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Meta-Analysis of Predictive Modelling Approaches and Systematic Reviews for Maternal Healthcare Outcomes

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Abstract - **Enhancing parental care is of utmost importance in ensuring the well-being of pregnant women throughout their pregnancy and childbirth journey. Although there have been significant advancements in this area, persistent challenges such as infections, hemorrhage, hypertension, unsafe abortions, and other concerns remain. Prioritizing maternal health could greatly reduce mortality rates and promote safer pregnancies. This meta-analysis assesses research methodologies in maternal healthcare outcomes, evaluating their strengths and weaknesses. We also explore the prevalence of systematic reviews in maternal health to enhance healthcare outcomes. We examined five major databases—Google Scholar, PubMed, Elsevier, PLOS, and BMC—encompassing descriptive and computational research on maternal outcomes between 2000 and 2021. Our search terms included predicting, modeling, maternal, outcome, healthcare forecasting, demonstrating, consequence, diagnosis, machine learning, mathematical, and statistical. Forty-four papers related to maternal outcomes were reviewed. Google Scholar yielded 50 articles (46.30%), PubMed 33 articles (31.48%), Elsevier 12 articles (11.11%), BMC nine articles (9.26%), and PLOS two articles (1.85%). Our findings highlight a high awareness of maternal outcome prevalence. Multiple factors contribute to maternal risk, including maternal education, economic circumstances, financial constraints, and access to antenatal care. Therefore, this work advocates for the adoption of additional methods and mathematical models to predict maternal outcomes, ultimately improving maternal healthcare.**
Keywords: **Maternal Health, Predictive Modeling, Healthcare Outcomes, Systematic Review, Pregnancy**

I. INTRODUCTION

Maternal healthcare is extremely important for women of childbearing age and requires the unwavering attention and efforts of both governmental and non-governmental organizations. The primary objective is to ensure that women receive comprehensive care throughout pregnancy, childbirth, and child-rearing phases. Prioritizing maternal health is vital in addressing the alarming reality of hundreds of thousands of women losing their lives annually due to childbirth-related complications. Unfortunately, many low- and middle-income countries continue to struggle with persistently high maternal mortality rates, with Nigeria being a significant contributor to this global burden. The Maternal Mortality Ratio (MMR) in Nigeria alone stands at an overwhelming 814 per hundred thousand live births, highlighting the pressing need for continuous efforts to improve maternal healthcare [1], [2].

Maternal mortality poses a significant concern and is influenced by a multitude of factors, including risky behaviours exhibited by expectant mothers [3], [4], their socio-economic status [7], [8], and inadequate antenatal care. It is recommended that every pregnant woman undergo at least four antenatal check-ups, with additional visits as needed based on circumstances and requirements. Unfortunately, some women begin their antenatal care later than recommended, which can increase the risk of complications and maternal mortality.

Notably, some women opt to start antenatal care late, as highlighted by Tola *et al.,* [9], which revealed that a significant proportion of women commence antenatal care later in their pregnancies. Additionally, Alene et al. [10] found low early reproductive care attendance among women of childbearing age, underscoring the importance of early engagement with proper antenatal care. Early engagement with prenatal care can substantially manage and mitigate risk factors that could negatively impact pregnancy outcomes [11], [12], [13], such as maternal mortality. Causes of maternal death may include conditions such as postpartum bleeding, eclampsia, obstruction, sepsis, and others. However, many emerging economies may lack satisfactory care and contraception, leaving pregnant women with limited access to skilled labour and urgent care [16], [17]. Statistical approaches such as Poisson regression, descriptive, and correlational surveys have been implemented to address maternal fatality [19], [20], [21]. Research has provided clear evidence of variations in the causes of maternal mortality among women of childbearing age, prompting the consideration of alternative approaches. Consequently, one of the pivotal interventions for enhancing maternal health outcomes involves integrating multidisciplinary methods to address health issues in women with high-risk co-morbidities during preconception care, pregnancy, post-delivery, and beyond.

Presently, novel computational approaches are being proposed to assist healthcare professionals in addressing maternal outcome-related challenges, diverging from conventional methods. For instance, Nishtala *et al.,* [22] employed an artificial intelligence approach to enhance maternal health outcomes by constructing robust deep-learning models for predicting short- and long-term dropout risks. Other studies have also advocated for the promotion of predictive modeling in maternal outcomes, emphasizing its critical role in providing valuable and widely utilized knowledge [22], [24].

The following questions guide the research: RQ1 explores the scope and variety of methodologies employed in maternal healthcare outcomes research, shedding light on diverse approaches within the field. RQ2 delves into the prevalent utilization of descriptive and computational tools, identifying those most commonly used for predicting maternal healthcare outcomes. In line with RQ3, we investigate the extent of systematic reviews conducted within the maternal health domain, offering insights into the breadth of research in this area and highlighting key findings. RQ4 involves identifying pivotal related works and research articles that significantly contribute to our understanding of maternal healthcare outcomes, providing a comprehensive overview of the existing knowledge landscape in this field.

This study aims to achieve several objectives, including evaluating the methodologies employed in maternal health outcome research, analyzing the strengths and weaknesses of methodologies utilized by different researchers, assessing the extent of systematic reviews conducted in the field of maternal health, and investigating the body of work related to maternal outcomes. As a result, this work is organized into the following sections: Section Two will focus on "Materials and Methods," Section Three will present the "Results," Section Four will delve into the "Conclusion," and Section Five will offer "Recommendations."

II. MATERIALS AND METHODS

A systematic literature review (SLR) can be a valuable tool for gaining a deeper understanding of specific subjects, such as maternal outcomes. It can help to establish a solid foundation of knowledge and identify any gaps that require further investigation. To ensure that an SLR is effective, it is important to consider several critical elements, such as research methodology, search strategy, information sources, study selection, data collection procedures, quality assessment, and data synthesis. By utilizing these essential components, you can ensure that the review is comprehensive and provides valuable insights [26]–[28].

A. Study Design, Search String Strategy and Information Sources

Our inclusion and exclusion criteria focused solely on studies that provide guidance on the methodology of conducting a literature review on maternal outcomes. Our search strategy involved four key steps: constructing search terms by identifying major keywords, determining synonyms or alternate words for those keywords, establishing exclusion criteria to eliminate irrelevant studies during the search, and applying Boolean operators to construct the search term. You can find a summary of each step in the Table I.

Our selection process involved sourcing peer-reviewed articles from databases, including Google Scholar, PubMed, Elsevier, PLOS, and BMC, as detailed in Table I. We specifically focused on predictive modelling for maternal health outcomes, utilizing a query phrase constructed as "Results for (d)," which became the definitive search term for this study. Our inclusion criteria encompassed journal articles, book chapters, books, and conference articles.

