comorbidities among elderly patients in the ICU, including diabetes, kidney disease, myocardial infarction, congestive heart failure, and cerebrovascular disease (Tables 4 and 5) (Figure S3). Calibration curve analysis demonstrated a high degree of consistency between the predicted and actual observed outcomes. ROC analysis yielded AUC values around 0.8, indicating the model's robust discriminatory power. DCA results further confirmed the model's clinical utility in each subgroup, with additional benefits for clinical decision-making when applying the model. These findings suggest that the nomogram not only performs well in the overall population but also maintains high accuracy and reliability across different subgroups, providing strong support for clinicians to predict AKI risk and make treatment decisions in various patient populations. To validate the performance of our prediction model relative to traditional scoring systems, we compared the AUC values of nomogram with those of the SOFA and SAPS II scores in both the training and validation cohorts (Figure S5, S6). The results demonstrated that our nomogram outperformed these

Table 1. Demographic and clinical characteristics of the study population at baseline.

Variables	Total (n = 14,373)	Non-AKI (n = 2826)	AKI (n = 11,547)	p value
Sex, male, n (%)	7721 (53.7)	1392 (49.3)	6329 (54.8)	<0.001
Age (years)	77.18 [70.86, 84.03]	76.06 [69.96, 83.56]	77.42 [71.10, 84.12]	<0.001
Weight (kg)	76.00 [64.00, 89.80]	70.00 [59.30, 81.50]	77.80 [65.60, 91.00]	<0.001
Ethnicity, n (%)				0.772
White	10,143 (70.6)	1979 (70.0)	8164 (70.7)	
Black	1112 (7.7)	221 (7.8)	891 (7.7)	
Other	3118 (21.7)	626 (22.2)	2492 (21.6)	
Myocardial infarct, n (%)	3304 (23.0)	452 (16.0)	2852 (24.7)	<0.001
Congestive heart failure, n (%)	5615 (39.1)	733 (25.9)	4882 (42.3)	<0.001
Peripheral vascular disease, n (%)	2251 (15.7)	327 (11.6)	1924 (16.7)	<0.001
Cerebrovascular disease, n (%)	3080 (21.4)	785 (27.8)	2295 (19.9)	<0.001
Dementia, n (%)	897 (6.2)	226 (8.0)	671 (5.8)	<0.001
Chronic pulmonary disease, n (%)	4245 (29.5)	748 (26.5)	3497 (30.3)	<0.001
Rheumatic disease, n (%)	628 (4.4)	109 (3.9)	519 (4.5)	0.151
Peptic ulcer disease, n (%)	437 (3.0)	96 (3.4)	341 (3.0)	0.242
Liver disease, n (%)	1178 (8.2)	172 (6.1)	1006 (8.7)	<0.001
Diabetes, n (%)	4813 (33.5)	756 (26.8)	4057 (35.1)	<0.001
Paraplegia, n (%)	1088 (7.6)	322 (11.4)	766 (6.6)	<0.001
Renal disease, n (%)	3995 (27.8)	521 (18.4)	3474 (30.1)	<0.001
Cancer, n (%)	2374 (16.5)	553 (19.6)	1821 (15.8)	<0.001
Aids, n (%)	18 (0.1)	2 (0.1)	16 (0.1)	0.537
Sepsis, n (%)	6196 (43.1)	871 (30.8)	5325 (46.1)	<0.001
Heart rate (beats/minute)	84.00 [73.00, 98.00]	83.00 [72.00, 96.00]	85.00 [74.00, 99.00]	<0.001
MBP (mmHg)	81.00 [70.00, 93.00]	84.00 [73.00, 96.00]	80.00 [69.00, 93.00]	<0.001
Respiratory rate (beats/minute)	18.00 [15.00, 23.00]	18.00 [15.25, 22.00]	18.00 [15.00, 23.00]	0.576
Body temperature (°C)	36.67 [36.39, 37.00]	36.72 [36.44, 37.00]	36.67 [36.33, 37.00]	<0.001
SpO_2 (%)	98.00 [95.00, 100.00]	98.00 [95.00, 100.00]	98.00 [95.00, 100.00]	<0.001
Hematocrit (%)	32.60 [27.70, 37.70]	33.80 [28.70, 38.30]	32.30 [27.60, 37.60]	<0.001
Hemoglobin (g/dL)	10.60 [9.00, 12.40]	11.10 [9.40, 12.70]	10.50 [8.90, 12.30]	<0.001
Platelets ($\times 10^9$/L)	197.00 [143.00, 265.00]	205.00 [154.00, 265.00]	195.00 [140.00, 265.00]	<0.001
WBC ($\times 10^9$/L)	10.90 [7.90, 15.00]	9.70 [7.30, 13.50]	11.20 [8.10, 15.30]	<0.001
Anion gap	15.00 [12.00, 17.00]	14.00 [12.00, 17.00]	15.00 [12.00, 18.00]	<0.001
bicarbonate (mmol/L)	23.00 [21.00, 26.00]	24.00 [21.00, 26.00]	23.00 [20.00, 26.00]	<0.001
BUN (mg/dL)	23.00 [16.00, 36.00]	20.00 [14.00, 30.00]	23.00 [16.00, 37.00]	<0.001
Serum calcium (mg/dL)	8.40 [8.00, 8.90]	8.60 [8.10, 9.00]	8.40 [7.90, 8.90]	<0.001
chloride (mmol/L)	104.00 [99.00, 108.00]	103.00 [99.00, 107.00]	104.00 [99.00, 108.00]	<0.001
Serum creatinine (mg/dL)	1.10 [0.80, 1.60]	0.90 [0.70, 1.20]	1.10 [0.80, 1.70]	<0.001
Serum glucose (mg/dL)	131.00 [108.00, 167.00]	125.00 [105.00, 157.00]	133.00 [109.00, 170.00]	<0.001
Serum sodium (mmol/L)	139.00 [136.00, 141.00]	139.00 [136.00, 141.00]	139.00 [136.00, 141.00]	0.444
Serum potassium (mmol/L)	4.20 [3.80, 4.70]	4.10 [3.80, 4.60]	4.20 [3.80, 4.70]	<0.001
INR	1.30 [1.10, 1.50]	1.20 [1.10, 1.40]	1.30 [1.10, 1.60]	<0.001
PT (s)	13.90 [12.30, 16.70]	13.00 [11.80, 15.30]	14.20 [12.50, 17.00]	<0.001
PTT (s)	30.70 [26.90, 37.50]	29.20 [26.30, 34.30]	31.10 [27.10, 38.40]	<0.001
Dialysis, n (%)	573 (4.0)	15 (0.5)	558 (4.8)	<0.001
Vasopressors use, n (%)	774 (5.4)	37 (1.3)	737 (6.4)	<0.001
Mechanical ventilation, n (%)	12,043 (83.8)	1878 (66.5)	10,165 (88.0)	<0.001
Urine output (L)	1.40 [0.88, 2.09]	1.82 [1.28, 2.55]	1.29 [0.80, 1.95]	<0.001
SOFA score	5.00 [3.00, 8.00]	3.00 [2.00, 5.00]	6.00 [4.00, 9.00]	<0.001
SAPS II	40.00 [33.00, 49.00]	35.00 [29.00, 42.00]	42.00 [35.00, 51.00]	<0.001

