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Predictive Analytics Models for Identifying Maternal Mortality Risk Factors in National Health Datasets

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Abstract

Maternal mortality remains one of the most pressing public health challenges worldwide, disproportionately affecting low- and middle-income countries where health system capacity and access to care are limited. Identifying and addressing the risk factors associated with maternal deaths is critical for achieving global health targets, including the Sustainable Development Goals. Traditional methods of analyzing maternal health data have provided valuable insights but are often constrained by limited scalability, delayed analysis, and the inability to capture complex interactions among diverse risk factors. Predictive analytics models, drawing from machine learning, statistical modeling, and data mining techniques, present a promising approach to overcome these limitations by leveraging large-scale national health datasets to identify high-risk populations with greater accuracy and timeliness. These models can integrate multidimensional data, including demographic, clinical, socioeconomic, and environmental variables, to uncover patterns that may not be immediately apparent through conventional methods. Techniques such as logistic regression, random forests, gradient boosting, and neural networks have shown potential in predicting maternal mortality by capturing both linear and nonlinear associations. Furthermore, spatiotemporal modeling and clustering approaches allow for the identification of geographic disparities and community-level determinants of maternal health risks. By generating predictive insights, these models can guide policymakers, health systems, and frontline workers in targeting interventions, optimizing resource allocation, and designing preventive strategies tailored to vulnerable groups. The application of predictive analytics to maternal mortality surveillance not only enhances early risk detection but also supports evidence-based decision-making for maternal health programs. However, challenges remain, including data quality, ethical considerations regarding sensitive health information, and the need for model interpretability to ensure clinical and policy relevance. This study underscores the importance of integrating predictive analytics into national maternal health monitoring systems as a transformative step toward reducing preventable maternal deaths and improving equity in maternal healthcare outcomes.

Keywords: Predictive Analytics, Maternal Mortality, Risk Factors, National Health Datasets, Machine Learning, Statistical Modeling, Maternal Health, Healthcare Access, Socioeconomic Determinants

1. Introduction

Maternal mortality remains a critical indicator of population health and a persistent challenge for global health systems (Abass *et al*., 2019; Adeleke and Olajide, 2024) [1, 3]. Despite considerable progress over the past two decades, an estimated 287,000 women died from pregnancy and childbirth-related complications in 2020, with the vast majority of deaths occurring in low- and middle-income countries (LMICs). Sub-Saharan Africa and South Asia account for nearly 86% of all maternal deaths, reflecting stark inequities in access to quality care, availability of skilled health professionals, and functioning health infrastructure. In contrast, high-income countries have seen significant declines in maternal mortality ratios, underscoring the disparities between regions in maternal health outcomes (Adeleke *et al*., 2024 [4]; Adenekan *et al*., 2024). These variations highlight not only systemic gaps in healthcare delivery but also the influence of broader socioeconomic and environmental determinants that shape women's health trajectories during pregnancy and childbirth (ADESHINA and NDUKWE, 2024; Adeyelu *et al*., 2024) [7, 8].

Early identification of maternal mortality risk factors is essential for reducing preventable deaths and improving maternal outcomes. Traditional maternal health surveillance systems often focus on retrospective reporting of mortality events, which, while valuable for assessing overall trends, fail to provide real-time insights into populations at greatest risk (Ajayi *et al*., 2024 [9]; Ajiga *et al*., 2024). The ability to recognize risk factors such as pre-existing conditions, inadequate antenatal care, obstetric complications, and social determinants including poverty and limited education, is vital for timely interventions. Proactive identification enables policymakers and health systems to strengthen antenatal and perinatal services, allocate resources efficiently, and implement preventive measures before complications escalate into life-threatening conditions (Appoh *et al*., 2024; Awe *et al*., 2024 [15]).

Predictive analytics offers a transformative opportunity to address these limitations by leveraging national health datasets that capture vast amounts of clinical, demographic, and administrative information (Balogun *et al*., 2023; Benjamin *et al*., 2024) [16, 17]. Through machine learning, statistical modeling, and data mining techniques, predictive analytics can identify complex, non-linear relationships between multiple variables that may not be apparent using conventional analytical approaches (Didi *et al*., 2023; Eneogu *et al*., 2024) [20, 21]. National health datasets, including civil registration and vital statistics systems, hospital records, and household surveys, provide a rich foundation for developing models that detect patterns, stratify populations by risk, and generate actionable forecasts (Bukhari *et al*., 2024; Chianumba *et al*., 2024) [18, 19]. The application of predictive models can bridge the gap between data collection and decision-making, thereby enhancing maternal health surveillance systems with timely, evidence-based insights.

The purpose of this, is to outline a framework for building and applying predictive models for maternal mortality risk assessment using national health datasets. Such a framework encompasses defining relevant outcomes, selecting and preprocessing diverse data sources, applying robust modeling techniques, and validating predictive performance in real-world settings. Beyond technical considerations, it emphasizes the importance of contextual adaptation, ethical safeguards, and integration into existing public health infrastructures (Komi *et al*., 2024; Kufile *et al*., 2024 [40]). By advancing predictive analytics for maternal mortality, this framework seeks to improve early warning systems, inform resource allocation, and guide targeted interventions, ultimately contributing to the reduction of preventable maternal deaths and the advancement of global health equity.

2. Methodology

The methodology for this systematic review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency and reproducibility. A structured search strategy was applied across multiple electronic databases including PubMed, Scopus, Web of Science, Embase, and Google Scholar to identify relevant studies published up to 2025. Additional searches were performed in regional databases and grey literature sources such as government health reports, institutional repositories, and conference proceedings to capture non-indexed studies. The search strategy combined controlled vocabulary terms and free-text keywords related to "maternal mortality," "predictive analytics," "machine learning," "risk prediction models," "national health datasets," and "mortality risk factors." References of retrieved articles were also manually screened to identify additional eligible studies.

Eligibility criteria were defined a priori using the Population, Intervention, Comparator, and Outcome (PICO) framework. Studies were included if they involved women of reproductive age and reported the development, validation, or application of predictive analytics or statistical models for identifying maternal mortality risk factors using national or large-scale health datasets. Both prospective and retrospective study designs were eligible, including cohort studies, case-control studies, and secondary analyses of national health survey or surveillance data. Exclusion criteria included studies that did not apply predictive or statistical models, those that relied solely on small clinical datasets without population-level data, studies not reporting maternal mortality outcomes, and non-English publications where translation was not feasible.

