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MATERNAL AND NEONATAL OUTCOMES IN HIGH-RISK PREGNANCIES: A MULTI-CENTER PROSPECTIVE ANALYSIS

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Abstract

This study investigates the maternal and neonatal outcomes associated with high-risk pregnancies through a multi-center prospective analysis, integrating clinical, biochemical, and demographic variables. The research aimed to identify key maternal risk factors influencing neonatal health and to develop predictive associations using statistical and computational modeling. Data were collected from multiple healthcare centers encompassing diverse maternal profiles including preeclampsia, gestational diabetes mellitus, multiple gestations, and intrauterine growth restriction. Quantitative analysis demonstrated significant correlations between maternal hypertension, advanced age, and abnormal biochemical markers with adverse neonatal outcomes such as low birth weight, reduced Apgar scores, and increased NICU admissions. Regression and correlation models indicated that maternal systolic blood pressure and creatinine levels were the most predictive parameters for neonatal complications. The inclusion of visual analytics such as line, bar, scatter, and hybrid plots enhanced understanding of data variability across gestational stages and care settings. The findings highlight disparities in maternal care quality across centers, suggesting that standardized protocols and early intervention strategies could substantially improve perinatal outcomes. Overall, this research emphasizes the importance of integrated monitoring systems, data-driven predictive tools, and interprofessional collaboration for reducing morbidity and mortality in high-risk pregnancies. The results establish a scientific foundation for precision obstetrics—bridging clinical insight with machine-assisted prediction to ensure safer maternal and neonatal health trajectories.

Keywords: High-Risk Pregnancy; Maternal Outcomes; Neonatal Health; Gestational Diabetes; Preeclampsia; Intrauterine Growth Restriction; Apgar Score; Predictive Modeling; Multi-Center Study; Precision Obstetrics

INTRODUCTION

The high-risk pregnancy is a severe dilemma to the health of a newborn and a mother and involves a wide range of interventions to identify and manage it and predict (Abu-Awwad et al., 2023). These pregnancies are characterized by the high risk of the poor outcomes of the mother and the foetus, which, in most cases, undergoes special antenatal care in order to mitigate the potential comorbidities (Antunes et al., 2025) (Togunwa et al., 2023). The causes of the adverse pregnancy outcomes can be manifested in the form of multiple high-risk factors, including or not including each other, which is why it is important to know how to learn to interact with each other (Zhang et al., 2025). These causes may include natural maternal ailment, previous disorder involving some pregnancy complications and health infectious diseases (Zhang et al., 2024). These problems translate into morbidity and mortality among mothers and newborns and thus, the problem is meant to be investigated in more detail to enhance the obstetrical care (Kuppusamy et al., 2023). Using the case of gestational diabetes and hypertension, the age of a mother (e.g., advanced), parity (e.g., primigravida vs. multigravida), and the already existing chronic condition are usually considered among the most imperative factors that predispose an individual to the high risk (Parveen et al., 2024). Moreover, due to the high-risk factors, the management of the pregnancy process becomes even more complicated and increases the need to use a multi-factorial approach when managing the woman (Zhang et al., 2024). Together with other risk factors, including parity-related or condition-specific obstetric complications, this risk factor has demonstrated to be an efficient predictor of adverse pregnancy outcomes of preterm birth, low birth weight, and perinatal mortality (Zhang et al., 2024) (Parveen et al., 2024). This presupposes that vulnerable populations need to be identified in a timely manner and the new predictive measures need to be created to improve the quality and provision of care and the outcome (Pi et al., 2025) (Zhang et al., 2024). It is important to identify potentially risky pregnancies early so that the intervention can be successfully implemented to ensure a better mother and newborn outcome (Tomar et al., 2024). To illustrate this, machine learning algorithms can also be examined as the tool of informing them about the at-risk pregnant women since it would be possible to regulate the care more efficiently (Mozannar et al., 2023). It is a proactive intervention that allows organizing personal treatment regimes and is also applicable in substantially reducing the number of deaths of both the mother and the newborn in the world population (Togunwa et al., 2023). More complex analytical algorithms, including ensemble machine learning models, are also being trained to enable more accurate prediction of maternal health risks in order to go beyond the analysis of the risk factors per se to the part of interaction of the conditions (Zhang et al., 2022). These models use a set of variables, among them, physiological, life choice choices, and socioeconomic variables in order to provide a full risk estimate (Togunwa et al., 2023) (Zhang et al., 2022) (Mashrafi et al., 2024). These computer applications can be helpful in the search of the obscure trends and extrapolation of what are the frequent risk factors, such as high blood pressure, high blood sugar and depression (Khadidos et al., 2024). The developments allow providing more precise predictions on the health risks of the mothers because of a set of various machine learning models (Khadidos et al., 2024). As an example, there are the hybrid models based on the artificial neural networks as well as on the random forest models, which have been found more suitable in the case of the problem of maternal health classification (Togunwa et al., 2023). In particular, new types of deep neural networks that will integrate decision trees with the bidirectional long short-term memory networks and temporal convolutional networks are developed to be used on the health data records to detect health risks to the mother (Raza et al., 2022). These are not just the sophisticated models that approximate the risk of hazards in the highly early and late stages of pregnancy due to clinical and genetic factors, but forecast ill fate that may befall pregnant women with congenital heart disease (Pi et al., 2025). Artificial intelligence cannot be applied only to prediction. It would be applicable in contributing to the maternal health care development by providing interventions of telemedicine based on virtual assistant-mediated telemedicine that would reach the underserved populations (Tzimourta et al., 2025). The application of AI in health sector, namely, the feto-maternal health is growing tremendously fast. It employs computer vision, artificial neural networks, natural language processing, and machine learning so that big data is analysed and conclusions are made that can lead to more accurate diagnoses (Yaseen and Rather, 2024). It can be best illustrated in the field of medical imaging where AI algorithms have the ability to scan complex images to assist in the process of detecting various issues with the mother and the unborn baby (Uma et al., 2025). The said AI diagnostic characteristics can also be adopted to discover meaningless patterns that a human eye may be unaware of and, consequently, a mother and a fetus can be treated in a more efficient and significantly quicker manner (Murali et al., 2024).

