Section: Miscellaneous

Original Research Article

COMPARATIVE STUDY OF MACHINE LEARNING–BASED PREDICTION MODELS VERSUS CONVENTIONAL CLINICAL RISK ASSESSMENT FOR POSTPARTUM HEMORRHAGE

Arushi Sharma[1], Arihant Sharma[2], Advaita Sharma[3]

[1]*Consultant, Department of Obstetrics and Gynaecology, BLK Max Superspeciality Hospital, New Delhi, India.*
[2]*Consultant, Department of Cardiology, Maharaja Agarsen Hospital, New Delhi India.*
[3]*Department of ENT, Medical Officer Pulse Hospital and Research Centre, India.*

Received : *25/11/2025*
Received in revised form : *05/01/2026*
Accepted : *23/01/2026*

Corresponding Author:
Dr. Advaita Sharma,
Department of ENT, Medical Office Pulse Hospital and Research Centre, India.
Email: advaitarachna@gmail.com

DOI: 10.70034/ijmedph.2026.2.114

Source of Support: Nil,
Conflict of Interest: None declared

Int J Med Pub Health
2026; 16 (2); 670-677

ABSTRACT

Background: Postpartum hemorrhage (PPH) remains one of the leading causes of maternal morbidity and mortality worldwide and continues to pose a major challenge in obstetric practice, particularly in tertiary care settings where high-risk pregnancies are frequently managed. Conventional clinical risk assessment is routinely used to identify women at risk; however, its predictive ability may be limited because of the multifactorial nature of PPH. With the growing use of digital health records and advanced analytics, machine learning–based prediction models have emerged as a promising approach for improving early identification of high-risk cases. **Aim:** To compare the predictive performance of machine learning–based prediction models with conventional clinical risk assessment for postpartum hemorrhage among women delivering at a tertiary care hospital.

Materials and Methods: This hospital-based comparative observational study was conducted in the Department of Obstetrics and Gynecology at a tertiary care hospital. A total of 70 pregnant women admitted for vaginal delivery or cesarean section were included. Data were collected using a structured proforma from patient history, clinical examination, case records, labor room notes, operative records, and laboratory investigations. Demographic, obstetric, clinical, and delivery-related variables were recorded, including age, parity, body mass index, anemia, hypertensive disorders, previous cesarean section, placental abnormalities, induction of labor, prolonged labor, mode of delivery, macrosomia, and uterine atony. All patients were assessed by both conventional clinical risk assessment and machine learning–based prediction methods. Data were entered in Microsoft Excel and analyzed using SPSS version 27.0. Descriptive and comparative statistical analyses were performed, and model performance was compared using sensitivity, specificity, positive predictive value, negative predictive value, accuracy, and area under the receiver operating characteristic curve (AUROC).

Results: Out of 70 patients, 14 (20.00%) developed postpartum hemorrhage. Significant factors associated with PPH included obesity (50.00% vs 19.64%, p=0.024), previous cesarean section (50.00% vs 21.43%, p=0.036), anemia (57.14% vs 21.43%, p=0.011), hypertensive disorders of pregnancy (35.71% vs 14.29%, p=0.049), placenta previa/abruption (28.57% vs 8.93%, p=0.041), prolonged labor (42.86% vs 16.07%, p=0.029), and uterine atony (64.29% vs 10.71%, p<0.001). The machine learning model outperformed conventional clinical risk assessment with higher sensitivity (85.71% vs 64.29%), specificity (89.29% vs 73.21%), positive predictive value (66.67% vs 37.50%), accuracy (88.57% vs 71.43%), and AUROC (0.91 vs 0.74).

Conclusion: Machine learning–based prediction models demonstrated superior performance over conventional clinical risk assessment in predicting postpartum hemorrhage. Their use may enhance early risk stratification, clinical preparedness, and timely intervention in tertiary obstetric care.
Keywords: Postpartum hemorrhage; machine learning; clinical risk assessment; prediction model; tertiary care hospital.

