

Pregnancy Health Monitoring System Using Artificial Intelligence: A Review

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ABSTRACT- Pregnancy-related complications such as gestational diabetes, preeclampsia, preterm birth, and fetal distress remain major causes of maternal and perinatal morbidity, and timely detection depends on regular, accurate monitoring that many women cannot easily access. Advances in wearable sensing, mobile health, and artificial intelligence (AI) have made continuous, data-driven pregnancy monitoring technically feasible. This paper presents a structured narrative review of AI-based pregnancy health monitoring, drawing mainly on recent systematic, scoping, and narrative reviews together with selected primary studies. It examines the data sources and sensing modalities used, the machine learning and deep learning techniques applied, and the main application areas: gestational diabetes and preeclampsia prediction, fetal monitoring through cardiotocography, preterm birth and imaging, and wearable and IoT-based remote monitoring. The review finds that AI methods show consistent promise across these areas, but that the evidence base is limited by small single-centre datasets, geographic concentration of research, class imbalance, scarce external validation, and an unresolved tension between accuracy and interpretability. Privacy, sensor accuracy, and user compliance further constrain real-world deployment. The paper proposes a five-layer reference architecture for an AI-based pregnancy health monitoring system and outlines research directions relevant to resource-constrained settings such as India.

Keywords: Pregnancy Monitoring, Artificial Intelligence, Machine Learning, Wearable Sensors, Gestational Diabetes, Preeclampsia, Cardiotocography, Maternal Health

I. INTRODUCTION

Maternal health remains a global priority. The World Health Organization estimated that about 287,000 women died from pregnancy-related causes worldwide in 2020 [1]. India has made substantial progress, with the maternal mortality ratio falling from 130 per 100,000 live births in 2014–16 to 93 in 2019–21 according to the Sample Registration System [2], yet this remains above the Sustainable Development Goal target of fewer than 70. Many complications that lead to maternal and neonatal harm give early warning signs, but those signs are detected only if women are monitored regularly and the data are interpreted correctly.

Conventional antenatal care relies on periodic clinic visits, which can miss changes occurring between appointments and are harder to access for women in rural and remote areas. Wearable sensors, smartphone applications, and Internet of Things (IoT) devices now allow home-based, long-term, non-invasive monitoring [3], and AI can analyse the resulting data to support early detection, diagnosis, and risk stratification [3], [4]. At the same time, machine learning is changing obstetric prediction, from disease risk models to automated analysis of fetal heart rate and imaging [5].

For India, where much antenatal care in rural areas is delivered through primary health centres and community health workers, monitoring tools that extend the reach of a limited clinical workforce are especially relevant [13],[14]. The value of AI in this setting lies less in replacing clinicians than in helping them identify the women who most need

attention, so that scarce consultation time is directed to those at highest risk.

Existing reviews tend to focus on a single condition, a single sensor type, or a single algorithm family. This review brings these strands together from the perspective of a complete monitoring system. Its objectives are: (i) to summarise the data sources and sensing modalities used; (ii) to describe the AI techniques applied; (iii) to review the main application areas and their evidence; (iv) to propose a reference system architecture; and (v) to identify challenges and future research directions, with attention to the Indian context.

II. REVIEW METHODOLOGY

A structured narrative review was undertaken. Searches combined terms for pregnancy and maternal health (pregnancy, maternal, antenatal, obstetric) with terms for the technology (artificial intelligence, machine learning, deep learning, wearable sensors, IoT, remote monitoring) and for specific conditions (gestational diabetes, preeclampsia, preterm birth, cardiotocography, fetal hypoxia).

Priority was given to recent systematic, scoping, and narrative reviews, supplemented by selected primary studies and national statistics. The PRISMA 2020 statement [6] was used as a guide for documenting the criteria in Table 1; as this is a narrative review, no meta-analysis or formal risk-of-bias assessment was performed.

