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Construction and validation of a predictive model for sleep disorders among pregnant women

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Abstract

Background Sleep disorders are among the most common major problems during pregnancy. Most studies on sleep disorders of pregnant women are closely related to adverse birth outcomes. In this study, our aim was to develop and validate a predictive model for the risk of sleep disorders in pregnant women.

Methods A total of 2,467 healthy pregnant women were enrolled and randomly partitioned into a training set and a validation set at a ratio of 7:3. During the variable selection stage, the Pearson's chi-square test was employed to identify variables with a *p*-value below 0.05, which were then designated as candidate variables for subsequent logistic regression analysis. Concurrently, the LASSO regression technique was utilized to sift through and isolate the most valuable variables. Ultimately, we developed binary Logistic regression models predicated on the Pearson's chi-square test (Model 1) and the LASSO regression (Model 2). The performance of the nomograms was evaluated using the Bootstrap resampling procedure, the sensitivity and specificity of the receiver-operating characteristic (ROC), the area under the ROC curve (AUC), and decision curve analysis (DCA).

Results A total of 439 (25.4%) pregnant women in the training set and 208 (28.1%) in the validation set exhibited sleep disorder, respectively. The prediction models shared 6 risk factors (age, anxiety, depression, family functions, degree of pregnancy reaction, pre-pregnancy physical condition). In the Model 1, the sensitivity was 69.4%, and specificity was 59.6%. When pregnancy weeks, residence, only child were included in Model 2, the sensitivity was 82.4% and specificity was 54.8%. In the validation set, the areas under the curve of the Model 1 and Model 2 were 0.678 (0.635, 0.720), and 0.719 (0.678, 0.761), respectively. The risk prediction model of sleep disorders in pregnant women showed that the calibration curve is approximately distributed along the reference line. Decision curve analyses demonstrated a favorable net benefit within the range of the threshold probability in the nomograms.

Conclusion Model 2 exhibited superior performance, can serve as a convenient and reliable tool for predicting the risk probability of sleep disorders in pregnant women.

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Keywords Prediction model, Sleep disorders, Pregnant women, LASSO, Logistic regression

Introduction

As an essential physiological requirement, sleep plays an extremely crucial role in our health [1]. Sleep disturbance during pregnancy is a common complication which can lead to significant maternal distress and adverse pregnancy outcomes [2]. Obstructive sleep apnea, insomnia, and restless legs syndrome are the most common sleep disorders in pregnancy [3]. Sleep disorders can exacerbate negative emotions, increase the risk of depression during pregnancy and postpartum, prolong labor, raise the risk of obstructed labor and postpartum hemorrhage, and boost the rate of cesarean deliveries [4–6]. Several prospective studies suggest that maternal sleep disturbance during pregnancy may increase the risk of preterm birth [7–10]. Mindell et al.'s study, in which they surveyed 2427 pregnant women, indicated that 76% of the women reported poor sleep quality and 38% had insufficient sleep [11]. Particularly, for pregnant women with sleep disorders, there is currently no comprehensive risk assessment system available.

Sleep disorders present a complex and ambiguous symptom profile within the pregnant population and are frequently confused with normal physiological responses during pregnancy [12]. There are numerous factors that influence sleep quality. Previous research indicates that sleep disorders might be associated with psychiatric symptoms, such as depression, anxiety, insomnia, alcohol use, and post-traumatic stress disorder [13–15]. Women have mentioned several reasons for sleep disturbance during pregnancy, including an increased urge to urinate, difficulty in finding comfortable sleeping positions, and body aches [16]. Frequent nighttime urination can disrupt sleep because of renal hyperfiltration, reduced bladder capacity due to external pressure, and increased urine volume resulting from salt accumulation [17]. In addition to these factors, older age [18], and trimester/gestational age [19] have been reported to affect sleep quality in pregnancy. These factors render it challenging to accurately diagnose sleep disorders solely based on subjective symptoms. Traditional diagnostic methods like polysomnography (PSG) can monitor sleep in detail. However, they are less suitable for pregnant women due to the complexity of the equipment and the requirement of monitoring in a specific environment, which brings inconvenience to pregnant women [20]. As well as subjective assessment methods like questionnaires are prone to cognitive bias and recall bias among pregnant women, thereby reducing diagnostic accuracy [21]. Although there has been a great deal of research on the objective physiological reasons that influence sleep disorders during pregnancy, there has been little research on prediction models for sleep disorders of pregnant women with different individual characteristics [22–24]. In order to enhance the awareness of sleep disorders, accurate, inexpensive and easily administered screening tools are needed.

A machine learning model is an equation that is constructed by utilizing a variety of statistical models to quantify an individual's risk of experiencing a relevant event [25]. It serves to assist in estimating the risk of developing a specific disease or the current condition [26]. Given the drawbacks of traditional diagnostic methods, machine learning models are capable of leveraging data collected by wearable devices for analysis. Several studies have demonstrated that machine learning models acquire pregnant women's sleep data (encompassing heart rate variability, sleep stages, and so on) via smart bracelets. This data can be collected continuously and non-invasively, thereby furnishing abundant information for the model. In the meantime, the model can mitigate the effect of bias in subjective assessment and augment the accuracy and reliability of diagnosis through continuous learning and updating [27–29]. Our research aims to develop and validate novel models for anticipating sleep disorders in pregnant women. Not only does it help improve the health of pregnant women and their fetuses, but it also provides important scientific support and practical guidance for the healthcare field.

Materials and methods

Participants

From February 2023 to June 2023, participants were recruited using a continuous sampling method at an obstetrics clinic in a tertiary care hospital in Ningxia Hui Autonomous Region, China. The inclusion criteria were as follows: pregnant women aged 18 and above and at least 4 weeks pregnant, who voluntarily participated in this study. When all pregnant women visited the hospital obstetric clinic for prenatal examination, they were provided with a set of questionnaires. A total of 2,588 questionnaires were distributed and 2,467 valid questionnaires were eventually collected, with a valid response rate of 95%. In this study, early pregnancy encompasses the first 12 weeks of gestation; mid-pregnancy commences from the 13th week and lasts until the end of the 27th week; whereas late pregnancy begins from the 28th week and continues until delivery. All subjects signed an informed consent form prior to data collection. Ethical approval for the study was obtained from the Ethics Committee of Ningxia Medical University (No. 2022-G007) before the commencement of the study.

