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ORIGINAL RESEARCH

Development and Validation of a Nomogram Model for Accurately Predicting Depression in Maintenance Hemodialysis Patients: A Multicenter Cross-Sectional Study in China

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Purpose: Depression is a major concern in maintenance hemodialysis. However, given the elusive nature of its risk factors and the redundant nature of existing assessment forms for judging depression, further research is necessary. Therefore, this study was devoted to exploring the risk factors for depression in maintenance hemodialysis patients and to developing and validating a predictive model for assessing depression in maintenance hemodialysis patients.

Patients and Methods: This cross-sectional study was conducted from May 2022 to December 2022, and we recruited maintenance hemodialysis patients from a multicentre hemodialysis centre. Risk factors were identified by Lasso regression analysis and a Nomogram model was developed to predict depressed patients on maintenance hemodialysis. The predictive accuracy of the model was assessed by ROC curves, area under the ROC (AUC), consistency index (C-index), and calibration curves, and its applicability in clinical practice was evaluated using decision curves (DCA).

Results: A total of 175 maintenance hemodialysis patients were included in this study, and cases were randomised into a training set of 148 and a validation set of 27 (split ratio 8.5:1.5), with a depression prevalence of 29.1%. Based on age, employment, albumin, and blood uric acid, a predictive map of depression was created, and in the training set, the nomogram had an AUC of 0.7918, a sensitivity of 61.9%, and a specificity of 89.2%. In the validation set, the nomogram had an AUC of 0.810, a sensitivity of 100%, and a specificity of 61.1%. The bootstrap-based internal validation showed a c-index of 0.792, while the calibration curve showed a strong correlation between actual and predicted depression risk. Decision curve analysis (DCA) results indicated that the predictive model was clinically useful.

Conclusion: The nomogram constructed in this study can be used to identify depression conditions in vulnerable groups quickly, practically and reliably.

Keywords: nomogram, depression, maintenance hemodialysis, risk factors, prediction

Introduction

Chronic Kidney Disease (CKD) is a debilitating condition with various physical and psychological repercussions, affecting approximately 14.3% of the global population. Progressive CKD is associated with adverse clinical outcomes such as end-stage renal disease (ESRD), cardiovascular disease, and increased mortality.[1] Renal replacement therapy, particularly Maintenance Hemodialysis (MHD), is the predominant treatment option for ESRD, with MHD accounting for about 90% of patients. The prevalence of ESRD has been steadily rising,[2] with an annual growth rate of 8%.[3]

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Depression, a significant and prevalent disorder, poses a global public health challenge. It affects around 4.4% of the global population and incurs substantial economic costs, estimated in trillions of dollars due to lost productivity.[4] Between 2005 and 2015, the global prevalence of clinical depression increased by 18.4%, reaching an estimated 322 million cases in 2017. In addition, depression has been recognized by the World Health Organization as the leading cause of disability globally, placing a tremendous burden on society.[5]

Previous studies have indicated that depressive states are prevalent psychiatric disorders among maintenance hemodialysis patients.[6] The prevalence of depression in patients undergoing hemodialysis ranges from 5% to 69%, with symptoms often emerging during dialysis or even earlier during chronic kidney disease.[7] Some studies have shown that the prevalence of depression in patients with end-stage renal disease is five times higher than in the general population.[8] Despite significant advancements in medical technology that have extended the survival of hemodialysis patients, depression seriously impacts their ability to self-care and their quality of life, affecting them physically, psychologically, and socially.[9] Moreover, depression increases the risk of cardiovascular events and mortality.[10] However, nowadays, most of the diagnoses of patients' depressive states are in the form of questionnaires, which are lengthy and require the cooperation of the patient in order to determine whether or not the patient has a depressive state, so the establishment of a simple tool to determine whether or not the patient has a depressive state at an early stage is highly desirable.

Clinical prediction models, represented by nomograms, are mathematical equations that link multiple predictors (risk factors, covariates) to the probability of a disease or the likelihood of future events.[11,12] Various disease prediction models have been developed in previous research.[13–15] However, these findings cannot be directly applied to depressed patients undergoing maintenance hemodialysis. To our knowledge, age, gender, education, handgrip strength, vascular access, dialysis modality, comorbidities, rural domicile, worsening economic status, fatigue, insomnia, vascular pain, employment, leukocytes, blood creatinine, albumin, ferritin, iron, and uric acid have been identified as risk factors for depression in MHD patients.[14] Nevertheless, the prevalence and risk factors associated with depression in maintenance hemodialysis patients remain largely unclear, necessitating further investigation.

Therefore, the aim of this study was to investigate the factors associated with depression in maintenance hemodialysis patients and to develop a reliable predictive model for the risk of depression in maintenance hemodialysis patients. The use of this column-line diagram consisting of a few simple factors enables clinicians to identify those at high risk of depression at an earlier stage and helps them to implement targeted preventive measures.

