Efficacy of machine learning in predicting preeclampsia in pregnant women: a scoping review.

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Preeclampsia is a major hypertensive complication of pregnancy, associated with high maternal and perinatal morbidity and mortality. Traditional diagnostic methods have limitations, particularly in early detection, while machine learning emerges as a promising alternative for risk prediction. This scoping review aimed to map the evidence on the effectiveness of machine learning models in predicting preeclampsia. Searches were conducted in the PubMed/MEDLINE, Embase, and Virtual Health Library databases in June 2025, including original studies that applied machine learning techniques and reported performance metrics. A total of 24 studies were included, revealing methodological heterogeneity and a predominance of internal validation. The models demonstrated moderate to high discriminative performance, with better results in approaches integrating clinical data and biomarkers, as well as greater accuracy in predicting early-onset forms of the disease. Despite the promising potential, gaps such as limited external validation, underreporting of calibration, and lack of methodological standardization still limit the clinical application of these models.

INTRODUCTION

Preeclampsia (PE) represents one of the main hypertensive complications of pregnancy, affecting approximately 2–8% of pregnant women worldwide and contributing to more than 70,000 maternal deaths annually, in addition to significant risks to the fetus, such as prematurity and intrauterine growth restriction (1). Traditionally, diagnosis is based on clinical criteria such as hypertension (blood pressure ≥140/90 mmHg) and proteinuria after 20 weeks of gestation; however, these methods have limitations, including low sensitivity for early-onset cases and false negatives in up to 20% of occurrences (2).

The advancement of machine learning (ML) emerges as a transformative promise in risk prediction for maternal health. ML algorithms, such as LightGBM, neural networks, and others, integrate data broadly, including biomarkers (e.g., PlGF, sFlt-1), clinical history, and maternal data to generate predictions with AUCs exceeding 0.85 across several studies (3). These approaches outperform conventional statistical models, such as the Fetal Medicine Foundation (FMF) model, by handling imbalanced and high-dimensional datasets, enhancing risk stratification in low-resource settings (4).

Despite the notable advances, the literature on ML applications in PE prediction reveals significant heterogeneity in methodologies, studied populations, and evaluation metrics, such as sensitivity, specificity, and precision in real clinical contexts (5). This fragmentation hinders translation into clinical practice, especially in developing countries with limited resources, where false negatives may worsen adverse maternal-fetal outcomes (6). This scoping review aims to present the available evidence on the effectiveness of ML in predicting preeclampsia in pregnant women.

METHODS

The conduct of this scoping review followed a previously developed protocol registered on the Open Science Framework (OSF), aiming to ensure transparency, reproducibility, and methodological rigor at all stages of the study. The protocol previously defined the research question, eligibility criteria, search strategy, selection procedures, screening, and data extraction, all of which were systematically followed throughout the development of the review. The protocol was registered on April 24, 2025, on the Open Science Framework (OSF).

Search strategy and selection criteria

The search strategy was systematically developed based on the PIRO framework (Population, Index, Reference, and Outcome), aiming to identify studies that investigated the application of machine learning models in predicting preeclampsia in pregnant women. Controlled descriptors and free terms were used according to the DeCS, MeSH, and Emtree vocabularies, combined using Boolean operators (AND and OR).

Searches were conducted in the Virtual Health Library (BVS), PubMed/MEDLINE, and Embase databases on June 15, 2025. Population-related terms included variations referring to pregnant women, pregnancy, and preeclampsia. For the index, descriptors related to machine learning and artificial intelligence were used. The diagnostic reference, such as traditional methods for diagnosing preeclampsia, was considered secondarily and was not mandatory in the composition of the main strategies, in accordance with the exploratory objective of the scoping review.

The search strategies (Table 1) were adapted to the specificities of each database, respecting their indexing and syntax particularities. No restrictions were applied regarding publication period or methodological design, in order to ensure a comprehensive and sensitive search.

