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Advancements in Fetal Heart Rate Monitoring: A Report on Opportunities and Strategic Initiatives for Better Intrapartum Care

Aimée Lovers[1] | Martin Daumer[2] | Martin G. Frasch[3] | Austin Ugwumadu[4] | Philip Warrick[5,6] | Rik Vullings[7] | Nicolò Pini[8,9] | John Tolladay[10] | Olav Bjørn Petersen[11,12] | Christian Lederer[2] | Liu Yang[13] | Petar M. Djurić[13] | Farhad Abtahi[14,15] | Malin Holzmann[16,17] | Samuel Boudet[18] | Agathe Houzé de l'Aulnoit[19] | Antoniya Georgieva[10,20]

[1]Department of Obstetrics and Gynaecology, Amsterdam UMC, Amsterdam, the Netherlands | [2]School of Computation, Information and Technology, Technische Universität München, Munich, Germany | [3]Department of Obstetrics and Gynecology and Institute on Human Development and Disability, University of Washington, Seattle, Washington, USA | [4]Department of Obstetrics & Gynecology, St. George's Hospital, University of London, UK | [5]PeriGen Inc., Cary, North Carolina, USA | [6]Department of Biomedical Engineering, Faculty of Medicine and Health Sciences, McGill University, Montreal, Quebec, Canada | [7]Department of Electrical Engineering, Eindhoven University of Technology, Eindhoven, the Netherlands | [8]Department of Psychiatry, Columbia University Irving Medical Center, New York, New York, USA | [9]Division of Developmental Neuroscience, New York State Psychiatrics Institute, New York, New York, USA | [10]Oxford Labour Monitoring Group, Nuffield Department of Women's & Reproductive Health, University of Oxford, Oxford, UK | [11]Department of Clinical Medicine, University of Copenhagen, Copenhagen, Denmark | [12]Department of Gynecology, Fertility and Obstetrics, Copenhagen University Hospital, Rigshospitalet, Denmark | [13]Electrical and Computer Engineering, Stony Brook University, Stony Brook, New York, USA | [14]Department of Clinical Science, Intervention and Technology, Karolinska Institutet, Stockholm, Sweden | [15]Department of Clinical Physiology, Karolinska University Hospital, Stockholm, Sweden | [16]Department of Women's and Children's Health, Karolinska Institutet, Stockholm, Sweden | [17]Medical Unit Pregnancy and Delivery Care, Karolinska University Hospital, Stockholm, Sweden | [18]Faculty of Medicine, Midwifery and Health Sciences, Lille Catholic University, Lille, France | [19]Obstetrics Department, Saint Vincent de Paul Hospital, Lille Catholic University, Lille, France | [20]Big Data Institute, University of Oxford, Oxford, UK

Correspondence: Antoniya Georgieva (antoniya.georgieva@wrh.ox.ac.uk)

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ABSTRACT

Cardiotocography (CTG), introduced in the 1960s, was initially expected to prevent hypoxia-related deaths and neurological injuries. However, more than five decades later, evidence supporting the evidence of intrapartum CTG in preventing neonatal and long-term childhood morbidity and mortality remains inconclusive. At the same time, shortcomings in CTG interpretation have been recognised as important contributory factors to rising caesarean section rates and missed opportunities for timely interventions. An important limitation is its high false-positive rate and poor specificity, which undermines reliably identifying foetuses at risk of hypoxia-related injuries. These shortcomings are compounded by the technology's significant intra- and interobserver variability, as well as the subjective and complex nature of fetal heart rate interpretation. However, human factors and other environmental factors are equally significant. Advancements in fetal heart rate monitoring are crucial to support clinicians in

improving health outcomes for newborns and their mothers, while at the same time avoiding unnecessary operative deliveries. These limitations highlight the clinical need to enhance neonatal outcomes while minimising unnecessary interventions, such as instrumental deliveries or caesarean sections. We believe that achieving this requires a paradigm shift from subjective interpretation of complex and nonspecific fetal heart rate patterns to evidence-based, quantifiable solutions that integrate hardware, engineering and clinical perspectives. Such transformation necessitates an international, multidisciplinary effort encompassing the entire continuum of pregnancy care and the broader healthcare ecosystem, with emphasis on well-defined, actionable health outcomes. Achieving this will depend on collaborations between researchers, clinicians, medical device manufacturers and other relevant stakeholders. This expert review paper outlines the most relevant and promising directions for research and strategic initiatives to address current challenges in fetal heart rate monitoring. Key themes include advancements in computerised fetal heart rate monitoring, the application of big data and artificial intelligence, innovations in home and remote monitoring and consideration of human factors.