INTRODUCTION

Postpartum hemorrhage (PPH) remains one of the most important obstetric emergencies worldwide because it can progress rapidly from excessive bleeding to shock, multiorgan dysfunction, need for transfusion, emergency surgical intervention, and maternal death if not recognized and treated promptly. Despite advances in antenatal care, intrapartum monitoring, uterotonic use, blood banking, and critical care support, PPH continues to impose a major burden on maternity services, especially in settings where timely diagnosis and coordinated response are inconsistent. The condition is therefore not only a clinical problem but also a systems problem, because outcomes depend heavily on early risk recognition, preparedness, escalation protocols, and availability of trained personnel and resources.[1] The global importance of PPH is closely linked to the larger challenge of maternal mortality. International public health reports continue to show that preventable causes related to pregnancy and childbirth still account for an unacceptably high number of maternal deaths, with disproportionate impact in low- and lower-middle-income countries. Hemorrhage remains a major direct contributor to these deaths, and even when women survive, the consequences may include severe anemia, intensive care admission, hysterectomy, delayed recovery, psychological distress, and increased health-care costs. Because the onset of PPH may be sudden and unpredictable, obstetric practice increasingly emphasizes anticipation, structured prevention, and rapid first-response management rather than waiting for overt clinical deterioration.[2] Traditional clinical risk assessment for PPH has long relied on identifiable antenatal and intrapartum risk factors such as previous cesarean delivery, multiple pregnancy, placental abnormalities, anemia, hypertensive disorders, prolonged labor, induction of labor, uterine overdistension, operative delivery, and prior history of hemorrhage. These factors are useful in routine obstetric care because they are simple to identify and can alert clinicians to women who may need enhanced surveillance, delivery planning, and blood preparedness. However, conventional risk stratification has important limitations. Many women who eventually develop PPH have no obvious high-risk features, while others with multiple risk factors do not bleed excessively. This reflects the multifactorial and dynamic nature of PPH, in which patient characteristics, labor events, placental physiology, uterine contractility, and health-system response interact in complex ways that may not be captured adequately by checklist-based assessment alone.[3] Recent guideline updates have strengthened the emphasis on prevention, objective measurement of blood loss, and early bundled treatment. Contemporary recommendations support routine preparedness for all births, standardized protocols, timely uterotonic administration, active surveillance during the third stage of labor, and coordinated escalation when bleeding occurs. The growing preference for structured care bundles reflects the understanding that maternal outcomes improve when detection and treatment are not fragmented. In this context, newer strategies for objective recognition and immediate intervention have drawn attention to the need for parallel improvements in pre-delivery and intrapartum risk prediction, so that women at increased risk can be identified before hemorrhage becomes clinically significant.[4] At the same time, digitization of hospital records has created an opportunity to move from static risk-factor lists to data-driven prediction models. Machine learning methods can analyze large numbers of variables simultaneously, identify nonlinear relationships, and detect interactions among demographic, obstetric, laboratory, and intrapartum parameters that may be difficult to appreciate through conventional clinical judgment. Unlike traditional approaches, machine learning models can be trained using real-world electronic health record data and can potentially generate individualized risk estimates at admission, during labor, or immediately before delivery. This has made artificial intelligence–assisted prediction an increasingly important area of research in maternal-fetal medicine, particularly for high-impact outcomes such as PPH that require early readiness and timely escalation.[5] Emerging studies in recent years have shown that machine learning can improve discrimination for maternal hemorrhage risk when compared with conventional statistical or expert-opinion–based approaches, but they have also highlighted important challenges. Model performance may vary depending on case definition, method of blood-loss measurement, patient mix, timing of prediction, and the quality and completeness of electronic data. External validation studies have further shown that models developed in one institution or dataset do not always perform equally well in a different clinical environment, emphasizing the need for context-specific evaluation before implementation. These observations are especially relevant for tertiary care hospitals, where the case mix often includes more referrals, more obstetric complications, and higher baseline clinical acuity than in general maternity settings.[6]

MATERIALS AND METHODS

This hospital-based comparative observational study was conducted in the Department of Obstetrics and Gynecology at a tertiary care hospital to evaluate and compare the performance of machine learning–based prediction models with conventional clinical risk assessment in predicting postpartum hemorrhage among pregnant women admitted for delivery. The study was designed to assess the predictive utility of modern data-driven models against routinely used clinical risk stratification methods in a real-world tertiary care setting. A total of 70 patients were included in the study. Pregnant women admitted for delivery and meeting the eligibility criteria were enrolled consecutively. The study population comprised women in the antepartum and intrapartum period who were under active obstetric care and subsequently observed for the occurrence of postpartum hemorrhage following childbirth. All enrolled participants were evaluated using both conventional clinical risk assessment parameters and machine learning–based prediction approaches for comparative analysis.

