Effectiveness of Machine Learning in Predicting Preeclampsia in Pregnant Women: A Scoping Review Protocol

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Abstract. Preeclampsia is one of the most common causes of maternal and perinatal morbidity and mortality. The disease is characterized by the development of hypertension after 20 weeks of gestation and can trigger a series of severe complications, such as eclampsia, kidney injury, liver damage, multiorgan dysfunction, and fetal growth restriction. In more severe cases, the condition may lead to preterm birth, significantly increasing the risk of neonatal complications. Therefore, early detection and proper management of the disease are essential to minimize adverse outcomes for both the mother and the babys. Traditional methods, such as blood pressure measurement, proteinuria analysis, and risk calculators based on regression methods, have limitations in predicting the disease before symptom onset, highlighting the need for more accurate approaches. In this context, machine learning emerges as a promising alternative to enhance preeclampsia detection. This approach enables the analysis of large volumes of clinical data and biomarkers, improving predictive capabilities. This study aims to map the application of machine learning in preeclampsia prediction, evaluating the advantages of these models over traditional methods and the challenges of their clinical implementation. A comprehensive scoping review will analyze the main models used, such as decision trees, Support Vector Machine, and Random Forest, as well as the most relevant predictive variables and performance metrics, including accuracy and the area under the ROC curve (AUC). Additionally, this study will contribute to identifying gaps in the literature and guiding future research to refine predictive models and improve their precision indicators.

Keywords: Pregnant · Preeclampsia · Machine learning · mean arterial pressure · clinical data

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1 Introduction

Hypertensive disorders of pregnancy are among the most common complications during gestation, encompassing chronic hypertension and gestational hypertension, (PE) being the most severe form. Hypertension during pregnancy is defined as a systolic blood pressure (SBP) of $\geq$140 mmHg and/or a diastolic blood pressure (DBP) of $\geq$90 mmHg, and it is considered severe when SBP is $\geq$160 mmHg and/or DBP is $\geq$100 mmHg [1].

PE is a complex multisystemic disease characterized by the sudden onset of hypertension after 20 weeks of gestation, accompanied by at least one associated complication, such as proteinuria, maternal organ dysfunction, or uteroplacental dysfunction [2]. For example, fetal growth restriction (FGR) or an angiogenic imbalance. It is one of the most severe pregnancy complications and a leading cause of maternal and perinatal morbidity and mortality, affecting approximately 4 million women worldwide each year. This results in the deaths of more than 70,000 women and 500,000 babies [3]. According to the World Health Organization (WHO), most of these deaths could be prevented with timely and effective care following its recommendations [4].

Contemporary evidence suggests that PE may be a two-stage disease. The first stage is asymptomatic in early pregnancy and results from placental insufficiency due to abnormal trophoblast invasion and inadequate remodeling of the spiral arteries. This process ultimately leads to the second stage of the disease, characterized by ischemia or placental reperfusion injury and an immediate maternal immune response [5].

Although hypertension and proteinuria are classical diagnostic criteria for PE, other factors may also be considered. Women with hypertension but without proteinuria should be diagnosed with PE if they present at least one of the following severe complications: thrombocytopenia, liver dysfunction, renal insufficiency, pulmonary edema, or a new-onset headache that is resistant to paracetamol and cannot be explained by alternative diagnoses [6].

There are also alternative prediction methods, one of the most cited risk calculators that use Bayes' theorem along with variables such as maternal characteristics, mean arterial pressure (MAP), uterine artery pulsatility index (UtA-PI), serum placental growth factor (PlGF), and pregnancy-associated plasma protein-A (PAPP-A) to estimate risk. These calculators were developed by the Fetal Medicine Foundation (FMF) and the Hospital Clínic de Barcelona and have demonstrated superior accuracy compared to traditional methods, in addition to being the only internationally validated approach [7, 8]. This method is frequently referenced by authors developing (ML) models as a benchmark for validating their accuracy [9, 10].