Data extraction was performed independently by two reviewers using a standardized form, and disagreements were resolved through consensus or by a third reviewer. Extracted data included study characteristics (year, country, dataset used, sample size), type of predictive model (e.g., logistic regression, decision trees, random forests, neural networks), predictor variables considered (demographic, socioeconomic, clinical, environmental), model performance metrics (sensitivity, specificity, AUC, calibration), and identified maternal mortality risk factors. Particular attention was given to whether models incorporated contextual variables such as healthcare access, regional disparities, and socioeconomic inequalities.

Risk of bias and quality assessment of included studies were conducted using appropriate appraisal tools for predictive model studies, including the Prediction model Risk of Bias ASsessment Tool (PROBAST). Criteria assessed included clarity of outcome definition, appropriateness of predictor selection, handling of missing data, methods for model validation, and reporting of model performance. Studies were categorized as having low, high, or unclear risk of bias.

Data synthesis involved a narrative approach due to heterogeneity in predictive model types, datasets, and performance measures. Where sufficient homogeneity was identified, pooled estimates of model accuracy and common maternal mortality risk factors were summarized. Subgroup analyses explored variations by region, dataset type, and modeling approach. The results were presented in a PRISMA flow diagram detailing the number of records identified, screened, included, and excluded with reasons.

This methodological approach ensured that the review systematically identified, appraised, and synthesized evidence on predictive analytics models for identifying maternal mortality risk factors using national health datasets, providing insights into model effectiveness, data challenges, and implications for health system strengthening.

2.1 Conceptual Basis

Predictive analytics in healthcare represents a dynamic and evolving field that leverages advanced computational methods to forecast future health outcomes based on historical and real-time data. At its core, predictive analytics is concerned with identifying patterns, risk factors, and relationships in large datasets to anticipate events such as disease onset, hospital admissions, or mortality. In the maternal health context, predictive analytics can help forecast maternal mortality risk by integrating diverse forms of data, including clinical records, demographic characteristics, and environmental exposures (Akpe *et al*., 2024; Adenekan *et al*., 2024). By doing so, it moves beyond descriptive assessments of maternal health trends and into the realm of actionable foresight, enabling health systems to prioritize interventions and resources toward individuals and communities most at risk.

A key distinction between predictive analytics and traditional statistical analysis lies in their scope and methodological orientation. Traditional statistical approaches, such as logistic regression or survival analysis, often rely on predefined hypotheses and a limited number of variables to test associations between exposures and outcomes. These methods are powerful in controlled scenarios but may fail to capture the complexity of real-world health systems, where numerous interacting determinants influence outcomes simultaneously. Predictive analytics, on the other hand, embraces complexity by employing machine learning algorithms, ensemble models, and artificial intelligence techniques that can process high-dimensional datasets. Rather than testing a single hypothesis, predictive models are designed to optimize predictive accuracy, identify hidden patterns, and adapt to non-linear relationships among variables (Essien *et al*., 2024; Fidel-Anyanna *et al*., 2024 [24]). This distinction is critical in maternal health, where traditional epidemiological methods have identified risk factors such as parity, anemia, or access to skilled birth attendants, but often overlook subtle interactions or contextual influences that contribute to maternal mortality.

The rise of big data in healthcare provides an unprecedented foundation for predictive analytics. National health datasets—such as civil registration and vital statistics systems, household surveys, antenatal care records, and hospital-based data—offer diverse and extensive sources of information on maternal health. These datasets capture not only clinical factors but also social determinants, including socioeconomic status, geographic location, and educational attainment. Advances in electronic health records (EHRs) and digital health systems further expand the volume and granularity of available data, allowing for near-real-time monitoring of maternal outcomes. By integrating these multiple streams, predictive models can detect emerging risks, stratify populations based on vulnerability, and provide actionable insights to public health officials and clinicians (Ajiga *et al*., 2024; Appoh *et al*., 2024). The ability to harness big data enhances the scalability and adaptability of maternal health surveillance systems, particularly in regions where resources are limited and the burden of maternal mortality remains high.

Maternal mortality is inherently a multifactorial outcome shaped by an interplay of clinical, social, and systemic determinants. Clinical factors such as pre-existing conditions (hypertension, diabetes, anemia), obstetric complications (postpartum hemorrhage, sepsis, eclampsia), and inadequate antenatal care directly affect maternal outcomes. However, maternal mortality cannot be understood solely through a biomedical lens. Social determinants, including poverty, malnutrition, early marriage, limited education, and gender inequities, profoundly influence access to care and the ability of women to seek timely medical attention. Systemic determinants, such as weak health infrastructure, shortages of skilled health personnel, gaps in emergency obstetric services, and limited transportation networks, exacerbate vulnerabilities by delaying or preventing access to life-saving interventions (Komi *et al*., 2024; Obadimu *et al*., 2024 [41]). In fragile contexts—such as conflict-affected regions or areas experiencing humanitarian crises—these systemic weaknesses become particularly acute.

Predictive analytics is uniquely positioned to integrate these diverse determinants into a coherent framework for understanding and addressing maternal mortality. By combining clinical and demographic data with systemic and contextual indicators, predictive models can provide a comprehensive assessment of risk. For instance, models may reveal that women with moderate anemia living in remote rural areas with limited emergency obstetric facilities face disproportionately high risks of mortality compared to women with similar clinical profiles in urban centers. Such insights can inform targeted policies, including the expansion of mobile health units, training of midwives, or improved referral systems (Frempong *et al*., 2024; Frndak *et al*., 2024) [25, 26].

The conceptual basis of predictive analytics for maternal mortality lies in its ability to move beyond traditional statistical paradigms, harness the potential of big data, and address the multifactorial nature of maternal health outcomes (Gbabo *et al*., 2024; Gobile *et al*., 2024) [27, 28]. By doing so, it provides a powerful tool for transforming maternal mortality surveillance from retrospective reporting into proactive, data-driven decision-making, with the potential to reduce preventable deaths and advance global health equity.

2.2 Data Sources for Maternal Mortality Risk Prediction

Accurate prediction of maternal mortality risk relies heavily on the availability, quality, and integration of diverse data sources that capture both individual-level and contextual factors. Maternal mortality is influenced not only by clinical and biological determinants but also by socioeconomic, environmental, and systemic factors. To build robust predictive models, researchers and policymakers must draw upon multiple complementary datasets, each offering unique insights into health risks and outcomes (Halliday, 2021; Essien *et al*., 2024). Four primary categories of data sources—national health information systems, demographic and health surveys, clinical and administrative datasets, and socioeconomic and environmental data—form the foundation of maternal mortality risk prediction.

