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Models for predicting vaginal birth after cesarean section: scoping review

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Abstract

Background Women who are pregnant again after a prior cesarean section are faced with the choice between a vaginal trial and another cesarean section. Vaginal delivery is safer for mothers and babies, but face the risk of trial labor failure. Predictive models can evaluate the success rate of vaginal trial labor after cesarean section, which will help obstetricians and pregnant women choose the appropriate delivery method.

Objective To review the existing prediction models of vaginal delivery after cesaean.

Methods Seven databases, including CNKI, Wanfang Data, Chinese Science and Technology Periodical Database, China Biomedical Literature Database, PubMed, Embase, and Web of Science, were searched for studies on the predictive model of VBAC from inception to July 20, 2022. Two researchers independently screened the literature and extracted the data. The risk of bias and applicability of the included researches was evaluated using the Prediction model Risk of Bias Assessment Tool.

Results Twenty-six studies that covered 26 models were included. The overall property of the included models was good, but validation of the included models was insufficient. The methodological quality of the included studies was generally low, with 3 studies rated as having a low risk of bias and 23 studies rated as having a high risk of bias. The main predictors in the models were the Bishop score, history of vaginal delivery, neonatal weight, maternal age, and BMI.

Conclusions Although a variety of prediction models have been developed globally, the methodology of these studies has limitations and the models have not been adequately validated. In the future, more prospective and high-quality research is needed to develop visual models to serve clinical work more effectively and conveniently. Obstetricians or midwives could use predictive models to help a woman choose the right delivery method.

Keywords Prediction model, Scoping review, Trial of labor after cesarean delivery, Vaginal birth after cesarean, VBAC, TOLAC

Introduction

The cesarean section rate has been increasing worldwide over the current decade [4]. Data showed that the cesarean delivery rate increased from 5% to 30–32% over the last 10 years in America [2]. A large Chinese study showed that the cesarean section rate rose from 28.8% in 2008 to 34.9% in 2014 [22]. The latest available data shows that 21.1% of women gave birth by cesarean worldwide [4]. The increasing cesarean section rates have led to an increase in maternal mortality and morbidity [2]. Affected by the dictum "once a cesarean always a cesarean", women with a prior cesarean section often choose to have another cesarean section in the next delivery, which in turn contributes to the high cesarean section rates.

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Women with a prior cesarean section once become pregnant again face a choice between a trial of labor after cesarean (TOLAC) and an elective repeat cesarean delivery (ERCD). The vaginal birth after cesarean (VBAC) guidelines of the American College of Obstetricians and Gynecologists recommend a TOLAC for women with a prior cesarean section who become pregnant again [16]. Outcomes of a TOLAC include VBAC and emergency cesarean delivery after a failed trial of labor. A successful TOLAC helps mothers avoid abdominal surgery, leading to a lower incidence of bleeding, thromboembolism, and infection and a shorter recovery period than those undergoing an ERCD [16]. However, a TOLAC has the risk of failure. There are more complications and possibly uterine rupture when the mother undergoes emergency cesarean delivery after a failed TOLAC. The inability to predict the probability of success for a trial of labor has become a barrier for obstetricians and mothers in choosing a TOLAC. If the probability of VBAC can be accurately predicted, it will help obstetricians screen suitable candidates for a TOLAC, help mothers establish confidence in a vaginal trial of labor, avoid complications caused by a second cesarean section, and reduce the overall cesarean section rate. VBAC predictive models have been researched in many developed countries and various predictive models have been developed and validated in different populations [7, 14, 31]. China implemented the two-child policy in 2016, allowing a couple to have two children. In 2021, the three-child policy was introduced, permitting a couple to have three children. Prior to these changes, China had been adhering to a one-child policy for several decades, encouraging couples to have only one child as a response to rapid population growth. In recent years, with the launch of the "Two-Child Policy" and "Three-Child Policy", there has been increasing research on developing VBAC predictive models in China [8, 10, 33]. However, the factors and model performance of the predictive models of various studies are quite different, and there is a lack of external validation. In this review, the construction, factors, and performance of relevant predictive models worldwide were reviewed to guide the selection of appropriate predictive models in a clinical setting and related research in the future.