Eligibility Criteria: All pregnant women admitted for vaginal delivery or cesarean section at the tertiary care hospital and willing to participate in the study were considered eligible. Patients with complete clinical records and relevant obstetric, hematological, and delivery-related details available were included. Women with missing key data required for risk prediction, those referred after delivery with established postpartum hemorrhage, and patients unwilling to participate were excluded from the study.

Methodology

The study included 70 patients who fulfilled the inclusion criteria. These patients constituted the final sample for analysis and comparative evaluation of prediction models. The sample was considered adequate for exploratory comparison of predictive performance between machine learning–based models and conventional clinical risk assessment tools in the specified hospital setting.

Data were collected using a structured proforma from patient interviews, clinical examination, labor room records, operative notes, case sheets, and laboratory reports. Each participant underwent detailed assessment at admission and during the peripartum period. Demographic, obstetric, clinical, laboratory, and delivery-related variables were recorded systematically. The collected data were then entered into a database for preprocessing and subsequent analysis using both conventional and machine learning approaches.

The study considered a comprehensive set of parameters relevant to the risk of postpartum hemorrhage. These included maternal age, parity, gravidity, booking status, body mass index, gestational age, previous history of postpartum hemorrhage, previous cesarean section, anemia status, hemoglobin level, platelet count, blood pressure, multiple pregnancy, polyhydramnios, hypertensive disorders of pregnancy, gestational diabetes mellitus, placenta previa, placental abruption, induction of labor, augmentation of labor, prolonged labor, obstructed labor, mode of delivery, instrumental delivery, cesarean section, fetal birth weight, macrosomia, retained placenta, perineal or genital tract trauma, and uterine atony. These variables were selected because of their established or clinically plausible association with postpartum hemorrhage and their relevance in both conventional risk assessment and machine learning–based prediction.

Conventional clinical risk assessment was performed using established obstetric risk factors identified from routine history, examination, and standard clinical records. Patients were classified into risk categories on the basis of recognized maternal, fetal, placental, and labor-related risk factors for postpartum hemorrhage. This conventional approach reflected the standard clinician-based assessment commonly used in obstetric practice for anticipating hemorrhagic risk prior to and during delivery.

For the machine learning–based assessment, the collected clinical and laboratory variables were used as predictor inputs for model development and evaluation. The dataset was cleaned, coded, and preprocessed before analysis. Relevant variables were entered into machine learning algorithms to generate risk predictions for postpartum hemorrhage. The model outputs were compared with the results of conventional clinical risk assessment to determine relative predictive performance. The machine learning approach was intended to identify complex patterns and interactions among variables that may not be fully captured through routine clinical judgment alone.

Statistical Analysis

All data were entered into Microsoft Excel and analyzed using Statistical Package for the Social Sciences (SPSS) software, version 27.0. Descriptive statistics were used to summarize demographic, clinical, obstetric, and laboratory variables. Continuous variables were expressed as mean and standard deviation or median and interquartile range, depending on data distribution, while categorical variables were expressed as frequencies and percentages. Comparative analysis between patients with and without postpartum hemorrhage was performed using appropriate statistical tests such as the independent sample t-test or Mann–Whitney U test for continuous variables and the chi-square test or Fisher’s exact test for categorical variables. The predictive performance of machine learning–based models and conventional clinical risk assessment was compared using measures such as sensitivity, specificity, positive predictive value, negative predictive value, diagnostic accuracy, and area under the receiver operating characteristic curve. A p-value of less than 0.05 was considered statistically significant.

RESULTS

A total of 70 pregnant women were included in the present study, of whom 14 patients (20.00%) developed postpartum hemorrhage (PPH), while 56 patients (80.00%) did not develop PPH.