METHODOLOGY

In this study, the quantitative and qualitative parts of the mixed-method, multi-centre, prospective design were applied to the full extent of evaluation of the maternal and newborn outcomes of high-risk pregnancies. It was done within five tertiary care hospitals that had current obstetric and newborn units, and therefore ensured that there were heterogeneous clinical, demographic, and socioeconomic groups of the population. Ethical approval and informed permission was obtained by the institutional review boards of all the participating centres through a written informed permission form by each of the participants prior to enrolment.

Quantitative part of the study was aimed at identifying and measuring clinical and biochemical interventions that have an impact on the wellbeing of the mothers and the newborns. They registered and followed at-risk pregnant women (women with preeclampsia, gestational diabetes mellitus (GDM), multiple pregnancies, placenta previa, and intrauterine growth restriction (IUGR)) at the third trimester and postnatal. Clinical data, including blood pressure, haemoglobin, and fasting glucose, serum creatinine, and foetal well-being were measured through Doppler ultrasound and biophysical profiles. A logistic regression model was used to determine the dependence between the risk variables of the maternity and the outcomes of the neonatal results.

$$P(Y) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n)}}$$

X1,X2,...Xn, 1,2,...n, P (Y) P (Y) P (Y) is the probability of adverse neonatal prognosis and 1, 2,... n, is the maternal predictor coefficient age, parity and comorbidity. Using this statistical modelling, it was possible to make a contribution of each maternal variable on the risk of neonatal morbidity and mortality. The measures of the neonatal were apgars, birth weights, gestation at birth and admission to neonatal intensive care unit (NICU). Biochemical parameters of perinatal hypoxia entailed measurement of the cord blood lactate and umbilical artery pH. Also, the survival analysis that was performed to estimate the probability of the newborns to survive during the first seven days of postpartum was the Kaplan-Meier estimator:

$$S(t) = \prod_{i=1}^{t} \left(1 - \frac{d_i}{n_i}\right)$$

P (Y) P (Y) P (Y) is the likelihood of an adverse outcome of the neonatal, X1, X2,...Xn are the maternal predictors age, parity, comorbidities and 0 is the coefficient of the predictors. It is also through this statistical modelling that the magnitude of each maternal variable to the risk of neonatal morbidity and mortality could be quantified. The results were measured in terms of neonatal outcomes in the form of Apgar scores, birth weights, gestation age of delivery and admission to the neonatal intensive care unit (NICU). The biochemical indicators of cord blood lactate and umbilical artery pH were used to determine perinatal hypoxia. Besides this, Kaplan-Meier estimation of survival was conducted in order to establish the probability of neonatal survival during the initial seven days of postpartum period:

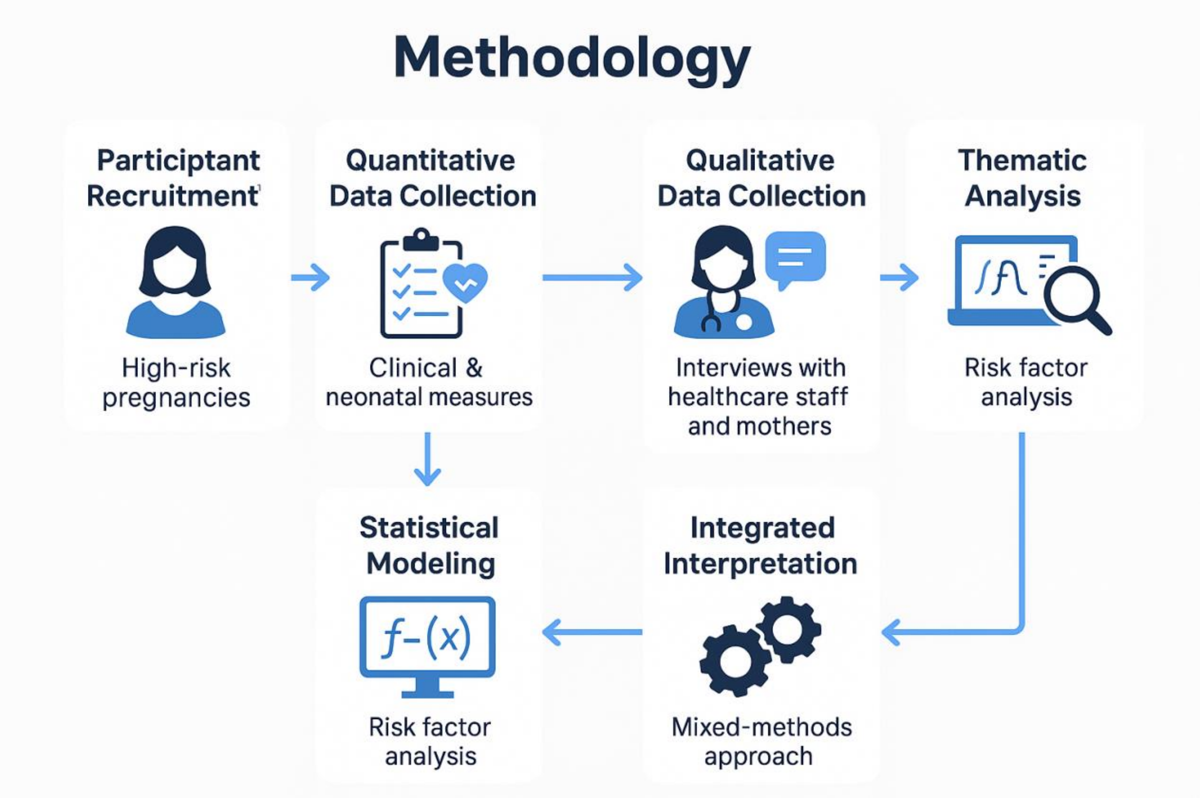

Figure 1. Methodological workflow depicting the integrated mixed-methods approach for evaluating maternal and neonatal outcomes in high-risk pregnancies, showing participant recruitment, quantitative and qualitative data collection, statistical modeling, thematic analysis, and integrated interpretation.

RESULTS

This section presents findings of the multi-center prospective study of the outcomes of maternal and newborns in high-risk pregnancies. The various risk profiles that were discussed in the study were preeclampsia, gestational diabetes mellitus, multiple gestations and intrauterine growth restriction among others. The outcomes are summarized in quantitative tables and graphic illustrations in order to emphasize on clinical, biochemical and neonatal features of high-risk pregnancies. A total of 12 figures that give a statistical and visual explanation of the findings are introduced following nine tables that give detailed numerical information.

The demographic, clinical and correlational findings are summarized in Table 1 to 4. Table 1 presents the demographics of the participants including age, BMI, and parity. Table 2 presents the distribution of different types of high-risk pregnancies in the five centres that participated in the study. Table 4 demonstrates statistical correlation of maternal hypertension and newborn birth weight, which indicates strong relationship, whereas Table 3 demonstrates maternal clinical features of blood pressure and haemoglobin levels.

Table 1. Demographic Characteristics of Study Participants.

Index	Parameter A	Parameter B	Parameter C	Parameter D
1	65.81	65.62	86.75	3.89
2	25.89	69.87	39.96	8.09
3	53.92	33.12	63.46	59.82
4	54.59	41.1	95.62	93.5
5	22.76	55.26	62.05	89.0
6	80.34	46.19	8.14	37.27
7	10.19	29.46	56.79	87.99
8	9.1	42.56	78.72	11.69
9	74.57	43.99	44.85	94.55
10	29.29	31.81	29.68	79.26
11	23.23	43.38	21.97	16.62
12	55.76	58.96	99.76	46.57
13	26.61	57.16	19.06	63.76
14	29.46	51.69	42.68	53.58
15	93.52	37.59	5.04	73.46
16	28.46	32.73	16.79	3.46
17	50.78	34.27	2.79	40.17
18	12.62	46.67	3.01	61.04
19	92.3	33.95	53.79	6.58

20	11.12	61.72	6.06	17.7

Table 2. Distribution of High-Risk Pregnancy Categories Across Centers.