National health information systems represent the cornerstone for maternal mortality monitoring at the population level. Vital registration systems that capture births and deaths provide essential baseline data on maternal mortality ratios and trends. In many high-income countries, these systems are comprehensive and reliable, offering granular data on causes of death that can be directly linked to maternal outcomes. Hospital records and routine surveillance systems supplement vital statistics by recording clinical complications such as hemorrhage, hypertensive disorders, and infections, which are leading contributors to maternal deaths (Jejeniwa *et al*., 2024; Johnson *et al*., 2024) [34, 35]. However, in low- and middle-income countries, gaps in coverage, underreporting, and misclassification of maternal deaths remain common challenges. Despite these limitations, national health information systems are critical for constructing large-scale predictive models that capture both temporal and geographic variations in maternal risk.

Demographic and Health Surveys (DHS) are another valuable source of maternal health data, particularly in countries where routine health information systems are weak. DHS provide nationally representative, household-level data on health, education, fertility, and demographic variables. These surveys capture indicators such as maternal age, parity, access to antenatal care, nutritional status, and use of skilled birth attendants, all of which are relevant predictors of maternal mortality. Importantly, DHS also collect data on broader determinants, including education and socioeconomic status, which help contextualize risk within household and community environments. While DHS are conducted at multi-year intervals and therefore lack real-time applicability, their standardized methodology across countries makes them particularly useful for cross-national comparisons and for validating predictive models.

Clinical and administrative datasets offer detailed insights into the direct medical factors associated with maternal outcomes. Electronic medical records (EMRs) capture individual-level data from antenatal visits, labor, delivery, and postnatal care. These records can include vital signs, laboratory results, obstetric history, and documented complications, providing high-resolution predictors for risk modeling. Antenatal care logs, often maintained in primary healthcare facilities, track routine maternal assessments and interventions, while obstetric registries compile information on high-risk pregnancies, cesarean sections, and maternal near-miss cases. Administrative datasets, such as hospital discharge records and insurance claims, can provide additional information on healthcare utilization patterns and outcomes. Together, these clinical and administrative sources strengthen the capacity of predictive models to identify individual-level risks, although they may be limited by incomplete coverage in rural or informal health sectors.

Socioeconomic and environmental data provide the broader context necessary to understand systemic contributors to maternal mortality. Poverty indices, derived from national household surveys or census data, highlight financial barriers to healthcare access. Education levels, particularly maternal education, are strongly linked to health literacy, care-seeking behaviors, and nutritional practices. Geographic accessibility data, such as distance to healthcare facilities, travel time, and transportation availability, capture structural determinants of maternal outcomes. Environmental datasets, including information on seasonal flooding, heat exposure, or poor air quality, can be integrated into predictive models to account for indirect stressors that exacerbate maternal risk. Increasingly, geospatial technologies and satellite imagery are being used to map environmental exposures and infrastructure gaps, allowing for more precise targeting of high-risk regions (Isa, 2024; Iziduh *et al*., 2024 [33]).

In practice, the greatest potential for maternal mortality risk prediction lies in the integration of these data sources. Linking national health information systems with DHS, clinical datasets, and socioeconomic indicators provides a more holistic picture of maternal risk pathways. For example, combining obstetric complication data from hospital records with poverty indices and geographic accessibility measures allows for the identification of both clinical and systemic drivers of maternal deaths. However, challenges remain in data harmonization, interoperability, and privacy, particularly in resource-limited settings.

Maternal mortality risk prediction requires a multi-layered data approach that integrates clinical, demographic, socioeconomic, and environmental sources. National health information systems provide population-level surveillance, DHS capture household determinants, clinical datasets offer detailed individual-level insights, and socioeconomic-environmental data contextualize systemic inequities. Harnessing these diverse data streams enables the development of predictive models that are not only accurate but also sensitive to the multifactorial nature of maternal mortality. Strengthening data systems and improving their integration across sectors remain critical steps for advancing maternal health outcomes globally.

2.3 Key Maternal Mortality Risk Factors Captured in Datasets

Understanding maternal mortality requires capturing a wide range of risk factors that span biological, healthcare, socioeconomic, and environmental domains. National health datasets, including civil registration systems, household surveys, hospital records, and demographic surveillance data, provide a vital foundation for identifying these risk factors and applying them in predictive models as shown in Fig 1 (Isa, 2024; Komi *et al*., 2024). This highlight the major categories of maternal mortality risk factors commonly captured in such datasets and their implications for prediction and prevention.

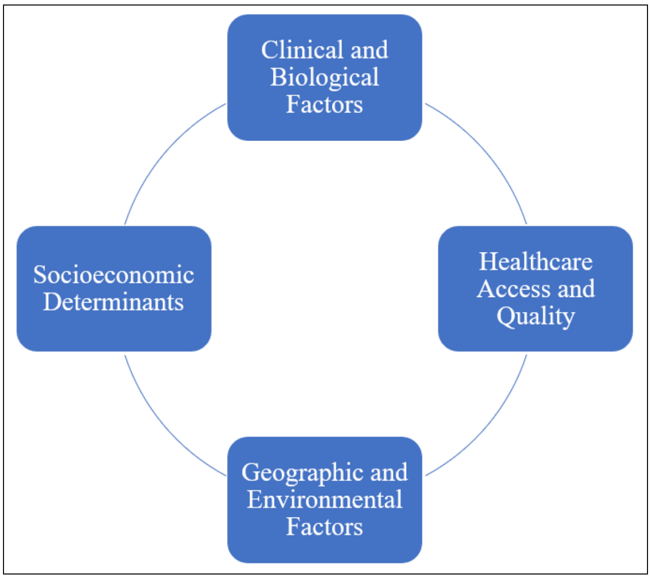

Fig 1: Key Maternal Mortality Risk Factors Captured in Datasets

Clinical and biological factors remain the most direct determinants of maternal outcomes. Pre-existing conditions such as hypertension, diabetes, and anemia are strongly associated with higher risks of complications during pregnancy and childbirth. Hypertension can lead to pre-eclampsia and eclampsia, both of which are major causes of maternal mortality globally. Similarly, poorly managed diabetes during pregnancy increases risks of obstructed labor, infection, and poor neonatal outcomes. Anemia, prevalent in many low- and middle-income countries (LMICs), weakens maternal resilience during childbirth and significantly elevates the risk of postpartum hemorrhage—the leading cause of maternal death worldwide.