AKI: acute kidney injury, Aids: acquired immune deficiency syndrome, MBP: Mean Blood Pressure, SpO_2: oxygen saturation, WBC: white blood cell, BUN: blood urea nitrogen, INR: international normalized ratio, PT: prothrombin time, PTT: partial thromboplastin time, SOFA: sequential organ failure assessment, SAPS II: Simplified Acute Physiology Score II.

conventional methods in predicting AKI risk, providing more accurate predictions. This comparison highlights the superior predictive capability of our nomogram over traditional scoring systems, further supporting its potential value in clinical practice for predicting AKI in elderly ICU patients.

Construction and validation of a simplified nomogram

Although the nomogram constructed by combining 15 predictor variables could provide comprehensive predictive information, its complexity was also apparent. To achieve more effective visualization and simplify the model, we further applied the RF algorithm to assess the importance of variables. By ranking the importance of the variables in the RF model, the five variables with the highest weights for AKI risk were screened, including age, weight, SOFA score, urine output, and SAPS II (Figure S2).

The results of multivariate logistic regression were applied to construct a simplified nomogram of AKI in elderly patients in the ICU, and scores were assigned to the screened variables according to their regression coefficient (Table 3 and Figure 2b). Simplified nomogram also demonstrated good predictive performance in the training and validation cohorts, with AUC values of 0.780 (95% CI 0.769 to 0.790) and 0.776 (95% CI 0.760 to 0.793), respectively (Figure 3c and 3d). These results indicated that simplified nomogram could effectively distinguish patients with AKI from those without AKI, even with the simplified model (Figure 4c and 4d). DCA results also support the clinical use of simplified nomogram, confirming its additional value in treatment

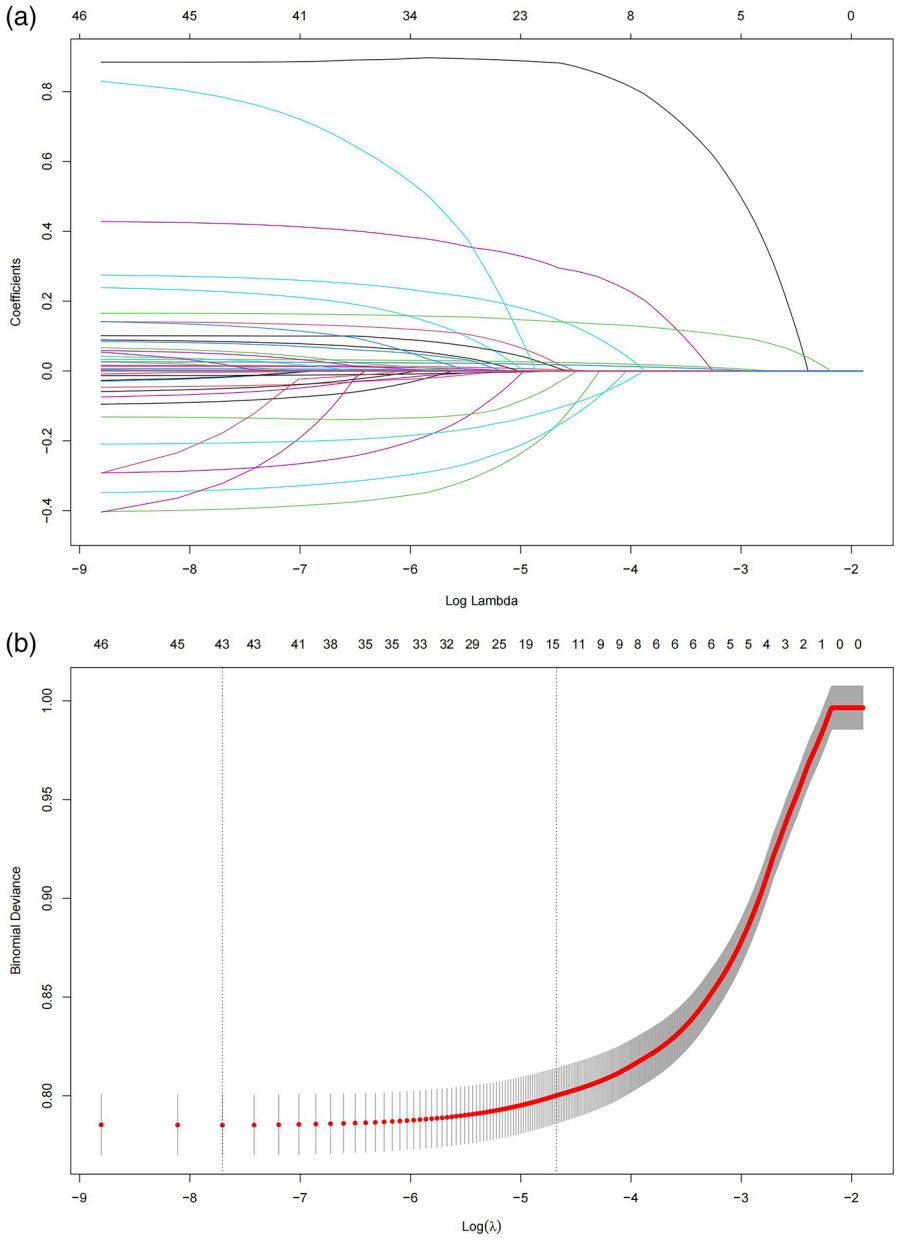

Figure 1. Lasso regression to identify prediction variables.
The process of variable selection through a LASSO binary logistic regression model is as follows: (a) The LASSO model adjusts the parameter (λ) based on the lowest criterion selected through 10-fold cross-validation. Place the vertical dashed line at the optimal values determined by the minimum criterion and the 1-SE criterion. (b) The LASSO coefficient curve for 46 variables. The optimal lambda selects 15 variables with non-zero coefficients.

