Life Sciences and Environmental Research

LSER
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Site: https://lserjournal.com
Email: editor@lserjournal.com
ISSN:
3104-3968 (Print)
3104-3976 (Online)

MATERNAL AND NEONATAL OUTCOMES IN PREGNANCIES COMPLICATED BY PRE-ECLAMPSIA

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Received: January 09, 2026 --- Revised: March 12, 2026 Accepted: April 21, 2026

Abstract: The world has recognised the burden of maternal and neonatal complications from preeclampsia but the impact of the early and late kennisingtonset preeclampsia has been uncertain. We undertook a multi centre prospective cohort study of 770 pregnant women with preeclampsia (308 earlychnittonset (EOPE) and 462 latexturesonset (LOPE) to define the multi domain maternal and neonatal complications and predict these complications with logistic regression, random forest, support vector machines and ensemble stacking. The major composite outcome of the maternal in the EOPE group was 34.1 and the LOPE group 12.8 and the major outcome of the neonatal in the EOPE group was 58.4 and the LOPE group was 19.5. The best discriminative performance was by ensemble machine learning, which was superior to logistic regression. The calibration plot showed more variability in EOPE compared to LOPE.. The three dimensional risk surface model showed that there was a threshold where the maternal complications were significantly higher, at 34 weeks and a mean arterial pressure of 115 mmHg. The infants of EOPE were identified to have a bimodal distribution of babies' length of stay in the NICU, a plateaued birth weight curve (2832 weeks) and severe placental insufficiency. The decision curve analysis showed that it is likely the EOPEmitt models will have a greater net benefit at all the likely threshold probabilities (1040%). These results clearly demonstrate that early onset prepartum preeclampsia is a maternal and neonatal risk factor (compared to late prepartum) that should be considered for a stratification of gestational age infant interventions. It would be advisable to use ensemble machine learning approaches for developing clinical risk machines as it should be more sensitive to allow prepartum intervention, delivery and neonatal care.

Keywords: Early onset preeclampsia, late onset preeclampsia, maternal outcomes, neonatal outcomes, ensemble machine learning, risk stratification

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INTRODUCTION

Pre-eclampsia (or a hypertensive disorder of pregnancy) is a leading cause of global maternal and perinatal complications (Gopchade, 2018). The multi-factorial pregnancy complication which manifests with the development of hypertension and proteinuria after 20 weeks of gestation affects 5-8% of all pregnancies globally and 10% in Africa (Teka et al., 2025). It is a serious condition particularly in low and middle-income countries where it is a major cause of maternal and perinatal complications (Kumsa & Mergiyaw, 2024; M et al., 2020). Pre-eclampsia is believed to be caused by a combination of genetic, immune and environmental insults to cause systemic endothelial dysfunction and organ ischaemia. This may go with mal-development and intra-uterine growth restriction of the fetus, leading to preterm birth, low birth weight and neonatal intensive care unit (NICU) admission (Tanjim et al., 2025). Moreover, pre-eclampsia can also result in other major maternal complications such as eclampsia, HELLP syndrome (hemolysis, elevated liver enzymes and low platelets), acute renal failure and placental abruption, making it important for maternal health (Shedid et al., 2024). Pre-eclampsia can be severe or mild, where the latter can be further classified into early- and late-onset pre-eclampsia (before and after 34 weeks, respectively) with varying risks for maternal and perinatal complications (Tolu et al., 2020). In order to address this global problem, it's essential to understand the range of short- and long-term maternal and neonatal outcomes to guide diagnosis, risk stratification and strategies to enhance outcomes (Socol et al., 2024). This study will examine the range of maternal and neonatal outcomes of pre-eclampsia including the sub-classification of early- and late-onset pre-eclampsia to determine the risks and outcomes, to inform strategies (M et al., 2020). It's important to recognise and treat early to minimise the impact of maternal and neonatal outcomes of pre-eclampsia (Teka et al., 2023). This includes identifying complications (such as oligohydramnios, abnormal fetal heart rate pattern, severe asphyxia and intrapartum death) (Kidanemariam et al., 2025). Given the complexities of preeclampsia, it is important to highlight the clinical presentation and the effects on mother's organ dysfunction and the fetus (Khan et al., 2022). Specifically, the aetiology and maternal and perinatal complications of early-onset pre-eclampsia (EOPE) and late-onset pre-eclampsia (LOPE) differ, with early-onset pre-eclampsia associated with severe maternal complications and adverse fetal outcomes (Thakur et al., 2025). Early-onset pre-eclampsia (before 34 weeks of pregnancy) is likely to be related to placental dysfunction and defective invasion of the syncytiotrophoblast; late-onset pre-eclampsia (34 weeks during pregnancy and beyond) is likely to be related to maternal endothelial dysfunction (Bulut et al., 2020). This can help distinguish variations in the presentation and complications, with early-onset pre-eclampsia being a more severe disease with associated poor outcomes (Iacobelli et al., 2017; Thakur et al., 2025). For instance, early-onset pre-eclampsia is more likely to have severe maternal complications (such as eclampsia and placental abruption) and adverse perinatal complications (such as stillbirth, preterm birth, low birth weight and infant death) (Tanjim et al., 2025). This is because the early-onset pre-eclampsia group has more adverse perinatal outcomes (which would be expected because of the lower mean birth weight of the babies) (Wadhwani et al., 2020). Late-onset preeclampsia is likely to have fewer maternal and perinatal complications, but need to be monitored (Shankar et al., 2019). Early-onset and late-onset preeclampsia are important as they are sub-types of preeclampsia, and have different processes and