Sample size

A total of 2467 eligible pregnant patients were included in our cohort after applying inclusion and exclusion criteria. The cohort was randomly partitioned at a ratio of 7:3 into two groups, namely the training set and the testing set. Considering that each candidate prediction parameter in the machine learning algorithm is standardized based on 10 events [30], the 36 prediction parameters utilized in our study require, at a minimum, 360 individuals with corresponding events. Meanwhile, in our study, the 439 patients in the training set meet the optimal sample size requirements.

Questionnaries measures

A systematic questionnaire was employed to acquire general demographic characteristics, psychological status during pregnancy, level of family functioning, and sleep quality.

Demographics

This section encompassed age, gender, gestation, gestational week, number of embryos, pre-pregnancy BMI, place of residence, education, occupation, personality, per capita monthly income, history of miscarriage, history of abnormal induced abortion, number of conceptions, degree of early pregnancy reaction, willingness to carry a pregnancy to term, pregnant women's desire for the sex of the fetus, their family members' desire for the sex of the fetus, their pre-pregnancy physical condition, and the presence of any underlying diseases.

Pregnancy depression

The Edinburgh Postnatal Depression Scale (EPDS) is the most widely-used screening tool for depression worldwide and is the preferred assessment scale for maternal depression as recommended by the guidelines. The EPDS was initially developed in 1987 by Cox et al. [31], and it consists of 10 items namely mood, interest, regret, anxiety, panic, insomnia, coping, sadness, sobbing, and self - injury. Each item is rated on a 4-point Likert scale ranging from 0 to 3, and the sum of the scores of each item results in a total scale score ranging from 0 to 30, with higher scores indicating more severe levels of depression. In the current study, the Cronbach's α coefficient was 0.88. In this study, a score of ≥ 9 was adopted as a criterion for pregnancy-related depression in pregnant women.

Pregnancy anxiety

Pregnancy-related anxiety was assessed using the pregnancy-related anxiety questionnaire developed by Xiaoxu Wang et al. [32]. The scale comprises 13 items, including three subscales: concern about self, worry about fetal health, and worry about delivery. For each item on the scale, a score of 1 was assigned for "no worrying", 2 for "occasional worrying", 3 for "frequent worrying", and 4 for "constant worrying". The higher the score, the greater the risk of pregnancy-related anxiety. Women were considered to have pregnancy-related anxiety when they total score was ≥ 24. In the current study, the Cronbach's α coefficient was 0.81.

Family caringness

The Family Caringness Index Questionnaire (APGAR), which was developed by Dr. Smilkstein in 1978 based on the functional characteristics of the family, has a Cronbach's α coefficient of 0.86 [33]. The questionnaire consists of five items, covering five aspects: family adaptation (Adaptation), cooperation (Partnership), growth, affection (Affection), and intimacy (Resolve). The total score is used to reflect the degree of family care an individual experiences. A 3-point scale is adopted, where "Often" is scoring 2 points, "Sometimes" as 1 point, and "Seldom" as 0 point. The scores of the five items are summed up to obtain a total score. The higher the total score, the greater higher the family care an individual perceives. In this study, a total score ranging from 7 to 15 is classified as strong family functioning, and a score of less than 7 is categorized as family dysfunction.

Pregnancy sleep quality

The sleep quality of the study subjects was evaluated by Pittsburgh Sleep Quality Index (PSQI). The PSQI was compiled by Buysse et al. [34], a sleep specialist at the Center for Psychiatric Sleep and Biorhythm Studies, University of Pittsburgh Medical Center, USA, in 1989. It was translated into Chinese and utilized to assess the subjective sleep quality within the past year. Its reliability has been examined by Liu Xianchen et al. [35]. The scale comprises 19 items, 7 dimensions, and a total score of 21. A higher score indicates poorer sleep quality. In this study, a total PSQI score > 7 was defined as poor sleep quality. Additionally, this study converted the PSQI scores into binary variables and employed them as outcome variables. The Cronbach's α in this study was 0.83.

Data cleaning and missing management

Before conducting data processing, a data check should be carried out. This check encompasses verifying whether the research subjects meet the inclusion and exclusion criteria, whether there are duplicate entries, and whether there are any omissions or logical errors within the questionnaire. In the event that cases of non-compliance with the exclusion criteria or duplicate inclusion are identified during the review, the relevant questionnaires will be promptly deleted. Should there be omissions or logical errors in the questionnaire, a timely telephone interview

will be arranged to guarantee the accuracy of the questionnaire information.

Data analysis

We employed the mean ± standard deviation and the number (composition ratio) to delineate the distribution patterns of general demographic characteristics, psychological states during pregnancy, levels of family functioning, and sleep quality. The Shapiro-Wilk test was utilized to ascertain the normality of the data. In cases where continuous variables were either non-normally distributed or heterogeneous, the Mann-Whitney U test was adopted to compare the baseline characteristics between the sleep-disordered and non-sleep-disordered groups within both the training and test sets.

In this study, Pearson's chi-square test was used to identify the characteristic variables related to sleep disorders. All the variables with statistical significance ($p < 0.05$) in Pearson's chi-square test were taken as candidate variables for further binary Logistic regression analyses. Then, the variables screened by the binary Logistic regression were used to establish a Logistic regression model, named Model (1) Secondly, we also applied the least absolute shrinkage and selection operator (LASSO) regression to screen the most valuable variables. The feature selection step was performed on the complete data. Then, the variables selected by LASSO regression were used to establish another Logistic regression model, named Model (2) The results obtained from Model 1 and Model 2 were employed to construct two nomograms. The final prediction model was presented in the form of nomograms, which constituted the main process employed in this study to develop a prediction model for pregnant women's sleep quality (see Fig. 1). Additionally, the study entailed evaluating the calibration, identification, and clinical application of each nomogram. The performance of the nomograms was evaluated using the Bootstrap resampling procedure, the sensitivity and specificity of the receiver-operating characteristic (ROC), the area under the ROC curve (AUC), and decision curve analysis (DCA). Statistical analyses were carried out using R software version 4.3.0, and a two-tailed p-value of < 0.05 was considered significant.

