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Review Article

Predicting risk of postpartum hemorrhage using machine learning approach: A systematic review

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ABSTRACT

Background: Postpartum hemorrhage (PPH) could be avoided by identifying high-risk women. The objective of this systematic review is to determine PPH predictors using machine learning (ML) approaches.
Method: This strategy included searching for studies from inception through November 2022 through the database included: Cochrane Central Register, PubMed, MEDLINE, EMBASE, ProQuest, Scopus, WOS, IEEE Xplore, and the Google Scholar database. The search methodology employed the PICO framework (population, intervention, control, and outcomes). In this study, “P” represents PPH populations, “I” represents the ML approach as intervention, “C” represents the traditional statistical analysis approach as control, and “O” represents prediction and diagnosis outcomes. The quality assessment of each included study was performed using the PROBAST methodology.
Results: The initial search strategy resulted in 2048 citations, which were subsequently refined by removing duplicates and irrelevant studies. Ultimately, four studies were deemed eligible for inclusion in the review. Among these studies, three were classified as having a low risk of bias, while one was considered to have a low to moderate risk of bias. A total of 549 unique variables were identified as candidate predictors from the included studies. Nine distinct models were chosen as ML algorithms from the four studies. Each of the four studies employed different metrics, such as the area under the curve, false positive rate, false negative rate, and sensitivity, to report the accuracy of their models. The ML models exhibited varying accuracies, with the area under the curve (AUC) ranging from 0.706 to 0.979. Several weighted predictors were identified as significant factors in PPH risk prediction. These included pre-pregnancy maternal weight, maternal weight at the time of admission, fetal macrosomia, gestational age, level of hematocrit at the time of admission, shock index, frequency of contractions during labor, white blood cell count, pregnancy-induced hypertension, the weight of the newborn, duration of the second stage of labor, amniotic fluid index, body mass index, and cesarean delivery before labor. These factors were determined to have a notable influence on the prediction of PPH risk.
Conclusion: The findings from ML models used to predict PPH are highly encouraging.

1. Introduction

Pregnancy-related deaths remain a significant cause of mortality among women worldwide. Approximately 500,000 pregnant women are estimated to lose their lives each year, with hemorrhage accounting for up to 25% of all deaths.[1] Postpartum hemorrhage (PPH) is the most serious clinical problem associated with childbirth, accounting for a significant portion of maternal mortality worldwide. PPH is a problem in

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developing countries but is also becoming more common in industrial countries.[2] Prompt detection is critical in managing PPH, but the diagnosis of PPH can be challenging due to its reliance on the amount of blood loss. PPH was conventionally defined as vaginal blood loss exceeding 500 mL after normal childbirth or more than 1000 mL after cesarean delivery.[3] The American College of Obstetrics and Gynecology (ACOG) redefined this criterion in 2017 as a cumulative blood loss of exceeding 1 L, accompanied by signs and symptoms of hypovolemia within the first 24 h of delivery, regardless of the mode of childbirth.[4] This modification was implemented due to the recognition that blood loss during delivery is frequently underestimated.

On the other hand, blood loss exceeding 500 mL during vaginal delivery should be considered abnormal and may necessitate intervention. PPH typically occurs within 24 h of childbirth but can occur up to 12 weeks later. Early PPH refers to bleeding within the first 24 h after delivery, while late PPH refers to bleeding occurring between 24 h and 12 weeks after delivery.[5] PPH could be prevented by identifying high-risk pregnant women and implementing measures such as active management of the childbirth process, which includes the presence of experienced physicians and midwives, as well as prompt access to essential resources like medications and blood banks. Many researchers have identified individual risk factors for PPH, but combining multiple factors does not consistently identify pregnant women at a higher risk. In practice, it is common to encounter a combination of risk factors, but accurately calculating the relative risk without the assistance of a clinical predicting model is challenging. Once a reliable predictable model with excellent performance is established, it can be transformed into a user-friendly application such as an online risk calculator within electronic health records.[6–8] To predict a woman's risk of PPH on labor admission, the obstetrician would need to incorporate established risk factors and utilize a risk stratification scheme to approximate the likelihood of PPH.[9] With a growing emphasis on standardized preventive guidelines to manage PPH,[4,5] there are few tools available to accurately predict which women are at the greatest risk of PPH. Recent advancements in computer science, particularly artificial intelligence (AI), have propelled the field forward. The most significant distinction is that traditional statistics are driven by models, whereas AI and machine learning (ML) are driven by data, without any prior knowledge of the relationship between data and outcome. The application of AI and ML concerning women's health settings has extended over the past few years.[10,11] A systematic review of existing prognostic models was deemed necessary to help to identify pregnant women at risk of PPH as soon and precisely as possible. This would allow existing models to be evaluated for their appropriateness for actual use to determine clinical use. This approach has the potential to be more efficient than adding a new model to aid in PPH prevention. This systematic review aims to identify PPH predictors using ML approaches reported in previous studies in this field.