Materials and Methods

Setting and Participants

This multicenter cross-sectional study was conducted from May to December 2022, involving patients from the hemodialysis center wards at The First Hospital of Jiaxing Affiliated Hospital of Jiaxing University and Jiaxing Hospital of Traditional Chinese Medicine. The inclusion criteria were as follows: 1) age ≥16 years;2) meeting the diagnostic criteria of ICD-10 for end-stage renal disease and having a stable dialysis duration of ≥3 months;3) voluntary participation in completing the depression scale. Exclusion criteria: 1) those with congenital mental retardation or psychiatric history;2) those who could not complete the depression scale because of visual or hearing impairment or physical dysfunction; 3) weekly dialysis time <10 h; 4) those who suffered from severe infections, acute cardiovascular events, active autoimmune diseases, malignant tumors, and other comorbidities in the last 3 months. Prior to the interview, the purpose and content of the study were explained to the participants, and informed consent was obtained through their voluntary cooperation in completing the depression scale. External validation of a model is a test of the generalisability and portability of a model to check whether the model is applicable to data outside the training set. A model that works well on one dataset may not be applicable on other datasets. Therefore, in this study, R software was used to randomly divide the data in 8.5:1.5 into a training set and test set; the training set was used to build the predictive model and the data from the test set was used to externally validate the model. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki and was approved by the Ethics Committee of The First Hospital of Jiaxing Affiliated Hospital of Jiaxing University and Jiaxing Hospital of Traditional Chinese Medicine (2022-KY-163, SL-2022-0362).

Data Collection

Demographic data and biochemical measurements collected included gender, age, body mass index (BMI), age at dialysis, degree, marital status, smoking, employment status, alcohol drinking, exercise, economic status, social support, number of children, vitamin D (VD), hemoglobin (Hb), serum ferritin (SF), parathyroid hormone (PTH), calcium blood (Ca), total cholesterol (TC), Triglyceride (TG), serum creatinine (Scr), phosphorus (P), alkaline phosphatase (ALP), c-reactive protein (CRP), albumin (ALB), blood urea nitrogen (BUN), Uric Acid (UA), folic acid (FA), serum iron (SI), Vitamin B12 (VB12), Transferrin Saturation (TSAT), serum potassium (K), and complication. Biochemical measurements were taken from blood samples collected prior to dialysis. These tests were conducted by trained technicians in the hospital's central laboratory, adhering to clinical guidelines.

Depression Screening

All participants underwent the Self-Rating Depression Scale (SDS), a 20-item questionnaire designed to assess depressive symptoms. This self-administered questionnaire possesses good reliability and validity and is widely utilized. Symptoms are categorized into four levels, represented by integers between 1 and 4, and the total SDS score is calculated by summing the responses to all 20 questions. The standardized score is obtained by multiplying the total SDS score by 1.25 and rounding it. According to the Chinese conventional model, SDS scores are interpreted as follows: <53 indicates a normal range, 53–62 corresponds to mild to moderate depression, 63–72 indicates moderate to severe depression, and ≥73 represents severe depression. The Cronbach's alpha and split-half correlation coefficients for the SDS were determined to be 0.73 and 0.84, respectively.[16]

Statistical Analysis

The patients with complete clinical data were included in this study and analyzed using R 4.3.1. Normally distributed variables were described using mean and standard deviation, while non-normally distributed variables were described using median and interquartile range. Categorical variables were reported as frequencies and percentages. Group comparisons were performed using Student's *t*-test, Mann–Whitney *U*-test, chi-square test, or Fisher's exact test, as appropriate. Six variables were identified by one-way logistic regression analysis, and those with $p < 0.01$ were included in the multifactorial logistic regression analysis. Lasso regression was employed to identify independent predictors for the onset of depression and develop a predictive model. The diagnostic performance of markers or panels was assessed using receiver operating characteristic (ROC) curves, and cutoff levels were determined using the Jordon index. The area under the curve (AUC) was calculated using the trapezoidal method, with higher values indicating better diagnostic performance. The nomogram model was validated using bootstrapped validation with 1000 bootstrap samples in the training and validation sets. The predictive performance of the model was evaluated using calibration curves and the consistency index (C-index), which ranges from 0 to 1, with higher values indicating better discriminative ability. Decision curve analysis (DCA) was employed to compare the diagnostic value of different clinical diagnostic models. Statistical significance was set at $p < 0.05$, and the results were analyzed and discussed.

Results

Characteristics of Participants

A total of 175 maintenance hemodialysis patients were included in the study, ranging in age from 16 to 89 years, with a median age of 64 years and an interquartile range of 23 years. Among them, 124 (70.9%) were male and 51 (29.1%) were female. Of all participants, 51 were depressed and 124 were not, for a prevalence of 29.1%. Univariate analysis revealed significant correlations between depression and the following factors: age ($P < 0.001$), degree ($P < 0.001$), employment status ($P < 0.001$), alcohol drinking ($P = 0.02$), number of children ($P = 0.017$), serum creatinine (Scr) ($P < 0.001$), albumin (ALB) ($P < 0.001$), and blood uric acid (UA) ($P = 0.004$). Table 1 presents additional characteristics of the participants. Multifactorial analysis suggests correlation between Degree (odds ratio [OR]: 4.36, P=0.026), Employment status (OR: 0.15, P=0.020), P (OR: 0.85, P=0.020), ALB (OR: 1.00, P=0.036) and depression in maintenance hemodialysis patients (Table 2).