Methods

Search strategy

We searched CNKI, Wanfang Data, Chinese Science and Technology Journal Database, China Biomedical Literature Database, PubMed, Embase, and Web of Science for publication from inception to July 20, 2022. We used a search method that involved combining MeSH Terms and free-language terms. The search formula was as follows: ("vaginal birth after cesarean" [MeSH Terms] OR "trial of labor after cesarean" [Title/Abstract] OR "VBAC" [Title/Abstract] OR "TOLAC" [Title /Abstract]) AND ("prediction" [Title/Abstract]). Subsequently, a manual search of references of the included research papers was performed.

Inclusion and exclusion criteria for the literature

The inclusion criteria were as follows: 1) the research subjects underwent a TOLAC, the gestational age was more than 37 weeks, there was a single live fetus; the subjects had a previous history of cesarean section, and the re-pregnancy was more than 2 years postoperatively; 2) the study was to construct or to validate a predictive model of VBAC section or to test the predictive power of a model on VBAC section; and 3) the article was the original study for model construction or validation, such as a cohort study, case-control studies, and cross-sectional studies.

The exclusion criteria were as follows: 1) non-Chinese or non-English literature; 2) unavailable full text; 3) low-quality literature; and 4) reviews.

Literature screening

The citations obtained from the search were imported into the Endnote X9 software to check for bibliographic duplicates. After eliminating the duplicates, 2 postgraduate researchers trained in evidence-based nursing practice independently conducted preliminary screening by reading titles and abstracts according to the research topic. After initial screening, they read the full text and re-screened the research according to the inclusion and exclusion criteria. If there was any disagreement during the screening process, a third researcher was consulted, and these disagreements were resolved by consensus. Finally, the research that met the criteria was determined.

Data extraction and analysis

Two researchers independently extracted data from the chosen literature. In the event of a disagreement, a third researcher was consulted, and these disagreements were resolved by consensus. Data extracted are as follows: author, year, country, study site, sample size, model construction, validation method, model predictors, presentation format, performance, and others.

Evaluation of methodological quality

Two researchers independently assessed the methodological quality of the included researches according to the Prediction Model Risk of Bias Assessment Tool (PROBAST) [38], including the risk of bias and applicability assessments. The PROBAST list includes four evaluation areas, including research objects, predictors,

results, and analyses, with 20 questions. In this study, all areas of the included researches were evaluated for risk of bias, and the first 3 were evaluated for applicability. The risk of bias evaluation questions were answered with either "yes"/ "maybe," "no"/"maybe," or "no information;" the applicability evaluation questions were evaluated by "low applicability risk," "high applicability risk," or "unclear." In disagreement during the evaluation process, a third researcher was consulted, and these disagreements were resolved by consensus.

Results

Literature search and screening results

A total of 970 articles were obtained from the preliminary search, including 563 English and 407 Chinese articles. After a series of screening processes of duplicate checking, reading the title and abstract, and reading the complete text, 26 articles were finally included. All studies were model-constructing studies to construct predictive models for VBAC section to validate their properties. The flow chart of literature screening is shown in Fig. 1.

Methodological quality evaluation of the included researches

The quality of the included researches was assessed using PROBAST. Among the 26 chosen studies, 3 had a low risk of bias, and 23 had a high risk of bias; the overall methodological quality needs improvement. The risk of bias assessment results are shown in Table 1.

Basic features of the chosen studies

Among the 26 included studies, the design types were primarily retrospective cohort studies, retrospective case-control studies, and prospective cohort studies. Seventeen studies were single-center studies, and 9 were multi-center studies. The included studies came from 7 countries: 15 from China, 2 from the United States, 2 from India, 2 from Sweden, 3 from Israel, 1 from the Netherlands, and 1 from Australia. The construction of the model for the included studies is shown in Table 2.

Construction and validation of the predictive model for VBAC section

Model construction method and presentation

Twenty-six VBAC predictive models were built from the 26 included studies. 23 studies used logistic regression to construct the predictive models, 1 used LASSO regression, and 2 used machine learning algorithms. 11 models are presented in the form of regression equations, which have a clear mathematical form, making them easy to understand and interpret. 7 models in the form of nomograms which can visually display data distribution and trends. 5 models as scoring systems which simplify complex information into one or more scores, facilitating quick assessment and decision-making. 2 models as machine learning models which can handle large amounts of complex data with high predictive accuracy. can handle large amounts of complex data with high predictive accuracy. 1 model as a web-based calculator which is interactive, allowing users to input data in real-time and receive immediate feedback.

