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Machine learning approach to predict postpartum haemorrhage: a systematic review protocol

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ABSTRACT

Introduction Postpartum haemorrhage (PPH) is the most serious clinical problem of childbirth that contributes significantly to maternal mortality worldwide. This systematic review aims to identify predictors of PPH based on a machine learning (ML) approach.

Methods and analysis This review adhered to the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Protocol. The review is scheduled to begin on 10 January 2023 and end on 20 March 2023. The main objective is to identify and summarise the predictive factors associated with PPH and propose an ML-based predictive algorithm. From inception to December 2022, a systematic search of the following electronic databases of peer-reviewed journal articles and online search records will be conducted: Cochrane Central Register, PubMed, EMBASE (via Ovid), Scopus, WOS, IEEE Xplore and the Google Scholar search engine. 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 metrics, including area under the receiver operating characteristic curve, accuracy, precision, sensitivity and specificity. Non-English language papers will be excluded. Data extraction will be performed independently by two investigators. The PROBAST, which includes a total of 20 signallings, will be used as a tool to assess the risk of bias and applicability of each included study.

Ethics and dissemination Ethical approval is not required, as our review will include published and publicly accessible data. Findings from this review will be disseminated via publication in a peer-review journal.

PROSPERO registration number The protocol for this review was submitted at PROSPERO with ID number CRD42022354896.

STRENGTHS AND LIMITATIONS OF THIS STUDY

⇒ A systematic review will provide most of the evidence for developing the predictive model for postpartum haemorrhage.
⇒ This review will be thorough, with independent double-checking at each stage and following best practice guidelines.
⇒ To obtain a larger number of publications to review, a comprehensive search strategy will be used in conjunction with an extensive list of electronic databases and grey literature sources.
⇒ The exclusion of non-English language papers may limit results.

INTRODUCTION

Death in pregnancy remains a major cause of premature mortality in women worldwide. An estimated 500 000 women die each year from this cause, with up to a quarter of deaths due to haemorrhage.[1] Postpartum haemorrhage (PPH) is the most serious clinical problem of childbirth that contributes significantly to maternal mortality worldwide. Traditionally, PPH was defined as an estimated blood loss of more than 500 mL for a vaginal delivery or more than 1000 mL estimated blood loss for caesarean delivery.[2] This was redefined in 2017 by the American College of Obstetrics and Gynecology as cumulative blood loss greater than 1000 mL with signs and symptoms of hypovolaemia within 24 hours of delivery, regardless of the mode of delivery.[3] This change was made with the knowledge that blood loss at the time of delivery is routinely underestimated. However, blood loss at the time of vaginal delivery greater than 500 mL should be considered abnormal and intervention may be required. PPH usually occurs within 24 hours after birth, but may occur up to 12 weeks after delivery. Primary PPH is bleeding that occurs in the first 24 hours after delivery, while secondary PPH is bleeding that occurs 24 hours to 12 weeks after delivery.[4]

PPH may occur in 1%–5% of deliveries in developed as well as developing countries and it is still the most common cause of maternal morbidity and mortality.[3] Conversely, the maternal mortality rate has declined in recent years.[5] Nevertheless, it is reported that there are at least 10 'maternal near misses' for every maternal death due to PPH, including multiorgan dysfunction, multiple

blood transfusion and peripartum hysterectomy.[6] Therefore, the proper identification of women at higher risk of PPH is crucial to enable the optimisation of the available interventions to reduce the associated maternal deaths or other adverse maternal outcomes. Predicting a woman's risk of PPH on labour admission requires the obstetrician to incorporate known risk factors and then approximate the probability of haemorrhage by using a risk strata scheme.[3] With an increasing focus on standardised guidelines to prevent and manage PPH,[3] limited tools exist to accurately predict which women are at the highest risk for haemorrhage.

Historically, many risk factors related to PPH have been studied. In a study published in 2013, the strongest independent risk factors for massive blood transfusion included abnormal placentation, placental abruption, severe preeclampsia and intrauterine fetal demise.[7]

Recent advances in computer science have driven the development of artificial intelligence (AI). Conventional general programming algorithms produce outputs using the input data and the given rules, whereas AI can produce rules and patterns using the input and output data. The pattern recognition and prediction performance of AI have been demonstrated in multiple realistic tasks.[8 9] This systematic review aims to identify PPH predictors using machine learning (ML) approaches that have been reported in previous studies in this field.