TABLE I CONSTRUCT SEARCH TERMS BY IDENTIFYING MAJOR KEYWORDS

Exploration criteria through identification of primary keywords	
Results for (a)	Predicting, Modelling, Maternal, Outcome, healthcare
Results for (b)	Forecasting, Demonstrating, Motherly , consequence, Diagnosis, Machine Learning, Mathematical, Statistical
Results for (c)	Budgeting, Animal, Drug, Vaccines, Children
Results for (d)	Predicting[All Fields] AND Modelling [All Fields] ("mothers"[MeSH Terms] OR "mothers"[All Fields] OR "maternal" [All Fields]) AND Outcome [All Fields]

B. Literature Selection and Data Evaluation Process for Inclusion

In this study, we followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, as outlined by Selcuk [29], and Swartz [30]. PRISMA aids in illustrating the progression of information selection across various stages in a systematic review. The flowchart shows identified records, included and excluded, with exclusion reasons. The papers included in our study were chosen based on their relevance to methods for predicting maternal health outcomes. The PRISMA flowchart for selection is shown in Fig. 1.

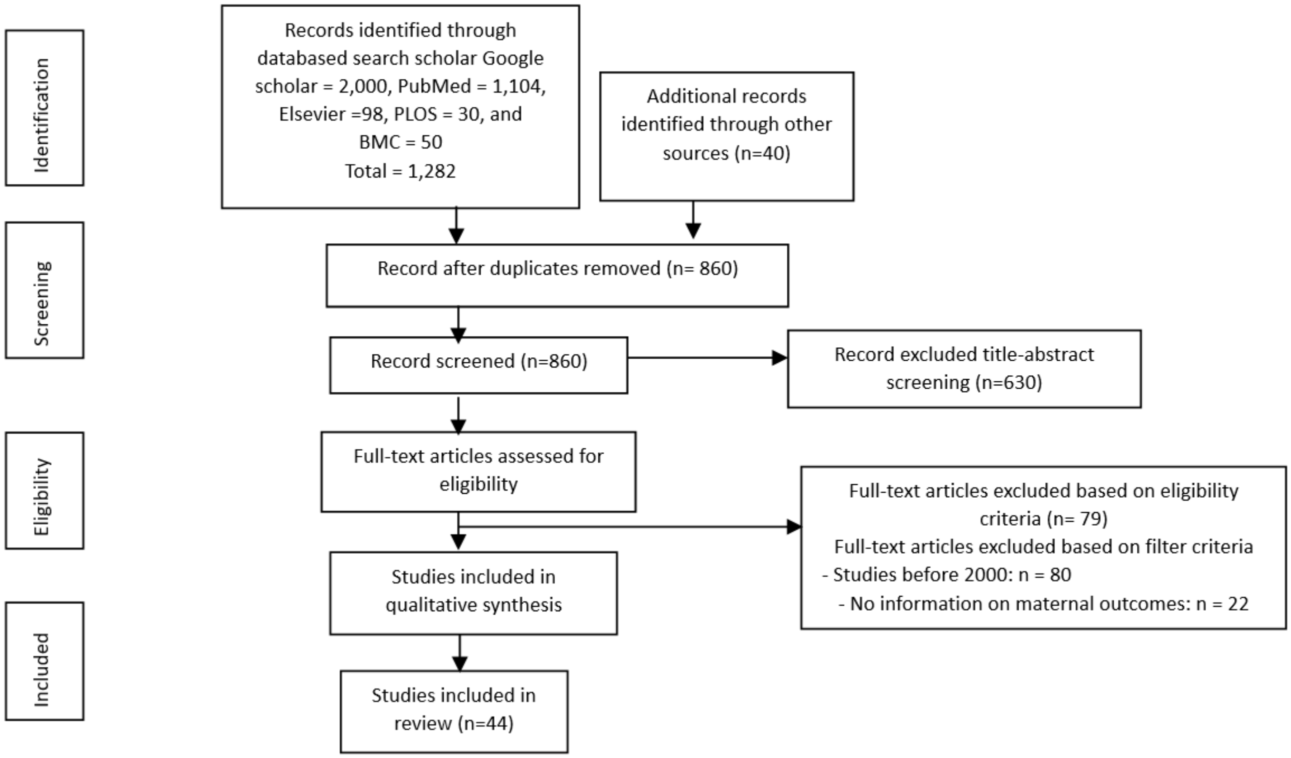

Fig. 1 Selection process for this systematic review (PRISMA flowchart)

Thus, the search terms include maternal health, computational, mathematical, statistical, soft computing, fuzzy logic, neural network and Probability.

C. Exclusion Measures

In this work we considered six databases which were Google scholar, PubMed, Elsevier, PLOS and BMC from 2000-2021. Thus, non-native speaker publications in English were not excluded. Hence studies were excluded only if they employed the following

1. Experiments/learning procedures
2. Incomplete/Inappropriate study design
3. Paternal predictions/modelling
4. Non-human/animal study

D. Choosing Primary Sources

The initial phase of crucial source selection involved identifying relevant studies centred on the specified search term and checking if their keywords aligned with the research focus. Then, the selection process assessed the quality of publications to minimize bias. Publication quality was determined by various criteria, including whether the study focused on maternal outcomes, used computational prediction methods, and focused mainly on maternal-related aspects. The titles and abstracts of the studies were considered during this selection process.

In addition, detailed data extraction from each publication included authorship, publication year, research problem areas, objectives, methodology, strengths, limitations, and the country where the research was conducted. These data were carefully compiled in Table I within Section 2. It is essential to emphasize that the ultimate selection of primary sources from the designated papers necessitated a thorough reading of the complete papers, aiming for a comprehensive understanding that extended beyond mere abstracts and titles.

Utilizing the PICO (Patient, Intervention, Comparison, Outcomes) framework, this study focused on the following components: the patient/population encompassed expectant mothers, pregnant women, and recipients of maternal healthcare. The intervention involved adopting predictive modelling approaches, computational and statistical methods, and machine learning techniques. The research entailed a comparative analysis of different modelling methods, a contrast between descriptive and computational tools, and an evaluation of systematic reviews detailed on page 5 and 6. The outcome assessment encompassed maternal healthcare outcomes, prevalence, and predictive accuracy, presented in Tables II, and III. Furthermore, the study aimed to identify contributing factors and trends depicted in Fig. 2, 3, 4, and 5.

III. RESULTS ON LITERATURE SEARCH

A. Procedure Search and Results

As illustrated in Fig. 1, our search using predefined terms yielded 1,282 papers from relevant sources. We conducted manual checks to eliminate duplicates, resulting in 860 unique works for initial review. Subsequently, we evaluated titles and abstracts against our exclusion criteria, excluding

630 papers, the same criteria were applied to the full-text articles comprising 230 manuscripts. Among these, 79 articles were excluded based on eligibility criteria, 81 were excluded for being published before 2000, and 22 were excluded for lacking information related to maternal outcomes. These exclusions culminated in a total of 182 articles remaining. The final refinement of the paper selection involved a qualitative synthesis, with 48 systematic reviews initially considered. After further evaluation, 44 papers were retained for the present study.

B. Study Characteristics

Out of the 44 works incorporated into this systematic review, the papers were categorized into those published in English and non-English articles. We identified studies conducted in various countries, including the USA (7), Nigeria (11), India (5), England (4), Uganda (1), Tunisia (1), Korea (1), China (1), South Asia (2), Canada (2), Saudi Arabia (1), Portugal (3), Malaysia (1), South Africa (1), Asia and Africa (1), China (1), and Brazil (1). We also encountered six systematic review studies, although they are not part of the total works considered in this research. It merits mentioning that our focus was primarily on works conducted between 2000 and 2021, employing both descriptive and computational methods. Among the 44 research works, 21 pertained to maternal outcomes using descriptive methods, while 23 utilized computational approaches.