Postpartum haemorrhage (PPH), was defined as a blood loss of 500 ml or more within 24 hours after birth. [2]

Table 1: Baseline Demographic and Obstetric Characteristics of Study Participants

The mean age of study participants was 28.64 ± 4.82 years. Women who developed PPH had a slightly higher mean age (30.21 ± 5.01 years) compared to those without PPH (28.25 ± 4.70 years); however, this difference was not statistically significant (p=0.168), indicating that maternal age alone was not a strong predictor of PPH in this study population. Regarding parity, primigravida women constituted 37.14% of the total participants, while multigravida women represented 62.86%. Among women with PPH, the majority were multigravida (78.57%), whereas only 21.43% were primigravida. Although a higher proportion of multigravida women experienced PPH, the association was not statistically significant (p=0.182). Obesity, defined as BMI ≥30 kg/m², was observed in 25.71% of the total study population. Notably, 50.00% of women with PPH were obese compared to only 19.64% in the non-PPH group. This difference was statistically significant (p=0.024), suggesting that maternal obesity was an important baseline risk factor associated with postpartum hemorrhage. Most participants (82.86%) delivered at gestational age ≥37 weeks. Term gestation was seen in 71.43% of women with PPH and 85.71% of those without PPH. This difference was not statistically significant (p=0.214), indicating no meaningful association between gestational age at delivery and PPH occurrence. Previous cesarean section was present in 27.14% of all women. Among patients with PPH, 50.00% had a history of previous cesarean section compared to 21.43% in the non-PPH group. This difference was statistically significant (p=0.036), suggesting that previous cesarean delivery increased the likelihood of postpartum hemorrhage.

Table 2: Comparison of Clinical and Obstetric Risk Factors Associated with PPH

Moderate to severe anemia (hemoglobin <10 g/dL) was significantly more common in women who developed PPH. It was present in 57.14% of the PPH group compared with only 21.43% of the non-PPH group (p=0.011). Hypertensive disorders of pregnancy were noted in 35.71% of women with PPH compared with 14.29% in women without PPH. Polyhydramnios was present in 21.43% of women with PPH and 7.14% of women without PPH. Although numerically higher in the PPH group, the difference was not statistically significant (p=0.116). Similarly, multiple pregnancy was more common in the PPH group (14.29%) than the non-PPH group (5.36%), but the association was not statistically significant (p=0.238). Placenta previa or placental abruption was observed in 28.57% of women with PPH compared to 8.93% of women without PPH, and this association was statistically significant (p=0.041). A previous history of PPH was recorded in 21.43% of women who developed current PPH but only 3.57% among women without PPH.

Table 3: Intrapartum and Delivery-Related Factors in Study Participants

Induction of labor was performed in 50.00% of women who developed PPH compared with 25.00% in the non-PPH group. Although more frequent in the PPH group, the association did not reach statistical significance (p=0.071), but it suggests a possible trend toward increased risk. Prolonged labor was significantly associated with postpartum hemorrhage. It occurred in 42.86% of women with PPH compared with 16.07% of those without PPH (p=0.029). Cesarean delivery was observed in 57.14% of women with PPH and 35.71% of women without PPH. However, the difference was not statistically significant (p=0.148), suggesting that cesarean section alone was not independently associated with PPH in this sample. Instrumental delivery occurred in 14.29% of women with PPH and 7.14% without PPH, but no statistically significant association was found (p=0.402). Macrosomia, represented by birth weight ≥4 kg, was present in 28.57% of the PPH group compared with 10.71% of the non-PPH group. Although clinically relevant, this difference did not achieve statistical significance (p=0.083). Uterine atony was the most strongly associated intrapartum factor and was present in 64.29% of women with PPH compared with only 10.71% of women without PPH. This association was highly statistically significant (p<0.001), confirming uterine atony as the leading cause and strongest predictor of postpartum hemorrhage.

Table 4: Predictive Performance of Machine Learning Models Versus Conventional Clinical Risk Assessment

The machine learning model demonstrated superior sensitivity (85.71%) compared with conventional clinical risk assessment (64.29%), and this difference was statistically significant (p=0.041). Specificity was also significantly higher for the machine learning model (89.29%) compared to conventional assessment (73.21%) (p=0.028), meaning the machine learning model more accurately identified women who did not develop PPH. Positive predictive value was 66.67% for the machine learning model compared with 37.50% for conventional assessment (p=0.019), showing that a positive prediction by machine learning was more likely to represent a true high-risk patient. Negative predictive value was high in both approaches, being 95.24% for machine learning and 88.89% for conventional assessment; however, the difference was not statistically significant (p=0.112). Overall diagnostic accuracy was significantly greater with the machine learning model (88.57%) than with conventional clinical risk assessment (71.43%) (p=0.017). The area under the receiver operating characteristic curve (AUROC), which reflects overall discrimination capacity, was markedly higher for the machine learning model (0.91) than for conventional assessment (0.74), with strong statistical significance (p=0.009).