Table 2. Logistic regression analysis of acute kidney injury prediction factors in ICU patients.

Term	OR	95% CI	*p* value
Age (years)	1.014	1.007–1.022	<0.001
Weight (kg)	1.031	1.028–1.036	<0.001
Myocardial infarction, *n* (%)	1.331	1.147–1.548	<0.001
Congestive heart failure, *n* (%)	1.542	1.354–1.758	<0.001
Dementia, *n* (%)	0.614	0.496–0.764	<0.001
Diabetes, *n* (%)	1.219	1.073–1.386	0.002
Paraplegia, *n* (%)	0.786	0.653–0.949	0.012
Cancer, *n* (%)	0.696	0.598–0.81	<0.001
Sepsis, *n* (%)	1.141	1.009–1.29	0.036
Body temperature (°C)	0.804	0.74–0.873	<0.001
BUN (mg/dL)	0.99	0.987–0.993	<0.001
Mechanical ventilation, *n* (%)	2.484	2.175–2.835	<0.001
Urine output (L)	0.596	0.563-0.631	<0.001
SOFA score	1.179	1.149–1.211	<0.001
SAPS II	1.027	1.02–1.035	<0.001

BUN: blood urea nitrogen, SOFA: sequential organ failure assessment, SAPS II: Simplified Acute Physiology Score II.

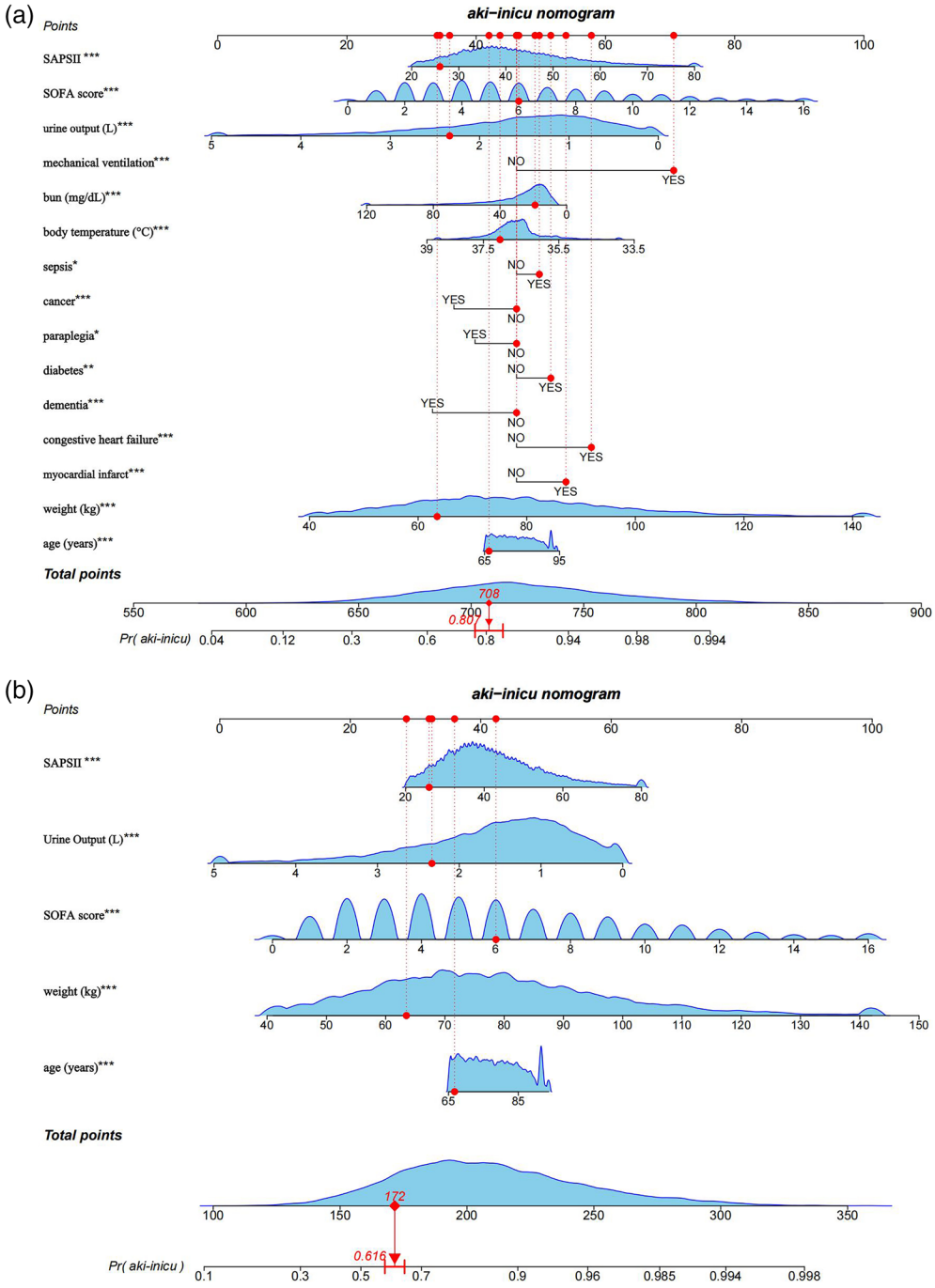

Figure 2. Nomogram for predicting the occurrence of AKI in elderly ICU patients.
(a) The nomogram was created with 15 variables validated by Lasso regression and logistic regression.
(b) The simplified nomogram was created with 5 variables selected using the Random Forest method.
BUN: blood urea nitrogen, SOFA: sequential organ failure assessment, SAPS II: Simplified Acute Physiology Score II.

decision-making (Figure 5c and 5d). To assess the validity of the simplified nomogram across diverse patient groups, we conducted subgroup analyses on patients of different genders and those with underlying conditions such as diabetes, renal disease, myocardial infarction, congestive heart failure, and cerebrovascular disease within both the training and validation sets (Tables 4 and 5). The assessment criteria included calibration curves, ROC curves, and DCA (Figure S4). The results indicate that the model demonstrates strong predictive performance across genders and various comorbidities, with high accuracy and reliability, effectively aiding clinicians in their decision-making processes. The simplified nomogram demonstrated superior performance in predicting AKI risk compared to the traditional SOFA and SAPS II scores (Figure S5, S6), indicating its potential for clinical application in elderly ICU patients.

