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Development and validation of a nomogram for predicting depression risk in patients with chronic kidney disease based on NHANES 2005–2018

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Abstract

Background Depression is common among patients with chronic kidney disease (CKD) and is associated with poor outcomes. This study aims to develop and validate a nomogram for predicting depression risk in patients with CKD.

Methods This cross-sectional study utilized data from the 2005–2018 National Health and Nutrition Examination Survey (NHANES) database. Participants were randomly divided into training and validation sets (7:3 ratio). A nomogram was developed based on predictors identified using Least Absolute Shrinkage and Selection Operator (LASSO) regression and multivariate logistic regression. Model performance was evaluated using ROC curves, calibration curves, and decision curve analysis.

Results A total of 4414 participants were included. Gender, age, race, poverty-to-income ratio, diabetes mellitus, cardiovascular diseases, trouble sleeping, sleep hours, and smoking were included as predictors in the nomogram. The area under the curve (AUC) of the nomogram for predicting depression risk in patients with CKD was 0.785 (95% CI: 0.761–0.809) in the training set and 0.773 (95% CI: 0.737–0.810) in the validation set. The corrected C-index, calculated using bootstrap resampling, was 0.776, indicating good predictive performance. Calibration curves and decision curve analysis showed good calibration and clinical utility. Subgroup and sensitivity analyses further confirmed the robustness of the nomogram. A web-based risk calculator based on the nomogram was developed to enhance clinical applicability. A flowchart demonstrating the application of the nomogram for risk assessment and clinical decision-making in routine practice is provided.

Conclusions This nomogram effectively predicts depression risk in patients with CKD and may serve as a user-friendly tool for the early identification of patients with CKD at high risk for depression using key demographic, comorbid, and lifestyle factors.

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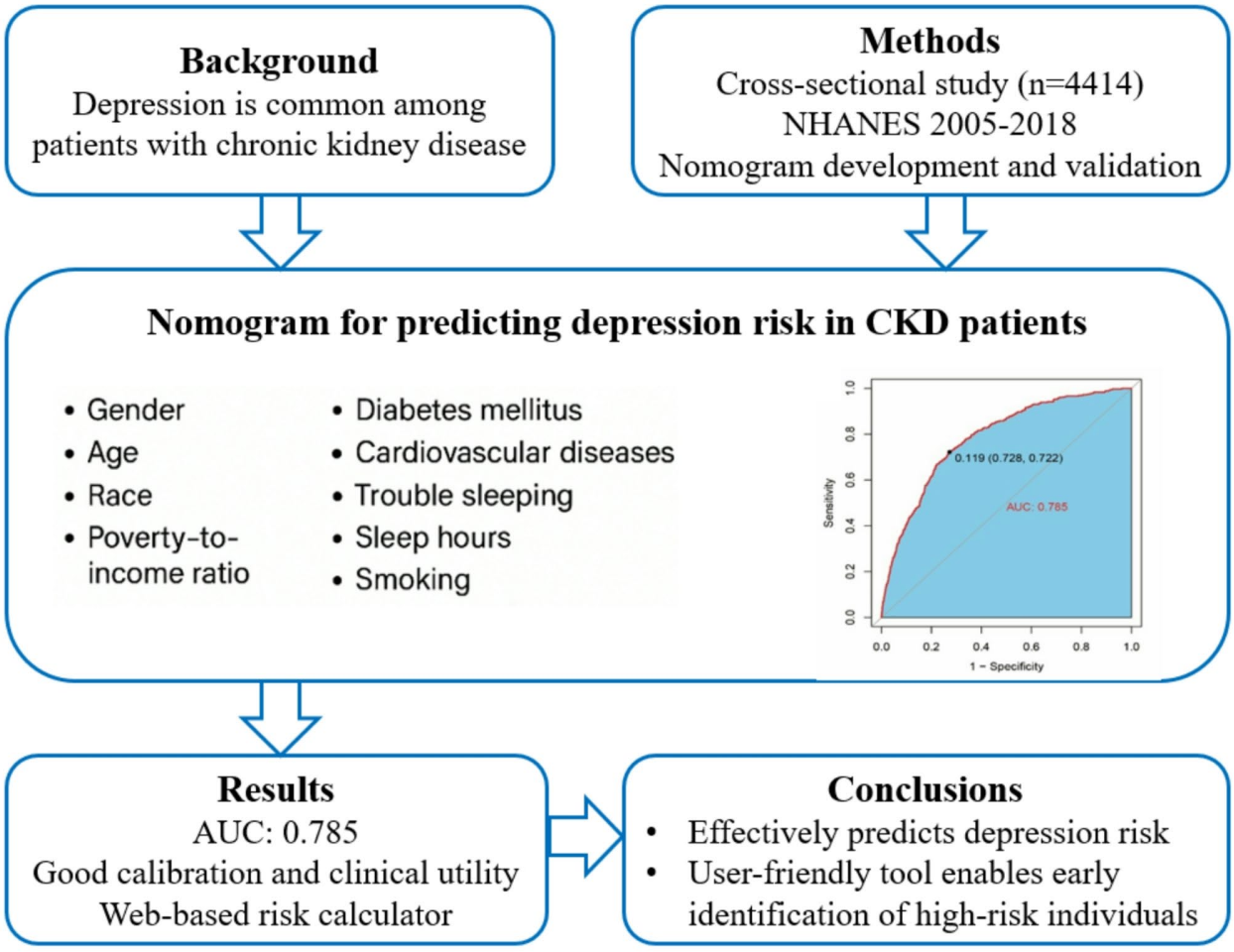
Graphical abstract



Highlights

- A nomogram was developed using key demographic, comorbid, and lifestyle factors to predict depression risk in CKD patients.
- The nomogram demonstrated good predictive performance, with subgroup and sensitivity analyses confirming its robustness.
- This nomogram may serve as a user-friendly tool for the early identification of CKD patients at high risk for depression.
- A flowchart demonstrating the application of the nomogram for risk assessment and clinical decision-making in routine practice is provided.