Table 1 Comparison of General Condition and Clinical Characteristics of Patients in Two Groups

Variables	Total (n = 175)	Normal (n = 124)	Depression (n = 51)	p
Sex, n (%)				0.816
Male	124 (71)	89 (72)	35 (69)	
Female	51 (29)	35 (28)	16 (31)	
Age (year), Median (Q1,Q3)	64 (50, 73)	59 (47, 71)	69 (64, 75)	< 0.001
BMI, n (%)				0.296
18.5–23.9kg/ m^2	93 (53)	61 (49)	32 (63)	
≥24kg/m^2	70 (40)	54 (44)	16 (31)	
<18.5kg/m^2	12 (7)	9 (7)	3 (6)	
Age at dialysis (month), Median (Q1,Q3)	24 (12, 48)	24 (12, 48)	24 (12, 51)	0.433
Degree, n (%)				< 0.001
Illiterate	27 (15)	17 (14)	10 (20)	
Primary education	26 (15)	10 (8)	16 (31)	
Junior high school or above	122 (70)	97 (78)	25 (49)	
Marriage status, n (%)				0.965
No spouse	22 (13)	15 (12)	7 (14)	
Have a spouse	153 (87)	109 (88)	44 (86)	
Smoking, n (%)				0.784
No	104 (59)	75 (60)	29 (57)	
Yes	71 (41)	49 (40)	22 (43)	
Employment status, n (%)				< 0.001
No	135 (77)	86 (69)	49 (96)	
Yes	40 (23)	38 (31)	2 (4)	
Alcohol drinking, n (%)				0.020
No	163 (93)	112 (90)	51 (100)	
Yes	12 (7)	12 (10)	0 (0)	
Exercise, n (%)				0.683
<1h	139 (79)	97 (78)	42 (82)	
>1h	36 (21)	27 (22)	9 (18)	
Economic status, n (%)				0.829
Less than ¥30,000/year	41 (23)	28 (23)	13 (25)	
Greater than ¥30,000/year	134 (77)	96 (77)	38 (75)	
Social support, n (%)				0.732
No	11 (6)	7 (6)	4 (8)	
Yes	164 (94)	117 (94)	47 (92)	
Number of children, n (%)				0.017
0	10 (6)	10 (8)	0 (0)	
1	96 (55)	71 (57)	25 (49)	
2	56 (32)	32 (26)	24 (47)	
3	12 (7)	10 (8)	2 (4)	
4	1 (1)	1 (1)	0 (0)	
Vitamin D, n (%)				0.458
<20ng/mL	63 (36)	42 (34)	21 (41)	
≥20ng/mL	112 (64)	82 (66)	30 (59)	
Hb, n (%)				0.123
≥115g/L	62 (35)	39 (31)	23 (45)	
<115g/L	113 (65)	85 (69)	28 (55)	
SF, n (%)				0.690
10.6–36.7 μmol/L	132 (75)	92 (74)	40 (78)	
<10.6μmol/L,>36.7 μmol/L	43 (25)	32 (26)	11 (22)	

(*Continued*)

Table 1 (Continued).

Variables	Total (n = 175)	Normal (n = 124)	Depression (n = 51)	p
PTH, n (%)				0.984
≤68.3 pg/mL	19 (11)	14 (11)	5 (10)	
>68.3 pg/mL	156 (89)	110 (89)	46 (90)	
Ca, n (%)				0.275
2.11 mmol/L-2.52 mmol/L	119 (68)	88 (71)	31 (61)	
<2.11 mmol/L	52 (30)	34 (27)	18 (35)	
≥2.52 mmol/L	4 (2)	2 (2)	2 (4)	
TC (mmol/L), Mean±SD	3.58 ± 0.9	3.53 ±0.82	3.71 ± 1.06	0.295
TG (mmol/L), Median (Q1,Q3)	1.51 (0.99, 2.07)	1.52 (1, 2.1)	1.49 (1, 2.05)	0.959
SCr (μmol/L), Mean±SD	940.56 ± 259.3	981.22 ± 258.41	841.72 ± 235.89	< 0.001
P (mmol/L), Mean±SD	1.64 ± 0.55	1.62 ± 0.57	1.7 ± 0.51	0.383
ALP, n (%)				0.152
40–150 U/L	141 (81)	96 (77)	45 (88)	
<40 U/L,>150 U/L	34 (19)	28 (23)	6 (12)	
CRP, n (%)				0.839
<8mg/L	144 (82)	103 (83)	41 (80)	
≥8mg/L	31 (18)	21 (17)	10 (20)	
ALB (g/L), Median (Q1,Q3)	41.3 (39.1, 43.1)	41.75 (39.8, 43.4)	40.1 (37.6, 42.1)	< 0.001
BUN, n (%)				0.499
<8 mmol/L	2 (1)	1 (1)	1 (2)	
≥8 mmol/L	173 (99)	123 (99)	50 (98)	
UA (μmol/L), Median (Q1,Q3)	421.5 (366.6, 476.05)	429.4 (382.28, 477.4)	375 (329.85, 451.65)	0.004
FA (nmol/L), n (%)				0.554
9.53–44.9 nmol/L	141 (81)	98 (79)	43 (84)	
<9.53, >44.9 nmol/L	34 (19)	26 (21)	8 (16)	
SI (μmol/L), Median (Q1,Q3)	11.4 (9.05, 14.95)	11.3 (9.1, 15.02)	11.7 (8.9, 14.55)	0.816
VB12, n (%)				0.470
≤883 pmol/L	151 (86)	105 (85)	46 (90)	
>883 pmol/L	24 (14)	19 (15)	5 (10)	
TSAT (%), Median (Q1,Q3)	29.84 (24.46, 35.8)	29.47 (24.48, 35.8)	30.75 (24.47, 35.58)	0.885
K (mmol/L), Median (Q1,Q3)	4.6 (4.14, 5.06)	4.71 (4.19, 5.05)	4.46 (4.1, 5.05)	0.253
Complication, Median (Q1,Q3)	4 (3, 7)	4 (3, 7.25)	5 (2.5, 7)	0.881