C. Prevalence of Works Done Towards Maternal Outcome

Various methods have been developed to predict maternal outcomes, including descriptive and computational approaches. Descriptive statistics summarize data in a way that makes it valuable and meaningful, providing insights into selected variables within a dataset and highlighting potential relationships between them. For instance, Jido's [31] study investigated eclampsia incidence and its impact on maternal and fetal outcomes, highlighting substantial risks to maternal and perinatal health. Also, suggested the importance of improving antenatal screening and using magnesium sulphate to alleviate convulsions, which can help reduce the incidence of associated morbidity and mortality.

Similarly, Liou *et al.*'s [32] explored the effects of stress experienced by mothers during pregnancy on preterm birth and low birth weight; moreover, highlighted the significance of implementing psychological evaluations for timely detection and intervention in order to mitigate adverse birth outcomes. It underscores the ongoing significance of investigating long-term maternal outcomes and the potential vertical transmission of COVID-19 from mothers to their unborn children. This was also noted in recent studies by Al-Matary *et al.,* [33], Choi *et al.,* [34], and among others.

Computational methods, also known as predictive analytics methods, have the ability to improve performance based on expert knowledge. Machine learning is a major branch of Artificial Intelligence (AI) that can mimic human intelligence with machines. Maternal outcomes are an important aspect of medicine, primarily associated with obstetric emergencies.

Dawodi, *et al.,* [35] proposed the use of ICT, pattern discovery, and machine learning algorithms to predict the risk level of maternal issues for women within productive age, with the aim of reducing maternal mortality and morbidity. One possible way of managing maternal outcomes is through the introduction of models that can reduce risk [36], [37]). In addition to the review, we considered a few recent papers that offer helpful insights into the methods used to predict maternal outcomes. It is of great importance to review works carried out adopting statistical, computational and systematic review methods used to predict maternal outcomes.

D. Statistical Analysis Assessment

Several maternal and perinatal health studies have provided valuable insights across different regions. Akinkugbe *et al.,* [39] found smoking during pregnancy adversely affected children's oral health using log-binomial regression in the US. Bakhsh, *et al.,* [40] used descriptive analysis in Saudi Arabia to highlight maternal diabetes as a significant risk factor for amniotic fluid disorders. Gwon, *et al.,* [41] found fluctuations in cotinine levels among smokers during pregnancy stages in the US using descriptive and repeated-measures ANOVA. Ashcroft, *et al.,* [42] found women with cystic fibrosis in the UK are at an elevated risk of preterm delivery and having smaller infants.

Delahoy, *et al.,* [43] studied birth outcomes among COVID-19 hospitalized pregnant women in the US and recommended precautionary measures. Nwogu, *et al.,* [44] investigated maternal homocysteine concentrations in Nigeria. Okonofua *et al.,* [45] evaluated EMOC knowledge and skills among providers in Nigeria. Deepak, *et al.,*[46] assessed maternal healthcare utilization in urban slums of India, highlighting the influence of socio-cultural and environmental factors.

Namatovu [47] devised an Antenatal Care System (ACS) in Uganda, while Lin *et al.,* [48] scrutinized the pervasiveness of anemia during pregnancy in China, proposing interventions such as complimentary medical services and targeted iron supplementation. Authors like Akhtar *et al.,* [49] in Pakistan, Ragolane, [50] in South Africa, and Fagbamigbe and Idemudia [51] in Nigeria delved into factors influencing antenatal care utilization, underscoring awareness and personal and provider-related determinants.

Additionally, studies by Wiebe, *et al.,* [52] in Canada, Maughan, *et al.,*[53] in England, and Adeoye, *et al.,* [54] in Nigeria scrutinized prenatal tobacco exposure, behavioural patterns, and near-miss events, respectively, utilizing diverse statistical analyses. Moreover, Ekure *et al.,* [55] and Omo-Aghoja, *et al.,* [56] in Nigeria, Goffman, *et al.,* [57] in the United States, and Lydon-Rochelle, *et al.,* [58] in the United States contributed to understanding perinatal mortality, maternal mortality, and maternal rehospitalization, respectively, employing sophisticated statistical methodologies. These collective efforts advance our comprehension of global maternal and perinatal health outcomes, thereby guiding the formulation of impactful public health interventions and policies.

E. Overview on Computational Procedures

The use of computational methods in maternal and perinatal health research has significantly improved predictive modeling, classification, and data analysis. In this article, we summarize the contributions of different authors from various regions. Nishtala, *et al.,* [59] from India employed random forest, convolutional neural disengagement predictor, and recurrent neural disengagement predictor to study obstetric factors associated with anaemia during pregnancy. Shastri and Mansotra [60], also from India, used Bayesian TAN and Naïve Bayes to classify maternal healthcare data and recommended awareness programs for institutional deliveries.

Ide, *et al.,* [61] developed a maternal mortality monitoring system in Nigeria using Naïve Bayes and highlighted the increasing maternal mortality rate. They suggested alternative classification algorithms as a way to address this issue. Kour, *et al.,* [62], also from India, focused on developing a classification model for maternal healthcare data using Naïve Bayes. Although they achieved high accuracy, they proposed the introduction of additional probabilistic classifiers for comprehensive analysis. In Nigeria, Egejuru, *et al.,* [63] proposed a predictive model for neonatal jaundice severity using deep learning techniques. They emphasized the need to clarify associated variables. Jhee, *et al.,* [64] from the United States developed a predictive model for late-onset preeclampsia using various algorithms. They suggested using unsupervised algorithms to compare maternal factors.

In a study conducted in Tunisia, Zaineb, *et al.,* [65] used multiple machine-learning techniques to predict short-term mortality in neonatal intensive care units. However, they also highlighted limitations in variable selection and study objectives. In the United States, Masino, *et al.,* [66] focused on early sepsis detection in neonates using machine learning models but did not specify a suitable predictive model. Meanwhile, Ting, *et al.,* [67] applied deep learning in ophthalmology in Malaysia and emphasized the importance of obtaining patient consent and feature extraction. In Nigeria, Idowu [68] developed a model for predicting maternal mortality using supervised machine learning algorithms and underscored the need for larger datasets and specified data collection instruments. In Portugal, Pereira, *et al.,* [69] predicted pre-triage waiting times in maternity emergency care using various classifiers and stressed the importance of incorporating waiting time considerations into decision support systems. In Ethiopia, Sahle [70] used decision trees and rule induction to explore factors influencing postnatal care visits, suggesting integrating economic, demographic, social, and genetic factors for better decision-making.

In India, Maitra and Kuntagod [71] developed a mobile application for maternal health workers, but the study lacked specificity on prevalent risks. Finally, in another study conducted in India, Chowdhury, *et al.,* [72] employed artificial neural networks to predict neonatal disease diagnosis and highlighted the need for mathematical model generation and fuzzy logic introduction. In conclusion, computational approaches are valuable tools for predictive modelling and data analysis in maternal and perinatal health, but further refinement and consideration of critical variables are necessary to optimize their utility and accuracy.