Table 1. Search strategies used in the electronic databases.

Database	Strategy applied	Search date	Registers
PubMed	(((((((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)	06/15/2025	116
BVS	(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)	06/15/2025	0
Embase	('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')	06/15/2025	201

Presents the databases consulted, the complete search strategies applied in each database, the date the searches were conducted, and the total number of records identified.

Eligibility Criteria

The eligibility criteria were defined based on the PIRO framework (Population, Index, Reference, and Outcome). Regarding the population (P), studies conducted with pregnant women were included, regardless of maternal age or gestational period, provided that preeclampsia was considered the clinical outcome of interest. Studies conducted exclusively in animal models or theoretical simulations were excluded.

Regarding the index (I), studies that applied machine learning models or artificial intelligence techniques for the purpose of predicting or identifying preeclampsia were considered eligible, including but not limited to supervised, unsupervised, or deep learning algorithms. Studies that used only traditional statistical methods without the incorporation of ML techniques were excluded.

Regarding the reference (R), studies that used traditional diagnostic methods or established clinical criteria for the identification of preeclampsia as a comparator were included, such as blood pressure measurements, proteinuria, or other recognized clinical-laboratory parameters. Studies that did not present any form of comparison with conventional diagnostic criteria or clinical validation were excluded.

Regarding the outcomes (O), studies that reported performance metrics of the predictive models were included, such as accuracy, sensitivity, specificity, area under the ROC curve (AUC), precision, recall, or equivalent metrics related to the predictive capacity for preeclampsia. Studies that did not present quantitative or qualitative results related to preeclampsia prediction were excluded.

Additionally, only original studies with full text available, published in English, Portuguese, or Spanish, were included. No restrictions were applied regarding publication year or methodological design, considering the objective of this scoping review to map the extent, diversity, and characteristics of the available evidence in the literature.

Selection and screening proces

The study selection and screening process was conducted with the assistance of the Rayyan platform (Qatar Computing Research Institute). Initially, all records identified in the databases were exported to the platform, where duplicate records were identified and removed. Screening was conducted by four authors, organized in independent pairs, to ensure greater methodological rigor.

Title and abstract screening was performed independently and blindly, with two authors responsible for evaluating studies published from 1997 to 2020, while the other two authors analyzed studies published between 2021 and 2025. Subsequently, articles considered potentially eligible were submitted to full-text reading, following the same paired evaluation logic.

Disagreements between reviewers were resolved by consensus, and when necessary, a third reviewer was consulted for the final decision. The complete process of identification, screening, eligibility, and inclusion of studies will be presented through a flowchart prepared according to OSF guidelines.

Data extraction and summary

Data extraction was performed systematically using a standardized form, previously developed and tested by the author team, aiming to ensure consistency and reproducibility of the process. Extraction was conducted independently by the authors, following the same paired organization adopted in the study screening stage.

Information related to the general characteristics of the studies was extracted, including author(s), year of publication, country of conduct, methodological design, and study context.

Data regarding population characteristics were also collected, such as sample size, gestational period evaluated, and diagnostic criteria used for the identification of preeclampsia.

Regarding the index, information about the machine learning models employed was extracted, including the type of algorithm, predictor variables used, model training and validation strategies, as well as the datasets employed. Regarding the diagnostic reference, traditional methods used for comparison or clinical validation were recorded, when applicable.