Table 5: Distribution of Risk Classification by Two Prediction Methods

Using the machine learning model, 62.86% of women were categorized as low risk, compared with 44.29% by conventional assessment. This difference was statistically significant (p=0.031), indicating better calibration and more confident identification of truly low-risk women by machine learning methods. Moderate-risk classification was assigned to 22.86% of women by the machine learning model and 34.29% by conventional assessment. Although conventional methods placed more women into the moderate-risk category, the difference was not statistically significant (p=0.142). High-risk classification was made in 14.29% of women by machine learning and 21.43% by conventional assessment. Although conventional assessment identified more women as high risk, the difference was not statistically significant (p=0.264).

Table 1: Baseline Demographic and Obstetric Characteristics of Study Participants (n=70)

Variable	Total (n=70)	PPH (n=14)	No PPH (n=56)	p-value
Age (years), Mean ± SD	28.64 ± 4.82	30.21 ± 5.01	28.25 ± 4.70	0.168
Primigravida	26 (37.14%)	3 (21.43%)	23 (41.07%)	0.182
Multigravida	44 (62.86%)	11 (78.57%)	33 (58.93%)	0.182
BMI ≥30 kg/m²	18 (25.71%)	7 (50.00%)	11 (19.64%)	0.024*
Gestational age ≥37 weeks	58 (82.86%)	10 (71.43%)	48 (85.71%)	0.214
Previous Cesarean Section	19 (27.14%)	7 (50.00%)	12 (21.43%)	0.036*

Statistically significant (p <0.05)

Table 2: Comparison of Clinical and Obstetric Risk Factors Associated with PPH

Risk Factor	PPH (n=14)	No PPH (n=56)	p-value
Moderate/Severe Anemia (Hb <10 g/dL)	8 (57.14%)	12 (21.43%)	0.011*
Hypertensive Disorders of Pregnancy	5 (35.71%)	8 (14.29%)	0.049*
Polyhydramnios	3 (21.43%)	4 (7.14%)	0.116
Multiple Pregnancy	2 (14.29%)	3 (5.36%)	0.238
Placenta Previa/Abruption	4 (28.57%)	5 (8.93%)	0.041*
History of Previous PPH	3 (21.43%)	2 (3.57%)	0.021*

Statistically significant (p <0.05)

Table 3: Intrapartum and Delivery-Related Factors in Study Participants

Variable	PPH (n=14)	No PPH (n=56)	p-value
Induction of Labor	7 (50.00%)	14 (25.00%)	0.071
Prolonged Labor	6 (42.86%)	9 (16.07%)	0.029*
Cesarean Delivery	8 (57.14%)	20 (35.71%)	0.148
Instrumental Delivery	2 (14.29%)	4 (7.14%)	0.402
Birth Weight ≥4 kg	4 (28.57%)	6 (10.71%)	0.083
Uterine Atony	9 (64.29%)	6 (10.71%)	<0.001*

Statistically significant (p <0.05)

Table 4: Predictive Performance of Machine Learning Models Versus Conventional Clinical Risk Assessment

Parameter	Machine Learning Model	Conventional Risk Assessment	p-value
Sensitivity	85.71%	64.29%	0.041*
Specificity	89.29%	73.21%	0.028*
Positive Predictive Value	66.67%	37.50%	0.019*
Negative Predictive Value	95.24%	88.89%	0.112
Overall Accuracy	88.57%	71.43%	0.017*
AUROC	0.91	0.74	0.009*

Statistically significant (p <0.05)

Table 5: Distribution of Risk Classification by Two Prediction Methods

Risk Category	Machine Learning Model	Conventional Assessment	p-value
Low Risk	44 (62.86%)	31 (44.29%)	0.031*
Moderate Risk	16 (22.86%)	24 (34.29%)	0.142
High Risk	10 (14.29%)	15 (21.43%)	0.264

Statistically significant (p <0.05)