F. Systematic Review Summary

Davidson and Boland [73] conducted a systematic review on informatics research to improve pregnancy outcomes. They suggested using machine learning and artificial intelligence techniques to enhance pregnancy outcomes and highlighted the need for future research to focus on less-explored pregnancy domains. Sufriyana, *et al.,* [74] investigated predictive capabilities in pregnancy care and found that random forest and gradient boosting yielded superior results compared to logistic regression. Saturno-Hernández, *et al.,* [75] aimed to improve maternal and neonatal quality care through systematic review. Lassi, *et al.,* [76] evaluated human resources for health interventions on maternal health outcomes delivered by skilled birth attendants. Aitken, *et al.,* [77] compiled a synthesis of research examining the effects of paid maternity leave on maternal health. Simkhada, *et al.,* [78] analysed factors influencing the utilization of antenatal care in developing countries.

In summary, studies on maternal healthcare outcomes using statistical, computational, and systematic approaches have provided valuable insights. Fig. 2 visually represents the various tools used to predict maternal health outcomes, contributing to a holistic understanding of the progress in this crucial area of healthcare. Fig. 2 shows scholars' efforts in addressing maternal health concerns, including D'Alton, *et al.,* [79] recommendation to use predictive tools. These tools proactively address issues, optimize performance, and enhance collaboration across fields. Table II, the Meta-summary table, provides further insight into improving maternal health outcomes.

1. Ob1. Level of Methodologies Adopted Towards the Maternal Outcome

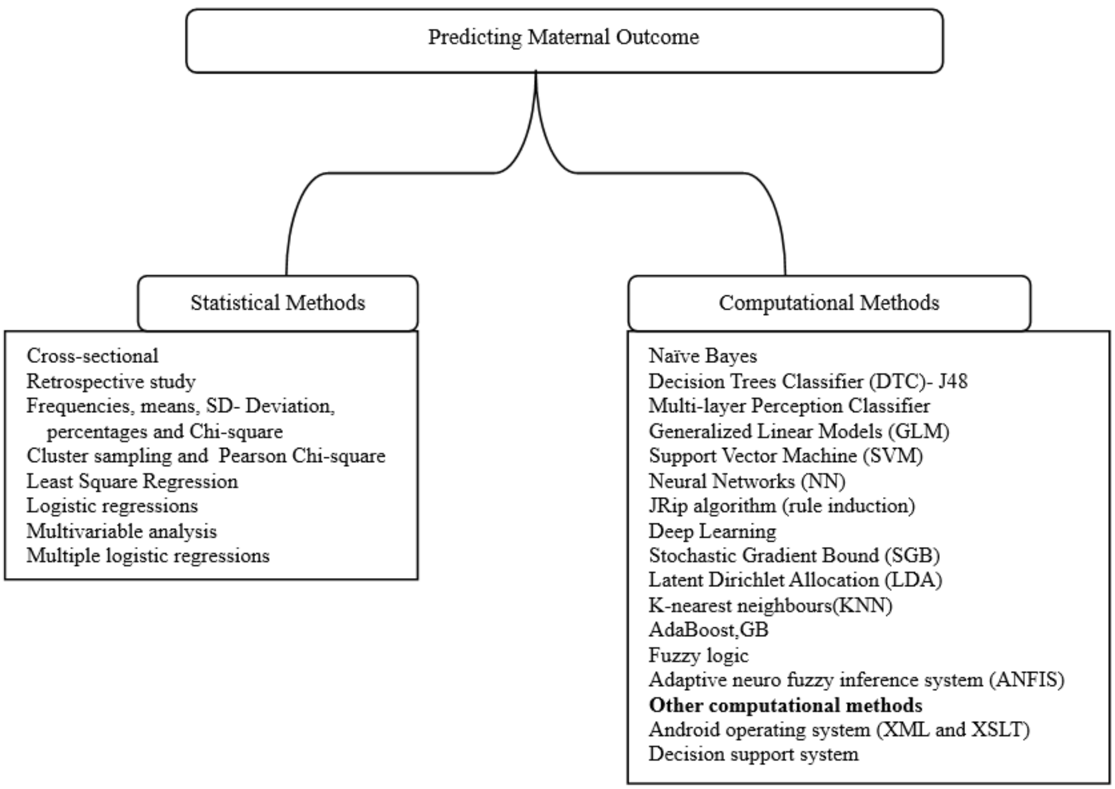

Fig. 2 Tools tailored towards predicting maternal outcome

TABLE II META SUMMARY OF METHODS USED TOWARDS MATERNAL HEALTH OUTCOME

Research Methods	Works	Number	Percent (%)
Statistical	(2013; 2018; 2021; 2020; 2021; 2018; 2020; 2011; 2015; 2007; 2021; 2018; 2000; 2018; 2021; 2020; 2019; 2010; 2017; 2015)	21	44.73
Computational	(2011; 2011; 2019; 2012; 2019; 2017; 2020, 2020; 2019; 2019; 2017; 2013; 2018; 2009; 2021; 2016; 2014; 2016; 2019; 2018; 2001; 2019; 2015; 2019)	23	55.35

Table II shows that statistical and computational methods have been widely employed in maternal health research. Statistical methods account for 44.73% of the research, while computational methods account for 55.35%. This trend is visually represented in Fig. 3. Fig. 3 shows that maternal outcomes research has increased since 2015, with significant activity in 2018 and 2019. Improving the health of women of childbearing age includes proper nutrition, early disease detection, and support for those with prior complications. Integrated approaches have been successful in improving maternal health services. However, fewer studies were conducted in other years, emphasizing the need for increased awareness among healthcare professionals and women of reproductive age.

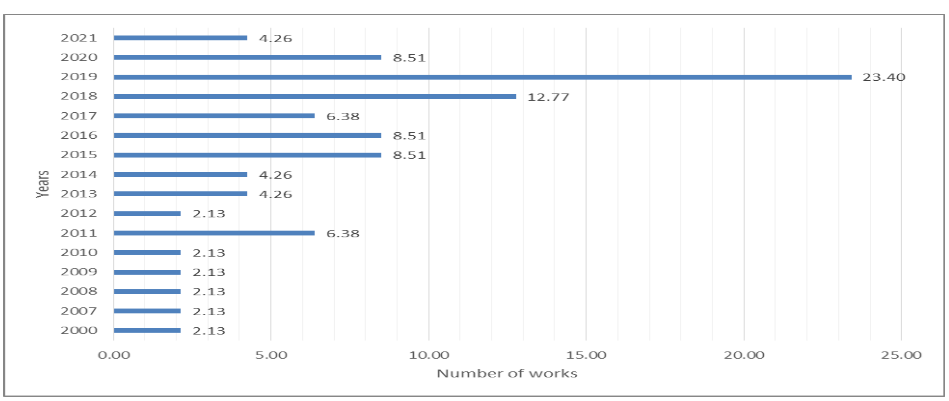

Fig. 3 Summary of works toward maternal outcome

2. Ob2. Frequent Descriptive and Computational Tools found for Prediction of Maternal Outcome

Our survey identified that statistical methods (such as, descriptive statistics, inferential approaches) and computational methods (machine learning algorithms) were commonly used for predicting maternal health outcomes. Various study designs and statistical modelling techniques were employed, providing a comprehensive toolkit for predicting maternal health outcomes.