Model predictors

Each of the chosen studies involved 1–10 predictors; the predictors involved in each predictive model were different due to demographic and child-birth-related factors. Among them, the predictors with the highest frequency

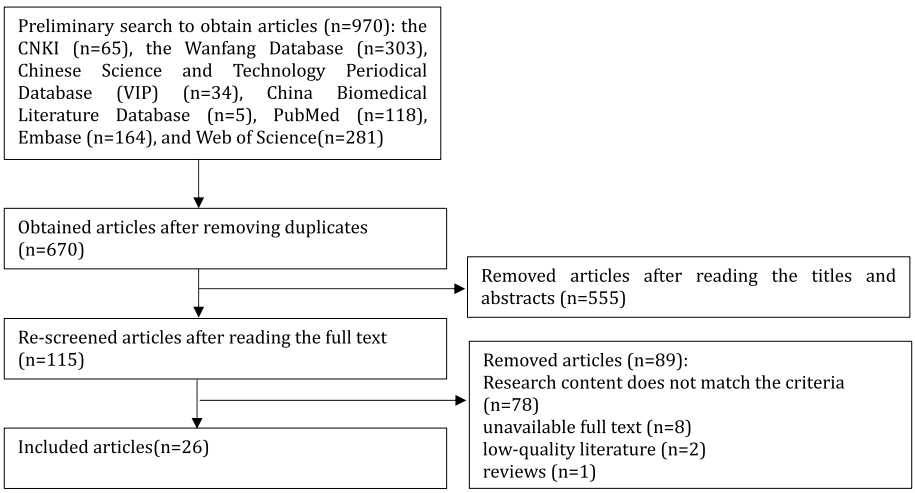


Fig. 1 Literature screening flowchart

Table 1 Risk of bias assessment of the included studies

Chosen study	Research subject			Predictor				Result							Statistical analysis										Overall risk of bias assessment
	①	②	Risk of bias	③	④	⑤	Risk of bias	⑥	⑦	⑧	⑨	⑩	⑪	Risk of bias	⑫	⑬	⑭	⑮	⑯	⑰	⑱	⑲	⑳	Risk of bias	
Grobman [15]	Y	Y	Low	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Y	Y	Y	Low	Low
Kiran [19]	Y	Y	Low	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	Y	Y	Y	N	Y	Y	Y	Y	High	High[a]
Lakra [21]	Y	Y	Low	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	Y	Y	Y	N	Y	Y	Y	Y	High	High[a]
Li [23]	Y	Y	Low	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	Y	Y	Y	N	Y	Y	Y	Y	High	High
Liao [25]	N	Y	High	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	Y	Y	Y	N	Y	Y	Y	Y	High	High[a]
Lin [26]	Y	Y	Low	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	Y	Y	Y	N	Y	Y	N	Y	High	High
Wollmann [27]	Y	Y	Low	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Y	Y	Y	Low	Low
Meyer [28]	Y	Y	Low	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	Y	Y	Y	N	Y	Y	Y	Y	High	High
Mi [29]	N	Y	High	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	Y	Y	Y	N	Y	Y	Y	Y	High	High
Mizrachi [30]	N	Y	High	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Y	Y	Y	Low	High[a]
Schoorel [32]	N	Y	High	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Y	Y	Y	Low	High[a]
Zhang [42]	N	Y	High	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	Y	Y	Y	N	Y	Y	Y	Y	High	High
Chen [8]	N	Y	High	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	Y	Y	Y	N	Y	Y	Y	Y	High	High
Fang [10]	N	N	High	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	N	Y	Y	Y	Y	Y	Y	Y	High	High
Hu [17]	Y	Y	Low	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	Y	Y	Y	N	Y	Y	Y	Y	High	High
Hua [18]	Y	N	High	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	N	N	Y	Y	N	Y	Y	Y	Y	High	High
Lai [20]	Y	Y	Low	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	Y	Y	Y	N	Y	Y	Y	Y	High	High
Li [24]	N	Y	High	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	Y	Y	Y	N	Y	Y	Y	Y	Low	High
Shui [33]	N	Y	High	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	Y	Y	Y	N	Y	Y	Y	Y	High	High
Sun [35]	N	N	High	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	Y	Y	Y	N	Y	Y	Y	Y	High	High
Yu [41]	N	Y	High	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	N	Y	Y	N	Y	Y	Y	Y	High	High
Bi [5]	N	Y	High	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	N	Y	Y	N	Y	Y	Y	Y	High	High
Carlsson [7]	N	Y	High	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	N	Y	Y	N	Y	Y	Y	Y	High	High
Gerhardy [11]	N	Y	High	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	N	Y	Y	Y	Y	Y	Y	Y	High	High
Gonen [12]	N	Y	High	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	N	Y	Y	Y	Y	NI	N	Y	High	High
Grobman [14]	Y	Y	Low	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Low	Y	Y	Y	Y	Y	Y	Y	Y	Y	Low	Low

