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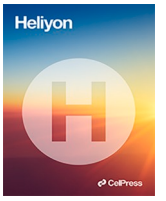

Research article

Development and validation of a dynamic nomogram for short-term survival in acute heart failure patients with acute kidney injury upon ICU admission

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ABSTRACT

Objective: The objective of this study is to develop and validate an effective prognostic nomogram for predicting the short-term survival rate of patients with acute heart failure (AHF) complicated by acute kidney injury (AKI) who are admitted to the intensive care unit (ICU).
Patients and methods: We conducted an analysis of data from patients of AHF with AKI spanning the period from 2008 to 2019, utilizing the MIMIC-IV database. Patients were randomly divided into training and validation sets. The training set employed the least absolute shrinkage and selection operator regression model to identify predictors of AKI. Subsequently, a dynamic nomogram was constructed using multivariate Cox regression analysis within the training set and was subsequently validated using the validation set. The nomogram's predictive accuracy, calibration, and clinical utility were evaluated through the concordance index (C-index), calibration plots, and decision curve analysis (DCA).
Results: A total of 978 AHF patients with AKI were analyzed. Multivariate analysis identified serum creatinine, race, age, use of human albumin, use of vasoactive drug, and hemoglobin as independent predictors significantly influencing the short-term prognosis of AHF patients with AKI upon ICU admission. The C-index for the training and validation sets were 0.81 (95%CI: 0.74–0.87) and 0.80 (95 % CI: 0.67–0.92), respectively. The calibration plot of the nomogram demonstrated a close alignment between predicted and observed probabilities. Furthermore, the DCA confirmed the clinical utility of the nomogram.
Conclusions: This study presents a dynamic nomogram that incorporates clinical risk factors and can be conveniently utilized to predict short-term prognosis for AHF patients with AKI upon ICU admission.

1. Introduction

Acute heart failure (AHF) is a clinically significant condition marked by the abrupt onset or exacerbation of heart failure symptoms

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and signs, necessitating immediate medical intervention. The rising incidence of AHF-related hospitalizations, particularly attributable to an aging population, has escalated this condition to a major public health issue [1-3]. It is crucial to acknowledge that acute kidney injury (AKI) frequently coexists with AHF, resulting in the manifestation of cardiorenal syndrome type 1 (CRS1). This comorbidity is linked to extended hospital stays and increased mortality rates [4,5]. Over 20 % of patients with AHF experience the development of AKI during hospitalization, which is associated with an increased 1–2 weeks risk of death in this population [6-8]. Therefore, the early identification and management of risk factors in patients with AHF concomitant with AKI can delay disease progression and enhance survival rates.

Despite the high incidence of AKI in patients with AHF and its association with adverse outcomes, there remains a paucity of research examining the prognostic determinants within this population [7]. In recent years, the interrelationship cardiac and renal pathologies, particularly in the context of heart failure, has undergone significant reevaluation. Advances have been made in the domains of disease recognition, risk stratification, and public awareness regarding this complex syndrome. Unfortunately, current treatments for heart failure demonstrate inconsistent efficacy, and there is a notable deficiency in evidence-based and effective therapeutic options for heart failure patients with concurrent deteriorating kidney function [9]. This issue may stem from the absence of a reliable method for clinicians to accurately identify patients with AHF who are at high risk of poor prognosis due to AKI [7]. Therefore, the development of a prognostic model to identify AHF patients with AKI who are likely to experience poor outcomes is critically needed.

Nomograms provide a robust method for generating an easily interpretable graphical representation of statistical predictive models, facilitating in the evaluation of clinical outcomes [10,11]. This study seeks to develop a prognostic nomogram to accurately and efficiently predict the 14-day survival rate following ICU admission of AHF patients with AKI with accuracy and efficiency. The objective is to elucidate the probability of adverse short-term outcomes and to offer guidance for the management and prevention of AHF patients with AKI.

2. Patients and Methods

The methodologies outlined in this article adhere to the principles set forth in the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD) statement [12].

2.1. Database

Data for the study was obtained from the publicly accessible MIMIC-IV database (version 2.2), a comprehensive critical care database based in the United States [13]. The database includes clinical data from 299,712 patients and 431,231 admissions at Beth Israel Deaconess Medical Center between 2008 and 2019, capturing detailed information on patient demographics, laboratory tests, medications, vital signs, surgical procedures, disease diagnoses, drug management, and follow-up survival outcomes.

2.2. Participants

The study's inclusion criteria consisted of adult patients aged 18 and older admitted to the intensive care unit (ICU) for AHF, including acute systolic and/or diastolic heart failure. Exclusion criteria encompassed patients with stage 5 chronic kidney disease (CKD), patients who had undergone hemodialysis or continuous renal replacement therapy prior to ICU admission. AHF was determined based on the primary discharge diagnosis codes recorded during hospitalization, specifically ICD-9 codes 42821, 42823, 42831,42833, 42841, and 42843, as well as ICD-10 codes I5021, I5023, I5031, I5033, I5041, I5043.Patients were allocated into groups using a pre-seeded random number generator (123) in R software version 4.3.3 and then divided into training and validation sets at a ratio of 7:3.

2.3. Data collection

Data extraction was performed using PostgreSQL tools (version 11.22) to retrieve a variety of information about AKI when is admitted to the ICU. The extracted data encompassed patient demographics (age and sex), laboratory variables, chronic medical conditions, comorbidities, mechanical ventilation records, the time of AKI onset, and drug administration. Specifically, laboratory variables such as hemoglobin (Hb), glucose, serum creatinine (Scr), and albumin (Alb) were extracted and analyzed at the time of AKI occurrence. The study population exhibited a range of chronic medical conditions, including chronic obstructive pulmonary disease (COPD), CKD, diabetes, chronic liver disease, and hypertension. Additionally, comorbidities such as acute pancreatitis and sepsis were identified through recorded ICD-9 or ICD-10 diagnostic codes in the MIMIC-IV database. Treatment protocols for patients included the administration of vasoactive drugs, diuretics, aminoglycosides, and human albumin.