3. Advantages and Limitations of Common Descriptive and Computational Approaches

a. Standard statistical tools like frequencies, means, standard deviation, percentages, and Chi-square statistics provide a comprehensive understanding of a subject Kaur [80] and Nick [81]. However, a sound statistical test is necessary to avoid distorted interpretations. Interpreting Chi-square statistics can be challenging in cases with large samples Bryant and Satorra, [43], ; Delahoy, *et al.,* [82]. Cross-sectional studies may not be optimal for establishing a link between exposure and outcome simultaneously. Alternative methods may offer better results. Furthermore, retrospective studies are prone to generating a substantial amount of missing data. However, these studies are cost-effective to conduct and can be valuable for investigating diseases with low incidence.
b. The Least Square Regression (LSR) method is valuable in statistical and computational approaches, particularly for linearly separable data, but it may suffer from noise susceptibility, overfitting, and the assumption of linearity between dependent and independent variables[83].
c. LR is a versatile method for binary classification, extending to multi-class tasks[84], yet it struggles with non-linear or high-dimensional data, leading to overtraining..
d. Multivariate analysis, as discussed by Lauth *et al.,* [85], explores correlations between dependent and independent variables, aiding both machine learning and descriptive statistics. However, its effectiveness relies on large datasets, and interpreting its outputs can be complex[85], [88].
e. Log-binomial regression, as emphasized by Williamson *et al.,* [88], facilitates adjusted relative risk calculations and binary outcome analysis. However, Karlsen *et al.,* [89] caution that it may not cover all research aspects, requiring additional considerations.
f. A longitudinal study, as noted by Smith *et al.,* [91], tracks variable trajectories over time, offering valuable insights into population development and changes. However, it requires a significant time investment [90]. Regarding computational methods, we focused on the commonly employed techniques, which will be elaborated upon in the following segments.
g. Naïve Bayes (NB) demands relatively small amounts of training data for test data estimation, leading to shorter training times. It offers ease of implementation and can handle both continuous and discrete data types. NB's performance is favourable in comparison to other models like logistic regression[64]. However, NB operates under the assumption that all attributes are mutually independent, which may not always hold in real-life scenarios where sets of predictors are not entirely independent [93].
h. Decision Trees Classifier (DTC)-J48 is proficient in classification tasks with minimal computational demands. It visually represents problem relationships and adeptly manages intricate scenarios concisely. However, DTC may face challenges involving continuous-valued attributes, data overfitting, mitigating poor attribute selections, and addressing missing attribute values[93].
i. The Multi-layer Perceptron Classifier (MLPC) employs multi-layer connections and offers a range of activation functions for handling non-linear scenarios. Its adaptive nature allows it to learn from the training data or initial experiences. However, MLPC may encounter challenges related to overfitting [95].
j. K-nearest neighbours (KNN) algorithm is a popular classification technique that predicts the value of a new query based on the classification of its neighbours. It has several notable attributes, such as power, simplicity, and non-parametric nature, and requires no training time. To use KNN, one must determine the number of neighbours, denoted as "k," and select the distance metric to be used, which can include Euclidean distance, Mahalanobis distance, and city-block distance. However, KNN's weakness lies in being a "lazy learner"; during the training period, it does not learn or derive discriminative functions from the training data [97].
k. AdaBoost and Gradient Boosting (GB) are two popular boosting algorithms used in modern machine learning. GB is a versatile algorithm that can be used to find approximate solutions to additive modeling problems. On the other hand, AdaBoost is specifically designed to enhance the performance of various machine learning algorithms, particularly when working with weak learners [98].
l. Fuzzy Logic (FL), as demonstrated in a study by[99], efficiently models non-linear systems and uncertainties by employing linguistic variables and membership functions to emulate human reasoning. Despite its advantage in result interpretation, FL may require additional input variables and measures, while the defuzzification process demands expert knowledge.
m. Support Vector Machine (SVM), as highlighted by Moreira *et al.,* [100], effectively tackles overfitting in linear learning models but encounters speed and size challenges during training and testing phases [101]. To improve performance, the study recommends integrating additional tools like Artificial Neural Networks (ANN).

n. Deep Learning has the advantage of being able to learn with minimal or no human intervention, which allows it to demonstrate adaptability to varying environments and effectively address various reflexive and cognitive challenges. However, it is worth noting that Deep Learning does have some limitations, particularly when it comes to object detection, human parts recognition, semantic boundaries, and segmentation [102], [103].

4. OB3. Level of Systematic Review Carried out towards Maternal Health

In this review, it becomes evident that only a handful of systematic reviews have been conducted on maternal health in various regions, including the USA [73], China[74], Mexico [75], Australia [77], the UK [78], Pakistan, and Canada [76]). The need for systematic reviews in this field is undeniable, as it plays a crucial role in advancing and advocating for the well-being of women in their childbearing years worldwide. Creating more awareness regarding maternal health is essential and pivotal in saving the lives of women at risk due to pregnancy and childbirth-related complications. We can significantly enhance women's overall well-being by imparting them the correct information and awareness. Systematic reviews help identify gaps within the subject area and provide a comprehensive understanding of the existing body of work, making them a valuable resource.

IV. RELATED WORKS FOR MATERNAL HEALTHCARE OUTCOMES

Maternal outcomes never fail to evoke a profound impact, regardless of whether the results are favourable or unfavourable. These maternal outcomes encompass various factors, such as the mode of delivery (caesarean or vaginal), pregnancy complications (arterial hypertension, pre-eclampsia, gestational diabetes, and hospitalization during pregnancy) as observed in studies by da Silva *et al.,* [104] and Roberts *et al.,* [105]. Miscarriage [106], preterm [107], full-term[86]stillbirth [104] and mortality[108]. In light of the frequency of these outcomes, numerous studies have been initiated to predict maternal health outcomes.

This section examines the prevalence of research focused on five specific sub-categories of maternal outcomes: miscarriage, preterm birth, full-term birth, stillbirth, and maternal mortality.