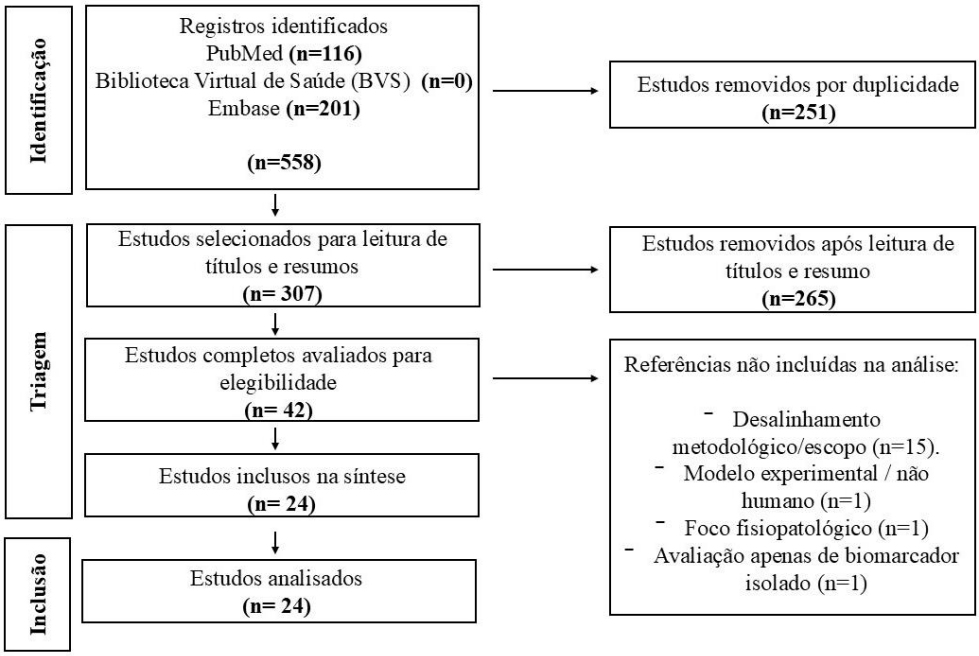
Regarding the outcomes, performance metrics of the predictive models were extracted, such as accuracy, sensitivity, specificity, area under the ROC curve (AUC), precision, recall, or other metrics reported by the studies. Additional relevant information, such as limitations identified by the authors and potential clinical implications, was also recorded.

The extracted data were organized and summarized in a descriptive and narrative manner, with presentation in tables and figures, allowing for the mapping of available evidence, identification of gaps in the literature, and analysis of methodological trends related to the use of machine learning in predicting preeclampsia. No assessment of methodological quality or risk of bias of the studies was performed, in accordance with the recommendations for scoping reviews.

RESULTS

The process of identification, screening, eligibility, and inclusion of studies is presented in Figure 1. A total of 558 records were initially identified in the electronic databases. After removal of duplicates, 307 studies were submitted to title and abstract screening. Of these, 42 were evaluated in full text for eligibility, resulting in the final inclusion of 24 studies in the qualitative synthesis.

Figure 1. PRISMA flowchart of the study selection process.



Flowchart of the study selection process from identification in the databases to final inclusion in the synthesis, according to PRISMA guidelines.

Overall, broad methodological heterogeneity was observed among the included studies, with significant variation in sample size, design, and validation strategies. Most studies used internal validation methods, while external validation was less frequent, indicating potential limitations in the generalizability of the models. The detailed methodological characteristics of the included studies are presented in Table 2.

Table 2. Methodological characteristics of the included studies (n=24)

Autor	Ano	País	Tipo de Estudo	População Estudada	Amostra	Modelos de aplicação
Zhou T et al. (7)	2024	China	Retrospective study	A	789	Deep Learning
Gil MM et al.(8)	2024	EspaIN	Prospective non-interventional cohort study	B	10110	Neural Network
Ansbacher-Feldman Z et al.(9)	2022	United Kingdom	Prospective non-interventional	C	60789	Neural Network
Lin YC et al. (10)	2024	United States	Prospective cohort	C	1857	Random Forest
Araujo DC et al.(11)	2024	Brazil	Case-control study	A	132 + 3552	ML Model

