

Review

Comparison of Multivariable Logistic Regression and Other Machine Learning Algorithms for Prognostic Prediction Studies in Pregnancy Care: Systematic Review and Meta-Analysis

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Abstract

Background: Predictions in pregnancy care are complex because of interactions among multiple factors. Hence, pregnancy outcomes are not easily predicted by a single predictor using only one algorithm or modeling method.

Objective: This study aims to review and compare the predictive performances between logistic regression (LR) and other machine learning algorithms for developing or validating a multivariable prognostic prediction model for pregnancy care to inform clinicians' decision making.

Methods: Research articles from MEDLINE, Scopus, Web of Science, and Google Scholar were reviewed following several guidelines for a prognostic prediction study, including a risk of bias (ROB) assessment. We report the results based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. Studies were primarily framed as PICOTS (population, index, comparator, outcomes, timing, and setting): Population: men or women in procreative management, pregnant women, and fetuses or newborns; Index: multivariable prognostic prediction models using non-LR algorithms for risk classification to inform clinicians' decision making; Comparator: the models applying an LR; Outcomes: pregnancy-related outcomes of procreation or pregnancy outcomes for pregnant women and fetuses or newborns; Timing: pre-, inter-, and peripregnancy periods (predictors), at the pregnancy, delivery, and either puerperal or neonatal period (outcome), and either short- or long-term prognoses (time interval); and Setting: primary care or hospital. The results were synthesized by reporting study characteristics and ROB and by random effects modeling of the difference of the logit area under the receiver operating characteristic curve of each non-LR model compared with the LR model for the same pregnancy outcomes. We also reported between-study heterogeneity by using τ^2 and I^2 .

Results: Of the 2093 records, we included 142 studies for the systematic review and 62 studies for a meta-analysis. Most prediction models used LR (92/142, 64.8%) and artificial neural networks (20/142, 14.1%) among non-LR algorithms. Only 16.9% (24/142) of studies had a low ROB. A total of 2 non-LR algorithms from low ROB studies significantly outperformed

LR. The first algorithm was a random forest for preterm delivery (logit AUROC 2.51, 95% CI 1.49-3.53; $I^2=86\%$; $\tau^2=0.77$) and pre-eclampsia (logit AUROC 1.2, 95% CI 0.72-1.67; $I^2=75\%$; $\tau^2=0.09$). The second algorithm was gradient boosting for cesarean section (logit AUROC 2.26, 95% CI 1.39-3.13; $I^2=75\%$; $\tau^2=0.43$) and gestational diabetes (logit AUROC 1.03, 95% CI 0.69-1.37; $I^2=83\%$; $\tau^2=0.07$).

Conclusions: Prediction models with the best performances across studies were not necessarily those that used LR but also used random forest and gradient boosting that also performed well. We recommend a reanalysis of existing LR models for several pregnancy outcomes by comparing them with those algorithms that apply standard guidelines.

Trial Registration: PROSPERO (International Prospective Register of Systematic Reviews) CRD42019136106; https://www.crd.york.ac.uk/prospero/display_record.php?RecordID=136106

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KEYWORDS

machine learning; pregnancy complications; prognosis; clinical prediction rule; meta-analysis; systematic review

Introduction

Background

Pregnancy is a common health condition that requires long-term rigorous care to anticipate adverse outcomes. Most pregnancy outcomes are identified after delivery; however, these are results of interactions among multiple factors occurring for many weeks beforehand. The number of factors and their interactions along with the time intervals make predictions of pregnancy outcomes very complicated. Multiple or multivariable logistic regression (LR) is widely used to deal with similar multifactorial problems in health outcome research [1]. Applied to medicine, statistics, and machine learning (computer science), this algorithm fits multiple parameters in a prediction model by assuming that predictors are linearly and additively related to an outcome [2]. Nevertheless, nonlinear problems commonly occur in human physiology because of complex interactions, such that a linear model might not be capable of adequately predicting outcomes [3]. With the growth of machine learning applications in health care, applying other algorithms may scale up the solution space for accurate predictions of pregnancy outcomes long before giving birth.

Despite improvements in maternal and neonatal mortality, conditions still differ between developing and developed countries or regions [4]. The most common causes of maternal deaths are hemorrhage, hypertension, and sepsis [5], whereas the causes of neonatal deaths are mostly due to prematurity, birth asphyxia, and infections [6]. Postpartum hemorrhage and sepsis are further compounded by multiple causes and risk factors [7,8], and hypertension in pregnancy or prematurity is associated with multiple mechanisms [9,10]. The aforementioned diseases and complications cannot be very easily predicted by a single epidemiological predictor, a single measure by a medical device, or a single biomarker. Furthermore, interactions among multiple predictors also might not be captured by a single machine learning algorithm including LR. Therefore, a prediction study may need to compare multiple machine learning algorithms to develop a prognostic prediction model that uses multiple predictors.

Machine learning algorithms have long been applied for clinical prediction purposes. A support vector machine demonstrated a

summary of receiver operating characteristics (ROCs) of >90% for breast cancer prognostic prediction [11]. To predict therapeutic outcomes in depression, the pooled estimated accuracy of machine learning algorithms was 0.82 (95% CI 0.77-0.87) [12]. However, the difference in the logit area under the ROC curve (AUROC) was 0.00 (95% CI -0.18 to 0.18) between LR and machine learning in studies with a low risk of bias (ROB) [13]. A similar conclusion was found for predicting intracerebral hemorrhage ($P=.49$) outlined in a systematic review [14]. These previous results imply that (1) machine learning algorithms may or may not perform better than traditional modeling by LR and (2) applying only a single algorithm may cause an investigator to lose the chance to obtain a model with optimal predictive performance using the same predictors. Meanwhile, a unique interaction should exist between a set of predictors and a pregnancy outcome. A particular predictive algorithm may work best to capture this predictor-outcome interaction. Prediction tasks are even more challenging in pregnancy care because they demand more prognostic instead of diagnostic predictions. Yet, unlike the common nature of other long-term conditions in health care (eg, diabetes mellitus), the onset, time to event, and target population in pregnancy care are rather apparent. However, unpredictable events leading to disabilities and death in a population such as pregnant women or newborns are also not easily accepted as in other populations (eg, patients with cancer and older adults). Thus, clinicians should apply several prediction models with satisfactory predictive performances throughout the pregnancy period. Clinicians and investigators would benefit from knowing whether an LR or other algorithms have a better chance of achieving satisfactory predictive performances for a particular pregnancy outcome. However, no previous systematic review in pregnancy care has reviewed multiple machine learning algorithms and compared their predictive performances, including LR, to predict pregnancy outcomes.

This review will allow investigators and clinicians in pregnancy care to consider the development or application of prediction models throughout the pregnancy period. This review demonstrates which algorithms have shown robust predictive performances for a particular pregnancy outcome using a similar set of predictors. Investigators in pregnancy care may also consider whether a reanalysis by another predictive algorithm

is needed by using existing data previously analyzed by an algorithm including LR. Beyond the algorithm issue, the development of machine learning models also requires an adequate methodology and interpretable results [15]. Biased conclusions should be avoided when describing machine learning predictive performances [11,16]. Standard guidelines are important when investigating and reviewing machine learning applications in clinical prediction modeling [15,17].

Objectives

By applying the standard guidelines, we aim to review machine learning models and compare their predictive performances between LRs and other machine learning algorithms. In this review, we focus on machine learning models either developed or validated for making prognostic predictions in pregnancy care intended to inform clinicians' decision making.

Methods

Protocol and Registration

We reported this study based on PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [18] and conducted the review based on several guidelines related to prediction studies. The review objective was defined according to a standard of key items [19]. Our eligibility criteria were composed of items elaborated with 2 guidelines for developing and reporting a prediction model and a guideline for assessing the applicability. These included transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD) [20] and another that focuses on machine learning modeling in biomedical research (hereafter referred to as guidelines for developing and reporting machine learning predictive models in biomedical research [MLP-BIOM]) [15]. Applicability was assessed using assessments that were a part of the *prediction model risk of bias assessment tool* (PROBAST) [17,21]. Data were extracted based on the checklist for critical appraisal and data extraction for systematic reviews of prediction modeling studies (CHARMS), which also describes items for the review objective. Our review protocol was registered with PROSPERO (CRD42019136106).

Eligibility Criteria

Before defining the eligibility criteria, we decided to view the LR as one of many algorithms in the machine learning field with respect to its use in statistics and data science. A prediction model development consisted of several elements: predictor selection, parameter fitting, and hyperparameter optimization [2]. In this review, the term *prediction model* refers to all those elements, whereas the term *prediction algorithm* refers to a parameter-fitting method. Using the same set of predictors, we would expect different predictive performances if the parameters of a model are fitted using different algorithms. A prediction algorithm in machine learning is a way for the computer to learn from data by fitting the parameters with respect to predicting a class measured by hyperparameters from the human user [22]. Several optimization algorithms have been developed to reduce the human role in determining these hyperparameters, such as sequential search, random search, and Bayesian optimization [23]. However, that is beyond the scope of this review.