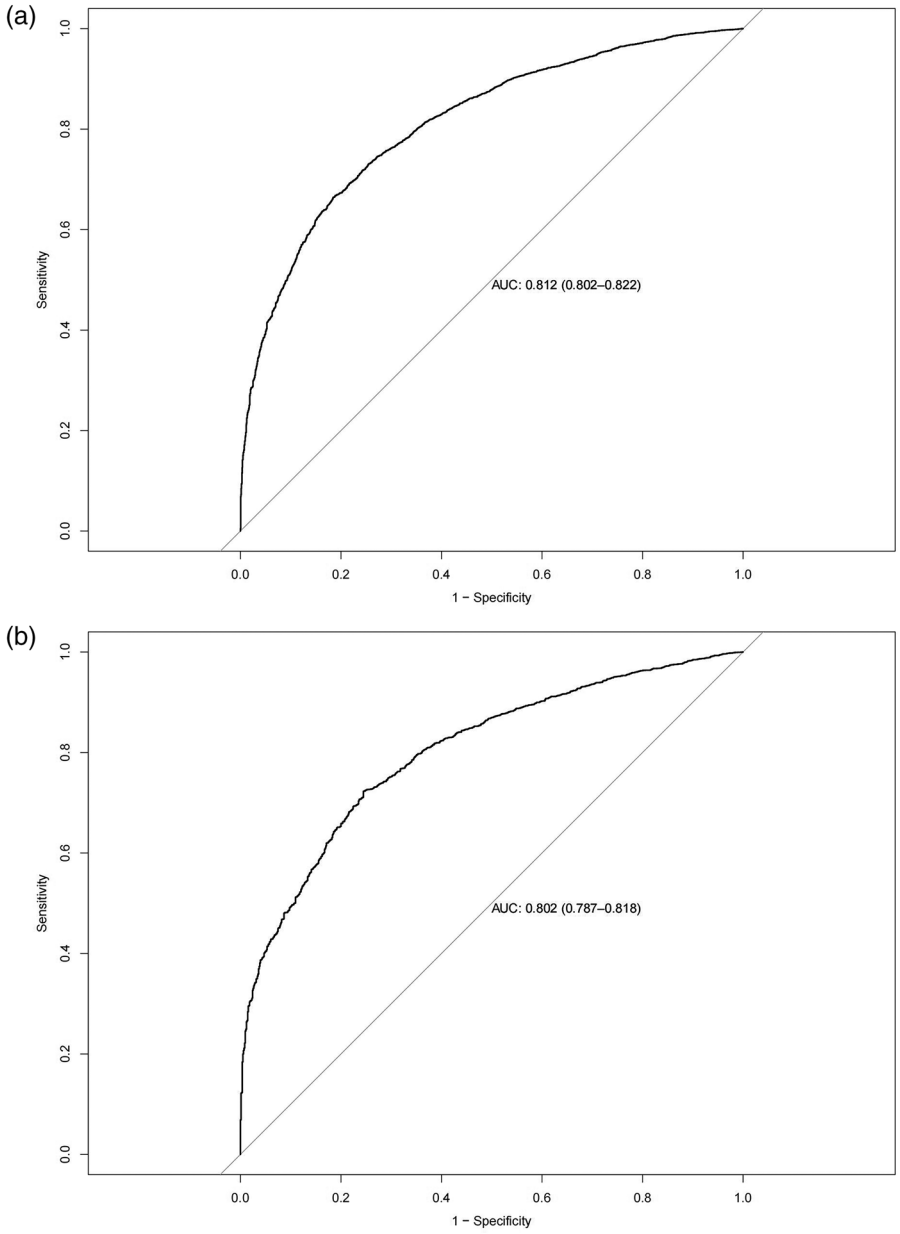

Figure 3. ROC curves for nomogram and simplified nomogram.
(a) Training set corresponding to nomogram. (b) Validation set corresponding to nomogram. (c) Training set corresponding to simplified nomogram. (d) Validation set corresponding to simplified nomogram.

Discussion

We successfully constructed two nomogram models, nomogram and simplified nomogram, to predict the risk of AKI in elderly ICU patients. There were many methods to predict AKI in the ICU, including clinical scoring systems such as SOFA, SAPS II, and Acute Physiology and Chronic Health Evaluation-II (APACHE-II) [8,14,15], as well as biomarkers like neutrophil gelatinase-associated lipocalin, liver-type fatty acid binding protein, and kidney injury molecule-1 [16]. The APACHE-II scoring system, which consisted of the acute physiology score, age component, and chronic health evaluation, effectively predicted disease severity and mortality risk but was complex and time-consuming due to its requirement for 12 physiological parameters, age, and chronic health status, which hindered early monitoring and the convenience of clinical application [17]. Compared to the above methods, our study introduced a simplified nomogram. It maintained predictive performance while simplifying the model, which was particularly important for clinical application. The simplified nomogram provided a concise and user-friendly tool that enabled clinicians to quickly and accurately assess a patient's risk of AKI and to take timely intervention measures. Compared to some biomarker prediction methods, which faced challenges such as high costs, insufficient specificity and sensitivity, lack of standardized detection methods, and other issues [18], this study offered significantly better cost-effectiveness and