Table 2 Multifactorial Analysis of Depression in Maintenance Hemodialysis Patients

Variables	OR (multivariable)	95% CI	p
Age	1.01	0.98–1.05	p=0.484
Degree			
Illiterate			
Primary education	4.36	1.19–16.00	p=0.026
Junior high school or above	0.68	0.24–1.91	p=0.464
Employment status			
No			
Yes	0.15	0.03–0.76	p=0.022
SCr	1.00	1.00–1.00	p=0.414
P	0.85	0.75–0.98	p=0.020
ALB	1.00	0.99–1.00	p=0.036

Feature Selection

In the training set, feature selection was conducted using Lasso logistic regression analysis, which included 33 parameters. Coefficient profiles were generated based on the log(λ) series (Figure 1). The tuning parameters (λ) were selected based on the minimum criterion, with the optimal λ determined through 10-fold cross-validation and a 1 standard error (1-SE) criterion, retaining the non-zero coefficients (Figure 2). The analysis identified four parameters with non-zero coefficients that minimized the mean squared error: age, employment status, ALB, and UA (Table 3).

Figure Development and Validation

Based on the results of the Lasso regression analysis, a nomogram model consisting of the four selected variables was constructed (Figure 3). Each variable's score at different levels was determined by drawing a straight line on the corresponding axis, and the total score was calculated by summing the scores of the predictors. The final sum was then used to determine the patient's probability of depression by drawing a line down on the total point axis. In the training set, the nomogram exhibited an AUC of 0.7918, a sensitivity of 61.9%, a specificity of 89.6%, and an optimal cutoff

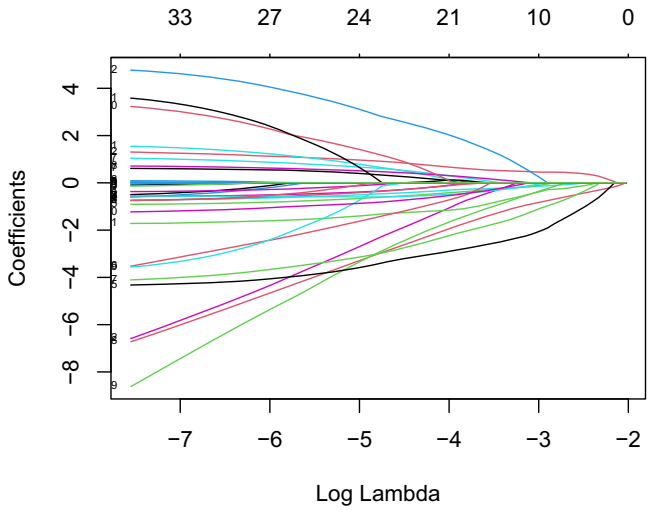

Figure 1 Distribution of LASSO coefficients for 33 predictors.

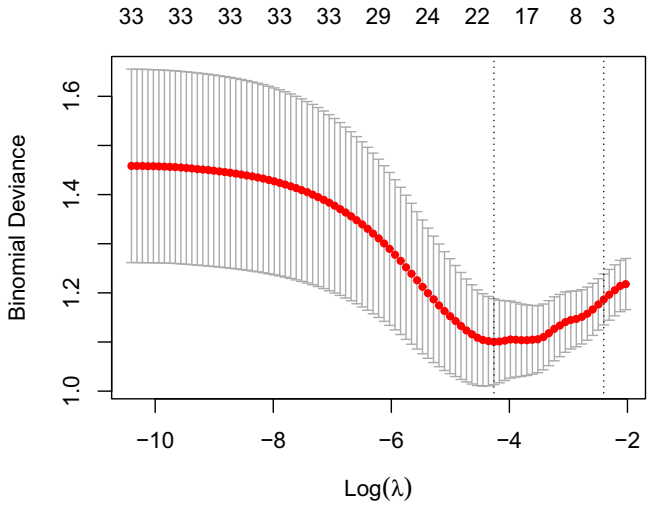

Figure 2 Distribution of predictors based on optimal λ selection.

Table 3 Parameters Chosen Based on Lasso Regression Age, Employment, Albumin and Blood Uric Acid

	Coef	S.E.	Wald Z	Pr(>|Z|)
Employment status	−1.2201	0.8231	−1.48	0.1383
ALB	−0.1737	0.0726	−2.39	0.0168
AGE	0.0305	0.0171	1.79	0.0741
UA	−0.0033	0.0021	−1.62	0.1043

value of −0.3624495 (Figure 4). In the validation set, the nomogram achieved an AUC of 0.8086, a sensitivity of 100%, a specificity of 61.1%, and an optimal cutoff value of −1.917893 (Figure 5). Bootstrap validation yielded a c-index of 0.792. The calibration plot (Figure 6) demonstrated a strong alignment between the predicted probability of depression by the nomogram and the actual observations. Decision curve analysis (DCA) results indicated that the nomogram outperformed the strategies of treating all patients or not treating any patients, affirming its clinical validity (Figure 7). Overall, the nomogram model exhibited excellent performance.

