

Construction and Validation of a Model for Predicting Fear of Childbirth: A Cross-Sectional Population Study via Machine Learning

Zhi-Lin Zhang , Kang-Jia Chen , Hui Chen , Miao-Miao Zhu, Jing-Jing Gu , Li-Shuai Jiang ,
Lan Zheng , Shu-Guang Zhou 

Department of Gynecology and Obstetrics, Maternal and Child Medical Center of Anhui Medical University, The Fifth Affiliated Clinical College of Anhui Medical University, Anhui Women and Children's Medical Center, Hefei, Anhui, People's Republic of China

*These authors contributed equally to this work

Correspondence: Shu-Guang Zhou, Email zhoushuguang@ahmu.edu.cn; Lan Zheng, Email zhenglan2022@163.com

Background: Fear of childbirth (FOC) is a psychological state of fear and distress that pregnant women experience when they approach labor. This fear can have significant negative effects on both the mother and the newborn, making it crucial to study the influencing factors of FOC to implement early interventions.

Objective: First, identify the risk factors for FOC occurrence, then construct a predictive model for FOC and evaluate its predictive efficiency.

Methods: A total of 901 pregnant women who underwent regular prenatal check-ups at Anhui Women and Children's Medical Center were selected. Participants completed questionnaires. General information and relevant medical data of the patients were collected for data aggregation. The data was randomly divided into a training set ($n = 632$) and a testing set ($n = 269$) in a 7:3 ratio. Univariate analysis of risk factors for FOC was performed on the training set data. Using univariate logistic regression and multivariate logistic regression to analyze the risk factors associated with the occurrence of FOC, we constructed a FOC risk predictive model via ten different machine learning methods and evaluated the predictive performance of the model.

Results: Our study indicated that educational level, history of adverse pregnancy outcomes, history of cesarean section, planned pregnancy, assisted reproduction, income, payment, SAS scores, and age are independent risk factors for FOC. The risk predictive model included six factors, such as gravidity, history of adverse pregnancy outcomes, history of cesarean section, planned pregnancy, payment, and SSRS scores. The model was built using ten types of machine learning and was evaluated to perform well.

Conclusion: Gravidity, history of adverse pregnancy outcomes, history of cesarean section, planned pregnancy, payment method, and SSRS score are risk factors for FOC in late-pregnancy women. The risk predictive model established in this study has a high clinical reference value.

Keywords: fear of childbirth, FOC, machine learning, risk factors, predictive model

Introduction

FOC is a complex phenomenon¹ that encompasses the anxiety surrounding impending labor² and worries about potential complications that may arise postpartum, including both physiological and psychological changes. With the widespread implementation of the two-child and three-child policies, the incidence of FOC has been increasing. For every pregnant woman and her family, pregnancy, childbirth, and then becoming parents are common social phenomena, a survival threshold that every woman of childbearing age must experience and overcome.^{3,4} Childbirth is a unique and delicate experience for every pregnant woman, and it is influenced by various social and familial factors.⁵ The birth of a new life brings joy and happiness to the pregnant woman and her family, but it is also accompanied by fear and anxiety. This fear includes the pregnant woman's apprehension and resistance towards childbirth, as well as worries about the unknown and

helplessness in raising a new life.⁶ Retrospective studies have shown that the global incidence of FOC is between 6% and 15%,⁷ with the global prevalence of severe FOC being 6–10%.⁸ The incidence of FOC among Asian pregnant women is 25%,⁹ 26.9% in the United States,¹⁰ 8% in Europe, and 24% in Australia.¹¹ Recent studies on FOC in China have also gained momentum, with the incidence of FOC among pregnant women in China during pregnancy being 79.2%.¹² This phenomenon is mainly related to the low literacy level and the imbalance of educational resources in China. This also reflects a subgroup of a particular population.

Many factors affect FOC, and the exact causes are currently unclear. A study based on optimal scale regression analysis found that the factors most strongly associated with FOC in the northwest region of China include place of residence, marital status, parity, gestational age, partner relationship, prenatal stress, social support, and depressive symptoms.¹³ A systematic review and research by Rondung et al found that women of childbearing age with lower educational levels and poorer economic conditions have a higher probability of experiencing FOC compared to those with higher education and better economic status.^{14,15} An article on factors related to FOC among pregnant women in Poland indicated that severe FOC is associated with risk factors such as depression, unplanned pregnancy or parity, and disagreement with the obstetrician's proposed birth plan.¹⁶ Additionally, the harms caused by FOC are diverse. Some studies have found that FOC can lead to severe adverse pregnancy outcomes, with the most significant impact being preterm birth. Other negative consequences of FOC include low Apgar scores, difficulties in newborn feeding, and postpartum depression.^{14,17} However, there are many reasons why FOC can lead to preterm birth, and a complete conclusion has yet to be reached. Therefore, to clarify the factors contributing to the occurrence of FOC, identify FOC patients early, and improve the prognosis of FOC patients, it is necessary to conduct this research.

Currently, although there are several studies report regarding risk predictive models for FOC, the results are not satisfactory. Additionally, there are very few cases of constructing FOC risk predictive models using machine learning methods. In this study, we selected variables related to FOC and conducted logistic regression analysis on the risk factors for FOC while also using ten machine learning algorithms to build a risk predictive model for FOC. Compared with traditional models, machine learning-based predictive models are usually trained with annotated datasets, ie, supervised

