

The Intelligent Regulation Model of Oxytocin for Women Having Vaginal Birth After Cesarean Section

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Abstract

Objective: To build an intelligent regulation model of oxytocin (OT) for women having a vaginal birth after cesarean section (VBAC) and further explore the intelligent and precise regulation of the scheme of the OT medication at delivery.

Methods: A cross-sectional study design was used by collecting the data of the VBAC parturitions who delivered in the Obstetrics Department of the First Affiliated Hospital of Wenzhou Medical University from January 2014 to May 2020 and used the OT during the labor process. The multiple linear regression was used to analyze the modeling variables from the electronic medical records and the variables such as fetal heart rate (FHR) and uterine contraction (UC) frequency extracted from the cardiotocography. The OT drip speed predictive model was established based on the XGBoost algorithm and was compared using the logistic regression model and traditional decision tree. The data set was divided into the training set and test set at the 8:2 ratio, and the predictive performance of the model was evaluated for the accuracy, precision, recall rate, and F1 score.

Results: A total of 1005 records with oxytocin regulation were included from 124 parturitions involving the VBAC. The XGBoost model performed the best prediction. Through the five fold crossover operation, the accuracy was 0.82, precision was 0.84, the recall rate was 0.80, and the F1 value was 0.82. Among them, the contraction duration, uterine pressure, FHR, UC frequency, and interval time from the previous cesarean section were the variables with great contribution to the modeling.

Conclusion: This study constructed an OT regulation model based on the XGBoost, which recognized that the real-time intelligent regulation of the prenatal OT, with fast response speed, high model accuracy, and strong extrapolation had positive significance to obstetric clinical nursing.

Introduction

With the universal two-child policy and the purpose of improving the medical and health conditions of people in China, the number of vaginal birth after cesarean (VBAC) has increased gradually^[1], and using oxytocin (OT) to induce or accelerate labor is more common in women undergoing the VBAC. Previous studies have shown that the use of OT to enhance uterine contractions (UC) during parturition with the VBAC is relatively safe and effective^[2]. However, if the previous cesarean section disrupted the continuity of the lower uterine muscle layer, the women undergoing the VBAC need to be more cautious with the infusion of OT than the healthy women. Some studies have^[3] identified that the OT dosage was an independent risk factor for uterine rupture. Improper administration of the OT increases the risk of uterine rupture and endangers the health of the mother and the fetus. Therefore, real-time, accurate, and effective OT monitoring in the women undergoing the VBAC is required in the current clinical practice.

In the era of digital health care, the application of intelligent medication systems based on computer technology has become a common tool, which is often employed in infusion therapies such as analgesia

pumps and insulin pumps^[8-9].

Compared with the traditional manual adjustment of the infusion therapies, the intelligent drug injection and transmission system automatically adjusts the infusion rate based on the real-time diagnosis and treatment effect to ensure the uniform and rational input of the drug, considering the accuracy and safety of the medication. At present, there have been elucidations on the systemic administration of the OT infusion regulation. Some studies have designed automatic adjustment devices for the OT administration that can provide an early warning regarding abnormal uterine contraction (UC) and fetal heart^[10]. Another study has designed an automatic oxytocin infusion regulator in obstetrics^[11] that adjusts the OT drip rate according to the frequency and intensity of the UC. However, the existing models do not analyze the data comprehensively during childbirth, and they only make judgments based on the established preset rules, which furnish a simple pre-warning.

At present, the OT intravenous infusion in clinical practice requires monitoring of uterine contraction and fetal heart in real-time and manually adjustment of the infusion speed of the pump accordingly by the midwives^[4]. However, under the current situation of the surging number of deliveries and a shortage of midwives, the OT infusion speed often cannot be adjusted on time and reasonably, and the adjustment process is frequently accompanied by subjective errors of the medical staff^[5]. With the development of big data analytics and artificial intelligence technology, the intelligent medical service system has become a new aid in clinical work^[6]. Therefore, this study proposes an intelligent OT infusion control method to reduce labor costs and achieve medication accuracy, which is of great significance in obstetric nursing.

