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Emerging Technologies for Maternal and Child Health: A Systematic Review on the Potential for Mortality Reduction

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ABSTRACT

Despite the evident achievements of every other sector, maternal and child mortality continues to be a significant public health problem in Nigeria due to preventable complications, delayed access to care, and low availability of skilled services. The goal of this systematic review is to investigate the potential of emerging technologies in reducing mortality in Nigeria, focusing on the technologies such as General Artificial Intelligence, fog computing, and federated learning. The literature identified, screened, assessed and selected relevant articles through a systematic review process, using the PRISMA guidelines 2020 protocol. 121 records initially were identified from major academic databases, 24 were removed as duplicates, 97 were screened and 54 were assessed for full-text reports and were eligible. After excluding studies based on their full text, 31 studies were included in the review. The findings show that the existing technologies AI and IoT can help to predict, monitor, diagnose, and make clinical decisions at early stages, and that mHealth and telemedicine can enhance the access to healthcare services and communication. However, Fog computing, a new technology, has a better potential to provide localized processing, latency reduction, and greater resilience in areas where connectivity will be unreliable, while federated learning allows for collaborative development of AI without the need for frequent centralization of patient data, thus embarrassing decentralization of patient data. The review thus underscores the potential of an integrated sustainable, equitable, context-sentitive maternal and child healthcare architecture to be based on the IoT–fog–federated learning–AI paradigm in Nigeria.

Keywords: Maternal and Child Health, Mortality Reduction, Fog Computing, Federated Learning, General Artificial Intelligence

INTRODUCTION

Despite advances in access to health care, immunization, maternal services and child survival interventions, maternal, newborn and child mortality continues to be a significant public health problem in Nigeria. Nigeria has a significant share of the global problem of maternal deaths. According to the World Health Organization (WHO), in 2020 Nigeria had a maternal mortality ratio of around 1,047 out of every 100,000 live births, representing approximately 28.5 percent of the world's deaths among women during their pregnancy or delivery (WHO, 2025). This burden is also high in infants and young children. According to recent estimates from the UNICEF, Nigeria's under-five mortality rate is about 115.6 deaths per 1,000 live births in 2024, whereas the infant mortality rate and the neonatal mortality rate in Nigeria are estimated to be around 70 and 39 deaths per 1,000 live births, respectively, in 2024 (UNICEF 2026). These figures show a death spiking at multiple points in a connected continuum of maternal, neonatal and child-health services, where interventions that can help to detect, refer, diagnose, treat and monitor can make a difference.

Maternal and child deaths in Nigeria are multi-faceted, with direct clinical factors, as well as health-system and socio-economic factors. Obstetric haemorrhage, hypertensive disorders of pregnancy, sepsis and

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childbirth complications are associated with maternal deaths, while prematurity, birth complications, neonatal infections, malaria, pneumonia, diarrhoeal diseases, and malnutrition, and inadequate immunization are associated with neonatal and child deaths. These factors are exacerbated by delayed access to care, low skilled workforce health coverage, suboptimal health infrastructure, limited access to essential medicines, equipment and materials, transportation challenges, and geographical disparities and socioeconomic disadvantage. There has also been reported significant geographical difference in neonatal mortality within Nigeria, which means that national averages can mask significant differences in health outcomes between regions (WHO, 2025). Thus, besides clinical interventions, there is a need for mechanisms to detect early warning signs and to link patients with relevant healthcare resources to reduce mortality.

But the availability of technology is not enough to guarantee reduction in mortality. A technology can perform very well in a laboratory or pilot project setting, but be evaluated as underperforming in a health facility in a developing country, with poor electricity supply, intermittent internet, limited computers, poor technical support and a disjointed information system. The healthcare setting in Nigeria is thus a context in which the technical sophistication of the technologies is not the only criteria by which they are to be judged, but also their ability to work well in the clinical, infrastructural, economic and institutional environments. This provides the foundation for exploring new technologies as part of a broader sustainable maternal and child-health ecosystem, instead of as a stand-alone technology solution. The IoT offers a valuable technological support for the continuous monitoring of maternal and child-health. Physiological data from connected medical devices like IoT sensor-based thermometers, pulse oximeters, blood-pressure monitors, heart-rate sensors, wearable devices and other connected medical equipment can be gathered and sent to healthcare platforms. This type of systems could enable remote monitoring and possibly allow for the earlier detection of abnormal conditions. mHealth and telemedicine work in tandem with IoT by facilitating mobile communication between patient, caregiver and health care personnel via mobile apps, messaging and remote consultation. There is some evidence from systematic reviews that mHealth has been studied for antenatal care, breastfeeding, health education, and treatment adherence and other maternal and child-health interventions, though the quality of evidence and consistency of findings with regard to mortality vary (Lee et al., 2016; Amoakoh-Coleman et al., 2016).