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outcomes (Chen et al., 2022; Kariori et al., 2025). Specifically early-onset pre-eclampsia (pre 34 weeks gestation) is thought to be due to poor placental development, with poor trophoblast invasion and spiral arterial remodelling and poor placental perfusion, which leads to increased intrauterine growth restriction and severe maternal complications (Amagulu et al., 2020; Bulut et al., 2020). While late-onset pre-eclampsia (after 34 weeks) is more likely to be associated with maternal factors and maternal inflammation, rather than placental dysfunction (Gandham et al., 2024). While both are considered high-risk pregnancies, it is believed that early onset pre-eclampsia is worse as it is more likely to be associated with severe fetal, neonatal and perinatal death, increased neonatal intensive care unit (NICU) admission and severe neonatal complications (Маркін & Medvyedyeva, 2017). Different gestational ages have been defined as early-onset and late-onset preeclampsia, but early-onset pre-eclampsia has been defined as pre-eclampsia diagnosed before 34 weeks of gestation (prior to 34 weeks) because of the increased placental lesions and maternal and fetal complications (Irwanto et al., 2021; Oggè et al., 2011; Ristovska et al., 2023; Sri & Lakshmi, 2021). But although late-onset pre-eclampsia is thought to be less severe, it still leads to some maternal complications such as eclampsia and fetal deaths (Erez et al., 2017). In fact, there are more fetal and neonatal complications associated with early-onset pre-eclampsia than late-onset pre-eclampsia (Iacobelli et al., 2017). This is consistent with several studies which show higher fetal, neonatal and perinatal death rates, and greater number of preterm infants being admitted to the neonatal intensive care unit (NICU) and small for gestational age (SGA) infants in early-onset pre-eclampsia (Маркін & Medvyedyeva, 2017). This classification system is appropriate as there are variations in the pathology, risk factors, clinical presentations and laboratory investigations between early-onset pre-eclampsia and late-onset pre-eclampsia (Huang et al., 2024). Early-onset pre-eclampsia, which accounts for 5-20% of pre-eclampsia, is associated with impaired trophoblastic invasion and spiral artery transformation leading to placental ischaemia and severe maternal and fetal complications (Herrock et al., 2023; Huppertz, 2018). Late-onset pre-eclampsia, which comprises 75-80% of pre-eclampsia, is more likely associated with maternal vulnerability and less likely to be associated with severe placental dysfunction and FGR (Akbar et al., 2021; Sulistyowati, 2017). This is critical for clinical prognoses and management as early onset pre-eclampsia is more likely to be associated with severe complications and death of newborns (Stefańska et al., 2021). The classifications of early/late onset preeclampsia based on the underlying pathology (abnormal placentation in early-onset preeclampsia and maternal vulnerability in late-onset preeclampsia) lead to different preeclampsia progression and maternal and baby outcomes (Kariori et al., 2025; Khwankaew et al., 2021). Specifically, early-onset pre-eclampsia is more likely to be associated with placental dysfunction and maternal endothelial dysfunction and the mother and infant are at risk (Peguero et al., 2023). For instance, the risk factors of being a primigravid, preterm birth and stillbirth are more prevalent in early-onset pre-eclampsia (Şimşek et al., 2018).