Edvinsson C et al.(12)	2024	Sweden	Pilot case-control study	B	81	XGBoost
Maric I et al. (13)	2020	United States	Retrospective cohort study	C	5245	ML Model
Sufriyana H et al. (14)	2020	Indonesia	Nested case-control	A	23201	Neural Network
Khalil A et al. (15)	2024	United States; Sweden; Ireland; United Kingdom; Australia; Spain	Secondary analysis of the Microdeletion and Aneuploidy Registry (SMART) study	A	17520	Neural Network
Schmidt LJ et al. (16)	2022	Germany	Retrospective study	B	1647	Random Forest
Bennett R et al. (17)	2022	United States	Methodological research	C	360943	Neural Network
Kaya Y et al. (18)	2024	Turkey	Retrospective study	C	100	Random Forest
Nguyen-Hoang L et al. (19)	2024	China; Japan; Thailand; Taiwan; India; Singapore	Secondary analysis	C	10935	ML Model
Zhao Z et al. (20)	2024	China	prospective	C	704	Random Forest
Jhee JH et al. (21)	2019	South Korea	Retrospective cohort study	A	11006	Random Forest
Li T et al. (22)	2024	China	Retrospective cohort study	B	4644	Logistic Regression
Butler L et al. (23)	2024	United States	Retrospective observational cohort study	C	720	Neural Network
Bulez A et al. (24)	2024	Turkey	Retrospective study	A	10307	ML Model
Eberhard BW et al. (25)	2023	United States	retrospective	C	120752	Random Forest
Jung YM et al. (26)	2024	South Korea	Retrospective observational	A	244	Deep Learning
Lv B et al. (27)	2025	China	Retrospective cohort	A	3237	Neural Network
Li T et al. (28)	2021	China	Retrospective observational	A	3759	Random Forest
Namazi M et al.(29)	2024	Austrália	Retrospective observational study	A	48250	Random Forest
Sofonyas Abebaw Tiruneh (30)	2025	Melbourne, Austrália	Temporal validation of predictive models	B	12549	Random Forest

Data are presented as descriptive characteristics of the included studies. Study population: A = Pregnant women; B = Women in general; C = Other specific populations. Outcome indicators: a = Area under the ROC curve (AUC); b = Sensitivity/Detection rate; c = Specificity; d = Accuracy.

In aggregate, the machine learning models demonstrated discriminative capacity ranging from moderate to high. The majority of studies fell within the ranges classified as "good" and "excellent" discriminative capacity, while only a minority exhibited performance below traditionally acceptable thresholds. The detailed distribution of AUROC ranges is

presented in Table 3. The observed variability was more associated with the type of outcome evaluated, the nature of the input data, and the validation strategy than with the study design.

Table 3. Distribution of discriminative capacity (AUROC)

AUROC Range	Nº of Studies	Proportion
Inadequate (<0,70)	2	8,3%
Acceptable (0,70-0,79)	6	25,0%
Good(0,80--0,89)	11	45,8%
Excellent (0,90-0,96)	6	25,0%

Values are presented as absolute frequencies and proportions, categorized according to area under the ROC curve (AUROC) ranges, representing the distribution of discriminative capacity of the evaluated models.

The stratified analysis by preeclampsia subphenotype demonstrated a consistent trend of better predictive performance in earlier-onset or more severe phenotypes. Models aimed at predicting early-onset preeclampsia and those with severe features showed higher discriminative capacity and sensitivity, while the prediction of term preeclampsia demonstrated greater heterogeneity and, in general, lower performance. The comparative synthesis by subphenotype is presented in Table 4.

Table 4. Differential performance by preeclampsia subphenotype

Tipo de PE	AUROC	Verdadeiros positivos(sensibilidade)	Nº Estudos
Early-onset PE (<34 weeks)	0,82--0,92	84,4%--93,7%	8
Preterm PE (<37 weeks)	0,80--0,91	57,5%--87,0%	7
Term PE (≥37 weeks)	0,71--0,92	30,7%--68,0%	4

PE with severe features	0,77--0,94	66,0%--95,0%	4

Values are presented as predictive performance metrics (AUROC and sensitivity), number of studies, and predictive difficulty classification, stratified by preeclampsia subtype.