Keywords Cross-sectional study, Chronic kidney disease, Depression, Nomogram, Questionnaire, Sociodemographic characteristics, NHANES

Introduction

Chronic kidney disease (CKD) is a significant global health issue characterized by a gradual decline in kidney function, affecting approximately 700 million adults worldwide [1]. As CKD progresses, patients face various complications, including cardiovascular diseases (CVD), metabolic disorders, and mental health disorders [2]. The relationship between CKD and mental health disorders is complex, influenced by biological, psychological, and social factors, such as family issues [3]. Depression, as a mental health disorder, is prevalent in patients with CKD, and increases the burden on healthcare costs [4].

The bidirectional relationship between CKD and depression [5], where each condition exacerbates the other, poses a significant challenge for patient care. Depression is associated with poor prognosis in patients

with CKD [6], and patients with CKD may experience anxiety, fatigue, low self-esteem, negative illness perception, and severe pain interference, which are closely related to the risk of depression [7]. Additionally, some common risk factors, including socioeconomic adversity and unhealthy lifestyle, play a crucial role in the development of both conditions [8]. Depression is typically diagnosed using self-report tools (85.3%), such as the Beck Depression Inventory and Patient Health Questionnaire-9 (PHQ-9) [9], However, because patients with CKD may experience uremic symptoms like fatigue, depression screening tools may inadvertently lead to overdiagnosis in this population [10]. Although previous studies have explored the risk factors for depression in CKD patients [11, 12], no research has developed reliable predictive models based on simple and easily obtainable risk factors, such as demographic, comorbid, and lifestyle factors.

This study utilizes data from the National Health and Nutrition Examination Survey (NHANES), a cross-sectional nationally survey, to develop a nomogram for predicting depression risk in patients with CKD. The aim is to provide a practical and easily accessible tool for clinicians to identify patients with CKD at high risk for depression early using key demographic, comorbid, and lifestyle factors, without relying on specialized laboratory tests or psychological assessments. By offering a simple, user-friendly tool for predicting depression risk, this study may contribute to improving mental health outcomes for patients with CKD through early detection and targeted interventions.

Methods

Data source and study population

This cross-sectional study utilized data from the 2005–2018 NHANES database, specifically including data from the 2005–2006, 2007–2008, 2009–2010, 2011–2012, 2013–2014, 2015–2016, and 2017–2018 NHANES cycles. NHANES is a nationally representative survey designed to assess the health and nutritional status of the non-institutionalized civilian population in the United States through interviews, physical examinations, and laboratory tests. The NHANES protocol was approved by the Ethics Review Committee of the National Center for Health Statistics (NCHS), and written informed consent was obtained from all participants. The inclusion criteria for this study were individuals aged > 20 years with CKD, defined as an eGFR < 60 ml/min/1.73 m^2 or a urine albumin-to-creatinine ratio > 30 mg/g [13]. eGFR was calculated using the formula of Chronic Kidney Disease Epidemiology Collaboration (CKD-EPI) [14]. Participants with incomplete clinical information on predictor variables or outcomes were excluded from the study.

Outcome and predictors

In this study, the primary outcome was the occurrence of depression among patients with CKD, assessed using the PHQ-9 (Additional file 1) [15], a reliable and validated tool for diagnosing depressive disorder. Participants with a PHQ-9 score of ≥ 10 were classified into the depression group, while those with scores below 10 were categorized as the non-depressed group. Based on previous research and clinical experience, we selected key variables that may influence the occurrence of depression in patients with CKD as potential predictive factors. To maintain simplicity and practicality in the model, we focused on analyzing only demographic factors, comorbid conditions, and lifestyle factors.

Demographic factors included age (years), gender (male, female), race (Mexican American, Other Hispanic, Non-Hispanic White, Non-Hispanic Black, Other), education level (less than high school, high school, more than high school), marital status (never married, married, separated/divorced/widowed, living with a partner), body mass index (BMI) (underweight: <18.5 kg/m^2, normal: 18.5–24.9 kg/m^2, overweight: 25–29.9 kg/m^2, obese: ≥30 kg/m^2), and poverty-to-income ratio (PIR). PIR, a measure of socioeconomic status, is calculated based on household income and poverty guidelines specific to the year of the survey and the state.

Comorbid conditions included hypertension (no, yes), diabetes mellitus (DM) (no, yes, border), and CVD (no, yes). Hypertension was identified based on self-report through the question: "Have you ever been told by a doctor or health professional that you have hypertension, also called high blood pressure?" DM was determined based on self-report using the question: "Have you ever been told by a doctor or health professional that you have diabetes or sugar diabetes?" CVD was ascertained by asking the following five questions: "Has a doctor or other health professional ever told you that you have congestive heart failure, coronary heart disease, angina/angina pectoris, heart attack, or stroke?" If the answer to any of these questions was "yes", the participant was classified as having CVD. If all answers were "no", "refused", or "don't know", the participant was classified as not having CVD.

Lifestyle factors included smoking, drinking, sleep hours, and trouble sleeping. Smoking status was categorized based on the number of cigarettes smoked during one's lifetime: never smoker (smoked fewer than 100 cigarettes), former smoker (smoked at least 100 cigarettes in life but no longer smokes), and current smoker (smoked at least 100 cigarettes in life and currently smoking either some days or every day). Drinking behavior was determined by asking participants: "In the past 12 months, how often did you drink any type of alcoholic beverage?" or "During the past 12 months, about how often did you drink any type of alcoholic beverage?" Based on their

responses, drinking was categorized as never drinking (0 days), low drinking (1–36 days), and heavy drinking (≥ 37 days) [16]. Sleep hours was self-reported through the question: "How much sleep do you usually get at night on weekdays or workdays?" and categorized into three groups: short sleep (< 7 h), normal sleep (7–9 h), and long sleep (> 9 h). Trouble sleeping was identified by asking: "Have you ever told a doctor or other health professional that you have trouble sleeping?" with responses categorized as yes or no.

Statistical analysis

The participants were randomly divided into a training set for model development and a validation set for model validation in a 7:3 ratio. Continuous variables were presented as median (interquartile range, IQR) for non-normally distributed data, and categorical variables were presented as numbers (percentages). The comparison of demographic, comorbidity, and lifestyle factors among participants was performed using the "CBCgrps" package.