Related work. In last year, Previously, an OT syringe pump feedback system^[7] has been established by this research group. The system used the internet technology as the carrier to connect the electronic fetal monitor (EFM), the infusion pump (IP), the nurse information system (NIS), and the electronic medical record system (EMRS). Among them, the Philips EFM (M2702A) was selected to monitor the fetal conditions in the uterus and measure the changes of uterine pressure and FHR through an external UCs probe and an ultrasonic Doppler probe. The Internet of Things Technology transmitted the information related to the diagnosis and treatment from the EMRS and the timing information from the EFM to the NIS for the analysis. Finally, the NIS issued a regulatory instruction to control the maternal bedside infusion pump to regulate the injection speed.

The OT regulation model established in this study was embedded into the NIS as a decision support module for the OT medication during delivery. Based on the modeling factors from the EMRS and EFM, the model intelligently determined the regulation of the OT drip speed immediately instead of manually judging the labor information, equipped the OT intelligent regulation system with the real-time monitoring of the labor progress, and automatically adjusted the infusion speed (Figure 1).

Materials And Methods

Participants. This study was a retrospective cohort study. The study subjects were women undergoing the VBAC who used oxytocin to induce or accelerate labor during delivery in the Obstetrics Department of the First Affiliated Hospital of Wenzhou Medical University from January 2014 to May 2020. A total of 124 samples with 1,005 records with OT regulation were included in this study, among which 312 records were labeled the OT as “drip speed maintaining”, 618 as “drip speed accelerating”, and 75 as “drip speed slowing down”. They were divided into the training sets (n=804) and the test sets (n=201) at the 8:2 ratio.

The inclusion criteria were: using oxytocin to induce or accelerate the labor. the subjects and their families, who understood the advantages and risks of the VBAC and had the willingness to try vaginal labor and to provide signed informed consent. the subjects who had only one cesarean section with a transverse incision in the lower segment of the uterus. the subjects who had the interval between the previous cesarean section and this delivery of more than 18 months, and no indication of the cesarean section need in this pregnancy. ultrasonography showed that the muscular layer of the lower segment of the anterior wall of the uterus was continuous. the clinical data was complete.

The exclusion criteria were: the subjects who had contraindications for vaginal delivery. there were contraindications for OT use. the subjects who used OT only in the third stage of labor. the continuous intravenous infusion time was less than 30 minutes. using drugs that affected the fetal heart rate (FHR) during delivery. the indication of induced labor was a stillbirth. still static OT was combined with other induction drugs.

Preliminary identification of predictors. Based on the literature review and the knowledge of a panel of experts, 18 factors that may affect the regulation of OT speed in the VBAC were selected from the electronic medical record system including age, BMI, gestational week, history of vaginal delivery, the thickness of lower uterine segment, interval time from the previous cesarean section, cervical receptivity, uterine dilatation, the position of presentation of fetus, state of the fetal membrane, uterine height, maternal abdominal circumference, analgesia used, amniotic fluid index, fetal biparietal diameter, fetal head circumference, fetal abdominal circumference, and fetal femoral length. A multiple linear regression to filter modeling variables was adopted.

Data preprocessing. The maternal and fetal conditions were evaluated by obtaining the cardiotocography (CTG) with access to the data port of the Philips EFM. The OT medication was usually assessed every 15 to 20 minutes by calculating the intrapartum variables including baseline FHR, maternal heart rate, uterine contraction frequency, duration of UCs, and the peak uterine pressure.

The FHR and maternal heart rate were output in the form of numerical variables (times/min) from the EFM, in which the average value during the time period was calculated. The average FHR during times when the baseline fluctuated within 5 beats/min took up more than 20% of the pattern (which could be discontinuous) during the assessing period. If the baseline FHR of the assessing period was uncertain, the baseline of the previous time period was substituted.