Results

Participants

There were 1726 pregnant women in the training set and 741 pregnant women in the validation set. In total, 439 (25.4%) pregnant women in the training set and 208 (28.1%) in the validation set presented sleep disorders. The demographic characteristics of these pregnant women are summarized in Table 1. In the training set, the women in the sleep-disorders group were older than those in non-sleep disorders group 31 (29–34) vs. 30 (28–33); $p < 0.001$). For factors such as pregnancy (early pregnancy), residence(city), only child, degree of early pregnancy response, and pre-pregnancy physical condition a higher proportion of sleep disorders was also observed. Notably, pregnant women with anxiety 144 (32.8%) vs. 271(21.1%), $p < 0.001$), depression 224 (51.0%)

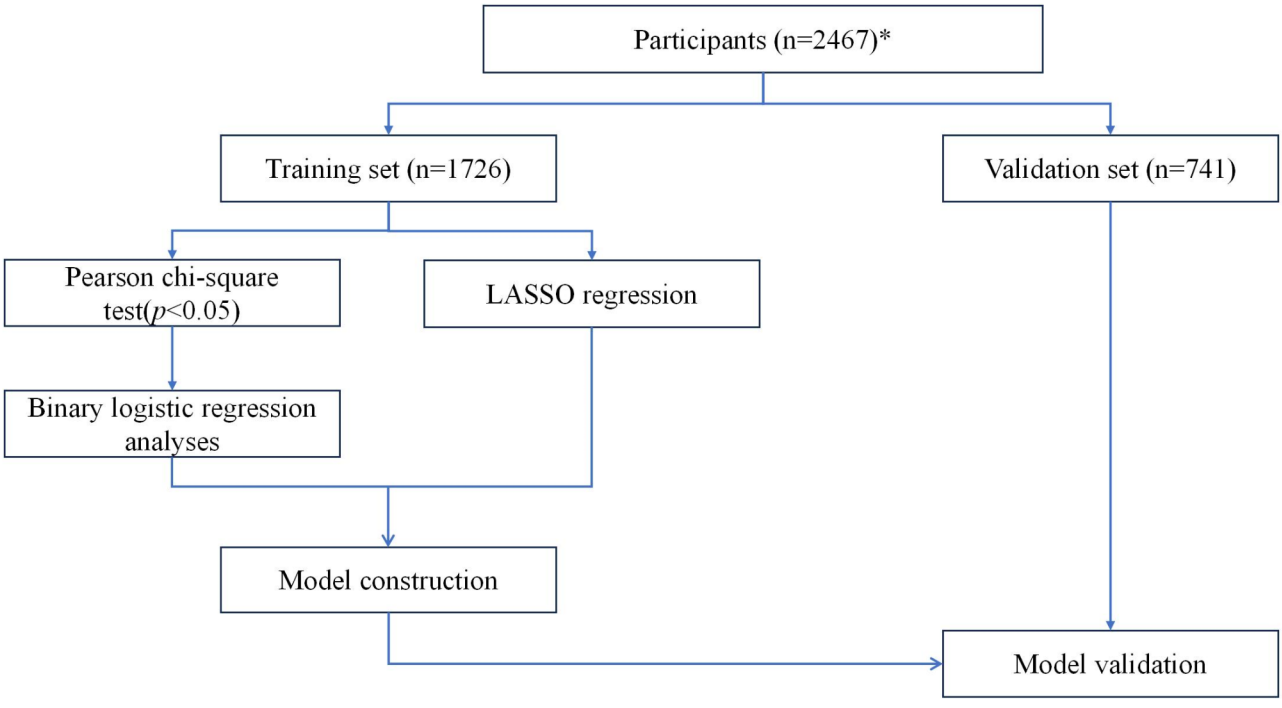

Fig. 1 Study flow chart. *Participants were randomly allocated into the training set and the validation set with a ratio of 7:3