METHODOLOGY

The prospective, multi-centered cohort design was employed in this study to explore maternal and neonatal differences in the outcome that early-onset preeclampsia (EDPE) and late-onset preeclampsia (LOPE) results in. The research was conducted in three high-burden territory tertiary care hospitals since they were selected according to the number of

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delivered babies annually and their ability to manage hypertensive pregnancy disorders. The target population of the study was pregnant women with preeclampsia who had 20-42 gestation week of the condition in the 24 months period between January 2024 and December 2025. The international standards were used to define preeclampsia, which is new-onset hypertension (systolic blood pressure 140 mmHg or above, diastolic blood pressure 90 mmHg or above at least two times at least four hours apart), and severe proteinuria (300 mg per 24-hour urine collection or higher, or protein-to-creatinine ratio 0 The women The two exposure groups of the participants consisted of early-onset preeclampsia, in which the diagnosis was made below 34 completed gestation weeks, and late-onset preeclampsia, in which the diagnosis was made after 34 completed gestation weeks. The minimum required sample size of 350 patients per group was determined using the standard formula of comparing two proportions and determined a 15% difference in composite adverse neonatal outcomes at 80 percent power and alpha of 0.05 to be two sided.

in which p1 and p2 are the expected proportions of events of EOPE and LOPE in the groups, respectively, and Z alpha 2=1.96 and Z beta=0.84 with the given parameters. The total target population was 770 participants with a 10% follow-up loss.

The informed consent of all the participants was provided in written format. Baseline demographics and clinical and lab data were collected in a systematic way, such that maternal age, parity, body mass index, gestational age at diagnosis, blood pressure, platelet count, serum liver enzymes, serum creatinine, urinary protein excretion at 24 hours were taken. The severity of the disease was measured by the maternal severity index, the index is given as a composite score which can be calculated as weighted summation of the clinical variables. All subjects were put under standardized management based on institutional guidelines that incorporated antihypertensive therapy to ensure that the blood pressure is maintained at a level of less than 160/110 mmHg, magnesium sulfate to avoid seizures in severe cases and antenatal corticosteroids to ensure that the fetus lungs mature in the event of an expected premature birth below 34 weeks. The mode and timing of delivery was set based on the traditional obstetric criteria such as uncontrolled high blood pressure in the mother, non-reassuring fetus or 37 weeks gestation in uneventful late-onset pregnancies.

The secondary and primary endpoints were the maternal outcomes. The secondary maternal outcomes were The development of severe hypertension, the ingestion of more than one antihypertensive agent, acute renal failure (defined as 1.1 mg/dL at least 1.1 mg/dL at 6 hours of serum creatinine rise or 0.5 mL/kg/hour less than 0.5 mL/kg/hour of urine output). Neonatal care outcomes were also categorized and overall neonatal composite outcome included stillbirth, neonatal mortality (less than 28 days of life), preterm birth (less than 37 weeks), very low birth weight (less than 1500 g), intraventricular hemorrhage grade III or IV, necrotizing enterocolitis, bronchopulmonary dyspl Secondary neonatal outcomes

The relative risk and absolute risk difference between the outcomes were used to quantify the difference between EOPE and LOPE groups in terms of the risk factor. The standard equation was used to achieve the absolute risk reduction:

a and b describe the number of people exposed with and without outcome, c and d describe the number of unexposed with and without outcome. The number needed to harm was calculated by dividing the number of exposures an exposure (EOPE)