Table 1: Review scope and criteria

Element	Criteria
Topic scope	AI, machine learning, or deep learning applied to monitoring, prediction, or detection of maternal or fetal conditions during pregnancy and labour
Evidence types	Systematic reviews, scoping reviews, narrative reviews, and selected primary studies; national statistics for context
Search focus	Wearable and IoT monitoring; gestational diabetes; preeclampsia; cardiotocography and fetal hypoxia; preterm birth and imaging
Exclusions	Studies without an AI or machine learning component; non-pregnancy applications; editorials and opinion pieces without evidence
Synthesis	Thematic narrative synthesis by data source, technique, and application area

III. DATA SOURCES AND SENSING MODALITIES

Table 2: Data sources and monitoring uses

Data source	Typical measures	Main monitoring use
Wearable sensors [3], [4]	ECG, heart rate, activity, sleep, uterine contraction, fetal movement	Continuous home-based maternal and fetal surveillance
Cardiotocography [9], [10]	Fetal heart rate, uterine contractions	Intrapartum detection of fetal hypoxia and distress
Imaging [5]	Ultrasound and MRI of fetus, placenta, cervix	Anomaly detection, fetoplacental and cervical assessment
Clinical and EHR data [7], [8]	Age, parity, BMI, blood pressure, diabetes, hypertension	Risk prediction for gestational diabetes and preeclampsia
IoT and mobile platforms [3], [11]	Remotely transmitted vitals and risk-factor data	Remote and rural monitoring with alerts to women and families

AI-based monitoring depends on the quality and variety of its inputs. Wearable sensors for pregnancy mainly capture

physiological signals such as electrocardiogram (ECG), uterine contractions, and fetal movement, and these can be combined into multimodal devices [3]. Systems reviewed in the maternal-infant literature use sensors to gauge health parameters and machine learning to predict health conditions that assist practitioners [4]. Clinical data from antenatal visits and electronic records, imaging data from ultrasound and magnetic resonance imaging, and cardiotocography (CTG) recordings complement these continuous streams [5]. Table 2 summarises the main modalities.

IV. ARTIFICIAL INTELLIGENCE TECHNIQUES

Two broad families of techniques dominate. Classical machine learning methods, including logistic regression, support vector machines, decision trees, random forests, and naive Bayes, work on structured clinical and tabular data. In gestational diabetes, studies have examined whether machine learning can outperform traditional logistic regression, and the review evidence stresses the value of integrating clinical data while noting that selecting and weighting variables remains complex [7]. In preeclampsia, random forest, support vector machine, logistic regression, decision tree, and naive Bayes were the most frequently used algorithms, and the commonly used predictors were age, number of pregnancies, body mass index, diabetes, hypertension, and blood pressure [8].

Deep learning methods are generally preferred for raw signals and images, where manual feature design is difficult. Several machine learning algorithms have been used to classify cardiotocography traces after signal processing and feature extraction [9], and reviews of imaging describe machine learning tools for automated analysis of fetal anomalies and for assessing fetoplacental and cervical function with ultrasound and MRI [5]. Comparing these families involves a trade-off: richer models can capture complex patterns but are harder to interpret, and the literature on preeclampsia explicitly concludes that future progress lies in balancing model performance with interpretability.

1. Evaluation And Reporting Considerations

Comparing studies is difficult because performance is reported with different metrics, datasets, and validation strategies. For screening and early-warning tasks, sensitivity and specificity, the area under the receiver operating characteristic curve, and calibration of predicted risks are all relevant, since a model that ranks women well but over- or under-estimates absolute risk can mislead clinical decisions. High accuracy on a balanced benchmark may overstate performance in practice, where adverse outcomes are rare. For this reason, handling of class imbalance, separation of training and test data, and external validation on independent

populations are essential reporting items, and the literature repeatedly identifies their absence as a weakness [8], [9].

2. Emerging Technical Approaches

Several approaches are emerging to address the limits of current models. Explainable AI methods aim to show which inputs drive a prediction, supporting clinician trust. Federated learning allows models to be trained across hospitals without moving patient records, which may help where data cannot be pooled. Edge computing moves part of the analysis onto the phone or a local gateway, reducing dependence on continuous connectivity. These approaches are discussed here as directions suggested by the problems identified in the literature rather than as proven solutions in pregnancy monitoring.

V. APPLICATIONS OF AI IN PREGNANCY MONITORING

1 Gestational Diabetes

A narrative review of fourteen studies on machine learning for gestational diabetes concluded that different models showed promise, highlighted the value of clinical data, and called for attention to diverse populations and emerging data sources [7]. Early prediction matters because screening and diagnosis help reduce complications such as macrosomia, preterm birth, preeclampsia, and neonatal intensive care admission.