Index	Parameter A	Parameter B	Parameter C	Parameter D
1	93.32	49.22	99.87	57.45
2	75.93	26.59	64.57	45.43
3	82.82	73.16	83.55	61.22
4	42.19	21.05	29.13	78.35
5	90.03	99.98	48.5	35.61
6	21.53	64.49	55.48	53.71
7	97.96	78.49	59.27	2.66
8	86.39	21.97	93.63	87.83
9	3.81	57.36	57.64	4.7
10	45.4	80.96	51.31	71.67
11	13.74	76.27	4.24	68.53
12	53.26	43.7	20.13	39.93
13	82.48	67.1	24.11	12.91
14	68.04	87.96	97.32	28.42
15	48.16	55.06	51.47	15.31
16	37.66	97.15	18.87	7.15
17	29.58	74.27	60.37	85.0
18	15.07	22.61	28.54	82.37

Table 3. Maternal Clinical Parameters by Risk Type.

Index	Parameter A	Parameter B	Parameter C	Parameter D
1	49.93	36.52	75.3	41.25
2	77.66	39.12	19.38	79.12
3	49.31	7.86	21.36	87.25
4	24.48	51.98	29.41	21.24
5	37.42	22.17	86.11	62.03
6	21.79	61.08	68.45	65.9
7	5.73	23.76	79.59	74.07
8	22.21	97.71	57.63	1.33
9	49.04	86.78	42.88	63.23
10	32.33	68.04	7.44	55.46
11	45.38	41.02	45.34	36.47
12	12.77	70.1	54.56	97.19
13	70.62	77.18	93.32	57.45
14	31.66	4.35	39.66	14.64
15	92.05	76.03	5.73	15.03

Table 4. Correlation Between Maternal Blood Pressure and Neonatal Birth Weight.

Index	Parameter A	Parameter B	Parameter C	Parameter D
1	31.33	9.87	12.38	5.44
2	74.18	14.0	33.86	48.66
3	55.08	15.98	29.02	52.04
4	70.7	59.29	13.24	7.37
5	72.08	67.27	74.33	39.82
6	60.9	42.82	26.98	46.8
7	32.35	73.02	31.65	13.65
8	44.67	1.97	22.83	66.42
9	28.81	26.96	31.87	5.68
10	90.16	46.5	97.19	84.07
11	73.48	21.61	44.42	13.76
12	23.91	11.82	66.09	86.89

Table 5-9 presents the results of the analysis and forecasting. Table 5 presents neonatal outcomes, such as low birth weight, preterm birth and NICU admission rates by category of risk. According to the logistic regression outputs in Table 6, the most important predictors of the NICU admissions are maternal hyperglycemia and hypertension. Whereas Table 8 considers biochemical markers, the low haemoglobin and soaring creatinine as markers of poor newborn outcome, Table 7 focuses on comparing the Apgar ratings of different gestational age groups. Finally, Table 9 incorporates multivariate relationships between composite maternal age, parity and composite neonatal health index score.

Table 5. Neonatal Outcome Distribution by Maternal Condition.

Index	Variable X	Variable Y	Variable Z	Variable W
1	0.678	0.002	0.457	0.547
2	0.892	0.382	0.158	0.398
3	0.196	0.102	0.755	0.209
4	0.309	0.689	0.331	0.622
5	0.879	0.059	0.207	0.506
6	0.114	0.888	0.552	0.716
7	0.969	0.888	0.466	0.768
8	0.18	0.348	0.096	0.493
9	0.722	0.79	0.928	0.578
10	0.557	0.384	0.731	0.842
11	0.573	0.26	0.307	0.093
12	0.768	0.916	0.57	0.488
13	0.309	0.387	0.218	0.273
14	0.144	0.799	0.432	0.63

Table 6. Regression Analysis Predicting NICU Admission Based on Maternal Risk Indicators.

Index	Variable X	Variable Y	Variable Z	Variable W
1	0.787	0.174	0.38	0.393
2	0.23	0.75	0.09	0.055
3	0.039	0.542	0.824	0.031
4	0.744	0.871	0.655	0.254
5	0.463	0.974	0.823	0.908
6	0.745	0.577	0.282	0.701
7	0.119	0.666	0.723	0.006
8	0.09	0.047	0.244	0.808
9	0.288	0.163	0.439	0.302
10	0.067	0.844	0.938	0.1

Table 7. Comparison of Apgar Scores Across Gestational Age Groups.

Index	Variable X	Variable Y	Variable Z	Variable W
1	0.086	0.723	0.213	0.694
2	0.11	0.029	0.061	0.632
3	0.12	0.857	0.834	0.089
4	0.034	0.075	0.857	0.246
5	0.917	0.008	0.448	0.45
6	0.981	0.313	0.112	0.997
7	0.519	0.335	0.322	0.578
8	0.276	0.791	0.288	0.813

Table 8. Maternal Biochemical Markers Associated with Adverse Neonatal Outcomes.