To identify potential predictive factors for depression risk in patients with CKD, Least Absolute Shrinkage and Selection Operator (LASSO) regression was utilized in the training set for variable selection [17]. The selected variables were then included in a multivariate logistic regression analysis, employing backward-stepwise regression for further variable refinement. Based on the results of the multivariate logistic regression, a nomogram model was constructed using the "rms" package with the lowest Akaike Information Criterion (AIC) value. The model's discrimination was evaluated using receiver operating characteristic (ROC) curves and the area under the curve (AUC). Calibration accuracy was assessed using calibration curves generated from 1,000 bootstrap resamples and the Hosmer-Lemeshow test, while decision curve analysis was performed to evaluate the nomogram's clinical utility. Detailed predictive performance metrics of the nomogram model at various risk thresholds were calculated, and the highest Youden index was used to determine the optimal cut-off value for the total score of the nomogram model, facilitating its clinical application. A web-based risk calculator based on the nomogram was developed using the "shiny" package.

Given that the "rms" package was not specifically designed to handle data with complex sampling designs, the nomogram model in this study was constructed without accounting for sampling weights [18]. To evaluate the robustness of the nomogram model, internal validation was performed using bootstrapping with 1000 resampling iterations on the training set to calculate the average C-statistic, and further evaluation of the model's predictive performance was conducted using the validation set [19]. We also conducted subgroup analyses to examine whether the model's performance varied by CKD stages. To further assess the robustness of our findings, we carried out rigorous sensitivity analyses. These included: (a) defining depression using PHQ-9 thresholds of ≥ 5; (b) defining depression using PHQ-9 thresholds of ≥ 15; and (c) performing multiple imputation using the "mice" package. For the multiple imputation, we specified distinct methods according to variable types: predictive mean matching for continuous variables, logistic regression for binary variables, multinomial logistic regression for unordered categorical variables, and proportional odds models for ordered categorical variables. All statistical analyses were performed using R (version 4.3.1), and a two-sided P-value < 0.05 was considered statistically significant.

Results

Participant characteristics

A total of 4414 participants were included in the study, with 3095 in the training set and 1319 in the validation set. The detailed participant selection process is presented in Fig. 1. The amount of missing data for each variable was shown in Additional file 2. The comparison of demographic, comorbid, and lifestyle factors between included and excluded participants was presented in Additional file 3. No significant differences were observed in any variables between the training and validation sets (Additional file 4). Table 1 shows significant differences between the depression and non-depression groups in terms of gender, age, race, education level, marital status, PIR, BMI, DM, hypertension, CVD, trouble sleeping, sleep hours, smoking, and drinking (all $P < 0.05$).

Predictor screening

The optimal tuning parameter λ for the LASSO regression model, determined through 10-fold cross-validation, was 0.011 based on the one standard error criterion. At this optimal value of λ, the ten predictors identified for depression among patients with CKD included gender, age, race, marital status, PIR, DM, CVD, trouble sleeping, sleep hours, and smoking (Fig. 2). Those predictors were then included in a multivariate logistic regression analysis, and the results showed that marital status was excluded from the final model (Table 2).

Development of nomogram

The nomogram model for predicting depression risk among patients with CKD includes nine predictors: gender, age, race, PIR, DM, CVD, trouble sleeping, sleep hours, and smoking (Fig. 3). The mean variance inflation factor was 1.29, suggesting that the predictors do not exhibit significant multicollinearity. Detailed predictive performance metrics of the nomogram at various risk thresholds were shown in Additional file 5. The