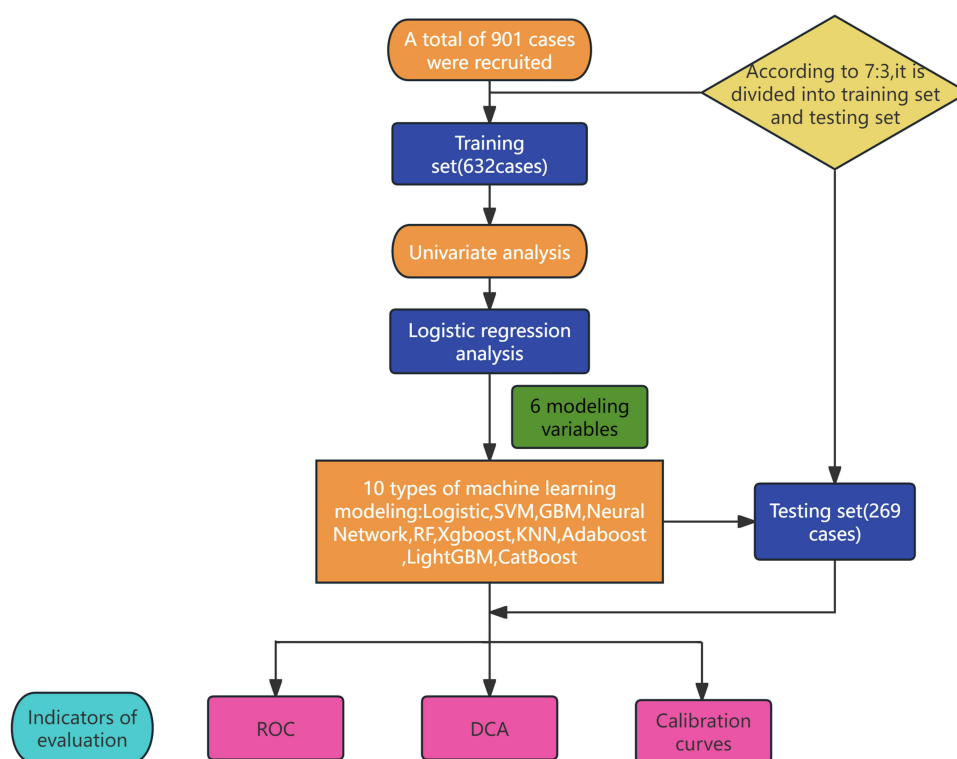


Figure 1 Experimental design flow chart.

Table 1 Univariate Analysis of Risk Factors for FOC in Late-Term Pregnancy

	Non-FOC	FOC	P
n	383	249	
Residential area = city (%)	205 (53.5)	138 (55.4)	0.699
Gravidity (%)			<0.001
1	89 (23.2)	56 (22.5)	
2	120 (31.3)	30 (12.0)	
3	100 (26.1)	82 (32.9)	
4	31 (8.1)	76 (30.5)	
5	43 (11.2)	5 (2.0)	
Parity (%)			0.001
0	154 (40.2)	129 (51.8)	
1	182 (47.5)	108 (43.4)	
2	47 (12.3)	12 (4.8)	
Work Situation (%)	271 (70.8)	180 (72.3)	0.744
Educational Level (%)			<0.001
High school/secondary school or below	258 (67.4)	150 (60.2)	
College/Undergraduate	123 (32.1)	77 (30.9)	
Postgraduate and above	2 (0.5)	22 (8.8)	
Adverse Pregnancy Outcomes (%)	59 (15.4)	160 (64.3)	<0.001
Infertility (%)	4 (1.0)	69 (27.7)	<0.001
Cesarean Section (%)	10 (2.6)	96 (38.6)	<0.001
Planned Pregnancy (%)	299 (78.1)	229 (92.0)	<0.001
ART (%)	2 (0.5)	52 (20.9)	<0.001
Income (%)			<0.001
<2000	14 (3.7)	15 (6.0)	
2000–5000	145 (37.9)	49 (19.7)	
5000–10,000	214 (55.9)	156 (62.7)	
>10,000	10 (2.6)	29 (11.6)	
Medical insurance (%)	218 (56.9)	116 (46.6)	0.014
SAS (mean (SD))	34.85 (5.90)	55.18 (8.54)	<0.001
CBSEI (mean (SD))	222.39 (17.49)	164.76 (24.94)	<0.001
SSRS (mean (SD))	41.14 (4.59)	35.74 (4.75)	<0.001
Age (mean (SD))	27.20 (3.03)	27.73 (3.49)	0.044
Weeks (mean (SD))	37.61 (1.51)	37.44 (1.40)	0.171

Notes: Values in parentheses are percentage, and $p < 0.05$ indicates that it is statistically significant.

Abbreviations: ART, assisted reproductive technology; SD, standard deviation.

learning, which can obtain better robustness and generalization capabilities. The aim of this study is to provide reliable evidence for clinical medical staff in the early detection and diagnosis of FOC and to offer better-optimized solutions for clinical intervention and treatment of FOC patients.

Materials and Methods

Research Design

We conducted a cross-sectional study involving pregnant women who gave birth at Anhui Women and Children's Medical Center from January 1, 2021, to December 31, 2021. We gathered general information about the participants through the electronic medical record system, and the women completed questionnaires that included the Anxiety Self-Rating Scale, Childbirth Self-Efficacy Scale, Social Support Rating Scale, and Childbirth Fear Scale. A total of 901 women were screened based on the following inclusion criteria: (1) age ≥ 18 years; (2) gestational age ≥ 28 weeks; (3) regular prenatal check-ups in the hospital. Exclusion Criteria: (1) the data is incomplete; (2) patients with mental illness;

Table 2 Logistic Regression Model Evaluating Potential Independent Predictors of FOC in Late-Term Pregnant Women

Name	Desc	Non-FOC (N=383)	FOC (N=249)	OR (Univariable)	OR (Multivariable)
Residential area	Countryside	178 (46.5%)	111 (44.6%)	1.08 (0.78–1.49, p=0.640)	
	City	205 (53.5%)	138 (55.4%)		
Gravidity	1	89 (23.2%)	56 (22.5%)	0.40 (0.24–0.67, p<0.001)	0.00 (0.00–0.16, p=0.013)
	2	120 (31.3%)	30 (12%)		
	3	100 (26.1%)	82 (32.9%)	1.30 (0.84–2.03, p=0.242)	0.01 (0.00–7.93, p=0.177)
	4	31 (8.1%)	76 (30.5%)	3.90 (2.28–6.65, p<0.001)	0.00 (0.00–1.13, p=0.053)
	5	43 (11.2%)	5 (2%)	0.18 (0.07–0.49, p<0.001)	0.00 (0.00–1774.08, p=0.187)
Parity	0	154 (40.2%)	129 (51.8%)	0.71 (0.51–0.99, p=0.043)	0.07 (0.00–4.80, p=0.214)
	1	182 (47.5%)	108 (43.4%)		
	2	47 (12.3%)	12 (4.8%)	0.30 (0.16–0.60, p<0.001)	0.50 (0.00–3852987905401617.50, p=0.970)
Educational Level	High school/secondary school or below	258 (67.4%)	150 (60.2%)	1.08 (0.76–1.53, p=0.678)	0.11 (0.00–6.79, p=0.298)
	College/Undergraduate	123 (32.1%)	77 (30.9%)		
	Postgraduate and above	2 (0.5%)	22 (8.8%)		
Work Situation	No	112 (29.2%)	69 (27.7%)	1.08 (0.76–1.54, p=0.677)	
	Yes	271 (70.8%)	180 (72.3%)		
History of Adverse Pregnancy Outcomes	No	324 (84.6%)	89 (35.7%)	9.87 (6.75–14.43, p<0.001)	18257.74 (18.08–18441273.14, p=0.005)
	Yes	59 (15.4%)	160 (64.3%)		
History of Infertility	No	379 (99%)	180 (72.3%)	36.32 (13.05–101.07, p<0.001)	0.03 (0.00–2.31, p=0.114)
	Yes	4 (1%)	69 (27.7%)		
History of Cesarean Section	No	373 (97.4%)	153 (61.4%)	23.40 (11.88–46.10, p<0.001)	74417.83 (110.24–50236206.49, p<0.001)
	Yes	10 (2.6%)	96 (38.6%)		
Planned Pregnancy	No	84 (21.9%)	20 (8%)	3.22 (1.92–5.40, p<0.001)	372.71 (1.47–94227.25, p=0.036)
	Yes	299 (78.1%)	229 (92%)		
ART	No	381 (99.5%)	197 (79.1%)	50.28 (12.13–208.48, p<0.001)	6.22 (0.08–476.81, p=0.409)
	Yes	2 (0.5%)	52 (20.9%)		
Age	Mean ± SD	27.2 ± 3.0	27.7 ± 3.5	1.05 (1.00–1.11, p=0.045)	1.04 (0.78–1.38, p=0.783)

(Continued)

Table 2 (Continued).