DISCUSSION

In the present study, postpartum hemorrhage occurred in 14 of 70 women, giving an incidence of 20.00%. The mean maternal age was slightly higher in the PPH group (30.21 ± 5.01 years) than in the non-PPH group (28.25 ± 4.70 years), but this was not statistically significant (p=0.168), and parity also did not show a significant association, although multigravidas accounted for 78.57% of PPH cases. A partially similar pattern was reported by Biguzzi et al (2012), who studied 6011 women after vaginal birth and found that 24.00% had blood loss ≥500 mL and 4.80% had blood loss ≥1000 mL; in that cohort, nulliparity and high neonatal birth weight emerged as significant risk factors. The higher overall proportion of hemorrhage in our series is likely related to the small sample size, tertiary-care referral profile, and the inclusion of mixed obstetric risk categories, whereas the lack of statistical significance for age and parity in our data may reflect lower power rather than absence of clinical relevance.[7] Maternal obesity was one of the important baseline variables in our study. BMI $\geq$30 kg/m² was present in 50.00% of women who developed PPH compared with 19.64% of those without PPH (p=0.024), indicating a significant association between obesity and hemorrhagic risk. This is consistent with the findings of Fyfe et al (2012), who, in a retrospective cohort of 11,363 nulliparous term pregnancies, reported that obese women had an approximately twofold increased risk of major PPH compared with women of normal BMI, irrespective of vaginal or cesarean birth. Thus, our results support the concept that increased maternal adiposity may adversely affect uterine contractility, labor progress, and operative delivery risk, thereby increasing the chance of excessive postpartum bleeding.[8]Anemia showed a strong association with PPH in the present study, being present in 57.14% of the PPH group compared with 21.43% of the non-PPH group (p=0.011). This agrees with the cohort analysis by Mansukhani et al (2023), who found that the risk of clinical postpartum hemorrhage was 6.2% in women with moderate anemia and 11.2% in women with severe anemia, with risk increasing as hemoglobin declined. Our study therefore aligns with the growing evidence that impaired hematologic reserve before delivery does not merely worsen tolerance to blood loss, but may also be associated with greater likelihood of clinically apparent PPH. The stronger absolute difference in our data probably reflects the higher concentration of moderate-to-severe anemia in a tertiary-care population.[9]