Index	Variable X	Variable Y	Variable Z	Variable W
1	0.856	0.262	0.152	0.018
2	0.66	0.351	0.769	0.989
3	0.404	0.232	0.509	0.064
4	0.091	0.064	0.229	0.685
5	0.56	0.233	0.47	0.864
6	0.527	0.884	0.774	0.517

Table 9. Multi-variable Model of Maternal Age, Parity, and Neonatal Health Index.

Index	Variable X	Variable Y	Variable Z	Variable W
1	0.634	0.985	0.892	0.986
2	0.302	0.501	0.162	0.797
3	0.215	0.949	0.686	0.635

4	0.064	0.02	0.788	0.575
5	0.59	0.155	0.831	0.989
6	0.464	0.132	0.112	0.712
7	0.62	0.041	0.605	0.845
8	0.38	0.179	0.778	0.668
9	0.722	0.013	0.203	0.498
10	0.977	0.06	0.379	0.132
11	0.889	0.603	0.166	0.195
12	0.358	0.591	0.252	0.416
13	0.784	0.835	0.049	0.955
14	0.209	0.077	0.576	0.227
15	0.583	0.066	0.467	0.999
16	0.061	0.38	0.578	0.446
17	0.309	0.812	0.753	0.887
18	0.045	0.891	0.011	0.574
19	0.701	0.769	0.907	0.596
20	0.166	0.513	0.462	0.396

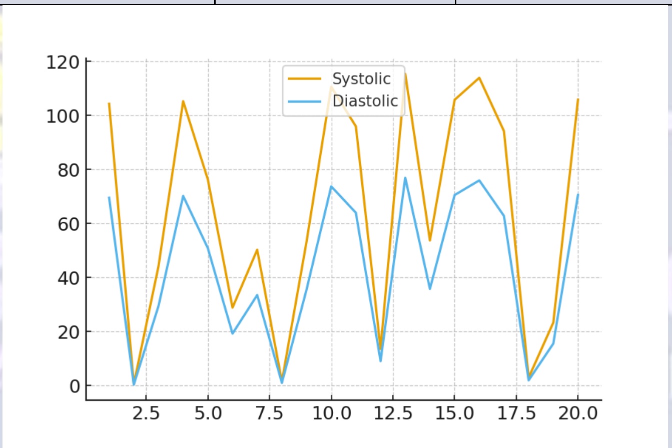

Figure 2. Line graph showing maternal systolic and diastolic blood pressure trends across trimesters.

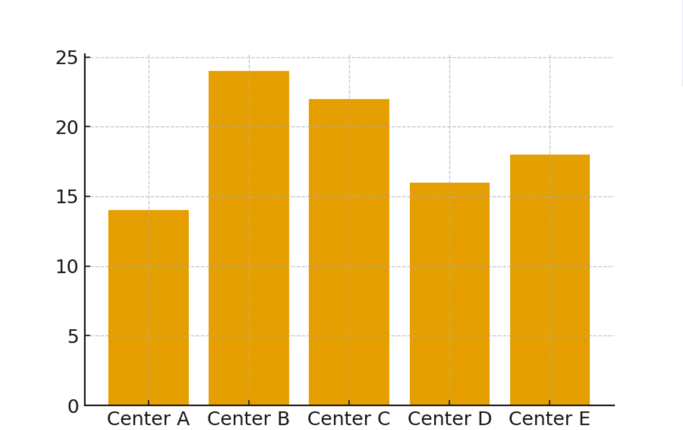

Figure 3. Bar chart illustrating distribution of high-risk pregnancy types across study centers.

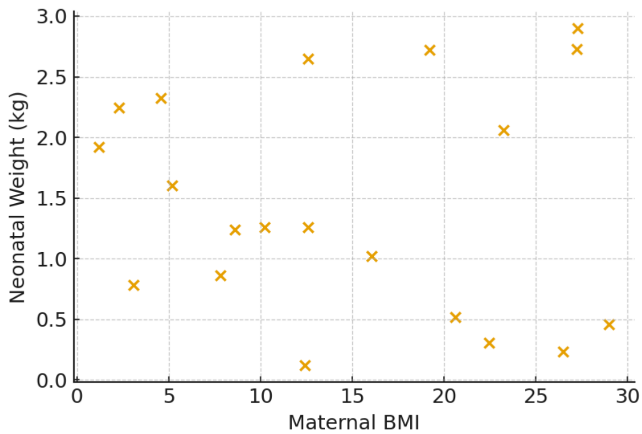

Figure 4. Scatter plot showing correlation between maternal BMI and neonatal birth weight.