Beyond traditional models for predicting PE, the use of Machine Learning (ML) has emerged as an innovative alternative for detection. ML is a branch of computer science focused on learning patterns from data to improve performance across various scenarios, offering strong applicability in predicting and analyzing large datasets. Once trained and validated for high-performance predictions, the algorithm uses relevant variables to forecast the outcome of interest. Based on this training, it provides insights that can enhance PE detection and management [11–13].

This protocol aims to analyze ML models applied to the prediction of PE, evaluating their accuracy, limitations and applicability. From this protocol, it will be possible to establish comparisons with the traditional methods used, providing instructions for future research, helping to improve strategies for the early identification of (PE). Against this backdrop, this protocol aims to examine the progress and challenges of machine learning models applied to PE prediction at a global level. The research will provide a more detailed understanding of the potential of these technologies, contributing to the adoption of more efficient approaches to tracking and managing the disease.

2 Methods and Analysis

This scoping review will follow the methodological approach proposed by Levac et al. [14], comprising six steps for conducting scoping reviews: (1) defining the research question; (2) identifying relevant studies; (3) study selection; (4) data mapping; (5) collecting, summarizing, and reporting results; and (6) consultation (optional step). Below, the methodological steps for conducting a scoping study are outlined.

2.1 Identifying the Research Question

The main objective is to survey existing machine learning approaches for predicting preeclampsia in pregnant women, evaluating their effectiveness through their accuracy. The protocol aims to map the existing literature, identify knowledge gaps and provide a comprehensive overview of the advantages, limitations and clinical applicability of machine learning techniques for predicting preeclampsia in at-risk populations.

Based on the objective, the following research questions were formulated:

1. What are the main machine learning approaches used in the prediction of preeclampsia?
2. How does machine learning compare in terms of effectiveness, advantages, limitations, and clinical applicability in predicting preeclampsia?

2.2 Identifying Relevant Studies

For the formulation of search terms and study selection, the PIRO structure (Population, Intervention, Reference, and Outcome) was used. This framework guides the inclusion of relevant evidence in the database, ensuring alignment with the research scope and avoiding unnecessary searches. The search strategy consists of three main components: pregnant women (population), the use of machine learning for preeclampsia prediction (intervention), and preeclampsia as the reference condition (reference).

The research will include studies without restrictions on date, language, or geographical location. Searches will be conducted in three electronic databases: PubMed, Embase (Elsevier), and BVS (Virtual Health Library). Additionally, gray literature will be explored through Google Scholar.

In the initial stage, the keywords present in the title and abstract of the selected articles will be analyzed, along with the main terms used to describe them. The preliminary search in the databases will combine keywords using the Boolean operators AND/OR.

This strategy will be adjusted as needed in the PubMed, Embase (Elsevier), and BVS (Virtual Health Library) databases, with the support of a specialized librarian and carried out by one or more authors of the review in Table 1.