1 | Introduction

Newborn health is influenced by many factors during pregnancy and labour. Appropriate fetal–maternal monitoring essential for clinicians to respond timely to potential risks, while avoid unnecessary interventions [1, 2]. Cardiotocography (CTG) is a widely used fetal monitoring method. However, CTG has not yet demonstrated a significant reduction in neonatal deaths or long-term neurological injuries, while its association with increased caesarean section rates has raised concerns [3, 4]. Adding to these concerns, perinatal audits have identified shortcomings in CTG as critical contributors to perinatal deaths and neurological injuries that could have been prevented [5–15].

Given these challenges, advancing fetal heart rate (FHR) monitoring is an important public health priority. Achieving this goal requires a multidisciplinary, integrated approach with both technological and clinical solutions (Figure 1). Sharing and combining expertise across clinical, data science, computing, bioengineering, physics, legal and public health domains might accelerate the much-needed progress in FHR monitoring. This expert review aimed to outline the most promising developments and opportunities to advance the field of FHR monitoring.

2 | Clinical Needs in Fetal Heart Rate Monitoring

Cardiotocography aimed to screen for (early) fetal hypoxia and is based on the theory that oxygen deprivation leads to protective and compensatory responses in the fetal heart rate [4, 16]. However, its visual interpretation is subjective and marked by significant intra- and interobserver variability [17]. Current guidelines for intrapartum fetal monitoring do not support clinicians sufficiently in distinguishing reliably between foetuses that require (immediate) intervention and those that can safely continue with pregnancy and labour [18, 19]. One limitation is that these guidelines are largely based on consensus and available evidence, which remains inconclusive and, at time, contradictory [3, 20]. Another limitation is that most guidelines emphasise hypoxia and presumes that this is the only, or most important, pathway to adverse perinatal outcomes. However, there is a growing recognition that these adverse outcomes are not solely caused by hypoxia but rather in combination with other noxious factors. These factors could amplify the effect of mild hypoxia (e.g., maternal fever, fetal host inflammatory response and meconium), exacerbate preexisting injury (e.g., excessive uterine contractions) or impair fetal adaptation to intrapartum stressors (e.g., fetal growth restriction, infection, gestational diabetes and placental disorders) [18, 19, 21]. Moving forward, clinicians need more effective, evidence-based clinical guidelines that provide clear and actionable recommendation to manage the different pathways to adverse perinatal outcomes. As these outcomes are relatively rare and heterogeneous, very large maternity data sets and the use of modern computing technology and data science are needed.

3 | Computerised CTG Evaluation

Dawes and Redman introduced the first computerised CTG system in the 1980s to alert clinicians to abnormal antepartum CTG recordings and help timely delivery [22, 23]. Over time, computerised CTG systems for intrapartum have been developed. These earlier studies focused primarily on computing classic CTG features (e.g., baseline, variability, accelerations and decelerations) [24, 25] or mimicking clinical expert interpretation [26–30]. These methods were neither based on data-driven technologies, nor had the most appropriate study designs. For a more detailed review, we refer to prior work by Georgieva et al. [31].

More recent research has centred on data-driven systems using machine learning (ML) and deep-learning (DL) methods [32–47]. These developments introduced nonclassic CTG features. For example, the phase-rectified signal averaging (PRSA) method measures the speed of FHR changes to assess fetal autonomic nerve system responses. These responses can be altered in conditions such as fetal growth restriction [48–50]. The PRSA metrices acceleration capacity and deceleration capacity have demonstrated similar or better performance compared to short-term variation at identifying growth-restricted foetuses [51–54] and predicting adverse neonatal outcomes [55–59]. Another approach involves combining physiology-based heart rate features with ML techniques to detect early [60] and late fetal growth restriction [61]. However, validation on external data sets is needed to ensure the model's clinical applicability across different populations and setting. Other nonclassic CTG features have been introduced, such as decelerative reserve [62, 63], deceleration area [64, 65], average state distance [66], multiparametric metrics (e.g., fetal reserve index) and composite metrics (e.g., distance-to-healthy-dynamics metric) [67, 68] and multichain