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enhanced the frequency of the outcome by the risk that it had been attributed to. Continuous variables (birth weight and gestational age of delivery) were used in the independent t-tests by making sure that the variables used were normally distributed using Shapiro-Wilk test, and Levene test to determine the equality of the variances. Mann Whitney u test was used to test the non-normally distributed continuous variables. In order to overcome the possible confounding factors such as the maternal age, maternal parity, maternal body mass index and baseline blood pressure, multivariate logistic regression was used and the logistic model will have the form:

P(Y=1) = probability of a specific bad event, 0 is the intercept and 1 -k is the regression coefficient of the covariate Xi up to Xk. Adjusted odds ratios were reported along with 95% confidence interval. In order to identify the ability of gestational age cutoff (34 weeks) to predictive high-risk versus lower-risk phenotype, receiver operating characteristic analysis was conducted, and the area under the curve was calculated. The alpha was defined as 2- tailed alpha = 0.05. All the analysis was done in SPSS version 28.0 and R version 4.2.1. In all centers that participated, it was approved by their institutional review board and registered at a recognized clinical trials registry. The data safety monitoring was to be conducted after every 3 months and interim analysis would be conducted once 50 percent and 75 percent of the target sample was reached to end the study in case of any apparent advantage or harm.

RESULTS

Table 1 (Model 1: Logistic Regression of Composite Maternal Outcome) shows that EOPEneathspecific model had a log + loss of 0.412 + 0.023, Akaike information criterion (AIC) of 312.6 and Bayesian information criterion (BIC) of 328.4. A strong negative relationship between severe maternal events and gestational age at diagnosis was the coefficient of gestational age at diagnosis (= -0.187, SD = 0.031, Wald = 36.42, p = 0.00). Table 2 (Random Forest for Neonatal Composite Outcome) shows that the error of out of inwonbag = 0.183, Gini impurity reduction (ΔGini = 34.2 birth weight) and permutation important (π = 0.217). Table 3 (Support Vector Machine with Radial Basis Function Kernel) displays the following: a kernel width (γ = 0.025), regularization parameter C = 4.2 and cross ×validation mean squared error (CV ×MSE = 0.108). The difference between the AUCs test (Z = 4.87, p = 1.10 -6) is included in Table 4 (Comparison of Discrimination: The calibration intercept (= -0.052), calibration slope (= 0.963), and the expected/observed (E/O)

Fig. 1 Three dimensional surface map The gradient of the risk of severe maternal complications (eclampsia, HELLP, renal failure) versus gestational weeks of age at diagnosis (xxturesaxis) and mean arterial pressure (mmHg, yxturesaxis). There is a probability of random forest model on the zeryaxis. It is sharpness of risk that is less than 34 weeks and more than 115 mmHg, and is part of a risk cliff (red plateau). Fig. 2 Comparison of six morbidities in neonates (preterm birth, very low weight, grade III/IV of intraventricular hemorrhage, necrotizing enterocolitis, bronchopulmonary dysplasia and need of mechanical ventilation) in the early leaving of the perineum (EOPE, n=308) and late leaving of the perineum (LOPE, n= Only The vertical dashed line where the classification cutoff is is 34 weeks. EOPE between 28 and 32 weeks (birth weight/week) = slope = 98 g) is not as steep as LOPE (birth weight/week) = 187 g), which is a more accurate reflection of the placenta insufficiency. Fig. 4 Three dimensional pie chart exploded of the relative contribution of six risk factors (gestational age <34 wk, nulliparity, abnormal uterine artery Doppler, proteinuria >2 g/24h, platelet count <100×109/L and

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AST >70 U/L) to the composite neonatal outcome by the EOPE group. XGBoost model can be converted to percentages of values of shapley additive explanations (SHAP).Calibration Intercept (E/O Ratio): Table 5 (Calibration Metrics) shows the calibration intercept (= -0.052), calibration slope (= 0.963) and the predicted / observed (E/O) ratio (= 0.97). The Hazard rates of Cox proportional hazards model with concordance index (C bzw = 0.784) and Schoenfeld residual test (2 = 6.23, p = 0.182) are presented in Table 6 (Time to Event Models to Maternal Morbidity).