By focusing on prediction algorithms, we defined eligibility criteria to screen studies by the title, abstract, and full text. We also assessed the applicability by examining the full text. These were the candidates we selected for the qualitative analysis. Key items of population, index, comparator, outcomes, timing, setting (PICOTS) [19] and additional items [15,20] composed the eligibility criteria. The first item of these criteria was a review question framed using PICOTS. The key items consisted of the following:

1. Population: men or women in procreative management, pregnant women, and fetuses or newborns.
2. Index: multivariable prognostic prediction models applying non-LR algorithms for risk classification tasks intended to inform clinicians' decision making.
3. Comparator: multivariable prognostic predictions applying an LR algorithm, excluding a scoring system in which the parameters determined by humans instead of using LR, for risk classification tasks intended to inform clinicians' decision making.
4. Outcomes: pregnancy-related outcomes of procreative management or pregnancy outcomes for pregnant women or fetuses or newborns.
5. Timing: with predictors being measured at the pre-, inter-, and peripregnancy periods and outcomes being assessed at the pregnancy, delivery, and either puerperal or neonatal period, short- and long-term prognoses were applied.
6. Setting: primary care or hospital.

Additional items were the availability of several reporting components as required by TRIPOD and MLP-BIOM. These components included (1) data sources, (2) outcomes, (3) evaluation metrics, (4) predictors, (5) descriptive statistics, (6) event sample sizes, (7) modeling methods or algorithms, and (8) model validation.

After briefly screening studies by eligibility criteria, we conducted an applicability assessment by thoroughly examining the full texts. Using PROBAST guidelines, we assessed the applicability according to the review question framed by PICOTS. Low, high, or unclear criteria were determined for applicable, not applicable, or unclear applicability, respectively. The assessment covered 3 domains of participants, predictors, and outcomes. Only those fulfilling *low* criteria were selected for the qualitative analysis.

For the quantitative analysis, studies had to report the AUROC. Studies were selected from those applicable for the qualitative analysis. If there were at least three LR models and a non-LR model from any studies for an outcome, all studies with that outcome were included in the meta-analysis. This was determined based on the requirement of a minimum number of data points to calculate the variance as part of the meta-analytical procedure. If studies did not report the AUROC, we estimated the sensitivity and specificity using the trapezoidal rule (see *Summary Measures* and *Synthesis of Results* sections).

Information Sources

We searched the MEDLINE, Scopus, Web of Science, and Google Scholar databases up to May 2020. There was no limit on the publication period. However, considering the limitations

of the search interface in Google Scholar, we only retrieved results from the last year with keywords in the abstract or the entire period with those keywords in the title. We also limited the publication period to the last 10 years for search results by keywords including “logistic regression multivariable prediction.” This was because we estimated that there would be enormous amounts of studies applying LR because we applied a broad range of outcomes in this study. In contrast, we might lack studies using other machine learning models, although the outcomes were broad.

Search

The initial search filter was limited to the title, abstract, keywords, or Medical Subject Heading (MeSH; MEDLINE only) using “machine learning” AND pregnancy. We also used “machine learning AND ([pregnancy outcome from initial search] NOT pregnancy).” Keywords for pregnancy outcomes were used based on MeSH to generalize a variety of terms for pregnancy outcomes from selected studies. If the MeSH term contained “pregnancy,” then we used the alternative entry terms in the webpage recorded for this MeSH term. If all entry terms also contained “pregnancy,” then we used the term without negating “pregnancy.” In addition, we also substituted the “machine learning” part with one of the keywords consisting of “decision tree,” “artificial neural network,” “support vector machine,” “random forest,” “artificial intelligence,” “deep learning,” and “logistic regression multivariable prediction.” All keywords are described in [Multimedia Appendix 1](#). These search terms were applied to all databases.

Study Selection

Duplicate records from multiple databases were removed. We refined the search results in the title or abstract using EndNote X8 (Clarivate Analytics) by “(supervised NOT unsupervised) OR prediction OR classification.” Records were screened by HS and AH, and the results were assessed by HS, AH, YC, CK, OS, TY, and YW. Disagreements were resolved by discussion with the last author (ES). Study selection was conducted in brief and thorough assessments. These brief assessments were intended to select studies by checking eligibility criteria from TRIPOD and MLP-BIOM in the title, abstract, and briefly in the full-text article. A thorough assessment of the applicability from PROBAST was conducted later before the ROB assessment.

Data Collection Process

We extracted data based on the CHARMS checklist, which includes (1) outcomes, (2) study design, (3) data sources, (4) data source design, (5) setting, (6) type of study, and (7) modeling methods or algorithms, and (8) predictive performance. Outcomes were pooled as distinct MeSH terms. Study and data source designs were classified into prospective, retrospective, nested case-control, case-control, and cross-sectional. We defined the type of study based on the model validation, which might be development, validation, or both. Eligible studies were described as developing prediction models by applying LR, non-LR, or both algorithms. Predictive performances were only taken from studies that were eligible for the meta-analysis (see *Eligibility Criteria* section). If there

were multiple models developed within a study using the same algorithm, we retrieved the AUROC from the best performing one among the models. If both LR and non-LR algorithms were applied in a study, we selected the predictive performances of the best models applying either the LR or non-LR algorithm. Model performances derived from external validation were preferred if available.

ROB Within and Across Studies

We used PROBAST to assess the ROB [17,21]. The ROB in individual studies was assessed as low, high, or unclear in 4 domains of participants, predictors, outcomes, and analyses. In addition, 20 signaling questions were answered for each study in a transparent and accountable form. Across studies, we described the proportion of low, unclear, or high ROB. ROB were compared for each domain. We also summarized the answers for each signaling question.

Summary Measures

We compared AUROCs from studies that reported this metric. Logit transformation was applied to the AUROCs. We computed logit AUROC differences between each non-LR and LR algorithm across studies. Summary measures from any eligible studies with all, low, or high ROB were pooled by random effects modeling, as previously described [24]. Assuming that selected studies were random samples from a larger population, we chose a random effects model that attempted to generalize findings beyond the included studies using that assumption [25]. Despite this, we did not conduct random effects modeling for all selected studies considering the broad range of target populations, outcomes, and algorithms. Meanwhile, we conducted this review within a narrower field compared with a previous systematic review of machine learning in medicine [13]. Therefore, we only applied random effects modeling to the predictive performances of selected studies using a particular pregnancy outcome. These studies consisted of a minimum number of non-LR and 3 LR models from any studies. This minimum number was considered to obtain a minimum number of data points of logit AUROCs to compute the interval estimates in a random effects model. We depicted the AUROCs using forest plots; thus, one can see which prediction algorithm may have a better chance of obtaining optimal predictive performance for a particular pregnancy outcome.

Pooled estimates of pairwise differences in logit AUROCs were described by points and the 95% CI [26]. A positive difference in logit AUROCs means that the non-LR algorithm had a higher logit AUROC than that of the LR algorithm. The difference was significant if 0 was not included within the 95% CI. The number of pairwise comparisons (k) for each random effects model was reported. We also reported variance across studies (τ^2) and I^2 as absolute and relative values of between-study heterogeneity, respectively.

If a study did not report the AUROC, we estimated this metric based on sensitivity and specificity. As a specificity of 0% means a sensitivity of 100% and *vice versa*, the AUROC could be estimated from the reported sensitivity and specificity using a common rule to calculate the area of the trapezoid (Equation 1). Before we subtracted the AUROC of a non-LR algorithm

from that of an LR algorithm, we applied a logit transformation (Equation 2).

$$\text{AUROC} = 0.5 \times (1 - \text{specificity}) \times \text{sensitivity} + \text{specificity} \times \text{sensitivity} + 0.5 \times (1 - \text{sensitivity}) \times \text{specificity} \quad (1)$$

$$\text{Logit}(\text{AUROC}) = \log (\text{AUROC} / (1 - \text{AUROC})) \quad (2)$$

We used RStudio 1.2 (RStudio) with R 3.6.1 and an additional package, metafor 2.4.0, for random effects modeling. We applied the restricted maximum likelihood estimator method [27]. These are common tools and recommended modeling methods for meta-analyses [28].

Synthesis of Results

We described the characteristics of the studies consisting of population, study design, timing, and setting. This was described as the number of algorithms used for prediction modeling. The algorithms were categorized into LR, non-LR, or both algorithms. We also show the proportion of each characteristic compared with all characteristics within the same algorithm category.