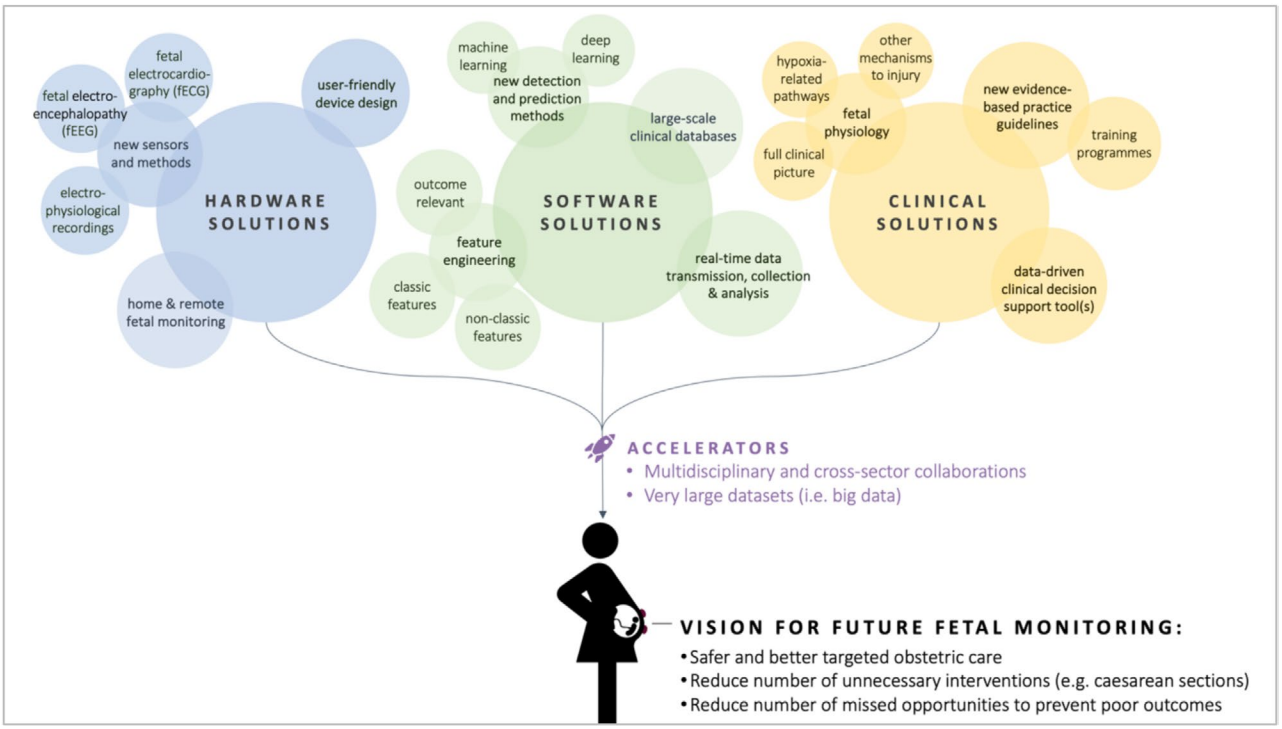


FIGURE 1 | Illustration of the integrated solution approach for future FHR monitoring. The size and position of the bubbles are random.

semi-Markov models [69]. Overall, the performance and clinical applicability of nonclassic CTG features remain under debate. Concerns include, but are not limited to, their development on retrospective, small data sets and limited consideration of the clinical context [31].

Hybrid approaches (i.e., that combine CTG metrics with clinical factors) are likely to lead to better performance and clinical relevance. In a retrospective cohort study ($n = 27\,927$), Georgieva et al. (2017) combined classic and nonclassic CTG features with clinical data into a computerised CTG system (OxSys). Their study showed increased sensitivity for compromise detection and reduced the false-positive rate [70]. Another cohort study using the same system and retrospective dataset assessed first-hour CTG traces and clinical factors in infants born with severe compromise. Their results suggest that clinical guidelines for the first hour may need to differ from those applied to the rest of labour, particularly in cases with small for gestational age and thick meconium [71]. Steer et al. [5] also highlighted the significance of relevant risk indicators in abnormal FHR patterns, with late preterm (RR 4.17; 95% CI 2.18–7.95) and small for gestational age (RR 5.43; 95% CI 3.08– 9.59) being more prevalent in the adverse outcome group.

While most research has centred on the fetus, the impact of maternal health on fetal health and development is often overlooked. Bester et al. (2022) demonstrated that the modulation of the autonomic nervous system on heart rate variability is significantly different between pregnant and nonpregnant women. Monitoring maternal health using computerised heart rate variability analysis could provide new insights into gestational physiology; early detection of pregnancy complications associated with maternal autonomic dysfunction, which may yield novel biomarkers [72].

To summarise, computerised CTG analysis can be a powerful tool for monitoring individual fetal and maternal health trajectories. However, further research is needed to transform these insights into actionable strategies for pregnancy and labour management (e.g., mode and timing of delivery). Future research will benefit from large datasets and well-defined labour outcomes, including relevant clinical characteristics and risk factors.

4 | Deep Learning in Fetal Monitoring

Artificial intelligence (AI) is increasingly making its mark in medicine, including obstetrics [73–77]. These models are well-suited to capture hidden nonlinear relationships across diverse types of data. If captured and presented correctly, these models could offer actionable insights about fetal health. Particularly when they are integrated into central monitoring and electronic patient record systems, as seen in SisPorto [78] and Trium CTG Online [79].

Artificial intelligence in CTG research encompasses traditional ML methods and DL methods. While these traditional methods require human-crafted feature selection and extraction, DL methods can learn directly from complex (raw) data and discover new features. Unlike traditional models, these features may not necessarily have a clear physiological meaning. Next to feature detection, DL methods have been developed to provide diagnostic information about the fetal condition (both antepartum and intrapartum) and to predict adverse neonatal outcomes at birth [80–88]. Other potential applications for DL in CTG monitoring include automatic identification of the maternal heart rate and false signals [89] and facilitate the creation of fully automated and optimised end-to-end routines [90, 91].

