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Editorial: New technologies improve maternal and newborn safety

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Editorial on the Research Topic
New technologies improve maternal and newborn safety

1 Introduction

Daily, it's reported that 800 women and 6,700 newborns lose their lives during or shortly after childbirth. Furthermore, approximately 5,400 babies are stillborn each day, with 40% of these losses occurring during the birthing process (1). A significant portion of these stillbirths, maternal deaths, neonatal fatalities, and injuries are preventable through the provision of safe, respectful, and quality care during pregnancy, childbirth, and the early days of a newborn's life. The World Health Organization (WHO) encourages healthcare facility administrators, policymakers, and healthcare providers worldwide to adopt five principal goals for World Patient Safety Day 2021 (2). These goals are directed at improving the safety of mothers and newborns at critical healthcare moments, particularly during childbirth (2). The goals encompass: "(1) Reducing unnecessary and harmful interventions for women and newborns during childbirth; (2) Strengthening the support and skills of healthcare workers to provide safe care for mothers and infants; (3) Promoting respectful care to ensure a positive birth experience; (4) Improving the safe use of medications and blood transfusions during childbirth; and (5) Methodically recording and analyzing safety incidents related to childbirth" (2).

There's a profound interest in pioneering innovations that enhance the safety of mothers and newborns, particularly in addressing the dangers posed by inadequate maternal and neonatal care during pregnancy, childbirth, and the initial postnatal period (3, 4). However, significant challenges hinder the efficacy and affordability of existing interventions. As such, this synopsis aggregates the recent breakthroughs (5) and methodologies (6–11), delves into potential impact on improving maternal and infant safety, and reflects on how these advancements may guide future academic research.

2 Intrapartum ultrasound in assessing labor dynamics

Approximately half of the world's stillbirths, as well as maternal and neonatal deaths, stem from complications during labor, delivery, and the immediate postnatal phase, especially prevalent in regions with limited resources (12). While these fatalities are largely avoidable through prompt interventions like cesarean sections, there are apprehensions surrounding both their underutilization and overutilization (13). Historically, the primary role of obstetric ultrasound has been in prenatal screenings for fetal anomalies (14). Yet, its utility in monitoring labor progression is emerging, bolstered by an increasing corpus of evidence attesting to its capability to objectively evaluate labor dynamics (15). The advent of true intrapartum ultrasound, an innovative facet of this technology, is gaining ground. This approach has illuminated the complex physiological mechanisms of labor, offering detailed insights into the phases of childbirth and potentially forecasting the outcomes of instrumental vaginal births. Nonetheless, the technique's complexity and susceptibility to inaccuracies, particularly when operated by obstetricians without specialized ultrasound training, cannot be overlooked. In this context, the integration of Artificial Intelligence (AI) could be revolutionary. AI has the potential to streamline and refine this process, improving the accuracy of measurements and diminishing the dependency on the individual clinician's expertise (16–19).

The Grand Challenge on Pubic Symphysis-Fetal Head Segmentation (PSFHS) from Transperineal Ultrasound Images (https://doi.org/10.5281/zenodo.7861699), a segment of the 26th International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI), marks a significant stride in this arena (https://ps-fh-aop-2023.grand-challenge.org/) (20, 21). This challenge drew over 100 teams to develop AI algorithms specifically for obstetric ultrasound imaging. The goal was not limited to analyzing images; it also encompassed the assurance that these AI solutions conform to clinical standards while assessing biometric parameters accurately (6, 22–25). The triumph of the MICCAI-PSFHS Challenge underscores the evolution of advanced intrapartum ultrasound technology, highlighting not just technological progress but also the potential of AI models to predict the most suitable delivery methods. For instance, we launched the Intrapartum Ultrasound Grand Challenge (IUGC) (https://zenodo.org/records/10979813) as part of MICCAI 2024 (https://codalab.lisn.upsaclay.fr/competitions/18413) (26). This challenge calls for the development of automatic, user friendly systems for fetal biometrics, aiming to minimize intra and inter observer variability and enhance the reliability of measurements. Such advancements could revolutionize labor management, blending the precision of technology with the nuances of human care.

3 Biosignal-based methods for fetal-maternal monitoring

Continuous fetal heart rate (FHR) monitoring via cardiotocography (CTG) stands as the primary technique for assessing fetal well-being during labor, simultaneously tracking FHR and uterine contractions (UC) (27). This dual monitoring allows for real-time analysis of these critical parameters. The extraction of FHR and UC data predominantly relies on either invasive or non-invasive methods, with the latter being more commonly used. Specifically, non-invasive methods like Doppler ultrasound and the tocodynamometer involve attaching two external transducers to the mother's abdomen. Despite their widespread use, these signals often encounter interference from fetal or maternal movements and may diminish in quality as maternal body mass index increases. This limitation in CTG data reliability poses a substantial challenge in meeting the performance criteria necessary for its extensive clinical deployment (7, 9, 28–32). This challenge underscores the urgent need for innovative monitoring techniques such as the non-invasive fetal electrocardiogram (33) and electrohysterogram (34) to improve the fundamental data quality vital for developing automated systems.

In response to this need, the biennial Workshop on Signal Processing and Monitoring in Labor (SPaM) serves as a collaborative platform, promoting a range of interdisciplinary research approaches and innovations. The SPaM Workshop (https://www.wrh.ox.ac.uk/research/spam-in-labour) aims to cultivate a truly interdisciplinary arena and create a shared language among clinicians, physiologists, and signal processing specialists (35). The development of novel data-driven methods for CTG analysis during labor necessitates comprehensive datasets that encapsulate uncommon clinical situations. Currently, only a limited number of public CTG datasets are available: (1) The Czech Technical University and University Hospital in Brno (CTU-UHB) dataset (36), which includes 552 CTG recordings with unprocessed FHR and UC signals, and (2) the Lille dataset, which contains 156 CTG recordings from the obstetric clinic at Saint Vincent de Paul Hospital (Lille, France) (37). Jinan University also provides two datasets under a data sharing agreement: one with 784 signals for signal categorization (29), and another with 331 signals for automated feature extraction from signals (7, 32).