[a] Indicates that no external verification has been carried out; all are evaluated as high risk

Table 2 Building of chosen study models

Author	Year	Country	Study site	Study design	Model construction sample size	Model validation sample size	Model building method	Model predictors	Model mode of presentation	Model validation method	Model performance	
											Discrimination	Calibration
Grobman [15]	2021	USA	Multi-center	Prospective cohort study	5741	5946	Logistic regression	Age, pre-pregnancy BMI, height, symptom stop, vaginal delivery before cesarean section, history of VBAC, chronic hypertension history	Web-based calculator	External (ROC)	0.75	Unclear
Kiran [19]	2020	India	Single-center	Prospective cohort study	194	Not reported	Logistic regression	Age, BMI, Bishop score, history of previous vaginal delivery	Scoring system	Unclear	0.853	0.804
Lakra [21]	2020	India	Single-center	Observational study	150	Not reported	Logistic regression	Number of previous deliveries, natural childbirth, Bishop score, gestational age, BMI	Scoring system	Unclear	0.77	Unclear
Li [23]	2019	China	Multi-center	Retrospective cohort study	1491	373	Logistic regression	Gestational age, history of vaginal delivery, estimated birth weight, BMI, onset of labor, Bishop score, premature rupture of membrane	Nomogram	External (ROC, Youden index)	0.77	0.82

Table 2 (continued)

Author	Year	Country	Study site	Study design	Model construction sample size	Model validation sample size	Model building method	Model predictors	Model mode of presentation	Model validation method	Model performance	
											Discrimination	Calibration
Liao [25]	2020	China	Single-center	Retrospective descriptive study	1062	1062	Logistic regression	Age, history of vaginal delivery, birth interval, cesarean section before trial labor, dystocia as an indication for previous cesarean section, internodular diameter, maternal prenatal BMI, gestational age, estimated fetal weight, hypertensive disorders	Scoring System	Unclear	0.777	0.71
Lin [26]	2019	China	Single-Center	Prospective Study	162	162	Logistic Regression	Bishop's score, natural childbirth	Nomogram	Unclear	0.953	0.948
Wollmann [27]	2021	Sweden	Multi-Center	Cohort Study	1558	1558	Conditional Inference Tree, Conditional Random Forest, LASSO binary regression	Indications for first cesarean section	Machine learning model	External	0.61–0.69	0.684–0.704
Meyer [28]	2020	Israel	Single-center	Cohort study	792	197	Random Forest, Generalized Linear Model, eXtremeGradient-Boosted Decision Trees	History of vaginal delivery, vaginal delivery after cesarean section, height, increased cervical disappearance and dilation, low fetal position, induction of labor, cessation of previous descent	Machine learning model	External	0.336–0.351	Unclear

Table 2 (continued)

