Heliyon 10 (2024) e39750

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Development and validation of a nomogram for predicting sleep disturbance in pregnant and postpartum women: A pilot study

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A R T I C L E I N F O

Keywords:
Pregnant and postpartum women
Sleep disturbance
Nomogram
Predictive model
Early intervention

A B S T R A C T

Background: Sleep disturbances are common in pregnant and postpartum women, impacting their health. Predictive tools for timely intervention are scarce.
Objective: To develop and validate a nomogram predicting sleep disturbance risk in this demographic.
Methods: We enrolled unipara with singleton pregnancies from Shenzhen hospitals in 2022, with complete data and survey cooperation. Data collected included demographics, pregnancy stage, systemic health, sleep status, and emotional state. Subjects were randomly assigned to training (70 %) and validation (30 %) groups. Risk factors were identified via logistic regression, and the nomogram was evaluated using calibration, ROC curves, and DCA.
Results: The study involved 727 women. Identified risk factors for sleep disturbance included education, income, and various systemic and emotional symptoms. The nomogram demonstrated strong predictive accuracy in both groups (AUC: 0.93 and 0.91), with calibration and DCA confirming its reliability.
Conclusion: The nomogram accurately predicts sleep disturbance risk, aiding early detection and improving sleep quality in pregnant and postpartum women. Its broader applicability will be confirmed in future studies.

1. Introduction

Sleep disturbance during pregnancy are highly prevalent. A study involving 486 participants found that 52.2 % of women experienced insomnia[1]. Another study indicated that more than half of pregnant women experience sleep disturbances[2], and this situation increases as pregnancy progresses[3]. Especially in the late stages of pregnancy, obstructive sleep apnea (OSA), insomnia, and restless leg syndrome are the most common sleep disorders[2]. Moreover, studies have shown that changes in sleep structure begin in early pregnancy and do not return to pre-pregnancy levels after delivery[4] (see Tables 1–5, Figs. 1–7).

The types of sleep disorders in pregnant and postpartum women are diverse, including insomnia, sleep apnea, and restless legs syndrome, among others [5]. These sleep disorders not only affect the health of the pregnant women themselves but may also have adverse effects on the fetus. For example, sleep apnea is associated with an increased risk of preterm birth, low birth weight, and neonatal hospitalization [6]. Sleep disorders in pregnant and postpartum women are associated with a range of adverse health outcomes. Studies have shown that sleep disorders are related to adverse pregnancy outcomes such as preeclampsia, preterm birth, low birth weight, and neonatal cardiac dysfunction[7,8]. In addition, sleep disorders are also related to psychological health issues in

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https://doi.org/10.1016/j.heliyon.2024.e39750
Received 10 July 2024; Received in revised form 22 October 2024; Accepted 22 October 2024
Available online 22 November 2024

Table 1
Baseline characteristics.

Variables	Total (n = 727)	test (n = 219)	train (n = 508)	Statistic	*P*
Age, Mean ± SD	29.56 ± 5.18	29.69 ± 5.50	29.50 ± 5.03	t = 0.46	0.646
Education, n (%)				$\chi^2 = 2.78$	0.596
Primary school and below	8 (1.10)	3 (1.37)	5 (0.98)		
Middle School	72 (9.90)	25 (11.42)	47 (9.25)		
High school/secondary school	147 (20.22)	37 (16.89)	110 (21.65)		
College/Vocational College	215 (29.57)	67 (30.59)	148 (29.13)		
Bachelor degree or above	285 (39.20)	87 (39.73)	198 (38.98)		
Job, n (%)				$\chi^2 = 3.65$	0.601
Civil servants, state-owned enterprises, public institution staff	116 (15.96)	42 (19.18)	74 (14.57)		
Self-employed/business service operators	135 (18.57)	36 (16.44)	99 (19.49)		
Unemployed	229 (31.50)	65 (29.68)	164 (32.28)		
Private enterprises, workers	193 (26.55)	60 (27.40)	133 (26.18)		
Soldier	1 (0.14)	0 (0.00)	1 (0.20)		
Others	53 (7.29)	16 (7.31)	37 (7.28)		
Income, n (%)				$\chi^2 = 3.46$	0.326
Less than 2000 yuan	179 (24.62)	51 (23.29)	128 (25.20)		
2000–5000 yuan	222 (30.54)	77 (35.16)	145 (28.54)		
5000–10000 yuan	211 (29.02)	61 (27.85)	150 (29.53)		
More than 10,000 yuan	115 (15.82)	30 (13.70)	85 (16.73)		
Pregnancy, n (%)				$\chi^2 = 3.35$	0.341
First trimester	59 (8.12)	17 (7.76)	42 (8.27)		
Second trimester	148 (20.36)	52 (23.74)	96 (18.90)		
Third trimester	102 (14.03)	25 (11.42)	77 (15.16)		
After delivery	418 (57.50)	125 (57.08)	293 (57.68)		
Sleep disturbance, n (%)				$\chi^2 = 0.19$	0.662
No	139 (19.12)	44 (20.09)	95 (18.70)		
Yes	588 (80.88)	175 (79.91)	413 (81.30)		
Complications, n (%)				$\chi^2 = 0.02$	0.878
No	246 (33.84)	75 (34.25)	171 (33.66)		
Yes	481 (66.16)	144 (65.75)	337 (66.34)		
Motor System symptoms, n (%)				$\chi^2 = 0.28$	0.600
No	252 (34.66)	79 (36.07)	173 (34.06)		
Yes	475 (65.34)	140 (63.93)	335 (65.94)		
Gastrointestinal Symptom, n (%)				$\chi^2 = 0.27$	0.603
No	180 (24.76)	57 (26.03)	123 (24.21)		
Yes	547 (75.24)	162 (73.97)	385 (75.79)		
Respiratory symptoms, n (%)				$\chi^2 = 0.33$	0.568
No	284 (39.06)	89 (40.64)	195 (38.39)		
Yes	443 (60.94)	130 (59.36)	313 (61.61)		
Circulatory symptoms, n (%)				$\chi^2 = 0.56$	0.452
No	287 (39.48)	91 (41.55)	196 (38.58)		
Yes	440 (60.52)	128 (58.45)	312 (61.42)		
Emotion, n (%)				$\chi^2 = 8.49$	0.075
Excellent	83 (11.42)	32 (14.61)	51 (10.04)		
Good	267 (36.73)	77 (35.16)	190 (37.40)		
Fair	314 (43.19)	84 (38.36)	230 (45.28)		
Poor	55 (7.57)	23 (10.50)	32 (6.30)		
Very Poor	8 (1.10)	3 (1.37)	5 (0.98)		

t: *t*-test, χ^2: Chi-square test.
SD: standard deviation.

pregnant women, such as depression[9]. Maternal sleep disorders may negatively impact the health of mothers and infants through biological pathways such as increasing inflammatory responses. Studies suggest that sleep disorders could contribute to the development of chronic diseases and adverse pregnancy outcomes by enhancing inflammatory responses, which are key biological pathways [8].