Regarding input data, consistent superiority was observed for models that combined clinical variables and biomarkers, representing half of the included studies. Strategies based exclusively on clinical data showed more variable performance, while approaches using isolated laboratory data, electronic health records, or imaging data presented context- and algorithm-dependent results. The comparative synthesis of effectiveness by data type is presented in Table 5.

Table 5. Effectiveness by input data type

Date Type	Nº Estudies	Mean AUROC	Proportion
Clinical + Biomarkers	12	0,80--0,92	50,0%
Clínical only	6	0,70--0,88	25,0%
Complete blood count (CBC)	2	0,90	8,3%
Imaging/Digital	2	0,71--0,85	8,3%
Electronic Health Records (EHR)	3	0,85--0,96	12,5%
cfDNA	1	0,71--0,80	4,2%

Values are presented as means of the area under the ROC curve (AUROC), number of studies, and proportions, stratified by the type of input data used in the models.

Additionally, a trend toward better discriminative performance was observed in models based on boosting techniques, including LightGBM, XGBoost, and Gradient Boosting. However, direct comparisons between algorithms should be interpreted with caution, considering the heterogeneity among populations, outcomes, and validation strategies used in the included studies.

DISCUSSION

The findings of this scoping review demonstrate that, despite the significant growth in the application of machine learning techniques in predicting preeclampsia, structural methodological gaps persist that limit the translational maturity of these approaches. External validation remains underexplored, present in only five of the twenty-four identified studies, restricting the assessment of model transportability across different populations and clinical settings. Studies that conducted validations in independent cohorts, such as those by Gil et al. (8) and Li et al. (31), still represent exceptions in the field. Similarly, temporal validation remains rarely explored, being more consistently addressed by Tiruneh et al. (29), which limits inferences about predictive stability and potential performance degradation over time in real clinical contexts.

In parallel, model calibration remains underreported in the mapped literature, despite evidence of misalignment between predicted and observed risk. Khalil et al. (15) highlighted the relevance of this metric for clinical model evaluation, while Tiruneh et al. (29) documented significant calibration issues, including a slope of 1.15 for XGBoost-based models and 0.62 for Random Forest, reinforcing the need for more comprehensive reports of predictive performance beyond traditional discriminatory metrics.

Furthermore, a predominance of retrospective designs is observed, as in the studies by Zhou et al. (7), Jung et al. (26), and Li et al. (4), with a scarcity of prospective studies evaluating model performance in the actual flow of prenatal care. This limitation reduces the understanding of the real clinical impact and operational applicability of these tools in healthcare settings.

Regarding the predictive phenotype, the prediction of term preeclampsia remains less developed and with lower performance compared to early-onset forms, as observed in studies by Gil et al. (8), Zhou et al. (7), and Khalil et al. (15), suggesting greater pathophysiological complexity and the influence of dynamic clinical factors throughout gestation.

Additionally, approaches incorporating longitudinal data throughout pregnancy and multimodal data integration emerge as promising strategies. Eberhard et al. (25) demonstrated progressive improvement in performance with temporal incorporation of variables throughout gestation, while Zhou et al. (7) explored the integration of clinical data with retinal images, pointing to the potential for expanding digital biomarkers. However, such approaches remain incipient in the available body of evidence.

Overall, the field is characterized by rapid expansion and high methodological diversity, reflecting both the potential of these technologies and the absence of standardization in study design, performance metrics, and validation strategies. This mapping reinforces the need for prospective studies, robust multicentric validations, systematic calibration assessment, and greater transparency in methodological reporting — essential elements for advancing from the exploratory phase to the safe and effective clinical implementation of these tools in prenatal care.