The uterine pressure signal reflected the state of the UC, which was affected by the position of the pressure probe, the thickness of abdominal subcutaneous fat, fetal movement, and the tightness of the probe fitting. Firstly, the Sym6 wavelet packet of the Matlab software was used to decompose the measured signal in 4 scales, and the profile coefficient was taken as the uterine contraction signal after denoising. Secondly, the feature of UC was extracted. The amplitude of the peak point w Firstly, the Sym6 wavelet packet of Matlab software is used to decompose the measured signal in 4 scales, and the profile coefficient is used as the uterine contraction signal after denoising. as regarded as the peak value of the uterine pressure, the ratio of unit time to peak interval was taken as the frequency of the UC, and the interval between the starting point of the UC and the endpoint of the UC was taken as the duration of the UC (Figure 2). Finally, the average value of each UC variable in this time period was calculated.

The establishment of the predictive model. The OT regulation model was constructed based on logistic regression (LR), classification and regression trees (CART), and the XGBoost algorithm. The Grid Search CV adjusted the best parameters. The core parameters of the XGBoost model were set as follows: For the Loss Function, multi: softmax, 200 as the Iteration Number, 6 as the Maximum Depth of the Tree, and 0.2 as the Learning Rate were selected. For the LR, we selected L-BFGS solver, L2 as the Cost Function, the parameter Multiclass set to Multinomial, and the Iteration Number of 200. For CART, we chose Gini to measure the purity of the spanning tree. The maximum depth of the tree was 6, and the minimum number of leaf nodes was 6.

The datasets were divided into the training set and test set in the ratio of 8:2. Under the 5-fold cross-validation, the performance of the model was evaluated for accuracy, precision, recall rate, and F1 value, and the confusion matrix was used to observe the performance of the model in each category.

Verification of the intelligent regulation model of oxytocin. The prediction by the intelligent model was compared with the manual decision by a junior midwife and the experts' opinions to test the predictive effect of the model. Ten samples were selected, and the OT was adjusted 10 times for each sample. The junior midwife has worked for less than 5 years with the junior professional title, and she independently judged the FHR, the UC, and other conditions to implement the OT drip rate control.

The decision from the 2 senior experts with the professional title of Deputy Chief Nurse or above was taken as the gold standard. If the experts' decisions were inconsistent, the final decision was taken after a consensus formed following the discussion. The correct rate (%) was calculated in comparing the junior midwife's adjustment and the prediction of the intelligent model with the experts' decision.

Statistical analysis. The SPSS vs. 22.0 was used for the data analysis. The linear regression was formed between the electronic medical record data and the dose of the OT. The continuous variables with the normal distribution are presented as Mean \pm SD, and the variables with the skewed distribution are presented as the Median (P25, P75). The categorized variables are presented as frequency and percentage (%). According to the results from the univariate linear regression analysis, the variables with $P < 0.1$ were included in the multiple linear regression model, and the stepwise regression method was used to screen the variables, with the 2-sided test. The $P < 0.05$ was considered significant. The PyTorch

framework based on the Python platform was established and validated for the different types of machine learning algorithms.

Ethical approval of the study protocol. This study has been reviewed by the Ethics Committee of Wenzhou Medical University (No. 2019089). As this study was a retrospective study, the data were all from the electronic medical record system, it was approved by the Ethics Committee of Wenzhou Medical University, and informed consent was exempted. We confirm that all methods were carried out in accordance with relevant guidelines and regulations.

Result

Independent influencing factors of the OT infusion. The results of univariate linear regression analysis showed statistically significant differences in the maternal BMI, time of previous cesarean section, cervical dilation, the maternal abdominal circumference, history of vaginal delivery, analgesia, and the OT dosage ($P < 0.05$). There was no statistical difference in the age, gestational age, lower uterine thickness, cervical effacement, rupture of membranes, fetal biparietal diameter, amniotic fluid index, head circumference, abdominal circumference, fetal femur length, uterine height, and the OT dosage ($P > 0.05$). Then, the statistically significant factors were considered independent variables for the multi-linear regression analysis. The results showed that the interval from the previous cesarean section, natural birth history, and labor analgesia were independent influencing factors of the OT dose difference, as shown in Table 1.