Author	Year	Country	Study site	Study design	Model construction sample size	Model validation sample size	Model building method	Model predictors	Model mode of presentation	Model validation method	Model performance	
											Discrimination	Calibration
Mi [29]	2021	China	Single-center	Retrospective cohort study	551	227	Logistic regression	Number of previous deliveries, BMI, Bishop score, history of vaginal delivery, newborn birth weight	Nomogram	External	0.730	Unclear
Mizrachi [30]	2017	Israel	Single-center	Retrospective cohort study	231	231	Logistic regression	Model 1: History of VBAC, cervical disappearance at TOLAC, head position at previous Cesarean section, neonatal weight at previous cesarean section Model 2: Cervical position at previous cesarean section, cervical disappearance at TOLAC, neonatal weight from previous cesarean section	Regression equation	Unclear	Model 1: 0.80 Model 2: 0.76	Unclear
Schoorel [32]	2014	Holland	Multi-center	Retrospective cohort study	515	515	Logistic regression	Estimated fetal weight, previous discontinuous deliveries, history of vaginal delivery, induction of labor, pre-pregnancy BMI, ethnicity	Equation	Internal validation (bootstrapping)	0.708	0.13

Table 2 (continued)

Author	Year	Country	Study site	Study design	Model construction sample size	Model validation sample size	Model building method	Model predictors	Model mode of presentation	Model validation method	Model performance	
											Discrimination	Calibration
Zhang [42]	2020	China	Single-center	Retrospective cohort study	483	225	LASSO regression	Maternal height, maternal BMI at delivery, fundus height, cervical Bishop Score, maternal delivery age, gestational age, history of vaginal delivery	Nomogram	Internal (ROC, bootstrap resampling, DCA), External	0.89	Unclear
Chen [8]	2021	China	Single-center	Retrospective case-control study	149	75	Logistic regression	Low maternal BMI on admission, high cervical Bishop score, spontaneous labor, thick myometrium in the lower uterine segment, and neonatal weight < 3500g	Regression equation	Unclear	0.908	Unclear
Fang [10]	2019	China	Single-center	Retrospective case-control study	430	Not reported	ANN, Logistic regression	Maternal age, weight gain during pregnancy, whether there is an indication for cesarean section in this pregnancy, whether this pregnancy has an artificial rupture of membranes or planned delivery, and Bishop score	Regression equation	Unclear	ROC curve OF ANN predictive models: 0.850 ROC curve for logistic regression prediction models: 0.810	Unclear

Table 2 (continued)

Author	Year	Country	Study site	Study design	Model construction sample size	Model validation sample size	Model building method	Model predictors	Model mode of presentation	Model validation method	Model performance	
											Discrimination	Calibration
Hu [17]	2019	China	Single-center	Prospective cohort study	290	Not reported	Logistic regression	Age, height, weight gain during pregnancy (kg), history of vaginal delivery, cervical disappearance on admission (%), induction of labor	Regression equation	Unclear	0.778	Unclear
Hua [18]	2009	China	Single-center	Prospective cohort study	94	Not reported	Logistic regression	Age, time since the last cesarean section, thickness of the lower uterine segment, combined with high blood pressure during pregnancy	Regression equation	Unclear	0.828	Unclear
Lai [20]	2018	China	Single-center	Prospective cohort study	532	Not reported	Logistic regression	Neonatal birth weight, cervical Bishop score on admission, rupture of membranes	Regression equation	Unclear	0.926	0.416
Li [24]	2020	China	Single-center	Retrospective case-control study	975	244	Logistic regression	Gestational age, number of abortions, history of vaginal delivery, BMI (kg/m^2), high blood pressure during pregnancy, labor induction, cervical Bishop score	Regression equation	External (ROC)	AUC = 0.83 (Internal) AUC = 0.81 (Assessment sample)	Unclear

Table 2 (continued)

Author	Year	Country	Study site	Study design	Model construction sample size	Model validation sample size	Model building method	Model predictors	Model mode of presentation	Model validation method	Model performance	
											Discrimination	Calibration
Shui [33]	2022	China	Multi-center	Retrospective case-control study	294	83	Logistic regression	Age, prenatal BMI, fetal weight, lower uterine segment myometrial thickness, Bishop score, number of prenatal training	Nomogram predictive model	Internal (Bootstrap)	0.927	Unclear
Sun [35]	2022	China	Single-center	Retrospective case-control study	184	Not reported	Logistic regression	Maternal labor admission, The Bishop score is high at admission (protective factor); Excessive pregnancy weight gain, high neonatal weight (risk factor)	Regression equation	Unclear	0.814	0.127
Yu [41]	2021	China	Single-center	Retrospective case-control study	324	Not reported	Logistic regression	Whether they are close to giving labor, premature labor, premature rupture of membrane, height, birth interval, neonatal weight, and indications for previous pregnancy surgery	Constructed scoring system	Unclear	0.918	0.826