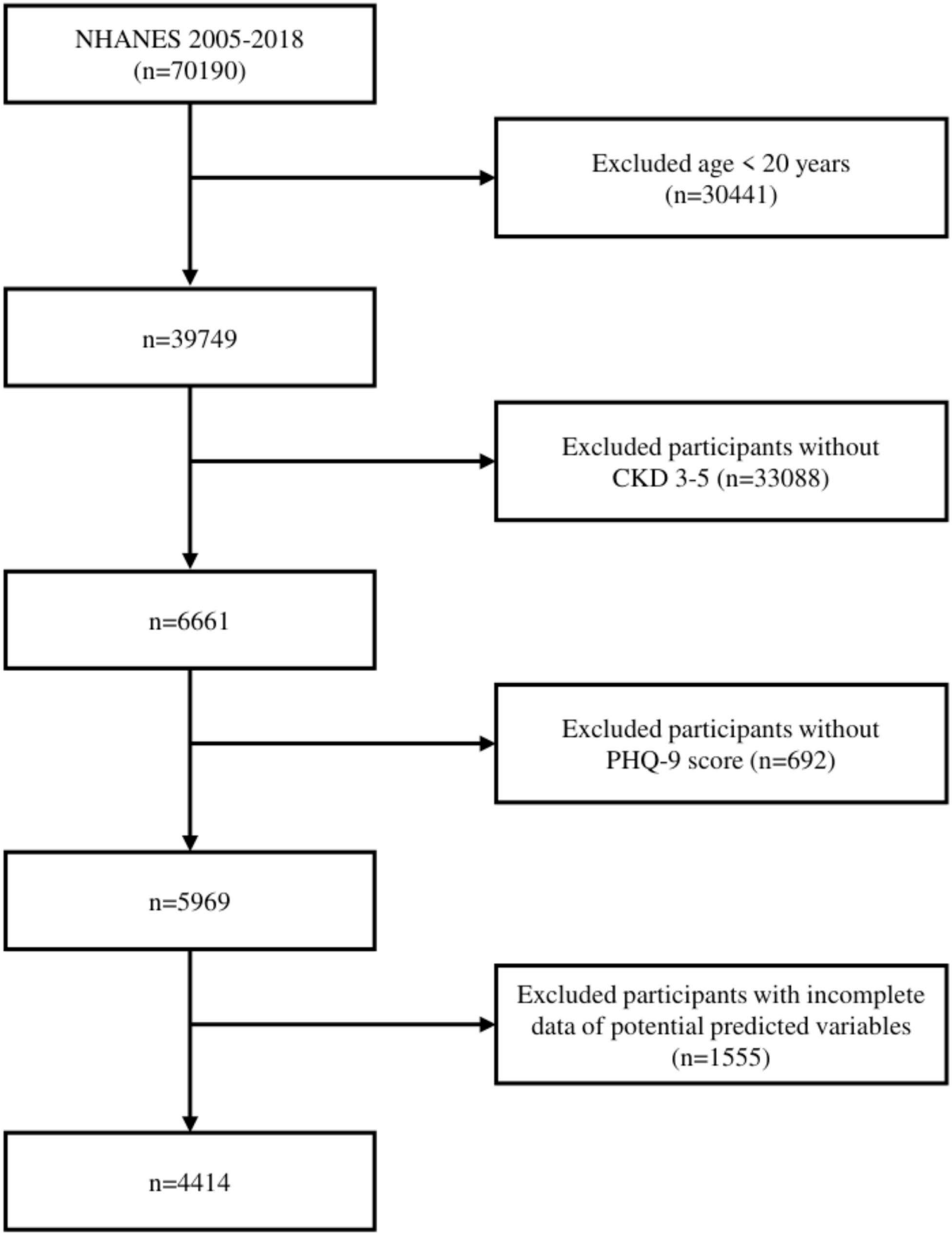


Fig. 1 Flowchart of study participants

Table 1 Demographic, comorbid, and lifestyle factors in the depression and non-depression groups

Variables	Total ($n=3095$)	Non-depression group ($n=2735$)	Depression group ($n=360$)	*P*-value
Gender				< 0.001
Male	1603 (51.79)	1448 (52.94)	155 (43.06)	
Female	1492 (48.21)	1287 (47.06)	205 (56.94)	
Age	65 (51, 76)	66 (51, 76)	60 (47, 71)	< 0.001
Race				0.044
Mexican American	380 (12.28)	330 (12.07)	50 (13.89)	
Non–Hispanic Black	831 (26.85)	738 (26.98)	93 (25.83)	
Non–Hispanic White	1460 (47.17)	1305 (47.71)	155 (43.06)	
Other Hispanic	217 (7.01)	179 (6.54)	38 (10.56)	
Other Race	207 (6.69)	183 (6.69)	24 (6.67)	
Education level				< 0.001
Less than high school	860 (27.79)	728 (26.62)	132 (36.67)	
High school	753 (24.33)	664 (24.28)	89 (24.72)	
More than high school	1482 (47.88)	1343 (49.10)	139 (38.61)	
Marital status				< 0.001
Never married	329 (10.63)	282 (10.31)	47 (13.06)	
Living with partner	154 (4.98)	128 (4.68)	26 (7.22)	
Married	1535 (49.60)	1404 (51.33)	131 (36.39)	
Separated/Divorced/Widowed	1077 (34.80)	921 (33.67)	156 (43.33)	
Poverty-to-income ratio	1.90 (1.10, 3.45)	2.03 (1.15, 3.65)	1.22 (0.80, 2.04)	< 0.001
Body mass index				< 0.001
Underweight	58 (1.87)	46 (1.68)	12 (3.33)	
Healthy weight	645 (20.84)	582 (21.28)	63 (17.50)	
Obese	1473 (47.59)	1273 (46.54)	200 (55.56)	
Overweight	919 (29.69)	834 (30.49)	85 (23.61)	
Diabetes mellitus				< 0.001
No	2027 (65.49)	1827 (66.80)	200 (55.56)	
Borderline	98 (3.17)	87 (3.18)	11 (3.06)	
Yes	970 (31.34)	821 (30.02)	149 (41.39)	
Hypertension				0.012
No	1100 (35.54)	994 (36.34)	106 (29.44)	
Yes	1995 (64.46)	1741 (63.66)	254 (70.56)	
Cardiovascular diseases				< 0.001
No	2241 (72.41)	2027 (74.11)	214 (59.44)	
Yes	854 (27.59)	708 (25.89)	146 (40.56)	
Trouble sleeping				< 0.001
No	2083 (67.30)	1943 (71.04)	140 (38.89)	
Yes	1012 (32.70)	792 (28.96)	220 (61.11)	
Sleep hours				< 0.001
Normal sleep hours	1909 (61.68)	1737 (63.51)	172 (47.78)	
Long sleep hours	68 (2.20)	51 (1.86)	17 (4.72)	
Short sleep hours	1118 (36.12)	947 (34.63)	171 (47.50)	
Smoking				< 0.001
Never	1324 (42.78)	1214 (44.39)	110 (30.56)	
Current	643 (20.78)	518 (18.94)	125 (34.72)	
Former	1128 (36.45)	1003 (36.67)	125 (34.72)	
Drinking				0.005
Never drinking	1096 (35.41)	948 (34.66)	148 (41.11)	
Heavy drinking	874 (28.24)	797 (29.14)	77 (21.39)	
Low drinking	1125 (36.35)	990 (36.20)	135 (37.50)	

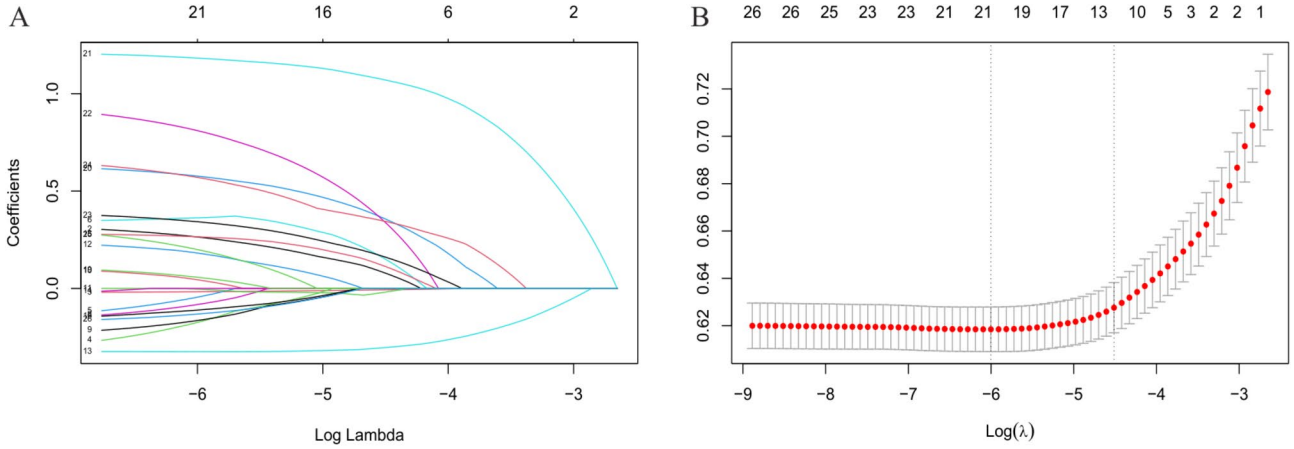


Fig. 2 Predictor selection using Lasso regression analysis. (**A**) Coefficient profiles show the change in variable coefficients across different values of λ. (**B**) The optimal λ was determined via 10-fold cross-validation, indicated by the right vertical line, corresponding to the minimum error within one standard error