1. The studies on miscarriage encompass various approaches and methodologies to understand and predict miscarriage occurrences. Asri [109]compares clustering algorithms for real-time miscarriage prediction and suggests the effectiveness of Kmeans and bisecting Kmeans over Gaussian Mixture. Rana, *et al.,* [110] gave a report on a single patient suffering from first-trimester miscarriage associated with SARS-CoV-1, highlighting the need for comprehensive models. Sacinti *et al.,* [111] explore the impact of SARS-CoV-2 infection during the first trimester on miscarriage rates, revealing a 25% rise during the COVID-19 pandemic. Tissot and Pedebos [112] propose straightforward knowledge embedding methods to improve risk assessment of miscarriage during pregnancy, suggesting the incorporation of machine learning approaches for enhanced assessment. Ali *et al.,* [106]identify a potential link between recurrent miscarriage and adverse maternal outcomes, emphasizing the need for early pregnancy monitoring and improved care for at-risk pregnant women. Wilcox *et al.,* [113]examine the burden of miscarriage and its association with maternal age and pregnancy history, suggesting the potential benefits of conducting longitudinal studies and integrating machine learning tools for analysis. Finally, San Lazaro Campillo *et al.,* [114] assess shifts in the frequency, treatment, and consequences of hospitalizations for early miscarriages, emphasizing the importance of investigating factors influencing hospitalizations to enhance management and healthcare services for women during the fruitful age.
2. The studies on preterm birth prediction utilize a range of machine learning algorithms and methodologies to improve accuracy and early detection of high-risk pregnancies. Begum *et al.,* [115] develop a predictive system achieving high accuracy rates by considering various independent factors such as maternal weight, age, and previous preterm births, while recommending further exploration of deep learning methods. Włodarczyk *et al.,* [116] review multiple machine learning algorithms used for preterm birth prediction, highlighting challenges in obtaining ethics approval and suggesting the integration of deep learning for image-based datasets. Koivu and Sairanen [117], propose innovative risk models for predicting early stillbirth, late stillbirth, and preterm birth, emphasizing the potential for more accurate detection of high-risk pregnancies with the incorporation of biochemical and biophysical markers. Souza, *et al.,* [107] examine maternal and perinatal outcomes across different categories of preterm and full-term births, stressing the need for strategies to identify high-risk women and prevent adverse outcomes, with a recommendation to explore additional machine learning methods. Prema and Pushpalatha [118], identify risk factors for preterm birth, highlighting the robust predictive capability of SVM and the use of SMOTE to enhance prediction accuracy for imbalanced data, while emphasizing the importance of considering various risk factors and constructing models suitable for extensive datasets.
3. The studies on full-term pregnancies employ various machine learning algorithms and methodologies to address different aspects such as autism prediction, maternal and infant outcomes during COVID-19 infection, prediction of vaginal birth after cesarean deliveries, and exploration of social-emotional functioning in infants. Bahado-Singh, *et al.,* [119]investigate placental DNA methylation changes

for early prediction of autism, emphasizing the clinical significance for early diagnosis and intervention. Chen and Bai, [120]report on maternal and infant outcomes of full-term pregnancies during COVID-19 infection, highlighting no complications or evidence of mother-to-child transmission. Lipschuetz *et al.,* [121]focus on predicting vaginal birth after cesarean deliveries using machine learning, emphasizing personalized risk scores for decision-making and potential reduction in cesarean delivery rates. Moe *et al.,* [122] explore the precursors of social-emotional functioning in full-term infants, stressing the importance of awareness and early intervention for maternal postpartum depression.

4. The studies on stillbirth utilize machine learning approaches to predict stillbirth occurrences, rank contributing features, develop predictive models, establish case definitions, and introduce smoothness to quantify stillbirth risk. Khatibi, *et al.,* [123] employ decision trees, gradient boosting classifiers, logistic regression, random forests, and support vector machines to distinguish stillbirth occurrences before and during delivery, emphasizing relevant features such as the number of miscarriages, maternal age, and perinatal abnormality. Malacova, *et al.,* [124] develop predictive models for stillbirth using multiple machine learning classifiers, highlighting the potential for ensemble classifiers to improve prediction. Da Silva, *et al.,*[125] focus on establishing case definitions and guidelines for collecting data on stillbirth as an adverse event following immunization during pregnancy. Starling, *et al.,* [126] introduce smoothness to quantify stillbirth risk using Bayesian tree-based and Bayesian Additive, Regression Trees (BART) models, emphasizing the adoption of the tsBART model.
5. The studies on mortality utilize various statistical and computational methods, including logistic regression, machine learning models (such as decision trees, artificial neural networks, random forests, Naïve Bayes, bagged trees, boosting, and linear support vector machines), and early warning scores. Conde-Agudelo, *et al.,* [108] employ multiple logistic regression to demonstrate the increased risk of significant maternal morbidity and mortality in women with multiple gestations. Mboya *et al.,* [127] compare machine learning models with logistic regression to predict perinatal death, finding that machine learning models exhibit superior predictive ability. Manik *et al.,* [128] utilize decision trees and Naïve Bayes to classify maternal mortality, with decision trees outperforming Naïve Bayes. Paternina-Caicedo, et al[129] evaluate the effectiveness of early warning scores in predicting mortality for pregnant women admitted to the intensive care unit. Singha *et al.,* [130] develop a machine learning model trained on historical data to predict mortality, finding that logistic regression performs the best among the models tested.

Studies have used statistical analyses, machine learning algorithms, and computational approaches to predict outcomes related to maternal and perinatal health. The goal is to improve accuracy, early detection, and risk assessment for miscarriage, preterm birth, full-term pregnancies, stillbirth, and mortality. The studies aim to improve outcomes for mothers and babies worldwide.

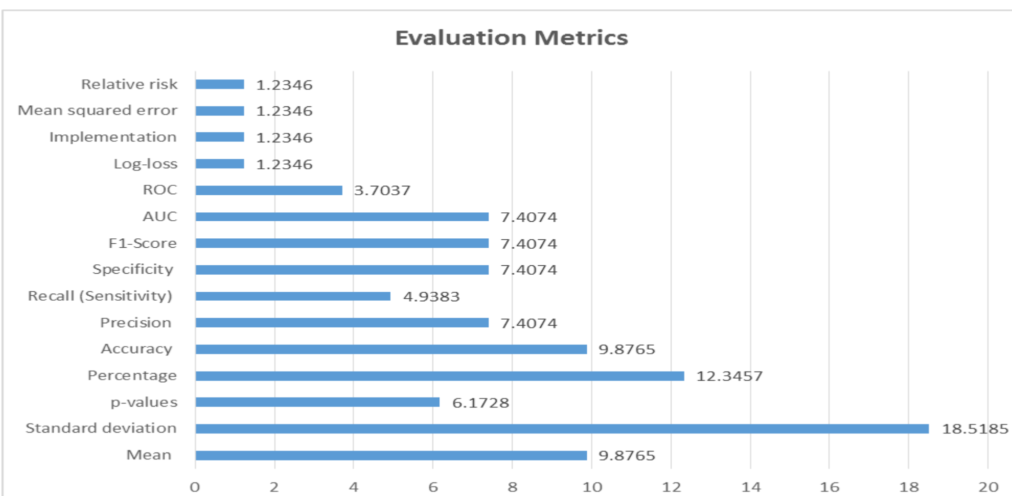

Fig. 3 Evaluation metrics

Fig. 4 presents the prevalence of various evaluation metrics, where Standard Deviation (SD) was found to be the most commonly utilized metric in our survey. SD is particularly useful in revealing data clustering around a mean value, considering positive and negative values and adhering to algebraic principles [87]. The percentage metric is another powerful means of comparing samples with varying observation numbers, as highlighted by Bhatia *et al.,* [132] and Gupta *et al.,* [133]. Mean and accuracy come next in terms of usage. Mean provides an overall overview of the data, especially when dealing with widely dispersed datasets, representing the typical value [134]. Accuracy, on the other hand, evaluates the correctness of results with minimal error and bias, ensuring precision and reliability in the information [135].