2.4. Missing data handling

The MIMIC-IV database exhibits a notable prevalence of missing data, which raises concerns regarding the potential bias introduced by the exclusion of patients with incomplete records. To address this issue, a comprehensive assessment of all variables utilized in the analyses was performed, revealing that less than 10 % of the data were missingacross the dataset. Consequently, imputation techniques were employed to address the missing values: means were used for continuous variables with normal distributions while

medians were applied for those exhibiting skewed distributions [14]. Furthermore, our study also did not include any missing dichotomous variables.

2.5. Definitions and outcome

The primary outcome analyzed in this study was mortality post-ICU admission. Survival status refers to whether the patient survives or dies following admission to the ICU. The Kidney Disease Improving Global Outcomes (KDIGO) criteria were employed for the definition of AKI [15]. Vasoactive medications, diuretics, and aminoglycosides were categorized based on their administration to patients during their stay in the ICU for any medical indication. The Triglyceride glucose (TyG) index was calculated using the formula: Ln (Triglycerides [mg/dl] $\times$ Glucose [mg/dl]/2) [16].

2.6. Statistical analysis

Statistical analyses were performed utilizing SPSS version 26.0 (IBM Corp, Armonk, NY, USA) and R (version 4.2.1, https://www.r-project.org/). Two-sided P values were employed, with a significance level set at $P < 0.05$. Descriptive statistics for continuous variables included mean $\pm$ SD, median (interquartile range), or range, depending on their distribution, while categorical variables were presented as percentages.

In some cases, statistical analyses such as t-tests or Wilcoxon rank sum tests were utilized for continuous variables, with chi-square tests being employed for comparing categorical variables. To enhance the interpretability and accuracy of predictions, least absolute shrinkage and selection operator(LASSO) regression analysis was conducted to select and regularize factors associated with the prognosis of AHF patients with AKI within the training set [17]. Subsequently, predictors of prognosis in AHF with AKI were identified by subjecting the variables selected from the LASSO regression analysis to further scrutiny using multivariate Cox regression model.

The prognostic nomogram was developed utilizing data derived from multivariate Cox regression analysis, as referenced in a previous study [18]. The predictive capability of the nomogram for estimating the 14-day survival probability from ICU admission in patients with AHF and AKI was assessed in both the training and validation cohorts. The Harrell's concordance index (C-index) was used to evaluate the discrimination of the prediction model. The Bootstrap method was used to draw the calibration curve, and the closer the slope is to 1, the higher the accuracy of the prediction model. The Brier score was also calculated to evaluate the calibration degree of the model, and the better the calibration of the model with a Brier score close to 0 [19]. The clinical utility of the nomogram was further assessed through decision curve analysis (DCA) [20].

3. Results

3.1. Characteristics of patients in the training and validation sets

The flowchart illustrating the cohort selection process is shown in Fig. 1. A total of 978 patients diagnosed with AHF complicated by AKI was analyzed, with 289 patients assigned to the validation set and 689 patients to the training set (Fig. 1). The demographic and clinical characteristics of the training and validation sets were comparable, as outlined in Table 1. Thereby supporting their combined use for model development and validation. Within the training set, the duration of hospital stays varied from 1 to 83 days (median: 9

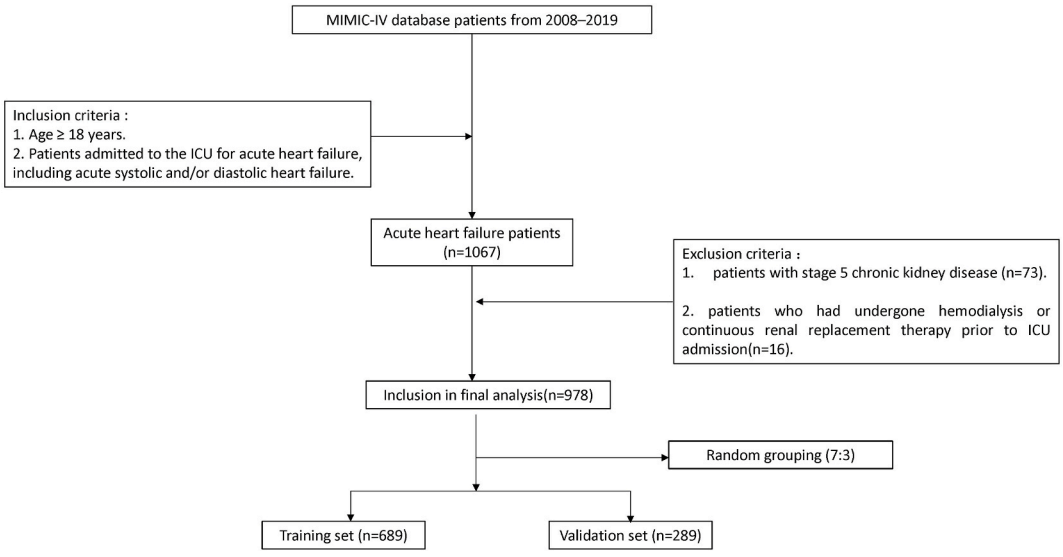

Fig. 1. Flow chart showing the patient selection for the study.

days), 83 patients (12 %) succumbed, and the 14-day cumulative survival rate was 91.3 %. The validation set demonstrated hospital stays ranging from 1 to 52 days, with a median duration of 10 days, Among the patients, 33(11.4 %) individuals experienced mortality, and the cumulative survival rates at 14 days was observed to be 90.7 %.