CONCLUSION

This scoping review demonstrates that machine learning-based models exhibit promising discriminative performance for predicting preeclampsia, with results predominantly classified as good to excellent, especially when based on the integration of clinical data and biomarkers. However, the literature is still marked by methodological heterogeneity, low frequency of external and temporal validations, and underreporting of calibration metrics, limiting the assessment of the robustness and clinical applicability of these models across different population and healthcare contexts. Despite the rapid advancement of the field, the transition to routine clinical implementation still depends on prospective studies, multicentric validations, and greater standardization in the development and reporting of models. Taken together, the findings reinforce the potential of machine learning as a strategic tool for risk

stratification in maternal health, while also highlighting the need for methodological advances to ensure its safe and effective adoption in prenatal care.

REFERENCIAS

1. Gopman S, Leeman L, Wagner LK. Preeclampsia. Nutrition and Health (United Kingdom) [Internet]. 2024 Feb 25 [cited 2026 Feb 11];Part F3934:221–9. Available from: https://www.ncbi.nlm.nih.gov/books/NBK570611/
2. Rana S, Lemoine E, Granger J, Karumanchi SA. Preeclampsia: Pathophysiology, Challenges, and Perspectives. Circ Res [Internet]. 2019 Mar 29 [cited 2026 Feb 11];124(7):1094–112. Available from: /doi/pdf/10.1161/CIRCRESAHA.118.313276?download=true
3. Garrido-Giménez C, Cruz-Lemini M, Álvarez F V., Nan MN, Carretero F, Fernández-Oliva A, et al. Predictive Model for Preeclampsia Combining sFlt-1, PlGF, NT-proBNP, and Uric Acid as Biomarkers. J Clin Med [Internet]. 2023 Jan 1 [cited 2026 Feb 11];12(2):431. Available from: https://pmc.ncbi.nlm.nih.gov/articles/PMC9866466/
4. Li T, Xu M, Wang Y, Wang Y, Tang H, Duan H, et al. Prediction model of preeclampsia using machine learning based methods: a population based cohort study in China. Front Endocrinol (Lausanne). 2024 Jun 11;15:1345573.
5. Mol BWJ, Roberts CT, Thangaratinam S, Magee LA, De Groot CJM, Hofmeyr GJ. Machine Learning Prediction Models for Preeclampsia: Systematic Review and Meta-Analysis. J Med Internet Res [Internet]. 2026 Jan 1 [cited 2026 Feb 11];28(10022):999–1011. Available from: https://doi.org/10.1016/S0140-6736(15)00070-7
6. Özcan M, Peker S. Preeclampsia prediction via machine learning: a systematic literature review. Health Systems [Internet]. 2025 Jul 3 [cited 2026 Feb 11];14(3):208–22. Available from: https://www.tandfonline.com/doi/abs/10.1080/20476965.2024.2435845
7. Zhou T, Shao F, Wan S, Zhou C, Zhou S, Hua X. Feasibility study on quantifying retinal vascular features for predicting preeclampsia based on artificial intelligence models. Journal of Shanghai Jiao Tong University (Medical Science) [Internet]. 2024 May 28 [cited 2026 Feb 11];44(5):552. Available from: https://xuebao.shsmu.edu.cn/EN/10.3969/j.issn.1674-8115.2024.05.002