TABLE III QUALITATIVE DATA ANALYSIS FOR THE FIVE DATABASES USED IN THIS WORK

Sl.No.	Author(s)	Google scholar	PubMed	Elsevier	PLOS	BMC	Total (5/5)
1	Akinkugbe[39]	+	+	+	-	-	3/5
2	Bakhsh *et al.,*[40]	+	+	-	-	+	2/5
3	Gwon *et al.,*[41]	+	+	-	-	-	2/5
4	Ashcroft *et al.,*[42]	+	+	-	-	-	2/5
5	Delahoy *et al.,*[43]	+	+	-	-	-	2/5
6	Nwogu *et al,*[44]	+	+	-	-	+	3/5
7	Okonofua *et al.,*[45]	+	+	-	+	-	3/5
8	Deepak *et al.,*[46]	+	+	-	-	-	2/5
9	Namatovu[47]	+	-	-	-	-	1/5
10	Lin *et al.,*[48]	+	+	+	-	+	3/5
11	Akhtar *et al.,*[49]	+	+	-	-	-	2/5
12	Ragolane[50]	+	-	-	-	-	1/5
13	Fagbamigbe and Idemudia [51]	+	+	+	-	+	4/5
14	Wiebe *et al.,*[52]	+	+	-	-	-	2/5
15	Maughan *et al.,*[53]	+	+	-	-	-	2/5
16	Adeoye *et al.,* [54]	+	+	-	-	+	3/5
17	Ekure *et al.,*[55]	+	+	-	-	+	3/5
18	Omo-Aghoja *et al.,*[56]	+	+	-	-	-	2/5
19	Goffman *et al.,*[57]	+	+	-	-	+	2/5
20	Lydon-Rochelle *et al.,*[58]	+	+	-	-	-	2/5
21	Ndukwu Geraldine *et al.,*[151]	+	-	-	-	-	1/5
22	Nishtala *et al.,*[59]	+	-	-	-	-	1/5
23	Shastri and Mansotra [60]	+	-	+	-	-	2/5
24	Ide *et al.,*[61]	+	-	+	-	-	2/5
25	Kour *et al.,*[62]	+	-	+	-	-	2/5
26	Egejuru *et al.,*[63]	+	-	+	-	-	2/5
27	Jhee *et al.,*[152]	+	-	+	-	-	2/5
28	Zaineb *et al.,*[65]	+	-	+	-	-	2/5
29	Kour *et al.,*[62]	+	-	+	-	-	2/5
30	Masino *et al.,*[66]	+	+	+	-	-	3/5
31	Ting *et al.,*[67]	+	+	+	+	-	4/5
32	Idowu [68]	+	-	-	-	-	1/5
33	Pereira *et al.,*[69]	+	-	-	-	-	1/5
34	Sahle [70]	+	+	-	-	-	2/5
35	Maitra and Kuntagod [71]	+	+	-	-	-	2/5
36	Cabral *et al.,*[153]	+	-	-	-	-	1/5
37	Sumon and Rahman [154]	+	-	-	-	-	1/5
38	Madaj *et al.,*[155]	+	+	-	-	-	2/5
39	Sahle,[70]	+	+	-	-	-	2/5
40	Umoh and Nyoho[156]	+	-	-	-	-	1/5
41	Premji[157]	+	+	-	-	-	2/5
42	Chowdhury *et al.,*[72]	+	+	-	-	-	2/5
43	Nascimento *et al*[158]	+	+	-	-	-	2/5
44	Davidson and Boland [73]	+	+	-	-	-	2/5
45	Davidson and Boland	+	+	-	-	-	2/5
46	Sufriyana *et al.,*[74]	+	+	-	-	-	2/5
47	Saturno-Hernández *et al.,*[75]	+	+	-	-	+	3/5
48	Lassi *et al.,*[76]	+	+	-	-	+	3/5
49	Aitken *et al.,*[77]	+	+	-	-	-	2/5
50	Simkhada *et al.,*[78]	+	+	-	-	+	2/5

The subsequent evaluation metrics include Area Under the Curve (AUC), specificity, F1-score, and precision. AUC measures the dataset's total exposure over time and is a valuable metric for assessing diagnostic accuracy and the classifier's ability to distinguish between classes. However, AUC alone may not consider the impact of changing prevalence on results for individual patients in terms of true positives and false negatives [136]. Specificity, also known as the True Negative Rate, represents the proportion of individuals without the disease who will receive a negative result, as documented by Toro Espinosa *et al.,* [137].

The F1 score is a metric used for binary classification tasks, and it ranges from 0 to 1. A score of 0 represents the worst-case scenario, while 1 indicates the best outcome, as explained by Haq *et al.,* [138]. Precision is another valuable evaluation metric that measures relevant data points and consistently serves as a crucial metric, as stated by Fangonil and Schultz [139]. The p-value is the fifth metric and measures how compatible the data is with a specified statistical model by random chance. Dubey and R. [140], Gila-Díaz *et al.,*[141], and Ramiro-Cortijo *et al.,* [142] have all discussed the importance of this metric.

Recall (sensitivity) is the sixth metric, which helps assess the number of false negatives, as pointed out by Day *et al.,* [143]. The seventh metric is the ROC (Receiver Operating Characteristics) curve, which is a measure of diagnostic accuracy. Assigning confidence scores to construct ROC curves can be challenging, as noted by Andersen *et al.,* [144] and Gebremariam *et al.,* [145].

The eighth metric encompasses Log-loss, relative risk, and mean squared error (MSE). MSE quantifies the average of the sum of squares of errors, representing the squared difference between estimated values and actual values. It is a quadratic equation form with no local minima. MSE penalizes the model for significant errors by squaring them, indicating how closely a fitted line aligns with data points.

Among others Duraccio *et al.,*[147] gave insight the importance of this metric. Log loss is another valuable metric for comparing models and is an essential classification metric based on probabilities, where a lower log-loss value indicates superior predictions. Kumar *et al.,* [149] have discussed the significance of this metric.

Relative risk evaluates the likelihood of an event occurring and its risk level based on statistical significance, as explained by Cuckle and Benn [151], and Parchem *et al.,* [150]. Finally, in this study, we conducted a qualitative data analysis in Table 5, based on the five databases used, with a sign (+) indicating data availability and a sign (-) indicating data unavailability.

Our findings revealed a higher number of works in Google Scholar, followed by the PubMed database, with Elsevier, BMC, and PLOS ranking third, fourth, and fifth, respectively. To enhance the visualization of these results, we created a pie chart illustrating the predominant source of articles from each database, as depicted in Fig. 5.