Name	Desc	Non-FOC (N=383)	FOC (N=249)	OR (Univariable)	OR (Multivariable)
Weeks	Mean ± SD	37.6 ± 1.5	37.4 ± 1.4	0.93 (0.83–1.03, p=0.171)	
Income	<2000	14 (3.7%)	15 (6%)		0.08 (0.00–2059.77, p=0.631)
	2000–5000	145 (37.9%)	49 (19.7%)	0.32 (0.14–0.70, p=0.004)	
	5000–10,000	214 (55.9%)	156 (62.7%)	0.68 (0.32–1.45, p=0.319)	0.00 (0.00–78.73p=0.267)
	>10,000	10 (2.6%)	29 (11.6%)	2.71 (0.97–7.53, p=0.056)	3174.90 (0.00–Inf, p=0.985)
Payment	At your own expense	165 (43.1%)	133 (53.4%)		
	Health insurance	218 (56.9%)	116 (46.6%)	0.66 (0.48–0.91, p=0.011)	56.38 (1.02–3126.80, p=0.049)
SAS	Mean ± SD	34.8 ± 5.9	55.2 ± 8.5	1.55 (1.44–1.68, p<0.001)	1.47 (1.07–2.02, p=0.016)
CBSEI	Mean ± SD	222.4 ± 17.5	164.8 ± 24.9	0.90 (0.88–0.92, p<0.001)	0.93 (0.87–0.98, p=0.014)
SSRS	Mean ± SD	41.1 ± 4.6	35.7 ± 4.8	0.77 (0.73–0.80, p<0.001)	0.65 (0.45–0.94, p=0.024)

Notes: Unbolded values in parentheses are 95% CI; Bolded values in parentheses are percentage. p<0.05 indicates that it is statistically significant.

Abbreviations: ART, assisted reproductive technology; SD, standard deviation.

(3) pregnant women who are transferred to the other hospital for delivery; (4) congenital dysplasia; (5) pregnant women who do not know Chinese. Consent was obtained from each eligible woman before they completed the questionnaires.

Our study included a total of 17 risk valuables. Nine hundred and one cases were divided into a training set and a testing set in a 7:3 ratio. Therefore, the sample size for the training set was $901 \times 0.7 = 632$ cases, and the sample size for the testing set was $901 \times 0.3 = 269$ cases.

Data Collection

In the medical record system, obtain information on age, gestational weeks, frequency of pregnancies and births, work situation, education level, adverse pregnancy outcomes history, infertility history, cesarean section history, planned pregnancy, assisted reproduction history, and medical insurance. At the same time, several questionnaires for participating pregnant women to fill out their household per capita monthly income, anxiety self-assessment scale, childbirth self-efficacy scale, social support assessment scale and FOC scale.

The Self-Rating Anxiety Scale (SAS) was developed by W.K. Zung in 1971 to assess individuals' subjective feelings of anxiety symptoms. It serves as a tool for measuring the severity of anxiety and tracking changes during treatment. Anxiety is a common emotional disorder encountered in psychological counseling clinics, and in recent years, the SAS has been utilized as a self-assessment tool to better understand anxiety symptoms in counseling settings.

The Childbirth Self-Efficacy Inventory (CBSEI) consists of two dimensions: outcome expectations and self-efficacy expectations. Each dimension includes 16 items, and each item is scored using a 10-point scale, where 0 points represent “not helpful at all/completely uncertain” and 10 points represent “very helpful/very certain.” The total score ranges from 32 to 320 points, with higher scores indicating greater self-efficacy in the subjects. The Cronbach's α coefficient of this scale is 0.96, and the structural validity is 0.85.¹⁸

The Social Support Rating Scale (SSRS) is an evaluation scale designed by Xiao Shuiyuan in 1986, consisting of ten items that explore social relationships and health. Since 1986, the SSRS has been used in over twenty studies in China and has been translated into Japanese for an international collaborative research project. Feedback indicates that the

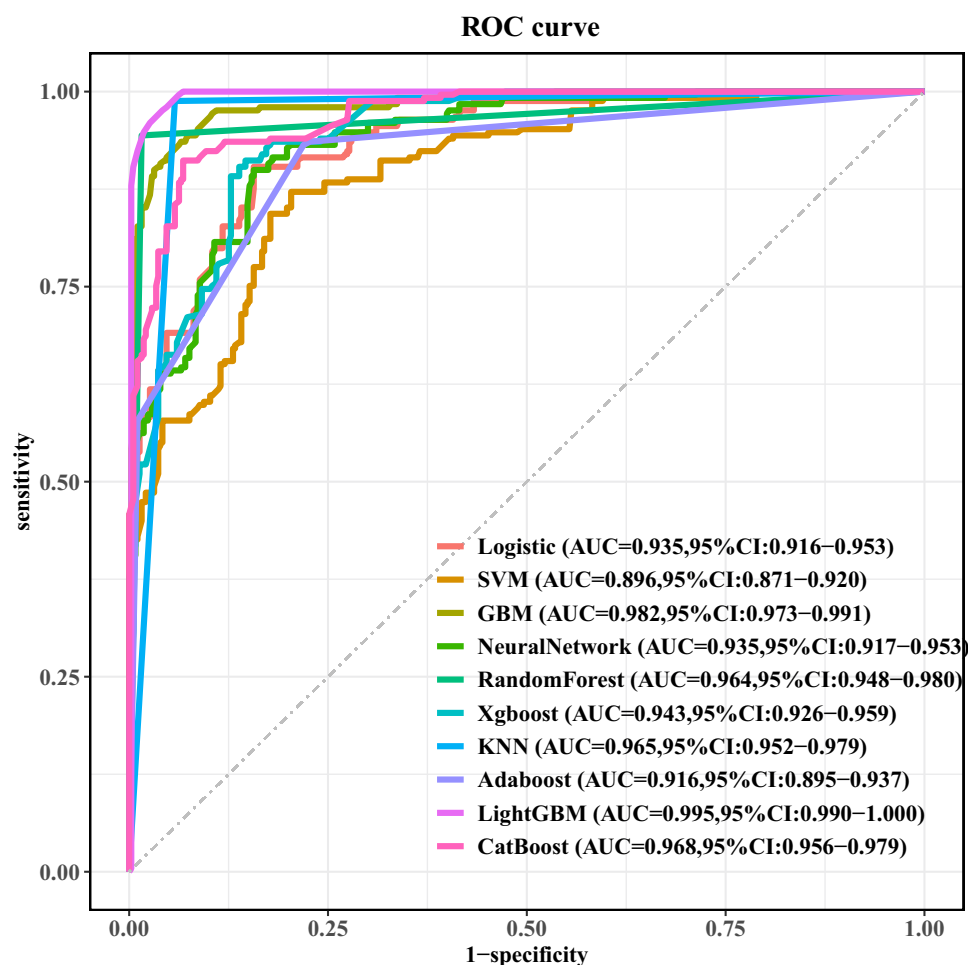


Figure 2 ROC curve of the training set.