2. Materials and methods

2.1. Eligibility criteria

All studies that meet the following criteria will be considered: (1) they include the general population with a clear definition of the diagnosis of PPH; (2) they include ML models for predicting PPH with a clear description of the ML models; and (3) they demonstrate the performance of the ML models with performance parameters, including area under the receiver operating characteristic curve (AUROC), accuracy, precision, sensitivity, and specificity. Non-English language papers will be excluded.

2.2. Protocol and ethical consideration

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines[12] were used to report this study. Because the study just included formerly published studies, no ethical approval was required. Patients or the public were not involved in this research. The protocol for this review was submitted at PROSPERO with ID number CRD42022354896. This review's protocol has previously been published.[13]

2.3. Search strategy and selection criteria

This strategy included searching systematically for published studies on datasets such as Cochrane Central Register, PubMed, MEDLINE (via PubMed), EMBASE, ProQuest, Scopus, WOS, IEEE Xplore, and Google Scholar from inception through November 2022. In addition, the citation list of each identified study was manually searched to find further studies. The search methodology employed the PICO framework (population, intervention, control, and outcomes). In our study, “P” represents PPH populations, “I” represents the ML approach as intervention, “C” represents the traditional statistical analysis approach as control, and “O” represents prediction and diagnosis outcomes such as sensitivity, specificity, and accuracy. Search terms include “postpartum hemorrhage” AND “artificial intelligence” OR “ML” OR “deep learning.”

All the databases were searched by an experienced researcher (A.R.). Two groups of researchers (Group 1: F. D and V.M, and Group 2: S.R and B·B) individually screened the titles and abstracts and the full texts of potentially eligible studies against the pre-defined eligibility criteria after eliminating duplicates. An agreement or an appeal to a senior researcher (A.R) was used to resolve disagreements. A PRISMA flow diagram was used to document the study selection process.[12]

2.4. Data collection and risk of bias assessment

Each study produced the following results: (1) demographic information (for example, the country where the data were collected, the setting, the data source, the study design, the prediction time, and the outcome definition); (2) the method of data partitioning, the algorithms used to select the features, the features used to train the model, the type of predictive model ML, and the validation and application of the model; and (3) the prediction results (for example, accuracy, sensitivity, specificity, and area under the curve(AUC)). The risk of bias and applicability of each included study was assessed using PROBAST,[14] which comprises 20 signaling questions categorized into four domains: participants, predictors, outcome, and analysis.

3. Results

The search strategy resulted in 2048 citations, and after removing duplicates and completing the screening process, 90 full-text published papers were evaluated for eligibility (see PRISMA Flow Diagram, Fig. 1). Four studies were included in this review. According to the risk of bias assessment, three studies were classified as having a low risk of bias, while one study had a low to moderate risk of bias (Table 1).

Table 2 presents the characteristics of the included studies. The setting of the included studies was hospitals in the United States, Japan, and China. All of the study designs included were retrospective cohort studies. The primary outcome assessed in all of the studies was PPH, defined as blood loss exceeding 1000 ml. A total of 549 unique variables were selected as candidate predictors from the four studies (ranging from 11 to 471 per study). Nine different ML algorithms were utilized across the four studies, with each study employing 2 to 5 distinct models. All four studies used different metrics, such as AUC, false positive rate (FPR), false negative rate (FNR), sensitivity, and specificity, to evaluate the accuracy of their models. The AUC of ML models varied from 0.706 to 0.979 in four studies. Several factors were found to be significant predictors in the weighted analysis including pre-pregnancy maternal weight, maternal weight at the time of admission, fetal macrosomia, gestational age, level of hematocrit at the time of admission, shock index, frequency of contractions during labor, white blood cell count, pregnancy-induced hypertension, the weight of the newborn, duration of