Currently, there is a variety of methods for predicting and assessing sleep disorders in pregnant and postpartum women, including questionnaires[10], scale assessments[4], machine learning algorithms[11], multidisciplinary team approaches[12], polysomnography[13], and the provision of education and resources[14]. Although these assessment methods can yield good results, the evaluation process is complex and requires more resources. In practical applications, especially in large-scale epidemiological studies, the use of scales and objective measurements may be limited by time and resources. From a data management standpoint, large-scale epidemiological studies necessitate the processing and coordination of diverse data types, including demographic, environmental, biological samples, laboratory, analytical, and molecular data. This task is not only voluminous but also demands sophisticated data mining techniques to extract meaningful insights [15]. In terms of resource planning, such extensive epidemiological surveys must address crucial questions related to resource allocation, including the study's time frame, personnel requirements, and cost estimations [16]. Effective planning in these areas is essential to ensure the study's feasibility and success.

Table 2
Incidence of sleep disturbance in the training group.

Variables	Total (n = 508)	No Sleep disturbance (n = 95)	Sleep disturbance (n = 413)	Statistic	*P*
Age, Mean ± SD	29.50 ± 5.03	30.65 ± 5.31	29.24 ± 4.94	t = 2.48	**0.013**
Education, n (%)				$\chi^2 = 9.16$	0.057
Primary school and below	5 (0.98)	3 (3.16)	2 (0.48)		
Middle School	47 (9.25)	8 (8.42)	39 (9.44)		
High school/secondary school	110 (21.65)	16 (16.84)	94 (22.76)		
College/Vocational College	148 (29.13)	24 (25.26)	124 (30.02)		
Bachelor degree or above	198 (38.98)	44 (46.32)	154 (37.29)		
Job, n (%)				$\chi^2 = 6.92$	0.226
Civil servants, state-owned enterprises, public institution staff	74 (14.57)	16 (16.84)	58 (14.04)		
Self-employed/business service operators	99 (19.49)	19 (20.00)	80 (19.37)		
Unemployed	164 (32.28)	21 (22.11)	143 (34.62)		
Private enterprises, workers	133 (26.18)	32 (33.68)	101 (24.46)		
Soldier	1 (0.20)	0 (0.00)	1 (0.24)		
Others	37 (7.28)	7 (7.37)	30 (7.26)		
Income, n (%)				$\chi^2 = 19.86$	**<.001**
Less than 2000 yuan	128 (25.20)	20 (21.05)	108 (26.15)		
2000–5000 yuan	145 (28.54)	16 (16.84)	129 (31.23)		
5000–10000 yuan	150 (29.53)	30 (31.58)	120 (29.06)		
More than 10,000 yuan	85 (16.73)	29 (30.53)	56 (13.56)		
Pregnancy, n (%)				$\chi^2 = 161.06$	**<.001**
First trimester	42 (8.27)	21 (22.11)	21 (5.08)		
Second trimester	96 (18.90)	39 (41.05)	57 (13.80)		
Third trimester	77 (15.16)	35 (36.84)	42 (10.17)		
After delivery	293 (57.68)	0 (0.00)	293 (70.94)		
Complications, n (%)				$\chi^2 = 128.20$	**<.001**
No	171 (33.66)	79 (83.16)	92 (22.28)		
Yes	337 (66.34)	16 (16.84)	321 (77.72)		
Motor System symptoms, n (%)				$\chi^2 = 165.93$	**<.001**
No	173 (34.06)	86 (90.53)	87 (21.07)		
Yes	335 (65.94)	9 (9.47)	326 (78.93)		
Gastrointestinal symptoms, n (%)				$\chi^2 = 101.88$	**<.001**
No	123 (24.21)	61 (64.21)	62 (15.01)		
Yes	385 (75.79)	34 (35.79)	351 (84.99)		
Respiratory symptoms, n (%)				$\chi^2 = 139.80$	**<.001**
No	195 (38.39)	87 (91.58)	108 (26.15)		
Yes	313 (61.61)	8 (8.42)	305 (73.85)		
Circulatory symptoms, n (%)				$\chi^2 = 161.38$	**<.001**
No	196 (38.58)	91 (95.79)	105 (25.42)		
Yes	312 (61.42)	4 (4.21)	308 (74.58)		
Emotion, n (%)				$\chi^2 = 33.61$	**<.001**
Excellent	51 (10.04)	17 (17.89)	34 (8.23)		
Good	190 (37.40)	53 (55.79)	137 (33.17)		
Fair	230 (45.28)	23 (24.21)	207 (50.12)		
Poor	32 (6.30)	2 (2.11)	30 (7.26)		
Very Poor	5 (0.98)	0 (0.00)	5 (1.21)		

t: *t*-test, χ^2: Chi-square test.
SD: standard deviation.

Direct inquiry into self-perceived symptoms and review of existing clinical diagnoses in medical records is a method that can efficiently collect data and is feasible for initial screening. For example, the "Health Line" is a simple and comprehensive method for collecting data on individuals' self-rated health changes over time, which has proven effective in practical applications[17]. Moreover, a new method of telephone symptom scoring is highly correlated with the results of the visual analog scale (VAS), and most patients prefer this new method because it is easier to estimate symptom severity and to execute[18]. To improve the accuracy of the collected data, the analysis of self-reported data can be enhanced by using clinical information from examination-based health surveys, thereby reducing the impact of measurement errors on health and health disparity measurements[19].

Nomograms, as predictive tools, have the advantage of being easy to use and visually presenting predicted probabilities ([20,21]; [35]). The significance of predictive models within the realms of medicine and public health is undeniable. These models ascertain the likelihood of specific diseases or health events by assimilating various individual variables, including age, sex, medical history, and

Table 3
Univariate analysis and multivariate logistic regression analysis.