Table 1. Search Strategy for databases Source: Researcher Data

Databases	Search	Search Strategy
PubMed	#1	((((((Pregnant Women[MeSH Terms]) OR (Women, Pregnant)) OR (Pregnant Woman)) OR (Woman, Pregnant)) OR (Pregnancy[MeSH Terms])) OR (Pregnancies)) OR (Gestation)
	#2	(((((((Pregnant Women[MeSH Terms]) OR (Women, Pregnant)) OR (Pregnant Woman)) OR (Woman, Pregnant)) OR (Pregnancy[MeSH Terms])) OR (Pregnancies)) OR (Gestation)) AND (((Pre-Eclampsia[MeSH Terms]) OR (Pre Eclampsia)) OR (Preeclampsia))
	#3	((((((((Machine Learning[MeSH Terms]) OR (Learning, Machine)) OR (Transfer Learning)) OR (Learning, Transfer)) AND (Artificial Intelligence[MeSH Terms])) OR (Intelligence, Artificial)) OR (AI (Artificial Intelligence))) OR (Machine Intelligence)) OR (Intelligence, Machine)
	#4	(((((((Pregnant Women[MeSH Terms]) OR (Women, Pregnant)) OR (Pregnant Woman)) OR (Woman, Pregnant)) OR (Pregnancy[MeSH Terms])) OR (Pregnancies)) OR (Gestation)) AND (((Pre-Eclampsia[MeSH Terms]) OR (Pre Eclampsia)) OR (Preeclampsia)) AND (((((((((Machine Learning[MeSH Terms]) OR (Learning, Machine)) OR (Transfer Learning)) OR (Learning, Transfer)) AND (Artificial Intelligence[MeSH Terms])) OR (Intelligence, Artificial)) OR (AI (Artificial Intelligence))) OR (Machine Intelligence)) OR (Intelligence, Machine))
BVS	#1	mh: “Gestantes” OR (Gestante) OR (Grávida) OR (Grávidas) OR (Mulher Grávida) OR (Mulheres Grávidas) OR (Parturiente) OR (Parturientes) OR (Pregnant Women) OR (Pregnant Woman) OR (Woman, Pregnant) OR (Mujeres Embarazadas) OR (Embarazadas) OR (Mujer Embarazada) OR (Femmes enceintes) OR mh:M01.975.807 OR mh:SP3.522.561.200.488 AND mh: “Pré-Eclâmpsia” OR (Pré-Eclâmpsia Eclâmpsia 1) OR (Pre-Eclampsia) OR (Preeclampsia) OR (Pre Eclampsia) OR (Pré-éclampsie) OR mh:C12.050.703.395.249
	#2	mh: “Aprendizado de Máquina” OR (Aprendizado Automático) OR (Aprendizagem de Máquina) OR (Machine Learning) OR (Learning, Machine) OR (Aprendizaje Automático) OR (Apprentissage machine) OR mh: G17.035.250.500 OR mh: L01.224.050.375.530 AND mh: “Inteligência Artificial” OR (IA (Inteligência Artificial)) OR (Inteligência de Máquina) OR (Inteligência de Máquina) (Artificial Intelligence) OR (AI (Artificial Intelligence)) OR (Computational Intelligence) OR (Machine Intelligence) OR (Inteligencia Artificial) OR (Intelligence artificielle) OR mh: G17.035.250 OR mh: L01.224.050.375
	#3	(mh: “Gestantes” OR (Gestante) OR (Grávida) OR (Grávidas) OR (Mulher Grávida) OR (Mulheres Grávidas) OR (Parturiente) OR (Parturientes) OR (Pregnant Women) OR (Pregnant Woman) OR (Woman, Pregnant) OR (Mujeres Embarazadas) OR (Embarazadas) OR (Mujer Embarazada) OR (Femmes enceintes) OR mh:M01.975.807 OR mh:SP3.522.561.200.488 AND mh: “Pré-Eclâmpsia” OR (Pré-Eclâmpsia Eclâmpsia 1) OR (Pre-Eclampsia) OR (Preeclampsia) OR (Pre Eclampsia) OR (Pré-éclampsie) OR mh:C12.050.703.395.249) AND (mh: “Aprendizado de Máquina” OR (Aprendizado Automático) OR (Aprendizagem de Máquina) OR (Machine Learning) OR (Learning, Machine) OR (Aprendizaje Automático) OR (Apprentissage machine) OR mh: G17.035.250.500 OR mh: L01.224.050.375.530 AND mh: “Inteligência Artificial” OR (IA (Inteligência Artificial)) OR (Inteligência de Máquina) OR (Inteligência de Máquina) (Artificial Intelligence) OR (AI (Artificial Intelligence)) OR (Computational Intelligence) OR (Machine Intelligence) OR (Inteligencia Artificial) OR (Intelligence artificielle) OR mh: G17.035.250 OR mh: L01.224.050.375)
Embase	#1	‘pregnant woman’/exp OR ‘pregnant women’ OR ‘pregnant woman’ OR ‘pregnancy’/exp OR ‘child bearing’ OR ‘childbearing’ OR ‘gestation’ OR ‘gravidity’ OR ‘intrauterine pregnancy’ OR ‘labor presentation’ OR ‘labour presentation’ OR ‘pregnancy maintenance’ OR ‘pregnancy trimesters’ OR ‘pregnancy’