The past decade has seen an influx of machine learning and deep learning approaches in the medical field, prompting numerous studies focusing on the analysis of CTG signals (38–45). Modern systems demonstrate impressive efficacy in detecting fetal hypoxia in retrospective patient groups. Nevertheless, several challenges must be overcome to facilitate their integration into clinical practices. Primarily, creating and disseminating comprehensive, open, and anonymized multicentric databases of perinatal and CTG data from labor is crucial to enhance system precision (31). Furthermore, these systems should provide comprehensible metrics along with risk assessments for fetal hypoxia to build trust and acceptance among medical professionals. Finally, it's vital to establish and adhere to universal evaluation standards for these systems using retrospective patient groups and to validate their clinical utility.

4 Biophysics-based computer modelling

The successful progression of labor is closely associated with changes in cervical compliance, particularly evident through cervical shortening. The proper timing of these uterine changes is crucial, as deviations can lead to significant clinical consequences. Notably, premature uterine activation, often accompanied by early cervical shortening, can result in preterm birth, affecting an estimated 15 million infants worldwide each year, as reported by the WHO (46). These early births significantly heighten the risk of neonatal death (constituting more than half of all neonatal deaths) and various long-term health issues. The relatively limited understanding of the physiology behind uterine activation constrains our ability to enhance clinical interventions for severe pregnancy complications such as preterm birth and uterine dystocia. Recognizing the potential of multi-scale computational modeling of the uterus is gaining momentum. This approach aims to integrate diverse pieces of information into a unified, predictive, and testable model of uterine behavior, thereby informing the creation of new diagnostic and treatment strategies for these pressing clinical challenges (47).

While uterine models offer an alternative to *in vivo* experiments on animal and human subjects through simulations, authentic data from these subjects are crucial for developing a uterine model that provides clinically relevant insights (48–50). Therefore, noninvasive methods of data collection are incredibly valuable. Pioneering work by researchers at Washington University School of Medicine in St. Louis has led to the development of innovative imaging technology that enables real-time, three-dimensional visualizations of the intensity and spread of uterine contractions across the entire surface of the uterus during labor (51). This technology, an extension of imaging techniques previously used for the heart, provides a noninvasive, intricately detailed view of uterine contractions, surpassing the capabilities of current tools that only detect the presence of contractions (52, 53). Although advancements in data recording technology have streamlined the process of gathering authentic clinical data, a significant portion of research still proceeds without experimental data. Even when experimental data is incorporated into research, the collected information may not be sufficient or suitable for both the development and validation of models.

5 Digital twin in fetal-maternal health

Digital twins (DTs) in healthcare represent sophisticated virtual models of patients, created by integrating individual patient data, wider population statistics, and real-time updates related to patient-specific and environmental variables (54). These DTs for precision health are complex virtual constructs designed to emulate the anatomy, context, and behavior of human bodies or healthcare systems, including their interconnections. They are regularly updated with information from their real-life counterparts and are characterized by their predictive functionality. The validity of a DT can be verified, making it an invaluable tool for decision-making, providing critical insights to inform the delivery of health and wellness care (8). At the heart of the digital twin concept is the dynamic, two-way communication between the virtual and physical realms. This continuous flow of data from the human health system to the computational model ensures the digital twin remains in lockstep with the human health system. Such a close alignment significantly improves the capacity to identify risk factors based on current or expected behaviors and/or adverse events. Although DTs are a relatively new concept in healthcare compared to other industries, they have demonstrated potential across various sectors of precision medicine (55, 56). Applications include managing chronic diseases like asthma and diabetes, tailored cancer treatments, personalized cardiovascular system models (57–60), and predictive simulations for treatment responses in infectious diseases. However, integrating DTs into healthcare presents several challenges and obstacles that must be addressed. Overcoming these challenges is imperative for DTs to fulfill their promise as a cutting-edge framework for individual health management and healthcare services.

In today's advancing landscape, sophisticated technologies such as medical imaging, data analytics, and AI are reshaping prenatal care for pregnant women and fetuses (61–64). These technologies significantly enhance the accuracy and efficacy of healthcare services, signifying a profound shift towards more individualized and predictive healthcare approaches. As these technologies continue to mature and merge with the digital twin concept, they are poised to unlock unparalleled capabilities in the monitoring, diagnosis, and treatment of health conditions, potentially transforming the realm of maternal and fetal medicine.

6 Conclusions

The research marks a significant stride forward in enhancing maternal and newborn safety, setting the stage for notable advancements in diagnosis and treatment. The promise of these developments lies not just in the individual technologies, but in the synergy of multidisciplinary research, the seamless integration of cutting-edge technologies, and the tailoring of care to individual needs. This holistic approach is pivotal in revolutionizing fetal-maternal health, promising to elevate the quality of life for countless patients globally. The path forward is one of collaboration and relentless innovation, leading to a future where fetal-maternal monitoring transcends its current boundaries to become more precise, efficacious, and universally accessible, thereby transforming the landscape of maternal and newborn healthcare.

Author contributions

JB: Writing – review & editing, Writing – original draft, Validation, Funding acquisition, Conceptualization. YL: Writing – review &

editing, Funding acquisition. HL: Writing – review & editing. FH: Writing – review & editing. XG: Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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