Table 2 Multivariate logistic regression analysis of predictors for depression among patients with chronic kidney disease

Variables	OR (95% CI)	*P*-value
Gender		
Male	Reference	
Female	1.52 (1.19, 1.96)	0.001
Age	0.98 (0.98, 0.99)	< 0.001
Race		
Mexican American	Reference	
Non–Hispanic Black	0.67 (0.45, 1.01)	0.053
Non–Hispanic White	0.77 (0.53, 1.14)	0.186
Other Hispanic	1.35 (0.82, 2.20)	0.237
Other Race	0.89 (0.50, 1.54)	0.673
Poverty-to-income ratio	0.69 (0.63, 0.76)	< 0.001
Diabetes mellitus		
No	Reference	
Borderline	0.99 (0.47, 1.90)	0.973
Yes	1.41 (1.09, 1.83)	0.009
Cardiovascular diseases		
No	Reference	
Yes	1.99 (1.52, 2.60)	< 0.001
Trouble sleeping		
No	Reference	
Yes	3.41 (2.68, 4.36)	< 0.001
Sleep hours		
Normal sleep hours	Reference	
Long sleep hours	2.63 (1.36, 4.91)	0.003
Short sleep hours	1.52 (1.19, 1.94)	0.001
Smoking		
Never	Reference	
Current	2.03 (1.49, 2.75)	< 0.001
Former	1.42 (1.05, 1.92)	0.022

OR: odds ratio; CI: confidence interval

optimal cut-off value for the nomogram, calculated using the Youden index, was 0.119, with a sensitivity of 0.722 and specificity of 0.728. A web-based risk calculator (https://yanxzsw.shinyapps.io/depression/) based on the nomogram model has been developed to enhance clinical applicability.

Assessment and validation of nomogram

In the training set, the AUC of the nomogram for predicting depression risk in patients with CKD was 0.785 (95% CI: 0.761–0.809) (Fig. 4A), while in the validation set, the AUC was 0.773 (95% CI: 0.737–0.810) (Fig. 4B). The corrected C-index, calculated using bootstrap resampling, was 0.776, indicating good predictive performance. Calibration curves demonstrated good calibration performance across the entire risk spectrum in both the training (Fig. 4C) and validation sets (Fig. 4D). Furthermore, the Hosmer-Lemeshow test confirmed no significant deviations from perfect calibration in both the training (χ^2=6.953, P = 0.542) and validation sets (χ^2=3.778, P = 0.877), further supporting the model's robustness. Decision curve analysis showed that the nomogram model provided significant net benefits in both the training (Fig. 4E) and validation sets (Fig. 4F), indicating its clinical utility in identifying depression risk among patients with CKD.

Subgroup and sensitivity analyses

Subgroup analyses stratified by CKD stages revealed crude depression rates of 12.7% in stage 1, 14.1% in stage 2, 8.6% in stage 3, 15.5% in stage 4, and 14% in stage 5. Due to the limited sample size in stage 5, stages 4 and 5 were combined for analysis. As shown in Table 3, the nomogram demonstrated stable discriminative performance across different stages. Sensitivity analyses further confirmed the robustness of the results using different