Pregnancy-specific complications, including obstetric hemorrhage, sepsis, and eclampsia, are critical events captured in hospital records and civil registration systems. Hemorrhage requires immediate intervention, but delays in treatment often prove fatal in resource-constrained settings. Sepsis, often linked to poor hygiene and inadequate infection control, underscores systemic gaps in maternal care. Eclampsia, characterized by seizures, demands timely recognition and management, yet continues to claim lives where access to skilled providers is limited.

Maternal age and parity also play crucial roles. Very young mothers, often adolescents, face biological risks such as obstructed labor due to underdeveloped pelvises, while older mothers experience increased risks of hypertension, gestational diabetes, and obstetric complications. Parity, or the number of previous pregnancies, influences outcomes as well; both primiparous women and those with multiple prior births face heightened risks under different circumstances. Together, these clinical and biological factors form the biomedical backbone of maternal mortality prediction models.

Access to and quality of healthcare are pivotal determinants of maternal survival. Antenatal care (ANC) attendance provides an opportunity to screen for pre-existing conditions, monitor pregnancy progression, and deliver preventive interventions such as tetanus immunization and iron supplementation. Datasets often capture the number and timing of ANC visits, which correlate strongly with maternal outcomes. However, quality of care—not just attendance—matters greatly, as poorly delivered services may fail to identify or mitigate risks.

The presence of skilled birth attendants at delivery is a well-documented protective factor. Skilled attendants can recognize complications, manage emergencies, and initiate timely referrals. Unfortunately, in many LMICs, large proportions of births occur at home or with untrained providers, increasing risks of fatal complications. Facility readiness also matters; even if women reach health facilities, shortages of drugs, equipment, and trained staff undermine survival chances. Referral systems are equally critical. Delays in recognizing emergencies, arranging transport, and receiving care at referral hospitals often result in the "three delays" framework: delay in decision to seek care, delay in reaching care, and delay in receiving adequate care (Ochefu *et al*., 2024; Odezuligbo *et al*., 2024) [42, 43]. Datasets capturing these aspects are invaluable for modeling the systemic gaps that contribute to maternal mortality.

Socioeconomic status exerts a powerful influence on maternal health outcomes. Household income and wealth determine the ability to afford transportation, medications, and delivery services. Poverty often forces women into unsafe deliveries or delays care-seeking, compounding risks from otherwise manageable complications.

Education level of the mother—and, in many contexts, her partner—shapes knowledge of pregnancy risks, recognition of danger signs, and health-seeking behavior. Women with higher education levels are more likely to access antenatal care, deliver with skilled attendants, and follow medical advice, thereby lowering their risk of mortality. Conversely, low education perpetuates cycles of vulnerability, particularly where traditional beliefs or misinformation about pregnancy care are prevalent.

Employment status and social protection are additional determinants. Women with stable employment or covered by social safety nets are more likely to access health services and afford necessary care. Conversely, informal employment or lack of social protection heightens vulnerability. National datasets that capture household wealth indices, maternal and partner education, and labor force participation provide essential socioeconomic dimensions for maternal mortality modeling.

Geography and environment strongly shape maternal survival odds. Urban versus rural residence is a recurrent predictor of outcomes. Women in urban settings typically benefit from closer proximity to health facilities, greater availability of skilled personnel, and better transportation infrastructure. In contrast, rural women often face long travel distances, limited access to emergency obstetric services, and shortages of qualified healthcare providers.

Travel time to health facilities is another crucial variable. Studies show that maternal mortality increases significantly when emergency obstetric care is more than two hours away. Datasets increasingly incorporate geospatial indicators to estimate travel times, improving the precision of risk modeling.

Regional disparities in health infrastructure further exacerbate inequalities. Some regions face chronic shortages of facilities equipped for cesarean deliveries or blood transfusions, while others benefit from robust health systems. Environmental factors such as seasonal flooding, conflict, or fragile ecosystems can further disrupt access to care, making geography a decisive determinant in maternal health outcomes (Odujobi *et al*., 2024; Ogedengbe *et al*., 2024) [45, 46].

Capturing maternal mortality risk factors in datasets requires attention to the interplay between biological, healthcare, socioeconomic, and geographic determinants. Predictive analytics can transform these variables into actionable insights by identifying women most at risk and guiding targeted interventions. Clinical data highlight direct causes of death, while socioeconomic and geographic variables contextualize systemic inequities. Healthcare access indicators bridge these perspectives, pointing to opportunities for strengthening maternal care delivery. Collectively, these risk factors underscore the complexity of maternal mortality and the necessity of multidimensional approaches to prediction and prevention.

2.4 Predictive Modeling Approaches

Predictive modeling has become a central tool in identifying maternal mortality risk factors, enabling healthcare systems to anticipate high-risk cases and allocate resources effectively. These models leverage clinical, demographic, socioeconomic, and environmental data to estimate the probability of adverse maternal outcomes as shown in Fig 2. Approaches range from traditional statistical models to advanced machine learning techniques, as well as hybrid frameworks that combine strengths from multiple methodologies (Ogunwale *et al*., 2024; Ojeikere *et al*., 2024) [47, 48]. Each approach offers unique advantages and limitations in terms of interpretability, accuracy, and applicability across diverse healthcare settings.

Statistical models have long been foundational in epidemiological research and remain widely applied in maternal mortality risk prediction. Logistic regression is frequently used for binary outcomes, such as the presence or absence of maternal death, enabling estimation of odds ratios associated with individual predictors like maternal age, parity, or pre-existing medical conditions. Cox proportional hazards models extend this framework to time-to-event analyses, accounting for the timing of maternal complications and enabling survival analyses that are critical in assessing risk during pregnancy, labor, and postpartum periods. Multilevel or hierarchical models are increasingly employed to address nested data structures, such as individuals within households, health facilities, or regions. These models allow researchers to account for clustering effects, contextual influences, and regional variability, improving the accuracy of risk estimation while preserving the interpretability of coefficients. The strength of statistical models lies in their transparency, well-understood assumptions, and established methods for hypothesis testing, making them particularly valuable for policy-oriented research and evidence synthesis.

