Utilizing machine learning to predict the risk factors of episiotomy in parturient women

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BACKGROUND: Episiotomy has specific indications that, if properly followed, can effectively prevent women from experiencing severe lacerations that may result in significant complications like anal incontinence. However, the risk factors related to episiotomy has been the center of much debate in the medical field in the past few years.

OBJECTIVE: The present study used a machine learning model to predict the factors that put women at the risk of having episiotomy using intrapartum data.

STUDY DESIGN: This was a retrospective cohort study design. Factors such as age, educational level, residency place, medical insurance, nationality, attendance at prenatal education courses, parity, gestational age, onset of labor, presence of a doula during labor, maternal health conditions like anemia, diabetes, preeclampsia, prolonged rupture of membrane, placenta abruption, presence of meconium in amniotic fluid, intrauterine growth retardation, intrauterine fetal death, maternal body mass index, and fetal distress were extracted from the electronic health record system of a tertiary-care medical center in Iran, from January 2022 to January 2023. The criteria for inclusion were vaginal delivery of a single pregnancy. Deliveries done through scheduled/emergency cesarean section or at the mother's request were excluded. The participants were divided into two groups: those who had vaginal deliveries with episiotomy and those who had vaginal deliveries without episiotomy. The significant variables, as determined by their *P*-values, were selected as features for the eight machine-learning models. The evaluation of performance included area under the curve (AUC), accuracy, precision, recall, and F1-Score.

RESULTS: During the study period, out of 1775 vaginal deliveries, 629 (35.4%) required an episiotomy. Each model had an AUC value assigned to it: linear regression (0.85), deep learning (0.82), support vector machine (0.79), light gradient-boosting (0.79), logistic regression (0.78), XGBoost classification (0.77), random forest classification (0.76), decision tree classification (0.75), and permutation classification—knn (0.70). Linear regression had a better diagnostic performance among all the models with the area under the ROC curve (AUC): 0.85, accuracy: 0.80, precision: 0.74, recall: 0.86, and F_1 score: 0.79). Parity, labor onset, gestational age, body mass index, and doula support were the leading clinical factors related to episiotomy, according to their importance rankings.

CONCLUSIONS: Utilizing a clinical dataset and various machine learning models to assess the risk factors of episiotomy resulted in promising results. Further research, focusing on intrapartum clinical data and perspectives of the birth attendant, is necessary to enhance the accuracy of predictions.

Key words: artificial intelligence, episiotomy, machine learning

Introduction

The most common surgical procedure done in midwifery care is episiotomy.[1] The general idea is to make a controlled incision in the perineum, for enlargement of the vaginal orifice, to facilitate difficult deliveries. It is usually done when the perineum is found to be tight. Sometimes, selective episiotomies can prevent soft-tissue tears during childbirth,[2] however, it has been the center of much debate in the medical field in the past few years. We should keep in mind that as with any medical procedure, episiotomy has specific indications that, if properly followed, can effectively prevent women from experiencing severe lacerations that may result in significant complications like anal incontinence.[3]

Based on the most reliable evidence, the World Health Organization (WHO) has firmly opposed the regular use of episiotomies and suggests an average episiotomy rate of 10% for uncomplicated deliveries.[4] It is recommended that episiotomy should only be performed when there is a vital need for it. This could include cases where the fetus is under distress and a prompt delivery is necessary, or to reduce the risk of larger tears occurring during childbirth.[5] In this study, we aimed to apply machine learning models to identify the risk factors of episiotomy using intrapartum data in parturient women.

Material and methods

This particular study utilized a retrospective cohort study design. The study was approved by the Research Committee Board of Hormozgan University of Medical Sciences (IR.HUMS.REC.1403.245). Factors such as age, educational level, residency place, medical insurance, nationality, attendance at prenatal education courses, parity, gestational age, onset of labor, presence of a doula during labor, maternal health conditions like anemia, diabetes,

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2666-5778/$36.00

http://dx.doi.org/10.1016/j.xagr.2024.100420

AJOG Global Reports at a Glance

Why was the study conducted?

The present study was conducted to predict the risk factors of episiotomy using intrapartum data in parturient women with machine learning approach.