2. Preeclampsia

A systematic review of 35 studies selected from 183 identified (2013–2023) found that most research came from China and the USA, that many studies relied on small datasets from single hospitals, and that factors such as medications, genetic data, and imaging were used less often than clinical variables [8]. These findings indicate rapid growth in the field but limited diversity and generalisability.

3. Fetal Monitoring And Cardiotocography

CTG is the most widely used method for intrapartum fetal surveillance, but visual interpretation has a relatively poor positive predictive value for an abnormal trace and significant inter- and intra-observer variability [9]. A scoping review of 36 studies applying signal processing and machine learning to CTG concluded that machine learning shows potential to predict fetal hypoxia from CTG, that most studies used an open-access CTG database, and that fetal metabolic acidosis was the usual benchmark for hypoxia [9]. A narrative review of fetal hypoxia detection similarly identified accurate classification of the "suspicious" CTG category as a persistent challenge that future work should address [10].

4. Preterm Birth And Imaging

Machine learning is also being applied to predict preterm birth and fetal growth restriction, to automate diagnostic imaging of fetal anomalies, to assess cervical and fetoplacental function, and to improve safety in intrapartum care [5]. These applications extend monitoring beyond vital signs to structural and functional assessment.

5. Wearable And Iot-Based Remote Monitoring

Table 3: Comparative summary of key reviewed studies

Reference	Focus	Scope	Key insight
Liu et al. [3]	Wearables and AI	Review of ECG, uterine contraction, fetal movement and multimodal sensors	Promising for early detection; accuracy, privacy and compliance are challenges
Ahmad et al. [4]	Maternal-infant systems	Review of sensors and AI algorithms, chronological	ICT and AI can reach rural, disadvantaged groups
Araim et al. [5]	ML in obstetrics	Narrative review: GDM, preeclampsia, preterm birth, imaging	Broad scope from prediction to intrapartum safety
Kokori et al. [7]	Gestational diabetes	Narrative review, 14 studies	Promise shown; variable selection complex; diverse data needed
Özcan and Peker [8]	Preeclampsia	Systematic review, 35 of 183 studies	RF, SVM, LR, DT, NB common; small single-hospital datasets
Francis et al. [9]	CTG	Scoping review, 36 studies	ML can predict fetal hypoxia; visual CTG has variability
Alharbi et al. [10]	Fetal hypoxia	Narrative review of CTG-based AI	"Suspicious" class remains hard to classify
Ahmed and Rahman [11]	IoT, remote areas	Public dataset plus small IoT-collected data	Logistic Model Tree most accurate in that study

Reviews of wearable sensing report that wearables, data processing, and AI are promising for early detection and smart diagnosis in pregnancy, but face challenges in accuracy, data privacy, and user compliance [3]. Reviews of maternal-infant systems emphasise that sensing and AI allow

health institutions to reach disadvantaged rural groups [4]. A study of risk factors in remote areas used IoT-enabled wearable sensing to notify pregnant women and their families of health conditions; it compared machine learning algorithms on an existing public dataset and a small set of data collected through IoT devices, and found the Logistic Model Tree most accurate [11]. The reliance on a small or repurposed dataset illustrates the data limitations discussed below.

VI. PROPOSED REFERENCE ARCHITECTURE

Drawing on the reviewed literature, Figure 1 presents a conceptual five-layer architecture for an AI-based pregnancy health monitoring system. It is a synthesis of components reported across studies, not an implemented or validated system. Data acquisition combines wearables, fetal and uterine sensors, CTG and ultrasound, and clinical records. An edge or mobile gateway cleans signals, extracts features, issues simple local alerts, and transmits data securely.

Cloud analytics hosts risk models for gestational diabetes, preeclampsia, and preterm birth, along with fetal-distress classification, explainability, and model monitoring. Clinical decision support presents risk-tiered alerts to obstetricians, nurses, and community health workers, and a patient interface delivers reminders, danger-sign alerts, and teleconsultation links. A cross-cutting governance layer covers consent, privacy, bias auditing, and regulation.

