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Artificial Intelligence for Women and Child Healthcare: Is AI Able to Change the Beginning of a New Story? A Perspective

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ABSTRACT

Background and Aims: Maternal and neonatal mortality remain critical global health challenges, particularly in low-resource settings where preventable deaths occur due to inadequate access to timely care. This article explores the potential of Artificial Intelligence (AI) to enhance maternal and child healthcare by improving early risk identification, diagnosis, treatment recommendations, and postpartum monitoring.

Methods: It explores the use of AI in identifying pregnancy-related risks, recommending treatments, predicting adverse outcomes, and monitoring postpartum and neonatal care. Various AI models, including supervised machine learning, Large Language Models (LLMs), and Small/Medium Language Models (SLMs/MLMs), are discussed in terms of their feasibility into resource-limited healthcare systems.

Results: AI has demonstrated significant potential in identifying pregnancy-related risks, recommending treatments, predicting adverse outcomes, and supporting postpartum and neonatal care. While AI-driven solutions can optimize healthcare decision-making and resource allocation, challenges such as data availability, integration into clinical workflows, and ethical considerations must be addressed for widespread adoption.

Conclusion: AI offers promising solutions to reduce maternal and neonatal mortality by enhancing risk detection and clinical decision-making. However, its real-world implementation requires overcoming barriers related to data quality, infrastructure, and equitable deployment. Future efforts should focus on data standardization, AI model optimization for resource-limited settings, and ethical considerations in clinical integration.

1 | Introduction

As highlighted in the documentary The Beginning of Life, *"If you change the beginning of the story, you change the whole story"* [1]. In this perspective article, I explore the potential of Artificial Intelligence (AI) for improving women and child health, highlighting its applications across the continuum of care—from pregnancy to delivery and the postpartum (neonatal) period. Is AI able to change the beginning of a new story? How can we use AI to change and improve stories of whole families?

Maternal, fetal, and neonatal mortality remain significant global public health challenges, with millions of lives lost annually [2, 3]. The risks associated with maternal and neonatal mortality are multifactorial, encompassing medical, socioeconomic, and systemic dimensions [4]. According to the World Health Organization (WHO), in 2020, approximately 287,000 women lost their lives to preventable causes associated with pregnancy and childbirth, with the vast majority (95%) occurring in low- and middle-income countries [2]. The primary causes of maternal mortality include postpartum hemorrhage, hypertensive disorders (such as pre-eclampsia and eclampsia), infections, obstructed labor, and complications arising from unsafe abortions [4, 5]. Furthermore, an estimated 2 million stillbirths [6] and 2.4 million neonatal deaths [7] are reported each year, emphasizing the need for more efficient interventions during pregnancy and the perinatal period.

I would like to highlight the term *"preventable causes"* as it underscores the potential to intervene effectively to avoid the majority of deaths related to maternity and the neonatal period. Beyond direct obstetric causes previously mentioned, these fatalities often result from lack of timely and quality medical care, and social inequities, creating accessibility and affordability barriers.

Using AI not only to address technical challenges but save lives, developing practical solutions for frontline healthcare professionals has been a key motivation driving my current research. We need to create tools that are not only effective but also seamlessly integrate into the daily workflows of those at the forefront of this critical battle, while carefully considering the significant resource constraints—both material and human—that many healthcare settings face.

1.1 | Identification of Risks During Pregnancy

Early detection of pregnancy-related risks is crucial for preventing adverse outcomes. However, many health systems, particularly in low- and middle-income countries, lack not only adequate infrastructure—ranging from basic laboratory tests to advanced diagnostic equipment—but also trained personnel to effectively monitor maternal and fetal health.

In this phase, AI models can be trained and utilized to aid in the identification of risk conditions, such as gestational diabetes mellitus (GDM) [8], pre-eclampsia [9], and preterm labour [10], which often go undiagnosed in resource-limited settings [11]. AI models could learn from structured data from electronic health records (EHRs), patient demographics, clinical history; when available, laboratory results and routine prenatal checkups could also be used as input for models' training.

By training supervised machine learning models (such as decision tree, random forest and gradient boosting) on historical data with labeled outcomes, AI models can learn to predict the likelihood of these conditions in patients during prenatal checkups, providing an opportunity to change negative outcomes through more effective and timely actions, reducing preventable complications.

1.2 | Recommendation for Treatments

Once risks are identified, the challenge of recommending appropriate treatments and interventions arises due to a combination of resource limitations, urgency, and complexity in decision-making. Particularly in low- and middle-income countries, the availability of essential medications, skilled personnel, and emergency care may be insufficient to address identified risks effectively.

Large Language Models (LLMs), such as OpenAI GPT and Meta's LLaMA, are an AI type designed to process and generate human-like text. These models were (and are constantly) trained on vast amounts of data, allowing them to understand human language, answer questions, and summarize information. Therefore, LLMs can be used to process clinical guidelines, patient data, and scientific literature to generate comprehensive, evidence-based medical recommendations. As these models can be trained with domain-specific documents, there are variations designed to meet the unique needs of healthcare and biomedical research, offering improved accuracy and relevance in their medical recommendations and predictions, such as BioBERT [12], PubMedGPT [13], and BioGPT [14].