Key findings

Linear regression had a better diagnostic performance among all the models with the area under the ROC curve (AUC): 0.85, accuracy: 0.80, precision: 0.74, recall: 0.86, and F_1 score: 0.79). Parity, the onset of labor, gestational age, body mass index, and doula support were the leading clinical predictors of episiotomy.

What does this study add to what is already known?

Machine learning models were a credible approach for improving prediction of the risk factors of episiotomy with high accuracy.

preeclampsia, prolonged rupture of membrane, placenta abruption, presence of meconium in amniotic fluid, intrauterine growth retardation, intrauterine fetal death, maternal body mass index, and fetal distress were extracted from the electronic health record system of Khaleej-e-Fars Hospital in Bandar Abbas, Iran, a tertiary-care medical center. Midwives routinely collect and update electronic health records for every delivery as part of their clinical care responsibilities.

The criteria for inclusion were vaginal delivery of a single pregnancy that took place at the research facility from January 2022 to January 2023. Deliveries done through scheduled/emergency cesarean section or at the mother's request were excluded from the study. The participants were divided into two groups: those who had vaginal deliveries with episiotomy and those who had vaginal deliveries without episiotomy.

The initial stage of the examination involved comparing two categories of women using the factors mentioned previously. The features selected for the machine learning process were those with a *P*-value lower than .5. The data was entered into eight different machine learning models: linear regression, logistic regression, decision tree classification, random forest classification, XGBoost classification, permutation classification (knn), light gradient-boosting (LGB), and deep learning. Except for tree-based models, all other machine-learning models were subjected to L2 normalization for feature standardization. The results of each machine learning model fell within the range of 0 to 1.

K-fold cross-validation was used for internal validation. A random number generator was utilized to assign demonstrations randomly to either the "training set" (70%) or the "test set" (30%). The frequencies of vaginal deliveries with episiotomy and without episiotomy remained constant in both the training and test sets compared to the original dataset. We used the training data to adjust the parameters of the prediction models, and the "test data" to assess their effectiveness. It took ten iterations to calculate the average performance. We utilized the precision and AUC of the receiver operating characteristic, the confusion matrix, recall, and F1-score for assessing the performance. Precision is the accuracy of predictions for a specific class, recall is the number of correct predictions for a class compared to all examples in the dataset, and F1-score is a weighted average of precision and recall with the best value at 1 and worst value at 0. Statistical analysis was conducted employing SPSS (version 25.0, IBM Corp, Armonk, NY, United States) and Python software (version 3.7.0).

Results

During the study period, out of 1775 vaginal deliveries, 629 (35.4%) required an episiotomy. The maternal demographic characteristics related to episiotomy are shown in Table 1. Factors such as younger age, residing in urban areas, higher education levels, and participation in prenatal education courses were linked to a higher episiotomy rate.

Table 2 illustrates the connection between episiotomy and various obstetrical factors. The occurrence of episiotomy was linked to factors such as parity, onset of labor, gestational age, and the presence of a doula.

Table 3 illustrates the relationship between maternal clinical factors and the need for an episiotomy. Maternal body mass index was found to be associated with the need for an episiotomy. Episiotomy was more performed in mothers with lower body mass index.

Each model had an AUC value assigned to it: linear regression (0.85), deep learning (0.82), support vector machine (0.79), light gradient-boosting (0.79), logistic regression (0.78), XGBoost classification (0.77), random forest classification (0.76), decision tree classification (0.75), and permutation classification—knn (0.70). The ROC curves for these machine-learning models are depicted in Figure 1.

The results of machine learning models' performance are displayed in Table 4. Linear regression had a better diagnostic performance among all the algorithms with AUC: 0.85, accuracy: 0.80, precision: 0.74, recall: 0.86, and F_1 score: 0.79.

Figure 2 illustrates an examination of the significance of different factors in the linear regression algorithm. The analysis revealed that parity, labor onset, gestational age, body mass index, and doula support were the leading clinical predictors of episiotomy, according to their importance rankings.