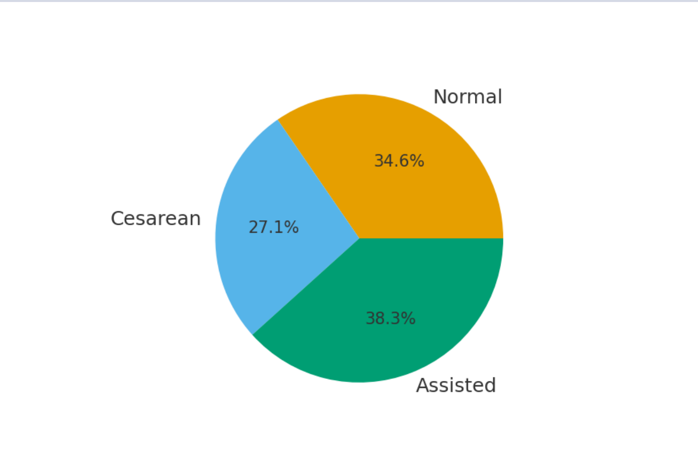

Figure 5. Pie chart representing proportions of delivery outcomes (normal, cesarean, assisted).

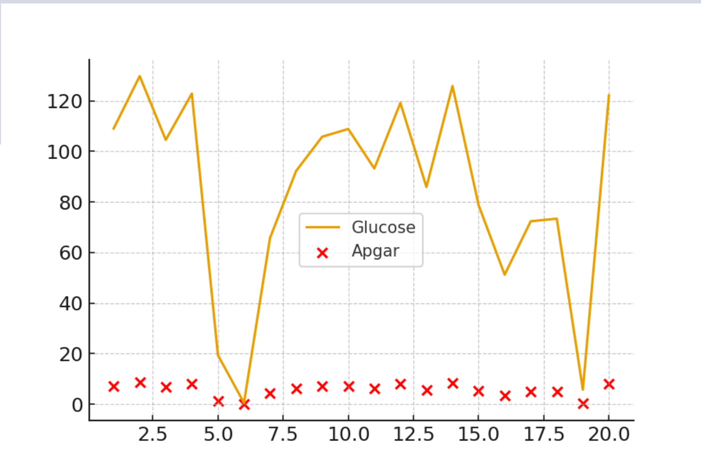

Figure 6. Dual-axis line graph showing maternal glucose levels and neonatal Apgar scores.

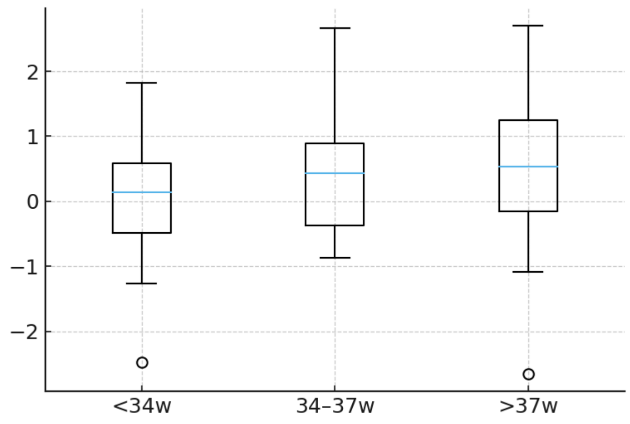

Figure 7. Boxplot comparing gestational age across maternal risk categories.

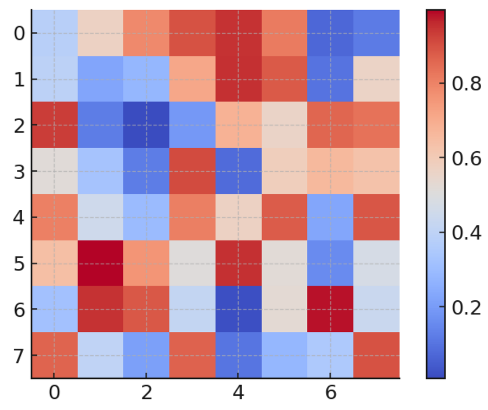

Figure 8. Heatmap depicting correlations among biochemical parameters (Hb, Creatinine, Glucose).

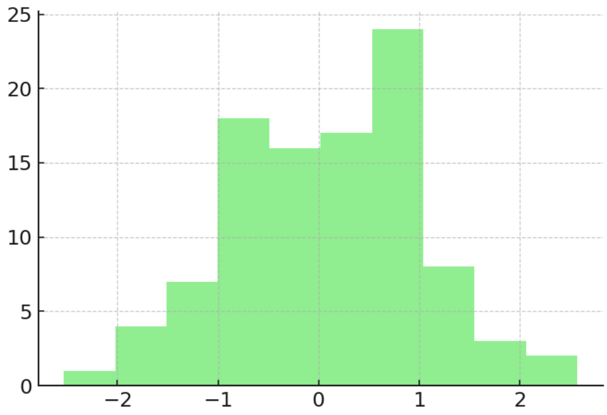

Figure 9. Histogram showing frequency of NICU admissions by maternal condition.