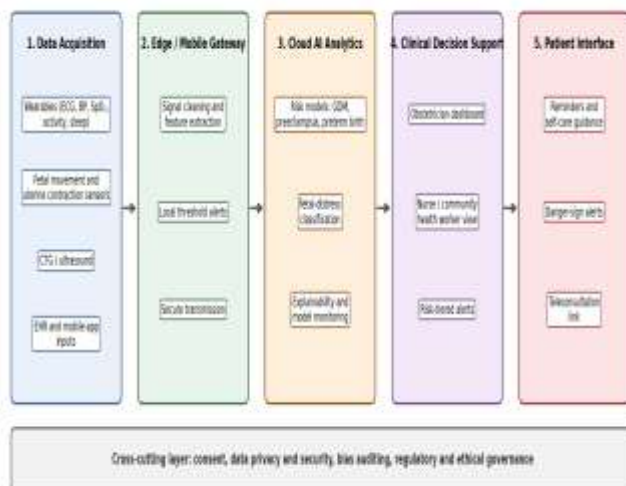


Figure 1: Conceptual reference architecture of an AI-based pregnancy health monitoring system

VII. CHALLENGES AND LIMITATIONS

Data quality and representativeness. Many studies use small datasets from single hospitals, and research is concentrated in a few countries [8]. Models trained on such data may not transfer to Indian populations with different risk profiles and care settings. CTG studies often rely on open-access databases and a limited range of outcome benchmarks [9].

Validation and class imbalance. The CTG literature includes strong reported performance, but minority classes, such as the suspicious category, remain difficult [10], and the pathway from retrospective classification to clinical use requires prospective, externally validated studies [9].

Interpretability. Clinicians need to understand why a woman is flagged as high risk; the preeclampsia literature points to balancing performance with interpretability as the central challenge [8].

Table 4: Key challenges and possible responses

Challenge	Why it matters	Possible response
Small, single-centre datasets [8]	Limits generalisability to other populations	Multi-centre and Indian datasets; federated learning
Class imbalance and weak validation [9], [10]	Inflates apparent accuracy; poor detection of rare outcomes	Imbalance handling; external and prospective validation
Limited interpretability [8]	Clinicians cannot verify or trust flagged risks	Explainable models; transparent risk factors
Sensor accuracy, privacy, compliance [3]	Unreliable data and low adherence reduce benefit	Validated sensors; secure design; user-centred devices
Equity and governance [12]	Risk of excluding rural and low-connectivity users	Offline-capable tools; ethical review; bias audits

Sensor accuracy, privacy, and compliance. Wearable-based systems face challenges in accuracy, data privacy, and user compliance [3]. Continuous collection of sensitive health data raises security and consent concerns, which become more demanding as data pass through sensors, gateways, networks, and cloud platforms.

Equity and governance. AI tools can widen inequalities if they work only for connected, well-resourced users. In India, development and deployment should follow national guidance on the ethical use of AI in biomedical research and

healthcare [12], including attention to consent, accountability, and bias.

1. Future Research Directions

Priorities include:

- building large, multi-centre, and Indian pregnancy datasets that include rural populations, with careful attention to consent and de-identification;
- multimodal models that fuse wearable, clinical, and imaging data rather than relying on a single source;
- explainable AI that gives clinicians transparent risk factors;
- privacy-preserving approaches that keep sensitive data local where possible;
- prospective trials and external validation that measure clinical outcomes, not only classification accuracy;
- low-cost, validated sensors and offline-capable mobile tools suited to areas with limited connectivity
- workflow integration so that alerts reach community health workers and doctors in ways that fit existing antenatal care.

2. Implications For Practice And Policy

For hospitals and public health programmes, the reviewed evidence suggests starting with decision support that augments existing antenatal workflows, such as risk-tiered lists for obstetricians and community health workers, rather than fully automated decisions. For policymakers, investment in shared, de-identified datasets, interoperable health records, and clear validation standards would reduce duplication and improve model quality. For developers, early engagement with clinicians and pregnant women, together with transparent reporting of performance across subgroups, is needed to build tools that are both trusted and equitable.

VIII. CONCLUSION

AI-based pregnancy health monitoring combines wearable and clinical data with machine learning to support earlier detection of gestational diabetes, preeclampsia, preterm birth, and fetal distress. The reviewed literature shows consistent promise but also clear limits: small and geographically concentrated datasets, imbalanced classes, scarce external validation, interpretability concerns, and privacy and compliance issues.

The reference architecture proposed here offers a structure for developing systems that are clinically useful, secure, and suited to resource-constrained settings. Progress will depend on larger and more representative datasets, explainable and validated models, and governance that protects women while extending quality antenatal monitoring to those who need it most.

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