3.2. Dynamic nomogram development

We utilized LASSO regression analysis to refine the initial set of 22 variables in the training dataset, ultimately identifying 13

Table 1
Characteristics of patients in the training and validation sets.

variable	training set (n = 689)	validation set (n = 289)	p value
Survival status,n (%)			
Survival	606 (88.0)	256(88.6)	0.866
Dead	83 (12.0)	33 (11.4)	
Survival time, days (median [IQR])	9 (5, 14)	10(6,16)	0.023
Race (%)			
White	459 (66.6)	206(71.3)	
Black	132 (19.2)	48 (16.6)	0.361
Other	98 (14.2)	35 (12.1)	
Sex,n (%)			
Female	336 (48.8)	137 (47.4)	0.750
Male	353 (51.2)	152 (52.6)	
Age,years	74 (63, 83)	76 (64, 86)	0.090
CKD,n (%)			
No	586 (85.1)	243 (84.1)	
Yes	103 (14.9)	46 (15.9)	0.774
COPD,n (%)			
No	664 (96.4)	279 (96.5)	1.000
Yes	25 (3.6)	10 (3.5)	
Coronary,n (%)			
No	607 (88.1)	247 (85.5)	0.306
Yes	82 (11.9)	42 (14.5)	
T2DM,n (%)			
No	605 (87.8)	260 (90.0 %)	0.394
Yes	84 (12.2)	29 (10.0)	
Hypertension,n(%)			
No	533 (77.4)	231 (79.9)	0.422
Yes	156 (22.6)	58 (20.1)	
Sepsis,n(%)			
No	459 (66.6)	196 (67.8 %)	0.772
Yes	230 (33.4)	93 (32.2)	
Chronic liver disease,n(%)	685 (99.4)		0.377
No	4 (0.6)	4 (1.4)	
Yes			
Use of human albumin,n(%)			
No	628 (91.1)	264 (91.4)	1.000
Yes	61 (8.9)	25 (8.7)	
Acute pancreatitis,n(%)			
No	689 (100.0)	288 (98.7)	0.654
Yes	0 (0.0)	1 (0.3)	
Use of diuretic,n(%)			
No	552 (80.1)	231(79.9 %)	1.000
Yes	137 (19.9)	58 (20.1)	
Use of vasoactive drug,n(%)			
No	426 (61.8)	180 (62.3)	0.951
Yes	263 (38.2)	109 (37.7)	
Mechanical ventilation,n(%)			
No	161 (23.4)	74 (25.6)	0.506
Yes	528 (76.6)	215 (74.4)	
Use of aminoglycosides,n(%)			
No	634 (92.0)	272 (94.1)	0.311
Yes	55 (8.0)	17 (5.9)	
Hemoglobin, g/L (median [IQR])	105 (98, 111)	105 (97, 111)	0.857
Scr, ummol/L (median [IQR])	185.6 (123.8, 282.9)	176.8 (123.8274.0)	0.387
BUN, mmol/L (median [IQR])	11 (8, 19)	12 (8, 19)	0.305
Alb, g/L (median [IQR])	36 (32, 40)	36 (33, 39)	0.968
TyG index (median [IQR])	8.9 (8.7, 9.1)	8.9 (8.6, 9.1)	0.920

Note: Survival status refers to whether the patient survives or dies following admission to the ICU. COPD, chronic obstructive pulmonary disease; CKD, chronic kidney disease; T2DM, Type 2 diabetes; ALB, albumin; BUN, Blood urea nitrogen; TyG index, triglyceride glucose index; IQR, interquartile range.

potential predictors pertinent to the prognosis of AHF patients with AKI (Fig. 2A and B). The predictors identified by LASSO regression analysis, with an optimal lambda value of 0.01288339, are detailed in Table 2. Following this selection, the variables were subjected to further scrutiny through univariate and multivariate Cox regression analyses.

In the final statistical analysis, 6 predictors associated with prognosis were identified. These predictors include Scr (OR,95%CI: 1.4 [1.16,1.7]), race (OR,95%CI: 0.3 [0.1, 0.7] for Black vs. White and 0.4 [0.2, 0.9] for Other vs. White), age (OR,95%CI: 1.5 [1.0,1.9]), use of human albumin (OR,95%CI: 0.3 [0.1, 0.8]), use of vasoactive drug (OR,95%CI: 2.5 [1.6, 4.0]), and hemoglobin levels (OR,95% CI: 1.2 [1.1, 1.4]).

The nomogram illustrated in Fig. 3A presents a model that integrates six independent predictors and is accessible online (https://dynamicnomogram6666.shinyapps.io/AHF-AKI-prognosis/), with a screenshot provided in Fig. 3B. To employ the interactive online nomogram, users are required to select "Yes" or "No" for the relevant options, input the necessary laboratory test results, and subsequently click " Predict survival probability" to determine 14-day survival probability for patients of AHF with AKI during their ICU stay.

3.3. Nomogram performance in training set

The C-index of the prediction nomogram for the 14-day survival rate was determined to be 0.81 (95%CI: 0.74–0.87) in the training set. The calibration curve, as depicted in Fig. 4A, demonstrates a satisfactory concordance between the predicted and observed outcomes for the probability of AHF with AKI in the training set, with a calibration slope of 0.93, and a Brier score of 0.141.

3.4. Nomogram performance in validation set

The C-index for the nomogram predictions is 0.80 (95 % CI: 0.67–0.92), demonstrating good discriminatory ability within the validation set. Furthermore, the calibration of 14-day survival rates for AHF patients with AKI in the validation cohort was also found to be satisfactory, with a calibration slope of 0.91, and a Brier score of 0.092 (Fig. 4B).

3.5. Clinical use of the nomogram

The was employed to assess the benefits associated with various risk thresholds and to evaluate the potential clinical utility of the nomogram (Fig. 5). The DCA curve demonstrated that applying a threshold probability for the nomogram to predict a 14-day survival probability within the range of 14 %–65 % could yield clinical advantages. The nomogram consistently exhibited a higher net benefit across a wide spectrum of risk thresholds compared to the strategies of classifying all patients as either high risk or low risk of death.