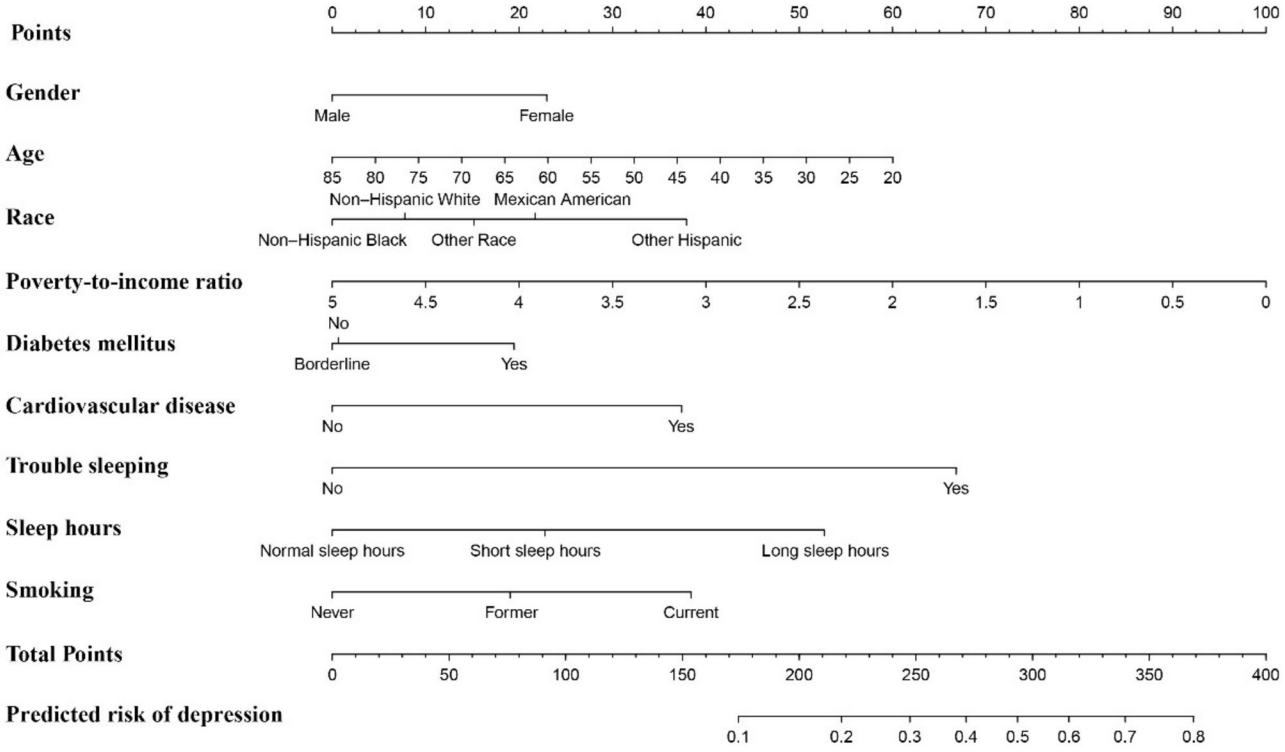


Fig. 3 Nomogram for predicting depression risk in patients with chronic kidney disease. For each factor listed on the left side of the nomogram, locate the corresponding value on the horizontal axis and draw a vertical line upward to the points scale at the top of the nomogram. The number of points is determined by the position of the factor on its scale. After assigning points for each factor, sum them to obtain the total points. Then, draw a vertical line downward from the total points to the "Predicted risk of depression" scale to determine the patient's predicted risk

methods, including different PHQ-9 threshold and filling missing values with multiple imputation.

Discussion

This study developed and validated a nomogram to predict depression risk in patients with CKD using data from the NHANES (2005–2018). The nomogram incorporates demographic, comorbid, and lifestyle factors, making it both easily accessible and straightforward to calculate.

Depression is common among patients with CKD and is associated with a poor prognosis. Given the challenges in treating psychological disorders and improving quality of life solely through medication, there is an urgent need to identify the risk factors for depression in patients with CKD. Early identification of those at high risk for depression facilitates comprehensive management and enables targeted early interventions. Considering the limitations of commonly used diagnostic tools for depression, such as the PHQ-9, which may lead to overdiagnosis, although several studies have explored depression risk factors in CKD patients, including a predictive model developed for Chinese CKD patients undergoing maintenance hemodialysis [20], no research has yet focused on developing a reliable predictive model using simple and easily obtainable risk factors such as demographic, comorbid, and lifestyle factors. The nomogram developed in this study offers several advantages. First, it integrates multiple variables, including demographic factors, comorbid conditions, and lifestyle factors, providing a comprehensive view of the factors influencing depression risk. Second, the visual nature of the nomogram enhances interpretability, allowing clinicians to easily assess individual risk. By using the nomogram, clinicians can identify the patient's values for each predictor, locate the corresponding points on the scale, sum the points, and convert the total score to a predicted probability of depression using the risk axis. Finally, with informed consent, patients identified as high-risk based on the nomogram should undergo further psychological assessment to confirm their risk status. Early intervention strategies may include lifestyle modifications, mental health referrals for psychological counseling, and, if necessary, pharmacologic treatment under the supervision of a healthcare professional (Fig. 5). The web-based risk calculator further simplifies this process, allowing for rapid risk estimation in clinical settings. By integrating it into routine kidney disease management and exploring its potential applications in telemedicine, it may help improve patient outcomes.

According to the results of LASSO regression and multivariate logistic regression, we identified 9 predictive factors for depression risk in patients with CKD, including gender, age, race, PIR, DM, CVD, trouble sleeping,