Deep-learning methods in CTG research often follow a discriminative approach, using neural networks (NNs) and their common architectural components such as feedforward NNs, convolutional NNs (CNNs) or long short-term memory (LSTM) units. While 'end-to-end' approaches are more common in other fields, these approaches are less prevalent in CTG research due to the noisy nature of CTG data. Therefore, most studies have applied preprocessing steps to improve the data quality [80, 85, 86]. For example, Asfaw et al. [86] explored methods to handle missing or noisy data, including linear interpolation, autoregression and Gaussian processes models. Spairani et al. [80] applied mathematical transformations, such as short-term Fourier series and various wavelet transforms, to preprocess the data. Future advancements may involve incorporating more powerful components such as Transformer architectures. Methods such as unsupervised and self-supervised learning could be valuable in addressing problems with partially labelled data, such as in the intrapartum context where outcome data is known only at birth [92].

However, many steps and challenges need to be addressed before DL methods can be implemented into clinical practice. A key limitation is that comparison between the different methods is difficult because most research uses local and small databases (i.e., hundreds to a few thousands) with different data and outcome definitions. Larger datasets with well-defined outcomes could help address this limitation. Another common limitation in studies predicting rare outcomes is that they often provide insufficient time for clinical intervention [93] and require a large number of compromised cases for effective model training [94]. Melaet et al. (2024) adopted a novel approach to avoid the need for many compromised cases. Their NN-based system was trained on healthy subjects ($n = 678$), reporting an area under the curve (AUC) of 0.96 for the distinction between normal and pathological events in majority-voted annotations [95]. Similarly, Frasch et al. (2021) proposed a single-shot detector (SSD) model using 36 CTG traces to describe whether a foetus still copes with the stress of labour in a way that is considered normal for that foetus. They achieved 94% accuracy in identifying early, preventable fetal injury during labour [87]. Other limitations for DL development include issues related to data quality, data integration, data privacy, model interpretation and regulatory challenges.

In summary, DL approaches present promising opportunities for building predictive and risk stratification models. To address the challenges in DL development, there is a need for larger, multicentre and shared CTG databases. These would help the development of actionable clinical decision-making tools that can learn from complex, real-world data. However, it remains uncertain how regulators (EU/MDR, FDA) and clinicians will view such AI-driven systems, particularly the 'black box' approaches. Other medical fields face similar challenges with clinical integration and regulatory issues, as seen in initiatives involving AI-driven intensive care unit (NICU) care [96].

5 | Big Data in Cardiotocography Research

Advancements in medical science and technology are driving personalised and predictive healthcare [97], which requires very large clinical datasets [98–100]. This section describes 'big data' opportunities and challenges for CTG research, including privacy protection and data location, software sharing, changing regulatory landscape and funding [101].

5.1 | Clinical Need

Adverse perinatal outcomes are rare and heterogeneous with each fetal injury resulting from a complex, multifactorial interaction between exposures and outcomes [102, 103]. While FHR alone poorly correlates with evolving fetal injury, clinicians are expected to infer any important information from noisy CTG signals [104, 105]. Adding to these challenges, there is a steep slope to fetal injury once fetal defence mechanisms fail, meaning clinicians need methods to 'predict' rather than 'diagnose' fetal injury [106]. Despite developments in computerised CTG analysis and AI-driven methods, larger datasets (i.e., hundreds of thousands to millions of observations) and well-defined labour outcomes are needed to test and validate discovered algorithms. However, current obstetrics care is far from realising the potential of very large maternity datasets.

5.2 | Privacy Protection and Data Location

Laws and regulations designed to protect patient privacy impose strict controls on how medical data can be stored and shared. These regulations make it difficult, if not impossible, to share pregnancy and labour data without patient consent. As a result, these data remain siloed within individual healthcare facilities and cannot easily leave their premises [107–110]. Various countries aim to centralise healthcare outcomes to audit, monitor and compare healthcare delivery. However, to our knowledge, Denmark is the only country with a centralised storage system for raw CTG data that can be linked to outcome data.

Another challenge is the sensitive nature of pregnancy and labour data. For example, serious adverse labour outcomes may be subject to litigation and, therefore, hospitals may prefer to withhold or restrict access to data associated with these cases [109, 110]. Other issues related to sharing or centralising maternity data include conflicts between commercial companies and academic researchers, particularly related to intellectual property or competitive advantage [111]. As CTG data is often stored in 'coded' proprietary formats controlled by commercial companies, these data are not easily accessible to academic researchers without permission or assistance from commercial companies.