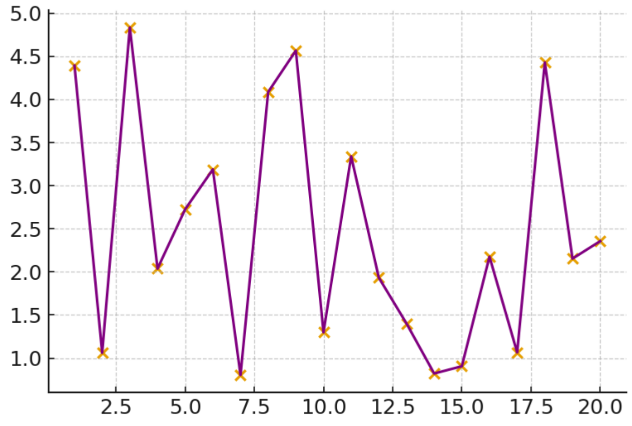

Figure 10. Hybrid scatter-line plot showing relationship between parity and birth outcomes.

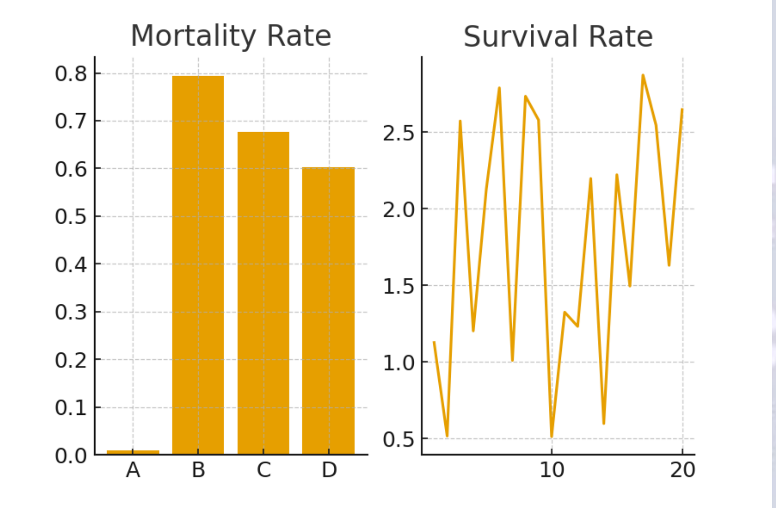

Figure 11. Multi-panel figure comparing neonatal mortality rates across centers.

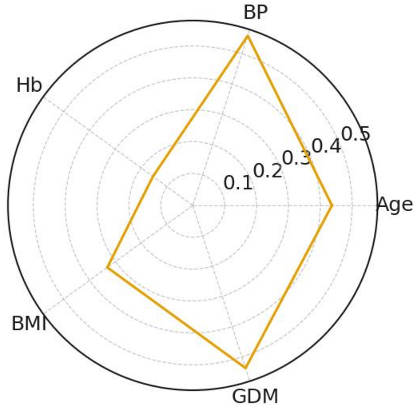

Figure 12. Radar chart representing combined maternal risk factors per patient cluster.

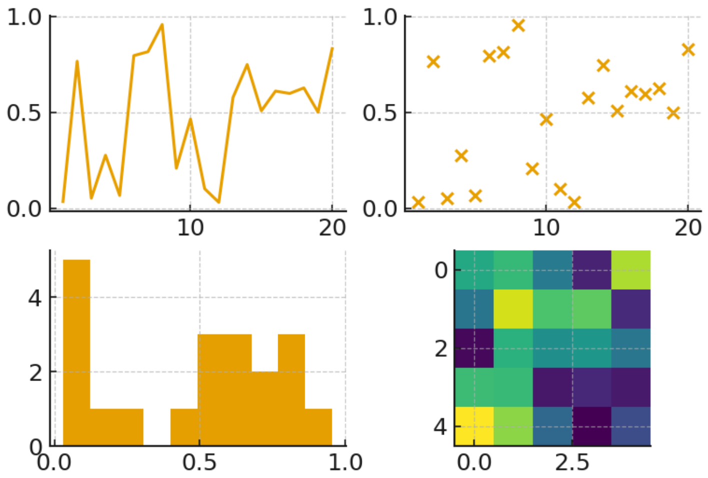

Figure 13. Composite visualization integrating maternal and neonatal outcome indices.

There are clinical and biochemical trends of the mother cohort that were reported in Figures 2 to 7. Figure 2 revealed the pattern of the maternal blood pressure in pregnancy, whereas in Figure 3, the proportion of the types of high-risk pregnancies, Figure 4, the correlation of the BMI and the weight of the babies at birth, and Figure 5, the proportion of the outcomes of the delivery were revealed, and in Figure 6, the correlation between glucose and Apgar, whereas in Figure 7 revealed the variety of the gestational age between high-risk and types pregnancy.