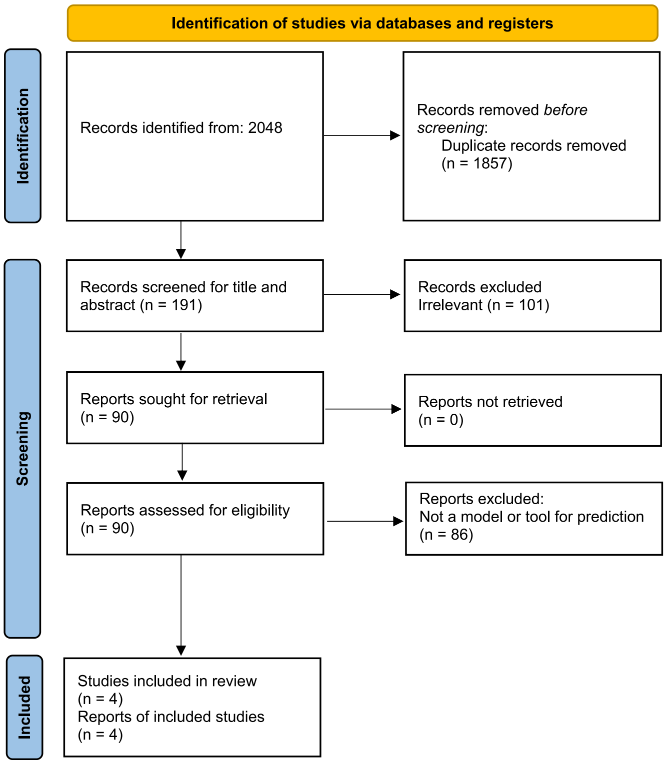

Fig. 1. Flowchart of the study.

the second stage of labor, amniotic fluid index, body mass index, cesarean delivery before labor.

4. Discussion

The prediction of PPH is crucial for preventing maternal deaths, and one potential avenue for accurate PPH prediction is through AI research. This systematic review represents the first attempt to identify published studies attempting to provide prognostic models for PPH prediction using ML approaches. Venkatesh et al.[15] developed and tested an ML approach (Random Forest and Extreme Gradient Boosting) as well as basic statistical models (logistic regression with and without lasso regularization) to determine which model works better in predicting PPH. The study analyzed 152,279 births, assessing fifty-five potential risk factors. Among the considered births, 7,279 cases were associated with PPH. The performance of each model was assessed using C-statistics, calibration, and decision curves. The findings revealed that the Gradient Boosting model demonstrated the highest performance (C statistic: 0.93; 95% CI: 0.92–0.93), followed closely by the Random Forest model (C statistic: 0.92; 95% CI: 0.91–0.92). In contrast, the two basic statistical models exhibited comparatively lower performance, yet still displayed promising predictive capabilities (C statistic: 0.87; 95% CI: 0.86–0.88 for the lasso regression model; and C statistic: 0.87; 95% CI: 0.86–0.87 for the logistic regression). Based on their findings, the researchers concluded that implementing ML predictive models could support obstetricians and midwives in accurately predicting PPH.[15]

In 2021, a study that used five ML classifiers, namely, logistic regression, support vector machine, random forest, boosting trees, decision tree random forest, and extreme gradient boosting to predict PPH was published. The analysis revealed that the best-performing learning model achieved a predictive performance with an AUC of 0.708, an accuracy of 0.686, an FPR of 0.312, and an FNR of 0.398.[16]

Among the various tools explored by Liu et al.[17] to enhance the accuracy of predicting PPH in vaginal deliveries, the combination of Light Gradient Boost and Logistic Regression ML model exhibited the highest performance. The top predictive characteristics for PPH included hematocrit, shock index, frequency of contractions during labor, white blood cell count, pregnancy-induced hypertension, the weight of the newborn, duration of the second stage of labor, amniotic fluid index, and body mass index. In another study conducted by Westcott et al.[18] an ML model based on regression, tree, and kernel techniques was employed to predict the risk of PPH. The study included 30,867 women who participated between July 2013 and October 2018, and data from electronic medical records were collected, encompassing 471 variables related to pregnancy, labor, and childbirth factors. Two sub-models were developed and compared: the first model utilized data from all stages of pregnancy, while the second model only utilized data from the labor and childbirth stage. The analysis revealed that among all the models employed, the XGBoost model exhibited the best performance in predicting PPH. When comparing the two sub-models, it was observed that the first sub-model, which included all data, performed slightly better (AUC: 0.979, 95% CI:0.971–0.986) than the second sub-model, which included limited pre-labor data (AUC 0.955, 95% CI: 0.939–0.970).