design of the questionnaire is generally reasonable, the items are easy to understand and unambiguous, and it has good reliability and validity.¹⁹

The Childbirth Anxiety Questionnaire (CAQ) was originally compiled by Tanglakmankhong et al to assess pregnant women's attitudes and expectations towards childbirth. It consists of four dimensions and 16 items: the fetal health dimension, the pain and injury dimension, the self-control dimension, and the medical care dimension. This study used the Chinese version of the CAQ, which has a Cronbach's α coefficient of 0.91, with factor Cronbach's α coefficients ranging from 0.678 to 0.853. Additionally, the test–retest reliability is reported at 0.803, with factor test–retest reliability ranging from 0.812 to 0.921. These results indicate that the scale demonstrates a significant level of stability over time.

Grouping Criteria

Based on the CAQ score results completed by the pregnant women during recruitment, they were categorized into two groups: the FOC group (score ≥ 28) and the non-FOC group (score < 28).¹⁶

Moral Considerations

This was a cross-sectional study, and exemption from informed consent was approved by the Medical Ethics Committee of Maternal and Child Health Hospital affiliated to Anhui Medical University (approval number YYLL20200425-LW-LL-05-1.0). All experimental protocols were approved by the Medical Ethics Committee of Anhui Maternal and Child Health Hospital and all methods were carried out in accordance with the Declarations of Helsinki. All participants were

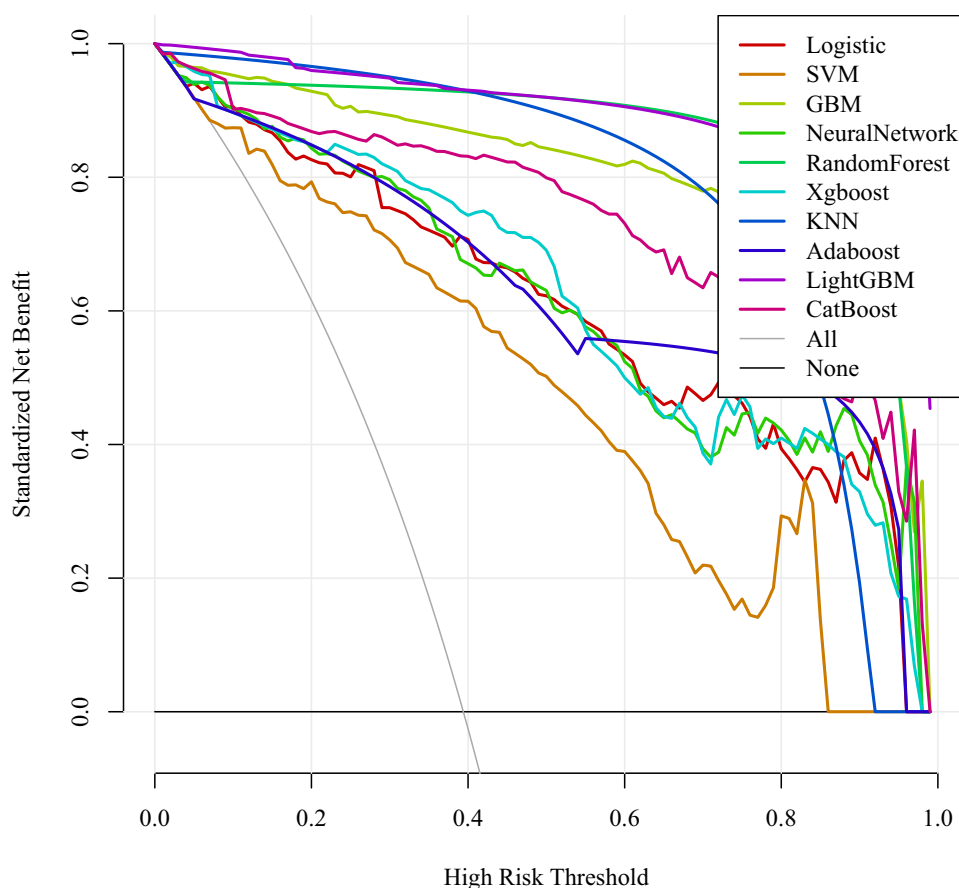


Figure 3 DCA curve of the training set.

informed of the purpose of the research prior to commencement and assured that the information collected would be used solely for research purposes.

Analysis of Risk Factors for FOC in Late-Term Pregnant Women

Seventeen risk factors affecting FOC were set as independent variables. Univariate logistic regression analysis was performed for the CAQ score as the dependent variable. The strength of the association between each independent variable and the dependent variable was analyzed separately. The variables of $p < 0.05$ were included in the multivariate logistic regression analysis, and the joint effect of these meaningful variables on the dependent variable (FOC) was studied. The variable $p < 0.05$ was an independent risk factor for FOC.

Construction of Risk Predictive Model via Machine Learning

Six meaningful variables after logistic regression analysis were modeled using machine learning methods. Ten types of machine learning were used, including Logistic, SVM, GBM, Neural Network, RF, Xgboost, KNN, Adaboost, LightGBM, and CatBoost. Based on the integration of 101 algorithm combinations of these 10 machine learning algorithms, the training set and testing set were used to apply the 101 algorithm combinations to construct the disease risk prediction model.