Discussion

Maintenance hemodialysis (MHD) patients are known to be at high risk for psychological disorders, including depression and anxiety.[17] Previous studies have investigated the factors influencing depression in MHD patients, but there is a lack of assessment tools specifically designed to evaluate depression in this population. In our study, we assessed the depression status of MHD patients and identified the factors associated with depression. Our findings revealed a depression incidence rate of 29.1%. This rate falls within the range reported in previous studies, which have reported rates between 5% and 69%.[18,19] The relatively low incidence of depression observed in our study might be attributed to increased awareness of MHD and improved access to medical care in recent years, leading to greater confidence in the treatment. However, it is important to note that other studies have reported higher rates of depression in different regions. Major depression in MHD patients has been linked to medication non-adherence, dialysis withdrawal, premature death, and suicide. Research indicates that individuals with psychological disorders in this population may experience a lifespan that is 10–20 years shorter than those without such disorders.[20] These findings underscore the significance of recognizing and addressing depression in MHD patients. Therefore, we developed the nomogram model and also confirmed that this predictive model has good efficiency in predicting depression in MHD patients and is clinically useful.

This study indicates that several factors, such as age, education, employment status, alcohol drinking, number of children, blood creatinine, albumin, and uric acid, are associated with depression in maintenance hemodialysis patients.

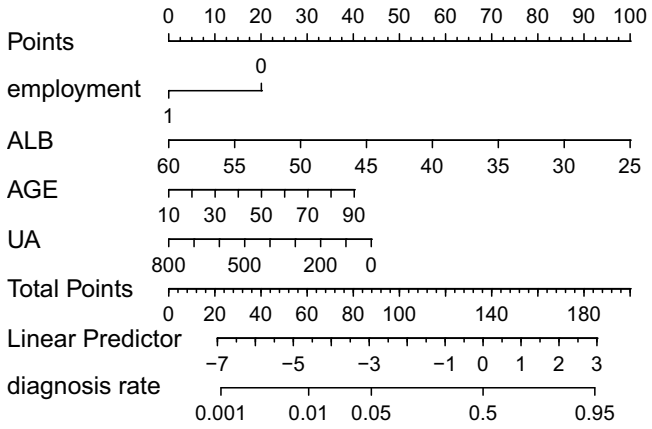

Figure 3 Nomogram prediction model of depression in maintenance hemodialysis patients.

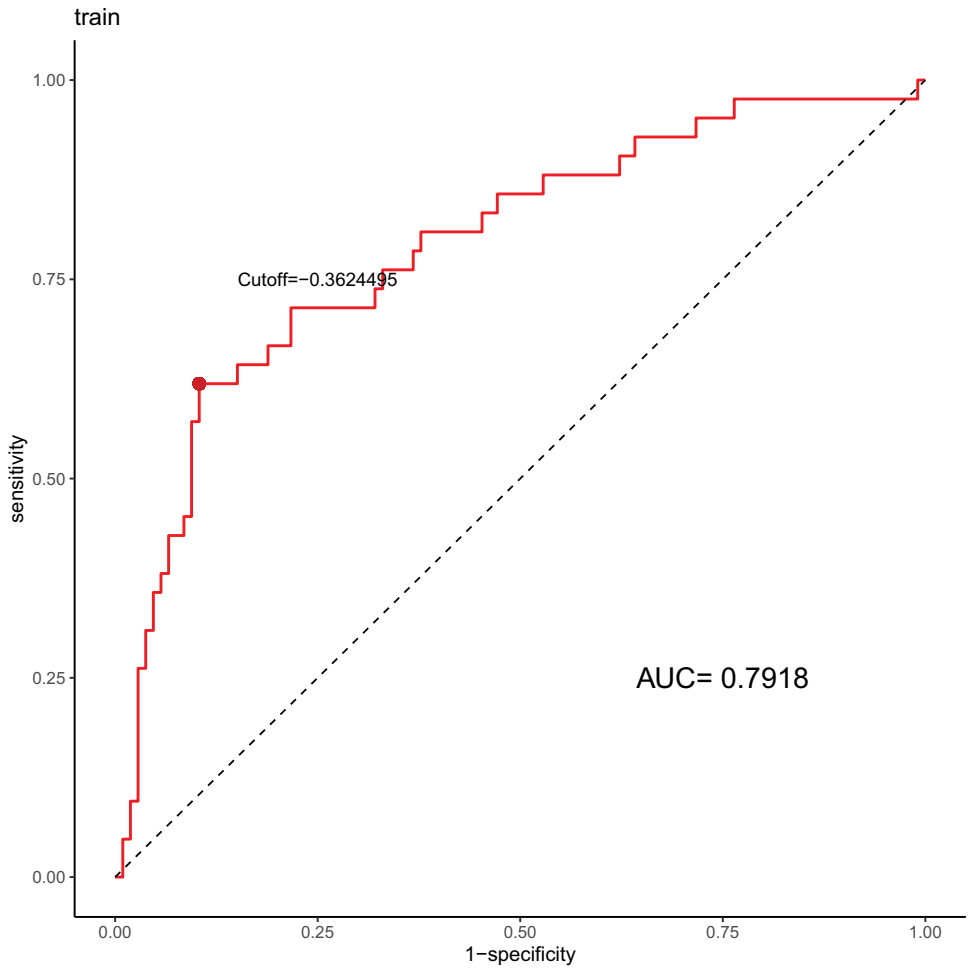

Figure 4 ROC curve analysis of the predictive model of depression for the training set.