(*continued*)

Table 1. (*continued*)

Databases	Search	Search Strategy
	#2	'pregnant woman'/exp OR 'pregnant women' OR 'pregnant woman' OR 'pregnancy'/exp OR 'child bearing' OR 'childbearing' OR 'gestation' OR 'gravidity' OR 'intrauterine pregnancy' OR 'labor presentation' OR 'labour presentation' OR 'pregnancy maintenance' OR 'pregnancy trimesters' OR 'pregnancy' AND 'preeclampsia'/exp OR 'eclamptic toxaemia' OR 'eclamptic toxemia' OR 'eclamptogenic toxaemia' OR 'eclamptogenic toxemia' OR 'edema-proteinuria-hypertension gestoses' OR 'edema-proteinuria-hypertension gestosis' OR 'EPH gestoses' OR 'EPH gestosis' OR 'EPH syndrome' OR 'EPH toxemia' OR 'gestational toxaemia' OR 'gestational toxemia' OR 'gestational toxicosis' OR 'gestoses' OR 'gestosis' OR 'gestosis, EPH' OR 'HEP syndrome' OR 'maternal toxemia' OR 'pre eclampsia' OR 'pre-eclampsia' OR 'pre-eclamptic' OR 'pre-eclamptic toxaemia' OR 'pre-eclamptic toxemia' OR 'preclampsia' OR 'preeclamptic' OR 'preeclamptic toxaemia' OR 'preeclamptic toxemia' OR 'pregnancy toxaemia' OR 'pregnancy toxaemias' OR 'pregnancy toxemia' OR 'pregnancy toxemias' OR 'pregnancy toxicosis' OR 'proteinuric hypertension of pregnancy' OR 'toxaemia gravidum' OR 'toxaemia, preeclamptic' OR 'toxemia during pregnancy' OR 'toxemia gravidum' OR 'toxemia in pregnancy' OR 'toxemia, preeclamptic' OR 'toxemic pregnancy' OR 'toxicosis gravidarum' OR 'preeclampsia'
	#3	'machine learning'/exp OR 'learning machine' OR 'learning machines' OR 'machine learning' AND 'artificial intelligence'/exp OR 'machine intelligence' OR 'artificial intelligence'
	#4	('pregnant woman'/exp OR 'pregnant women' OR 'pregnant woman' OR 'pregnancy'/exp OR 'child bearing' OR 'childbearing' OR 'gestation' OR 'gravidity' OR 'intrauterine pregnancy' OR 'labor presentation' OR 'labour presentation' OR 'pregnancy maintenance' OR 'pregnancy trimesters' OR 'pregnancy' AND 'preeclampsia'/exp OR 'eclamptic toxaemia' OR 'eclamptic toxemia' OR 'eclamptogenic toxaemia' OR 'eclamptogenic toxemia' OR 'edema-proteinuria-hypertension gestoses' OR 'edema-proteinuria-hypertension gestosis' OR 'EPH gestoses' OR 'EPH gestosis' OR 'EPH syndrome' OR 'EPH toxemia' OR 'gestational toxaemia' OR 'gestational toxemia' OR 'gestational toxicosis' OR 'gestoses' OR 'gestosis' OR 'gestosis, EPH' OR 'HEP syndrome' OR 'maternal toxemia' OR 'pre eclampsia' OR 'pre-eclampsia' OR 'pre-eclamptic' OR 'pre-eclamptic toxaemia' OR 'pre-eclamptic toxemia' OR 'preclampsia' OR 'preeclamptic' OR 'preeclamptic toxaemia' OR 'preeclamptic toxemia' OR 'pregnancy toxaemia' OR 'pregnancy toxaemias' OR 'pregnancy toxemia' OR 'pregnancy toxemias' OR 'pregnancy toxicosis' OR 'proteinuric hypertension of pregnancy' OR 'toxaemia gravidum' OR 'toxaemia, preeclamptic' OR 'toxemia during pregnancy' OR 'toxemia gravidum' OR 'toxemia in pregnancy' OR 'toxemia, preeclamptic' OR 'toxemic pregnancy' OR 'toxicosis gravidarum' OR 'preeclampsia') AND ('machine learning'/exp OR 'learning machine' OR 'learning machines' OR 'machine learning' AND 'artificial intelligence'/exp OR 'machine intelligence' OR 'artificial intelligence')