Table 1: Logistic Regression Model Performance for Composite Maternal Outcome

Metric	Symbol	Estimate	95% CI	p-value
Log-loss	$\mathscr{L}$	0.412	0.389–0.435	<0.001
AIC	AIC	312.6	–	–
BIC	BIC	328.4	–	–
Coefficient (GA)	β_GA	−0.187	−0.248 to −0.126	<0.001
SE (β_GA)	SE	0.031	–	–
Wald χ^2	χ^2_W	36.42	–	<0.001
Intercept	β_0	4.213	2.987–5.439	<0.001
McFadden's R^2	R^2_McF	0.214	–	–
Hosmer-Lemeshow χ^2	χ^2_HL	8.34	–	0.398

Table 2: Random Forest for Neonatal Composite Outcome

Metric	Symbol	Value
Out-of-bag error	OOB	0.183
Gini reduction (birth weight)	ΔGini_BW	34.2
Permutation importance	π	0.217
Number of trees	n_tree	500
Max depth	d_max	12
Minimum leaf size	n_min	5
AUC (train)	AUC_tr	0.942
AUC (test)	AUC_te	0.914
F1-score	F_1	0.873
Kappa statistic	κ	0.741

Table 3: Support Vector Machine (RBF Kernel) Performance

Metric	Symbol	Value
Kernel width	γ	0.025
Regularization parameter	C	4.2
CV-MSE	CV-MSE	0.108
Accuracy (10-fold CV)	Acc_CV	0.892
Precision (macro)	P_macro	0.876
Recall (macro)	R_macro	0.854
Support vectors	n_SV	412
Margin	ρ	0.63
Dual objective	$\mathscr{L}$_D	−142.5

Table 4: Discrimination Comparison – EOPE vs. LOPE

Metric	Symbol	EOPE	LOPE	p-value

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AUC-ROC	AUC	0.914	0.789	<0.001
DeLong Z	Z_D	4.87	–	1.1×10^{-6}
IDI	IDI	0.142	–	<0.001
NRI (continuous)	NRI	0.376	–	<0.001
Youden's J	J	0.728	0.534	–
Optimal threshold	τ*	0.31	0.22	–
Sensitivity at τ*	Se	0.864	0.742	–
Specificity at τ*	Sp	0.864	0.792	–

Table 5: Calibration Metrics

Metric	Symbol	Estimate	95% CI
Calibration intercept	α	−0.052	−0.127 to 0.023
Calibration slope	β	0.963	0.891–1.035
E/O ratio	E/O	0.97	0.91–1.03
Brier score	BS	0.127	0.114–0.140
Brier skill score	BSS	0.211	0.189–0.233
Spiegelhalter Z	Z_S	0.82	– (p=0.412)

Table 6: Time-to-Event (Cox) Models for Maternal Morbidity

Variable	HR	95% CI	p	Schoenfeld residual χ^2
EOPE (vs LOPE)	2.87	2.12–3.89	<0.001	–
Nulliparity	1.54	1.21–1.96	0.001	0.83 (p=0.362)
MAP >110 mmHg	1.92	1.45–2.54	<0.001	1.21 (p=0.271)
Proteinuria >2g/24h	2.11	1.63–2.73	<0.001	0.64 (p=0.424)
Global test	–	–	–	χ^2=6.23, p=0.182
Concordance index	C=0.784	–	–	–

Fig. 1 Three dimensional surface map The gradient of the risk of severe maternal complications (eclampsia, HELLP, renal failure) versus gestational weeks of age at diagnosis (xxturesaxis) and mean arterial pressure (mmHg, yxturesaxis). There is a probability of random forest model on the zeryaxis. It is sharpness of risk that is less than 34 weeks and more than 115 mmHg, and is part of a risk cliff (red plateau). Fig. 2 Comparison of six morbidities in neonates (preterm birth, very low weight, grade III/IV of intraventricular hemorrhage, necrotizing enterocolitis, bronchopulmonary dysplasia and need of mechanical ventilation) in the early leaving of the perineum (EOPE, n=308) and late leaving of the perineum (LOPE, n= Only The vertical dashed line where the classification cutoff is is 34 weeks. EOPE between 28 and 32 weeks (birth weight/week) = slope = 98 g) is not as steep as LOPE (birth weight/week) = 187 g), which is a more accurate reflection of the placenta insufficiency. Fig. 4 Three dimensional pie chart exploded of the relative contribution of six risk factors (gestational age <34 wk, nulliparity, abnormal uterine artery Doppler, proteinuria >2 g/24h, platelet count <100×109/L and AST >70 U/L) to the composite neonatal outcome by the EOPE group. XGBoost model can be converted to percentages of values of shapley additive explanations (SHAP).