ROBs within studies were described for the number of low, high, or unclear ROB studies. This was reported for overall assessment results and by domain in studies that used LR, non-LR, or both algorithms. ROBs across studies were described for the proportion of studies in which the answer to each signaling question led to low, high, or unclear ROB studies. We intended to show what makes most studies considered to have high ROBs.

Meta-analytical results were described by a forest plot faceted by outcome. Each facet showed comparisons of differences in logit AUROCs for each random effects model of non-LR versus LR algorithms. This demonstrated which algorithms tended to

outperform LR for each pregnancy outcome. Comparisons that included non-LR high ROB studies were color coded. The best predictive performance for each outcome was reported. Between-study heterogeneity for each random effects model was also reported.

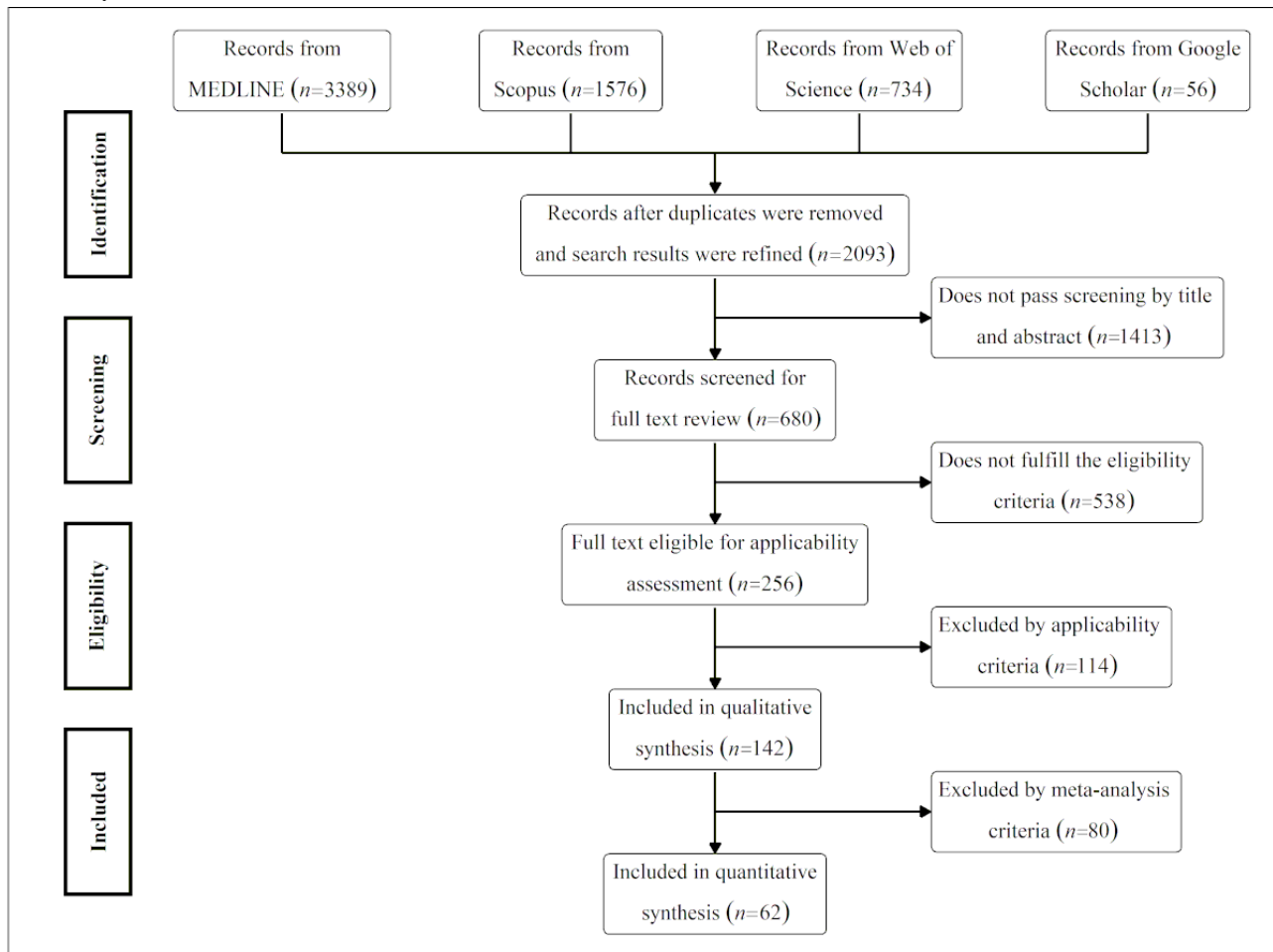
We described predictors in the prediction models from studies in the meta-analysis. For each outcome in the meta-analysis, we selected only random effects models in which an algorithm significantly outperformed the other. This was determined by the 95% CI of the difference in logit AUROCs between a non-LR and an LR model for an outcome. If any, we only selected those that included only non-LR low ROB studies. Only predictors in the final model were included. This was intended to elucidate predictor-outcome interactions that characterized an algorithm if it outperformed the others for a particular outcome.

Results

Study Selection

We found 2093 records from 4 literature databases (Figure 1). The search filters consisted of 144 combinations of keywords from 8 machine learning terms and 18 MeSH terms for pregnancy outcomes recursively derived from the keywords “machine learning AND pregnancy” (Multimedia Appendix 1). We refined the search results, identified research articles (not including conference abstracts or theses), and removed duplicates. After screening and eligibility assessment, we included 142 studies for the qualitative analysis, of which 62 were used for the quantitative analysis. A detailed description of the eligible criteria, process of study selection, and list of studies for the full-text review are given in Multimedia Appendix 1.

Figure 1. Study selection workflow.



Characteristics of the Studies

Briefly, we collected studies that either developed or validated a prediction model applying either LR (77/142, 54.2%) [29-105] or non-LR machine learning algorithms (50/142, 35.2%; Table 1) [106-155]. Overall, 15 studies applied both LR and non-LR algorithms (15/142, 10.6%) [156-170]. The cohort population of the studies in this review consisted of every type of population, study design, timing, and setting that we desired to discuss in this review. More studies discussed fetuses or newborns than pregnant women in non-LR prediction studies (26/50, 52% vs 11/50, 22%). Meanwhile, the opposite occurred in LR studies that focused more on pregnant women than fetuses or newborns (50/77, 65% vs 19/77, 25%). Most used data sets were from retrospective cohorts for LR (53/77, 69%) [29-36,38-42,47,49-54,56-61,64-66,68-71,76-80,83,87-90,92,94,95,97,100-105], non-LR prediction studies (27/50, 54%) [107,108,111-113,116,117,121,122,127,130-138,140,142,143,148,150,151,153,154], or both (9/15, 60%) [157-160,163-165,167-170]. A retrospective cohort is one of the recommended study designs for prognostic purposes instead of diagnostic prediction [21].

This corresponds to our review question that warrants prognostic predictions in pregnancy care intended to inform clinicians' decision making.

Only a few studies had prediction timing up to the puerperal or neonatal period for LR (2/77, 3%) [74,85], non-LR (3/50, 6%) [114,129,149], or both algorithms (2/15, 13%) [162,168]. This is because some predictors were assessed after delivery, whereas our review question demanded those be assessed up to delivery. We also considered studies using data sets from either primary care or hospital settings because the data are applicable for clinicians' decision making on a daily basis. As applicability was already included in the eligibility assessment before the qualitative analysis, eligible studies were not found to use data sets from either primary care or hospital settings, such as from a house-to-house survey or a screening program. Most used data sets were from hospital settings, whereas only a few of those were from primary care settings in the LR (6/77, 8%) [65,69,73,77,78,87], non-LR (6/50, 12%) [119,122,132,135,148,153], or both algorithms (1/15, 7%) [162]. A detailed description of this is also given in Multimedia Appendix 1.

Table 1. Characteristics of eligible studies.

Variable	Number of studies (percentage based on column total)			
	LR ^a (n=77), n (%)	Non-LR (n=50), n (%)	Both (n=15), n (%)	Total (n=142), n (%)
Population				
Pregnant women	50 (65)	11 (22)	6 (40)	67 (47.2)
Fetuses or newborns	19 (25)	26 (52)	7 (47)	52 (36.6)
Men or women in procreative management	8 (10)	13 (26)	2 (13)	23 (16.2)
Study design				
Retrospective	53 (69)	27 (54)	9 (60)	89 (62.7)
Nested case-control	4 (5)	14 (28)	2 (13)	20 (14.1)
Prospective	13 (17)	4 (8)	0 (0)	17 (12)
Cross-sectional	3 (4)	3 (6)	3 (20)	9 (6.3)
Case-control	4 (5)	2 (4)	1 (7)	7 (4.9)
Timing				
At delivery	28 (36)	26 (52)	7 (46.7)	61 (42.9)
At pregnancy	34 (44)	21 (42)	5 (33.3)	60 (42.3)
Mixed timing	13 (17)	0 (0)	1 (6.7)	14 (9.9)
Puerperal or neonatal period	2 (3)	3 (6)	2 (13.3)	7 (4.9)
Setting				
Hospital	61 (79)	43 (86)	9 (60)	113 (79.6)
Both	10 (13)	1 (2)	5 (33)	16 (11.3)
Primary care	6 (8)	6 (12)	1 (7)	13 (9.2)

^aLR: logistic regression.