Evaluation of Risk Predictive Model for FOC

The model is evaluated based on three key dimensions: indexing, calibration, and clinical utility. In this study, the area under the receiver operating characteristic (ROC) curve (AUC) is used to assess the model's identification ability for the modeling group. The calibration curve is used to determine the degree of consistency between predicted probabilities and

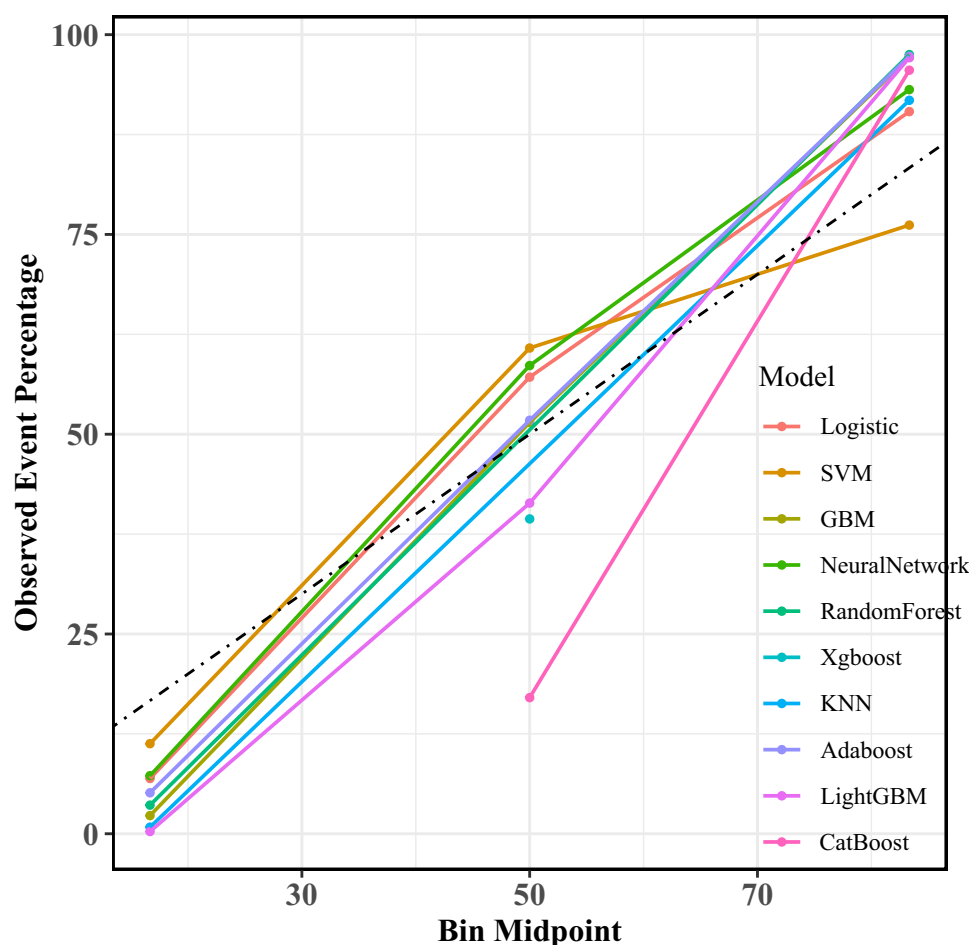


Figure 4 Calibration curve of the training set.

observed outcomes. Additionally, decision curve analysis (DCA) is employed to evaluate the model's clinical validity. The same three methods are applied to validate the model using the testing set data.

Statistical Methods

All analyses were performed using R software(version 4.4.1). Measurement data are presented as ($x \pm s$). For inter-group comparisons, the Wilcoxon rank-sum test is used. Count data are expressed as n (%), and inter-group comparisons are conducted using the chi-square test or Fisher's exact test. All tests are two-tailed, and a P value of <0.05 is considered statistically significant.

Results

Figure 1 We summarized the study's procedure. First, we recruited the population according to the inclusion and exclusion criteria, and finally recruited a total of 901 pregnant women, then collected their data and performed data cleaning. Second, according to a specific ratio, the data are divided into a training set ($n = 632$) and a testing set ($n = 269$). Third, the training set was divided into an FOC group and a non-FOC group, and then univariate analysis, univariate regression analysis, multivariate regression analysis, and machine learning modeling were carried out step by step. Finally, to assess the model's performance, we evaluated its reliability using both the training set and the testing set. This evaluation involved constructing Receiver Operating Characteristic (ROC) curves, Decision Curve Analysis (DCA) curves, and calibration curves.

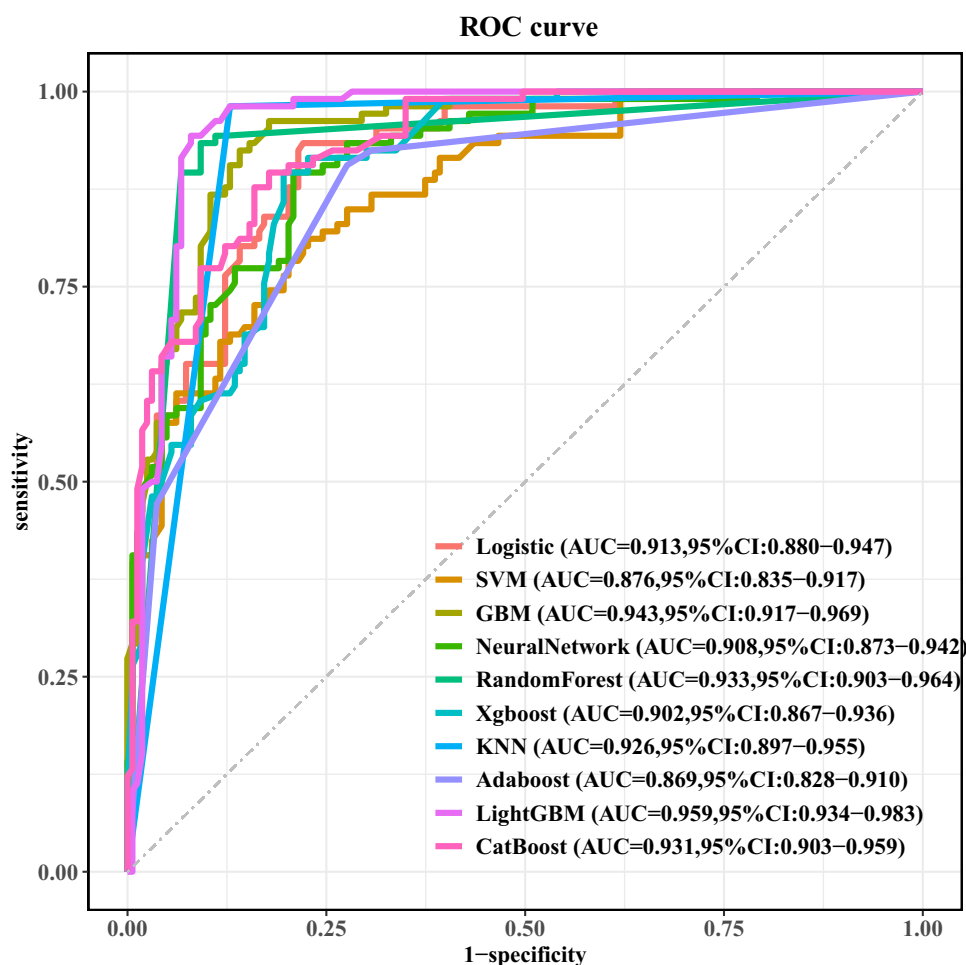


Figure 5 ROC curve of the testing set.