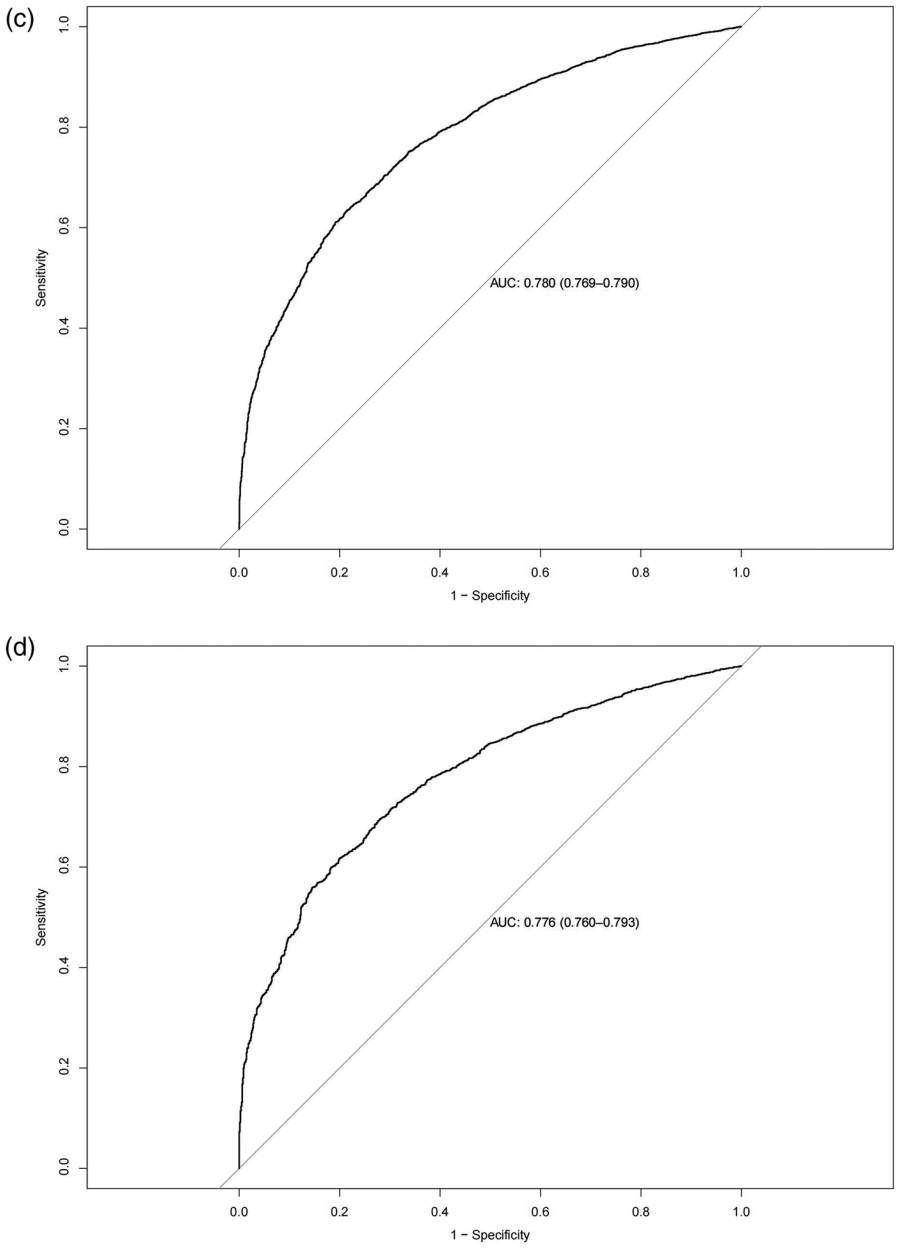

Figure 3. Continued.

accuracy. The nomogram integrated multiple variables closely related to clinical practice, demonstrating excellent discriminative power. With AUC values of 0.812 in the training set and 0.802 in the validation set, the model's high predictive accuracy was fully documented. Therefore, the results of this study represented a practical and highly accurate measure that could enhance the efficiency and accuracy of AKI risk assessment in elderly ICU patients. Certainly, other models for predicting AKI in elderly patients have also been developed. For instance, Xin et al. developed an early warning model for predicting the risk of AKI in elderly patients with sepsis [19]; Qiu et al. established a nomogram for predicting contrast-induced acute kidney injury (CI-AKI) in elderly patients with ST-segment elevation myocardial infarction undergoing emergency percutaneous coronary intervention (PCI) [20]. These models were designed for specific clinical contexts. In contrast, our model is applicable to a broader population of elderly patients in the ICU. Moreover, we employed a flexible dual-model strategy, including both a comprehensive 15-factor nomogram and a simplified nomogram, thus balancing predictive accuracy with clinical convenience. Notably, our model maintained stable predictive performance across subgroups stratified by gender and common comorbidities (including diabetes, kidney disease, myocardial infarction, congestive heart failure, and cerebrovascular disease), further demonstrating its robustness and practicality in a diverse elderly patient population.

This study showed that the risk of AKI was more significant in patients who were elderly, had abnormal weight,