LR and Other Machine Learning Algorithms

Most studies applied an LR (92/142, 64.8%) to develop a prediction model (Table 2). Meanwhile, an artificial neural network was mostly applied by non-LR studies (20/142, 14.1%). Studies that applied LR and non-LR algorithms mostly compared LR with an artificial neural network (5/15, 33%) [161,163,165,166,170] and decision tree (5/15, 33%) [156,159,167-169], but decision trees tended to be paired with an LR compared with an artificial neural network (5/7, 71% vs 5/20, 25%).

The characteristics of study populations showed that pregnant women and fetuses or newborns were the populations of most

studies developed using LR and non-LR models, respectively. Among pregnant women, the LR algorithm was mostly applied to develop predictions for outcome categories of obstetric labor (13/77, 17%) [36,46,47,54,57,62,64,70,83,86,91,97,103], pregnancy-induced hypertension (12/77, 16%) [30,31,43,48,55,65,66,68,76,81,93,105], and gestational diabetes (7/77, 9%) [33,45,49,84,94,100,104]. Among fetus or newborn populations, non-LR algorithms were mostly applied to develop predictions for outcome categories of premature birth (12/50, 24%) [111,112,115,116,118,119,121,122,125,130,141,143] and fetal distress (9/50, 18%) [113,124,128,137,138,145,146,152,155]. In addition, more non-LR algorithms (13/20, 65%) were applied for the outcome category of *in vitro* fertilization than for the LR algorithm.

Table 2. Machine learning algorithm and category of outcome.

Variable	Number of studies (percentage based on column total)			
	LR ^a (n=77), n (%)	Non-LR (n=50), n (%)	Both (n=15), n (%)	Total (n=142), n (%)
Machine learning algorithm				
Logistic regression	77 (100)	N/A ^b	15 (100)	92 (64.8)
Artificial neural network	N/A	15 (30)	5 (33)	20 (14.1)
Support vector machine	N/A	9 (18)	1 (7)	10 (7.0)
Deep neural network	N/A	8 (16)	1 (7)	9 (6.3)
Random forest	N/A	7 (14)	1 (7)	8 (5.6)
Decision tree	N/A	2 (4)	5 (33)	7 (4.9)
Gradient boosting	N/A	3 (6)	2 (13)	5 (3.5)
Naïve Bayes	N/A	4 (8)	0 (0)	4 (2.8)
Ensemble of algorithms	N/A	2 (4)	0 (0)	2 (1.4)
Category of outcome				
Premature birth	9 (12)	12 (24)	3 (20)	24 (16.9)
In vitro fertilization	7 (9)	13 (26)	2 (13)	22 (15.5)
Obstetric labor	13 (17)	1 (2)	2 (13)	16 (11.3)
Pregnancy-induced hypertension	12 (16)	4 (8)	0 (0)	16 (11.3)
Fetal distress	1 (1)	9 (18)	0 (0)	10 (7.0)
Gestational diabetes	7 (9)	2 (4)	1 (7)	10 (7.0)
Cesarean section	4 (5)	3 (6)	2 (13)	9 (6.3)
Fetal development	4 (5)	1 (2)	0 (0)	5 (3.5)
Small-for-gestational-age infant	3 (4)	1 (2)	1 (7)	5 (3.5)
Others	17 (22)	4 (8)	4 (27)	25 (17.6)

^aLR: logistic regression.

^bN/A: not applicable.

ROB Within and Across Studies

ROB is described for each eligible study in [Multimedia Appendix 1](#) [29-170]. Among the 142 eligible studies, there were 24 (16.9%) low ROB studies [38,61-63,71,98,104,110,113,115,117-119,128,134,141,142,145,147,149,155,157,158,169], 117 (82.4%) high ROB studies [29-37,39-60,64-70,72-97,99-103,105-109,111,112,114,116,120-123,125-127,129-133,135-140,143,144,146,148,150-154,156,159-168,170], and 1 (0.7%) unclear ROB study

([Table 3](#)) [124]. Among the low ROB studies, the categories of outcomes were premature birth (7/24, 30%) [38,63,115,118,119,141,169], fetal distress (5/24, 21%) [71,113,128,145,155], *in vitro* fertilization (4/24, 17%) [61,110,134,158], gestational diabetes (2/24, 8%) [104,157], cesarean section (CS; 2/24, 8%) [117,142], obstetric labor (1/24, 4%) [62], pregnancy-induced hypertension (1/24, 4%) [147], central nervous system malformations (1/24, 4%) [149], and others (1/24, 4%) [98].

Table 3. Risk of bias within studies.

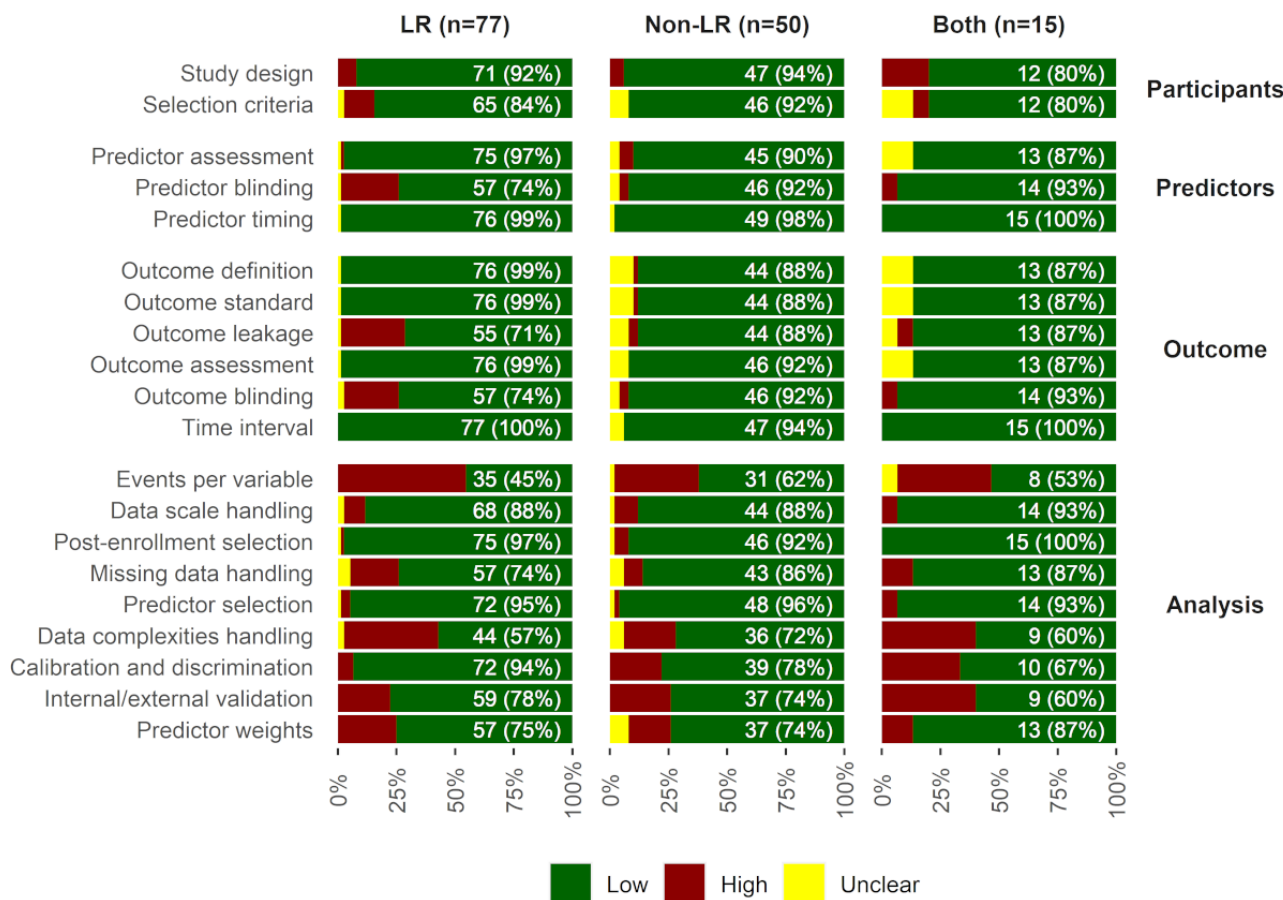
Assessment by domain	Studies by algorithm			
	LR ^a (n=77), n (%)	Non-LR (n=50), n (%)	Both (n=15), n (%)	Total (n=142), n (%)
Participants				
Low	60 (78)	44 (88)	11 (73)	115 (80.9)
High	15 (19)	3 (6)	4 (27)	22 (15.5)
Unclear	2 (3)	3 (6)	0 (0)	5 (3.5)
Predictors				
Low	54 (70)	43 (86)	12 (80)	109 (76.8)
High	20 (26)	5 (10)	1 (7)	26 (18.3)
Unclear	3 (4)	2 (4)	2 (13)	7 (4.9)
Outcome				
Low	51 (66)	40 (80)	11 (74)	102 (71.8)
High	24 (31)	4 (8)	2 (13)	30 (21.1)
Unclear	2 (3)	6 (12)	2 (13)	10 (7.1)
Analysis				
Low	8 (10)	15 (30)	3 (20)	26 (18.3)
High	69 (90)	35 (70)	12 (80)	116 (81.7)
Unclear	0 (0)	0 (0)	0 (0)	0 (0.0)
Overall				
Low	7 (9)	14 (28)	3 (20)	24 (16.9)
High	70 (91)	35 (70)	12 (80)	117 (82.4)
Unclear	0 (0)	1 (2)	0 (0)	1 (0.7)