Table 1 Characteristics of pregnant women in the training set and the test set

Variables	Training set			Test set		
	Sleep disorders group *n* = 439	non-sleep disorder group *n* = 1287	*p*	Sleep disorders group *n* = 208	non-sleep disorder group *n* = 533	*p*
Age [IQR]	31(29–34)	30(28–33)	<0.001	31(29–34)	31(28–34)	0.044
Pre-pregnancy BMI [IQR]	21.5(19.5–23.8)	21.6(19.5–24.0)	0.696	22.0(20.1–24.0)	21.8(20.0-24.2)	0.744
Pregnancy (%)						
Early pregnancy	28(6.4)	94(7.3)	<0.001	12(5.8)	29(5.4)	<0.001
Mid-pregnancy	154(35.1)	658(51.1)		57(27.4)	255(47.8)	
Late pregnancy	257(58.5)	535(41.6)		139(66.8)	249(46.7)	
Whether first pregnancy (%)						
Yes	172(39.2)	520(40.4)	0.651	87(41.8)	204(38.3)	0.374
No	267(60.8)	767(59.6)		204(38.3)	329(61.7)	
Place of residence (%)						
City	385(87.7)	1052(81.7)	0.004	186(89.4)	446(83.7)	0.047
Rural	54(12.3)	235(18.3)		22(10.6)	87(16.3)	
Education (%)						
Middle School and below	42(9.6)	158(12.3)	0.072	24(11.5)	74(13.9)	0.154
High School and below	61(13.9)	209(16.2)		41(19.7)	75(14.1)	
College/Bachelor	304(69.2)	857(66.6)		125(60.1)	349(65.5)	
Postgraduate and above	32(7.3)	63(4.9)		18(8.7)	35(3.6)	
Occupation (%)						
Unemployed	90(20.5)	300(23.3)	0.679	51(24.5)	127(23.8)	0.898
Farmer/Workers	16(3.6)	47(3.7)		9(4.3)	25(4.7)	
Enterprise	175(39.9)	490(38.1)		78(37.5)	214(40.2)	
Others	158(36)	450(35.0)		70(33.7)	167(31.3)	
Personality (%)						
Introverted	63(14.4)	150(11.7)	0.256	27(13.0)	65(12.2)	0.594
Moderate	277(63.1)	859(66.7)		133(63.9)	361(67.7)	
Extrovert	99(22.6)	278(21.6)		48(23.1)	107(20.1)	
Only child (%)						
Yes	74(16.9)	162(12.6)	0.025	33(15.9)	78(14.6)	0.673
No	365(83.1)	1125(87.4)		175(84.1)	455(85.4)	
Monthly income per capita (%)						
< 2000 RMB	15(3.4)	68(5.3)	0.237	15(7.2)	31(5.8)	0.770
2000 ~ 5000 RMB	226(51.5)	671(52.1)		98(47.1)	258(48.4)	
>5000 RMB	198(45.1)	548(42.6)		95(45.7)	244(45.8)	
Spontaneous abortions (%)						
Yes	69(15.7)	178(13.8)	0.330	30(14.4)	70(13.1)	0.644
No	370(84.3)	1109(86.2)		178(85.6)	463(86.9)	
Artificial abortion (%)						
Yes	49(11.2)	136(10.6)	0.728	17(8.2)	56(10.5)	0.338
No	390(88.8)	1151(89.4)		191(91.8)	477(89.5)	
Labor induction (%)						
Yes	3(0.7)	5(0.4)	0.427		4(0.8)	0.581
No	436(99.3)	1282(99.6)		208(100)	529(99.2)	
Conception method (%)						
Natural Conception	409(93.2)	1217(94.6)	0.280	201(96.6)	508(95.3)	0.425
Artificial insemination	30(6.8)	70(5.4)		7(3.4)	25(4.7)	
Degree of Pregnancy Reaction (%)						
Lighter	138(31.4)	560(43.5)	<0.001	77(37.0)	230(43.2)	0.01
Okay	186(42.4)	508(39.5)		76(36.5)	214(40.2)	
Heavier	115(26.2)	219(17.0)		55(26.4)	89(16.7)	
Pregnancy intention (%)						
Planned Pregnancy	175(39.9)	452(35.1)	0.095	76(36.5)	182(34.1)	0.321

Table 1 (continued)

Variables	Training set			Test set		
	Sleep disorders group *n* = 439	non-sleep disorder group *n* = 1287	*p*	Sleep disorders group *n* = 208	non-sleep disorder group *n* = 533	*p*
Let nature take its course	192(43.7)	640(49.7)		89(42.8)	259(48.6)	
Accidental	72(16.4)	195(15.2)		43(20.7)	92(17.3)	
Pregnant women's desire for the sex of the fetus (%)						
Boys	32(7.3)	73(5.7)	0.432	18(8.7)	51(9.6)	0.798
Girls	56(12.8)	157(12.2)		20(9.6)	58(10.9)	
Both can	351(80.0)	1057(82.1)		170(81.7)	424(79.5)	
Family's desire for the sex of the fetus (%)						
Boys	44(10.0)	93(7.2)	0.052	18(8.7)	38(7.1)	0.816
Girls	46(10.5)	113(8.8)		19(9.1	51(9.6)	
Both can	333(75.9)	1051(81.7)		162(77.9)	426(79.9)	
No idea	16(3.6)	30(2.3)		9(4.3)	18(3.4)	
Pre-pregnancy physical condition (%)						
Better	240(54.7)	893(69.4)	<0.001	133(63.9)	385(72.2)	0.084
General	184(41.9)	382(29.7)		71(34.1)	139(26.1)	
Poor	15(3.4)	12(0.9)		4(1.9)	9(1.7)	
Basic Diseases (%)						
Yes	35(8.0)	75(5.8)	0.112	191(91.8)	36(6.8)	0.501
No	404(92.0)	1212(94.2)		17(8.2)	497(93.2)	
Anxiety (%)						
Yes	144(32.8)	271(21.1)	<0.001	65(31.3)	103(19.3)	<0.001
No	295(67.2)	778(78.9)		143(68.8)	430(80.7)	
Home function (%)						
Obstacles	220(51.1)	509(39.5)	<0.001	116(55.8)	184(34.5)	<0.001
Good	219(49.9)	778(60.5)		92(44.2)	349(65.5)	
Depression (%)						
Yes	224(51.0)	446(34.7)	<0.001	111(53.4)	184(34.5)	<0.001
No	215(49.0)	841(65.3)		97(46.6)	349(65.5)	

Note: $p < 0.05$ means significant different

vs. 446 (34.7%), $p < 0.001$), and family dysfunction 220 (51.1%) vs. 509 (39.5%), $p < 0.001$) were more prone to suffer from sleep disorders compared with others.

Model construction

The prediction models for sleep disorders in pregnant women were developed based on 1,726 pregnant women in the training set. Variables with a significance level of $p < 0.05$ (see Table 1) were evaluated to construct a model for predicting the probability of sleep disorders among pregnant women. Subsequently, these variables were analyzed through binary Logistic regression to evaluate the risk of sleep disorders. In the binary Logistic regression analysis, age, degree of pregnancy reaction, pre-pregnancy physical condition, anxiety, family function and depression were identified as independent risk factors for sleep disorders (see Table 2). The LASSO analysis further incorporated 36 potential risk variables (see Fig. 2). Nine variables, namely age, degree of pregnancy reaction, pre-pregnancy physical condition, residence, pregnancy, being only child, anxiety, family function, and depression, were independently associated and selected by means of the LASSO regression analysis (Table 3).