Univariate Analysis of Risk Factors for FOC in Late-Term Pregnant Women

A total of 632 cases were included in the training set, among which 249 cases occurred FOC, resulting in an incidence rate of 39.4%. Univariate analysis revealed significant statistical differences ($P < 0.05$) between the FOC group and the non-FOC group in several areas, including gravidity, parity, education level, adverse pregnancy outcomes, cesarean section, infertility, planned pregnancies, assisted reproduction, family monthly income, medical insurance coverage, SAS scores, CBSEI scores, SSRS scores, and age, as detailed in [Table 1](#).

Logistic Regression Multi-Factor Analysis of FOC in Late-Term Pregnancy

In this study, risk factors were identified as independent variables, while the presence of FOC among pregnant women in late pregnancy was the dependent variable. A logistic regression analysis was conducted. The results, presented in [Table 2](#), indicated that the following factors are independent risk factors for FOC: educational level, history of adverse pregnancy outcomes, history of cesarean sections, whether the pregnancy was planned, whether the pregnancy was achieved through assisted reproduction, a family monthly income per capita, medical insurance coverage, the SAS score and age. The final model included six variables.

Evaluation of the Predictive Model for FOC via the Training Set

The area under the ROC curve (AUC) is used to validate the model and its discriminative ability. The AUC values for ten machine learning models are as follows: 0.935, 95% CI: 0.916–0.953; 0.896, 95% CI: 0.871–0.920; 0.982, 95% CI: 0.973–0.991; 0.935, 95% CI: 0.917–0.953; 0.964, 95% CI: 0.948–0.980; 0.943, 95% CI: 0.926–0.959; 0.965, 95% CI:

0.952–0.979; 0.916, 95% CI: 0.895–0.937; 0.995, 95% CI: 0.990–1.000; 0.968, and 95% CI: 0.956–0.979 (Figure 2). Using DCA to evaluate clinical validity, the decision curves for ten machine learning models are higher than the None line and the All line within the threshold range of clinical value, indicating that the model has a higher net benefit in practical clinical application (Figure 3). A calibration curve is utilized to assess the alignment between predicted probabilities and actual observations. The model's prediction results closely match the actual outcomes, indicating high reliability (Figure 4).

Evaluation of the Predictive Model for FOC via the Testing Set

A total of 269 cases were randomly assigned to the testing set, and the area under the ROC curve was used to verify the model and discriminative ability. The area under the ROC curve for the ten machine learning models are as follows: 0.913, 95% CI: 0.880–0.947, 0.876, 95% CI: 0.835–0.917, 0.943, 95% CI: 0.917–0.969, 0.908, 95% CI: 0.873–0.942, 0.933, 95% CI: 0.903–0.964; 0.902, 95% CI: 0.867–0.936; 0.926, 95% CI: 0.897–0.955; 0.869, 95% CI: 0.828–0.910; 0.959, 95% CI: 0.934–0.983; 0.931, 95% CI: 0.903–0.959 (Figure 5). Using decision analysis curve (DCA) to evaluate clinical validity. The decision curves for the ten machine learning models are higher than both the “None” line and the “All” line within the clinically valuable threshold range (Figure 6). This indicates that the models provide a greater net benefit for practical clinical application. A calibration curve is utilized to assess the alignment between predicted probabilities and actual observations. The model's prediction results closely match the actual outcomes, demonstrating a high level of reliability and accuracy (Figure 7).

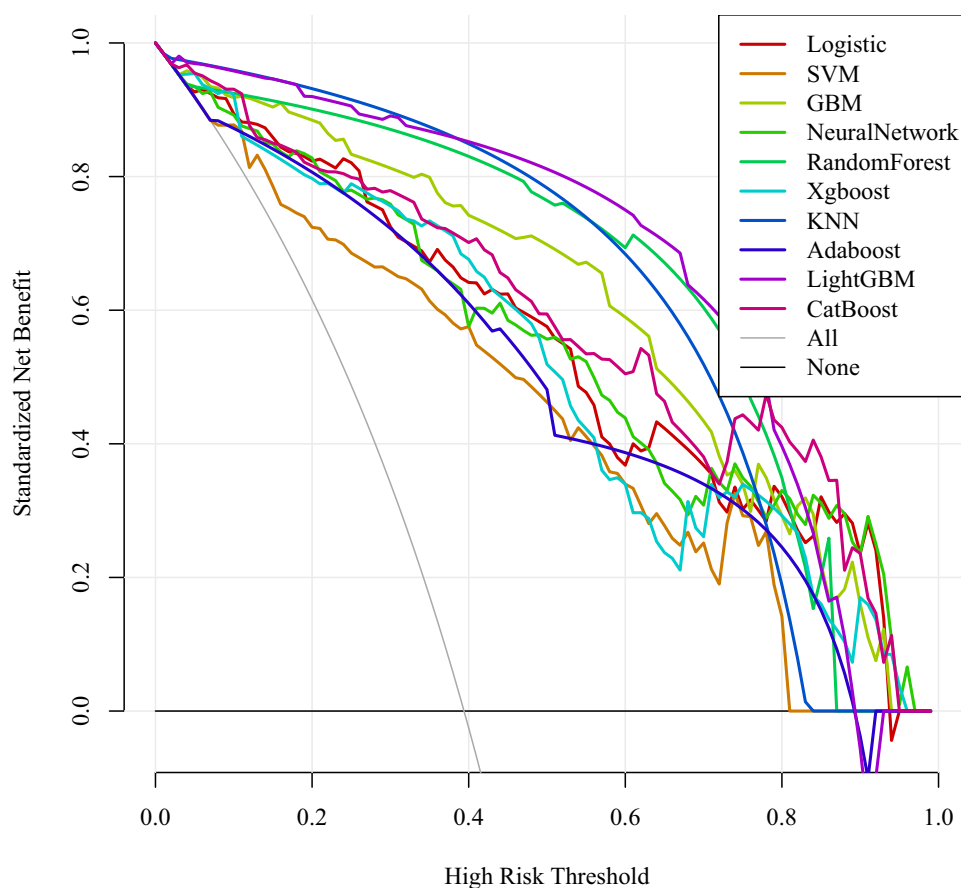


Figure 6 DCA curve of the testing set.