^aLR: logistic regression.

ROB is also described across the studies in [Table 3](#) and [Figure 2](#). The corresponding signaling questions for each term and the answers for each study are described in [Multimedia Appendix 1](#). Low ROB studies were the fewest in the analysis domain (26/142, 18.3%), consisted of the LR (8/77, 10%) [[38,61-64,71,96,98,104](#)], non-LR (15/50, 30%) [[63,110,113,115,117-119,124,128,134,141,142,145,147,155](#)], and both algorithms (3/15, 20%) [[157,158,169](#)]. In the analysis domain,

the fewest low ROB studies that achieved the minimum events per variable (EPV) consisted of LR (35/77, 45%) and non-LR (31/50, 62%) prediction studies. More calibration and discrimination tests were conducted using LR (72/77, 94%) than by non-LR (39/50, 78%) prediction studies. In contrast, more non-LR prediction studies appropriately handled missing data (43/50, 86%) compared with LR prediction studies (57/77, 74%).

Figure 2. Signaling questions with respect to ROB domains across studies. Bars from low/high/unclear ROB are stacked to be 100%. Domains are described on the right-hand side. The number on the bar is the number of low ROB studies (total LR/non-LR/both at top) based on a single signaling question summarized as a term on the left-hand side. LR: logistic regression; ROB: risk of bias.

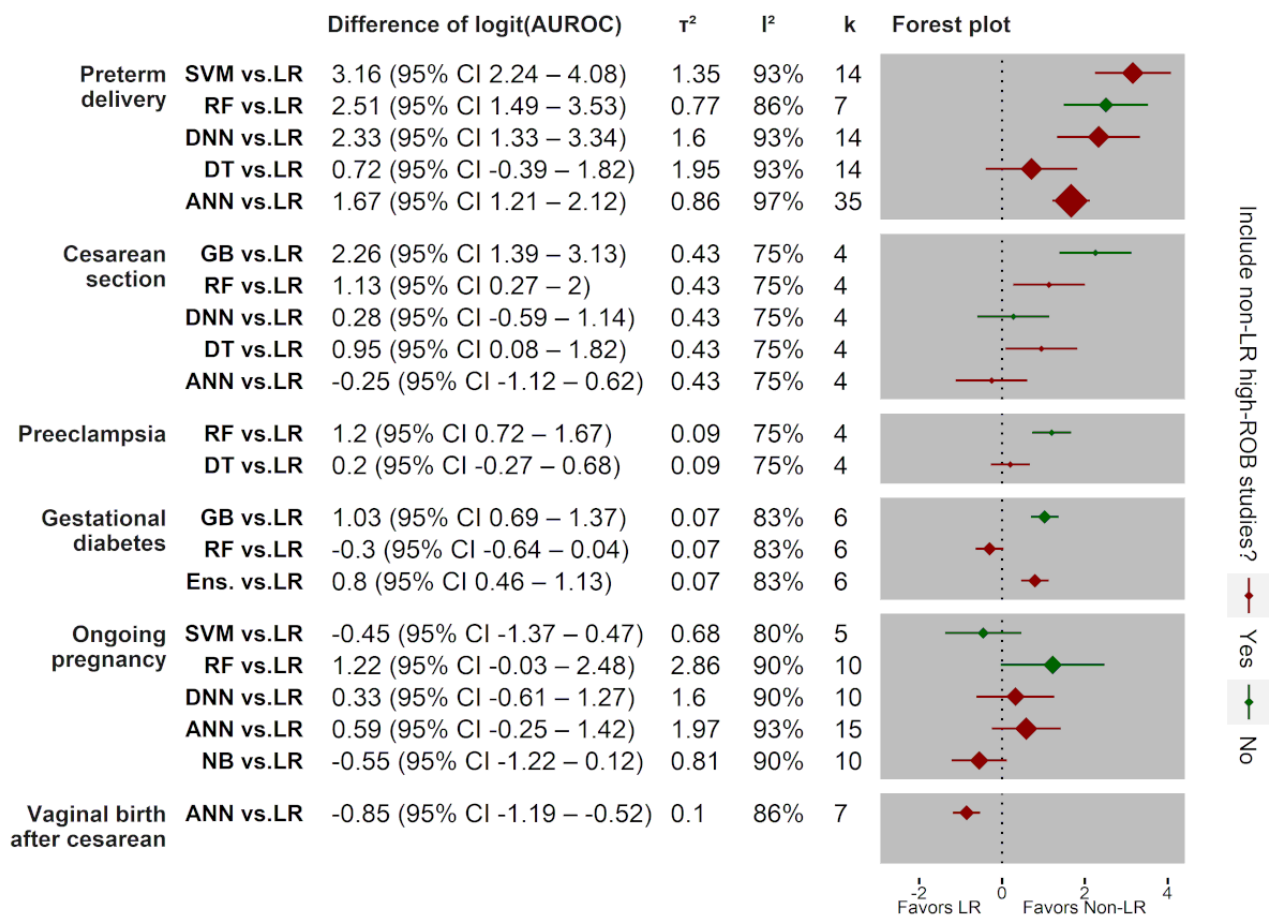


Comparison of the Predictive Performance

There were 62 studies in the meta-analysis that had outcomes that were predicted by at least one non-LR and 3 LR models (see *Summary Measures* section). Overall, 21 random effects models of the predictive performance by non-LR versus LR models are shown in a forest plot (Figure 3). Forest plots of logit AUROC differences for each random effects model are described (Multimedia Appendix 1). With respect to candidate studies (n) included in the final random effects models, we

developed 5 random effects models for preterm delivery (20/62, 32%) [32,44,60,63,75,87,96,111,112,115,118,119,121,125,130,141,143,156,163,169], 5 for CS (7/62, 11%) [79,90,106,117,142,166,167], 2 for pre-eclampsia (6/62, 10%) [31,48,65,76,123,147], 3 for gestational diabetes (9/62, 15%) [33,45,84,94,100,104,108,139,157], 5 for ongoing pregnancy (13/62, 21%) [73,78,99,110,132,134-136,148,150,153,158,170], and 1 for vaginal birth after CS (7/62, 11%) [36,47,57,64,83,97,165].

Figure 3. Forest plot of random effects models for differences in logit AUROCs from a non-LR with any LR prediction models. Plots were grouped by outcome. The lines indicate the 95% CI with diamonds whose sizes were determined by the number of pairwise comparisons (k). Absolute and relative values of between-study heterogeneities are denoted by τ^2 and I^2 , respectively. Colors of the boxes and lines were determined based on the existence of high ROB studies among those using non-LR algorithms. ANN: artificial neural network; AUROC: area under the receiver operating characteristic curve; DNN: deep neural network; DT: decision tree; Ens: ensemble of multiple algorithms; GB: gradient boosting; LR: logistic regression; NB: naïve Bayes; RF: random forest; ROB: risk of bias; SVM: support vector machine.