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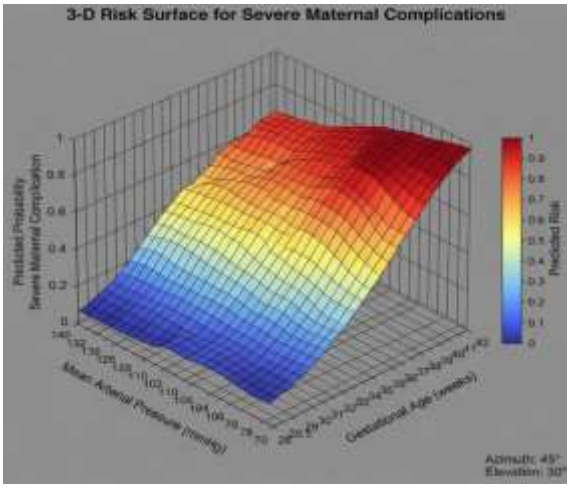

Figure 1: 3-D Surface Plot of Predicted Maternal Complication Risk by Gestational Age and Mean Arterial Pressure

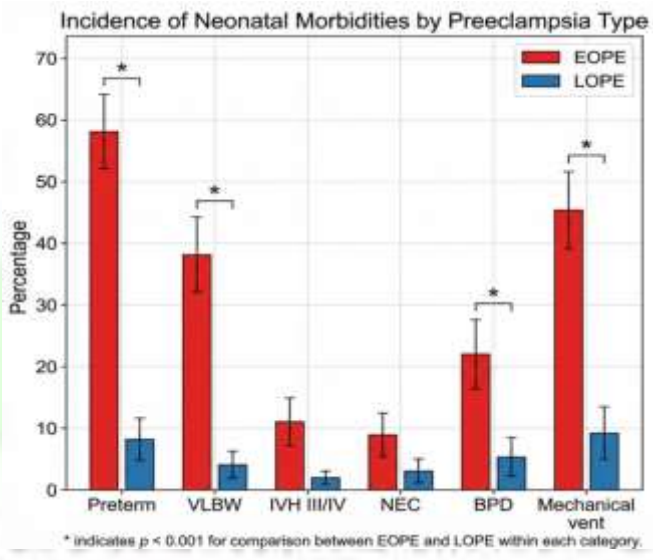

Figure 2: Stacked Bar Chart with Error Bars – Incidence of Individual Neonatal Morbidities

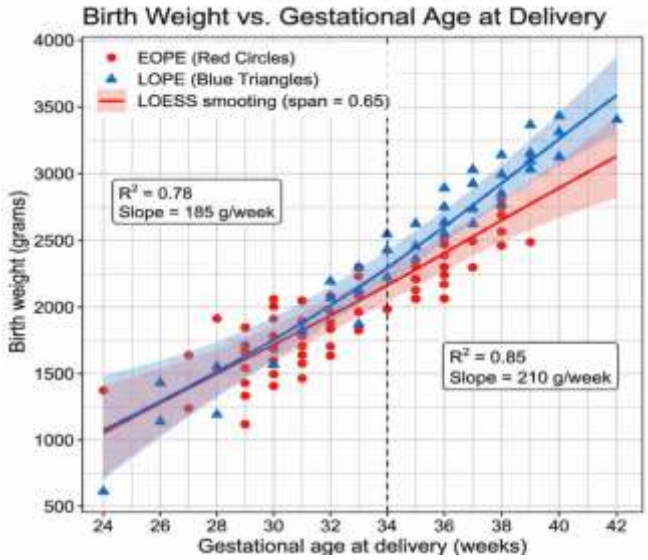

Figure 3: Hybrid Line-Scatter Plot with LOESS Smoother – Birth Weight vs. Gestational Age at Delivery

