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Machine learning for maternal risk prediction in resource- constrained antenatal care: evidence-to-implementation gaps and implications for Sustainable Development Goal 3

Luminsa Desire Alphonse
Universal Technology and Management University
Asiimwe Henry
Universal Technology and Management University
Gatkor Taban Michael Lam
Universal Technology and Management University
Muhanguzi Nimrod
Universal Technology and Management University
Fred Paul Mark Jjunju
fpmjjunju@utamu.ac.ug
Universal Technology and Management University
Denis Bbosa
Mbarara University of Science and Technology (MUST)

Short Report

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Abstract

Objective

Machine-learning (ML) models are increasingly proposed for earlier recognition of maternal risk, but strong discrimination does not itself establish clinical usefulness. This Research Note maps recent maternal-health ML evidence against practical requirements for resource-constrained antenatal care (ANC) and examines how prediction could contribute to Sustainable Development Goal (SDG) 3.

Results

Across the mapped studies and reviews, technical feasibility was common but prospective evidence of clinical benefit was limited. A Rwandan random-forest model reported 90.6% accuracy and an AUROC of 0.85 but only 46.5% recall, illustrating how headline accuracy can obscure missed adverse cases. A northern Ugandan pre-eclampsia model achieved an AUC of 0.849 but depended on laboratory and uterine-artery Doppler inputs that may not be consistently available. Recent syntheses also identify incomplete external validation, calibration, subgroup assessment and implementation evaluation. The evidence supports a prediction-to-action pathway in which predictor availability, temporal validity, calibration, equity, workflow integration, referral capacity and prospective impact are evaluated alongside discrimination. ML can plausibly support SDG 3 only when reliable predictions trigger accessible, timely and effective care.

Introduction

Maternal mortality remains a major global health challenge. The latest United Nations inter-agency estimates indicate that more than 700 women died each day in 2023 from preventable causes related to pregnancy and childbirth, while SDG target 3.1 calls for a global maternal mortality ratio below 70 deaths per 100,000 live births by 2030 [1, 2]. Antenatal care (ANC) offers repeated opportunities for screening, counselling, treatment and referral, and WHO recommends a minimum of eight contacts to improve maternal and perinatal care [3].

Machine learning (ML) is increasingly used to predict pregnancy complications, maternal morbidity and mortality, adverse pregnancy outcomes and patterns of service use [4–7]. Yet reported accuracy or area under the receiver operating characteristic curve (AUROC) is not equivalent to clinical utility. A model can contribute to maternal health only if it predicts a clinically meaningful future event at a defined decision point, uses data available at that time, performs reliably in the intended population and leads to an action that the health system can deliver. This Research Note therefore maps recent maternal-health ML evidence against those implementation requirements and relates the resulting gaps to SDG 3.

Main text

Evidence-mapping approach

This paper is a focused evidence map rather than a systematic review or meta-analysis. It uses representative recent primary studies from Africa and other resource-constrained settings together with contemporary evidence syntheses and prediction-model guidance. Studies were selected to illustrate differences in outcome definition, prediction timing, predictor burden, validation and implementation readiness. No pooled effect estimate or formal study-level risk-of-bias score was produced. Additional file 1 provides the structured evidence map and implementation questions used to organise the synthesis.

What current machine-learning evidence shows

Recent evidence shows that maternal-health ML can be technically feasible while remaining clinically immature. In Rwanda, Sylvain et al. analysed electronic medical records from 25 hospitals; after data cleaning, 32,783 of 117,069 records remained. A tuned random-forest model reported 90.6% accuracy and AUROC 0.85, but recall was 46.5% [8]. The contrast between overall accuracy and recall is important because a screening tool that misses a substantial proportion of adverse cases may have limited value even when aggregate performance appears strong. Large exclusions during cleaning also make missingness and representativeness central to interpretation.

Ugandan evidence demonstrates both local relevance and resource constraints. Awor et al. reported an AUC of 0.849 for pre-eclampsia prediction in northern Uganda using maternal history, clinical assessment, laboratory measures and uterine-artery Doppler [9]. The performance is encouraging, but the richer predictor set may not transfer directly to facilities with intermittent laboratory capacity or no Doppler access. By contrast, Malde et al. examined maternal-risk classification using a sparse set of age, vital-sign and glucose variables from a rural Bangladesh dataset [10], illustrating why lower-burden inputs may improve feasibility. Al Mashrafi et al. similarly compared multiple ML algorithms for maternal-risk classification, but the Oman dataset and outcome construction limit direct transfer to ANC prognosis in African settings [11].

Evidence syntheses reinforce these concerns (Table 1). Vasudevan et al. found maternal morbidity and mortality ML studies concentrated on model development rather than provider-facing clinical implementation [5]. A 2026 review focused on rural settings highlighted methodological quality, external validation and deployment feasibility as recurring weaknesses [6]. An Africa-wide scoping review likewise found that data quality, infrastructure, workforce capacity, stewardship and operational integration shape the real-world value of maternal, newborn and child-health AI [7].