As patients age, their physiological functions tend to decline. When patients experience disease-related limitations or become dependent on family members for care, they may perceive themselves as burdens to their families, leading to reduced self-esteem, diminished sense of self-worth, impaired interpersonal communication, and increased susceptibility to depression, which aligns with previous research.[21] Patients with higher levels of education exhibit a relatively higher prevalence of depression. This may be attributed to the higher costs, both in terms of time and resources, invested in the early stages of their careers, as well as their higher expectations for income and social status. Consequently, they may contemplate life more deeply, contributing to an increased incidence of depression. Employment status is closely linked to depression onset. The debilitating effects of the disease and the time-intensive nature of hemodialysis often result in a higher unemployment rate among young and middle-aged MHD patients.[22] Unemployment, accompanied by the negative life event of job loss and subsequent decline in income, can trigger depression. Similarly, retirees experience a loss of social roles and changes in status, which can evoke feelings of resistance and unease.[23] Therefore, both unemployed individuals and retirees are more susceptible to depression compared to employed patients. In this study, depressed patients were predominantly non-drinkers. This observation may be associated with some non-drinkers being required to abstain from alcohol due to their illness. Alcohol drinking can provide temporary happiness and relief from tension and fatigue. Finally, patients with a greater number of children exhibited a lower incidence of depression. This finding may be attributed to the additional financial support, caregiving, and emotional support (through increased interactions) received from having more children.

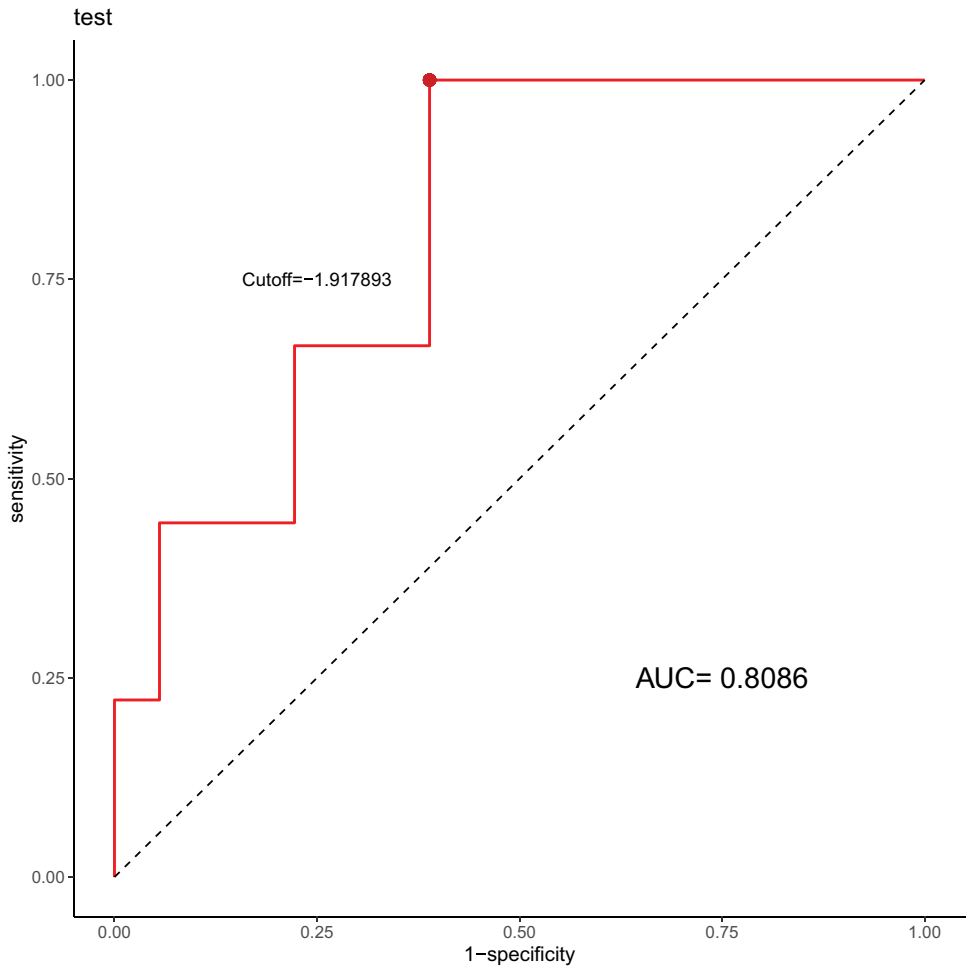

Figure 5 ROC curve analysis of the predictive model of depression for the testing set.