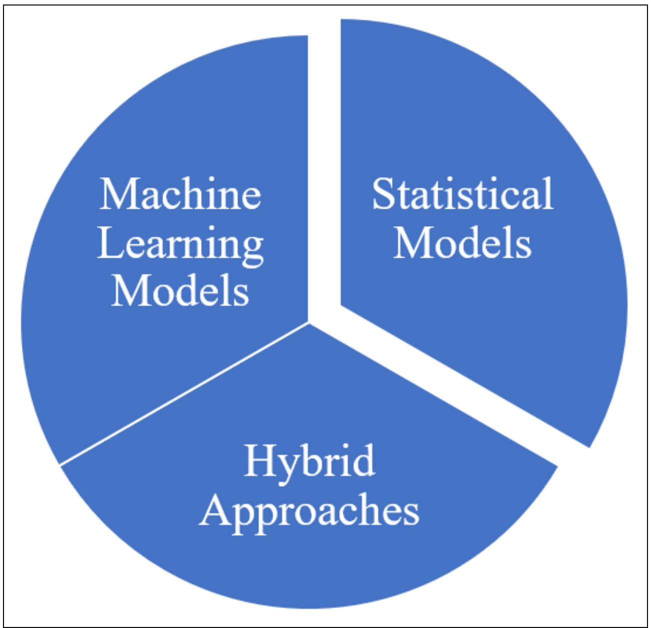

Fig 2: Predictive Modeling Approaches

Machine learning models, in contrast, offer the ability to detect complex and nonlinear relationships among predictors that traditional statistical models may not capture. Decision trees and ensemble methods like random forests and gradient boosting are commonly used for maternal mortality prediction because they handle high-dimensional datasets and automatically identify important features. These models excel at accommodating interactions between variables, such as the combined effects of comorbidities, socioeconomic status, and geographic access on maternal risk. Neural networks, including deep learning architectures, further extend predictive capacity by modeling highly nonlinear patterns in large datasets, including interactions that are difficult to pre-specify. Additionally, natural language processing (NLP) methods enable the extraction of information from unstructured clinical notes, such as physician observations, complication narratives, or hospital discharge summaries, which are otherwise inaccessible to conventional numeric models. While machine learning approaches often achieve superior predictive accuracy, their interpretability can be limited, posing challenges for clinical adoption and policy decision-making where understanding the contribution of individual risk factors is critical (Ojonugwa *et al*., 2024; Okare *et al*., 2024) [49, 50].

Hybrid approaches have emerged to bridge the strengths of traditional statistical modeling with machine learning's capacity for complex pattern recognition. These methods often involve integrating epidemiologically informed variables into machine learning frameworks, ensuring that models retain interpretability while leveraging nonlinear predictive power. Ensemble modeling is one such hybrid strategy, where multiple predictive models are combined to improve overall performance and reduce model-specific biases. For example, an ensemble may aggregate predictions from logistic regression, random forests, and gradient boosting to generate a more robust maternal mortality risk score. Hybrid models can also incorporate temporal or hierarchical components, capturing both individual-level risk factors and contextual determinants such as facility capacity or regional healthcare access. These approaches balance predictive accuracy with clinical relevance, offering practical advantages in real-world healthcare settings where model interpretability, resource constraints, and regulatory requirements must be considered.

The choice of modeling approach depends on the research objective, data availability, and operational context. Statistical models are well-suited for hypothesis-driven analyses and policy evaluation, particularly in settings with smaller datasets or well-characterized predictors. Machine learning approaches are advantageous when large, complex datasets are available, or when predictive performance is prioritized over interpretability. Hybrid frameworks provide a middle ground, enabling integration of domain knowledge and advanced computational techniques to achieve both accuracy and actionable insights. Regardless of the approach, careful attention to model validation, handling of missing data, overfitting, and generalizability across populations is essential for producing reliable and ethically responsible predictions (Okereke *et al*., 2024; Okuwobi *et al*., 2024) [51, 52].

Predictive modeling for maternal mortality risk encompasses a spectrum of methodologies from traditional statistical models to advanced machine learning and hybrid approaches. Statistical models offer interpretability and established epidemiological rigor, machine learning models provide capacity for complex, nonlinear pattern detection, and hybrid strategies integrate both strengths to enhance predictive performance while retaining clinical relevance. The careful selection and combination of these approaches, informed by data availability and policy needs, can improve early identification of high-risk pregnancies, optimize resource allocation, and ultimately contribute to the reduction of maternal mortality at national and regional levels.

2.5 Data Preparation and Processing

Effective predictive modeling of maternal mortality relies heavily on rigorous data preparation and processing as shown in Fig 3. National health datasets, hospital records, antenatal care registries, and demographic surveys provide rich sources of information, but these data often contain inconsistencies, missing values, and imbalances that must be addressed before meaningful analysis can occur (Komi *et al*., 2024; Odezuligbo *et al*., 2024 [43]). The quality of data preparation directly impacts model performance, generalizability, and the reliability of predictions.

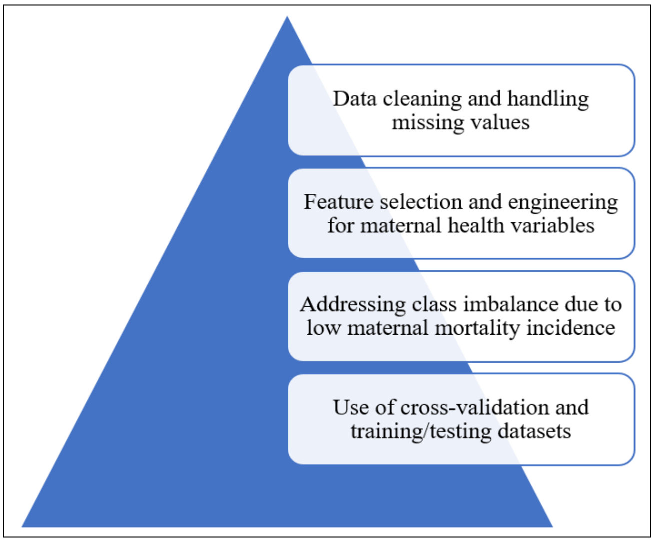

Fig 3: Data Preparation and Processing

Data cleaning is the initial and essential step in preparing maternal health datasets. These datasets frequently contain missing, duplicated, or inconsistent entries, which can bias model outcomes if left unaddressed. Missing values in maternal datasets may arise due to incomplete clinical records, unreported deaths, or gaps in household survey responses. Common strategies for handling missing data include deletion, mean or median imputation, regression-based imputation, and multiple imputation techniques. For example, missing hemoglobin values or antenatal care visit counts can be imputed based on correlated variables such as maternal age, parity, or socioeconomic status. Outliers must also be identified and assessed, as extreme values in variables like birth weight or blood pressure may represent errors rather than genuine clinical conditions. Standardization and normalization of continuous variables are critical to ensure comparability across different measurement scales, particularly when combining data from multiple sources.