This systematic review provides the most evidence for developing the predictive model for PPH with a generally low to moderate risk of bias overall and a substantial sample size. This review demonstrates thoroughness by employing independent double-checking and following best practice guidelines throughout the process. The findings of this review support the feasibility of utilizing ML models to enhance the accuracy of PPH prediction. However, further efforts are necessary to fully leverage the potential of ML and address potential shortcomings as we transition from theory to practice implementation. Such limitations could undermine the trust of healthcare professionals and patients in ML practices, carrying legal and ethical implications. Therefore, experts must take responsibility for the outcomes of the models they design and evaluate while recognizing that accurate and reliable predictions require large, high-quality training datasets, as smaller or poorer-quality datasets may yield inferior results. It should be noted that restricting the review to English-language studies may limit the generalizability of the findings, but based on the search conducted, no eligible non-English studies were identified.

5. Conclusion

The results obtained from ML models for predicting PPH are promising. The prediction models identified in this systematic review exhibit a low to moderate risk of bias overall and were based on substantial sample size. It is imperative to develop and validate PPH prediction tools that can be applied to the general obstetric population. Despite the challenges that need to be addressed, it is evident that ML has the potential to make

Table 1
PROBAST risk of bias/applicability assessment.

Study	Risk of Bias				Applicability			Overall	
	Participants	Predictors	Outcome	Analysis	Participants	Predictors	Outcome	Risk of Bias	Applicability
1	+	+	+	+	+	+	+	+	+
2	–	+	+	+	+	+/−	+	+/−	+/−
3	+/−	+	+	+	+	+	+	+	+
4	+	+	+	+	+	+	+	+	+

(+) indicate low risk of bias, (±) indicate low/moderate risk of bias, (−) indicate high risk of bias.

Table 2
Summary of studies.

Study Number	Author	Country	Study Population	Definition of PPH	Type of ML	Findings		
						Best ML performance	Performing parameters	Predicting factors
1	Venkatesh et al.[15]	United States	152,279 women delivering vaginally or by cesarean section	Blood loss of $\geq$ 1000 mL within 24 h	RF EGBM	EGBM	AUC: 0.930	Pre-pregnancy maternal weight Maternal admission weight Prenatal diagnosis of fetal macrosomia
2	Akazawa et al.[16]	Japan	9,894 women delivering vaginally	Blood loss of $\geq$ 1000 mL within 24 h	DL LR RF BT DT	DL	AUC: 0.706 FPR: 32.6% FNR: 37.9%	Gestational age The maternal weight upon admission of labor Pre-pregnancy maternal weight
3	Liu et al.[17]	China	25,098 women aged delivering vaginally or by cesarean section	Blood loss of $\geq$ 1000 mL within 24 h	RF KNN LR LGB	LGB + LR	AUC: 0.729 Sensitivity: 69.4%	Hematocrit Shock index Frequency of contractions White blood cell count Gestational hypertension Neonatal weight Duration of the second stage of labor Amniotic fluid index Body mass index
4	Westcott et al.[18]	United States	30,867 women aged delivering vaginally or by cesarean section	Blood loss of $\geq$ 1000 mL within 24 h	LR RF GB DT SP	GB	AUC:0.979 Accuracy:98.1% Sensitivity: 76.3%	Body mass index Admission hematocrit Cesarean delivery before labor or rupture Scheduling status of cesarean delivery Admission platelet count

AUC: Area under curve; FPR: False positive rate; FNR: False negative rate; ML: machine learning; RF: Random forest; EGBM: Extreme gradient boosting models; DL: Deep learning; LR: Logistic regression; BT: Boosted tree; DT: Decision tree; KNN: K nearest neighbor; LGB: Light gradient boost; SP: support vector.

significant contributions across various clinical areas in obstetrics. Therefore, researchers must continue exploring and harnessing the vast potential of ML in this field.

Consent for publication

All authors had full access to the study's data and accepted responsibility for submitting it for publication.

Conflict of interests

The authors report no conflicts of interest in this study.

Data availability

Data will be provided upon request.

Contributions

FD is responsible for conception and design; A.R is responsible for administrative support; VM, FD, SR, and BB are responsible for the provision of study materials; AR and FD are responsible for data analysis and interpretation; FD is responsible for manuscript writing; all authors agree on the final approval of the manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gocm.2023.07.002.

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