Table 1. The results of the multiple linear regression analysis on the effect of oxytocin dosage

Factors	Regression coefficient	Standard error	Standardized regression coefficient	t	P
Constant item	-5.243	2.391		-2.192	0.030
BMI	0.303	0.085	0.264	3.184	0.002
Time of previous cesarean section	0.206	0.095	0.177	2.169	0.032
History of vaginal delivery	-1.746	0.773	-0.189	-2.259	0.026
Analgesia	1.631	0.512	0.264	3.184	0.002

Note $R^2=0.223$, and adjusted $R^2=0.196$

The establishment of the predictive model. The OT regulation model was constructed based on logistic regression (LR), classification and regression trees (CART), and the XGBoost algorithm. The Grid Search CV adjusted the best parameters. The core parameters of the XGBoost model were set as follows: For the Loss Function, multi: softmax, 200 as the Iteration Number, 6 as the Maximum Depth of the Tree, and 0.2

as the Learning Rate were selected. For the LR, we selected L-BFGS solver, L2 as the Cost Function, the parameter Multiclass set to Multinomial, and the Iteration Number of 200. For CART, we chose Gini to measure the purity of the spanning tree. The maximum depth of the tree was 6, and the minimum number of leaf nodes was 6.

The datasets were divided into the training set and test set in the ratio of 8:2. Under the 5-fold cross-validation, the performance of the model was evaluated for accuracy, precision, recall rate, and F1 value, and the confusion matrix was used to observe the performance of the model in each category.

Using the 5-fold cross-validation, the XGBoost model had the best prediction ability for the OT drip velocity control, significantly outperforming the LR and CART methods, as shown in Table 2. One set of the XGBoost cross-verified confusion matrix is shown in Table 3, and the model recognition showed that the accuracy of “drip velocity reduction” was the highest, the accuracy of “drip velocity increase” was weaker, and the accuracy of “drip velocity maintenance” was the weakest. The error focused on the error points of “drip velocity increase” and “drip velocity maintenance”.

Table 2. Comparison of the accuracy, precision, recall rate, and F1 value of the different models in predicting oxytocin drip velocity

Model	Accuracy	Precision	Recall rate	F1 value
LR	0.74	0.79	0.73	0.76
CART	0.76	0.75	0.73	0.74
XGBoost	0.82	0.84	0.80	0.82

Table 3. Comparison of the actual drip velocity regulation of the oxytocin and model prediction

Actual drip speed control	XGBoost model prediction results			
	Drip speed accelerated	Drip speed maintained original	Drip speed slowed down	Accuracy
Drip speed accelerated	106	18	0	85.5%
Drip speed maintained original	12	49	1	79.0%
Drip speed slowed down	0	1	13	92.9%

The distribution of the variables incorporated in the XGBoost prediction model is shown in Figure 3. The duration of the UC, intrauterine pressure, baseline FHR, and the UC frequency are the variables that contribute greatly to the model.

Verification of the intelligent regulation model of oxytocin. Comparing the XGBoost prediction model with the best performance of the manual regulation of midwives and expert decision-making, the results showed that the accuracy of manual adjustment of “drip speed increase”, “drip speed maintenance”, and “drip speed decrease” was 82.7%, 77.7%, and 100%, respectively. The prediction accuracy of the model was 87%, 80.7%, and 100%. Compared with the manual regulation by midwives who lacked clinical experience, the actual clinical application effect of this model was better, which was close to the expert decision-making level with rich clinical experience, as shown in Table 4