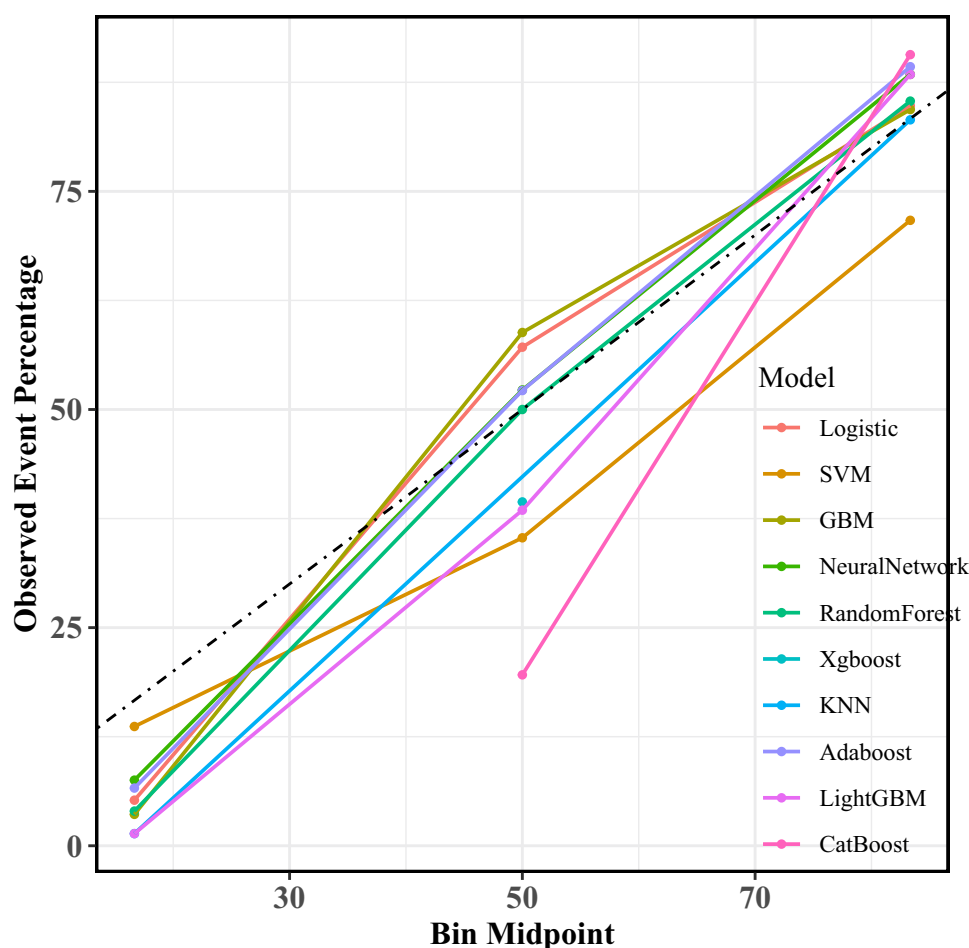


Figure 7 Calibration curve of the testing set.

Discussion

FOC is a unique psychological illness and one of the major causes of maternal mortality, which has a detrimental effect on maternal and infant pregnancy outcomes.^{14,17} The early diagnosis and intervention of FOC is of great clinical significance. However, there is limited research on the pathogenesis and etiology of FOC. Most existing predictive models for FOC have been developed using regression analysis, with few studies exploring models constructed using machine learning methods. To address this gap, we utilized ten effective machine learning algorithms to create prediction models for FOC. Our models significantly enhance efficiency, and the AUC value we achieved is higher than that of the model established by Min Gaohui et al²⁰ providing greater research value to the medical field.

The incidence of FOC in this study was 39.4%. Pregnant women with multiple pregnancies, planned pregnancies, have a history of previous adverse pregnancy outcomes and cesarean sections, self-payment by Medicare, and high SSRS scores are at high risk of developing FOC. This is different from the incidence of FOC in Chinese pregnant women found by Zheng et al, probably because the sample size of this study was not diverse enough. The results are somewhat similar to those of Rong Xu et al.²¹ This study found a strong association between gravidity and FOC in pregnant women. This is consistent with the findings of Wijma et al¹⁹ in terms of pregnancies, possibly because the fewer pregnancies, the more unfamiliar the pregnant woman is with this new experience and the more intense her feeling of FOC. In this study, it is believed that adverse pregnancy outcomes history could lead to the occurrence of FOC, and it had been reported that pregnant women with unplanned pregnancies have a higher incidence of FOC,²² and pregnant women with unplanned pregnancies are more stressed, and pregnant women are not psychologically and physically prepared for pregnancy, resulting in an increased risk of FOC.²³ A history of previous adverse pregnancy outcomes can interfere with the

psychology of pregnant women, leading to the development of FOC, and the majority of women in the FOC group in this study had a history of adverse pregnancy outcomes, consistent with a study in Sweden.²⁴ Cesarean section is a traumatic event, and pregnant women who undergo cesarean section are at greater risk of emotional problems than vaginal delivery,²⁵ as is the case in this study. Social support is an important factor affecting people's social life, and pregnant women are psychologically fragile due to the influence of hormones during pregnancy and are prone to depression and fear without the support of family and society.²⁶ Additionally, this study found that pregnant women in the FOC group utilized Medicare, while those in the non-FOC group paid out of pocket, aligning with existing research findings.

Finally, it should be noted that the SAS score and CBSEI score were included in the predictors, and machine learning established a disease prediction model. The model's clinical effectiveness was assessed using a DCA curve ([Supplementary Figure S1](#)). Calibration curves are used to evaluate the fit of the model ([Supplementary Figure S2](#)). We found the AUC value of the ROC curve was between 0.9 and 1 ([Supplementary Figure S3](#)). The DCA curve of testing set indicates that the models provide a greater net benefit for practical clinical application ([Supplementary Figure S4](#)). The calibration curves of testing set demonstrated a high level of reliability and accuracy ([Supplementary Figure S5](#)). The AUC value of the ROC curve of the testing set was between 0.9 and 1 ([Supplementary Figure S6](#)). We consider that the accuracy of the model is too high, which may be similar to some items in the SAS scale, CBSEI scale, and CAQ scale, leading to overfitting of the model. This overfitting may result in filling out these questionnaires meantime in real life to predict the occurrence of FOC with inaccuracy. With such models in everyday practice, we need to train clinicians or integrate models into existing healthcare systems, which is a challenge.

Conclusion

In this study, appropriate statistical methods were used to detect FOC in late-term pregnant women before their delivery. We used machine learning to construct a FOC risk predictive model, which included six risk factors: gravidity, history of adverse pregnancy outcomes, history of cesarean section, planned pregnancy, medical insurance payment, and SSRS score. This model holds significant clinical value. In future clinical work, psychological counseling could be carried out for pregnant women with high-risk factors of childbirth fear to reduce their incidence and adverse outcomes. However, the study has some limitations, including a small sample size, being conducted at a single center, and limited data. This can have an impact on the generalizability of the results. To enhance the prediction accuracy of the model, it is essential to conduct further large-sample, multi-center prospective studies. This will improve the effectiveness of the model for screening and intervening in high-risk clinical populations. The results of the study highlight the influencing factors of childbirth fear, providing targeted intervention measures for clinical medical staff to alleviate pregnant women's FOC and enhance the childbirth experience.