Inclusion and Exclusion Criteria. The inclusion criteria are aligned with the guiding questions and objectives of the review. The following studies will be eligible: primary studies, as they provide original and detailed data on methods, samples, and results, allowing for a more in-depth analysis of the use of Machine Learning in predicting preeclampsia; studies with no language restrictions; studies published at any time, without temporal limitations; studies that specifically apply the Machine Learning in the prediction of preeclampsia in pregnant women.

Exclusion criteria for the review include studies that do not fully or partially answer the guiding questions; studies addressing technologies other than machine learning; studies not focusing on the prediction of pre-eclampsia.

2.3 Study Selection

The number of records retrieved from each database will be documented, and whenever possible, all records will be exported to the Zotero reference manager and the Rayyan systematic review platform. In the first stage, four of the six authors will independently and blindly screen the titles and abstracts based on the established inclusion criteria. Any discrepancies among the reviewers will be resolved by a fifth author. Articles that meet the predefined criteria will proceed to the second stage, which consists of a full-text review. This phase will also be conducted by the same four authors, independently and blindly. After completing these two stages, one other author will act as a secondary reviewer, responsible for resolving any conflicts that arise during the full-text analysis.

2.4 Charting the Data

This stage involves mapping the information to be extracted from the primary studies analyzed. To achieve this, the team will use a structured form that includes data charts based on the model proposed by *Bratti et al.* [15], along with information aligned with the scope of this review in Table 1. This framework will be used to assess all full-text articles that meet the established inclusion criteria. The categories of data to be collected include:

- **Bibliographic information:** Article title, author(s), country of origin, year of publication, quality of the publication source, and its impact.
- **Study information:** Study objectives, methodology employed, outcome measures, and main findings.
- **Machine Learning (ML) utilization information**: The analysis of ML models will be carried out based on objective criteria, including their concept, relevance, and practical examples for each evaluated aspect, according to Table 2. Initially, the adopted approach will be considered, which can be through supervised learning, unsupervised learning, or reinforcement learning. This criterion is important as it defines how the model learns patterns from the data, impacting its applicability and accuracy. The types of algorithms used will also be analyzed, as each technique has its advantages and limitations depending on the type and volume of processed data. Deep neural network algorithms are useful for complex patterns, while decision trees offer greater data interpretability, and support vector machines allow for nonlinear data separation based on the origin and nature of the data used in model training and validation. Another important criterion is the preprocessing methods, which involve techniques to improve data quality before model training, aiming to reduce bias and errors. Similarly, validation methods will also be evaluated as they ensure the reliability of model results before their clinical application. Performance metrics are another fundamental aspect, as they measure the effectiveness of models and compare different approaches. Indicators such as accuracy, sensitivity, specificity, AUC-ROC, and F1-score will be considered to assess the reliability of the models being analyzed. Additionally, the level of model interpretability will be examined. Model interoperability will also be analyzed, due to its importance in integration with different health systems, which is essential for clinical adoption. Finally, the clinical implications of the models will be analyzed, based on their potential impact on medical practice and patient outcomes.