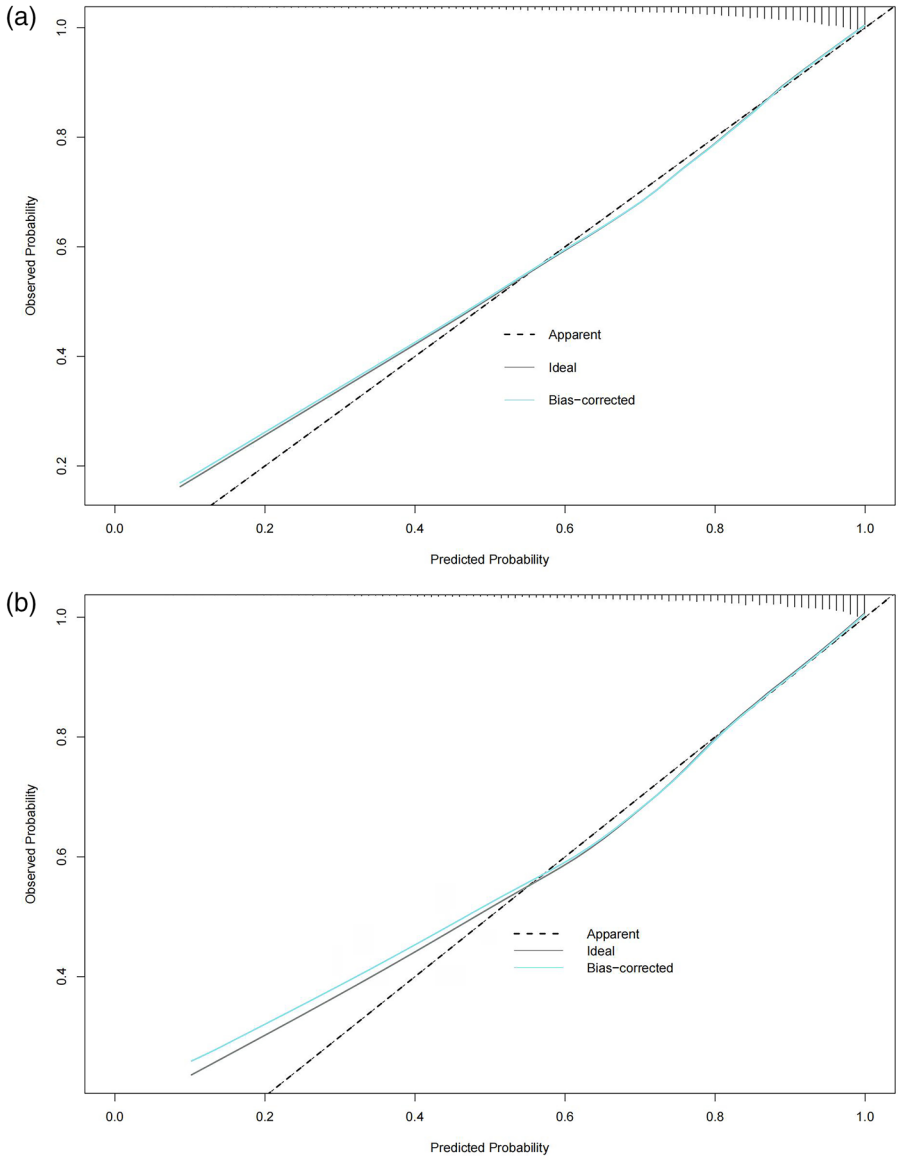

Figure 4. Calibration curves for nomogram and simplified nomogram.
(a)Training set corresponding to nomogram. (b) Validation set corresponding to nomogram. (c) Training set corresponding to simplified nomogram. (d) Validation set corresponding to simplified nomogram.

abnormal body temperature, higher blood urea nitrogen levels, lower urine output, higher SOFA scores, and SAPS II, and suffered from complications such as myocardial infarction, congestive heart failure, dementia, diabetes, paraplegia, cancer, sepsis, and those undergoing mechanical ventilation. Age plays a key role in predicting the risk of AKI [21]. As we age, the structure and function of the kidneys change, such as arteriosclerosis of the renal blood vessels and atrophy of the renal tubules [22]. This leads to an increased susceptibility of the kidneys to ischemia, medications, inflammation, and injury, as well as a decrease in their ability to regenerate and repair [23]. Therefore, elderly patients are more likely to develop AKI when facing the same pathological factors. In addition, the elderly are often accompanied by underlying diseases such as diabetes and hypertension, which increase the risk of AKI [2]. The impact of body weight on AKI is multifaceted [24]. Obesity might increase the risk of AKI by affecting renal hemodynamics and filtration functions while being underweight could be associated with malnutrition and a weakened immune system, both of which could also elevate the risk of AKI [25,26]. Abnormal body temperature, either elevated or lowered, can be potentially harmful to the kidneys. These changes may trigger inflammatory responses and immune system disruptions, affecting kidney function [27]. Elevated blood urea nitrogen and decreased urine output are significant predictive indicators of AKI, suggesting that the kidney's filtration and excretory functions are severely compromised [3]. SOFA score, as an effective tool for assessing multiple organ failure in ICU patients, is

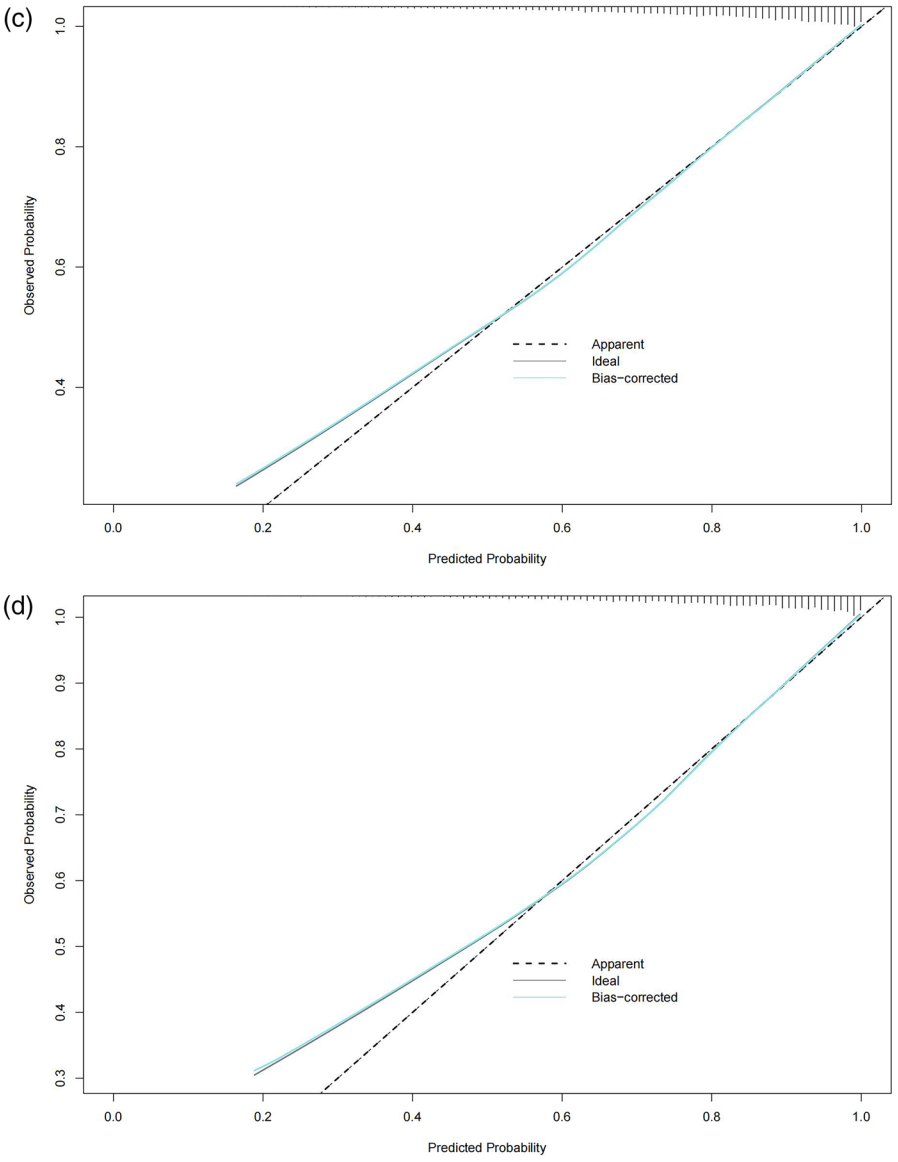

Figure 4. Continued.