5.3 | Data and Software Sharing

Federated approaches could offer a more practical solution for large-scale CTG research. These approaches adhere to regulatory requirements, because the data remain stored within individual hospitals, and algorithms or parameters are trained and refined locally at each setting. Alternatively, if data were centrally pulled by a type of consortium, it would be crucial to censor location and other identifiable data. However, such an approach presents significant barriers to research as removing such data impacts the ability to adjust analyses for confounding factors (e.g., fetal

monitoring equipment, clinical practice bias, socioeconomic factors). Additionally, as there are multiple complex confounding factors, multicentre data sets are needed to capture and represent discrepancies between settings [112, 113]. The European Medical Device Regulation (EU/MDR) could help address barriers to building very large, high-quality data sets. These could be beneficial for academic researchers and medical device manufacturers to demonstrate, in joint efforts, that their medical device has clinical and economic benefits that outweigh risks.

Next to data-sharing approaches, there is potential benefit in making open-source algorithms that cover areas such as preprocessing, feature extraction and ML/DL techniques [114]. Open-course algorithms present numerous opportunities, including enhanced transparency, improved auditability and better interoperability. However, a significant challenge may arise from the 'investor's dilemma', where developers may not reap commercial benefits from their developed and validated algorithm [115].

5.4 | Data Standards

Cardiotocography is likely to remain a widely used tool for continuous risk assessment during labour. As such, future research should prioritise large-scale, multicentre clinical data sets (in the order of millions of births). To achieve this, data need to be easily combined, compared and analysed. This sets the stage for a multistakeholder consortium that would aim to agree upon minimal and/or desirable data standards [100]. These well-defined and harmonised labour outcomes should include relevant clinical, demographical and environmental risk factors. Data standard examples are provided in Table 1.

5.5 | A Multicentre Big Data Initiative

For this paper, four research institutes (UK, Sweden, France, United States) and one collaborative research group participated in a multicentre initiative to highlight the potential of shared datasets. The collaborative research group from McGill University, University of California San Francisco, PeriGen Inc. and Kaiser Permanente Northern California have developed a large-scale database of over 250 000 births that include both CTG and comprehensive clinical data, described in Kearney et al. [116]. All participants collected data on FHR decelerations in the last 2 h of intrapartum CTG monitoring, using a Python computer-based method developed by UK's Oxford Labour Monitoring group. This method extracts decelerations automatically. Figure 2 demonstrates the distribution of decelerations'

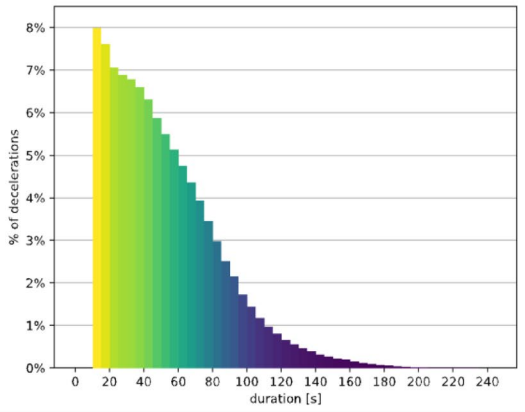
TABLE 1 | A selection of data aspects for 'big data' standards in fetal heart rate monitoring.

Category	Subcategory	Data examples
Fetal monitoring data	Hardware	Noninvasive equipment: Doppler ultrasound, transabdominal electrocardiograph Invasive equipment: fetal scalp electrode, intrauterine pressure catheter
	Software	On-device preprocessing algorithms (e.g., data sampling, imputation of missing CTG values), integration with obstetric health information system
Pregnancy and labour data	Clinical parameters	Maternal demographics, obstetric history, gestational age, maternal pregnancy complications (e.g., hypertensive disorders)
	Risk factors	Antenatal: congenital anomalies, fetal growth restriction, premature rupture of membranes, chorioamnionitis, maternal conditions (e.g., gestational diabetes, hypertensive disorders) Intrapartum: meconium-stained liquor, maternal fever
	Labour management	Labour stage, cervical dilation, delivery mode, reason for operative delivery
	Labour outcomes	Mortality: stillbirth, early neonatal death (< 7 days of life), maternal mortality Morbidity: umbilical cord gases, Apgar scores, neonatal intensive care unit admission, resuscitation, neurological deficits, severe maternal morbidity
	Maternal outcomes	Patient-reported outcomes: quality of life, postpartum depression, mother–infant attachment, longer-term neuropsychological deficits Patient satisfaction: birth experience, shared decision making, results of the care
Neonatal data	Short-term outcomes	Mortality: late neonatal death (between 7 and 28 days of life) Morbidity: respiratory distress syndrome, intraventricular haemorrhage, hypoxic-ischaemic encephalopathy diagnosis, MRI results, hypothermia treatment, follow-up assessments
	Long-term outcomes	Mortality: under-five neonatal mortality Morbidity: cerebral palsy, epilepsy

