

**MODELING THE RISK OF PREECLAMPSIA DEVELOPMENT USING
ARTIFICIAL INTELLIGENCE METHODS.****Нематова Маржона Зикриллаевна**

Ассистент кафедры акушерства и гинекологии №1

Бухарский государственный медицинский институт, Узбекистан, Бухара.

<https://orcid.org/0009-0000-4105-1064><https://doi.org/10.5281/zenodo.17612067>

Summary. Preeclampsia is a multifactorial obstetric complication that occurs in the second half of pregnancy and is characterized by hypertension and dysfunction of various organs, significantly increasing the risk of maternal and perinatal morbidity and mortality.

Despite considerable progress in understanding the pathophysiological mechanisms, effective methods for early detection and prediction of preeclampsia remain a pressing issue in clinical practice. This article presents an overview of modern approaches to predicting preeclampsia using artificial intelligence (AI) technologies. Machine learning algorithms, including random forests, gradient boosting, and deep neural networks, are discussed in the context of analyzing clinical, biochemical, and ultrasound data of pregnant women. Particular attention is given to the integration of multimodal data to improve prediction accuracy.

Keywords: preeclampsia, artificial intelligence, hypertension, pathophysiological mechanisms.

Currently, there are three most commonly used preeclampsia risk assessment systems (RAS):

1. the NICE risk assessment system (National Institute for Health and Clinical Excellence, UK);
2. the ACOG risk assessment system (American College of Obstetricians and Gynecologists, USA);
3. the FMF risk assessment system (Fetal Medicine Foundation, UK).

The NICE RAS identifies moderate- and high-risk groups based on the following factors: age ≥ 40 years; BMI ≥ 35 kg/m²; nulliparity; family history of preeclampsia; interpregnancy interval > 10 years; hypertensive disorders in previous pregnancies; chronic hypertension; chronic kidney disease; diabetes mellitus; and autoimmune diseases. [1].

The ACOG RAS identifies moderate- and high-risk groups based on the following factors: age ≥ 35 years; BMI > 30 kg/m²; first pregnancy; family history of preeclampsia; chronic hypertension; kidney disease; autoimmune diseases; and type 1 or type 2 diabetes mellitus. [2].

According to FIGO recommendations, the prediction of preeclampsia risk should be based on the patient's medical history and risk factors identified through first-trimester prenatal screening. [3].

In a study by N. O'Gorman et al., the predictive accuracy of the NICE and ACOG [4]. risk assessment systems was evaluated. The detection rates of preterm and term preeclampsia using the NICE scale were 39% and 34%, respectively. Corresponding detection rates using the ACOG scale were 90% and 89%, with a false-positive rate of 64.3%.

Predicting preeclampsia using artificial intelligence algorithms

Due to the insufficient effectiveness of current preeclampsia prediction methods proposed by major international obstetrics and gynecology organizations—NICE and ACOG [4]. — research laboratories worldwide are continuing to search for reliable methods of assessing preeclampsia risk based on biophysical factors, biochemical markers, and AI algorithms. [5].

This approach aims not only to improve predictive accuracy but also to provide an individualized risk estimate.

Currently, the list of FIGO-recommended parameters for first-trimester screening in singleton pregnancies includes:

- maternal characteristics, medical history, and comorbidities;
- placental growth factor (PlGF), secreted by trophoblast cells;
- pregnancy-associated plasma protein-A (PAPP-A), secreted by the syncytiotrophoblast;
- uterine artery pulsatility index (PI);
- mean arterial pressure (MAP).

One of the first attempts to combine the analysis of biochemical markers with machine learning algorithms to develop a predictive model for preeclampsia (PE) was made by L.C. Kenny et al. [6]. The researchers used genetic programming to identify patterns in the changes of plasma metabolite levels in patients with PE. The analysis included 87 plasma samples from pregnant women with PE and 87 control samples from healthy pregnant women. Gas chromatography was performed, and the resulting data were processed using genetic programming algorithms. As a result, a model was developed with sensitivity and specificity of 100% and 98%, respectively.

Various combinations of maternal history data, instrumental studies, or laboratory markers can be used to generate predictions. Each research team independently determines which features to include in the model. In their study, S.M. van Kuijk et al. limited the number of variables used to predict recurrent early-onset PE to five: [7]. body mass index (BMI), gestational age at previous delivery, fasting blood glucose level, presence of hypertension, and birth weight of the previous baby being small for gestational age. According to the authors, this limited set of features helps prevent model overfitting due to the small dataset. Their database included 407 pregnant women with a history of early-onset PE leading to preterm delivery. After statistical processing, a predictive model was developed that can identify women at low risk of recurrent PE using the five features listed above. The model achieved an AUC of 0.65. Given the small sample size, the authors emphasized the need for external validation on a larger dataset.

R.M. Villa et al. conducted a study to identify factors that influence both the risk and severity of PE [8]. Their database consisted of 903 cases of pregnant women with known PE risk factors. The researchers used a Bayesian algorithm for cluster analysis, classifying patients into groups based on observed combinations of risk factors. A total of 25 risk factor combinations were identified. For each group, the risk of different PE subtypes was calculated, and a heatmap was created for visualization. The study found that the risk of developing PE increases exponentially with the number of risk factors. It was also noted that the risk profiles of women with severe PE and preterm delivery differ from those with term pregnancies.

Two subsequent studies on PE prediction were based on neural network technology. E. Tejera et al. proposed using heart rate variability (HRV) indices to classify patients into groups with normal blood pressure, hypertension, and PE [9]. A total of 568 short ECG recordings were collected from 217 pregnant women, with varying gestational ages.

Maternal history and blood pressure data were also included. The best performance was achieved by a predictive model based on an artificial neural network, with an AUC of 0.95.

S.K. Neocleous et al. employed a multi-slab neural network structure [10]. Their database included 6,838 birth records. The model used 15 input features, including mean arterial pressure (MAP), uterine artery pulsatility index (PI), racial and ethnic background, and more. The resulting model showed high predictive accuracy: 83.6% on the training set and 93.8% on the test set.

Conclusion

Every year, approximately half a million women around the world die from causes related to hypertensive disorders of pregnancy (HDP), and about 12% of maternal deaths result from severe complications associated with these conditions. Despite the availability of effective preventive measures, preeclampsia (PE) and eclampsia remain among the leading causes of maternal morbidity and mortality, primarily due to the lack of accurate risk assessment and prediction methods.

Therefore, the implementation of predictive analytics and clinical decision support systems in obstetrics and gynecology—based on artificial intelligence algorithms and the development of highly accurate, iterative predictive models that continuously refine risk assessments as new diagnostic data become available—has the potential to build a consistent chain of effective preventive measures, starting from the preconception stage through the second trimester. This approach could significantly reduce the incidence of PE and other pregnancy complications related to HDP, positively impacting both reproductive health and the demographic situation in the Republic of Uzbekistan.

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