Feature selection and engineering are vital for maximizing predictive performance while minimizing model complexity. Relevant maternal health variables include pre-existing conditions (hypertension, diabetes, anemia), pregnancy complications (hemorrhage, sepsis, eclampsia), maternal age, parity, antenatal care attendance, skilled birth attendance, socioeconomic indicators, and geographic attributes. Feature selection techniques such as correlation analysis, recursive feature elimination, and mutual information scores help identify variables most strongly associated with maternal mortality. Feature engineering can enhance model capacity by creating derived variables, such as travel time to the nearest health facility, risk scores for comorbidities, or cumulative antenatal care quality indices. Temporal features, such as trimester-specific exposure to complications, can also be encoded to improve the model's ability to capture dynamic risk patterns throughout pregnancy.

Maternal mortality is a relatively rare event, often resulting in highly imbalanced datasets where the majority of cases represent survival. This class imbalance can cause predictive models to be biased toward the majority class, reducing sensitivity to high-risk cases. Various strategies can mitigate this challenge, including oversampling techniques such as SMOTE (Synthetic Minority Oversampling Technique), undersampling of the majority class, or a combination of both. Cost-sensitive learning and class-weighted algorithms can also adjust model training to prioritize accurate prediction of maternal deaths. Evaluation metrics such as precision, recall, F1-score, and area under the precision-recall curve are particularly important in assessing model performance in imbalanced datasets, as accuracy alone can be misleading.

To ensure model generalizability and prevent overfitting, data must be partitioned into training and testing sets, with further subdivisions for cross-validation. Common approaches include k-fold cross-validation, where the dataset is divided into k subsets, with each subset serving as a validation set in turn while the remaining data train the model. This technique provides robust estimates of predictive performance across different data segments and reduces variance associated with a single train-test split. Stratified sampling can be employed to maintain the proportion of maternal mortality cases across folds, preserving the distribution of rare events. Additionally, in longitudinal datasets, temporal validation may be used, where models are trained on historical data and tested on more recent records to assess predictive performance over time.

Data preparation and processing form the foundation of reliable maternal mortality prediction. Cleaning and imputing missing values, selecting and engineering informative features, addressing class imbalance, and implementing rigorous cross-validation collectively enhance model accuracy and applicability. By carefully curating and preprocessing maternal health datasets, predictive models are better positioned to identify high-risk cases, support timely interventions, and inform evidence-based maternal health policies (Olinmah *et al*., 2024; Oloruntoba and Omolayo, 2024) [53, 54]. Well-prepared data ensures that analytical insights translate into actionable strategies capable of reducing preventable maternal deaths.

2.6 Evaluation Metrics for Predictive Models

The development of predictive models for maternal mortality risk requires rigorous evaluation to ensure their accuracy, reliability, and practical utility. Evaluation metrics serve as essential tools to quantify model performance, assess clinical relevance, and guide model selection and deployment. In the context of maternal mortality, where outcomes are relatively rare and consequences are severe, appropriate evaluation strategies must balance statistical rigor with interpretability, ensuring that models can effectively inform both clinical decision-making and policy interventions (Olulaja *et al*., 2024 [55]; Oluoha *et al*., 2024). Key evaluation metrics include sensitivity, specificity, area under the receiver operating characteristic curve (AUC), precision, recall, F1-score, calibration assessments, and considerations of interpretability and explainability.

Sensitivity and specificity are foundational metrics in assessing binary classification models, such as predicting whether a maternal case is at high risk of mortality.

Sensitivity, or true positive rate, measures the proportion of actual maternal deaths correctly identified by the model. High sensitivity is critical in maternal health contexts because failing to identify a high-risk case may result in preventable death. Specificity, or true negative rate, measures the proportion of non-mortality cases correctly classified. While high specificity reduces false alarms and unnecessary interventions, there is often a trade-off between sensitivity and specificity. Optimizing these metrics requires careful consideration of the clinical and public health context, as prioritizing sensitivity may be more desirable in high-stakes maternal health applications, even if it slightly increases false positives. The area under the receiver operating characteristic (ROC) curve (AUC) provides a combined measure of a model's ability to discriminate between positive and negative cases across all possible classification thresholds. An AUC of 1 indicates perfect discrimination, whereas an AUC of 0.5 suggests performance no better than random chance. AUC is particularly useful for comparing different predictive models, including logistic regression, decision trees, or ensemble methods.

In maternal mortality prediction, where events are rare, traditional metrics such as sensitivity and specificity may not fully capture model performance. Metrics that emphasize the identification of rare events, including precision, recall, and F1-score, are especially informative. Precision, or positive predictive value, measures the proportion of predicted high-risk cases that are actual maternal deaths, reflecting the reliability of model alerts (Omolayo *et al*., 2024; Osabuohien, 2024 [61]). Recall, equivalent to sensitivity, emphasizes the model's ability to capture all actual maternal deaths. The F1-score provides a harmonic mean of precision and recall, offering a single metric that balances the trade-off between false positives and false negatives. These metrics are particularly relevant when the prevalence of maternal mortality is low, as they prevent misleading conclusions that may arise from accuracy measures dominated by the majority class (non-deaths).

Calibration is another critical component in model evaluation, as it assesses whether predicted probabilities correspond to observed outcomes. Calibration plots, or reliability diagrams, compare predicted risk with actual incidence rates across deciles or percentiles of risk. Well-calibrated models ensure that a predicted probability—for example, a 10% risk of maternal mortality—accurately reflects the real-world likelihood of the event. Calibration is essential for clinical and policy decision-making because interventions often depend not only on classification but also on the magnitude of predicted risk. Poor calibration can lead to misallocation of resources, over-treatment, or under-preparedness in high-risk settings. Techniques such as isotonic regression or Platt scaling can be applied to improve calibration, particularly for machine learning models that may produce overconfident or biased probability estimates.

Finally, interpretability and explainability are essential for translating predictive models into actionable insights. Policymakers and clinicians require transparent models to understand why a particular individual or population is classified as high risk. Interpretability facilitates trust, guides clinical decision-making, and informs targeted policy interventions. Approaches such as feature importance rankings, partial dependence plots, and SHapley Additive exPlanations (SHAP) allow stakeholders to visualize the contribution of predictors, such as maternal age, pre-existing conditions, or antenatal care utilization, to risk estimates. Ensuring model explainability is especially important in maternal health contexts, where decisions often involve life-saving interventions, resource allocation, and ethical considerations.