Table 4. Verification of the clinical effect using the XGBoost predictive model

Sample	Drip speed increase		Drip speed maintenance		Drip speed decrease	
	Manual regulation	Model prediction	Manual regulation	Model prediction	Manual regulation	Model prediction
1	85.7%	85.7%	50.0%	100.0%	100.0%	100.0%
2	80.0%	80.0%	100.0%	60.0%	-	-
3	100.0%	100.0%	75.0%	75.0%	100.0%	100.0%
4	71.4%	85.7%	50.0%	100.0%	100.0%	100.0%
5	87.5%	75.0%	100.0%	50.0%	-	-
6	66.7%	83.3%	66.7%	66.7%	100.0%	100.0%
7	100.0%	87.5%	100.0%	100.0%	100.0%	100.0%
8	85.7%	85.7%	75.0%	75.0%	-	-
9	75.0%	87.5%	100.0%	100.0%	100.0%	100.0%
10	75.0%	100.0%	60.0%	80.0%	100.0%	100.0%
Average	82.7%	87.0%	77.7%	80.7%	100.0%	100.0%

Note: “-” indicates that the number of sample adjustments is 0

Discussion

The maternal OT regulation model constructed for the VBAC in this study was based on the real clinical OT medication training and simulation experience for the clinical medication, making it closer to the expert decision-making level. The VBAC parturitions were more cautious regarding the control of the OT dosage. Compared with the current manual OT regulation, this method considered the real-time monitoring, accuracy, and safety of the OT regulation, which further guaranteed the safety of the OT medication in this population. The model verification showed that compared with the junior midwives and expert decision-making opinions, this model achieved the OT regulation accuracy of the professional medical staff, which reduced the human error caused by the less clinical experience of the medical staff.

At the same time, it also reduced the labor intensity of the medical staff. In future studies, the internet and other information technologies can also be used for the remote monitoring and evaluation of the OT medication to replace the midwives for the OT infusion, save the medical resources, and improve the quality of care.

Compared with the woman having a non-scarred uterus, the interval from the previous cesarean section was included in the model as a unique variable to the VBAC women in this study. The study showed that the uterine pressure tolerance by the VBAC women was much lower than that of the woman having a non-scarred uterus^[12], and therefore, it was different from the traditional infusion schemes in the medication adjustment, starting dose, and total use. Previous studies have shown that the low-risk pregnant women with 2 to 3 years from the last cesarean section had a higher success rate of using the OT to induce labor, and the OT medication was usually increased according to the actual clinical needs. As in pregnant women with the too-long interval from the last cesarean section, the organization of the scar tissue increased the risk of uterine rupture. Therefore, compared with the former ones, the dose of OT medication was more strictly limited in this group^[13]. This study also found that the history of childbirth, BMI, and labor analgesia were independent factors affecting the OT medication, which was consistent with the results of the study by Adams, MD et al.^[14-15]. The possible reason was that the obesity, labor analgesia, and other factors would have inhibited the contractile ability of the uterine smooth muscle, requiring the increase of the exogenous OT dose for the OT receptors in vivo to enhance the contractions. As in the women with a history of normal delivery, the cervix and vagina were fully dilated during the previous pregnancy, the delivery progress accelerated, and therefore, the use of OT was relatively reduced^[16]. The distribution of the important variable was the description of the contribution of the included variables in the model. Figure 2 shows that the duration of contractions, uterine cavity pressure, baseline FHR, contraction frequency, and the interval from the previous cesarean section were the variables that contributed the most to the model, which was consistent with the indicators for the OT regulation and the guidance observation required by the clinical medical staff^[3], indicating that the OT regulation model established in this study highly simulated the clinical thinking, and the modeling results had the high credibility.

The results of this study showed that the intrapartum OT control model based on the XGBoost algorithm had a prediction accuracy of 0.82, which was better than the LR, CART methods, and the OT regulation by a junior midwife. The XGBoost was a parallel construction of a regression tree and improved the model training speed and prediction accuracy based on the improvement of the gradient boosting optimization. It was widely used in the classification, regression, and other application scenarios in the obstetric medical data analysis, such as early warning of the postpartum hemorrhage^[17] and early prediction of newborn birth weight^[18]. This study included more variables, complex relationships between the variables, and high response and accuracy requirements to the model. The XGBoost supported the characteristics of the column sampling calculation and characteristic granularity parallel optimization, having the advantages of the fast training speed and highly accurate results^[19], and therefore, establishing an OT regulation model based on the XGBoost was more advantageous.