Comment

Principal findings

The incidence of episiotomy in our population was 35.4%. Demographic factors (younger age, residing in urban areas, higher education levels, and participation in prenatal education courses), obstetrical factors (parity, onset of labor, gestational age, and the presence of a doula), and maternal clinical factor (body mass index) were linked to a

TABLE 1
Demographic factors associated with the application of episiotomy

Demographic characteristics	Nonepisiotomy (*n*=1146)	Episiotomy (*n*=629)	*P*-value
Age (Years)			<.001
18–35	861 (75.1)	580 (92.2)	
Above 35	285 (24.9)	49 (7.8)	
Residency place			.013
Urban	819 (71.5)	484 (76.9)	
Rural	327 (28.5)	145 (23.1)	
Maternal education			<.001
Primary	320 (27.9)	102 (16.2)	
High school/diploma	583 (50.9)	362 (57.6)	
Advanced	243 (21.2)	165 (26.2)	
Medical insurance			.771
Yes	994 (86.7)	542 (86.2)	
No	152 (13.3)	87 (13.8)	
Prenatal education course			.003
Yes	54 (4.7)	52 (8.3)	
No	1092 (95.3)	577 (91.7)	
Nationality			.825
Iranian	1131 (98.7)	622 (98.9)	
Non-Iranian	15 (1.3)	7 (1.1)	

Data are presented as *n* (%).

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TABLE 2
Obstetric factors associated with the episiotomy

Variables	Nonepisiotomy (*n*=1146)	Episiotomy (*n*=629)	*P*-value
Parity			<.001
Nuliparity	94 (8.2)	429 (68.2)	
Multiparity	1052 (91.8)	200 (31.8)	
Onset of labor			<.001
Induced	787 (68.7)	342 (54.4)	
Spontaneous	359 (31.1)	287 (45.6)	
Gestational age (week)			.022
Preterm (Less than 37)	101 (8.8)	48 (7.6)	
Term (37–41)	889 (77.6)	466 (74.1)	
Late-term (more than 41)	156 (13.6)	115 (18.3)	
Attending of Doula			<.001
Yes	351 (30.6)	288 (45.8)	
No	795 (69.4)	341 (54.2)	

Data are presented as *n* (%).

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higher episiotomy rate. All machine learning showed a high performance in predicting the risk factors of episiotomy. The AUC ranged from 0.70–0.85. Linear regression had a better diagnostic performance among all the algorithms with AUC: 0.85, accuracy: 0.80, precision: 0.74, recall: 0.86, and F_1 score: 0.79. The analysis of weighted factors in linear regression model showed that parity, labor onset, gestational age, body mass index, and doula support were the leading clinical predictors of episiotomy.

What is known?

There is significant variability in the frequency of episiotomy performed globally, with rates ranging from 4% in Denmark[6] to as high as 91% in Thailand.[7] In our research, the frequency of episiotomy among our participants was 35.4%, which is higher than the rate suggested by the World Health Organization,[4] but still considered satisfactory when compared to other groups. The variation in rates may be because of a lack of skills among health workers and differences in national policies regarding when episiotomies should be performed.

Based on our findings, various factors such as being younger, living in cities, having higher levels of education, attending prenatal classes, having higher gestational age, being nulliparous, induced labor, and having a lower body mass index were found to be correlated with a higher likelihood of undergoing an episiotomy. On the other hand, having the support of a doula during labor was linked to a decreased likelihood of needing an episiotomy. According to research,[8,9] it is widely accepted that nuliparity is a major risk factor for requiring episiotomy. This could be because the perineal muscles of women who have not given birth before are tighter compared to women who have had multiple births, leading birth attendants to more often opt for performing an episiotomy.