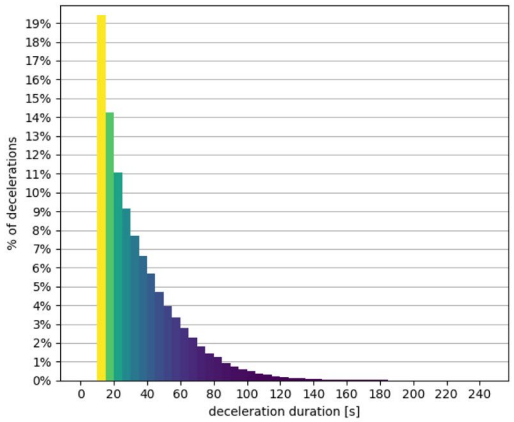
length in the different cohorts ($n = 78\,184$ births) using the same shared software to detect them (except for Kaiser Permanente Northern California data, which used the proprietary software PeriGen Patterns).

This multicentre initiative demonstrates the capability to extract and jointly analyse and compare data from multiple sites using the same algorithm and instructions, opening up opportunities for future work with shared software. We observed

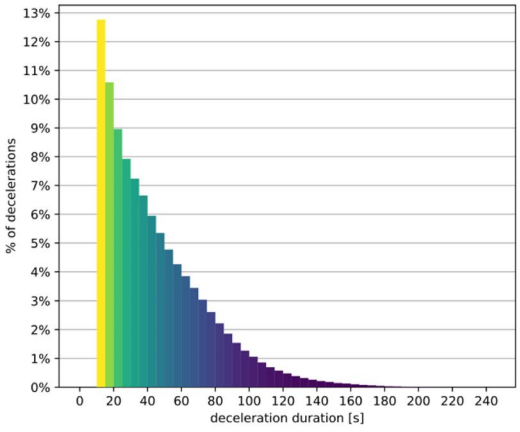
A. Oxford, United Kingdom
940 724 decelerations during the last 2 hours of labour from 40 070 FHR traces



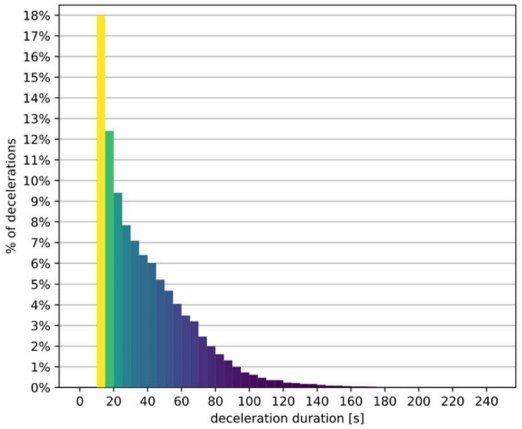
B. New York, United States
297 784 decelerations during the last 2 hours of labour from 6168 FHR traces



C. Lille, France (163)
462 840 decelerations during the last 2 hours of labour from 11 653 FHR traces



D. Karolinska, Sweden
33 168 decelerations during the last 2 hours of labour from 1422 FHR traces



E. McGill University, Canada
254 185 decelerations during the last 2 hours of labour from 18 871 FHR traces

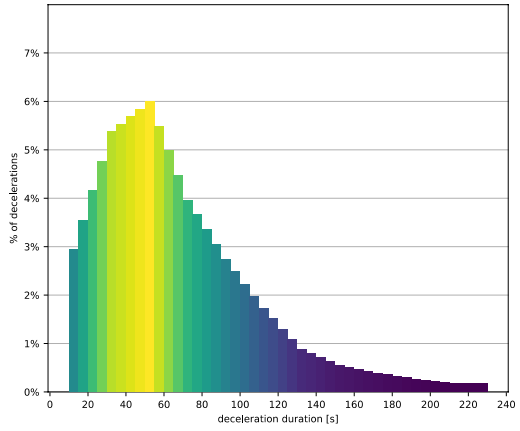


FIGURE 2 | Collection of one fetal heart rate parameter (i.e., deceleration) from multiple research centres using a shared algorithm.

differences in distributions due to data acquisition and preprocessing methods excluding in some settings spurious fetal heart rates and noise. In conclusion, the initiative serves as an early proof-of-principle step, demonstrating the concept and capability.

5.6 | Funding

There are various initiative and programmes aimed to advance medical research and healthcare delivery through 'big data'. For example, the European Commission has allocated € 2 billion for 'big data' research [117], and the United Kingdom has been building national-level databases for research, audits and policy development [118, 119]. Additionally, life sciences companies and venture capitalists increasingly recognise the value and profitable opportunities of healthcare data [120]. However, funding for research with limited financial returns, such as studies on rare outcomes, remains scarce. As a result, CTG research depends on high-quality, very large clinical data sets to support funding applications. Securing funding to build such data sets is particularly challenging in this field, because clinical trials are already constrained by ethical and methodological challenges [100]. Other challenges include selecting and establishing the appropriate legal entities, obtaining ethical approvals, negotiating data-sharing contracts and setting up and maintaining the necessary software infrastructure. Moreover, multicentre data or software sharing introduces additional complexities, such as conflicts of interest and regulatory requirements.