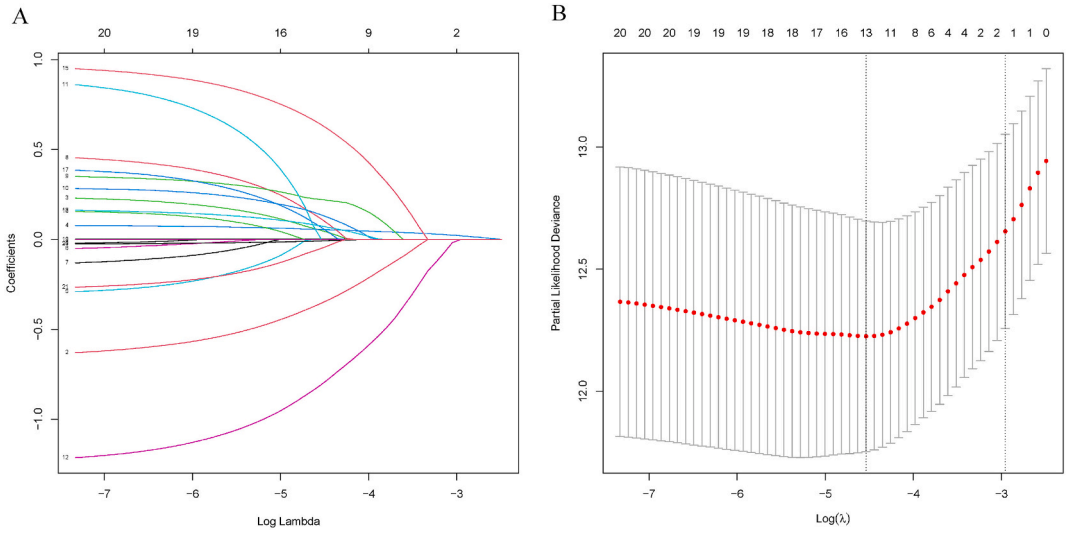

Fig. 2. Lasso Regression Path and Cross-Validation for Predictors Selection (A) Lasso coefficient profiles of the 22 predictors. Each curve corresponds to a predictor, displaying the path of its coefficient against the log of the regularization parameter lambda (λ). As λ increases (moving from left to right), the coefficients shrink towards zero, demonstrating the effect of lasso regularization on the predictor variables. The optimal λ minimizes the prediction error by finding a balance between bias and variance. (B) Cross-validation results for selecting the optimal λ. The plot shows the mean squared error (MSE) on the y-axis and log(λ) on the x-axis. Each red dot represents the MSE for a given λ value, with error bars indicating the standard error of the MSE. The vertical dotted lines represent the lambda values at minimum MSE (left line) and the one-standard-error rule (right line). The optimal λ selected by cross-validation is used to achieve the best predictive performance while maintaining model simplicity. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 2
Multivariate COX regression analyses of variables relating to prognosis in the training set.

Variable	OR (95 % CI)	P-value
Age	1.5 (1.0,1.9)	<0.001
Scr	1.4 (1.16,1.7)	<0.001
Hemoglobin	1.2 (1.1, 1.4)	0.008
Alb	0.8 (0.6, 1.1)	0.247
TyG index	0.9 (0.7,1.1)	0.246
Race		
White	Reference	
Black	0.3 (0.1, 0.7)	0.007
Other	0.4 (0.2, 0.9)	0.033
Sex		
Female	Reference	
Male	0.9 (0.6,1.4)	0.631
T2DM		
No	Reference	0.209
Yes	1.5 (0.8, 3.0)	
Hypertension		
No	Reference	
Yes	1.3 (0.7, 2.2)	0.381
Use of human albumin		
No	Reference	0.016
Yes	0.3 (0.1, 0.8)	
Sepsis		
No	Reference	
Yes	1.4 (0.8, 2.2)	0.208
Use of vasoactive drug		
No	Reference	
Yes	2.5 (1.6, 4.0)	<0.001
Use of aminoglycosides		
No	Reference	0.374
Yes	1.4 (0.7, 3.0)	

ALB, albumin; Scr, serum creatinine; T2DM, Type 2 diabetes; TyG index, triglyceride glucose index.

4. Discussion

AKI frequently occurs in patients with AHF and is correlated with adverse outcomes. Furthermore, individuals suffering from both AHF and AKI exhibit persistently elevated level of mortality rates [21]. Consequently, there is a critical need for a predictive model to evaluate the prognosis of AHF patients with AKI, especially those admitted to the ICU. This study employed Cox regression analysis to identify risk factors influencing short-term prognosis and developed a prognostic prediction model based on clinical parameters and demographic characteristics of AHF patients with AKI at the time of ICU admission. The findings of our study indicate a significant association between Scr, race, age, the use of human albumin, the use of vasoactive drug, and hemoglobin levels with adverse clinical outcomes in patients with AHF complicated by AKI. The nomogram constructed based on these risk factors exhibits superior discriminatory and calibration capabilities, as well as notable clinical utility. This predictive model holds promise for enhancing prognostication in AHF patients with AKI and for informing personalized treatment decisions and monitoring strategies.

This study is significant due to its employment of a large cohort of ICU patients to develop a nomogram, that integrates a wide range of variables known to impact the prognosis of AHF patients with AKI [7,22,23]. Our analysis identified that Scr, race, age, hemoglobin levels, the administration of vasoactive drugs, and the use of human albumin were significantly associated with patient survival outcomes. Scr, as a marker of renal function, is particularly important because its elevation generally indicates impaired kidney function, which is frequently associated with poorer outcomes. Age, a thoroughly documented determinant of survival, indicates that older patients generally exhibit reduced survival rates attributable to the cumulative impact of age-associated comorbidities. Additionally, low hemoglobin levels, which signify anemia, impair the body's oxygen transport capacity, thereby exacerbating the prognosis. The observed positive correlation between the administration of vasoactive drugs and improved prognosis likely underscores the significance of prompt and efficacious management of circulatory failure. Patients who respond favorably to these medications often attain hemodynamic stability consequently experiencing enhanced clinical outcomes. Notably, the administration of human albumin was inversely correlated with survival rates. Patients who received albumin exhibited poorer outcomes compared to those who did not. Although it is commonly believed that albumin administration may facilitate the alleviation and recovery of AKI [24], intravenous albumin has been associated with an elevated incidence of pulmonary edema in certain patients [25,26]. Furthermore, the variable of race revealed substantial disparities, with Black patients demonstrating the lowest survival probability and White patients exhibiting a higher likelihood of survival. This observation may indicate underlying socioeconomic disparities, differences in healthcare access, or other unmeasured factors contributing to these outcomes. These findings highlight the critical importance of individualized treatment strategies and underscore the necessity for further research to address the underlying disparities in prognosis among diverse patient