Blood albumin levels can partly reflect the nutritional status of patients. Previous studies by Ford, Li X et al have demonstrated a significant correlation between depression and serum albumin levels.[24,25] Depression in dialysis patients can affect their appetite, leading to reduced food intake. Additionally, protein loss in patients with nephropathy can further contribute to poor nutritional status, decreased muscle mass and strength, lower quality of life, and an increased risk of depression.[26] Albumin serves as a non-enzymatic antioxidant in the body and regulates the activity of astrocytes and microglia. It plays a role in brain tissue repair through the management of oxidative stress.[27] Furthermore, albumin is involved in depression through antioxidant responses.[28] Creatinine, as a surrogate marker for muscle mass, is associated with reduced total muscle mass, skeletal muscle mass, and limitations in physical activity when serum creatinine levels are low.[29] Additionally, skeletal muscle produces and secretes actin molecules, which play a role in regulating brain function, including mood, learning, exercise, and neuronal protection.[30] The decline in physical and psychological functioning associated with lower creatinine levels can contribute to the development of depressive symptoms in patients. However, further research is needed to fully understand the exact mechanism underlying the relationship between depressive symptoms and blood creatinine levels. Research conducted by Bartoli et al has demonstrated that untreated depressed patients exhibit significantly lower blood uric acid levels compared to healthy individuals. After treatment, blood uric acid levels tend to increase significantly, confirming the close association between blood uric acid levels and depression.[31] Uric acid acts as a potent antioxidant in the central nervous system and is involved in preventing associated inflammatory responses and tissue damage.[32,33] Moreover, current hypotheses suggest that major depressive disorder is linked to inflammatory and oxidative stress pathways.[34,35] Purines, such as adenosine and ATP, play crucial roles in neurotransmission

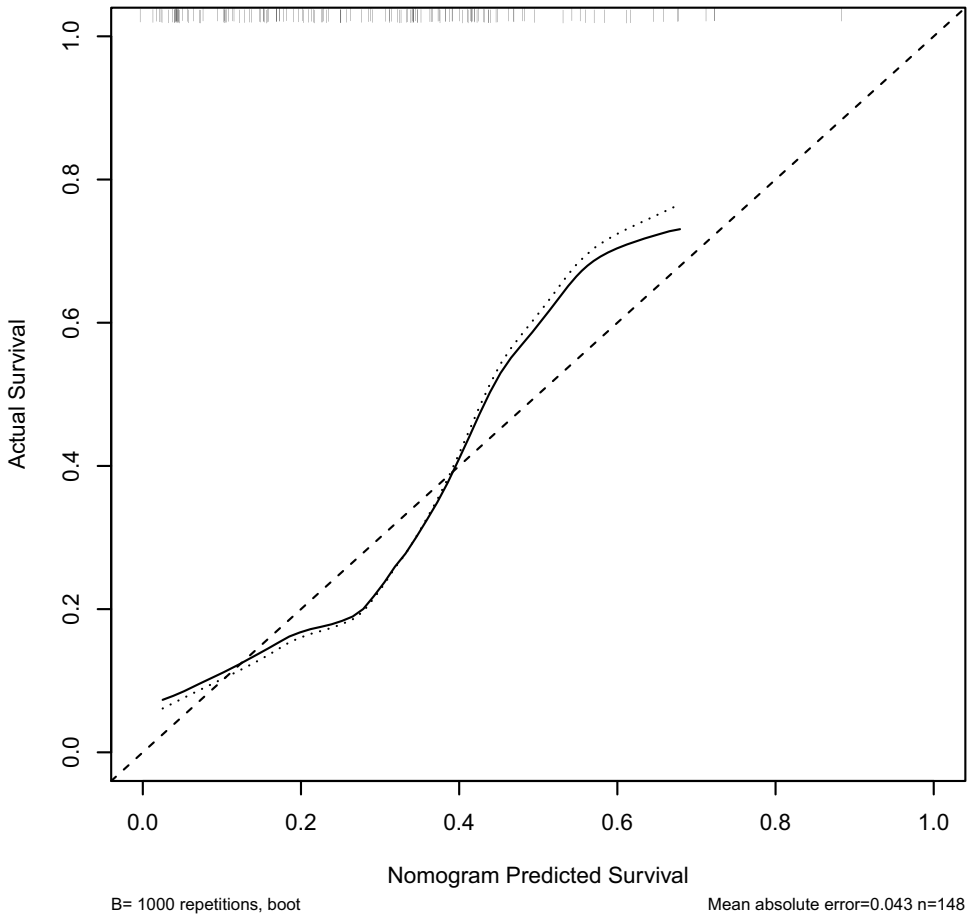

Figure 6 Calibration curve of the nomogram predictive model.

and neuromodulation,[35] and previous studies have shown a relationship between adenosine activity and depressive symptoms.[36] Uric acid, as an end metabolite of adenosine and the purinergic system, is involved in the neurobiological mechanisms underlying suicidal behavior in depressed patients.[37] Purinergic signaling, particularly through adenosine A2A receptors, may influence depression-associated suicidal behavior,[38] further substantiating the correlation between uric acid and depression.