Table 2 (continued)

Author	Year	Country	Study site	Study design	Model construction sample size	Model validation sample size	Model building method	Model predictors	Model mode of presentation	Model validation method	Model performance	
											Discrimination	Calibration
Bi [5]	2020	China	Multi-center	Retrospective case-control study	1013	Not reported	Logistic regression	Gravity, parity, number of previous deliveries, source of referral, premature rupture of membrane, prenatal hemorrhage, placental hyperplasia profile, preeclampsia, neonatal weight, oxytocin induction	Nomogram	Unclear	AUC in the first trimester model = 0.661 Prenatal model AUC = 0.743	Unclear
Carlsson [7]	2019	Sweden	Multi-center	Retrospective cohort study	19343	19343	Logistic regression	Previous VBAC and previous non-cephalic cesarean delivery	Regression equation	Unclear	0.67	Unclear
Gerhardy [11]	2022	Australia	Multi-center	Retrospective cohort study	13237	4412	Logistic regression	Maternal place of birth, BMI, parity, if last birth was CS, any previous vaginal births, number of previous CS(s), maternal age, diabetes (pre-existing or gestational diabetes), hypertensive disorders (pre-existing, gestational or preeclampsia) and fetal abnormalities	Regression equation	Unclear	Full model AUC = 0.7887 Prenatal model AUC = 0.7384	Unclear

Table 2 (continued)

Author	Year	Country	Study site	Study design	Model construction sample size	Model validation sample size	Model building method	Model predictors	Model mode of presentation	Model validation method	Model performance	
											Discrimination	Calibration
Gonen [12]	2004	Israel	Single-center	Retrospective cohort study	475	Not reported	Logistic regression	Abnormal presentation as an indication for primary CS, previous VBAC, cervical dilation, gestational age < 41 weeks, low gestational age at primary CS	Scoring system	No information	No information	Unclear
Grobman [14]	2007	USA	Multi-center	Prospective cohort study	7660	Not reported	Logistic regression	Age, BMI, ethnicity, prior vaginal delivery, the occurrence of a VBAC, a potentially recurrent indication for the cesarean delivery	Regression equation, nomogram	Internal	0.75	Unclear

were the Bishop score, vaginal childbirth history, neonatal weight, maternal age, and BMI.

Model's property

The property evaluation of the predictive models includes discrimination and calibration [39]. Among the 26 studies included, 25 used the area under the receiver operating characteristic curve to evaluate the discriminative degree of the model. Among them, 3 models had a discriminatory capacity of less than 0.7, 17 had a discriminatory capacity between 0.7 and 0.9, and 5 had a discriminatory capacity of more than 0.9. This indicates that most of the prediction models had good discrimination, and only 1 study did not report the model's discriminatory capacity [12]. The Hosmer-Lemeshow test was used in 9 studies to verify the models' calibration; the models in 6 studies showed a reasonable degree of calibration.

Model validation

Model validation is either internal or external [39]. Of the 26 models included, 4 were validated internally, 6 were validated externally, and only 1 was validated internally and externally. Most models (11 researches) are presented in the form of regression equations; other modes include nomograms (7 researches), machine learning models (2 researches), scoring systems (5 researches), and web-based calculators (1 research).