positively correlated with the risk of AKI. A higher score indicates a more severe degree of multiple organ failure in the patient and a greater risk of AKI [28]. The SAPS II, which reflects the severity of a patient's illness, is used to predict mortality in ICU patients. A higher score means that the patient is more likely to have underlying renal hypoperfusion and toxin accumulation, thereby increasing the risk of AKI [7]. Congestive heart failure and myocardial infarction can lead to a decrease in the heart's pumping function, thereby reducing renal blood flow and triggering pre-renal AKI [29]. Although dementia and paraplegia do not directly cause AKI, they may be associated with a patient's overall health status and treatment requirements, indirectly affecting renal health. Patients with cancer may face the risk of AKI due to factors such as the type of cancer, its stage, anti-cancer treatments, and the patient's general condition [30]. Antineoplastic drugs may possess nephrotoxicity, which can directly impair kidney function, while the cancer itself can cause metabolic disorders and inflammatory responses within the body, leading to kidney damage [30]. Mechanical ventilation may not directly damage the kidneys, but it is one of the indicators of critical illness in patients. Patients who require mechanical ventilation often have severe respiratory dysfunction or other organ failures, which can lead to renal hypoperfusion or an exacerbation of systemic inflammatory responses, thereby increasing the risk of AKI [31]. In addition to the aforementioned factors, characteristics of the study population at baseline reveal that there are gender differences in the development of AKI, with males being more susceptible. Relevant studies indicate that estrogen exerts a protective effect on the kidneys. In contrast, males with higher levels of testosterone are more prone to AKI under the same stressors [32]. Moreover, differences in sex

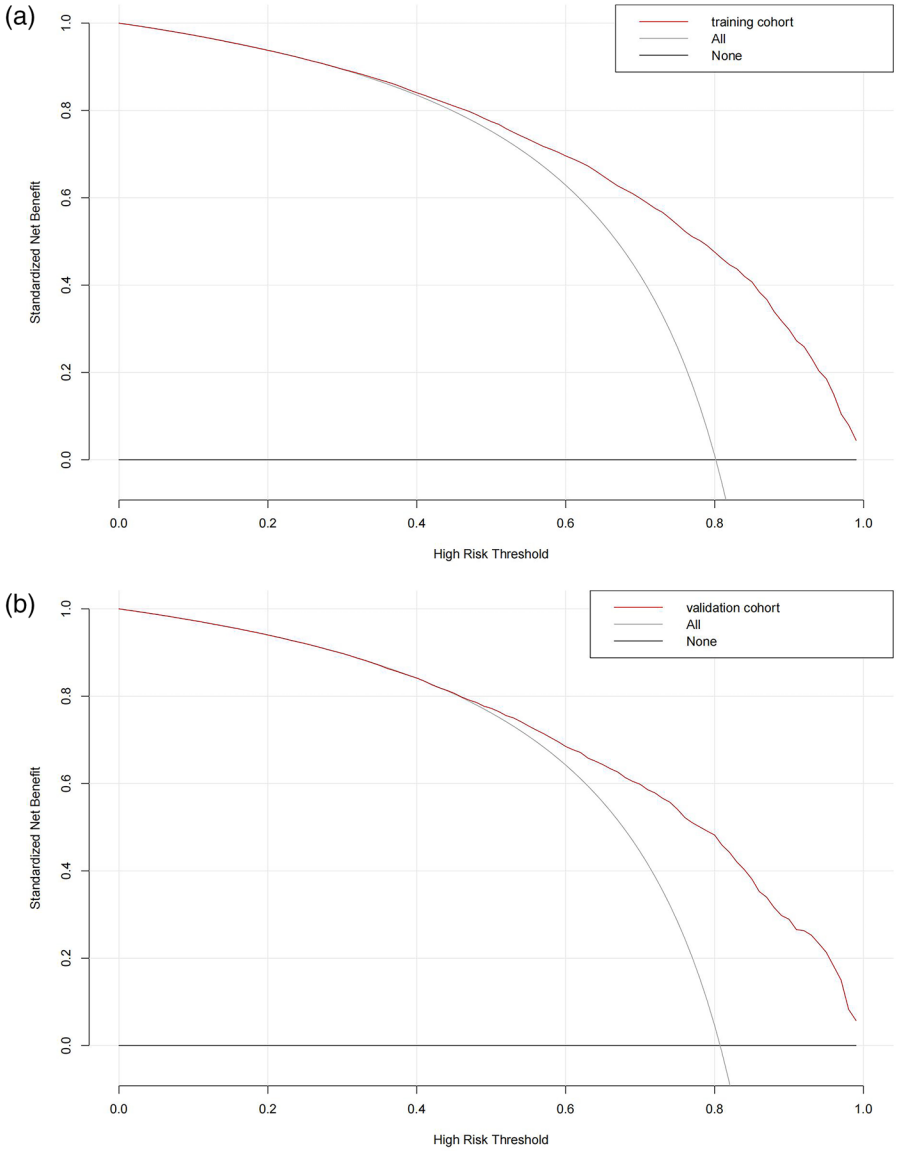

Figure 5. Decision curve analysis for nomogram and simplified nomogram.
(a) Training set corresponding to nomogram. (b) Validation set corresponding to nomogram. (c) Training set corresponding to simplified nomogram. (d) Validation set corresponding to simplified nomogram.

chromosomes also lead to the retention of more Sirtuin members with protective functions in females when the kidneys are damaged [33], and the specific reasons for this require further analysis.