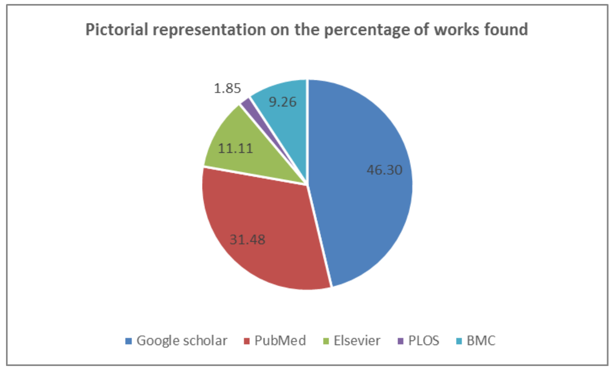

Fig. 4 Pictorial Representation on the Percentage of works found

The results indicated that 50 articles (46.30%) were retrieved from Google Scholar, 33 articles (31.48%) from PubMed, 12 articles (11.11%) from Elsevier, nine articles (9.26%) from BMC, and two articles (1.85%) from PLOS. For quality assessment, we utilized the Newcastle-Ottawa Scale (NOS). This scale assesses the quality of studies by assigning a maximum of five stars/points to each study. A score of three or more points indicates high quality.

V. DISCUSSION

In this work, Tables 1 and 2 analysis reveals that more research efforts have been focused on predicting maternal outcomes using computational approaches compared to descriptive methods. Among the countries with works based on descriptive methods, the distribution is as follows: USA (5), Nigeria (6), India (1), Uganda (1), China (1), South Asia (Pakistan) (2), Canada (1), England (2), and Saudi Arabia (1), totalling twenty-one (21) works. On the other hand, researchers using computational approaches hail from the following countries: USA (2), Nigeria (5), India (4), Tunisia (1), Korea (1), South Asia (1), Canada (1), England (1), Portugal (2), Ethiopia (2), Malaysia (1), Portugal (1), and Brazil (1), making a total of twenty-three (23) works utilizing computational approaches. The studies in this field emphasize the importance of addressing maternal mortality rates in developed and less-developed countries. The insights from Olonade *et al.,* [159] and Tikkanen *et al.,* [160] reinforce the need to reduce maternal mortality rates globally.

Fig. 2 provides an overview of the statistical and computational techniques used to address maternal outcomes. The analysis indicates that many research studies employ a combination of tools, with statistical and computational techniques being the most widely used to address maternal health issues. In terms of statistical methods, some studies have used hybrid approaches. However, these hybrid approaches did not involve direct comparisons and only provided descriptive insights into the variables under consideration. To complement these descriptive methodologies, computational approaches were integrated. The computational methods used in these studies compared results using multiple algorithms. The minimum number of algorithms compared in these studies was two, which allowed for an assessment of each technique's performance on the dataset. This comparison was crucial in determining the preferable algorithm for implementation.

Scholarly works by Dell'Aversana [161], Inyang *et al.,*[23], and Sufriyana *et al.,*[74] strongly advocate for the use of a diverse set of tools for prediction. According to their findings, employing multiple methods yields better outcomes than relying on a single technique. Sufriyana, *et al.,* [74], further recommend revaluating single methods for predicting pregnancy outcomes. The systematic review incorporates tables and figures to provide a comprehensive and visually accessible overview of maternal healthcare research. Table III is a rich resource, offering a detailed meta-summary of methods used in maternal health research, revealing methodological diversity and trends. Fig. 3 visually summarizes the extensive work in maternal healthcare outcomes, making it easier to identify key research areas. Table III offers an in-depth analysis of related works, providing insights into prevalent themes and trends in maternal health research. Fig. 4 visually represents the evaluation metrics used in assessing predictive models. Table V provides a qualitative data analysis of the databases used. Fig. 5 depicts the percentage distribution of research articles, highlighting significant contributors. These tables and figures collectively enhance our understanding of the maternal healthcare research landscape.

In like manner, Venkatesh *et al.,* [162] emphasize the significance of machine learning and statistical models, highlighting their potential to yield excellent results in maternal outcomes. However, they argue that further clinical applications are essential to prepare healthcare providers and triage at-risk women better. Our findings underscore the necessity for conducting systematic reviews on maternal outcomes, particularly in Nigeria, to raise awareness and enhance maternal healthcare. This systematic review aims to identify areas requiring further research and attention.

Our investigation revealed a limited number of studies that employed an individual as the sample size, exemplified by the works of Rana *et al.,* [111] and Sacinti *et al.,* [112]. The parameters used for evaluation played a significant role, enriching the research body while highlighting dataset variations. A predominant selection of researchers effectively utilized standard deviation, percentage, mean, and accuracy, while another group opted for area under the curve, specificity, F1-score, and precision. In addition, some researchers employed specificity, F1-score, precision, p-value, ROC, recall (sensitivity), log-loss, relative risk, and mean squared error. The choice of evaluation metrics hinged on the dataset's characteristics and the research's objectives. Interestingly, we observed limited works that leveraged XGBoost and deep learning methodologies, with Asri *et al.,* (2018) being a notable exception.

Suggestion to Further Studies

Exploring additional tools like the Intuitionistic Fuzzy Sets method and embracing various hybridization techniques is essential. Comparative analyses among these methods can yield diverse strategies for managing maternal outcomes effectively. Additionally, incorporating Explainable AI into the research framework can elucidate the diverse methods employed, thereby enhancing maternal healthcare outcomes comprehensively.

VI. CONCLUSION

This systematic literature review underscores the ongoing importance of maternal outcomes within the healthcare sector. Our analysis revealed a heightened awareness of the prevalence rates of maternal outcomes. Several factors contribute to the increased risk of adverse maternal outcomes, including maternal education level, economic circumstances, financial resources, and proximity to antenatal care facilities. We introduced rigor into the critical review of the existing literature by examining renowned databases such as Google Scholar, PubMed, Elsevier, PLOS, and BMC, which collectively house a wealth of significant articles on the subject. Our choice of search terms served as a roadmap to ensure comprehensive coverage of all relevant articles. We adhered to systematic review standards and best practices by following established methodologies like SLR, PRISMA, and Meta-analysis. Despite the extensive database we surveyed, our work encountered some limitations. A few articles were behind paywalls, necessitating funds to access specific commercial databases. Future research efforts should explore funding opportunities to expand the database. Additionally, we acknowledge that we did not develop a mathematical model for predicting maternal outcomes. While our work shares similarities with previous SLRs, such as those by Lietz *et al.,* (2020), Ogunbodede *et al.,* (2017), and Yadav and Jena (2020), our unique contribution lies in our focus on the methodologies applied to maternal outcome research, their strengths and weaknesses, the prevalence of systematic reviews in maternal health, and an evaluation of the metrics employed in these assessments. Furthermore, our work aligns with the core protocol for conducting systematic literature reviews. The critical nature of maternal health prediction, particularly for high-risk mothers, outweighs the potential misclassification of low-risk cases. Researchers have exerted considerable efforts to enhance awareness of maternal outcomes, especially regarding miscarriage, preterm birth, stillbirth, and mortality. However, given the associated risks, there remains a need to direct more attention toward full-term pregnancies. While some studies have limited datasets despite utilizing current tools, we advocate for broader exposure to contemporary methodologies. In summary, this review highlights the importance of improving maternal outcomes through additional computational tools and measurement techniques to enhance the speed and accuracy of maternal outcome predictions. Using contemporary approximation and hybridization methods could lead to earlier detection of maternal health issues, thereby improving the quality of life and life expectancy for mothers and their unborn children, especially in both developed and less-developed countries.

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