Evaluating predictive models for maternal mortality risk requires a multifaceted approach. Sensitivity, specificity, and AUC provide foundational discrimination metrics, while precision, recall, and F1-score emphasize rare event detection. Calibration assessments ensure probability estimates are trustworthy for decision-making, and interpretability facilitates clinical and policy adoption. Combining these evaluation strategies enables the development of robust, reliable, and actionable predictive models capable of improving maternal health outcomes in diverse healthcare settings. Proper evaluation not only validates model performance but also ensures that predictive analytics can effectively guide interventions and reduce preventable maternal deaths (Osamika *et al*., 2024; Oyeyemi *et al*., 2024) [62, 63].

2.7 Challenges and Limitations

Predictive analytics for maternal mortality holds immense promise, yet its effective implementation faces significant challenges and limitations. The robustness of predictive models is highly dependent on the quality, completeness, and representativeness of the underlying health datasets. Incomplete or poor-quality data is a major barrier, particularly in low- and middle-income countries (LMICs), where gaps in civil registration, vital statistics, and health facility reporting are common. Missing entries, inconsistent coding of clinical events, and lack of standardized data collection practices can compromise model performance and limit the generalizability of findings (Romo *et al*., 2024; Shah *et al*., 2024) [64, 65]. In many instances, essential variables such as comorbidities, antenatal care attendance, or delivery outcomes are underreported or inaccurately documented, creating an incomplete picture of maternal health risks.

Biases in data collection further complicate predictive modeling. Underreporting of maternal deaths, misclassification of causes of death, and selective documentation of high-risk cases introduce systematic errors that distort risk estimates. For example, deaths occurring outside health facilities or in remote areas are frequently absent from national datasets, leading to underestimation of mortality rates in vulnerable populations. Similarly, variability in diagnostic capabilities across health facilities can result in misclassification of pregnancy complications, affecting the reliability of predictors such as eclampsia, hemorrhage, or sepsis. These biases necessitate careful data preprocessing, sensitivity analyses, and robust validation strategies to mitigate their impact on model outputs.

Ethical and privacy concerns are paramount when using sensitive maternal data. Personal health information, including reproductive history, pregnancy complications, and socioeconomic indicators, must be protected to maintain confidentiality and comply with ethical standards. Data breaches, unauthorized access, or misuse of information can have serious social and legal consequences. Strategies such as de-identification, secure data storage, and controlled access protocols are essential but may limit the granularity of data available for modeling, potentially reducing predictive accuracy.

Technical capacity limitations also hinder effective application of predictive models in LMICs. Many settings lack trained personnel in data science, epidemiology, and health informatics, as well as the computational infrastructure required to process large-scale datasets. These constraints can impede model development, maintenance, and integration into routine health system workflows, reducing the practical utility of predictive analytics for maternal health interventions. Capacity-building initiatives and partnerships with international agencies are crucial for addressing these gaps.

Finally, a trade-off exists between model interpretability and predictive accuracy. Complex machine learning and deep learning models often achieve high predictive performance but operate as "black boxes," making it difficult for healthcare providers and policymakers to understand the rationale behind individual predictions (Omisola *et al*., 2024 [58]; Omolayo *et al*., 2024). Conversely, simpler statistical models may be more interpretable but may fail to capture intricate nonlinear relationships or interactions among risk factors. Balancing interpretability with predictive power is critical to ensure that model outputs are actionable, transparent, and trusted by health professionals and decision-makers.

Challenges related to data quality, collection biases, ethical considerations, technical capacity, and model transparency present substantial barriers to the effective use of predictive analytics in maternal mortality. Addressing these limitations requires robust data governance, standardized reporting protocols, investment in technical infrastructure and training, and thoughtful model design to optimize both accuracy and usability. Overcoming these hurdles is essential for translating predictive insights into effective interventions and ultimately reducing maternal mortality rates.

2.8 Policy and Public Health Implications

The application of predictive models to maternal mortality risk has significant implications for policy development and public health planning, particularly in low- and middle-income countries where maternal deaths remain a major challenge. By identifying high-risk individuals and populations, predictive analytics can inform evidence-based strategies that enhance resource allocation, improve care delivery, and ultimately reduce preventable maternal deaths (Sobowale *et al*., 2020 [66]; Oluoha *et al*., 2024). To realize these benefits, integration of predictive modeling into national maternal health strategies, capacity building, health system strengthening, cross-sector collaboration, and equity considerations must be prioritized.

Integration of predictive models into national maternal health strategies represents a transformative step toward data-driven policymaking. Predictive tools can guide prioritization of interventions, such as targeted antenatal care, emergency obstetric services, and maternal referral systems. When incorporated into strategic planning, predictive outputs enable policymakers to anticipate regions or demographic groups with elevated risk, allowing proactive deployment of human, financial, and logistic resources. Moreover, predictive models can support monitoring and evaluation frameworks, providing real-time feedback on intervention effectiveness and enabling continuous policy refinement. Embedding predictive analytics in national strategies requires alignment with existing maternal health goals, integration with routine monitoring, and formal mechanisms for decision-making based on model outputs.

Building capacity for data science within health ministries is essential for effective utilization of predictive models. Technical expertise is needed to clean, manage, and analyze large-scale health datasets, as well as to interpret model outputs accurately. Training programs for epidemiologists, statisticians, and public health officers can strengthen the workforce's ability to implement and maintain predictive analytics initiatives. Capacity building should also extend to understanding ethical and privacy considerations, ensuring that sensitive maternal health data are managed securely while maximizing public health benefits. Partnerships with academic institutions and international organizations can provide additional support and facilitate knowledge transfer, fostering sustainable data-driven decision-making.

Strengthening health information systems is another critical public health implication. Reliable predictive models depend on high-quality, timely, and comprehensive data. Improvements in civil registration and vital statistics, hospital reporting, and electronic medical records enhance the completeness and accuracy of inputs for maternal risk prediction. Real-time data capture and integration across facilities allow models to generate timely risk estimates, enabling rapid response to emergent threats such as obstetric complications or geographic clusters of maternal deaths. Investments in interoperability, standardized coding, and secure data sharing protocols are necessary to maximize the utility of predictive models and avoid fragmentation of health information systems.