However, LLM models typically require substantial computational resources, extensive datasets, and significant time to be trained, demanding powerful hardware, such as high-performance GPUs or TPUs, and large-scale cloud infrastructure, making them computationally expensive and resource-intensive. In contrast, Small Language Models (SLMs) and Medium Language Models (MLMs) offer a more cost-effective and computationally efficient alternative. While they have fewer parameters and require less data for training, they can be useful in domain-specific applications in resource-constrained settings, such as providing tailored interventions aligned with local healthcare needs. These models can be trained on regional data tailors interventions, considering the limited availability of certain medications or referral options in that specific setting, accounting for the specific challenges faced by low- and middle-income countries.

This area of research is particularly new, with limited studies currently available in the literature; it highlights an opportunity for further exploration, paving the way for new investigations into how LLMs, SLMs, and MLMs can be leveraged to address these critical gaps in maternal and neonatal healthcare.

1.3 | Predicting Diseases and Negative Outcomes

Predicting the likelihood of adverse outcomes, such as stillbirth or neonatal death, is essential for proactive care planning. Accurate risk stratification allows healthcare providers to focus on the most vulnerable populations.

From a technical perspective, this challenge is closely related to the both issues related previously. By learning from historical cases, AI models can estimate the probability of stillbirth or neonatal death, providing actionable insights that guide proactive care [15]. For example, high-risk patients can be flagged for closer monitoring, such as more frequent prenatal visits or additional diagnostic tests like ultrasounds. AI models can also assist in resource prioritization, ensuring that limited healthcare resources, like Neonatal Intensive Care Unit (NICU) beds or specialized care, are allocated to those most in need.

Additionally, LLM models can also be applied here to recommend tailored interventions, such as prescribing corticosteroids to promote fetal lung development or advising early labor induction when complications are detected. However, I would like to emphasize that AI-generated recommendations must always be reviewed and validated by healthcare professionals before implementation. While LLMs can assist in processing vast amounts of medical literature and clinical guidelines to generate evidence-based suggestions, they do not replace the expertise, clinical judgment, and ethical considerations of health specialists.

1.4 | Monitoring and Support During Postpartum and Neonatal Care

Effective monitoring and support during the postpartum and neonatal periods are critical for ensuring the health and well-being of both mother and baby.

AI models can monitor postpartum mothers for signs of complications such as postpartum hemorrhage and infections [16], or mental health issues like postpartum depression [17]. For newborns, AI can assist in identifying conditions such as jaundice or respiratory distress by analyzing data from wearable devices, vital sign monitors, or electronic health records [18]. Real-time alerts and risk assessments can guide healthcare providers in initiating necessary interventions, ensuring prompt and effective care.

However, a significant challenge lies in the availability of real-time data, as these solutions often require additional devices and infrastructure that are frequently unavailable in low- and middle-income countries. Addressing this gap requires innovative solutions, such as low-cost monitoring devices, integration with existing healthcare technologies, and the use of AI models optimized for limited or intermittent data inputs (SLMs and MLMs).

2 | Conclusions

In my point of view, AI holds immense potential to transform maternal and neonatal healthcare by *"preventing preventable deaths"* through early risk identification, tailored interventions, and efficient resource allocation. However, despite all these mentioned opportunities, there remains a long and challenging road ahead before these AI-based solutions can be effectively implemented in real-world clinical settings, particularly regarding data availability and integration into existing healthcare systems. The collection and availability of primary data is crucial for training and improving AI models, and especially In low- and middle-income countries, however, the lack of data infrastructure and standardized electronic health records can hinder—or even delay—the effective implementation of any AI-driven solution. Therefore, I think it is crucial to establish a dedicated task force to raise awareness about the importance of comprehensive health records collection and reporting.

In my point of view, future works should focus on: (a) enhancing (or even starting the process of having) data collection and standardization, ensuring that AI models can be trained on high-quality and representative datasets; (b) developing AI models optimized and focused on low- and middle-income countries constraints; (c) ensuring ethical and equitable AI deployment, addressing biases in training data.

AI cannot be viewed solely as a technological advancement; it must be an integral part of a broader, integrated solution that addresses systemic healthcare challenges. By aligning technological innovations with the realities of resource-limited environments, AI can enhance the decision-making process and contribute to changing (whole) lives where it is needed most.

Author Contributions

Patricia Takako Endo: conceptualization, investigation, writing – original draft, data curation, writing – review and editing, visualization, project administration, supervision, resources, formal analysis, validation, funding acquisition.

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Ethics Statement

I declare that the work submitted to Health Science Reports has been done in accordance to Wiley's Best Practice Guidelines on Publishing Ethics and that is has been performed in an ethical and responsible way, with no research misconduct, which includes, but is not limited to data fabrication and falsification, plagiarism, image manipulation, unethical research, biased reporting, authorship abuse, redundant or duplicate publication, and undeclared conflicts of interest.

Conflicts of Interest

The author declares no conflicts of interest.

Data Availability Statement

The author confirm that the data supporting the findings of this study are available within the article.

Transparency Statement

Patricia Takako Endo affirms that this manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned (and, if relevant, registered) have been explained. All authors have read and approved the final version of the manuscript. Patricia Takako Endo had full access to all of the data in this study and takes complete responsibility for the integrity of the data and the accuracy of the data analysis.

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