In this research model, the dependent variable was the output based on the actual medication situation as “the drip rate maintains the original rate”, “the drip rate decreases” and “the drip rate increases” to determine the direction of the medication for the next moment. The reason was that there was currently no unified clinical medication guidance for the OT induction of labor in the VBAC population, and only a low-dose medication regimen was the principle, but the initial drip rate and the standard of each adjustment of the drug drip rate were different between the major medical institutions^[12]. Therefore, considering the differences of actual medication, this research model now judged the regulatory direction of the OT medication, making the model better applicable and expandable. Among the three conditions of the drip rate adjustment, the model had the highest accuracy for “drip-rate slowing down”, in line with the actual needs of clinically supported drug safety. When the VBAC maternal OT medication caused the FHR deceleration, over-frequent contractions, and over-density, it was necessary to make an accurate decision of the “drip-rate slowing down” to reduce the risk of fetal distress and uterine rupture. And the error focused on the predictions of the “drip-rate acceleration” and “drip-rate maintenance”. The main reason may have been that the clinical decision of the “drip-rate acceleration” for the VBAC women was conservative, and the OT dosage needed to be carefully controlled to avoid the potential adverse reactions. In addition, the main complaints of maternal pain, the personality and clinical experience of the medical staff, and the tightness of the UC probe were all the causes for the error. ^[20-21].

However, the limitation of this study was a single-center retrospective study with small sample size. It is recommended to further verify via the prospective studies involving multi-centers and large samples in the future.

Conclusion

this study constructed an OT regulation model based on the XGBoost, with the fast-training speed, high model accuracy, strong extrapolation, and embedment in the existing intelligent OT injection feedback system, which effectively solved the contradiction behind the dependence of the traditional infusion schemes by personal experience and the shortage of human resources.

Declarations

Acknowledgment

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Author contributions

H.T.T.contributed to the data collection and wrote the first draft ,revised the manuscript. Z.Y.C.contributed to performed the data analysis. G.R.contributed to the data collection. Y.Z.M.and L.J.H.contributed to revise manuscript. L.Z.Q.and Z.X.L.is the principal investigator, contributed to the study idea and design, prepared and verified the clinical coding, and contributed to the subsequent drafts.

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Conflict of Interest

None declared.