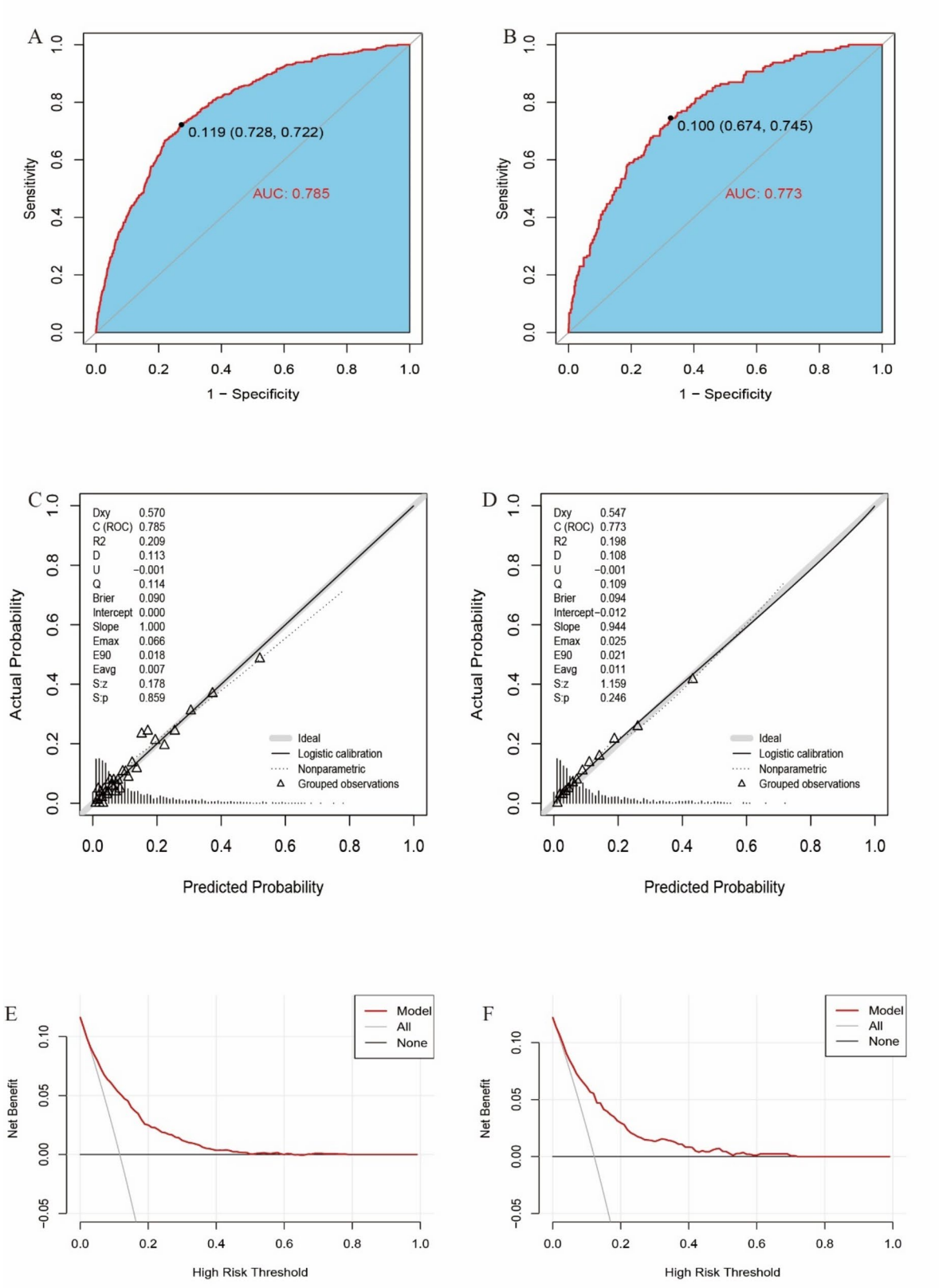


Fig. 4 Evaluation of the nomogram's predictive performance for depression risk in patients with chronic kidney disease. (**A**) ROC curve of the nomogram in the training set. (**B**) ROC curve in the validation set. (**C**) Calibration curve of the nomogram in the training set. (**D**) Calibration curve in the validation set. (**E**) Decision curve analysis of the nomogram in the training set. (**F**) Decision curve analysis in the validation set

Table 3 Nomogram performance in subgroup and sensitivity analyses

Analysis	AUC (95% CI) in the training set	AUC (95% CI) in the validation set
Nomogram model	0.785 (0.761–0.809)	0.773 (0.737–0.810)
Subgroup by CKD Stages		
CKD stage 1	0.767 (0.720–0.815)	0.760 (0.688–0.833)
CKD stage 2	0.838 (0.798–0.878)	0.779 (0.708–0.850)
CKD stage 3	0.789 (0.745–0.833)	0.724 (0.647–0.801)
CKD stage 4 and 5	0.830 (0.732–0.929)	0.617 (0.430–0.804)
Sensitivity analyses		
PHQ-9 ≥ 5	0.734 (0.715–0.754)	0.720 (0.689–0.751)
PHQ-9 ≥ 15	0.782 (0.746–0.818)	0.757 (0.702–0.813)
Multiple imputation	0.757 (0.736–0.778)	0.775 (0.746–0.805)

AUC: area under the curve; CI: confidence interval; CKD: chronic kidney disease; PHQ-9: Patient Health Questionnaire-9

sleep hours, and smoking. Among these, trouble sleeping (OR = 3.41), long sleep duration (OR = 2.63), current smoking (OR = 2.03), and CVD (OR = 1.99) emerged as the most influential predictors. Given their effect magnitude and clinical actionability, these factors may serve as priority targets for depression prevention and early intervention strategies in CKD patients.

Previous studies have shown that being female is an independent risk factor for depression [21]. The mechanisms underlying the increased susceptibility of females to depression remain unclear, but they may be related to hormonal regulation of circuit function [22]. Among patients with CKD, females are more likely to experience severe depression, and the incidence of severe depression tends to decrease with increasing age [11]. Depression is prevalent among adolescents. From 1990 to 2019, the majority of adolescents with depression in the Western Pacific Region were aged 20 to 24 [23]. Another study indicates that younger Americans are more likely to experience depression compared to older Americans, potentially due to economic instability [24]. Additionally, the increasing proportion of young women who smoke, an important risk factor for depression, may contribute to their increased susceptibility to this condition [25]. A study of Japanese adults demonstrated that household