Variables	Univariate logistic regression analysis					Multivariate logistic regression analysis				
	β	S.E	Z	*P*	OR (95%CI)	β	S.E	Z	*P*	OR (95%CI)
Education										
1					1.00 (Reference)					1.00 (Reference)
2	1.99	0.99	2.01	**0.045**	7.31 (1.05–51.10)	16.73	1376.09	0.01	0.990	18401898.28 (0.00 ~ Inf)
3	2.18	0.95	2.29	**0.022**	8.81 (1.36–56.95)	16.47	1376.09	0.01	0.990	14250442.97 (0.00 ~ Inf)
4	2.05	0.94	2.18	**0.029**	7.75 (1.23–48.89)	16.31	1376.09	0.01	0.991	12071834.31 (0.00 ~ Inf)
5	1.66	0.93	1.79	0.074	5.25 (0.85–32.41)	16.83	1376.09	0.01	0.990	20457300.70 (0.00 ~ Inf)
Job										
1					1.00 (Reference)					1.00 (Reference)
2	0.15	0.38	0.39	0.694	1.16 (0.55–2.45)	−0.17	0.53	−0.33	0.744	0.84 (0.29–2.40)
3	0.63	0.37	1.72	0.085	1.88 (0.92–3.85)	0.39	0.77	0.51	0.612	1.48 (0.33–6.62)
4	−0.14	0.35	−0.40	0.690	0.87 (0.44–1.72)	−0.11	0.47	−0.23	0.818	0.90 (0.36–2.24)
5	12.28	535.41	0.02	0.982	214961.07 (0.00 ~ Inf)	−29.45	31706.68	−0.00	0.999	0.00 (0.00 ~ Inf)
6	0.17	0.51	0.33	0.741	1.18 (0.44–3.19)	−0.57	0.80	−0.72	0.472	0.56 (0.12–2.69)
Income										
1					1.00 (Reference)					1.00 (Reference)
2	0.40	0.36	1.11	0.265	1.49 (0.74–3.02)	1.38	0.70	1.96	0.050	3.96 (1.00–15.72)
3	−0.30	0.32	−0.94	0.345	0.74 (0.40–1.38)	0.77	0.78	0.98	0.327	2.15 (0.47–9.93)
4	−1.03	0.33	−3.08	**0.002**	0.36 (0.19–0.69)	−0.12	0.83	−0.14	0.890	0.89 (0.17–4.56)
Pregnancy										
1					1.00 (Reference)					1.00 (Reference)
2	0.38	0.37	1.02	0.308	1.46 (0.70–3.03)	0.32	0.43	0.75	0.454	1.38 (0.59–3.23)
3	0.18	0.38	0.47	0.635	1.20 (0.57–2.55)	0.27	0.47	0.56	0.573	1.31 (0.52–3.30)
4	20.57	1035.82	0.02	0.984	854535428.53 (0.00 ~ Inf)	31.02	1948.82	0.02	0.987	29621973965783.54 (0.00 ~ Inf)
Complications										
0					1.00 (Reference)					1.00 (Reference)
1	2.85	0.30	9.53	**<.001**	17.23 (9.60–30.93)	0.05	0.41	0.12	0.904	1.05 (0.47–2.32)
Motor										
0					1.00 (Reference)					1.00 (Reference)
1	3.58	0.37	9.66	**<.001**	35.81 (17.32–74.02)	1.45	0.47	3.10	**0.002**	4.25 (1.70–10.62)
Gastrointestinal										
0					1.00 (Reference)					1.00 (Reference)
1	2.32	0.25	9.11	**<.001**	10.16 (6.17–16.73)	0.62	0.34	1.86	0.063	1.87 (0.97–3.61)
Respiratory										
0					1.00 (Reference)					1.00 (Reference)
1	3.42	0.39	8.87	**<.001**	30.71 (14.41–65.45)	−0.46	0.59	−0.79	0.430	0.63 (0.20–1.99)
Circulatory										
0					1.00 (Reference)					1.00 (Reference)
1	4.20	0.52	8.03	**<.001**	66.73 (23.93–186.08)	0.69	0.67	1.02	0.306	1.99 (0.53–7.43)
Emotion										
1					1.00 (Reference)					1.00 (Reference)
2	0.26	0.34	0.76	0.448	1.29 (0.67–2.51)	0.25	0.51	0.50	0.618	1.29 (0.48–3.49)
3	1.50	0.37	4.07	**<.001**	4.50 (2.18–9.28)	1.17	0.53	2.20	**0.028**	3.23 (1.13–9.21)
4	2.01	0.79	2.56	**0.011**	7.50 (1.60–35.17)	1.66	1.05	1.59	0.112	5.27 (0.68–41.00)
5	14.87	650.87	0.02	0.982	2878906.43 (0.00 ~ Inf)	18.83	12123.54	0.00	0.999	150026818.42 (0.00 ~ Inf)

OR: Odds Ratio, CI: Confidence Interval.

physiological measurements. Consequently, they offer valuable decision-making support to both medical professionals and patients [36]. In settings characterized by resource constraints, the implementation of predictive models is especially crucial. They facilitate the swift identification of high-risk patient groups by healthcare providers, thereby enabling preemptive interventions and tailored treatments. This capability is pivotal for enhancing patient outcomes and alleviating the strain on healthcare systems [22,23].

This study aims to develop a rapid and straightforward evaluation method that focuses on the self-perceived symptoms of the research subjects and existing clinical diagnoses, without the need for scale assessment results or other objective indicators that require re-evaluation. This method is highly convenient in large-scale epidemiological surveys, aiding in the quick screening and identification of individuals in need of further professional assessment, thereby providing support for clinical decision-making.

2. Methods

2.1. Study design

The purpose of this research is to develop a nomogram for predicting the risk of sleep disturbance in pregnant and postpartum women and to validate its effectiveness. This study employed a cross-sectional design aimed at collecting baseline data and self-perceived symptom data from pregnant and postpartum women to establish a predictive model.

Table 4
Multivariate logistic regression analysis.

Variables	β	S.E	Z	*P*	OR (95%CI)
Intercept	−18.30	1379.07	−0.01	0.989	0.00 (0.00 ∼ Inf)
Education					
Primary school and below					1.00 (Reference)
Middle School	17.03	1379.07	0.01	0.990	24893423.20 (0.00 ∼ Inf)
High school/secondary school	16.84	1379.07	0.01	0.990	20483959.66 (0.00 ∼ Inf)
College/Vocational College	16.69	1379.07	0.01	0.990	17801915.27 (0.00 ∼ Inf)
Bachelor degree or above	17.23	1379.07	0.01	0.990	30442360.17 (0.00 ∼ Inf)
Income					
Less than 2000 yuan					1.00 (Reference)
2000–5000 yuan	1.00	0.51	1.97	**0.049**	2.72 (1.01–7.34)
5000–10000 yuan	0.27	0.50	0.54	0.589	1.31 (0.49–3.46)
More than 10,000 yuan	−0.59	0.57	−1.04	0.298	0.55 (0.18–1.69)
Pregnancy					
First trimester					1.00 (Reference)
Second trimester	0.33	0.43	0.76	0.445	1.38 (0.60–3.19)
Third trimester	0.30	0.46	0.64	0.519	1.34 (0.55–3.30)
After delivery	31.51	1954.67	0.02	0.987	48416825394569.44 (0.00 ∼ Inf)
Complications					
No					1.00 (Reference)
Yes	0.04	0.40	0.09	0.928	1.04 (0.47–2.28)
Motor System symptoms					
No					1.00 (Reference)
Yes	1.49	0.46	3.23	**0.001**	4.45 (1.80–11.02)
Gastrointestinal symptoms					
No					1.00 (Reference)
Yes	0.63	0.33	1.91	0.056	1.88 (0.99–3.60)
Respiratory symptoms					
No					1.00 (Reference)
Yes	−0.48	0.58	−0.83	0.405	0.62 (0.20–1.92)
Circulatory symptoms					
No					1.00 (Reference)
Yes	0.64	0.67	0.96	0.336	1.90 (0.51–7.02)
Emotion					
Excellent					1.00 (Reference)
Good	0.29	0.49	0.59	0.555	1.34 (0.51–3.53)
Fair	1.19	0.52	2.28	**0.023**	3.30 (1.18–9.20)
Poor	1.80	1.03	1.74	0.081	6.04 (0.80–45.62)
Very Poor	18.75	10694.70	0.00	0.999	139565202.77 (0.00 ∼ Inf)

OR: Odds Ratio, CI: Confidence Interval.