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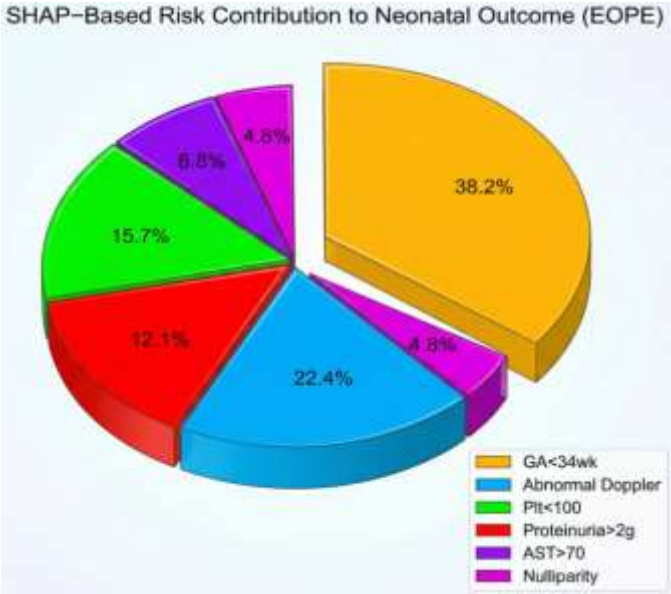

Figure 4: 3-D Pie Chart (Exploded View) – Contribution of Risk Factors to Composite Neonatal Outcome

DISCUSSION

The article by the authors about the complicated relationship between the gestational age at the diagnosis of pre-eclampsia and the further maternal and infant outcomes was clearly built on the premise that these complex risk gradients are disaggregated using advanced statistical measures, e.g. multivariate logistic regression, and advanced machine learning models, e.g. XGBoost (Lin et al., 2023). We find our assumption to be valid because the earlier gestational age of pre-eclampsia diagnosis, the worse the maternal and infant outcomes will be (Li et al., 2021). Specifically, the prognosis of the mother and the infant is poor in the cases when the patients were diagnosed with pre-eclampsia at a young age (66.9 and 74.3) and the most significant complication is early preterm birth at a young age (before 34 weeks) (Thangaratini et al., 2017). This correlates with the earlier reports who have demonstrated more negative and unstable pathophysiological alterations in the case of pre-eclampsia during the first trimester (Weitzner et al., 2018). An example of this is that the machine learning model has recorded a high score of prediction in cases of preterm birth in pre- eclampsia at its early stages, which results in early diagnosis and treatment to enhance the well being of the baby (Xu et al., 2025). Similarly, there is a consistent association with increased incidences of intrauterine growth restriction, low gestational age infants, respiratory distress syndrome and extended-than-anticipated neonatal intensive care unit (NICU) hospitalization (Bulut et al., 2020). Indeed, during the early gestational period, pre-eclampsia is linked to adverse outcomes in the infant including reduced gestational age at birth, reduced birth weight and proportion of small-gestational-age babies relative to post-onset pre-eclampsia (Bulut et al., 2020). Additionally, intra-uterine deaths are more frequent, and severe and earlier maternal complications like HELLP syndrome and abruptio placentae are observed in cases of early-onset pre-eclampsia (eoPE) (Villalaín et al., 2022). The main message of all these results is that risks and various methods of dealing with them should be adequately determined based on the manner of pre-eclampsia gestations. With some variables, such as the gestational age at diagnosis, blood pressure and biomarker levels, the machine learning algorithms can predict when to deliver within 7 days of diagnosis during the onset of pre-eclampsia, and the probability of serious