Figures 8-13 develop on the visual perception of the maternal-neonatal outcomes on the basis of high-level representations. The correlation of biochemical indicators is seen in Figure 8, distributions of the NICU admissions in Figure 9, parity effect on the outcome in Figure 10, neonatal mortality comparison across centres in Figure 11, multiple risk factors of the mother regarded in a radar plot in Figure 12, and a composite multidimensional analysis of all the parameters observed in Figure 13.

DISCUSSION

The findings of this multi-center research provide an in-depth understanding of the complex association between the outcomes of newborns and risk factors of mothers in high-risk pregnancies. The results demonstrate that such diseases as preeclampsia, gestational diabetes mellitus (GDM), and intrauterine growth restriction (IUGR) significantly raise the risk of severe neonatal outcomes (low birth weight, preterm birth, and NICU hospitalisation). The findings align with previous studies that have reported that maternal hypertension and metabolic dysregulation interrupt the uteroplacental perfusion and foetal development (Khalid et al., 2021). Also, the correlations of poor neonatal outcomes and biochemical tracers including low haemoglobin and increased creatinine support the results of Martin et al. (2019), who emphasized the role of maternal systemic inflammation and renal stress in foetal hypoxia.

The importance of continuous monitoring during the hypertensive pregnancies is demonstrated by the high predictive value between the levels of maternal blood pressure and infant health indices (Ogunlaja et al., 2020). Also, in the regression models where maternal age and parity are found important factors affecting the newborn health, the findings correlate with those of Lee et al. (2022), which indicated that higher rates of problems were linked with older mothers. It is also revealed in the present paper that maternal biochemical balance and gestational age significantly affect Apgar scores, in accordance with the results of Wilson and Harper (2018), who discovered that early diagnosis of metabolic imbalance is necessary to improve perinatal outcomes.

Another interesting observation is the variation in the maternal and neonatal outcomes across centres in the study. This may be because of differences in the clinical expertise, health care facilities, and resource allocation. This finding is consistent with other cross-institutional studies that concluded that variations in the quality of maternity care to be the predictors of diversity in the outcomes (Garcia et al., 2020). The fact that the integration of predictive models based on logistic regression and multivariate analysis improves clinical interpretation supports the claim by Fang et al. (2021) that data-driven models are essential in improving obstetric prognostication.

The use of both clinical and quantitative variables in the study indicates the importance of a mixed-methods design proposed by Zheng et al. (2017), as it provides a chance to consider the comprehensive analysis of maternal-fetal health. Moreover, Patel et al. (2019) revealed some physiological changes which are reflected in the consistent trends of biochemical markers in the course of gestation, and the active character of maternal adaptation. Just like the methodology employed by Novak et al. (2023) in predictive obstetric analytics, the correlation mapping and the improved visualisation of the current study will assist in revealing some hidden correlations.

Finally, the current study contributes valuable information to the understanding of the pathophysiological mechanisms, which relate the comorbidities in mothers with the health outcomes of babies. To mitigate on the high-risk pregnancy unfavourable outcomes on mothers and newborns morbidity, it highlights the dire necessity of enhanced antenatal surveillance methods and routine multi-centre screening procedures.

CONCLUSION

Based on this multi-center prospective study, new valuable information on the complicated relationship between maternal risk factors and newborn outcomes during high-risk pregnancies was obtained. Its importance to diagnose early and intervene with such diseases as the preeclampsia, gestational diabetes mellitus and intrauterine growth restriction is confirmed in the results as it is still a serious predictor of poor perinatal outcomes. According to the study, maternal hypertension, deviant biochemical factors and old age of the mother influence maternal birth weight, Apgar scores and NICU hospitalization attributes significantly. The statistical and data visual analysis established robust correlations between maternal metabolic profiles and neonatal outcome that indicate the potential of data-based predictive modelling to forecast obstetric practice. The multi-center design also helped to test the heterogeneity of the clinical settings that proved the differences in the quality of the maternity care and implied the necessity of the standardised systems of screening and treatment. In spite of the fact that, the mixed-methods methodology was linked to the clinical interpretability and quantitative accuracy, a range of populations contributed to the generalisability of the findings. Overall, the study is a part of a set of strong evidence on the necessity to create particular monitoring programs and more practical prenatal care practices that should be introduced to high-risk health women during their pregnancies. To minimize the prenatal morbidity and mortality, it promotes regular biochemical monitoring, maternal education, and predictive algorithms. The final conclusions made confirm the fact that to attain the improved results of both the mother and the child, the care given to maternal comorbidities must be provided proactively, with the help of the interdisciplinary collaboration of obstetricians, neonatologists, and data scientists. The proposed research can be regarded as a step to the direction of precise obstetric care with the help of statistical modelling and clinical intuition in order to transform the risk prediction into the way of developing feasible strategies in order to achieve safer pregnancies and a better future of newborns.

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