To determine the final random effects model for each comparison, we identified studies that were responsible as the source of heterogeneity and removed those AUROCs from the random effects model. We excluded a non-LR [121] and an LR study [84] that developed a prediction model for preterm delivery and gestational diabetes, respectively. This is because their AUROCs were outliers compared with those for the same outcome and algorithm. We also excluded 3 LR studies [32,63,87]. In those studies, preterm delivery was defined as delivering within 1 to 2 weeks of preterm labor presentation. Meanwhile, the majority of studies for this outcome defined preterm delivery as that before 37 weeks of gestation.

The non-LR models significantly outperformed the LR models in preterm delivery (4/5 non-LR models), CS (3/5 non-LR models), pre-eclampsia (1/2 non-LR models), and gestational diabetes (2/3 non-LR models). From those that examined preterm delivery, a prediction model did not include a non-LR high ROB study [115] compared with those from 7 LR studies [32,44,60,63,75,87,96]. This model applied a random forest (differences in logit AUROC 2.51; 95% CI 1.49-3.53). The same algorithm was applied to a prediction model from a non-LR low ROB study in pre-eclampsia [147]. For random effects modeling, this model also significantly outperformed those from 4 LR studies (1.2, 95% CI 0.72-1.67) [31,48,65,76].

Meanwhile, prediction models from non-LR low ROB studies of Saleem et al [142] and Artzi et al [157] significantly outperformed those from the corresponding LR studies as an aggregate for CS (2.26, 95% CI 1.39-3.13) and gestational diabetes (1.03, 95% CI 0.69-1.37). Interestingly, the models were developed using a gradient boosting algorithm that used multiple decision trees similar to a random forest.

In contrast, a prediction model using a non-LR algorithm significantly underperformed compared with those using an LR in a random effects model (-0.85, 95% CI -1.19 to -0.52). This applied an artificial neural network to predict vaginal birth after a CS [165]. This model underperformed compared with those from 7 LR studies [36,47,57,64,83,97,165]. However, the non-LR study was a high ROB study.

A random effects model developed for comparison of artificial neural networks and LR to predict preterm delivery had the highest heterogeneity by I^2 (97%; $k=35$). This number means that 97% of the total variability among 35 data points of differences in logit AUROCs was caused by between-studies heterogeneity instead of sampling error within each study [171]. This is reasonable because a higher variance occurs with a larger number of comparisons within a random effects model. In contrast, a random effects model with the smallest number of

comparisons ($k=4$) also had the lowest heterogeneity by I^2 (75%). This random effects model was developed to analyze comparisons of non-LR and LR algorithms for either CS or pre-eclampsia. Nevertheless, a diverse target population and hyperparameter optimization conceivably caused the heterogeneity of the predictive performance, although the same outcome was predicted using the same data set and machine learning algorithm. The lowest I^2 in this meta-analysis remains classified as substantial heterogeneity instead of moderate or unimportant; thus, performing random effects instead of fixed effect modeling is recommended to address this issue [172].

However, I^2 only indicates that the difference in logit AUROCs substantively varies across studies but does not tell how much this metric varies [173]. To interpret the absolute heterogeneity for the difference in logit AUROCs, we needed to consider the observed AUROC of a non-LR model for each of the random effects models. The observed AUROCs were described for each of the original studies in this meta-analysis in [Multimedia Appendix 1](#).

A random effects model developed for comparison of random forests and LR to predict ongoing pregnancy had the highest absolute value of heterogeneity ($\tau^2=2.86$). In this random effects model, random forests were applied to develop predictions in 2 studies that reported AUROCs of 0.740 (95% CI 0.710-0.770) [158] and 0.9820 [134]. We simulated a sequence of logit AUROCs to identify equivalent differences in AUROCs to approximate a difference of the logit value in the random effects model (1.22, 95% CI -0.03 to 2.48). AUROC differences of 0.206 and 0.026 were equivalent to a difference in the logit AUROC of 0.91, compared with those aggregated from LR models for the random forest models of Blank et al [158] and Mirroshandel et al [134], respectively. Using τ^2 , one can calculate the 95% prediction interval (PI) of the logit AUROC difference, as previously described [173]. This estimates the potential AUROC of the random forest to predict ongoing pregnancy with respect to an LR using different populations. For this random effects model, the 95% PI of the logit AUROC difference ranged from -4.75 to 7.19. This is equivalent to 0.257 lower and >0.73 higher than AUROCs of any LRs in the random effects model for the random forest model of Blank et al [158]. For the random forest model of Mirroshandel et al [134], the 95% PI was equivalent to 0.018 lower and 0.943 higher than the AUROCs of any LRs in the random effects model. This is a reasonably wide PI for the highest τ^2 in this meta-analysis, although the non-LR study had a low ROB. This is because ROB only reflects the risk of a predictive performance that differs from the true value of the training sample. However, the ROB does not reflect the difference if the predictive performance is compared with other samples across different populations.

For the random effects model with the lowest τ^2 and including a non-LR low ROB study, the random effects model had a logit AUROC difference of 1.03 (95% CI 0.69-1.37) for a prediction model of gestational diabetes using gradient boosting. The prediction study reported an AUROC of 0.875 (95% CI 0.868-0.885) [157]. The 95% PI of the logit AUROC difference estimated an equivalent AUROC that ranged from 0.0096 lower

to 0.425 higher than the AUROCs of any LR in the random effects model. The gradient boosting model from this study is likely to outperform an LR to predict gestational diabetes.

In addition, we may need to know the τ^2 meaning for the random effects model with the highest I^2 and larger numbers of comparisons (k). This random effects model had an AUROC difference of 1.67 (95% CI 1.21-1.94; 95% PI -2.08 to 5.42; $k=35$) for a prediction model of preterm delivery using an artificial neural network. Overall, 5 non-LR studies were included in this random effects model. The remaining studies reported AUROCs of 0.88 [111], 0.94 [118], 0.945 [125], 0.9115 [163], and 0.911 (95% CI 0.862-0.960) [130]. Considering only the lowest (0.862) and highest (0.960) that covered all of the AUROCs, the artificial neural network model may have AUROCs of 0.119 lower and 0.864 higher than those of any LR. The AUROC interval was also as wide as that of the random effects model with the highest τ^2 .

Descriptive Analysis of Predictors

A random effects model was selected for each outcome except for ongoing pregnancy, which fulfilled our criteria to describe the predictors. For each outcome in the meta-analysis, we selected random effects models in which either a non-LR algorithm significantly outperformed the LR or it was significantly underperformed by the LR. This was determined by the 95% CI of the difference in the logit AUROCs between the non-LR and LR models for an outcome. If any, we only selected those including only non-LR low ROB studies. The random effects models were random forest versus LR for preterm delivery, gradient boosting versus LR for CS, random forest versus LR for pre-eclampsia, gradient boosting versus LR for gestational diabetes, and artificial neural network versus LR for vaginal birth after a CS. As we only extracted the AUROC of either the best LR or non-LR model, only predictors and outcomes of that model were considered if there were multiple models for different subtypes of the outcome in a study.

For preterm delivery, Despotovic et al [115] developed a random forest model using a previously published standardized electrohysterogram (EHG) data set [174]. This data set was also used by other studies in this meta-analysis to predict the same outcome using different algorithms [118,125,130,141,143,169]. All predictors were features extracted from the multichannel EHG obtained at around 22 and 32 weeks of gestation to predict delivery after 39 and 34 to <37 weeks of gestation for term and preterm delivery, respectively. Compared with their counterparts, LR models used predictors consisting of maternal demographics or lifestyle [44,60,75,96,163], medical or obstetric histories [44,75,96,156,163], clinical predictors from obstetrical examinations [44,163], EHG [169], and biomarkers [75]. These were obtained before pregnancy [60,96,156,163], at 11 to 14 weeks of gestation [75], 18 to 34 weeks of gestation [44,163,169], or near events within 1 to 2 weeks [44]. The LR models were developed to predict preterm delivery at 20 to <37 weeks of gestation [44,75,96,163,169] and any delivery at <37 weeks of gestation (predictors could be taken before pregnancy) [60,156].

For CS, Saleem et al [142] developed a gradient boosting model using a previously published standardized cardiotocogram (CTG) data set [175]. This data set was also used by Fergus et al [117] in this meta-analysis to predict the same outcome using a deep neural network. All predictors were features extracted from the CTG data set obtained at first- and second-stage labor for a maximum of 90 min preceding delivery to predict a CS. Compared with their counterparts, LR models used predictors consisting of maternal characteristics [79,90,166], medical histories [167], obstetric histories [90,166,167], and clinical predictors from obstetric examinations [90,166,167], ultrasound measures [79], routine laboratory tests [90], and medications [90]. These were obtained before [90,166,167] and during pregnancy [79,90,166,167]. The LR models were developed to predict CS [166,167], emergency CS [79], and CS in pregnant women with gestational hypertension or mild pre-eclampsia at term [90].