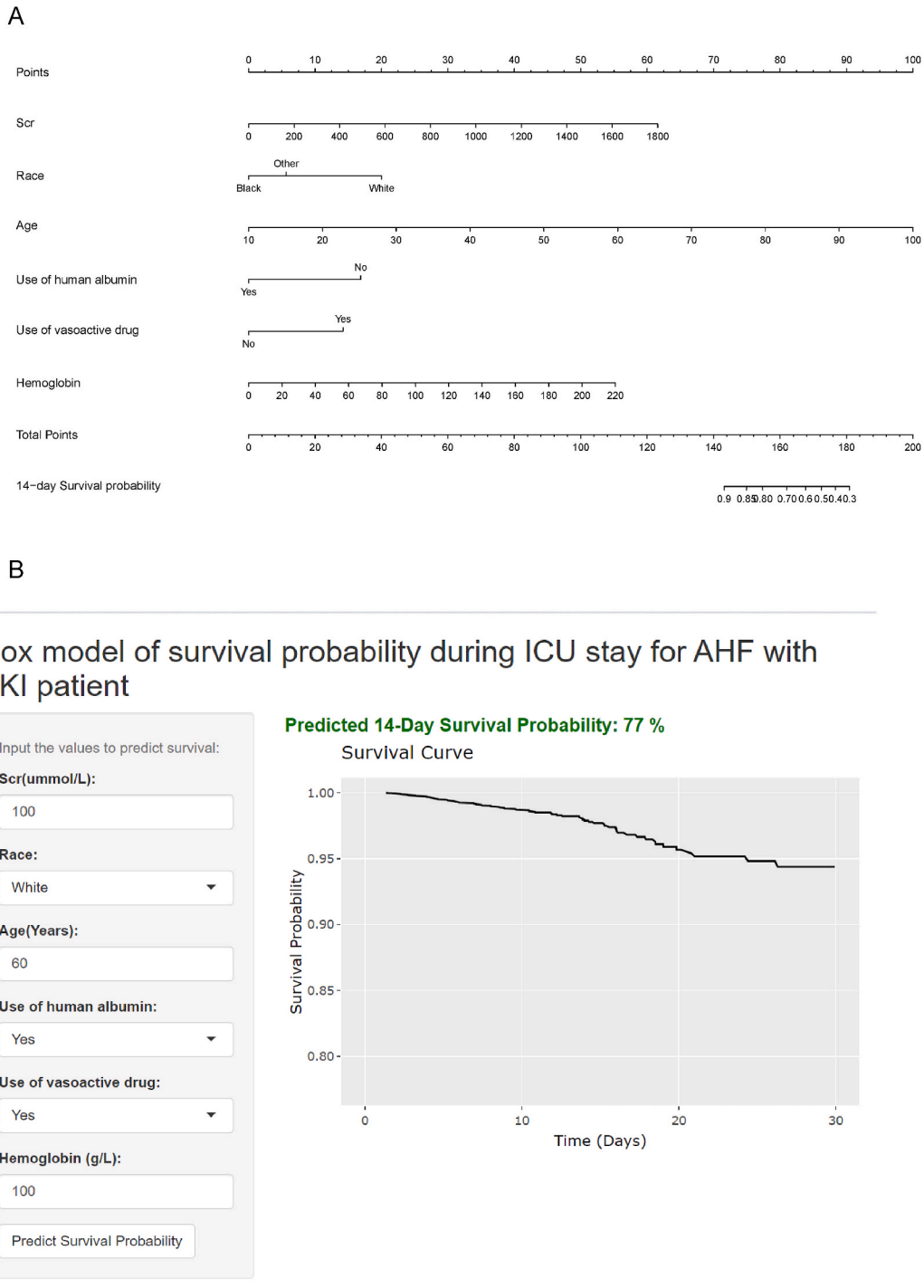

Fig. 3. Dynamic Nomogram for Predicting Survival Probability for AHF Patients with AKI. (A) Dynamic nomogram for predicting the 14-day survival probability of AHF Patients with AKI during their stay in the ICU. Points are assigned for each predictor, and the total points correspond to the 14-day survival probability. (B) Web-based dynamic nomogram interface for predicting survival probability. Users can input values for Scr, race, age, use of human albumin, use of vasoactive drugs, and hemoglobin levels to predict the 14-day survival probability. The predicted survival probability for the input values is displayed as a percentage, and the survival curve shows the probability of survival over a 30-day period.

populations.

The etiology of AKI within the context of AHF involves a range of pathological alterations, such as prerenal azotemia, cardio-renal syndrome, and acute tubular necrosis. However, heterogeneity of patient populations complicates the application of a standardized