Inducing labor is a significant risk factor associated with the occurrence of episiotomy. Our research found that women who underwent induced labor

TABLE 3
Maternal and neonatal clinical factors associated with the episiotomy

Outcome	Nonepisiotomy (n=1146)	Episiotomy (n=629)	P-value
Maternal anemia			.701
No	1128 (98.4)	617 (98.1)	
Yes	18 (1.6)	12 (1.9)	
Prolonged rupture of membrane			.512
No	1132 (98.8)	619 (98.4)	
Yes	14 (1.2)	10 (1.6)	
Diabetes			.095
No	923 (80.5)	527 (83.8)	
Yes	223 (19.5)	102 (16.2)	
Maternal body mass index			.002
Less than 18.5	54 (4.7)	45 (7.2)	
18.5−24.9	758 (66.1)	449 (71.4)	
25−29.9	266 (23.2)	108 (17.2)	
30 and above	68 (5.9)	27 (4.3)	
Preeclampsia			.522
No	1116 (97.4)	616 (97.9)	
Yes	30 (2.6)	13 (2.1)	
Hypothyroidism			.586
No	1019 (88.9)	554 (88.1)	
Yes	127 (11.1)	75 911.9)	
Placenta abruption			.141
No	1143 (99.7)	624 (99.2)	
Yes	3 (0.3)	5 (0.8)	
Meconium			.796
No	1041 (90.8)	574 (91.3)	
Yes	105 (9.2)	55 (8.7)	
Intrauterine growth retardation			.066
No	1097 (95.7)	606 (96.3)	
Yes	49 (4.3)	23 (3.7)	
Intrauterine fetal death			.710
No	1135 (99.0)	628 (99.8)	
Yes	11 (1.0)	1 (0.2)	
Fetal distress			.999
No	1139 (99.4)	625 (99.4)	
Yes	7 (0.6)	4 (0.6)	

Data are presented as n (%).

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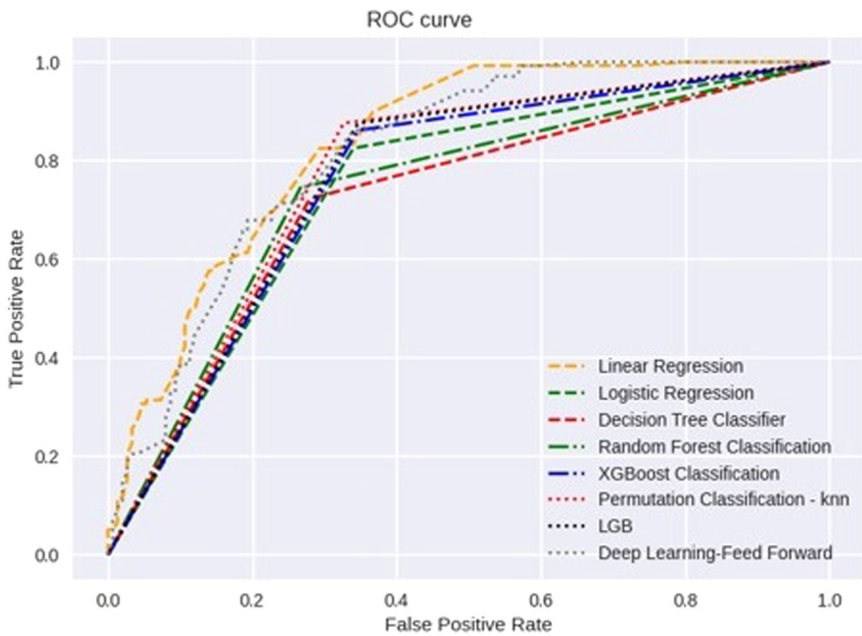
were more likely to have an episiotomy compared to those who went into labor spontaneously. Similar results have been reported in studies conducted in various regions worldwide.[10−13] The possible explanation might be that, if labor does not start and progress naturally, there may not be a physiological reduction of the perineal muscles, possibly leading to the need for perineal intervention.[14] In addition, inducing labor can lead to strong and frequent contractions of the uterus, which can cause abnormal fetal heart rate patterns that may require the birth attendant to perform an episiotomy to shorten the labor process.[15]

Gestational age is an important factor related to episiotomy. Guidelines suggest that a larger episiotomy may be necessary for cases of preterm labor to lower the risk of birth injuries.[16] However, based on research and the experiences of birth attendants, a higher gestational age is more likely to require an episiotomy due to the increased size of the fetus's head diameters.[17]