For pre-eclampsia, Sufriyana et al [147] developed a random forest model that used a nationwide health insurance data set. The predictors consisted of maternal demographics and medical histories but excluded obstetric ones. These were obtained before and during pregnancy up to 2 days before the events (pre-eclampsia or eclampsia of any severity and timing). Meanwhile, the LR counterparts used maternal demographics or lifestyle [31,65,76], medical histories [31,65,76], obstetric histories [31,65,76], family histories [31,76], clinical or obstetric examinations [31,65], ultrasound measures [65], routine laboratory tests [76], and biomarkers [48,65]. These predictors were obtained before pregnancy [31], at 11 to 13 weeks of gestation [65], and at <20 weeks of gestation [48]. LR models were developed to predict pre-eclampsia of any severity and timing [31,48,65,76]. The predictors were taken before pregnancy, and this disorder occurs after 20 weeks of gestation by definition.

For gestational diabetes, Artzi et al [157] developed a gradient boosting model that used a nongovernmental, nationwide health care database. The predictors consisted of maternal demographics, medical histories, obstetric histories, clinical or obstetric examinations, routine laboratory tests, and medications. These predictors were obtained before pregnancy and up to 22 weeks of gestation to predict gestational diabetes diagnosed at 24 to 28 weeks of gestation. The LR counterparts used maternal demographics or lifestyle [33,100,104], medical histories [33], obstetric histories [104], family histories [33,45], clinical examinations [33], obstetric examinations [33], routine laboratory tests [33,45,94,100,104], medications, and biomarkers [33,45]. The predictor timing was 6 to 14 weeks of gestation [33,45,94,100,104] and >14 to 22 weeks of gestation [45,100,104]. Meanwhile, the outcome timing was 24 to 28 weeks of gestation [33,45,94,100,104].

For vaginal birth after a CS, Macones et al [165] developed an artificial neural network model that used a medical records database. The predictors used maternal characteristics, medical histories, obstetric histories, obstetric examinations, and labor procedures. These were obtained before pregnancy, during pregnancy, and at labor to predict successful vaginal birth after a CS. The LR counterparts used maternal characteristics [36,47,64,83,97], medical histories [57], obstetric histories

[36,47,57,64,83,97], obstetric examinations [97], and labor procedures [97]. These were obtained before pregnancy [36,47,57,64,83,97], during pregnancy [97], and at labor [97]. The models predicted vaginal birth after a CS with the same definition as those of non-LR studies [36,47,57,64,83].

Discussion

Summary of Evidence

Of the 2093 records from 4 literature databases using 144 keywords, we found 142 eligible studies, among which 24 had a low ROB. These eligible studies developed prediction models for outcome categories of premature birth, *in vitro* fertilization, obstetric labor, pregnancy-induced hypertension, fetal distress, gestational diabetes, CS, fetal development, small-for-gestational-age infants, and others.

There were 4 models with non-LR algorithms from low ROB studies that had significantly higher differences in logit AUROCs than those with LR algorithms. The models used random forest algorithms to predict preterm delivery (2.51, 95% CI 1.49-3.53), gradient boosting algorithms to predict CS (2.26, 95% CI 1.39-3.13), random forest algorithms to predict pre-eclampsia (1.2, 95% CI 0.72-1.67), and gradient boosting algorithms to predict gestational diabetes (1.03, 95% CI 0.69-1.37). The first model that applied a random forest used only EHG records to predict preterm delivery. The second random forest model used only maternal demographics and medical histories but excluded obstetric ones for pre-eclampsia prediction. Meanwhile, the first model that applied a gradient boosting algorithm used only CTG records to predict CSs. The last model was developed by applying a gradient boosting algorithm for gestational diabetes. This model used maternal demographics, medical histories, obstetric histories, clinical or obstetric examinations, routine laboratory tests, and medications.

Comparisons With Prior Work

We compared our systematic review and meta-analysis with prior works related to either machine learning algorithms or pregnancy outcomes similar to those in our study. A recent paper described applications of artificial intelligence in obstetrics and gynecology [176]. That paper was a narrative instead of a scoping or systematic review. Our systematic review and meta-analysis covered all pregnancy outcomes in obstetrics, as described in that paper. These were described as fetal heart monitoring and pregnancy surveillance, gestational diabetes mellitus, preterm labor, parturition, and *in vitro* fertilization.

Nevertheless, the predicted outcomes by non-LR models in our review were still insufficient. Diseases that cause maternal deaths should receive higher priority than those causing neonatal deaths. The risks were higher for pregnant women with antepartum hemorrhage (incidence rate ratio [IRR]=3.5, 95% CI 2.0-6.1) or hypertension (IRR=1.5, 95% CI 1.1-2.2) compared with those without these diseases [177]. Maternal sepsis was also associated with fetal or neonatal deaths (odds ratio [OR] 5.78, 95% CI 2.89-11.21) [178]. Accordingly, the impact of the prediction models may be insufficient to reduce both maternal and neonatal deaths.

LR was found in our study to be the most often used algorithm to develop a prediction model in pregnancy care, including predicted outcomes that caused the most maternal deaths, followed by artificial (shallow) neural networks, support vector machines, and deep neural networks. These corresponded to a systematic review and meta-analysis [13] that showed a similar majority of machine learning algorithms in medicine, except that the study reported classification and regression trees to be the second most often used algorithms (30/71, 42%). All models within eligible studies in that review were included instead of only choosing the best one within each study. Using the same summary measures as we did, the aforementioned review demonstrated that non-LR models from low ROB studies did not outperform LR models. A decision tree showed a difference of logit AUROCs of -0.34 (95% CI -0.65 to -0.04 ; $k=16$) compared with an LR. The review selected 125 eligible studies of 927 candidates from one database. Between-study heterogeneity was not described in that review.

Similar to a previous study [13], a systematic review and meta-analysis did not consider LR as a machine learning algorithm and only compared the predictive performances of non-LR algorithms [179]. This study compared machine learning models to predict any outcomes using routinely collected intensive care unit data. Most of the algorithms were artificial neural networks (72/169, 42.6%), support vector machines (40/169, 23.7%), and decision trees (35/169, 20.7%). However, since 2015, most of the algorithms were support vector machines (37/125, 29.6%) and random forests (72/169, 42.6%). These corresponded to the majority of machine learning algorithms for pregnancy care in our systematic review.

We hold a particular assumption to determine whether interaction of predictors and outcome may be best predicted by a prediction algorithm. If the same predictors and outcomes were used by the best prediction algorithm applied in either non-LR or LR models but not used by the other outcomes in this meta-analysis, then the prediction algorithm may be the best for the pregnancy outcome using those predictors. To predict preterm delivery with predictors that included EHG in either non-LR or LR models [115,169], the random forest outperformed the LR algorithm. Similar to this model in terms of using biomedical signals, gradient boosting also outperformed LR using CTG [142], but none of the LR counterparts used the same predictor. Other predictors were used across outcomes and algorithms (LR or non-LR). These included maternal demographics, lifestyle, medical or obstetric histories, clinical examinations, ultrasound measures, routine laboratory tests, biomarkers, and medication or procedures. Family histories were used in the LR models to predict gestational diabetes in this meta-analysis but were not used by the gradient boosting model (the non-LR counterpart). Therefore, we could not find a convincing pattern of predictors with respect to the best algorithms for each of the other pregnancy outcomes beyond preterm delivery.

Interestingly, the random forest significantly outperformed the LR for almost all of the pregnancy outcomes included in the meta-analysis. Although the gradient boosting algorithm significantly outperformed the LR for CS and gestational diabetes instead of the random forest, gradient boosting also

uses multiple decision trees as in the random forest. For ongoing pregnancy predictions in *in vitro* fertilization, a random forest model from low ROB studies also showed the largest difference in logit AUROCs outperforming LR (1.22, 95% CI -0.03 to 2.48) compared with other non-LR algorithms. For predicting vaginal delivery after a CS, a non-LR algorithm, particularly an artificial neural network in our meta-analysis, did not significantly outperform LR.

Comparing differences in AUROCs and focusing on multiple prediction algorithms, a study with individual participant data also compared LR and non-LR algorithms, particularly Poisson regression, random forest, gradient boosting, and an ensemble of a random forest with either LR or support vector machine [180]. Several models were developed to predict all-cause readmissions in patients with heart failure within 30 and 180 days. The random forest significantly outperformed the LR (0.601, 95% CI 0.594-0.607 vs 0.533, 95% CI 0.527-0.538) for 30-day readmissions. Similar to the random forest, the gradient boosting algorithm (0.613, 95% CI 0.607-0.618) also significantly outperformed the LR. The predictors consisted of medical histories and routine laboratory tests.