Development of predicting nomograms

According to the results of using the Model 1 and Model 2 respectively (see Figs. 3), 6 and 9 risk predictors from the binary Logistic regression and LASSO regression analysis, respectively, were incorporated into the final prediction model. We constructed two nomograms for sleep disorders based on the screened variables. As depicted in Fig. 3, the score in the first row of this figure corresponds to the score of each influencing factor. Subsequently, the total score of all influencing factors can be computed for each pregnant woman, and the probability of experiencing sleep disorders can be obtained. A total score of 200–404, corresponding to an overall probability of having a sleep disorder of approximately 6.0-80.0%, was obtained by calculating and summing the weighted scores for each predictor in the model (see Fig. 3A). The

Table 2 Binary logistic analysis of risk factors for sleep disorders

Variables	OR	95%CI	*p*-values
Age	1.050	1.023–1.079	<0.001
Pregnancy			
Early pregnancy			reference
Mid-pregnancy	0.785	0.491–1.254	0.331
Late pregnancy	1.828	1.154–2.898	0.010
Place of residence			
City			reference
Rural	0.674	0.481–0.945	0.022
Only child			
No			reference
Yes	0.701	0.514–0.956	0.025
Degree of Pregnancy Reaction			
Lighter			reference
Okay	1.494	1.155–1.933	0.002
Heavier	1.940	1.432–2.628	<0.001
Pre-pregnancy physical condition			
Better			reference
General	1.871	1.479–2.367	<0.001
Poor	5.187	2.317–11.61	<0.001
Anxiety			
No			reference
Yes	1.619	1.258–2.084	<0.001
Family functions			
Good			reference
Obstacles	1.468	1.169–1.844	0.001
Depression			
No			reference
Yes	1.769	1.406–2.225	<0.001

Abbreviations: 95% CI, 95% confidence interval; OR, odds ratio;

total scores in the model for the combination of non-zero variables selected in the LASSO regression analysis ranged from 200 to 450, which corresponds to an overall probability range of 4.0-80.0% (see Fig. 3B).

Table 3 Coefficients and Lambda.1se values of the LASSO regression

Variables	Coefficients	lambda.1se
Age	0.003413166	0.02321508
Pregnancy		
Mid-pregnancy	-0.009577495	
Late pregnancy	0.077532466	
Residence	-0.010066029	
Only child	-0.004552276	
Degree of pregnancy reaction (Heavier)	0.036752621	
Pre-pregnancy physical condition		
General	0.053732756	
Poor	0.116491705	
Anxiety	0.042513948	
Family functions	0.014647170	
Depression	0.065748325	

Validation of the predictive nomograms

The performances of the prediction models were internally evaluated using the validation sets. First, all the proposed nomograms exhibited good performance in distinguishing the risk of sleep disorders within the validation sets. The AUC of the Model 1 was 0.678 (95% CI:0.635–0.720), with sensitivity and specificity based on the ROC being 69.4% and 59.6%, respectively (see Fig. 4A). The AUC of Model 2 was 0.719 (95% CI:0.678–0.761), with a sensitivity of 82.4% and a specificity of 54.8% (see Fig. 4B), indicating that the prediction model had a good capacity for identifying sleep disorders.

Second, the calibration curve of the model was shown in Fig. 5. The red solid line represents the ideal value,

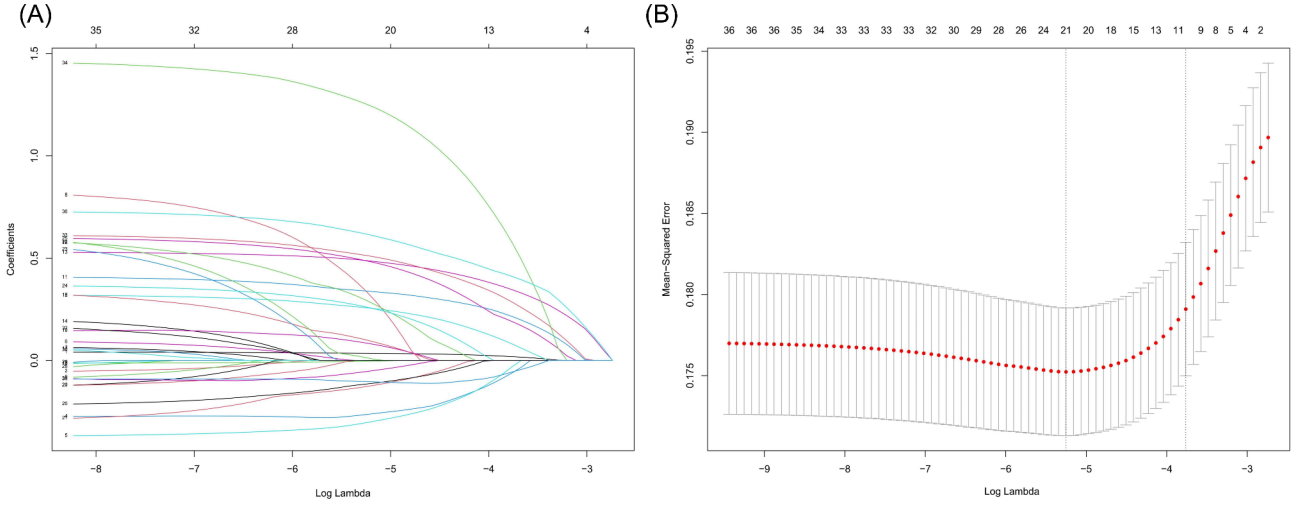

Fig. 2 Predictors were chosen through LASSO regression. (**A**) LASSO coefficient curves were plotted for 36 variables in accordance with the log(lambda) series. (**B**) The LASSO regression employed 10-fold cross-validation. Binomial deviance was plotted against log (lambda). Vertical dashed lines were drawn at the optimal values based on the minimum value criterion (left dashed line) and the 1 standard error criterion (right dashed line)