Table 5
Confusion matrix.

Data	AUC (95%CI)	Accuracy (95%CI)	Sensitivity (95%CI)	Specificity (95%CI)	PPV (95%CI)	NPV (95%CI)	cut off
Train	0.93 (0.91–0.95)	0.87 (0.84–0.90)	0.86 (0.79–0.93)	0.88 (0.84–0.91)	0.62 (0.53–0.70)	0.97 (0.95–0.98)	0.619
Test	0.91 (0.87–0.95)	0.85 (0.80–0.90)	0.75 (0.62–0.88)	0.88 (0.83–0.93)	0.61 (0.48–0.74)	0.93 (0.90–0.97)	0.619

2.2. Study site and time frame

The study was conducted in outpatient clinics of various hospitals in Shenzhen City, with a time span from June 2022 to June 2023. In this investigation, we utilized a convenience sampling approach to collect samples from hospitals across the 10 administrative districts encompassing the city in which our research institute is situated. The sample size was meticulously determined in alignment with the demographic distribution of each district, ensuring a proportional representation that mirrors the population size.

Our study has been approved by Ethics Committee of Shenzhen Maternal and Child Health Care Hospital with the ethics approval number SFYLS2022006. We are committed to the ethical standards of the Helsinki Declaration and to protecting the rights and privacy of all participants in our research.

2.3. Study subjects

Inclusion Criteria: Pregnant and postpartum women included in this study met the following conditions: receiving physical examinations in the hospital's obstetrics department or delivering in the hospital, all unipara, all with singleton pregnancies, with complete clinical data, and willing to cooperate with the survey. All study subjects and their families provided informed consent for this study.

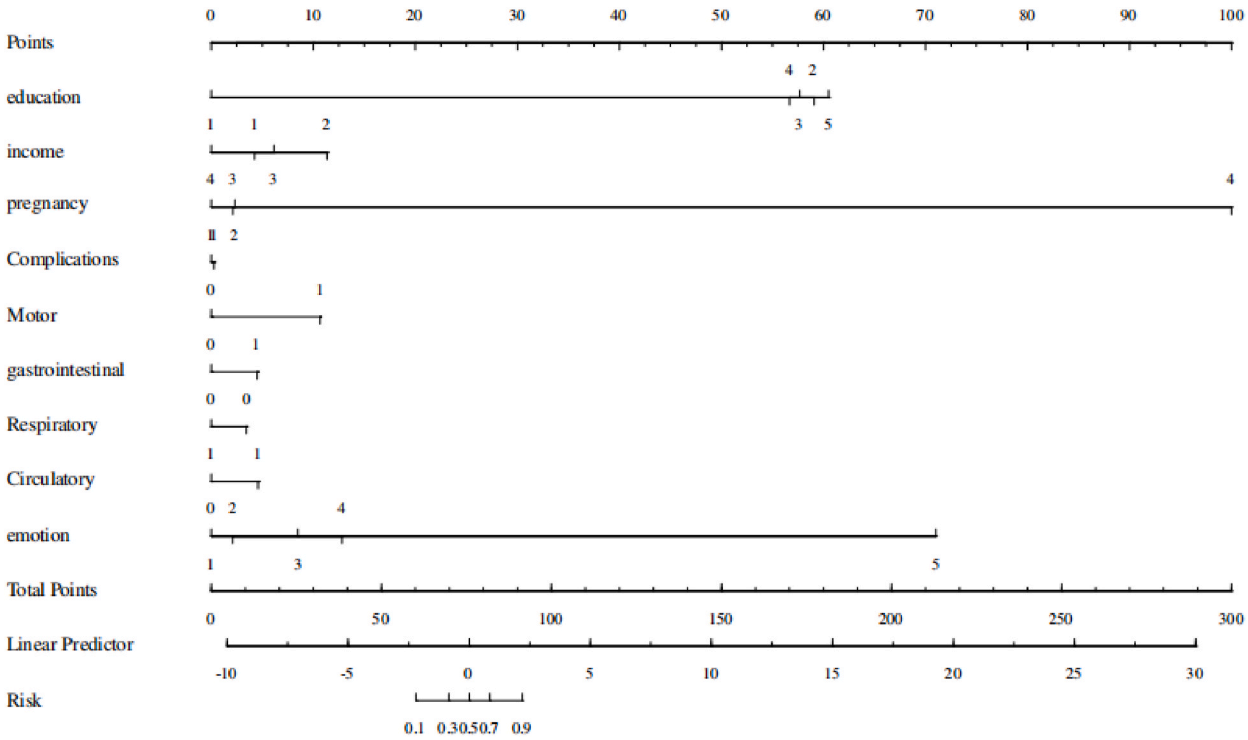

Fig. 1. Nomogram model.
The education level is coded as follows: Primary school and below (1), Middle School (2), High school/secondary school (3), College/Vocational College (4), and Bachelor degree or above (5). Income is categorized into Less than 2000 yuan (1), 2000 to 5000 yuan (2), 5000 to 10000 yuan (3), and More than 10,000 yuan (4). Pregnancy stages are denoted as First trimester (1), Second trimester (2), Third trimester (3), and After delivery (4). Complications are marked with No (0) and Yes (1). Symptom presence is similarly coded as No (0) and Yes (1) for Motor System, Gastrointestinal, Respiratory, and Circulatory symptoms. Emotional states are quantified as Excellent (1), Good (2), Fair (3), Poor (4), and Very Poor (5).
Initially, ascertain the numerical value associated with each predictor for an individual. For instance, if the variable in question is "level of education," and the individual's educational attainment is "college," locate the corresponding value, "4," on the "education" axis. Should the individual present with a "gastrointestinal" issue, identify the "gastrointestinal" axis and the corresponding value, "1," on the graph. Subsequently, construct a straight line from the value point of each predictor to the "Points" axis at the top. These lines should intersect on the "Points" axis. The subsequent step involves calculating the aggregate score, which is the sum of the individual scores corresponding to the values of all predictors. Ultimately, based on the computed total score, extend a straight line to the "risk" axis at the bottom, representing the probability of risk occurrence associated with the total score.

Exclusion Criteria: Those with severe mental disorders, communication barriers, incomplete clinical data for pregnant and postpartum women, severe organ dysfunction such as heart, liver, and kidney, and those who for various reasons did not cooperate with the survey.

2.4. Data collection

2.4.1. Baseline data

Basic information of pregnant and postpartum women was collected, including age, occupation, income, education, and pregnancy stage.

2.4.2. Symptoms of various body systems

Symptoms of various body systems were determined based on the study subjects' self-perceived physical symptoms and hospital diagnoses. These include: ① Pregnancy-related complications: such as diabetes, hypertension, anemia, etc.; ② Musculoskeletal system symptoms: such as muscle and joint pain; ③ Gastrointestinal symptoms: such as nausea, vomiting, constipation, and gastrointestinal discomfort; ④ Respiratory system symptoms: such as colds, cough, and pneumonia; ⑤ Circulatory system symptoms: such as palpitations and edema; ⑥ Nervous system symptoms: such as headaches and dizziness.