Our predictive model can visualize the total score of risk factors and the risk probability of developing depression, which can help physicians to identify depressed patients among maintenance hemodialysis patients early and provide more helpful advice to patients. For example, for an 80-year-old unemployed maintenance hemodialysis patient, if his hemodialysis uric acid value is 100μmol/L and albumin is 30 g/L, the total score of risk factors provided by the predictive model is 177.5, which corresponds to about 90% probability of depression. Therefore, the physician can determine that the patient is at high risk for depression and recommend that the patient actively control risk factors through lifestyle and behavioral changes and take individualized therapeutic measures to reduce the risk of depression, thereby improving the patient's quality of life and reducing the incidence of adverse prognosis and mortality.

However, it is important to acknowledge the limitations of this study. Firstly, the sample size and representativeness of the participants, which were limited to patients from only two hospitals in China, may affect the generalizability and applicability of the model to a broader population. Further validation in larger and more diverse cohorts is needed. Additionally, the study did not stratify the risk of depression, preventing the establishment of graded interventions for patients with varying risk levels.

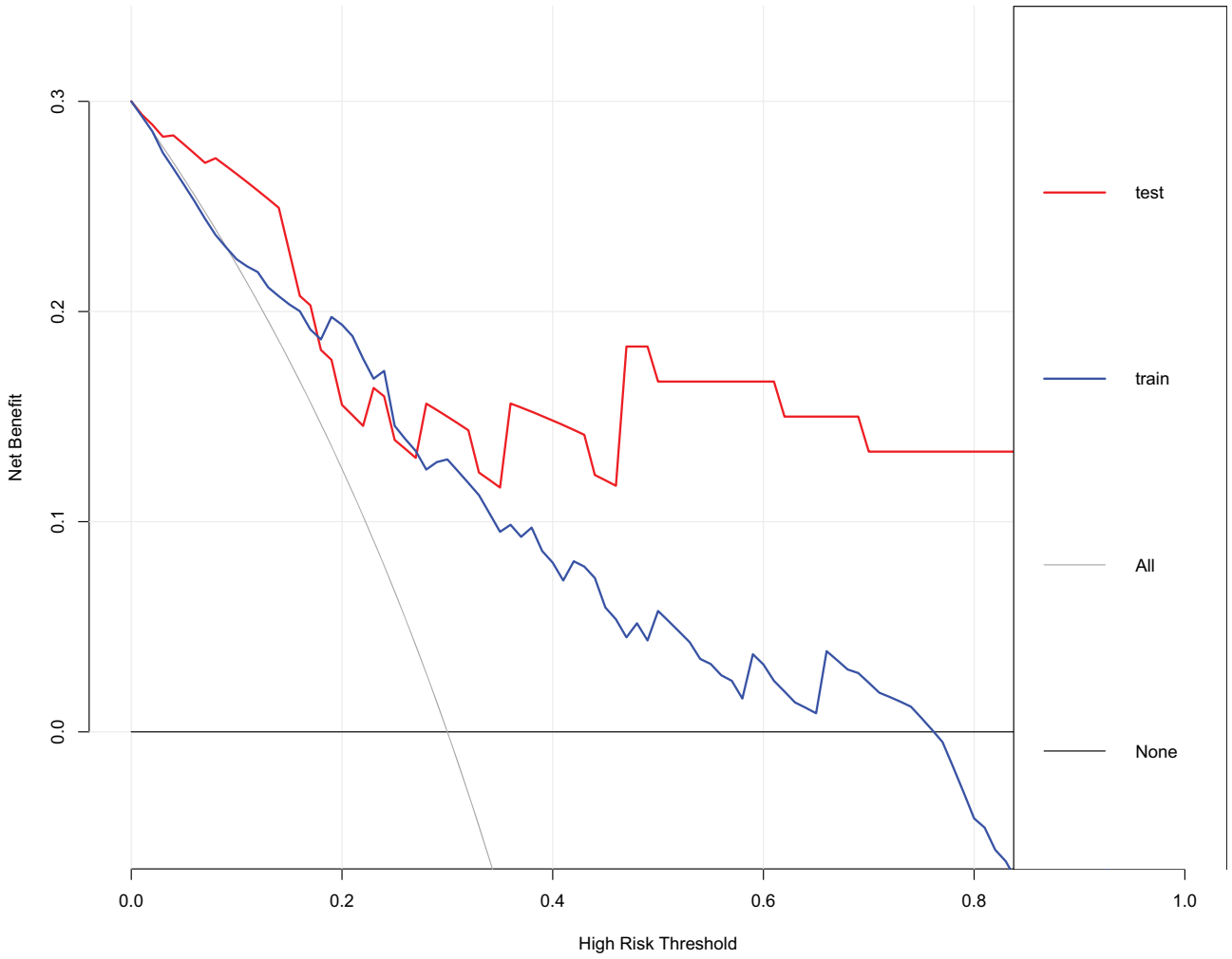

Figure 7 Decision curve analysis illustrating the clinical application of predicting depression in maintenance hemodialysis patients.

Conclusion

In conclusion, our study identified age, employment status, albumin levels, and blood uric acid as key factors associated with depression in Chinese maintenance hemodialysis patients. Furthermore, we developed a predictive nomogram model to assess the risk of depression in this population. The validation results demonstrated the model's strong predictive performance. Therefore, our nomogram serves as a convenient and reliable tool for predicting depression in maintenance hemodialysis patients.

Disclosure

The authors report no conflicts of interest in this work.

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