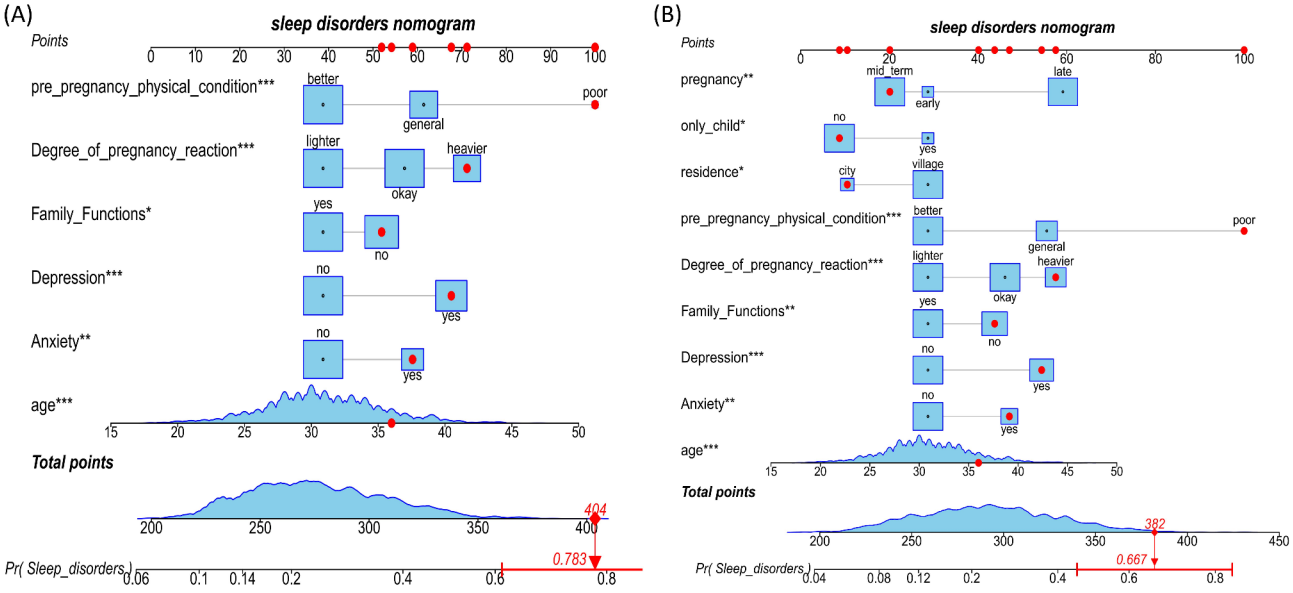

Fig. 3 Nomograms developed for predicting sleep disorders in pregnant women. (**A**) Nomogram of Model 1. At a baseline of 0-100 points, score lines were drawn for pre-pregnancy physical condition, degree of pregnancy reaction, family functions, depression, anxiety, and age, each having its own score range. (**B**) Nomogram of Model 2, score lines were assigned to pregnancy, only child, residence, pre-pregnancy physical condition, degree of pregnancy reaction, family function, depression, anxiety and age. As an example of using a nomogram, red dots are added to the graphs. The red dots on each variable in the graphs represent the patient's data values for each variable. A line is drawn upward to determine the number of points obtained for each variable value. After adding the points from all the variables, a line is drawn from the total points axis to determine the incidence of sleep disorders in pregnant women

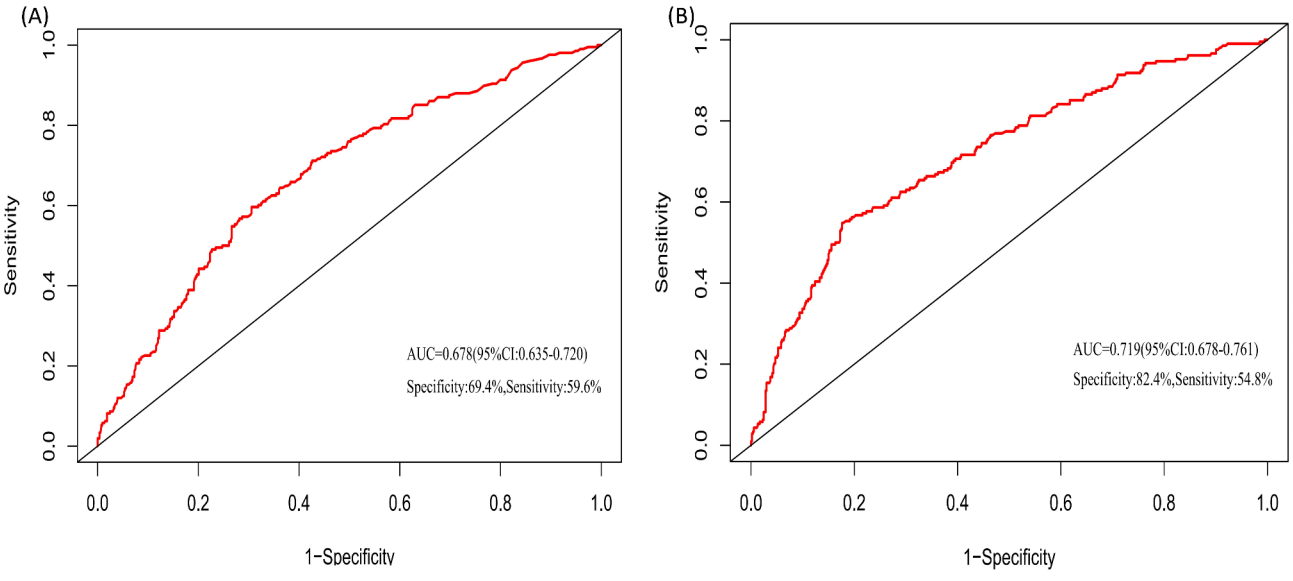

Fig. 4 The ROC curves for the prediction models. (**A**) The Model 1 achieved an AUC score of 0.678 (95% CI: 0.635–0.720), along with a sensitivity of 69.4% and a specificity of 59.6%. (**B**) Model 2 achieved an AUC score of 0.719 (95% CI: 0.678–0.761), along with a sensitivity of 82.4% and a specificity of 54.8%

the green solid line indicates the deviation correction through 1000-time Bootstrapping repetition, and the black dashed line shows the real value, as well as the diagonal dashed line. The closer the fit, the better the calibration effect and, consequently, the better the prediction effect. The calibration curve of Model 2 (see Fig. 5B) exhibits superior results in comparison to that of the Model 1 (see Fig. 5A).