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Figures

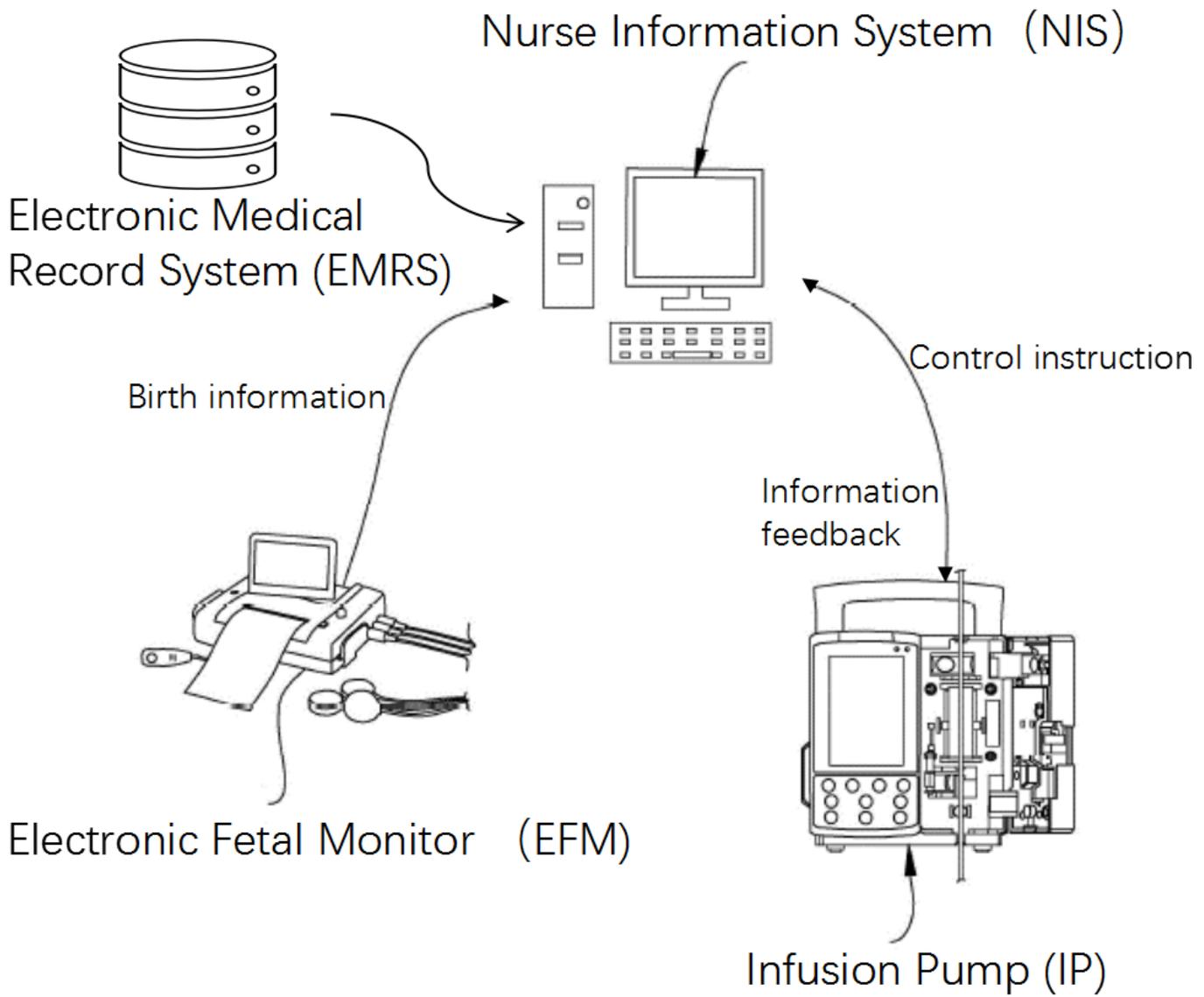


Figure 1

The intelligent regulation system of the oxytocin infusion

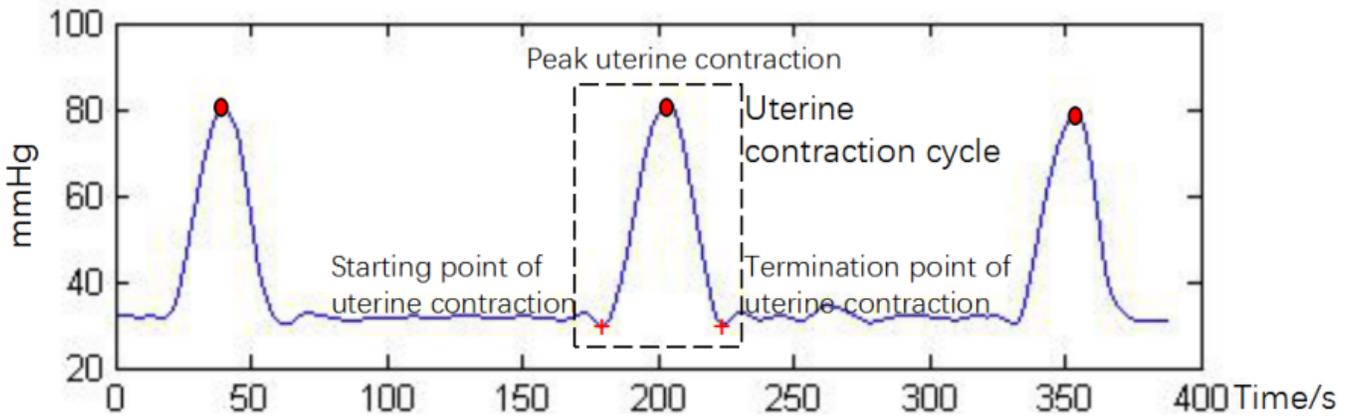