The most conflicting results are related to maternal age and body mass index. Some research suggests that obesity is a risk factor of episiotomy,[18,19] while other studies, like ours, have found a lower rate of episiotomy among obese women.[20,21] These results suggest that obstetrics clinics should possibly adopt a more cautious strategy regarding episiotomy for obese patients. Another important factor to consider when deciding on the necessity of episiotomy is the mother's age. Our research revealed that younger mothers tended to undergo more episiotomies. Soleimanzadeh and colleagues (2020) demonstrated that mothers who underwent an episiotomy had a lower average age compared to those who did not have the procedure.[22] This finding was also supported by Aguiar and team (2020).[23] This could be because younger mothers are often first-time mothers, leading to a higher incidence of episiotomies being performed on them compared to older mothers. This potentially indicates that relaxing tense muscles in women who have given birth multiple times could result in a longer release period for the baby's head positioning, possibly eliminating the need for health professionals to perform an episiotomy.

Factors linked to empowering women may reduce the fear of episiotomy and increase autonomy for

FIGURE 1
The ROC curves of machine learning models.



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mothers to consent to the procedure.[24] This could explain the increased rate of episiotomy among mothers with higher education, residing in urban areas, and participating in prenatal classes in our research sample.

The importance of doulas in assisting women during childbirth has been discussed before.[25] We feel that doulas play a significant role in educating and aiding women during labor, specifically in terms of birthing positions and breathing techniques like Lamaze. This involvement may contribute to the decreased rate of episiotomy among women who have a doula.

Clinical implications

As far as we know, no predictive models have been previously used to identify the risk factors of episiotomy. We created machine learning models using patient data from past cases to assess how well various algorithms can assist in making decisions about episiotomies.

Research implications

More research should be conducted to analyze appropriate variables and prepare big data to determine the best model.

Strengths and limitations

Our study's main advantage is the utilization of eight various machine-learning models. Nevertheless, there are several limitations to our study. One limitation is its retrospective nature. To reduce selection bias, we made efforts to include all consecutive mothers who delivered babies during the study period. One of the main factors considered when deciding whether to perform an episiotomy is the expertise of the birth attendant (midwife/obstetrician/obstetric resident). It is important to recognize that not including this factor as a key variable in predicting episiotomy is a significant limitation of our study. Last, determining the exact number of mothers who received episiotomy

TABLE 4
The performance of machine learning models

Machine learning model	AUC	Accuracy	Precision	Recall	F1-score
Linear regression	0.85	0.80	0.74	0.86	0.79
Deep learning	0.82	0.77	0.72	0.82	0.77
Support vector machine	0.79	0.79	0.74	0.83	0.79
Light gradient-boosting	0.79	0.78	0.74	0.83	0.78
Logistic regression	0.78	0.78	0.74	0.83	0.76
XGBoost classification	0.77	0.77	0.73	0.80	0.77
Random forest classification	0.76	0.75	0.72	0.80	0.75
Decision tree classification	0.75	0.75	0.72	0.78	0.75
Permutation classification—knn	0.70	0.69	0.60	0.83	0.79

XXXXX

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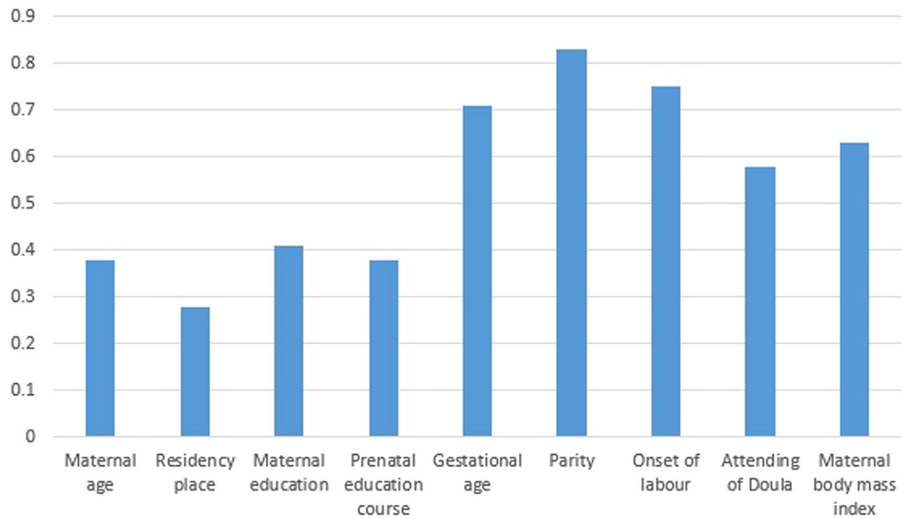
FIGURE 2

Feature importance of the linear regression in the prediction of episiotomy.