Finally, the DCA presented the threshold probabilities of the validation set in the Model 1 and Model 2, respectively, and was utilized to evaluate the clinical effects of the nomogram more intuitively, suggesting that the nomogram had optimal predictive power (see Fig. 6). The

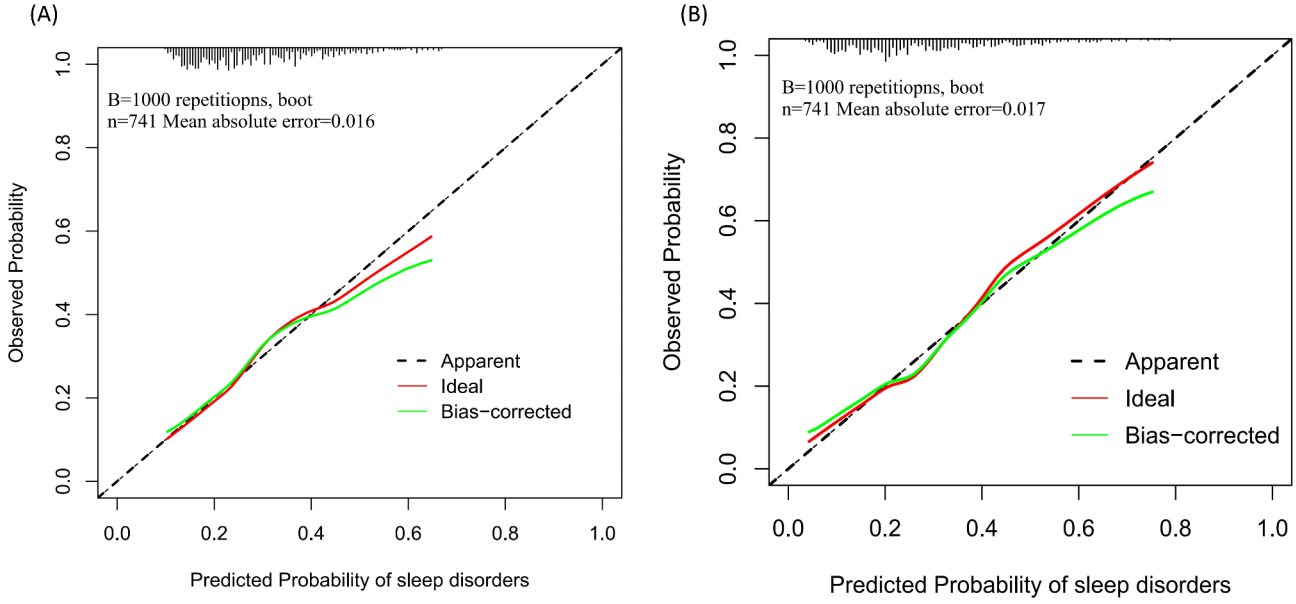

Fig. 5 Calibration plots of the prediction models in the validation set. In different prediction probability ranges, the apparent and bias-corrected curves show significant agreement with a certain deviation from the ideal line. (**A**) Calibration plot of Model 1. (**B**) Calibration plot of Model 2

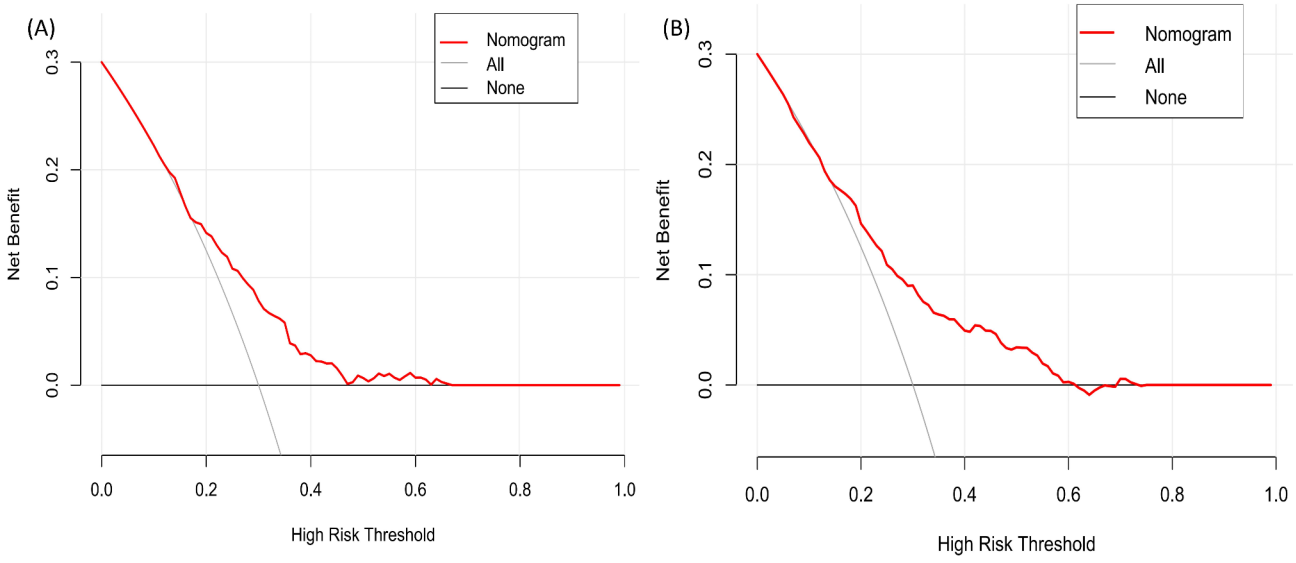

Fig. 6 The DCA curves for the prediction models. The solid black line denotes the assumption that all pregnant women are free from sleep disorders. The dotted line indicates the hypothesis that the pregnant woman has a sleep disorder. The red curving line represents the risk nomogram. (**A**) DCA curve of Model 1. (**B**) DCA curve of Model 2

DCA results reveal that Model 2 (see Fig. 6B) surpasses the Model 1 (see Fig. 6A) in terms of net benefit for assisted decision-making. Additionally, this model has significant clinical utility in predicting the risk of sleep disorders among pregnant women.

Discussion

In this study, we developed and validated a suitable and easy-to-calculate nomogram for predicting sleep disorders in pregnant women by using questionnaire data from pregnant women undergoing routine prenatal checkups at an outpatient clinic of a tertiary hospital in Ningxia. Among the 36 candidate variables analyzed, the Model 1 incorporated six key variables as predictors of maternal sleep disorders: age, anxiety, depression, family functioning, pre-pregnancy physical condition, and degree of early pregnancy reaction. Model 2 encompassed nine risk variables, with place of residence, whether the child was an only child, and gestation period being different from the Model 1. The remaining six variables were the same. Two nomograms based on the predictors of each of the two prediction models were constructed to predict the

risk of sleep disorders in pregnant women in the training set. Additionally, we verified the performance of the two nomograms in the validation set through an internal validation method. The plotted ROC and calibration plots indicated that Model 2 have better discriminatory ability and higher accuracy for disease risk of sleep disorders in pregnant women than the Model 1. Importantly, decision curve analysis has shown that these predictive models have significant clinical utility. Furthermore, Model 2 surpasses the Model 1 in terms of the net benefit of using nomogram-assisted decision-making techniques.