2.4.3. Manifestations of sleep disturbance and negative emotions

The manifestations of sleep disturbance and negative emotions were also based on the study subjects' self-perceived symptoms and hospital diagnoses. In this study, "sleep disturbance" was defined based on the presence of any of the following symptoms: insomnia,

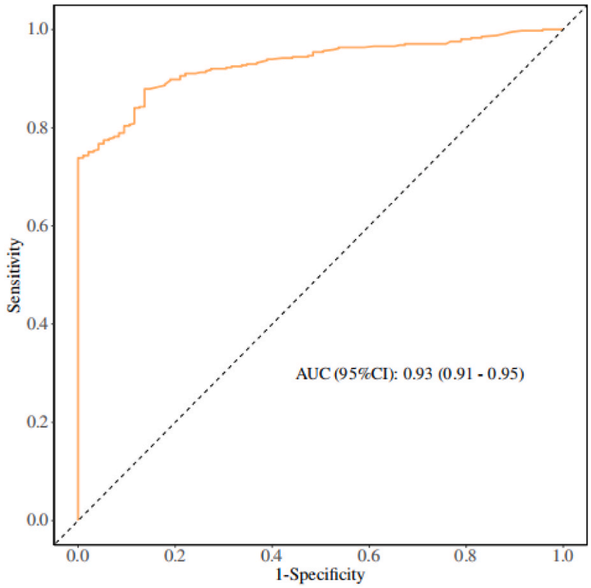

Fig. 2. ROC curve for the training group.

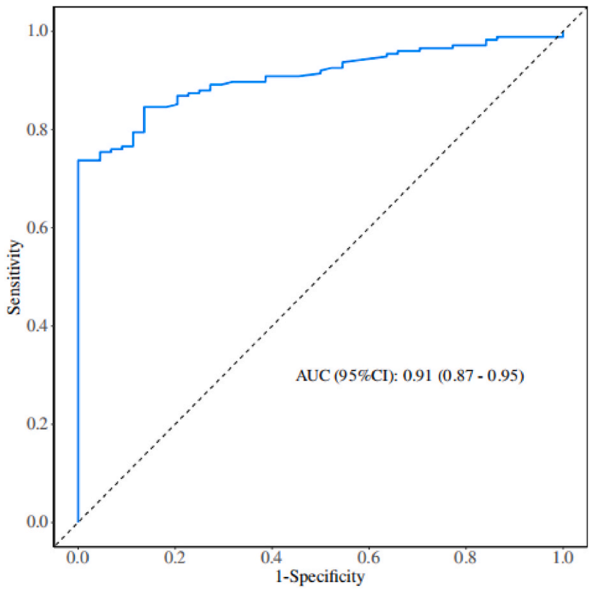

Fig. 3. ROC curve for the validation group.

sleep-disordered breathing, excessive sleepiness, frequent dreaming, disturbed sleep rhythm, shortened sleep duration, or other conditions that impede sleep, as delineated by the International Classification of Sleep Disorders (ICSD). Our focus was particularly on common sleep issues encountered during the postpartum period, including nocturnal awakenings, sleep deprivation, and diminished sleep quality.

"Negative emotions" were quantified through self-reported questionnaires, wherein subjects rated their emotional state on a scale from 0 to 100, with 0 indicating the most adverse mood and 100 indicating the most favorable mood. The emotional status was stratified into five categories based on the scores: very poor (0–20), poor (21–40), fair (41–60), good (61–80), and very good (81–100). Negative emotional states include psychological conditions such as irritability, anxiety, depression, and fear. We ensured that all participants were thoroughly briefed on the scoring guidelines, and these definitions were rigorously applied in our analysis to categorize and discuss the data.

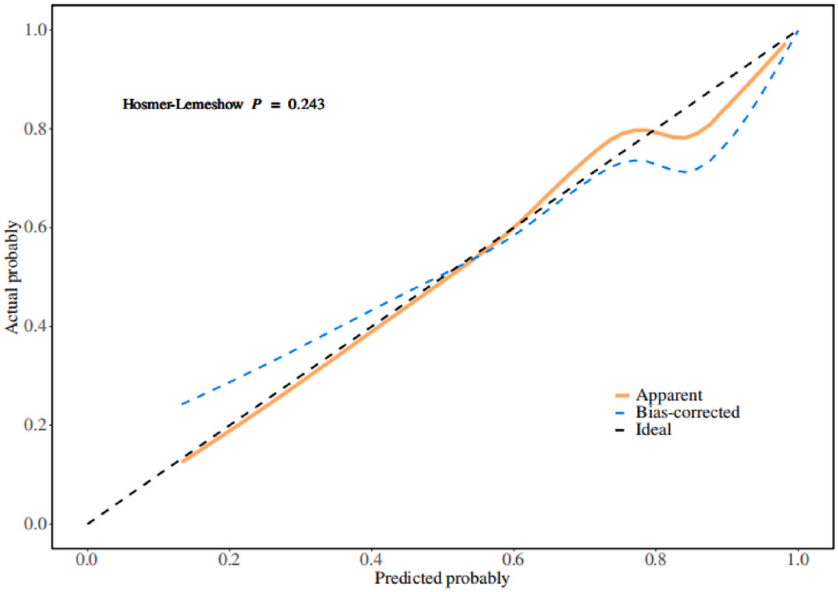

Fig. 4. Calibration curves for the training set.

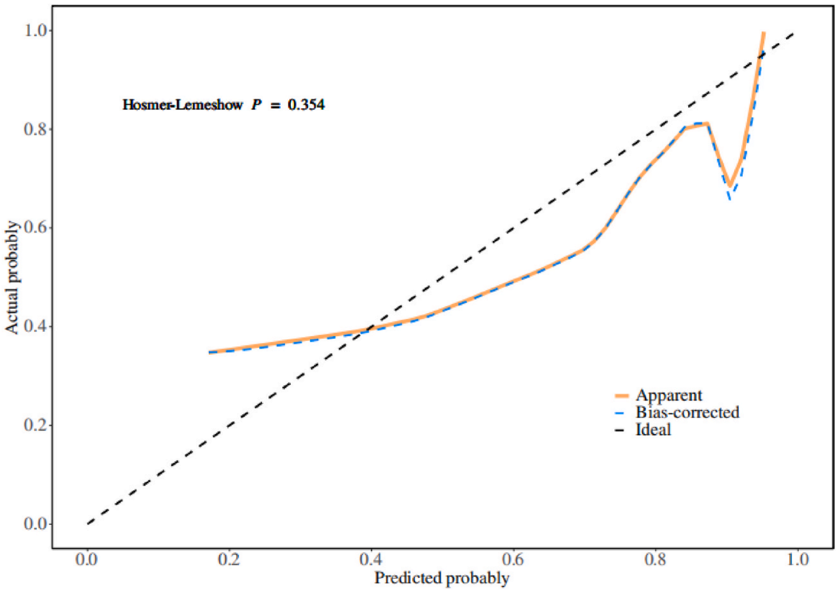

Fig. 5. Calibration curves for the validation set.