Cross-sector collaboration is vital for addressing the multifactorial risk factors contributing to maternal mortality. Predictive models often identify socioeconomic, geographic, and environmental determinants alongside clinical variables. Addressing these risks requires coordinated action between health, transportation, education, social welfare, and local government sectors. For example, improving road infrastructure to reduce delays in accessing emergency obstetric care, or implementing nutrition programs to address maternal undernutrition, directly mitigates risks identified through predictive analytics. Collaborative planning ensures that interventions are comprehensive and target upstream determinants, thereby enhancing the effectiveness of maternal health policies.

Equity considerations are central to the public health application of predictive models. Marginalized populations—such as rural residents, low-income households, and ethnic minorities—often experience the highest maternal mortality rates. Predictive models can highlight disparities in risk, enabling targeted interventions that prioritize these vulnerable groups (Tiamiyu *et al*., 2024; Uddoh *et al*., 2024) [67, 68]. Equity-focused policies should ensure that predictive analytics do not inadvertently reinforce existing inequities, such as by privileging areas with better data availability or higher service capacity. Incorporating social determinants of health into models and designing inclusive interventions helps promote equitable access to maternal healthcare and reduces systemic disparities.

Predictive models for maternal mortality have profound implications for policy and public health practice. Their integration into national strategies enables proactive, evidence-based planning; building data science capacity ensures sustainable implementation; strengthening health information systems enhances data quality and timeliness; cross-sector collaboration addresses the complex determinants of risk; and equity-focused approaches ensure that interventions reach the most vulnerable populations. Together, these measures can transform maternal health programs, improving outcomes and advancing progress toward global maternal mortality reduction goals.

2.9 Future Directions

The evolving landscape of maternal health surveillance and predictive analytics presents significant opportunities for improving maternal mortality outcomes. A key future direction involves the deployment of real-time predictive dashboards that integrate maternal health data from multiple sources, offering actionable insights to health system planners, policymakers, and frontline health workers. These dashboards can provide dynamic risk assessments for individual pregnancies, track trends at the facility and population levels, and enable timely identification of emerging high-risk clusters (Umezurike *et al*., 2024) [69]. By presenting complex predictive outputs in an accessible and visually intuitive format, dashboards facilitate evidence-based decision-making, resource prioritization, and rapid response to prevent adverse maternal outcomes.

The incorporation of mobile health (mHealth) technologies and wearable devices represents another transformative opportunity. Smartphones, portable monitoring devices, and wearable sensors can capture granular, patient-level data such as heart rate, blood pressure, blood glucose, and adherence to antenatal care schedules. Integrating these data streams into predictive models enhances the temporal resolution and accuracy of maternal risk assessments, while also empowering women to actively participate in their own healthcare management. mHealth applications can provide automated alerts, reminders for antenatal appointments, and educational content, bridging gaps in access to healthcare and promoting adherence to recommended practices, particularly in resource-constrained settings.

AI-driven decision support tools for frontline health workers constitute a complementary direction for strengthening maternal care delivery. Machine learning models embedded within clinical workflows can provide risk stratification, suggest intervention protocols, and highlight potential complications before they become critical. These tools enable healthcare providers to make informed, timely decisions, optimize the allocation of scarce resources, and reduce preventable maternal deaths. Integration of predictive algorithms into electronic health record systems ensures seamless data flow and reinforces continuity of care.

Global data-sharing frameworks are crucial to expand the utility and generalizability of maternal mortality prediction models. Collaborative initiatives that facilitate the aggregation of de-identified health data across countries and regions can enrich training datasets, enhance model robustness, and enable comparative analyses of maternal health determinants. Standardized data formats, interoperability protocols, and ethical governance frameworks will be essential to ensure privacy, security, and equitable access to shared datasets, particularly in low- and middle-income countries.

Finally, continuous updating of predictive models with new health data streams is imperative for maintaining relevance and accuracy. Maternal health is influenced by evolving clinical practices, emerging epidemiological patterns, and socioeconomic and environmental changes. Adaptive learning models that incorporate longitudinal data, seasonal variations, and real-time inputs can refine predictions, identify emerging risk factors, and ensure that intervention strategies remain aligned with current realities. Such continuous improvement mechanisms also support the evaluation of implemented policies, providing feedback for evidence-based refinement of maternal health programs.

Future advancements in maternal mortality prediction lie at the intersection of real-time data integration, mHealth and wearable technologies, AI-driven decision support, global data collaboration, and adaptive modeling (Abass *et al*., 2022; Umoren *et al*., 2023) [2, 70]. These innovations offer the potential to transform maternal healthcare delivery, enhance early identification of high-risk pregnancies, and ultimately reduce preventable maternal deaths worldwide. The integration of technology, data, and policy will be pivotal in achieving equitable and sustainable improvements in maternal health outcomes.

3. Conclusion

Predictive analytics has emerged as a transformative tool in the effort to reduce maternal mortality, offering the ability to anticipate high-risk pregnancies and inform timely, evidence-based interventions. By leveraging large-scale health data, predictive models can identify both individual and population-level risk factors, enabling policymakers and clinicians to allocate resources more efficiently and prioritize preventive measures. The integration of predictive analytics into maternal health strategies represents a shift toward proactive, data-driven decision-making, moving beyond reactive responses to adverse events.

National health datasets are particularly valuable in this context, providing comprehensive information on demographic characteristics, clinical histories, healthcare utilization, and socioeconomic and environmental determinants. Vital registration systems, hospital records, demographic and health surveys, and clinical databases collectively allow for robust risk modeling, capturing the multifactorial nature of maternal mortality. These datasets facilitate the development of predictive models that are sensitive to local and regional patterns, improving the accuracy and relevance of risk identification. When effectively harmonized and analyzed, national data resources can serve as the foundation for scalable and sustainable maternal mortality reduction initiatives.

To maximize the potential of predictive analytics, there is a clear need for approaches that are sustainable, ethical, and context-specific. Models must be designed to respect patient privacy, ensure equitable consideration of vulnerable populations, and remain adaptable to changing healthcare landscapes. Capacity building within health ministries, strengthening of health information systems, and incorporation of local social, cultural, and infrastructural factors are essential to contextualize predictions and support actionable interventions. Ethical oversight and transparent communication of model limitations further ensure responsible application.

Predictive analytics, underpinned by comprehensive national datasets, offers a powerful mechanism to identify maternal mortality risk factors and guide targeted interventions. By emphasizing sustainability, ethics, and local context, predictive modeling can serve as a cornerstone of modern maternal health strategies, supporting the global goal of reducing preventable maternal deaths and improving outcomes for women and communities worldwide.

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