Massive evaluation of 179 algorithms from 17 machine learning families was conducted using 121 data sets [181]. The best results were achieved using random forests. In our review, there were 13 studies in which the best models applied either a random forest [106,108,115,134,144,147,155,158] or gradient boosting [127,140,142,157,160]. Random forests used multiple subsets of all samples and predictors randomly with replacement to grow multiple parallel decision trees [182]. Although gradient boosting also uses multiple decision trees, the advantages of random forest over gradient boosting are robust to noise and overfitting [183]. Meanwhile, gradient boosting randomly uses multiple subsets of all samples without replacement to sequentially construct additive regression models [184]. The advantages of gradient boosting over random forests are state-of-the-art predictive performance on tabular data and the customizability of loss of function [181,185]. Hence, several gradient boosting algorithms were developed, and some studies in our review applied these algorithms. To predict gestational diabetes, Artzi et al [157] applied LightGBM, a scalable gradient boosting machine. This algorithm was optimized to speed up the training process by up to 20-fold with the same accuracy [186]. Another gradient boosting system (ie, XGBoost) [187] was applied in a study by Qiu et al [140] to predict live births after *in vitro* fertilization. This study was not included in our meta-analysis because there was an insufficient number of LR [61,69] and gradient boosting [140] algorithms for predicting live births.

Of the pregnancy outcomes predicted by non-LR algorithms in this review, most outcomes were *in vitro* fertilization, premature birth, and fetal distress, possibly because of several reasons. Using keywords of “machine learning IVF” in MEDLINE, we found a review paper from 2011 call for a need for artificial intelligence in *in vitro* fertilization [188]. Only one machine learning study for *in vitro* fertilization was found before that study [189]. All machine learning studies for *in vitro* fertilization were published after the review paper, and most studies were identified within 2093 records in our review

[110,140,150,153,158,190-193]. As prediction for *in vitro* fertilization had already begun by 1989 [194], the machine learning prediction (non-LR) possibly arose because of the 2011 review. Meanwhile, for machine learning predictions of premature birth, fetal distress, and CS, many data sets (25/43, 58%) were secondary instead of primarily collected data. The secondary data sets consisted of predictors and outcomes of EHG and preterm delivery [174] (7/25, 28%), CTG, and acidotic blood pH of the umbilical artery [175] (4/25, 16%), CTG and CS [175] (2/25, 8%), CTG and acidotic blood pH of the umbilical artery [195] (3/25, 12%), EHG and preterm delivery [196] (2/25, 8%), and others (7/25, 28%). This implied that shared data sets drive more machine learning predictions compared with self-collected data sets. This indicates that the increase in publicly available data has driven progress in machine learning applications in health care [197].

For non-LR algorithms, the lack of shared data sets may have been the reason for few prediction studies for maternal outcomes compared with those for neonatal outcomes in this systematic review. Meanwhile, pregnancy-induced hypertension was found in pregnant women of newborns who were born prematurely [198]. Prematurity was also associated with maternal sepsis (OR 2.81, 95% CI 1.99-3.96), including antenatal cases [178]. Therefore, more shared data sets for maternal outcomes are needed. Future studies using machine learning algorithms should develop more prediction models for maternal outcomes in pregnancy care.

In addition, sample sizes of data sets for model development may contribute to bias in predictive performance. For example, in our meta-analysis, prediction models of ongoing pregnancy in *in vitro* fertilization had point estimates of AUROCs ranging from 0.575 to 0.982. These were developed using a support vector machine [110], artificial neural networks [132,136,170], random forests [134,158], deep neural networks [148,153], naïve Bayes algorithms [126,135,150], and LRs [73,78,99,158,170]. Compared with a recent systematic review focusing on prediction for *in vitro* fertilization [143,194], the range of AUROCs was wider than that of the previous review. The AUROCs ranged from 0.59 to 0.775 without non-LR machine learning predictions. A previous review also reported that the sample sizes ranged from 110 to 288,161 instances, whereas our review found that studies that applied non-LR algorithms alone or combined with LR had sample sizes ranging from only 46 [158] to 8836 [148] instances. Meanwhile, non-LR machine learning algorithms require larger sample sizes relative to the number of candidate predictors [199].

A meta-analysis of multivariable LR was also previously conducted for premature birth from 4 studies [200]. In a previous systematic review, the 2 highest AUROCs were 0.67 (95% CI 0.62-0.72; low ROB) and 0.64 (95% CI 0.60-0.68; high ROB). Non-LR models of premature birth in our systematic review showed AUROCs of 0.75 (95% CI 0.67-0.82) [121] and 0.911 (95% CI 0.862-0.96) [130], but these models were developed from high ROB studies. The other models only reported point estimates of the AUROC, which were a minimum of 0.6 by a decision tree [156] and a maximum of 0.991 by a support vector machine [143].

Minimizing the bias of model performance is the first thing to consider when developing a clinical prediction model. Several concerns need to be addressed when developing prognostic machine learning predictions of pregnancy care. In our review, most studies had problems of insufficient EPV (either LR and non-LR studies), single imputation (mostly LR studies), and no assessment of calibration (mostly non-LR studies). This may expose the studies to high ROB [21]. The overestimation of the predictive performance is larger, with fewer participants with events relative to the number of predictor candidates, as described in the PROBAST guidelines. Most ROB in our review were contributed by the domain of analysis, and answers to which the EPV signaling question mostly led studies to high ROB assessment results. Insufficient EPV mean that the study developed a model using a data set with a sample size that was less than the minimum requirement for events relative to the number of predictors. LR only requires 20 EPV, whereas non-LR algorithms require 50 to 200 EPV. Meanwhile, single imputation means that missing values are imputed by any random value, mean, median, mode, or one-time regression. Multiple imputations are more recommended than single imputations, in which the preferred method is multiple equations by chained equations. For the assessment of calibration, a study should show the incidence of events (true probability) for each subset of samples that belongs to the same range of predicted probability by the model. We recommend these based on PROBAST guidelines and other guidelines for machine learning prognostic predictions in pregnancy care [15,21].

Strengths and Limitations

Our systematic review and meta-analysis will allow investigators or clinicians in pregnancy care to consider whether trying multiple machine learning models provides benefit to their studies. If more prediction models are needed for the outcomes with more specific problems or subpopulations, then predictive modeling may consider comparisons of LR and non-LR algorithms for specific outcomes that were compared in our meta-analysis. We also reported heterogeneity measures to interpret the predictive performances of algorithms across studies.

However, the diverse populations and hyperparameters caused substantial heterogeneity of predictive performance in our meta-analysis. Future meta-analyses will be needed if more machine learning models are developed for the same outcome using the same algorithm. However, we tried to minimize the heterogeneity by excluding several studies to ensure more homogenous outcome definitions and normally distributed AUROCs. We also applied random effects modeling as recommended [172].

Conclusions

Prediction models using non-LR machine learning algorithms significantly outperformed those using LR for several pregnancy outcomes. These non-LR algorithms were random forests for predicting preterm delivery and pre-eclampsia and gradient boosting for predicting CS and gestational diabetes. In our review, studies that developed models using these algorithms had low ROB. For predicting ongoing pregnancy in *in vitro* fertilization, non-LR algorithms did not significantly outperform

LR. Prediction models using non-LR algorithms for vaginal birth after a CS significantly underperformed LR, but the study with the non-LR algorithm had a high ROB.

On the basis of our meta-analysis, we recommend comparing multiple machine learning models, which include both LR and non-LR algorithms, to develop a prediction model. In our

systematic review, we also found that many studies had high ROB in the domain of analysis. In this domain, many studies lacked EPV to develop a prediction model. Hence, we also recommend the future development of a prediction model to pursue standard EPV and other standards based on guidelines to minimize ROB.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Details on forest plots, search filter, eligibility criteria, study selection, list of reviewed studies, risk of bias assessment, signaling questions and the answers, predictive performance and sample size, R code for meta-analysis, and records of studies.

[[DOCX File, 2653 KB-Multimedia Appendix 1](#)]

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Abbreviations

AUROC: area under the receiver operating characteristic curve

CHARMS: checklist for critical appraisal and data extraction for systematic reviews of prediction modeling studies

CS: cesarean section

CTG: cardiotocogram

EHG: electrohysterogram

EPV: events per variable

IRR: incidence rate ratio

LR: logistic regression

MeSH: Medical Subject Heading

MLP-BIOM: guidelines for developing and reporting machine learning predictive models in biomedical research

OR: odds ratio

PI: prediction interval

PICOTS: population, index, comparator, outcomes, timing, and setting

PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses

PROBAST: prediction model risk of bias assessment tool

ROB: risk of bias

ROC: receiver operating characteristic

TRIPOD: transparent reporting of a multivariable prediction model for individual prognosis or diagnosis

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