However, this study has several limitations. Firstly, although this study has undergone internal validation, external validation is necessary to confirm the accuracy of the results further. Secondly, due to the retrospective design of this study, selection and information biases may exist, which could influence the interpretation and extrapolation of the outcomes. Lastly, as this study was conducted at a single center, the generalizability of the results may be limited. Consequently, additional validation through prospective randomized clinical trials across various centers is warranted to assess the generalizability and applicability of the results.

Conclusions

Age, weight, myocardial infarction, congestive heart failure, dementia, diabetes, paraplegia, cancer, sepsis, body temperature, blood urea nitrogen, mechanical ventilation, urine volume, SOFA score, and SAPS II were significant predictors. We developed two nomogram models, namely, a nomogram and a simplified nomogram, to predict the risk of AKI in elderly patients admitted to the ICU. The models have good predictive performance and can provide valuable predictive information for clinical decision-making.

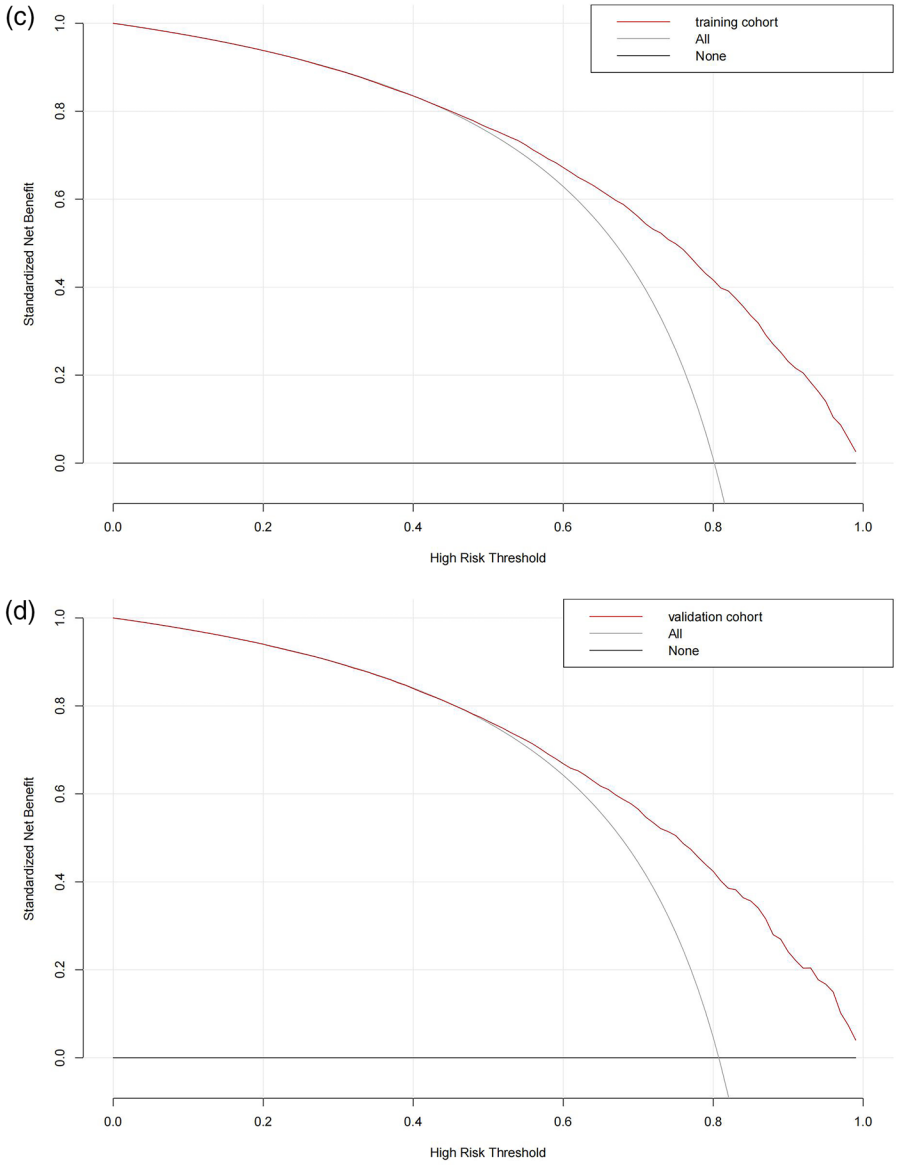

Figure 5. Continued.

Table 3. Logistic regression was performed with the five significant variables.

Term	OR	95% CI	*p* value
Age (years)	1.019	1.012–1.027	<0.001
Weight (kg)	1.033	1.029–1.036	<0.001
urine output (L)	0.641	0.607–0.677	<0.001
SOFA score	1.225	1.195–1.255	<0.001
SAPS II	1.022	1.015–1.029	<0.001

SOFA: sequential organ failure assessment, SAPS II: Simplified Acute Physiology Score II.

Table 4. The number of individuals in different subgroups and the number of endpoint events in the training set.

Group	Total count	Endpoint event count
Total	10,061	8065
Male	5409	4443
Female	4652	3622
Diabetes	3390	2874
Renal disease	2813	2438
Myocardial infarct	2320	2014
Congestive heart failure	3974	3453
Cerebrovascular disease	2157	1617

Table 5. The number of individuals in different subgroups and the number of endpoint events in the validation cohort.

Group	Total count	Endpoint event count
Total	4312	3482
Male	2312	1886
Female	2000	1596
Diabetes	1423	1183
Renal disease	1182	1036
Myocardial infarct	984	838
Congestive heart failure	1641	1429
Cerebrovascular disease	923	678

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Ethics approval and consent to participate

MIMIC-IV was set up with the approval of the Institutional Review Board at the Massachusetts Institute of Technology. All participant data were anonymized to safeguard their

privacy. Due to the use of anonymized health records, ethical approval and informed consent were not required. This study adheres to the ethical criteria outlined in the Helsinki Declaration of 1964.

Authors contributions

Conceptualization: Li Zhao, Xunliang Li, Deguang Wang; Methodology: Li Zhao, Xunliang Li, Wenman Zhao; Investigation: Li Zhao, Xunliang Li, Wenman Zhao; Formal analysis: Xunliang Li, Writing original draft: Li Zhao; Writing review & editing: Xunliang Li; Supervision: Xunliang Li. All authors read and approved the final manuscript.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Data availability statement

The datasets presented in the current study are available in the MIMIC-IV database (https://physionet.org/content/mimiciv/1.0/).

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