8. Ricci CA, Crysup B, Phillips NR, Ray WC, Santillan MK, Trask AJ, et al. Machine learning: a new era for cardiovascular pregnancy physiology and cardio-obstetrics research. https://doi.org/101152/ajpheart001492024 [Internet]. 2024 Aug 1 [cited 2026 Feb 11];327(2):H417–32. Available from: /doi/pdf/10.1152/ajpheart.00149.2024?download=true
9. Ansbacher-Feldman Z, Syngelaki A, Meiri H, Cirkin R, Nicolaides KH, Louzoun Y. Machine-learning-based prediction of pre-eclampsia using first-trimester maternal characteristics and biomarkers. Ultrasound in Obstetrics and Gynecology [Internet]. 2022 Dec 1 [cited 2026 Feb 11];60(6):739–45. Available from: /doi/pdf/10.1002/uog.26105
10. Lin YC, Mallia D, Clark-Sevilla AO, Catto A, Leshchenko A, Yan Q, et al. A comprehensive and bias-free machine learning approach for risk prediction of preeclampsia with severe features in a nulliparous study cohort. BMC Pregnancy and Childbirth 2024 24:1 [Internet]. 2024 Dec 24 [cited 2026 Feb 11];24(1):853-. Available from: https://link.springer.com/article/10.1186/s12884-024-06988-w
11. Araújo DC, de Macedo AA, Veloso AA, Alpoim PN, Gomes KB, Carvalho M das G, et al. Complete blood count as a biomarker for preeclampsia with severe features diagnosis: a machine learning approach. BMC Pregnancy and Childbirth 2024 24:1 [Internet]. 2024 Oct 1 [cited 2026 Feb 11];24(1):628-. Available from: https://link.springer.com/article/10.1186/s12884-024-06821-4
12. Edvinsson C, Björnsson O, Erlandsson L, Hansson SR. Predicting intensive care need in women with preeclampsia using machine learning–a pilot study. Hypertens Pregnancy [Internet]. 2024 Dec 31 [cited 2026 Feb 11];43(1). Available from: https://www.tandfonline.com/doi/pdf/10.1080/10641955.2024.2312165
13. Marić I, Tsur A, Aghaeepour N, Montanari A, Stevenson DK, Shaw GM, et al. Early prediction of preeclampsia via machine learning. Am J Obstet Gynecol MFM [Internet]. 2020 May 1 [cited 2026 Feb 11];2(2):100100. Available from: https://doi.org/10.1111/nure.12055
14. Sufriyana H, Wu YW, Su EC. Prediction of Preeclampsia and Intrauterine Growth Restriction: Development of Machine Learning Models on a Prospective Cohort. JMIR Med Inform [Internet]. 2020; Available from: https://doi.org/10.2196/15411
15. Khalil A, Bellesia G, Norton ME, Jacobsson B, Haeri S, Egbert M, et al. The role of cell-free DNA biomarkers and patient data in the early prediction of preeclampsia: an

artificial intelligence model. Am J Obstet Gynecol [Internet]. 2024 Nov 1 [cited 2026 Feb 11];231(5):554.e1-554.e18. Available from: https://doi.org/10.1002/uog.20117

16. Schmidt LJ, Rieger O, Neznansky M, Hackelöer M, Dröge LA, Henrich W, et al. A machine-learning-based algorithm improves prediction of preeclampsia-associated adverse outcomes. Am J Obstet Gynecol [Internet]. 2022; Available from: https://doi.org/10.1016/j.ajog.2022.01.026
17. Bennett R, Mulla ZD, Parikh P, Hauspurg A, Razzaghi T. An imbalance-aware deep neural network for early prediction of preeclampsia. PLoS One [Internet]. 2022; Available from: https://doi.org/10.1371/journal.pone.0266042
18. Kaya Y, Bütün Z, Çelik Ö, Salik EA, Tahta T. Risk Assessment for Preeclampsia in the Preconception Period Based on Maternal Clinical History via Machine Learning Methods. J Clin Med [Internet]. 2025;14(1). Available from: ["https://www.embase.com/search/results?subaction=viewrecord&id=L2032913005&from=export",
19. Nguyen-Hoang L, Sahota DS, Pooh RK, Duan H, Chaiyasit N, Sekizawa A, et al. Validation of the first-trimester machine learning model for predicting pre-eclampsia in an Asian population. International Journal of Gynecology and Obstetrics [Internet]. 2024;167(1):350–9. Available from: ["https://www.embase.com/search/results?subaction=viewrecord&id=L2029565432&from=export",
20. Zhao Z, Dai J, Chen H, Lu L, Li G, Yan H, et al. A Prospective Study on Risk Prediction of Preeclampsia Using Bi-Platform Calibration and Machine Learning. Int J Mol Sci [Internet]. 2024;25(19). Available from: ["https://www.embase.com/search/results?subaction=viewrecord&id=L2031852718&from=export",
21. Jhee JH, Lee S, Park Y, Lee SE, Kim YA, Kang SW, et al. Prediction model development of late-onset preeclampsia using machine learning-based methods. PLoS One [Internet]. 2019; Available from: https://doi.org/10.1371/journal.pone.0221202
22. Li T, Xu M, Wang Y, Wang Y, Tang H, Duan H, et al. Prediction model of preeclampsia using machine learning based methods: a population based cohort study in China. Front Endocrinol (Lausanne) [Internet]. 2024; Available from: https://doi.org/10.3389/fendo.2024.1345573