To secure funding, researchers must present a compelling case that demonstrates return on investment, particularly on improved perinatal outcomes, enhanced (workflow) productivity and long-term health economic benefits. Furthermore, a clinical tool or application must be commercially viable in order to obtain regulatory clearance, secure reimbursement and to be integrated into clinical practice. A strong argument for securing funding is that the costs of developing large-scale maternity datasets are far smaller than the ongoing expenses of not pursuing it. This is supported by the fact that the financial burden of medicolegal lawsuits related to perinatal injuries is extremely high [121, 122].

6 | Remote and Home Fetal Heart Rate Monitoring

Antepartum fetal–maternal monitoring close to home, or even within their home, could improve patient satisfaction, improve access to care barriers and contribute to more resilient healthcare systems. For example, home-based monitoring could improve access to care in rural areas and reduce the need for frequent hospital visits for high-risk pregnancies. 'Home monitoring' refers to simpler solutions that are typically used for low-risk pregnancies or in resource-limited settings. 'Remote monitoring' or 'telemonitoring' involves more advanced solutions that healthcare provider to actively monitor the pregnant women, making these solutions more suitable for high-risk pregnancies.

6.1 | Current Evidence

Remote and home fetal monitoring has a long history, beginning as early as 1983 [123]. However, only a few randomised controlled trials have been conducted in this area, which suggested that hospital-based monitoring may be associated with higher caesarean section rates [124–126]. Some countries more than others have advanced in remote and home fetal monitoring solutions. These countries have demonstrated their potential to enhance patient care, reduce healthcare costs and reduce hospital admissions in high-risk pregnancies.

The Netherlands has a long-standing tradition of providing home care and has offered home-based pregnancy services since the 1990s. Currently, home-based monitoring is used in 23% of high-risk pregnancies as an alternative to hospital admission, which has been shown to increase patient satisfaction [127,128]. A randomised controlled noninferiority trial ($n = 201$) demonstrated the safety of remote monitoring, even for complicated pregnancies such as preeclampsia, fetal growth restriction, preterm rupture of membranes and fetal anomalies. The trial found fewer adverse perinatal outcomes in the remote monitoring group compared with the hospital admission group, with a reported risk difference (RD) of 10.3% · 95% CI (−22.4 to 2.2). Additionally, remote monitoring resulted in a significant cost reduction in 18% [129].

Denmark is emerging as a leader in fetal telemonitoring solutions, with all regions collaborating to provide remote monitoring for intermediate- and high-risk pregnancies. A recent study involving over 400 intermediate and high-risk pregnancies demonstrated that fetal telemonitoring is a safe alternative to hospital-based monitoring [130]. According to the Danish Ministry of Health, fetal telemonitoring is also cost-effective. Decreased hospital admission and outpatient visits reduced costs by 40%–50% compared with traditional hospital-based care [130, 131].

Other developments have been reported in Germany, where telemedicine solution Trium CTG Mobile provided secure access to real-time fetal monitoring and maternal information from any location. More recently, Trium CTG Online integrated a smart Doppler device (HeraBEAT) to their 'mobile fleet' [132, 133].

6.2 | Outlook and Future Research

Home-based monitoring presents promising opportunities for obstetric care. The reduced need for hospital visits and (re-)admissions could save costs and increase patient satisfaction [134–137]. However, obstetric care is far from implementing home-based fetal monitoring at scale, particularly due to financial incentives, reimbursement issues and liability concerns. A shift to value-based care could help resolve the issues related to financial incentives. This payment model incentivises healthcare providers to improve patient outcomes rather than provide more services [138]. To encourage market access and reimbursement, the United Kingdom has introduced the Digital Technology Assessment Criteria and Germany

launched the Digital Health Applications Assessment Framework. However, digital health solutions are being developed at a faster pace than the regulatory frameworks, quality standards and reimbursement pathways specific to digital health. Additionally, clear guidelines need to ensure the safety of home-based monitoring, covering eligibility criteria and escalation pathways. For example, patients with limited access to health care (e.g., long travel times, language barriers) or those with unstable fetal–maternal conditions may not be ideal candidates for home-based monitoring due to the risk of delays in intervention when needed.

7 | Fetal Monitoring Technologies

Most CTG methods used in clinical practice are noninvasive, using Doppler ultrasound and tocodynamometer. Some methods combine noninvasive and invasive methods, such as using fetal scalp electrode (FSE) with tocodynamometer. The invasive intrauterine pressure catheter (IUPC) is not routinely used. Invasive methods suffer less from signal loss [139] and could provide additional information such as quantitative intrauterine pressure, fetal electrocardiography (fECG) and fetal electroencephalography (fEEG) [140]. However, these methods are less commonly used due to the small risk of neonatal complications such as neonatal scalp injury and cephalohematoma [141].