Figure 2

Sample extraction of the UC signal

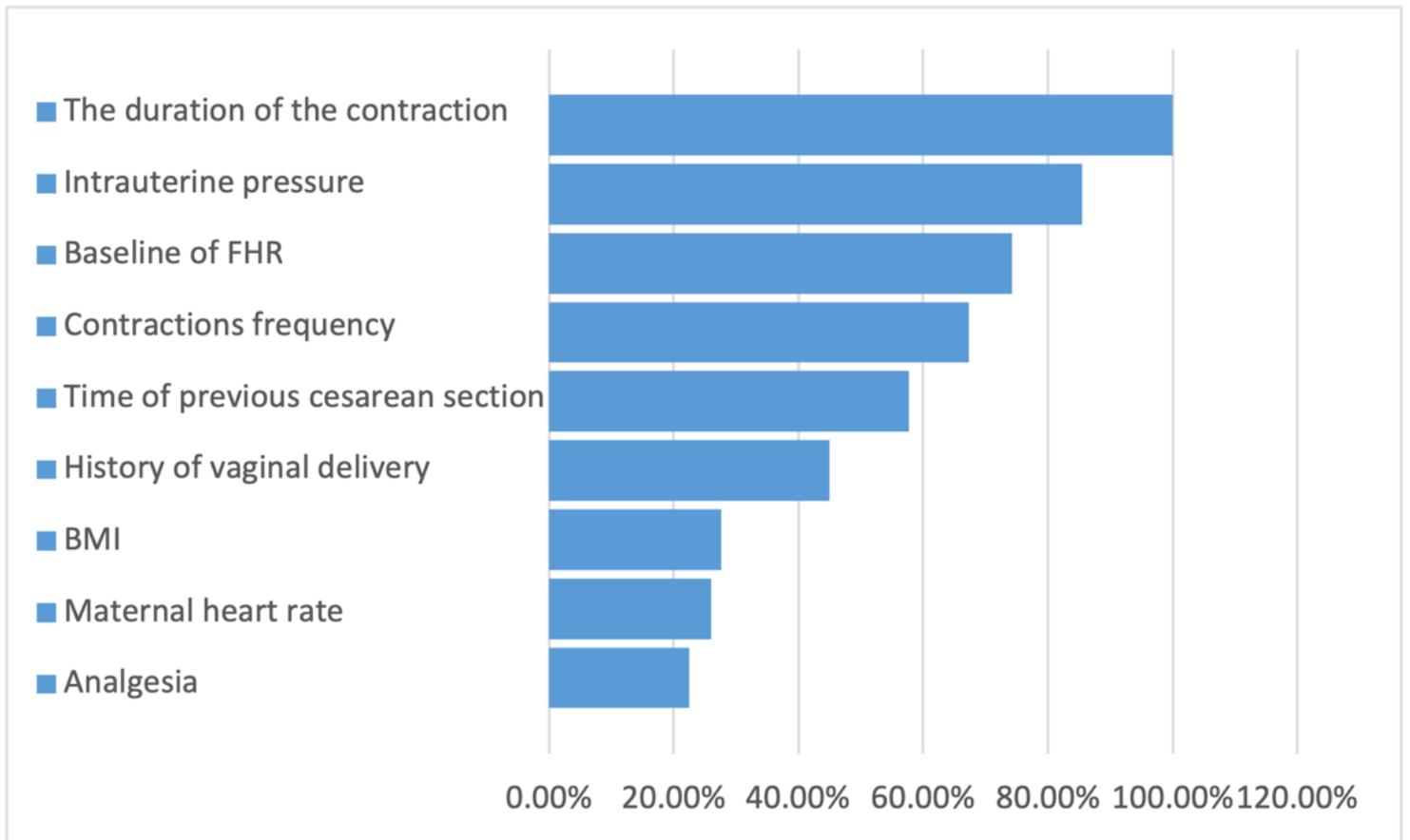


Figure 3

Ranking of the importance of variables included in the model that XGBoost predicts