Discussion

In this review, we summarized 26 predictive models for vaginal birth after cesarean (VBAC). Due to differences in medical and cultural backgrounds across regions, there is a wide variety of VBAC predictive models. However, most of these models are presented in the form of regression equations and have not been visualized, which increases the complexity of clinical use. Regarding model validation, the majority of models lack external validation, indicating deficiencies in the verification aspects of existing VBAC predictive model studies. In terms of study populations, 15 of these predictive models originate from China. The predominance of Chinese literature can be attributed to the surge in second-child pregnancies in China following the implementation of the two-child policy in 2016. This demographic shift included a significant number of women with a history of cesarean delivery, who were faced with the decision to attempt a trial of labor after cesarean (TOLAC). This may explain the abundance of related Chinese literature. Since most of the included studies are concentrated in China, these predictive models may primarily be applicable to the medical environment and population characteristics in China. Differences in medical resources, cultural backgrounds, and maternal health status across regions suggest that the applicability of these models in other countries and regions needs further validation and adjustment to ensure their effectiveness and reliability. Regarding research methods, these models primarily employed various statistical techniques, including logistic regression, LASSO regression, and machine learning algorithms. Logistic regression is a commonly used statistical method that establishes a model by estimating the relationship between independent variables and a binary dependent variable. It is suitable for handling data with binary outcomes and can provide probability estimates. LASSO regression is a regularized linear regression method that introduces a penalty term to constrain regression coefficients, thereby achieving feature selection. This method can effectively address issues of multiple collinearity, enhancing the interpretability and predictive power of the model. Additionally, some studies employed machine learning algorithms such as random forests and support vector machines (SVM), which can handle complex nonlinear relationships and perform well on large datasets.

Existing models were not fully validated and had low methodological quality

In this review, we summarized the property of 26 VBAC prediction models. Among which 15 [5, 8, 10, 17, 18, 20, 23–26, 29, 33, 35, 41, 42] models were developed in China. The main reason was that after the launch of the "two-child policy" in 2016, a large number of women chose to give birth to a second child, including those women who had prior cesarean sections. Because of this special reason, there have been many studies on the prediction model of vaginal delivery after cesarean section in China. In terms of model validation, except for one study [12] that did not report the discrimination (AUROC), all other studies reported the discrimination (AUROC = 0.336 ~ 0.927), and most of the models showed good discrimination(AUROC > 0.7). Only 9 [19, 20, 23, 25–27, 32, 35, 41] of the models reported Calibration. Reporting on model performance was incomplete and may affect the use of the model. Our study also found that the vast majority of the researches lacked external validation. These all show that existing studies on VBAC prediction model still have deficiencies in model validation. External validation is an important step in evaluating the generalizability of a model, helping to determine its applicability across different populations and settings. The lack of external validation may result in poor performance of the models on new datasets, limiting their practical application value. Thus, subsequent studies need improvement in model validation.Methodologically, of the 26 researches included, 23 had methodological limitations. Only 3 researches [14, 15, 27] were at low risk of

bias after quality assessment. The main reason for the risk of methodological bias was that most of the researches used univariate factor analysis to screen the predictors. The significant variables in the univariate analysis were included in the regression model. For example, Liao's [25] research adopted Chi-square test, T-test or fisher's exact test to conduct univariate factor analysis, and the variables with significant differences were incorporated into the logistic regression model. Although this is a commonly used method to screen variables, it may miss some key variables and lead to bias, especially when the sample size is small. The second main reason for bias was the data came from inappropriate sources. Data from randomized controlled studies, prospective cohort studies, nested case-control studies, or case cohort studies are appropriate [38]. In the researches we included, 15 [5, 7, 8, 10, 11, 23, 25, 29, 30, 32, 33, 35, 41, 42] were retrospective, and retrospective researches were more likely to have bias. The third major reason was for the bias was the processing of independent variables. Continuous variables were not suitable for conversion to categorical variables [38], which were found in 7 researches [5, 7, 10–12, 18, 41]. All these evidence indicate that the methodological quality of the current researches on VBAC prediction model is poor, and the follow-up research needs to improve methodological quality to reduce the risk of research bias.

Various types of VBAC prediction models exist, and there is an urgent need for model unification and visualization

Various types of predictive models were included in this study. Due to the research subjects' different races, backgrounds, and nationalities, different studies involve various predictors with different weights, which does not facilitate the scaling up of clinical studies. Furthermore, some models are presented as regression equations [7, 8, 10, 11, 17, 18, 20, 24, 30, 32, 35], increasing the complexity of clinical use. Model visualization such as nomogram and machine learning models are more intuitive and can reduce the tedious and complicated steps in use. Machine learning technique can provide diagnosis and analytical amenities so that it can be used in disease prediction to making effective decisions [36]. Future research can consider visualizing the predictive model using a nomogram, scoring system, and machine learning model.