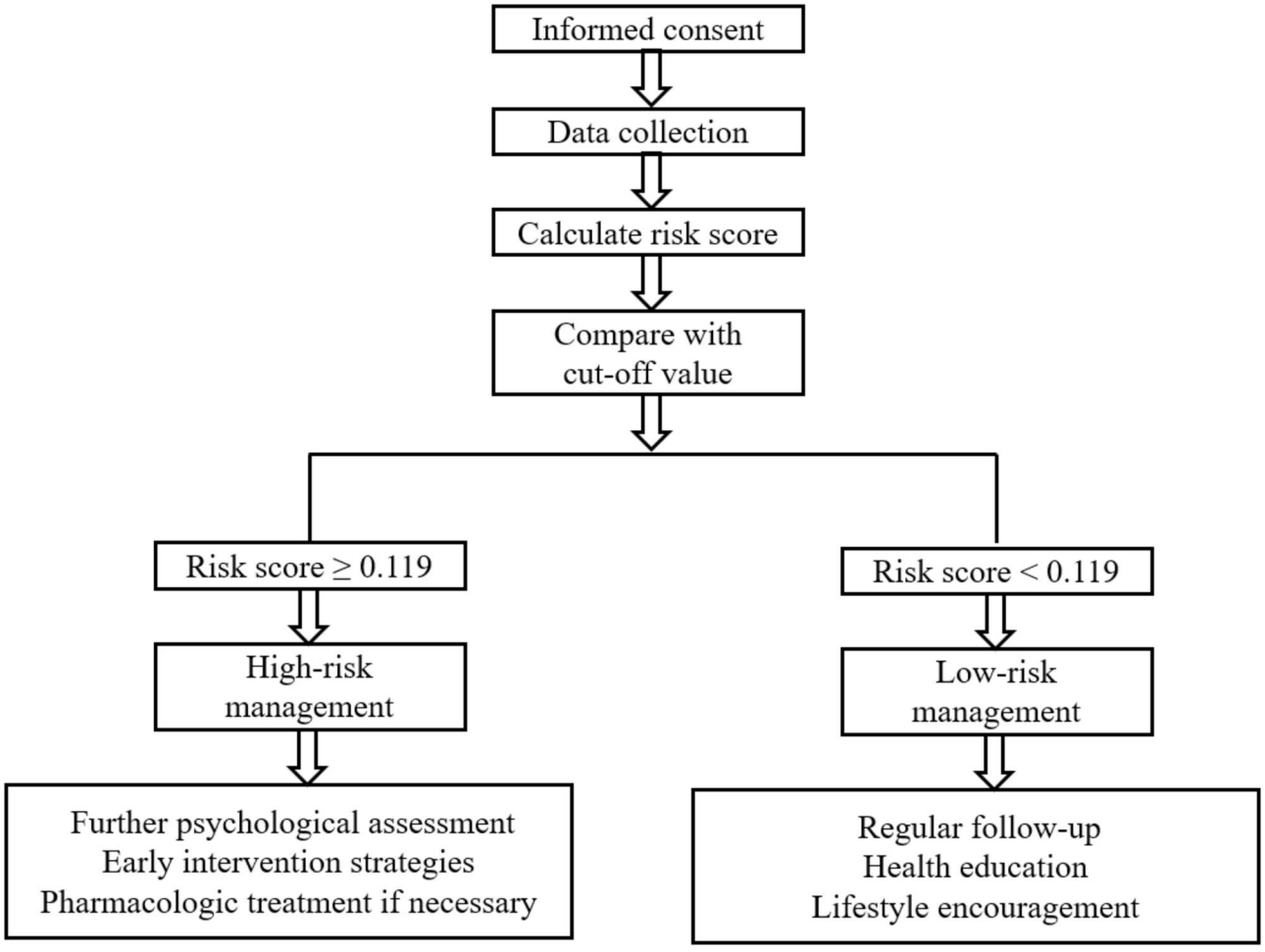


Fig. 5 Flowchart demonstrating the application of the nomogram for risk assessment and clinical decision-making in routine practice

income level is independently associated with the prevalence of depression [26], which is consistent with our research findings. This may be due to lower income levels leading to increased stress and reduced access to healthcare resources, contributing to a higher risk of depression.

In this study, we found that DM and CVD are significant risk factors for depression in patients with CKD. A study involving 170 patients with CKD who undergoing peritoneal dialysis showed that those with DM or CVD had a higher likelihood of developing depression [12]. Another study with 37,037 participants reported a significant association between poor diabetes control and an increased risk of moderate to severe depression [27]. There is a bidirectional relationship between DM and depression, potentially influenced by both mental health and physiological mechanisms, including inflammation and oxidative stress [28]. Similarly, depression and CVD share a bidirectional relationship, with common pathophysiological factors such as inflammatory and oxidative & nitrosative stress pathways [29]. In summary, the presence of DM and CVD not only impacts physical health through inflammation and other mechanisms, but also contributes to feelings of helplessness, which can adversely affect mental health.

Trouble sleeping and sleep hours have also been identified as predictors of depression in patients with CKD. Numerous previous studies demonstrate a significant association between sleep disorders and depression, highlighting sleep disorders as a risk factor for its development [30]. In the general United States population, unhealthy sleep duration is positively correlated with depression [31]. A study focusing on menopausal women indicates that both insufficient and excessive sleep may increase the risk of depression [32]. The relationship between sleep hours and depression is complex and may involve various interactions. Tian et al. proposed that short sleep hours precede the onset of depression, and the activation of the hypothalamic pituitary adrenal axis may be a key biological pathway linking insufficient sleep to depression [33]. Long sleep hours may reflect circadian disorders and decreased physical activities, both of which are also risk factors for depression [34, 35].

The relationship between smoking and depression has been extensively explored. Research shows a positive correlation between smoking and the prevalence of depression [36], with current smokers exhibiting a higher prevalence than former smokers [37]. Individuals with higher stress levels are more likely to smoke as a means of emotional regulation, which may explain the close association between smoking and depression [38]. Additionally, the associations between smoking and mental health may be influenced by shared genetic and environmental factors [39].

This study has several limitations. First, the cross-sectional design precludes causal inference between predictors and depression. Second, depression assessment relied on self-reported PHQ-9 scores, which may introduce bias, as individuals may underreport or overreport their symptoms. Third, due to the limited data available in the NHANES database, we were unable to distinguish between dialysis and non-dialysis patients, nor could we account for all potential predictive factors. Given that eGFR and ACR may have important associations with depression in this population, we attempted to incorporate both variables during model development. However, their inclusion did not significantly improve model performance, and as a result, they were not retained in the final nomogram. Fourth, although our study utilized NHANES, a nationally representative database, certain selection criteria and survey methodologies may introduce differences from the general CKD population. Additionally, as all participants were from the United States, caution is needed when generalizing the findings to other populations. Finally, the nomogram has only undergone internal validation, further external validation in an independent cohort is necessary to ensure the model's reliability and generalizability. All in all, these limitations highlight the need for future studies to employ longitudinal designs, improve depression measurement methods, address data gaps, and conduct external validation to enhance the applicability and robustness of the model.

Conclusions

This study successfully developed and validated a nomogram for predicting the risk of depression in patients with CKD. The nomogram provides a user-friendly tool for clinicians, allowing them to identify patients with CKD at high risk for depression early using key demographic, comorbid, and lifestyle factors, which may improve their outcomes through timely detection and targeted interventions.

Abbreviations

CKD	Chronic kidney disease
CVD	Cardiovascular diseases
eGFR	Estimated glomerular filtration rate
NHANES	National Health and Nutrition Examination Survey
NCHS	National Center for Health Statistics
PHQ-9	Patient Health Questionnaire-9
BMI	Body mass index
PIR	Poverty-to-income ratio
DM	Diabetes mellitus
LASSO	Least Absolute Shrinkage and Selection Operator
ROC	Receiver operating characteristic
AUC	Area under the curve
OR	Odds ratio
CI	Confidence interval

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s41043-025-00890-7.

Additional file 1

Additional file 2

Additional file 3

Additional file 4

Additional file 5

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Author contributions
Q.Y. designed the study, performed analysis, and drafted the manuscript. D.W. designed and directed the study. G.L., R.W., and D.L. revised the manuscript. All authors read and approved the final manuscript.

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Data availability
The data used in this study is from NHANES (2005–2018). Data are publicly available and can be downloaded from NHANES website: http://www.cdc.gov/nchs/nhanes.htm.

Declarations

Ethics approval and consent to participate
The NHANES protocol was approved by the Ethics Review Committee of the NCHS, and written informed consent was obtained from all participants.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Clinical trial number
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