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care for a medical reason versus those who received it unnecessarily was challenging.

Conclusion

Utilizing a clinical dataset and various machine learning models to identify the risk factors of episiotomy resulted in promising results. If validated in other populations, the predictive system could offer personalized guidance to expectant mothers, allowing them to participate in the decision-making process regarding episiotomy. Further research, focusing on intrapartum clinical data and perspectives of the birth attendant, is necessary to enhance the accuracy of predictions.

CRediT authorship contribution statement

Mojdeh Banaei: Writing – review & editing, Conceptualization. **Nasibeh Roozbeh:** Supervision. **Fatemeh Darsareh:** Writing – original draft, Project administration. **Vahid Mehrnoush:** Investigation, Data curation. **Mohammad Sadegh Vahidi Farashah:** Software, Formal analysis. **Farideh Montazeri:** Investigation, Data curation.

ACKNOWLEDGMENT

All of the authors acknowledged Hormozgan University of Medical Sciences and the principals of Khaleej-e-Fars Hospital.

REFERENCES

1. Béchard F, Geronimi J, Vieille P, Letouzey V, de Tayrac R. Are we performing episiotomies correctly? A study to evaluate French technique in a high-risk maternity unit. J Gynecol Obstet Hum Reprod 2018;47(7):331–8. https://doi.org/10.1016/j.jogoh.2018.04.010.

2. Corrêa Junior MD, Passini Júnior R. Selective episiotomy: indications, technique, and association with severe perineal lacerations. Rev Bras Ginecol Obstet 2016;38(6):301–7. https://doi.org/10.1055/s-0036-1584942.

3. Corrêa Junior MD, Passini Júnior R. Selective episiotomy: indications, technique, and association with severe perineal lacerations. Rev Bras Ginecol Obstet 2016;38(6):301–7. https://doi.org/10.1055/s-0036-1584942.

4. World Health Organization. WHO recommendation on episiotomy policy. Geneva: The WHO Health Library; 2018.

5. Shmueli A, Gabbay Benziv R, Hiersch L, et al. Episiotomy—risk factors and outcomes. J Matern Fetal Neonatal Med 2017;30(3):251–6. https://doi.org/10.3109/14767058.2016.1169527.

6. Blondel B, Alexander S, Bjarnadóttir RI, et al. Variations in rates of severe perineal tears and episiotomies in 20 European countries: a study based on routine national data in Euro-Peristat Project. Acta Obstet Gynecol Scand 2016;95(7):746–54. https://doi.org/10.1111/aogs.12894.

7. SEA-ORCHID Study GroupLaopaiboon M, Lumbiganon P, et al. Use of evidence-based practices in pregnancy and childbirth: South East Asia optimising reproductive and child health in developing countries project. PLoS One 2008;3(7):e2646. https://doi.org/10.1371/journal.pone.0002646.

8. Pebolo F, Judith A, Dan KK. Prevalence and factors associated with episiotomy practice among primiparous women in Mulago National Referral Hospital Uganda. Int J Preg Child Birth 2019;5:197–201. https://doi.org/10.15406/ipcb.2019.05.00176.

9. Chigbu B, Onwere S, Aluka C, Kamanu C, Adibe E. Factors influencing the use of episiotomy during vaginal delivery in South Eastern Nigeria. East Afr Med J 2008;85(5):240–3. https://doi.org/10.4314/eamj.v85i5.9618.

10. Ballesteros-Meseguer C, Carrillo-García C, Meseguer-de-Pedro M, Canteras-Jordana M, Martínez-Roche ME. Episiotomy and its relationship to various clinical variables that influence its performance. Rev Lat Am Enfermagem 2016;24:e2793. https://doi.org/10.1590/1518-8345.0334.2686.