METHODS/DESIGN

This review adhered to the guidelines set by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Protocol guidelines[10] (online supplemental additional file 1). The protocol for this review was submitted at PROSPERO with CRD82022354896. The review is scheduled to begin on 10 January 2023 and end on 20 March 2023.

Patient and public involvement

Patients and/or the public were not involved in this research.

Objectives

To identify and summarise the predictive factors of PPH using an ML approach.

Review question

What is the extent of use and the comparative performance of ML models for PPH prediction in clinical and community settings?

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 metrics, including area under the receiver operating characteristic curve (AUROC), accuracy, precision, sensitivity and specificity. Non-English language papers will be excluded.

Search strategy

This strategy will include searching for published and unpublished studies. From inception through December 2022, a systematic search of the following electronic databases of peer-reviewed journal articles and online search records will be conducted: Cochrane Central Register, PubMed, EMBASE (via Ovid), Scopus, WOS, IEEE Xplore and the Google Scholar search engine. In addition, the reference list of each identified study is manually searched to find additional studies. The search strategy will be constructed according to PICO (population, intervention, control and outcomes). In our study, 'P' represents PPH populations, 'I' represents the machine learning 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 'machine learning' OR 'deep learning'. Words and phrases are selected from a controlled vocabulary (MeSH, ENTREE and others) and a free-text search for each database (online supplemental additional file 2).

The search strategy will look for both published and unpublished studies. First, a search of databases will be conducted to identify relevant articles. The titles, abstracts and keywords will be reviewed after analysing the text. The search strategy, which includes all specified keywords and index terms, is tailored to each of the included information sources. Using similar keywords from the search strings, researchers will search for additional studies from the grey literature from government agencies, international agencies, academic institutions and major journals such as *Obstetrics & Gynecology*, *American Journal of Obstetrics & Gynecology*, *BMC Women's Health*, *Human Reproduction Update and BJOG: an International Journal of Obstetrics & Gynecology*. In addition, we will snowball the references of the identified articles for potentially relevant studies. In addition, the identified search strategy will be retrieved and managed using Endnote X8 software (Thomson Reuters, Philadelphia, Pennsylvania, USA). Potential publication bias may limit the scope of the review; therefore, databases will be searched for unpublished studies such as dissertations and conference proceedings to reduce the risk of publication bias. We will employ NoteExpress V.3.2 (Aegean)[11] and EndNote X7 (Clarivate)[12] to manage the studies and remove duplicate items.

The study selection method

The studies will be reviewed for eligibility by two authors. The review will be done in two steps. First, the reviewers will review the titles and abstracts of the studies found through the search. In the second stage, the full-text screening will be used to review the full texts selected in the previous stage. For articles that are not accessible through online databases, an extended reference search

of the included studies will be considered. If the articles are not freely accessible, we will contact the corresponding author two times. We will exclude an article if the authors refuse to provide the full text. The reasons for the exclusion of all excluded studies will be provided in the PRISMA 2020 flowchart. Finally, we will generate a list of articles from which we extract data.

Data extraction

Two investigators will independently extract data. Each study will yield the following information: (1) demographic information (eg, 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; (3) the results of the prediction such as accuracy, sensitivity, specificity and AUROC.

Quality assessment of studies

The PROBAST,[13] which consists of 20 signalling questions divided into 4 domains (participants, predictors, outcome and analysis), will be used as a tool to assess the risk of bias and applicability of each included study.

Data synthesis and analysis

Measures of discriminative ability, calibration and classification accuracy will be used to describe model performance. In tabular form, key findings on study design, data sources, prediction model types, sample size, participant characteristics, model objectives, methods, presentation of the final prediction model and outcome measures will be summarised.

Handling missing data

If studies have missing data, authors will be contacted to avoid inappropriate descriptions of study results.

Ethics and dissemination

Ethical approval is not required, as our review will include published and publicly accessible data. Findings from this review will be disseminated via publication in a peer-review journal. The protocol for this review was submitted at PROSPERO with ID number CRD42022354896.

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Contributors BB and FD were in charge of protocol design and manuscript conception. AR and VM are in charge of determining study eligibility and reviewing collected data. The full text of papers and data collection is the responsibility of FB, MS and VM. The authors also read the manuscript, provided significant revisions and approved the final version.

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Competing interests None declared.

Patient and public involvement Patients and/or the public were not involved in the design, or conduct, or reporting, or dissemination plans of this research.

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