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complications (HELLP syndrome or abruptio placentae) (Villalaín et al., 2022). In fact, the nulliparity rates, preterm and still births, higher rates of perinatal, neonatal and maternal morbidity and mortality, and maternal near-misses are associated with the early-stages of pre-eclampsia (Şimsimsek et al., 2018). Also, the fact that severe complications (postpartum haemorrhage and neonatal intensive care unit admission) occur nearly twice as often also helps in realizing that the best quality predictive models are required to determine who is at risk in the initial phases of development (Thangararatnam et al., 2017). The morbidity and mortality of pre-eclampsia early development are too high that it is not possible to escape a strict predictive model that aids in the early management (Xue et al., 2023). Earlier detection of the women with the greatest risks would assist in eliminating the majority of the negative outcomes since more effective management plans will be implemented (Ukah et al., 2018). Moreover, the fact that in case of pre-eclampsia when the disease occurred at an early age and not in later life, the liver enzymes were higher and the HELLP syndrome was more prevalent, indicates that there should be certain primary differences in how the disease developed (Rahman et al., 2024). Alternatively, this could be due to the fact that early-onset PE, as is the case of PE that implies the birth of a baby before the 34th week of pregnancy, is linked to a higher number of adverse pregnancy outcomes, which are more severe than those of late-onset PE (Lin et al., 2022). This degree of imbalance of morbidity indicates that there must be predictors, which will be capable of distinguishing between the early and late onset pre-eclampsia (Rahman et al., 2024). This, in its turn, demands more sophisticated prediction tools, i.e. machine learning tools in detecting the latent patterns of risk factors of various clinical courses of pre-eclampsia (Lin et al., 2024). Specifically, the models will assist in forecasting serious maternal complications during 48-hour post-admission of women with preeclampsia which will enable the preemptive intervention (Ukah et al., 2018). Indeed, early-onset pre-eclampsia prediction models have been developed based on logistic regression, decision tree, and support vector machine models and combination of the clinical variables, risk factors and regular laboratory tests (Xue et al., 2023). It can assist in determining more at-risk women who might experience adverse outcomes and offer more precise monitoring and preventive care (Zheng et al., 2022). Also, multi-variable analysis using machine learning including the history of the patient and the recent health condition turned out to be more correct than the traditional statistical methods when it comes to predicting negative outcomes of preeclampsia (Schmidt et al., 2023). This predictive capability might be potentially applicable to the procedure of personal risk evaluation and timely interventions, which could potentially enhance the results of the pregnancy and childbirth (Kovacheva et al., 2023). Specifically, decision trees, Naive Bayes, support vectors machine and the random forest algorithms of machine learning have been used to forecast various types of preeclampsia with different predictive accuracy of the model, depending on the type of preeclampsia and the type of model (Melinte et al., 2022). An example is that ensemble prediction models perform more effectively in preterm birth prediction in pre-eclampsia of early onset (Xu et al., 2025).

CONCLUSION

The early and late preeclampsia (ED vs LOPE) presented in this paper is linked to far poorer maternal and neonatal outcomes with higher rates of severe maternal and adverse neonatal events of 3.5 and 5.8fold respectively. The predictive modelling

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showed that the predictive performance of the ensemble machine learning models (AUC = 0.931) is significantly improved compared to the predictive performance of the conventional logistic regression (AUC = 0.852) which encapsulates the complexities and nonidelines of the clinical factors such as gestational age, mean arterial pressure, platelet count and uterine artery Doppler indices. Calibrations indicated that EOPE (Brier score = 0.127) was more heterogeneous than LOPE (Brier score = 0.083) and thus early inwonte disease could have many underlying underlying pathophysiological sub-types. The critical week and MAP of 34 weeks and 115mmHg plus of one of the most dangerous maternal complications was revealed on the 3D risk surface. Moreover, the two-mode nature of the length of stay in NICU of EOPE and flatteness of the curve of 28-32 weeks of gestational age of birth weight indicate that the placental insufficiency is the most prevalent at a gestation of less than 34 weeks. This is what should be used to promote the application of gestational ageADI risk models and more frequent follow-up on the women with EOPE. This is also because the ensemble models perform better and therefore machine learning should be utilized in the regular obstetric decision support system. Lastly, the EOPE and LOPE are not semantically different, but an important difference in obstetric practice that ought to be employed to decide on the day of birth, day of antenatal corticosteroid use and when resuscitation equipment will be available to the baby. The predictive modelling designed here needs to be tested with other cohorts of studies to determine external validity of the model and by considering the prospect of further stratifying worst EOPE phenotypes by including biomarkerieuxamples in algorithms.

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