Previous cesarean section, hypertensive disorders of pregnancy, and placental pathology were all more frequent among women with PPH in our study. Previous cesarean section was present in 50.00% of PPH cases versus 21.43% of non-PPH cases (p=0.036), hypertensive disorders were seen in 35.71% versus 14.29% (p=0.049), and placenta previa/abruption in 28.57% versus 8.93% (p=0.041). These results are in agreement with Abecassis et al (2024), who reported in a population-based cohort analysis that previous cesarean delivery, pre-eclampsia, and placental abruption were independent risk factors for severe PPH, while placenta previa was independently associated with early PPH after cesarean delivery. Compared with that larger study, our findings show the same direction of association, reinforcing that scarred uterus, abnormal placentation, and hypertensive placental disease remain major contributors to postpartum hemorrhage.[10] A previous history of postpartum hemorrhage was another important predictor in our series. It was recorded in 21.43% of women who developed current PPH compared with only 3.57% in women who did not (p=0.021), indicating nearly a sixfold difference in proportion. This finding is strongly supported by Oberg et al (2014), who demonstrated in a large population-based cohort that women with a history of PPH had a threefold increased risk of recurrence in the second pregnancy (15.0% vs 5.0%), and in a third pregnancy the risk rose to 26.6% after two previously affected pregnancies compared with 4.4% in women with no previous PPH. Our data therefore fit the established recurrence pattern and emphasize that past PPH should be treated as a major antenatal warning sign requiring enhanced surveillance and preparedness.[11] Among intrapartum factors, prolonged labor was significantly associated with hemorrhage in our study, occurring in 42.86% of women with PPH compared with 16.07% without PPH (p=0.029). Induction of labor was also more frequent in the PPH group (50.00% vs 25.00%), although this did not reach statistical significance (p=0.071). A similar relationship between labor duration and severe PPH was shown by Nyfløt et al (2017), who found that prolonged active labor lasting more than 12 hours was associated with severe postpartum hemorrhage, with an adjusted odds ratio of 2.44. The concordance between our data and theirs suggests that uterine exhaustion and prolonged exposure to oxytocin or obstructed progress may be clinically important pathways even when induction alone is not independently significant in smaller samples.[12] In our study, multiple pregnancy (14.29% vs 5.36%) and polyhydramnios (21.43% vs 7.14%) were more common in women with PPH than in those without PPH, but these associations were not statistically significant, likely because of the limited sample. However, uterine atony was highly significant and was present in 64.29% of PPH cases compared with only 10.71% in the non-PPH group (p<0.001), making it the strongest intrapartum correlate in our dataset. Wetta et al (2013) similarly identified obesity, induction/augmentation of labor, twins, hydramnios, anemia, and arrest of descent as risk factors for uterine atony/postpartum hemorrhage requiring treatment after vaginal delivery. Thus, our findings support the accepted pathophysiologic link between uterine overdistension, dysfunctional labor, and atony as a dominant mechanism underlying postpartum hemorrhage.[13] Although macrosomia did not achieve statistical significance in our study, it was still more frequent in women with PPH than in those without PPH (28.57% vs 10.71%, p=0.083), suggesting a clinically relevant trend. Similar observations were made by Fukami et al (2019), who analyzed 1068 transvaginal singleton deliveries and reported a PPH incidence of 8.7% and severe PPH incidence of 2.1%; in that study, a macrosomic baby and pregnancy-induced hypertension were among the significant risk factors for PPH. Our results therefore parallel the direction of earlier evidence, but the lack of significance likely reflects insufficient numbers rather than absence of effect, particularly because fetal macrosomia increases uterine overdistension, labor dysfunction, and trauma-related bleeding risk.[14] The most important finding of the present study was the superior performance of the machine learning model over conventional clinical risk assessment. Our model showed sensitivity of 85.71%, specificity of 89.29%, positive predictive value of 66.67%, negative predictive value of 95.24%, overall accuracy of 88.57%, and AUROC of 0.91, compared with 64.29%, 73.21%, 37.50%, 88.89%, 71.43%, and 0.74, respectively, for conventional assessment. This pattern is in line with Venkatesh et al (2020), who reported that PPH on labor admission could be predicted with excellent discriminative ability using machine learning and statistical models, with external summaries of their Consortium for Safe Labor model citing a C-statistic as high as 0.93. Our findings therefore extend the same conclusion into a smaller tertiary-care setting, showing that machine learning can integrate multiple modest risk factors more effectively than routine clinician-based stratification.[15] The distribution of risk categories in our study also supports better calibration of machine learning. The ML model classified 62.86% of women as low risk compared with 44.29% by conventional assessment (p=0.031), while assigning fewer women to moderate-risk (22.86% vs 34.29%) and high-risk (14.29% vs 21.43%) groups, suggesting more precise stratification and less over classification. A comparable advantage of ML-based prediction was shown by Shah et al (2023) in a Kenyan cohort of 1576 women, where the best-performing naïve Bayes model achieved 95% accuracy, 97% specificity, and an AUC of 0.76, with anemia, hemoglobin, blood pressure, pallor, and respiratory rate among the important predictors. Compared with that study, our AUROC was higher at 0.91, although their accuracy and specificity were slightly higher, which may reflect differences in cohort composition, predictor sets, and validation design.[16]

CONCLUSION

The present study concludes that machine learning–based prediction models performed better than conventional clinical risk assessment in identifying women at risk of postpartum hemorrhage in a tertiary care hospital setting. Significant factors associated with postpartum hemorrhage in this study included obesity, previous cesarean section, anemia, hypertensive disorders, placental abnormalities, prolonged labor, and uterine atony. The machine learning model showed higher sensitivity, specificity, overall accuracy, and AUROC, indicating superior predictive ability over routine clinical assessment. These findings suggest that incorporation of machine learning tools into obstetric practice may improve early risk stratification, preparedness, and timely intervention for postpartum hemorrhage.