11. Braga GC, Clementino STP, Luz PFNd, Scavuzzi A, Noronha Neto C, Amorim MMR. Risk factors for episiotomy: a case-control study. Rev Assoc Med Bras 2014;60(5):465–72. https://doi.org/10.1590/1806-9282.60.05.015.

12. Woretaw E, Teshome M, Alene M. Episiotomy practice and associated factors among mothers who gave birth at public health facilities in Metema district, northwest Ethiopia. Reprod Health 2021;18(1):142. https://doi.org/10.1186/s12978-021-01194-9.

13. Rasouli M, Keramat A, Khosravi A, Mohabatpour Z. Prevalence and factors associated with episiotomy in Shahroud City, northeast of Iran. Int J Womens Health Reprod Sci 2016;4:125–9. https://doi.org/10.15296/ijwhr.2016.29.

14. Kacvinska A, Drab M, Totka A, Holoman K, Gabor M. The effect of prostaglandin induced labor and selected factors on the occurrence and extent of birth-canal injuries. Bratisl Lek Listy 2016;117(9):511–4. https://doi.org/10.4149/bll_2016_099.

15. Simpson KR, James DC. Effects of oxytocin-induced uterine hyperstimulation during labor on fetal oxygen status and fetal heart rate patterns. Am J Obstet Gynecol 2008;199 (1):34.e1–34.e345. https://doi.org/10.1016/j.ajog.2007.12.015.

16. WHO recommendations: intrapartum care for a positive childbirth experience. Geneva: World Health Organization; 2018.

17. Seijmonsbergen-Schermers A, Thompson S, Feijen-de Jong E, et al. Understanding the perspectives and values of midwives, obstetricians and obstetric registrars regarding episiotomy: qualitative interview study. BMJ Open 2021;11(1):e037536. https://doi.org/10.1136/bmjopen-2020-037536.

18. Landy HJ, Laughon SK, Bailit JL, et al. Characteristics associated with severe perineal and cervical lacerations during vaginal delivery. Obstet Gynecol 2011;117(3): 627–35. https://doi.org/10.1097/AOG.0b013e31820afaf2.

19. Khajehei M, Assareh H. Temporal trend of diabetes in pregnant women and its association with birth outcomes, 2011 to 2017. J Diabetes Complicat 2020;34(4):107550. https://doi.org/10.1016/j.jdiacomp.2020.107550.

20. Fikadu K, Boti N, Tadesse B, et al. Magnitude of episiotomy and associated factors among mothers who give birth in Arba Minch General Hospital, Southern Ethiopia: observation-based cross-sectional study. J Pregnancy 2020;1:8395142. https://doi.org/10.1155/2020/8395142.

21. Tavakoli A, Panchal VR, Mazza GR, Mandelbaum RS, Ouzounian JG, Matsuo K. The association of maternal obesity and obstetric anal sphincter injuries at time of vaginal delivery. AJOG Glob Rep 2023;3(4):100272. https://doi.org/10.1016/j.xagr.2023.100272.

22. Soleimanzadeh Mousavi SH, Miri M, Farzaneh F. Episiotomy and its complications. Zahedan J Res Med Sci 2020;23:104127. https://doi.org/10.5812/zjrms.104127.

23. Aguiar BM, Silva TPRD, Pereira SL, et al. Factors associated with the performance of episiotomy. Rev Bras Enferm 2020;73:e20190899. https://doi.org/10.1590/0034-7167-2019-0899.

24. Darsareh F, Aghamolaei T, Rajaei M, Madani A. Exploring first-time pregnant women's motivations for planning vaginal delivery: a qualitative study. Iran J Nurs Midwifery Res 2018;23(6):465–70. https://doi.org/10.4103/ijnmr.IJNMR_175_17.

25. Sobczak A, Taylor L, Solomon S, et al. The effect of doulas on maternal and birth outcomes: a scoping review. Cureus 2023;15(5):e39451. https://doi.org/10.7759/cureus.39451.