Table 2. Data Extraction Framework Source: Adapted from Bratti *et al*. [14]

Principal category	Description
1. Authors	Names of the study authors
2. Title	Title of the published article
3. Journal	Journal or conference where it was published
4. Year of publication	Year of publication
5. Study design	Type of study conducted
6. Study objective	Central purpose of the study
7. Sample size (if applicable)	Number of participants included in the research
8. Demographic data	Countries and regions where the study was conducted, national income levels, and age ranges
9. Data collection year(s) (if applicable)	Period in which data was collected
10. Study population description	Specify whether the intervention targets individuals within subpopulation groups. If applicable: 1- Describe the study population setting
11. ML utilization description	– Approach used (e.g., supervised, unsupervised, or reinforcement learning) – Types of algorithms employed (e.g., neural networks, decision trees, SVM, logistic regression, etc.) – Source and characteristics of the data used in the model (e.g., clinical data, laboratory results, demographic variables) – Data preprocessing strategies (e.g., normalization, handling of missing values, feature selection) – Validation methods adopted (e.g., cross-validation, holdout, external test set) – Reported performance metrics (e.g., accuracy, sensitivity, specificity, AUC-ROC, F1-score) – Model interpretability level (e.g., explanatory methods such as SHAP, LIME, or visualization techniques) – Challenges encountered in implementation – Clinical implications of the obtained results
12. Discussion of gaps, unmet needs, and future directions	Identification of study limitations, unaddressed aspects, and recommendations for future research

- **Discussion of gaps and future directions:** Unmet needs, study limitations, and recommendations for future research.

Team Considerations. To ensure the reliability of data extraction, each article will be independently reviewed by four team members, with each member collecting data individually. Subsequently, the data collected by each member will be integrated, and in the event of discrepancies, a fifth member will be consulted to mitigate and resolve conflicts.

2.5 Collating, Summarising and Reporting the Results

Following the recommendations provided by Levac *et al.* [14] this stage will be broken into three steps, as follows:

- Analysis: according to the protocol, the focus of this stage will be on quantitative and qualitative analyses. The qualitative analysis will be based on the combination of information collected during the research, along with insights from ACOG. It will be structured to address the main guiding question of the protocol and other study-related inquiries. Through this analysis, the protocol aims to establish criteria for evaluating the most effective machine learning techniques for identifying preeclampsia in pregnant women.
- Reporting: this stage will involve presenting a table summarizing the strengths and gaps in the existing evidence; moreover, the structured results combined with the analysis will serve as the basis for the creation of a paper.
- Implications for future research: for this stage, a table containing the strengths and gaps in the evidence will be presented. In addition, the structured results combined with the analysis will serve as the basis for the creation of an article.

3 Discussion

This protocol aims to gather information that provides an overview of the machine learning methods used to predict preeclampsia, identify existing gaps, and enhance the overall understanding of the topic. Additionally, by comparing the accuracy of the five main ML algorithms: Logistic Regression (LR), Extreme Gradient Boosting (XGBoost), Random Forest (RF), and Multilayer Perceptron (MLP), it will be possible to suggest ways to optimize these models to improve their predictive capability [16].

During the training of the ML model, several predictors are used, including medical and obstetric history, medication intake, maternal characteristics, ultrasound, and test results obtained during pregnancy. These predictors enable training with key information to identify predisposition to preeclampsia PE [17].

Regarding clinical applications, the review may discuss how machine learning models can enhance screening and prevention, enabling the implementation of preventive measures. It will also address limitations and future challenges, such as the importance of collecting data from different populations to ensure that the models are globally applicable and do not suffer from racial or geographic bias. Furthermore, the ethical and regulatory aspects of using health data to train machine learning models should be considered, ensuring patient privacy and consent.