3. Statistical analysis

3.1. Data cleaning and outlier management

Initially, we conducted a comprehensive review of the dataset to identify any missing values. To address these gaps, we employed multiple imputation, a technique that estimates missing values by generating plausible replacements based on the relationships among other variables within the dataset. All imputation processes were executed using statistical software, ensuring the randomness and validity of the imputed data. For outlier detection, we utilized statistical methods such as boxplots and z-scores to scrutinize the data. Each outlier was subjected to a detailed examination to ascertain whether it stemmed from data entry errors or other discernible causes. For outliers that could not be explained by such reasons, we implemented appropriate corrective actions, including substitution or removal, to prevent any negative impact on the analytical outcomes.

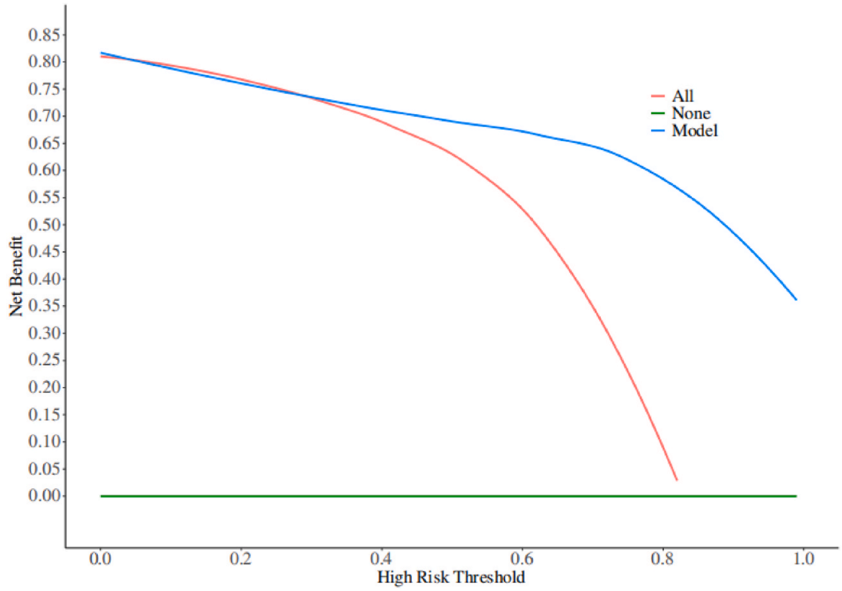

Fig. 6. Decision curve analysis for the training set.

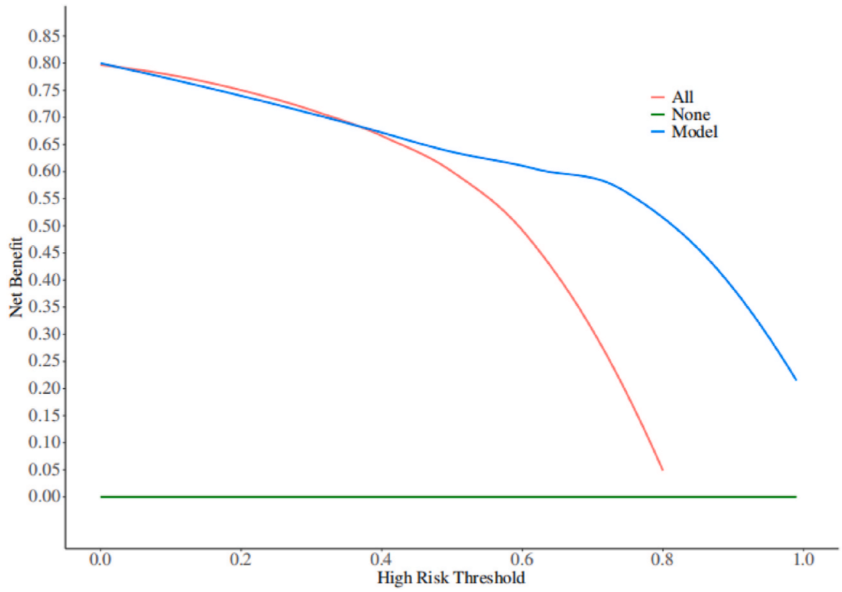

Fig. 7. Decision curve analysis for the validation set.

3.2. Randomization and grouping

Pregnant and postpartum women were randomly assigned to the training group (70 %) and the validation group (30 %).

3.3. Descriptive statistics

Descriptive statistical methods such as frequency, percentage, mean, and standard deviation will be used to describe the baseline characteristics of pregnant and postpartum women.

3.4. Risk factor identification

We initiated our analysis with a descriptive statistical approach to comprehend the fundamental characteristics and distribution patterns of the data. Subsequently, logistic regression analysis was employed to identify potential risk factors linked to sleep disorders. In the initial analysis, all conceivable descriptive variables and complications were considered as candidate variables for inclusion in the model.

Univariate and multivariate logistic regression analysis will be conducted to identify independent risk factors associated with sleep disorders in pregnant and postpartum women.

3.5. Nomogram development

Based on the results of the multivariate regression analysis, a nomogram prediction model will be developed, and scores will be assigned to each independent risk factor.

3.6. Model validation

The predictive accuracy and clinical utility of the nomogram will be assessed using calibration curves, ROC curves, and DCA. Calibration curves will be used to assess the agreement between the predicted probabilities and the actual outcomes. Receiver Operating Characteristic (ROC) curves will be generated to evaluate the model's discriminative ability. The area under the ROC curve (AUC) will be calculated, and its interpretation in terms of the model's performance will be provided. Decision Curve Analysis (DCA) will be performed to determine the net benefit of the nomogram at various threshold probabilities.

3.7. Statistical software

Data analysis will be performed using R software and SPSS software.

4. Results

4.1. Baseline characteristics of study subjects

A total of 727 pregnant and postpartum women were included in this study and randomly assigned to the training group (70 %) and the validation group (30 %). The baseline characteristics of the training and validation groups are shown in the following table.

4.2. Incidence of sleep disturbance

In the training group, 413 pregnant and postpartum women (accounting for 81.30 % of the training group) reported sleep disturbance. In the validation group, 175 pregnant and postpartum women (accounting for 79.91 % of the validation group) reported sleep disturbance. The average age of these women was 29.24 $\pm$ 4.94 years. In terms of education level, pregnant and postpartum women with a secondary school education level had the highest proportion, accounting for 9.44 % of the group with sleep disturbance. Among all occupational statuses, unemployed pregnant and postpartum women had the highest proportion, reaching 34.62 %. Among all income levels, those with a monthly income of 2000–5000 yuan had the highest proportion, accounting for 31.23 % of the group with sleep disturbance. Among all stages of pregnancy, postpartum women had the highest proportion, reaching 70.94 %, which may be related to the challenges of postpartum physical recovery and neonatal care. For more details, see the table.