Table 1
Selected evidence and its implication for resource-constrained antenatal care

Source	Setting/task	Key reported result	Implementation implication
Sylvain et al. [8]	Rwanda; adverse pregnancy outcomes	RF accuracy 90.6%; AUROC 0.85; recall 46.5%	Accuracy can mask missed cases; exclusions and missing-data handling affect representativeness.
Awor et al. [9]	Northern Uganda; pre-eclampsia	Combined model AUC 0.849	Local evidence is valuable, but laboratory and Doppler inputs may limit transfer.
Malde et al. [10]	Rural Bangladesh; sparse-input risk classification	Feasibility using age, vital signs and glucose	Lower predictor burden may aid deployment, but prognosis and transportability still require validation.
Vasudevan et al. [5]	Scoping review; maternal morbidity/mortality ML	Evidence concentrated on model development	Provider-facing implementation remains a major gap.
Akuze et al. [7]	Africa-wide MNCH data-science review	Research activity exceeded routine operational integration	Infrastructure, data stewardship and workforce capacity shape real-world value.

From prediction performance to trustworthy clinical use

Prediction timing and data provenance are fundamental. A model intended for early ANC should use only information available at the index contact; variables recorded after referral, repeated later in pregnancy or at delivery can create temporal leakage. A 2025 review of first-trimester models found that calibration was reported for only 21 of 91 developed models and that high risk of bias was common, emphasising that discrimination alone is insufficient [12].

Evaluation should therefore include calibration, sensitivity, specificity, predictive values at clinically meaningful thresholds, uncertainty and geographically or temporally independent validation. Where repeated observations occur, splitting should prevent records from the same woman or pregnancy appearing across development and evaluation sets. TRIPOD + AI provides current reporting guidance for prediction-model studies and PROBAST + AI provides a framework for quality, risk-of-bias and applicability assessment [13, 14]. For tools moving into care, DECIDE-AI emphasises early clinical evaluation, human factors and workflow effects, while FUTURE-AI extends attention to fairness, universality, traceability, usability, robustness and explainability across the deployment lifecycle [17, 18].

Resource constraints, Uganda and the prediction-to-action pathway

Resource-constrained ANC adds a further test: whether a prediction can trigger care. Target 3.1 concerns maternal mortality reduction, not algorithmic discrimination, and target 3.8 concerns access to quality essential services [2]. A risk score has little value when the recommended laboratory test, referral transport, specialist review or definitive treatment is unavailable. WHO guidance on AI for health similarly stresses ethics, governance, accountability and protection against inequitable harm [16].

In Uganda, interpretable ML has also been used to examine skilled birth attendance, with education, ANC use, geography and perceived distance to care among important predictors [15]. That work is useful for population-level access planning but differs from individual clinical risk prediction at a defined encounter. For facility-level tools, future studies should prespecify the intended decision, use predictors available at that point, validate across facilities and later time periods, recalibrate locally, examine subgroup performance and measure downstream effects such as referral appropriateness, missed complications, alert burden, workload, time to definitive care and maternal outcomes.

The resulting prediction-to-action pathway is deliberately conditional: available ANC data must support a valid prediction; the prediction must trigger an appropriate action; the action must connect the woman to accessible and effective care; and the care must improve outcomes. Additional file 1 illustrates this pathway and the gap between model development and demonstrated clinical impact.

Limitations

- This is a focused evidence map, not an exhaustive systematic review; study selection may therefore be affected by availability and author judgement.
- The mapped evidence spans different populations, outcomes, prediction times and predictor sets, so model performance estimates should not be directly ranked.
- No source dataset was re-analysed and no formal PROBAST + AI ratings were assigned; methodological observations are interpretive rather than audited study-level judgements.
- The SDG 3 linkage is a conceptual implementation pathway. The cited prediction studies do not establish that ML use caused a reduction in maternal mortality or improved universal health coverage.

Abbreviations

ANC
antenatal care
AI
artificial intelligence
AUC
area under the receiver operating characteristic curve
AUROC
area under the receiver operating characteristic curve

ML
machine learning
SDG
Sustainable Development Goal
TRIPOD + AI
Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis plus Artificial Intelligence
PROBAST + AI
Prediction model Risk Of Bias ASsessment Tool plus Artificial Intelligence.

Declarations

Ethics approval and consent to participate

Not applicable. This article synthesises published literature and involved no participant recruitment, individual-level patient data, human tissue or animal research.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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Author Contribution

All authors contributed equally, read and approved the manuscript.

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Availability of data and materials

No new datasets were generated or analysed. Evidence discussed in the Research Note is available in the cited publications. The structured evidence map, implementation questions, SDG 3 pathway table and conceptual figures are provided in the supplementary information (SI).

Additional file

Supplementary Information. Structured evidence map; questions for trustworthy maternal-risk prediction in resource-constrained ANC; SDG 3 pathway table; and two conceptual figures illustrating the prediction-to-action pathway and evidence-to-implementation gap.

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