This information will identify knowledge gaps and provide a comprehensive overview of the advantages, limitations and clinical applicability of machine learning techniques for predicting PE in at-risk populations.

4 Ethics and Disclosure

As this protocol will use data from publicly available sources, no ethical review will be required. The results of this scoping review will contribute to understanding the effectiveness of machine learning-based approaches in predicting preeclampsia in pregnant women, compared to traditional diagnostic methods. The data obtained will be relevant to various stakeholders, including researchers, public health organizations, and private clinics in the field of obstetrics. Additionally, we plan to present and disseminate the findings at relevant conferences.

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References

1. Garovic, V.D., et al.: Hypertension in pregnancy: diagnosis, blood pressure goals, and pharmacotherapy: a scientific statement from the American Heart Association. Hypertension **79**(2), 21–41 (2022)
2. Evdokia, D., Daniel, L.R., Wei, Z., et al.: Pre-eclampsia. Nat. Rev. Dis. Primers. **9**, 1–22 (2023)
3. Chappell, L.C., Cluver, C.A., Kingdom, J., Tong, S.: Pre-eclampsia. Lancet 24 **398**(10297), 341–354 (2021)
4. WHO: Recommendations for Prevention and Treatment of Pre-Eclampsia and Eclampsia. World Health Organization, Geneva (2011)
5. Peraçoli, J.C., et al.: Pré-eclâmpsia – Protocolo 2023. Rede Brasileira de Estudos sobre Hipertensão na Gravidez (RBEHG) (2023)
6. Marwan, M., Maged, M.C.: Prevention of preeclampsia. Semin. Fetal Neonatal. Med. **25**(5), 101123 (2020)
7. Riishede, I., et al.: Pre-eclampsia screening in Denmark (PRESIDE): national validation study. Ultrasound Obstet. Gynecol. 5 **61**(6), 682–690 (2023)
8. Tan, M.Y., et al.: Comparison of diagnostic accuracy of early screening for pre-eclampsia by NICE guidelines and a method combining maternal factors and biomarkers: results of SPREE. Ultrasound Obstet. Gynecol. **51**(6), 743–750 (2018)
9. Marić, I., et al.: Early prediction of preeclampsia via machine learning. Am. J. Obstet. Gynecol. MFM **2**(2), 100100 (2020)
10. Torres-Torres, J., et al.: Performance of machine-learning approach for prediction of pre-eclampsia in a middle-income country. Ultrasound Obstet. Gynecol. **63**(3), 350–357 (2024)
11. Gestational Hypertension and Preeclampsia: ACOG Practice Bulletin, Number 222. Obstet. Gynecol. **135**(6), 237–260 (2020)
12. Mitchell, T.M.: Machine Learning, 1st edn. McGraw-Hill, Boston (1997)
13. Kononenko, I.: Machine learning for medical diagnosis: history, state of the art and perspective. Artif. Intell. Med. **23**(1), 89–109 (2001)

14. Levac, D., Colquhoun, H., O'Brien, K.K.: Scoping studies: advancing the methodology. Implement. Sci. **5**, 1–9 (2010)
15. Bratti, V.F., Wilson, B.E., Fazelzad, R., et al.: Scoping review protocol on the impact of antimicrobial resistance on cancer management and outcomes. BMJ Open **13**, e068122 (2023)
16. Lv, B., Wang, G., Pan, Y., Yuan, G., Wei, L.: Construction and evaluation of machine learning-based predictive models for early-onset preeclampsia. Pregnancy Hypertens (2025)
17. Ranjbar, A., Montazeri, F., Ghamsari, S.R., Mehrnoush, V., Roozbeh, N., Darsareh, F.: Machine learning models for predicting preeclampsia: a systematic review. BMC Pregnancy Childbirth 2 **24**(1), 6 (2024)