4.3. Analysis of risk factors in the training group

Univariate analysis in the training group revealed that education level (Middle School, High School/Secondary School, College/Vocational College), monthly income over 10,000 yuan, complications, and the presence of musculoskeletal symptoms, digestive system symptoms, respiratory system symptoms, and circulatory system symptoms were significantly associated with the occurrence of sleep disturbance ($P < 0.05$). Specifically, the odds ratio (OR) for sleep disturbance among pregnant and postpartum women with a middle school education level was 7.31, for high school/secondary school it was 8.81, and for college/vocational college it was 7.75. A monthly income over 10,000 yuan had an OR of 0.36, indicating that lower income is associated with an increased risk of sleep disturbance. The OR for complications was 17.23, showing a significant increase in the risk of sleep disturbance among those with complications. The OR for musculoskeletal symptoms was 35.81, for digestive system symptoms it was 10.16, for respiratory system symptoms it was 30.71, and for circulatory system symptoms it was 66.73, demonstrating a significant association between physical symptoms and the high risk of sleep disturbance.

Multivariate logistic regression analysis further confirmed that a monthly income of 2000–5000 yuan (adjusted OR value of 1.49, 95 % CI: 1.01 to 7.34), complications (adjusted OR value of 17.23, 95 % CI: 9.60 to 30.93), musculoskeletal symptoms (adjusted OR value of 35.81, 95 % CI: 17.32 to 74.02), digestive system symptoms (adjusted OR value of 10.16, 95 % CI: 6.17 to 16.73), and respiratory system symptoms (adjusted OR value of 30.71, 95 % CI: 14.41 to 65.45) are independent predictive factors for sleep disturbance. Additionally, "Fair" (adjusted OR value of 4.50, 95 % CI: 2.18 to 9.28) and "Poor" (adjusted OR value of 7.50, 95 % CI: 1.60 to 35.17) emotional states were also significantly associated with sleep disturbance. Among these, a monthly income of 2000–5000 yuan, musculoskeletal symptoms, and "Fair" emotional state were statistically significant.

4.4. Establishment and performance of the nomogram model in the training group

The data from the training group was used to establish a nomogram model that included variables such as the education level, income, pregnancy stage, complications, musculoskeletal symptoms, digestive system symptoms, respiratory system symptoms, circulatory system symptoms, and emotional state of pregnant and postpartum women. Each variable was assigned different scores based on its impact on sleep disturbance, thus calculating the total score of the pregnant and postpartum women and predicting their risk of sleep disturbance accordingly. The AUC of the ROC curve for the training group was 0.93, with a 95 % confidence interval (CI) of 0.91–0.95, indicating that the model has excellent discriminative ability and can accurately identify pregnant and postpartum women at risk of sleep disturbance.

4.5. Validation of the nomogram model in the validation group

In the validation group, the AUC of the nomogram model was 0.91, with a 95 % confidence interval (CI) of 0.87–0.95, indicating that the model has good predictive accuracy in an independent cohort.

4.6. Confusion matrix

The AUC of the ROC curve for the training set reached 0.93 (95 % CI: 0.91–0.95), indicating that the model has excellent discriminative ability on the training data. The accuracy of the model was 0.87 (95 % CI: 0.84–0.90), the sensitivity was 0.86 (95 % CI: 0.79–0.93), and the specificity was 0.88 (95 % CI: 0.84–0.91). The positive predictive value (PPV) was 0.62 (95 % CI: 0.53–0.70), while the negative predictive value (NPV) was as high as 0.97 (95 % CI: 0.95–0.98). These results further confirm the effectiveness of the model in predicting sleep disturbance.

In the independent validation set, the model also showed good performance, with an AUC of 0.91 (95 % CI: 0.87–0.95), an accuracy of 0.85 (95 % CI: 0.80–0.90), a sensitivity of 0.75 (95 % CI: 0.62–0.88), and a specificity of 0.88 (95 % CI: 0.83–0.93). These indicators are consistent with the results of the training set, verifying the generalization ability of the model.

4.7. Calibration curves for the training and validation sets

When evaluating the calibration curve of the model in the training set, we used the Hosmer-Lemeshow test to determine whether the predicted probabilities of the model are consistent with the actual observed events. The test result showed a P-value of 0.243, which means we did not find a statistically significant difference, indicating that our model has a good fit in predicting sleep disturbance in pregnant and postpartum women. The predicted probabilities are consistent with the actual occurrence of sleep disturbance, and the model is accurate and reliable. Similarly, when analyzing the independent validation set, the P-value of the Hosmer-Lemeshow test for the validation set was 0.354, showing good fit of the model on the validation set. This means that our model not only performs well on the training set but also accurately predicts the sleep disorder situation of pregnant and postpartum women on an independent dataset.

4.8. Decision curve analysis (DCA)

For the training set, when the acceptable risk threshold is set at 80 %, the nomogram model showed the maximum net benefit. This indicates that on the training data, the model can effectively distinguish between pregnant and postpartum women with and without sleep disturbance, maximizing the benefits of prediction under the selected risk threshold.

On the validation set, we observed similar results. When the risk threshold is set at 78 %, the model's net benefit on the independent dataset reaches its maximum. This verifies the model's generalization ability and indicates that it can provide accurate predictions on new, unseen data.

5. Discussion

There is a deficiency in research predicting sleep disturbance in pregnant and postpartum women. Although existing studies have shown an association between sleep disturbance during pregnancy and adverse pregnancy outcomes, such as preterm birth, low birth weight, and pregnancy-induced hypertension ([34]; [8,24]), these studies tend to focus on specific types of sleep disorders (such as sleep apnea), and there is relatively less research on other types of sleep problems, such as insomnia and nocturnal awakenings. Moreover, although some studies have pointed out the prevalence of sleep disorders during pregnancy and their potential impact on maternal and infant health [4,25,26], there is still a lack of research on how to effectively identify and manage these sleep issues. For instance, some studies have proposed the use of exhaled nitric oxide as a biomarker for screening obstructive sleep apnea during pregnancy[27], but this method has only moderate sensitivity and specificity, and it needs to be combined with other parameters to improve its identification capability. This makes the process of predicting sleep disorders complex and time- and resource-consuming. Overall, there is currently no simple, fast, and reasonably accurate tool available for widespread screening of sleep disorders during pregnancy.

Research on sleep disorders in pregnant and postpartum women often overlooks the importance of individual self-perceived symptoms. Pregnant and postpartum women's subjective feelings about sleep quality may differ from objective sleep parameters.

For example, one study found that compared with a healthy control group, women with psychological disorders reported significantly worse subjective sleep quality on a daily basis [28]. This indicates that even when objective sleep parameters do not change significantly, pregnant and postpartum women may experience a decline in sleep quality due to psychological factors[28]. This emphasizes the importance of considering individual self-perceived symptoms in the assessment and management of sleep disorders in pregnant and postpartum women.