23. Butler L, Gunturkun F, Chinthala L, Karabayir I, Tootooni MS, Bakir-Batu B, et al. AI-based preeclampsia detection and prediction with electrocardiogram data. Front Cardiovasc Med. 2024 Mar 4;11:1360238.
24. Bülez A, Hansu K, Çağan ES, Şahin AR, Dokumacı HÖ. Artificial Intelligence in Early Diagnosis of Preeclampsia. Niger J Clin Pract [Internet]. 2024;27(3):383–8. Available from: ["https://www.embase.com/search/results?subaction=viewrecord&id=L643851728&from=export",
25. Eberhard BW, Cohen RY, Rigoni J, Bates DW, Gray KJ, Kovacheva VP. An Interpretable Longitudinal Preeclampsia Risk Prediction Using Machine Learning. medRxiv [Internet]. 2023; Available from: ["https://www.embase.com/search/results?subaction=viewrecord&id=L2026945955&from=export",
26. Jung YM, Park S, Ahn Y, Kim H, Kim EN, Park HE, et al. Identification of Preeclamptic Placenta in Whole Slide Images Using Artificial Intelligence Placenta Analysis. J Korean Med Sci [Internet]. 2024;39(39):e271–e271. Available from: ["https://www.embase.com/search/results?subaction=viewrecord&id=L645513542&from=export",
27. 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 [Internet]. 2025 Mar 1 [cited 2026 Feb 11];39:101198. Available from: https://doi.org/10.1016/S0140-6736(20)32342-3
28. Li Y xin, Shen X ping, Yang C, Cao Z zeng, Du R, Yu M da, et al. Novel electronic health records applied for prediction of pre-eclampsia: Machine-learning algorithms. Pregnancy Hypertens [Internet]. 2021 Dec 1 [cited 2026 Feb 11];26(1):102–9. Available from: https://doi.org/10.1007/s10654-013-9762-6
29. Tiruneh SA, Rolnik DL, Teede HJ, Enticott J. Prediction of pre-eclampsia with machine learning approaches: Leveraging important information from routinely collected data. Int J Med Inform [Internet]. 2024 Dec 1 [cited 2026 Feb 11];192(SUPPL1):105645. Available from: https://doi.org/10.1111/nure.12055
30. Kassebaum NJ, Barber RM, Dandona L, Hay SI, Larson HJ, Lim SS, et al. Temporal validation of machine learning models for pre-eclampsia prediction using routinely collected maternal characteristics: A validation study. Comput Biol Med [Internet].

2025 Jun 1 [cited 2026 Feb 11];191(10053):110183. Available from: https://doi.org/10.1016/S0140-6736(16)31470-2

31. Gil MM, Cuenca-Gómez D, Rolle V, Pertegal M, Díaz C, Revello R, et al. Validation of machine-learning model for first-trimester prediction of pre-eclampsia using cohort from PREVAL study. Ultrasound Obstet Gynecol [Internet]. 2024;63(1):68–74. Available from: ["https://www.embase.com/search/results?subaction=viewrecord&id=L642244646&from=export"