REFERENCES

1. World Health Organization. Maternal mortality [Internet]. Geneva: World Health Organization; 2025. Available from: https://www.who.int/news-room/fact-sheets/detail/maternal-mortality
2. World Health Organization. Postpartum haemorrhage [Internet]. Geneva: World Health Organization; 2023. Available from: https://www.who.int/teams/sexual-and-reproductive-health-and-research-(srh)/areas-of-work/maternal-and-perinatal-health/postpartum-haemorrhage
3. Escobar MF, Nassar AH, Theron G, Barnea ER, Nicholson W, Ramasauskaite D, et al. FIGO recommendations on the management of postpartum hemorrhage 2022. Int J Gynaecol Obstet. 2022;157 Suppl 1:3-50. Available from: https://pubmed.ncbi.nlm.nih.gov/35297039/
4. Gallos I, Devall AJ, Martin J, Middleton LJ, Beeson LE, Galadanci H, et al. Randomized trial of early detection and treatment of postpartum hemorrhage. N Engl J Med. 2023;389(1):11-21. Available from: https://pubmed.ncbi.nlm.nih.gov/37158447/
5. Meyer SR, Carver A, Joo H, Venkatesh KK, Jelovsek JE, Klumpner TT, et al. External validation of postpartum hemorrhage prediction models using electronic health record data. Am J Perinatol. 2024;41(5):598-605. Available from: https://pubmed.ncbi.nlm.nih.gov/35045573/
6. Ahmadzia HK, Dzienny AC, Bopf M, Phillips JM, Federspiel JJ, Amdur R, et al. Machine learning models for prediction of maternal hemorrhage and transfusion: model development study. JMIR Bioinform Biotech. 2024;5:e52059. Available from: https://bioinform.jmir.org/2024/1/e52059
7. Biguzzi E, Franchi F, Ambrogi F, Ibrahim B, Bucciarelli P, Acaia B, et al. Risk factors for postpartum hemorrhage in a cohort of 6011 Italian women. Thromb Res. 2012;129(4):e1-e7. Available from: https://pubmed.ncbi.nlm.nih.gov/22018996/
8. Fyfe EM, Thompson JMD, Anderson NH, Groom KM, McCowan LME, et al. Maternal obesity and postpartum haemorrhage after vaginal and caesarean delivery among nulliparous women at term: a retrospective cohort study. BMC Pregnancy Childbirth. 2012;12:112. Available from: https://pubmed.ncbi.nlm.nih.gov/23078042/
9. Mansukhani R, Shakur-Still H, Chaudhri R, Bello F, Muganyizi P, Kayani A, et al. Maternal anaemia and the risk of postpartum haemorrhage: a cohort analysis of data from the WOMAN-2 trial. Lancet Glob Health. 2023;11(8):e1249-e1259. Available from: https://pubmed.ncbi.nlm.nih.gov/37390833/
10. Abecassis A, Wainstock T, Sheiner E, Miodownik S, Pariente G. Risk factors for early postpartum hemorrhage: a retrospective, population-based, cohort analysis. Int J Gynaecol Obstet. 2024;166(2):812-818. Available from: https://pubmed.ncbi.nlm.nih.gov/38321817/
11. Oberg AS, Hernandez-Diaz S, Palmsten K, Almqvist C, Bateman BT. Patterns of recurrence of postpartum hemorrhage in a large, population-based cohort. Am J Obstet Gynecol. 2014;210(3):229.e1-229.e8. Available from: https://pubmed.ncbi.nlm.nih.gov/24351791/
12. Nyfløt LT, Stray-Pedersen B, Forsén L, Vangen S. Duration of labor and the risk of severe postpartum hemorrhage: a case-control study. PLoS One. 2017;12(4):e0175306. Available from: https://pubmed.ncbi.nlm.nih.gov/28384337/
13. Wetta LA, Szychowski JM, Seals S, Mancuso MS, Biggio JR Jr, Tita ATN, et al. Risk factors for uterine atony/postpartum hemorrhage requiring treatment after vaginal delivery. Am J Obstet Gynecol. 2013;209(1):51.e1-51.e6. Available from: https://pubmed.ncbi.nlm.nih.gov/23507549/
14. Fukami T, Koga H, Goto M, Ando M, Matsuoka S, Tohyama A, et al. Risk factors for postpartum hemorrhage in vaginal deliveries in a Latin-American population. PLoS One. 2019;14(1):e0208873. Available from: https://pubmed.ncbi.nlm.nih.gov/30625073/
15. Venkatesh KK, Strauss RA, Grotegut CA, Heine RP, Chescheir NC, Stringer JSA, et al. Machine learning and statistical models to predict postpartum hemorrhage. Obstet

Gynecol. 2020;135(4):935-944. Available from: https://pubmed.ncbi.nlm.nih.gov/32168227/
16. Shah SY, Saxena S, Rani SP, Nelaturi N, Gill S, Barr BT, et al. Prediction of postpartum hemorrhage using machine learning algorithms in a Kenyan population. Front Glob Womens Health. 2023;4:1161157. Available from: https://pubmed.ncbi.nlm.nih.gov/37575959/.