This study compensates for the shortcomings of previous studies. Our predictive models offer several advantages, including their simplicity and cost-effectiveness. They are easier to implement than diagnostic methods that necessitate sophisticated equipment and specialized personnel, making them suitable for use in resource-limited environments. Additionally, the models are constructed using data that is readily collectible, which enhances their broad applicability across various clinical settings. Furthermore, the development of these models takes into full account the impact of the subjective experiences of maternal self-assessment.

This study found that numerous factors can affect the sleep quality of pregnant and postpartum women. These findings fit with those of other studies. For instance, the stage of pregnancy, women at different stages of pregnancy may experience different types and degrees of sleep problem [1]. Somatic symptoms are also worth noting. The psychological state of pregnant women (such as depression) can also affect their sleep quality[29]. This means that any research aimed at predicting or managing sleep disorders during pregnancy needs to take these factors into account. This study found that a lower level of education, lower income, symptoms of the musculoskeletal system, digestive system, respiratory system, circulatory system, and poor emotional state are risk factors for sleep disorders in pregnant and postpartum women. Low socioeconomic status is associated with poorer sleep quality and sleep fragmentation, and pregnant women with lower SES have worse sleep quality and are more easily disturbed[30]. In addition, low income can also lead to an unbalanced diet, further exacerbating health problems [31]. Emotional state, such as depression, is also an important factor affecting the sleep of pregnant and postpartum women. Studies have found that pregnant and postpartum women with poor emotional states are more likely to have sleep disorders[2,32,33]. Especially depressive symptoms are significantly associated with a decline in sleep quality, possibly because depressive mood increases the stress response in the brain, thereby affecting sleep patterns [32]. The physical changes of pregnant women during pregnancy can also affect sleep. Weight gain during pregnancy, changes in body posture, and changes in hormone levels can all lead to sleep disorders[5]. These physiological changes can lead to symptoms in multiple systems such as the respiratory and circulatory systems, thereby affecting sleep quality.

We reiterate and clarify that the sleep disturbance prediction nomogram introduced in this study is a potential clinical tool designed to assist healthcare professionals in identifying pregnant and postpartum women who may experience sleep disturbance. However, we acknowledge that, despite demonstrating preliminary efficacy in this study, this tool still requires further testing and validation to assess its applicability, feasibility, and utility across various populations and clinical settings.

The use of the nomogram is relatively straightforward and intuitive. Healthcare professionals can apply this tool through the following steps: First, assess individual risk factors by evaluating the age of the pregnant woman, her emotional state, and the presence of any pregnancy-related complications. Next, calculate a composite risk score for each pregnant woman based on the instructions on the nomogram, integrating all identified risk factors. Utilize the risk score to identify pregnant women at high risk for sleep disturbances; these individuals may require closer monitoring and early intervention. For those identified as high risk, develop personalized intervention plans, which may include sleep hygiene education, cognitive-behavioral therapy, or pharmacological intervention when necessary. Continuously monitor and adjust the sleep conditions of these high-risk pregnant women, tailoring intervention measures as required. In this way, our nomogram not only aids in the rapid identification of high-risk groups but also supports clinical decision-making, thereby improving the sleep health of pregnant and postpartum women.

Furthermore, future research directions should focus on several key areas: First, conduct multicenter, large-scale prospective studies to verify the predictive accuracy and stability of the nomogram; second, assess its applicability across different ethnicities, cultures, and socioeconomic backgrounds; and finally, explore the integration of this tool with existing electronic health record systems to enable automated risk assessment and intervention recommendations.

By focusing on these areas, we can further refine the nomogram and enhance its potential as a clinical tool, ultimately contributing to the improvement of sleep health among pregnant and postpartum women.

5.1. Limitations

Despite the progress made in developing a predictive nomogram model for sleep disturbances in pregnant and postpartum women, certain limitations are acknowledged. Firstly, the study's data is specific to the Shenzhen area, which may restrict the applicability of our findings to other regions. Variations in lifestyle, environment, healthcare, and socioeconomic status can significantly affect sleep patterns, implying that the results may not be generalizable to areas with different cultural and environmental backgrounds. Secondly, while we analyzed several factors affecting sleep, the list was not exhaustive. Unconsidered biological, psychological, and sociological factors, such as lifestyle habits, occupational stress, ambient noise, and hormonal fluctuations during pregnancy, could also influence sleep quality. Additionally, due to resource and time constraints, we were unable to validate our predictive model with an independent cohort. This limitation affects the model's generalizability, as its predictive accuracy across different populations and settings remains unconfirmed. In summary, these limitations suggest caution in interpreting the results. Future research should aim for broader variable inclusion and validation across diverse populations to improve the model's generalizability and applicability.

6. Conclusion

This study successfully developed and validated a nomogram model for predicting sleep disturbance in pregnant and postpartum women. Through meticulous analysis of the training and validation sets, we confirmed the model's effectiveness and accuracy in predicting sleep disturbance. The model includes multiple important predictive factors, such as the education level, income, pregnancy stage, complications, physical system symptoms, and emotional state of pregnant and postpartum women.

In the training set, the nomogram model showed excellent discriminative ability, with an AUC of the ROC curve reaching 0.93, indicating that the model can identify pregnant and postpartum women at risk of sleep disturbance with high accuracy. In addition, the P-value of the Hosmer-Lemeshow test was 0.243, further confirming the model's good fit on the training set. In the validation set, the model also showed good predictive performance, with an AUC of 0.91, which verified the model's generalization ability.

Decision curve analysis (DCA) provided valuable information about the clinical utility of the model. In both the training and validation sets, we determined the maximum net benefit of the model at specific risk thresholds, which helps clinicians make more accurate diagnostic decisions in practical applications.

Our study emphasizes the importance of predicting sleep disturbance in pregnant and postpartum women and provides a practical tool that can help medical professionals identify and intervene in this issue at an early stage. The development of the nomogram model not only helps improve the sleep quality of pregnant and postpartum women but may also have a positive impact on improving maternal and infant health outcomes.

Statement data availability

Data sets cannot be shared publicly due to privacy and ethical restrictions. However, data can be obtained by contacting the corresponding author after removing personal identifying information.

CRediT authorship contribution statement

Yingyu Zhong: Writing – original draft, Visualization, Validation, Supervision, Software, Formal analysis, Data curation, Conceptualization. **He Wang:** Writing – review & editing, Methodology, Investigation. **Yueyun Wang:** Writing – review & editing, Supervision, Resources, Project administration.

Declaration of generative AI in scientific writing

In the preparation of this manuscript, generative AI technology was employed solely to enhance the readability and clarity of the English language. It is important to note that the generative AI did not participate in the conceptualization, data analysis, or the formulation of viewpoints, which are the critical components of this research. The original thinking, interpretation of the data, and the perspectives presented in the paper are entirely the result of human effort and expertise. The use of AI was limited to refining the language to make the content more accessible to readers, without altering the scientific integrity or the originality of the work.

Funding note

This study was financially supported by Shenzhen Maternal and Child Healthcare Hospital.

Declaration of competing interest

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

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