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Artificial Intelligence In Antenatal Risk Assessment: Transforming Maternal–Fetal Monitoring In Nursing Practice

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Abstract

Artificial intelligence (AI) and machine learning (ML) are rapidly reshaping antenatal care by improving risk stratification, enabling earlier detection of complications (such as preeclampsia and fetal hypoxia), automating interpretation of fetal monitoring, and supporting patient-tailored interventions. For OBG nurses, these technologies promise improved surveillance, workflow efficiencies, and enhanced patient education — but also introduce new responsibilities, ethical questions, and implementation challenges (data quality, algorithm bias, explainability, and integration into clinical pathways). This article reviews current AI applications for antenatal risk assessment, summarizes evidence for key clinical use-cases (preeclampsia prediction and cardiotocography/CTG interpretation), explores implications for nursing practice, and outlines practical recommendations for safe, equitable adoption. Key recommendations include nurse involvement in development/validation, emphasis on explainable AI, local external validation before deployment, and strengthening digital literacy and policy frameworks to ensure patient safety and equity.

Keyword- Artificial Intelligence, Antenatal Risk Assessment, Maternal–Fetal Monitoring, Nursing Practice.

I. Introduction

Antenatal risk assessment is central to obstetric care: identifying women at higher risk of hypertensive disorders, gestational diabetes, fetal growth restriction, or intrapartum compromise enables timely intervention and better outcomes. Traditional risk stratification relies on clinical history, routine tests, and clinician judgment. Over the past decade, AI — especially supervised machine learning and deep learning — has demonstrated promise in extracting patterns from large and complex antenatal datasets (electronic medical records, ultrasound, cardiotocography, biochemical markers) that are not readily apparent to clinicians, offering more sensitive and earlier detection of risk states. Recent systematic reviews and scoping studies highlight substantial growth in AI models aimed at predicting pregnancy complications and automating fetal monitoring interpretation, with encouraging discrimination metrics in many development cohorts.

II. Key AI Applications in Antenatal Risk Assessment

1. Predicting Hypertensive Disorders (Preeclampsia)

Preeclampsia remains a major cause of maternal and perinatal morbidity. Multiple ML models — using routinely collected clinical variables, laboratory results, and sometimes biomarkers — have been developed to predict preeclampsia risk at different gestational ages. Systematic reviews show that several algorithms achieve acceptable-to-good discrimination in development datasets, but the literature consistently notes heterogeneity in predictors, model types, and a shortage of robust external validations across diverse populations. External validation and calibration are essential before clinical use because model performance often degrades when applied to different settings.

2. Automated Interpretation of Cardiotocography (CTG) and Fetal Monitoring

Interpretation of CTG traces is operator-dependent and can suffer from inter-observer variability. Deep learning and hybrid ML approaches have been used to classify CTG traces and predict fetal compromise (e.g., metabolic acidosis, low Apgar) with performance that in many studies matches or exceeds human readers on tested datasets. However, differences in data labeling (outcome definitions like pH thresholds), dataset composition, and clinical endpoints make direct comparison difficult; prospective and deployment studies remain limited.

3. Ultrasound and Prenatal Diagnosis Support

AI applied to imaging (ultrasound) can automate biometric measurements, detect structural anomalies, and assist in screening for chromosomal disorders through pattern recognition of screening markers. These systems can reduce repetitive measurement tasks and potentially increase detection rates, especially where sonographer expertise is limited.

4. Digital Triage, Remote Monitoring, and Patient-Facing Tools

AI-powered mobile apps and remote-monitoring platforms can triage symptoms, interpret home blood pressure or glucose data, and deliver tailored education to pregnant women. These tools extend surveillance beyond clinics and can be particularly useful in underserved or rural settings, but must be validated for clinical safety and equity. The WHO’s digital health initiatives and SMART Guidelines emphasize evidence-based digital interventions and the need for standardized, implementable recommendations.

III. Evidence Summary and Limitations

The recent literature shows rapid growth: systematic reviews and scoping studies (2022–2025) report promising model discrimination for several obstetric outcomes, but also recurrent methodological limitations — small or single-center datasets, lack of external validation, inconsistent outcome definitions, limited attention to fairness/bias and explainability, and sparse prospective deployment studies. These gaps mean that while AI can *augment* antenatal risk assessment, it should not replace clinical judgment until validated across representative populations and care settings.

IV. Implications for OBG Nursing Practice

Clinical care and monitoring

- **Enhanced triage and prioritization:** AI risk scores can help nurses prioritize higher-risk women for closer monitoring or expedited review, improving resource allocation in busy antenatal clinics.
- **Decision support at point-of-care:** Integrating AI outputs into electronic records or monitoring devices can provide actionable prompts (e.g., recommend earlier aspirin for high preeclampsia risk, prompt BP recheck), but outputs must be accompanied by clear guidance and thresholds to avoid alarm fatigue.
- **Improved fetal surveillance:** Automated CTG interpretation offers a second opinion and may reduce missed signs of fetal compromise when used as an adjunct; nurses must understand algorithm strengths/limits.

Nursing workflow and education

- **New competencies required:** Nurses will need training in digital literacy, interpretation of AI outputs (including uncertainty and confidence intervals), and in communicating AI-derived risk to patients compassionately and clearly.
- **Documentation and accountability:** When care decisions are informed by AI, nursing documentation should note the tool used and the rationale, while preserving clinician responsibility for final decisions.

Patient education and engagement

- Nurses play a crucial role in explaining what AI tools do, addressing patient concerns about privacy and bias, and supporting shared decision-making. Patient-facing AI must respect health literacy and cultural context.

V. Ethical, Legal and Equity Considerations

AI systems can propagate or amplify biases present in training data — for instance, underrepresenting marginalized groups leads to worse performance for those populations. Transparency (explainability), data governance, informed consent for use of patient data, and clear regulatory oversight are essential. Clinicians must be alert to automation bias (over-reliance) and ensure human oversight. The WHO and related bodies are actively developing frameworks and toolkits to guide safe digital health adoption, stressing equity and validation.

VI. Practical Recommendations for Safe Adoption in Nursing Settings

1. **Engage nurses early in design and validation** — front-line input improves usability and clinical relevance.
2. **Require external validation and local calibration** before clinical deployment; test models on local populations.
3. **Use explainable models or accompany black-box outputs with interpretable summaries** so nurses can justify recommendations to patients and clinicians.
4. **Implement training programs** for nursing staff on interpreting AI outputs, understanding limitations, and documenting use.
5. **Establish governance** for data privacy, model monitoring (performance drift), and incident reporting.
6. **Monitor equity metrics** (performance across subgroups) and be prepared to retract or adjust models that worsen disparities.

VII. Future Directions

To realize AI's potential in antenatal care, priorities include assembling large, diverse, and interoperable datasets; standardizing outcome definitions; conducting prospective, randomized or impact studies assessing clinical outcomes (not only model accuracy); and developing lightweight, explainable models suitable for low-resource settings. Nurse-led implementation research will be crucial to identify workflow effects, patient acceptability, and real-world safety.

VIII. Conclusion

AI has the potential to meaningfully improve antenatal risk assessment earlier detection of conditions like preeclampsia, more consistent fetal monitoring interpretation, and enhanced remote surveillance. For OBG nurses, this technology offers tools to improve triage, monitoring, and patient education while introducing new responsibilities around interpretation, documentation, and safeguarding equity and patient autonomy. Safe, effective integration requires robust validation, nurse involvement, education, clear governance, and attention to ethical and equity considerations. When implemented thoughtfully, AI can become a trusted ally in nursing practice to improve maternal and neonatal outcomes.

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