In our study, age was one of the predictors of the risk of sleep disorders among pregnant women. Previous studies have shown that increasing age is a determinant of sleep quality [36]. As age increased, pregnant women are more likely to experience sleep disorders during pregnancy, which is consistent with the study by Shao-Yu Tsai et al. [37]. Therefore, more attention and support should be given to the sleep health of senior pregnant women. Pregnant women residing in urban areas are more likely to have poor sleep quality than those in rural areas, possibly because rural-dwelling pregnant women are more likely to have adequate sleep time [38].

The findings of this study also indicate that anxiety and depression are significant factors in the prediction model as well. Previous studies have demonstrated that pregnant women with anxiety and depression [39], those with depression during the 20-30-week gestation period [40], and those with high levels of anxiety and depression at bedtime have a higher incidence of sleep disorders [41]. Huang, L.H. et al. also found that there is an association between shorter sleep duration and higher levels of anxiety or depression [42]. Moreover, a study by Qiu, C. et al. also revealed that women with depression or anxiety disorders are 1.95 times more likely to sleep no more than 6 h during early pregnancy [43].

Notably, a meta-analysis with data from 11,002 pregnant women indicated that the longitudinal study revealed a 1.68-percentage-point decrease in sleep quality from mid- to-late pregnancy [2]. The results of a recent study suggest that both mid and late pregnancy are predictors of poor sleep quality [44]. The results of this study demonstrated that a poorer prenatal physical condition is a predictor of sleep disorders among pregnant women. A study has shown that pregnant women with insomnia have higher subjective physical discomfort [45], which is consistent with our findings. Therefore, a healthy body can reduce the incidence of sleep problems in pregnant women. Meanwhile, our study found that being an only child, poor family functioning, and the degree of early pregnancy reaction are also risk factors for sleep disorders in pregnant women. This suggests that not being an only child, having good family functioning, and having a less severe degree of early pregnancy reaction can reduce the risk of sleep disorders in pregnant women.

The nomogram, a graphic calculation tool, has been used in medicine for decades to assist in analyzing clinical decisions at the patient's bedside [46]. Previous instruments, such as the PQSI, are scales for assessing sleep quality. Although these tools are of great value, the sleep-specific nomogram's ability to generate individualized predictions enables it to be used for the early identification of risk factors for sleep disorders in pregnant women. This, in turn, can lead to better prioritization and targeting of management interventions. Moreover, an increasing number of deep-learning-based models and methods that combine multiple biomarker assays are attracting significant attention in sleep science [47–49]. In some cases, these methods might exhibit high predictive accuracy; however, they may also face issues such as high data requirements and poor model interpretability. It is challenging for clinicians to understand how these models make predictions based on the internal structure of neural networks. In contrast, our method depends on easily accessible clinical and self-reported data and also has the advantages of simplicity and high interpretability. Thus, it is more suitable for routine use. In this study, both nomograms adhered to well-established standard processes for calibration, identification, and clinical application, and demonstrated satisfactory predictive performance.

The results of this study should be interpreted with several limitations in mind. First, the data were sourced from the same central hospital. Hence, a multicenter study is required to externally validate our nomogram prior to their wide application in clinical practice. Second, self-report instruments such as the PSQI are prone to recall bias and lack objective variables related to maternal sleep disorders, which will inevitably impact the predictive accuracy of the model. In future studies, multicenter collaborative studies should be carried out as much as possible to enhance the diversity and representativeness of the samples. More biomarkers, such as hormone levels in the blood and specific genetic markers that might be potentially associated with sleep disorders in pregnant women, should be considered for inclusion in the prediction model. At the same time, other types of data, like data on pregnant women's daily activities (obtained through wearable devices) and environmental factors (for example, the effect of noise, temperature, etc. on sleep), can be combined to further enrich the input information of the model and improve the accuracy and comprehensiveness of the model's prediction. Additionally, the specificity of the final prediction model of this study was 54.8%. The use of other advanced machine-learning algorithms or the improvement of the existing Logistic regression and LASSO regression should be explored. For instance,

deep-learning algorithms could be studied in conjunction with traditional methods, or hybrid models could be developed to characterize sleep disorders in pregnant women, thereby better capturing the nonlinear relationships and interactions among complex risk factors. Despite these limitations, the nomogram model is useful for predicting sleep disorders among pregnant women. The nomogram has proven to be a valid and instructive model, which can effectively provide clinicians with response times for implementing measures.

Conclusion

In summary, the proposed nomogram demonstrates excellent performances in terms of its discrimination capability, calibration, and clinical utility. Most importantly, Model 2 shows significant advantages over the Model 1 in predicting outcomes. Therefore, it can serve as a convenient and reliable tool for predicting the risk probability of sleep disorders among pregnant women.

Abbreviations

ROC	Receiver operating characteristic
AUC	Area under the ROC curve
DCA	Dcision curve analysis
PSQI	Pittsburg sleep quality index
EPDS	Edinburgh postnatal depression scale
APGAR	The Family Caringness Index Questionnaire

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Author contributions

SZG and DGY wrote the manuscript. YL made useful critique of this manuscript. All other authors (JJ, HYL, RW, JSZ, CL, SQM) critically revised the drafts of the manuscript. All authors read and approved the final manuscript.

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Data availability

The data that support the findings of this study are available from the corresponding author but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of the corresponding author.

Declarations

Ethics approval and consent to participate

All subjects signed an informed consent form prior to data collection. Ethical approval for the study was obtained from the Ethics Committee of Ningxia Medical University (No. 2022-G007) before the study started.

Competing interests

The authors declare no competing interests.

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