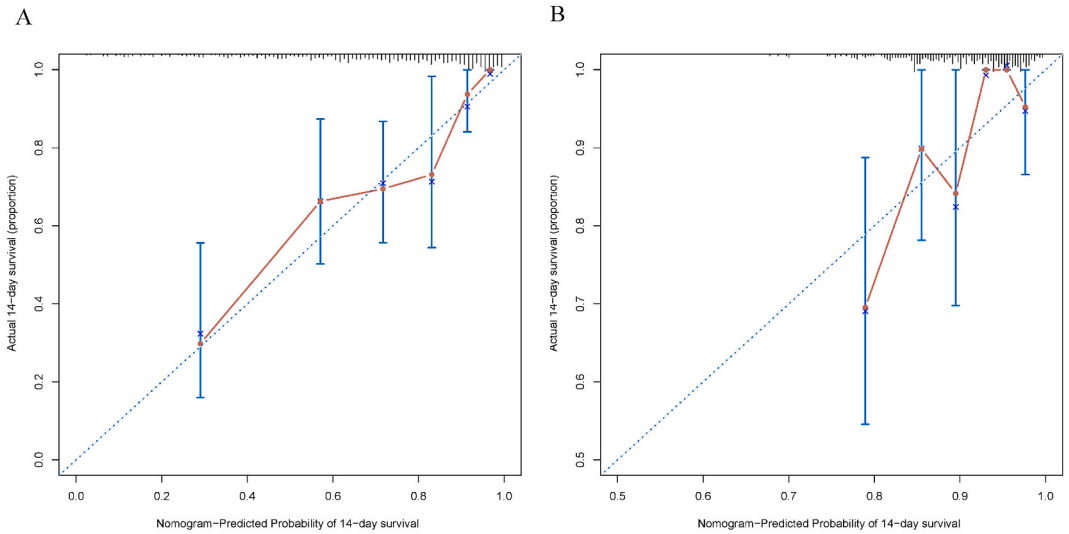

Fig. 4. Calibration Plots for the Nomogram Predicting 14-Day Survival in AHF Patients with AKI. (A) Calibration plot of the nomogram-predicted probability of 14-day survival versus the actual 14-day survival proportion for the training set. (B) Calibration plot of the nomogram-predicted probability of 14-day survival versus the actual 14-day survival proportion for the validation set. The x-axis represents the predicted 14-day survival probabilities generated by the nomogram, and the y-axis shows the actual observed 14-day survival rates. The blue crosses represent the observed outcomes, and the vertical bars indicate the 95 % confidence intervals. The red line connects the points, and the dotted diagonal line represents the ideal perfect calibration, where the predicted probabilities match the actual outcomes. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

mechanism for assessing disease progression, as the significance and impact of each pathological process vary with clinical conditions [27]. Despite the extensive documentation of factors associated with prognosis, there remains a significant lack of consensus on the primary determinants of prognosis and a deficiency in reliable prognostic tools. The intricacy of the treatment process necessitates ongoing modifications to treatment plans in response to fluctuations in the patient's condition, thereby complicating the comprehensive evaluation of patient prognosis based solely on individual risk factors. Consequently, it is posited that exclusive reliance on single prognostic factors may not yield precise individualized prognostic predictions. Clinicians must meticulously evaluate a spectrum of prognostic factors when formulating the most suitable treatment protocol. Our nomogram, developed to predict the prognosis of AHF patients with AKI, is congruent with the personalized medicine paradigm that is presently being prioritized in the medical domain.

In patients with AHF, the management of AKI necessitates comprehensive testing for a broad spectrum of pathogenic factors and the implementation of targeted therapeutic interventions [28]. Given the heterogeneous prognosis of AHF patients with AKI, accurately predicting their survival probability is of paramount importance. However, most contemporary research focuses on the development of single biomarkers or predictive models for the early diagnosis of AKI [7,22,23,29-31], which proves inadequate in identifying patients with a poor prognosis AKI. Unlike most contemporary studies, our research accounted for patient heterogeneity and integrated laboratory test results with clinical data of AHF patients during their ICU stay to develop a personalized prediction model for the short-term survival probability of AKI patients. This approach provides a clinical basis for individualized treatment strategies. To the best of our knowledge, this is the first study on constructing a short-term survival prognosis model based on laboratory examination results, demographic information, and treatment medications for AHF patients with AKI. This model has the potential to assist in identifying risk factors associated with an unfavorable prognosis for AHF patients with AKI during the initial stages, thereby enabling timely intervention to improve short-term outcomes. Furthermore., the current study employed a large sample size and LASSO regression to identify key independent predictors, while also accounting for correlations among dependent predictors.

Ultimately, a nomogram should be utilized to ascertain the specific requirements for subsequent treatment or care. Although discrimination and calibration are crucial for the accuracy of risk prediction, they do not fully capture the clinical implications associated with any particular level of discrimination or degree of miscalibration [32-34]. Consequently, the clinical utility of decision-making assisted by the nomogram was demonstrated by evaluating whether it led to improved patient outcomes. Given the clinical heterogeneity, this study opted for decision curve analysis over multi-institutional prospective validation of the nomogram. This innovative approach employs threshold probability to elucidate clinical outcomes, enabling the calculation of net benefit. Net benefit is typically determined as the ratio of true positives to false positives, adjusted for the relative harm of false positives and false negatives [21]. The decision curve analysis demonstrates that employing the nomogram for predicting 14-day survival and informing treatment modifications in this study yields greater benefit compared to a strategy of treating all patients or withholding treatment. This advantage is particularly evident when clinicians select a threshold probability between 14 % and 65 %. Additionally, we have developed a web-based calculator to facilitate the computation of survival probabilities for AHF patients with AKI.