Considerable research efforts have been directed towards noninvasive transabdominal electrophysiological recordings, which, in contrast to Doppler ultrasound, are less affected by maternal movement and body mass index. However, after decades of research, only a few electrophysiological-based device solutions are now ready for clinical practice. These include Novii (GE Healthcare, USA), Avalon Beltless (Philips, the Netherlands), Nemo Fetal Monitoring System (Nemo Healthcare, the Netherlands), Meridian (MindChild Medical Inc., USA) and INVU (Nuvo Group Ltd., Israel). However, these devices tend to have a relatively poor performance during the second stage of labour, limiting their clinical applicability [142, 143]. Although these solutions show promise as complementary modalities for monitoring pregnancy health, their current use is primarily restricted to provider-initiated, in-hospital monitoring. However, there are promising indications that these technologies (e.g., Nemo Fetal Monitoring System, INVU) may soon be extended for use in patients' homes.

8 | Human Factors

Obstetrics is a complex, dynamic environment for humans to work in with many roles and responsibilities in diverse clinical contexts. Furthermore, severe adverse events are rare and often unexpected, which makes these situations more susceptible to human error. Considering these aspects is important in developing and implementing (new) technologies, particularly in obstetrics where technologies need to ensure the health and safety of both mother and child.

The term 'human factors' refers to factors that impact health and safety [144], particularly focusing on operational systems and how their interactions affect performance [145]. 'Crisis resource management' (CRM) was introduced to medical training in the 1980s as a means to reduce medical errors, optimise workflows and enhance patient safety [146]. Obstetrics later adopted this human factors approach through 'simulation-based education'; a method adapted from the aviation industry. Simulation-based education focuses on practising effective communication, teamwork, leadership and clinical decision making [147, 148]. As shortcomings in CTG have been repeatably identified as a major area of preventable harm [5–10], there is an urgent need for advancements. While these shortcomings are often attributed to the technology itself, other influences such as systems, processes, decisions and actions are equally significant [149]. A qualitative study by Lamé et al. [150] emphasises this need. Their study showed that CTG interpretation involves multiple, complex interactions between people, tasks, tools and technology, organisation, culture and behaviour.

Moving forward, a systematic approach is needed to raise awareness about human factors to refine or develop new technologies in obstetric care. This starts with identifying factors where the obstetric care team, or their work environment, are more likely to contribute to the harm [151].

9 | Fetal Monitoring in Low and Middle Resource Settings

Some research has highlighted the importance of developing feasible and culturally appropriate methodological and technological approaches for advancing antepartum and intrapartum care in low- and middle-income settings (LMISs). This awareness is rooted in the notion that the majority of perinatal deaths worldwide occur in LMISs [152]. Limited resources in these contexts have significantly compromised the ability to deliver timely and high-quality antepartum and intrapartum care [153–155]. For example, as data collection and storage are limited in low-resource settings, algorithms should embed scalable and data-parsimonious solutions [156].

Another limitation from an algorithm development perspective is that there is often a substantial mismatch between the data sets used to train and test these solutions versus their effective implementation in LMISs [157]. A common issue is that AI solutions are often validated under the erroneous assumption that the obtained results would have universal validity. However, these validations do not include participants from diverse racial and ethnic groups. Similar considerations apply to designing and/or adapting technological solutions such as wearable devices for collecting fetal and maternal data throughout pregnancy. Any solution deployed in these settings should consider the different contextual and cultural acceptance of the approached participants and work in consultation with Diversity, Equity, Inclusion, Belonging and Justice (DEIBJ) experts.

As a community of researchers committed to substantially improving fetal and maternal well-being, we acknowledge the urgency of improving inclusivity, diversity and equity in the existing and future research studies and technological solutions able to address the needs of the communities and settings in which they are deployed [158, 159].

Author Contributions

A.G. conceived the article topic and defined the review objectives. A.L., M.D., O.B.P., C.L., M.G.F., A.U., P.W., R.V., N.P. and A.G. reviewed and summarised the evidence pertaining to selected themes. J.T. developed a Python computer-based method for the big data initiative. M.D., M.G.F., P.W., L.Y., P.M.D., F.A., M.H., S.B., A.H.d.l., J.T. and A.G. provided input to the big data initiative. All authors reviewed and contributed to writing the article.

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Ethics Statement

Ethical approval was not required for conducting this review.

Conflicts of Interest

MD is managing director of Trium Analysis Online GmbH, manufacturer of central CTG monitoring systems. MGF holds US patent US11,622,710 on fetal ECG monitoring, patent US9,215,999 on fetal EEG monitoring, as well as stock, executive and advisory roles in companies in pregnancy health areas. PW reports being employed by PeriGen Inc. The remaining authors report no conflicts of interest. RV is shareholder in Nemo Healthcare BV.

Data Availability Statement

Data sharing is not applicable to this article as no data sets were generated or analysed during the current study.

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