Usage status of the VBAC prediction model

Among the 26 models included in this study, the model developed by Grobman [14] in 2007 is the most widely used. This predictive nomogram incorporates six variables: maternal age, body mass index,ethnicity, prior vaginal delivery, the occurrence of a VBAC and a potentially indiction for the cesarean delivery. This model was validated in external populations in the US [9], in Japan [40], in Spanish [3],in Italy [1] and so on. The model was validated in different populations, and the area under ROC curve was 0.67–0.80. Consideration of race may influence the clinician's choice of TOLAC. Grobman developed a model in 2021 that did not involve race and ethnicity [15]. This model has demonstrated good predictive accuracy when applied to the Japanese population [34]. Schoorel's [32] model is another one that is used more frequently. The property of the model has been validated in populations in Western Europe [32] and Dutch [37]. The predictors included in Grobman 's model were mainly indicators early in pregnancy, such as maternal age, prepregnancy weight, height, indication for previous cesarean delivery, obstetrical history, and treated chronic hypertension [14]. Schoorel's model, by contrast, included indicators both in early pregnancy and pre-labor predictors [32]. Pre-labor predictor, such as estimated fetal weight, can only be obtained in late pregnancy, before delivery. This means that obstetricians can use Grobman 's model to tell pregnant women the success rate of vaginal trial labor after cesarean section early in pregnancy, so that pregnant women have plenty of time to consider which method of delivery to choose. However, Schoorel's model can only be used before delivery, which may not be conducive to full consideration by pregnant women.

Recommendations for future research and practice

Evidence suggests that women who try a TOLAC may have fewer complications than those who choose an ERCD if they are more than 60–70% more likely to predict VBAC [6, 13]. High-quality predictive models could help pregnant women choose appropriate delivery methods and minimize risks. Various models have been developed worldwide, In addition to Grobman's model low methodological bias, and is widely used, the methodological quality of most models in the development process is low; in addition, there is a high risk of bias and a lack of validation. The model's quality is not high and is complicated to use. In the future, it is necessary to conduct multi-center prospective cohort studies based on the domestic population to develop a high-quality predictive model VBAC, to improve the model evaluation and validation system, and to build a predictive model suitable for countries with different cultural backgrounds. For pregnant women who meet the clinical conditions of a TOLAC, the obstetrician or midwife should fully inform them of the benefits and possible risks of choosing a TOLAC so that pregnant women could choose a delivery method that is suits their vital interests.

Limitations

This study reviewed existing available studies on VBAC prediction models, however, the scope of literature searched was limited. Only Chinese databases and part of English databases were searched, and grey literature was not retrieved, so some relevant literature might be missed.

Conclusions

The extensive clinical use of the VBAC predictive model significantly reduces maternal complications and the overall cesarean section rate. This study systematically reviewed the characteristics of the construction, predictors, performance, and validation of VBAC prediction models of current researches. Evidence indicates that although a variety of prediction models have been developed globally, the methodology of these studies has limitations and the models have not been adequately validated. In the future, more prospective and high-quality research is needed to develop visual models to serve clinical work more effectively and conveniently. Obstetricians or midwifes could use predictive models to help a woman choose the right delivery method.

Abbreviations

VBAC	vaginal birth after cesarean
TOLAC	trial of labor after cesarean
ERCD	elective repeat cesarean delivery

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Authors' contributions

Made substantial contributions to conception and design, or acquisition of data, or analysis and interpretation of data: Hong CUI, Tong LIU Involved in drafting the manuscript or revising it critically for important intellectual content: Hong CUI, Wenhui SHAN Given final approval of the version to be published. Each author should have participated sufficiently in the work to take public responsibility for appropriate portions of the content: Hong CUI, Wenhui SHAN, Quan NA, Tong LIU Agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved:

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Data availability

All data generated or analyzed during this study are included in this published article.

Declarations

Ethics approval and consent to participate

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Consent for publication

All authors have been informed and agree to publication.

Competing interests

The authors declare no competing interests.

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