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Disclosure

The authors report no conflicts of interest in this work.

References

1. Jomeen J, Martin CR, Jones C, et al. Tokophobia and fear of birth: a workshop consensus statement on current issues and recommendations for future research. *J Reprod Infant Psychol*. 2021;39(1):2–15. doi:10.1080/02646838.2020.1843908

2. Ryding EL, Wirfelt E, Wångborg IB, et al. Personality and fear of childbirth. *Acta Obstetrica et Gynecologica Scandinavica*. 2007;86(7):814–820. doi:10.1080/00016340701415079
3. Fenwick J, Gamble J, Nathan E, et al. Pre- and postpartum levels of childbirth fear and the relationship to birth outcomes in a cohort of Australian women. *J Clin Nurs*. 2010;18(5):667–677. doi:10.1111/j.1365-2702.2008.02568.x
4. Nilsson C, Hessman E, Sjöblom H, et al. Definitions, measurements and prevalence of fear of childbirth: a systematic review. *BMC Pregnancy Childbirth*. 2018;18(1):28. doi:10.1186/s12884-018-1659-7
5. Larkin P, Begley CM, Devane D. Women's experiences of labour and birth: an evolutionary concept analysis. *Midwifery*. 2009;25(2):e49–e59. doi:10.1016/j.midw.2007.07.010
6. Wijma K, Wijma B, Zar M. "Psychometric aspects of the W-DEQ; a new questionnaire for the measurement of fear of childbirth. *J Psychosom Obstet Gynecol*. 1998;19(2):84–97. doi:10.3109/01674829809048501
7. Lukasse M, Schei B, Ryding EL. Prevalence and associated factors of fear of childbirth in six European countries. *Sex Reprod Healthc*. 2014;5(3):99–106. doi:10.1016/j.srhc.2014.06.007
8. O'Connell MA, Leahy-Warren P, Khashan AS, Kenny LC, O'Neill SM. Worldwide prevalence of tocophobia in pregnant women: systematic review and meta-analysis. *Acta Obstet Gynecol Scand*. 2017;96(8):907–920. doi:10.1111/aogs.13138
9. Hanna-Leena Melender R. Experiences of fears associated with pregnancy and childbirth: a study of 329 pregnant women. *Birth*. 2002;29(2):101–111. doi:10.1046/j.1523-536X.2002.00170.x
10. Stoll K, Edmonds JK, Hall WA. Fear of childbirth and preference for cesarean delivery among young American women before childbirth: a survey study. *Birth*. 2015;42(3):270–276. doi:10.1111/birt.12178
11. Toohill J, Creed DK, Gamble J, Fenwick J. A cross-sectional study to determine utility of childbirth fear screening in maternity practice-an Australian perspective. *Women Birth*. 2015;28(4):310–316. doi:10.1016/j.wombi.2015.05.002
12. Zheng DD, Zhou LH, Wu XL, Wang LP. Fear of childbirth in primiparas during the late stages of pregnancy and its influencing factors. *Matern Child Health Care China*. 2018;33(15):3525–3528.
13. Hall WA, Hauck YL, Carty EM, et al. Childbirth fear, anxiety, fatigue, and sleep deprivation in pregnant women. *J Obstet Gynecol Neonatal Nurs*. 2009;38:567–576. doi:10.1111/j.1552-6909.2009.01054.x
14. Dencker A, Nilsson C, Begley C, et al. Causes and outcomes in studies of fear of childbirth: a systematic review. *Women Birth*. 2019;32:99–111. doi:10.1016/j.wombi.2018.07.004
15. Rondung E, Thomtén J, Sundin Ö. Psychological perspectives on fear of childbirth. *J Anxiety Disord*. 2016;44:80–91. doi:10.1016/j.janxdis.2016.10.007
16. Iliska M, Brandt-Salmeri A, Kołodziej-Zaleska A, Banaś E, Gelner H, Cnota W. Factors associated with fear of childbirth among Polish pregnant women. *Sci Rep*. 2021;11(1):4397.
17. Golmakani N, Gholami M, Shaghghi F, et al. Relationship between fear of childbirth and the sense of cohesion with the attachment of pregnant mothers to the fetus. *J Educ Health Promot*. 2020;9:261. doi:10.4103/jehp.jehp_46_20
18. Smith CA, Levett KM, Collins CT, Armour M, Dahlen HG, Sukanuma M. Relaxation techniques for pain management in labour. *Cochrane Database Syst Rev*. 2018;3(3):CD009514. doi:10.1002/14651858.CD009514.pub2
19. Zhou X, Liu H, Li X, et al. Fear of childbirth and associated risk factors in healthy pregnant women in northwest of China: a cross-sectional study. *Psychol Res Behav Manag*. 2021;14:731–741. doi:10.2147/PRBM.S309889
20. Yan GH, Yan MQ, Ren YG, et al. Construction and validation of a risk prediction model for maternal fear of childbirth in the third trimester of pregnancy. *Chin Nurs res*. 2022;36(21):3810–3815.
21. Xu R, Wang J, Li Y, et al. Pre- and postpartum fear of childbirth and its predictors among rural women in China. *BMC Pregnancy Childbirth*. 2024;24(1). doi:10.1186/s12884-024-06585-x
22. Wu ZH, Liu H, Feng YL, et al. Research on the correlation between pregnant women's fear of childbirth and family care and psychological resilience. *J Shenyang Med Coll*. 2020;22(1):59–62.
23. Crump C, Sundquist K, Sundquist K. Adverse pregnancy outcomes and long-term mortality in women. *JAMA Intern Med*. 2024;184(6):631–640. doi:10.1001/jamainternmed.2024.0276
24. Ye L, Elstgeest LEM, Zhang X, et al. Factors associated with physical, psychological and social frailty among community-dwelling older persons in Europe: a cross-sectional study of Urban Health Centres Europe (UHCE). *BMC Geriatr*. 2021;21(1):1–11. doi:10.1186/s12877-021-02364-x
25. Skov SK, Hjorth S, Kirkegaard H, et al. Mode of delivery and short-term maternal mental health: a follow-up study in the Danish National Birth Cohort. *Int Gynaecol Obstet*. 2022;159(2):457–465. doi:10.1002/ijgo.14155
26. Hou Y, Zhou X, Yao M, et al. Fear of childbirth and its predictors in re-pregnant women after cesarean section: a cross-sectional multicenter study in China. *BMC Pregnancy Childbirth*. 2022;22(1):1–8. doi:10.1186/s12884-022-04721-z

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