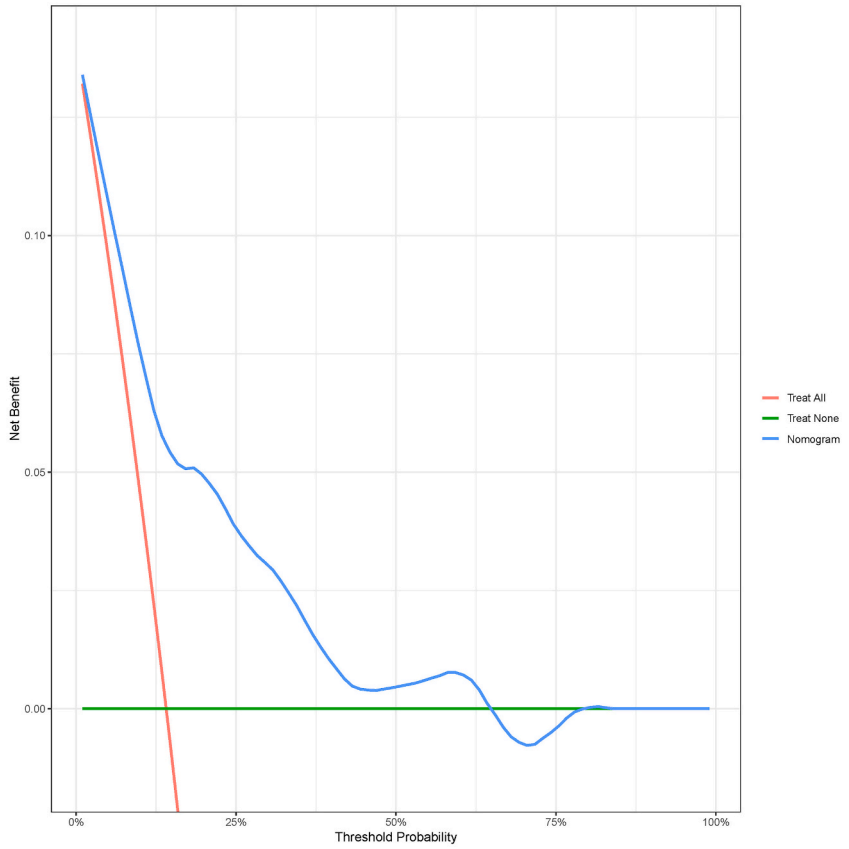

Fig. 5. Decision Curve Analysis for the Nomogram Predicting 14-Day Survival in AHF Patients with AKI. The decision curve analysis evaluates the clinical utility of the nomogram by plotting the net benefit against the threshold probability. The x-axis represents the threshold probability, which is the probability at which a patient would opt for a particular treatment. The y-axis represents the net benefit, calculated by combining the true positive and false positive rates. Blue line: Represents the net benefit of using the nomogram to predict 14-day survival. Red line: Represents the net benefit if all patients were treated.Green line: Represents the net benefit if no patients were treated. The nomogram provides the highest net benefit across 14 %–65 % of threshold probabilities compared to treating all or none, indicating its potential clinical value in guiding treatment decisions for AHF patients with AKI. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

The present study is subject to certain limitations. Firstly, the MIMIC-IV database, being a single-center, multi-ICU dataset, necessitates cautious interpretation of the results when generalizing to populations from different regions. Further research is required to validate the model's applicability across diverse settings. Secondly, as a retrospective study, the potential for bias cannot be completely eradicated. Nonetheless, stringentinclusion criteria were employed to ensure that the control and case groups accurately represent real-world scenarios. Finally, it is important to consider that an exclusive focus on baseline data may not adequately capture the impact of subsequent treatments, such as continuous renal replacement therapy, on patient outcomes. Nevertheless, the ability to predict short-term survival at the time of ICU admission remains clinically valuable for early risk stratification and decision-making prior to the implementation of further interventions.

5. Conclusion

This study introduces a dynamic nomogram that considers clinical risk factors. and can be conveniently utilized to predict short-term prognosis for AHF patients with AKI upon ICU admission.

CRediT authorship contribution statement

Tianbao Liao: Writing – original draft, Software, Investigation, Formal analysis, Data curation. **Tingting Su:** Writing – original draft, Validation, Software, Project administration, Methodology, Investigation. **Yang Lu:** Validation, Software, Data curation. **Lina Huang:** Validation, Software, Methodology, Data curation. **Lu-Huai Feng:** Writing – review & editing, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Conceptualization.

Ethics approval and consent of participate

Approval for the establishment of the MIMIC-IV database was granted by the Institutional Review Boards of Beth Israel Deaconess Medical Center (Boston, MA) and Massachusetts Institute of Technology (Cambridge, MA), leading to a waiver of informed consent participates and ethics approval for this study. Author L-H F obtained certification number 35897462 upon completion of the National Institutes of Health online training course to access the MIMIC-IV database (version 2.2).

Consent for publication

Not applicable.

Availability of data and materials

The data analyzed during the current study are available from the corresponding author on reasonable request.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] Z. Dai, Y. Zhang, H. Ye, G. Zhang, H. Jin, Z. Chen, Y. Yao, X. Tian, J. Zhou, P. Li, et al., Adiponectin is valuable in the diagnosis of acute heart failure with renal insufficiency, Exp. Ther. Med. 16 (3) (2018) 2725–2734.
[2] C.W. Tsao, A.W. Aday, Z.I. Almarzooq, C.A.M. Anderson, P. Arora, C.L. Avery, C.M. Baker-Smith, A.Z. Beaton, A.K. Boehme, A.E. Buxton, et al., Heart disease and stroke statistics-2023 update: a report from the American heart association, Circulation 147 (8) (2023) e93–e621.
[3] D. Mozaffarian, E.J. Benjamin, A.S. Go, D.K. Arnett, M.J. Blaha, M. Cushman, S. de Ferranti, J.P. Després, H.J. Fullerton, V.J. Howard, et al., Heart disease and stroke statistics–2015 update: a report from the American Heart Association, Circulation 131 (4) (2015) e29–e322.
[4] K.W. Prins, T. Thenappan, J.S. Markowitz, M.R. Pritzker, Cardiorenal syndrome type 1: renal dysfunction in acute decompensated heart failure, J Clin Outcomes Manag 22 (10) (2015) 443–454.
[5] N. Cosentino, S. Genovese, J. Campodonico, A. Bonomi, C. Lucci, V. Milazzo, M. Moltrasio, M.L. Biondi, D. Riggio, F. Veglia, et al., High-sensitivity C-reactive protein and acute kidney injury in patients with acute myocardial infarction: a prospective observational study, J. Clin. Med. 8 (12) (2019).
[6] R. Doshi, T. Dhawan, C. Rendon, M.A. Rodriguez, J.F. Al-Khafaji, M. Taha, T.T. Win, N. Gullapalli, Incidence and implications of acute kidney injury in patients hospitalized with acute decompensated heart failure, Intern Emerg Med 15 (3) (2020) 421–428.
[7] D. Seckinger, O. Ritter, D. Patschan, Risk factors and outcome variables of cardiorenal syndrome type 1 from the nephrologist's perspective, Int. Urol. Nephrol. 54 (7) (2022) 1591–1601.
[8] M. Prothasis, A. Varma, S. Gaidhane, S. Kumar, N. Khatib, Q.S. Zahiruddin, A. Gaidhane, Prevalence, types, risk factors, and outcomes of cardiorenal syndrome in a rural population of central India: a cross-sectional study, J Family Med Prim Care 9 (8) (2020) 4127–4133.
[9] J. Boulos, W. Darawsha, Z.A. Abassi, Z.S. Azzam, D. Aronson, Treatment patterns of patients with acute heart failure who develop acute kidney injury, ESC Heart Fail 6 (1) (2019) 45–52.
[10] Y-q Huang, C-h Liang, L. He, J. Tian, C-s Liang, X. Chen, Z-l Ma, Z-y Liu, Development and validation of a radiomics nomogram for preoperative prediction of lymph node metastasis in colorectal cancer, J. Clin. Oncol. 34 (18) (2016) 2157–2164.
[11] A. Iasonos, D. Schrag, G.V. Raj, K.S. Panageas, How to build and interpret a nomogram for cancer prognosis, J. Clin. Oncol. 26 (8) (2008) 1364–1370.
[12] G.S. Collins, J.B. Reitsma, D.G. Altman, K.G. Moons, Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): the TRIPOD statement. The TRIPOD Group, Circulation 131 (2) (2015) 211–219.
[13] A. Johnson, L. Bulgarelli, T. Pollard, S. Horng, L.A. Celi, R. Mark, MIMIC-IV, PhysioNet, 2023, https://doi.org/10.13026/6mm1-ek67 version 2.2.
[14] Z. Zhang, Missing data imputation: focusing on single imputation, Ann. Transl. Med. 4 (1) (2016) 9.
[15] J.A. Kellum, N. Lameire, Diagnosis, evaluation, and management of acute kidney injury: a KDIGO summary (Part 1), Crit. Care 17 (1) (2013) 204.
[16] Y. Jiang, P. Chen, Y. Zhao, J. Cai, J. Liang, S. Cheng, Y. Zhang, Association between triglyceride glucose index and all-cause mortality in patients with cerebrovascular disease: a retrospective study, Diabetol Metab Syndr 16 (1) (2024) 1.
[17] W. Sauerbrei, P. Royston, H. Binder, Selection of important variables and determination of functional form for continuous predictors in multivariable model building, Stat. Med. 26 (30) (2007) 5512–5528.
[18] L.H. Feng, Y. Lu, S. Ren, H. Liang, L. Wei, J. Jiang, Development and validation of a dynamic online nomogram for predicting acute kidney injury in cirrhotic patients upon ICU admission, Front. Med. 10 (2023) 1055137.
[19] A.C. Alba, T. Agoritsas, M. Walsh, S. Hanna, A. Iorio, P.J. Devereaux, T. McGinn, G. Guyatt, Discrimination and calibration of clinical prediction models: users' guides to the medical literature, JAMA 318 (14) (2017) 1377–1384.
[20] A.J. Vickers, A.M. Cronin, E.B. Elkin, M. Gonen, Extensions to decision curve analysis, a novel method for evaluating diagnostic tests, prediction models and molecular markers, BMC Med Inform Decis Mak 8 (2008) 53.
[21] B. Quiroga, A. Ortiz, J.F. Navarro-González, R. Santamaría, P. de Sequera, J. Díez, From cardiorenal syndromes to cardionephrology: a reflection by nephrologists on renocardiac syndromes, Clin Kidney J 16 (1) (2023) 19–29.
[22] T.H. Lee, P.C. Fan, J.J. Chen, V.C. Wu, C.C. Lee, C.L. Yen, G. Kuo, H.H. Hsu, Y.C. Tian, C.H. Chang, A validation study comparing existing prediction models of acute kidney injury in patients with acute heart failure, Sci. Rep. 11 (1) (2021) 11213.

[23] J.L. Holgado, C. Lopez, A. Fernandez, I. Sauri, R. Uso, J.L. Trillo, S. Vela, J. Nuñez, J. Redon, A. Ruiz, Acute kidney injury in heart failure: a population study, ESC Heart Fail 7 (2) (2020) 415–422.
[24] A. Davenport, Management of acute kidney injury in liver disease, Contrib. Nephrol. 165 (2010) 197–205.
[25] M.K. Nadim, G. Garcia-Tsao, Acute kidney injury in patients with cirrhosis, N. Engl. J. Med. 388 (8) (2023) 733–745.
[26] T. Thévenot, C. Bureau, F. Oberti, R. Anty, A. Louvet, A. Plessier, M. Rudler, A. Heurgué-Berlot, I. Rosa, N. Talbodec, et al., Effect of albumin in cirrhotic patients with infection other than spontaneous bacterial peritonitis. A randomized trial, Journal of hepatology 62 (4) (2015) 822–830.
[27] U. Kumar, N. Wettersten, P.S. Garimella, Cardiorenal syndrome: pathophysiology, Cardiol. Clin. 37 (3) (2019) 251–265.
[28] A.B. Méndez, M.A. Azancot, A. Olivella, M.J. Soler, New aspects in cardiorenal syndrome and HFpEF, Clin Kidney J 15 (10) (2022) 1807–1815.
[29] S. Higuchi, Y. Kabeya, K. Matsushita, S. Yamasaki, H. Ohnishi, H. Yoshino, Urinary cast is a useful predictor of acute kidney injury in acute heart failure, Sci. Rep. 9 (1) (2019) 4352.
[30] H. Phan Thai, Bui B. Hoang, Anh T. Hoang, Van M. Huynh, Value of plasma NGAL and creatinine on first day of admission in the diagnosis of cardiorenal syndrome type 1, Cardiol. Res. Pract. 2020 (2020) 2789410.
[31] L. Wang, Y.T. Zhao, Development and validation of a prediction model for acute kidney injury among patients with acute decompensated heart failure, Front Cardiovasc Med 8 (2021) 719307.
[32] A.R. Localio, S. Goodman, Beyond the usual prediction accuracy metrics: reporting results for clinical decision making, Ann. Intern. Med. 157 (4) (2012) 294–295.
[33] B. Van Calster, A.J. Vickers, Calibration of risk prediction models: impact on decision-analytic performance, Med. Decis. Making 35 (2) (2015) 162–169.
[34] G.S. Collins, J.B. Reitsma, D.G. Altman, K.G. Moons, Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): the TRIPOD statement, Bmj 350 (2015) g7594.