Another new technology that can help in healthcare data governance is blockchain. While not a clinical prediction technology, blockchain can offer tools for secure data sharing, auditability, authentication, consent management and traceability. It also has potential implications for EHRs, such as when maternal and child-health information must be transferred between primary health-care centres, hospitals, laboratories, pharmacies and other authorized parties. Blockchain-based EHR systems have been evaluated for their potential benefits, such as enhanced security, privacy, transparency, and data integrity, as well as their challenges, including scalability, performance, interoperability, regulatory considerations, and resource consumption (Ettaloui et al., 2024). Therefore, blockchain can be a component of the digital-health system, not the entire system, to ensure trust and governance, not to eradicate death. Cloud computing addresses storage and computational scalability, but its dependence on remote infrastructure can introduce latency, bandwidth requirements and connectivity dependence. Edge computing partially addresses these issues by moving computational functions closer to the devices generating the data. However, healthcare environments can involve numerous heterogeneous IoT devices distributed across wards, clinics, laboratories, ambulances and community settings. A single edge device may not possess sufficient computational capacity to coordinate and process all information generated across a healthcare facility or network of facilities. Fog computing therefore provides an intermediate architectural layer between IoT devices and the central cloud, allowing computing, storage, communication and analytics services to be distributed across local gateways, routers, servers and other network nodes. Research on fog computing identifies latency, bandwidth limitations, scalability, privacy and security as important motivations for bringing computation closer to IoT devices (Mouradian et al., 2018; Yousefpour et al., 2019).

Data governance presents another dimension of sustainability. Maternal and child-health records contain highly sensitive personal and clinical information, and centralizing data from multiple healthcare institutions can increase privacy and security concerns. Federated Learning (FL) provides an alternative approach in which healthcare institutions or local computing nodes can train machine-learning models using data

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maintained within their own environments rather than transferring all raw patient records to a central repository. Model parameters or updates can instead be exchanged and aggregated to construct a collaborative model. This approach is particularly relevant to maternal and child health because data may be fragmented across hospitals, primary healthcare centres, laboratories and community programmes. Systematic reviews have shown that federated learning can support collaborative healthcare AI while addressing some of the privacy and data-sharing limitations of conventional centralized machine learning, although communication costs, heterogeneous datasets, security risks and limited real-world clinical validation remain significant challenges (Yang et al., 2024; Zhang et al., 2024).

Despite the rapid development of emerging technologies for healthcare, an important gap remains between technological capability and practical applicability to maternal, newborn and child mortality reduction in Nigeria. Existing technologies address different aspects of the healthcare problem, but they are frequently investigated independently. IoT can provide continuous data collection, cloud computing can provide large-scale storage and analytics, blockchain can strengthen data integrity and trust, mHealth can improve communication, telemedicine can extend access to expertise, and AI can support prediction and decision-making. However, these technologies do not necessarily resolve the operational limitations associated with one another. For example, IoT generates large volumes of data but may depend on reliable network connectivity; cloud computing provides scalable resources but can introduce latency and connectivity dependence; blockchain can improve trust and auditability but may impose computational and scalability costs; and conventional AI often requires centralised access to large and diverse datasets.

The resulting gap is therefore not simply the absence of technology but the absence of an integrated technological architecture capable of combining complementary capabilities while addressing their limitations. In particular, there is a need for an intermediate computing layer capable of processing time-sensitive IoT health data closer to patients and healthcare facilities. Fog computing can potentially bridge the gap between resource-constrained IoT devices and geographically distant cloud platforms by supporting local data aggregation, filtering, storage, analytics and rapid decision support. In maternal and neonatal care, this capability may be relevant where abnormal physiological measurements require rapid identification despite intermittent connectivity. The literature on IoT healthcare similarly identifies cloud response time, availability, privacy and security as limitations that have stimulated interest in edge and fog-based architectures (Greco et al., 2020). A second gap concerns the centralization of healthcare data for AI development. Conventional AI models may benefit from combining large datasets from multiple hospitals, but healthcare data cannot always be freely transferred because of privacy, security, ethical and institutional constraints. Federated learning can address part of this problem by allowing institutions to collaborate in model development without directly pooling raw patient records. Recent systematic reviews, however, indicate that much of the federated-learning healthcare literature remains at the proof-of-concept stage and faces unresolved problems involving data heterogeneity, communication efficiency, privacy threats, model generalisation and clinical translation (Gooty et al., 2024; Yang et al., 2025). This indicates the need to assess federated learning not as a technology that automatically solves healthcare-data challenges but as one component of a broader privacy-preserving AI for decentralized architecture. A third gap concerns the limited integration of general AI capabilities with distributed healthcare infrastructure. AI models can support prediction, classification and decision-making, but their effectiveness depends on the availability of timely, high-quality and contextually appropriate data. An architecture combining IoT sensing, fog computing, cloud infrastructure, federated learning and AI could potentially establish a continuous pathway from data acquisition to local processing, collaborative learning and intelligent decision support. Such integration could allow time-sensitive analytics to occur closer to the point of care while enabling broader learning across institutions. Nevertheless, the evidence needs to be examined systematically to determine which technologies have actually been investigated for maternal and child health, what mortality-related problems they address, what implementation barriers they face and whether they are sustainable within Nigerian healthcare environments.

This study hence addressed fragmented understanding of emerging technologies for maternal and child healthcare in Nigeria. Although individual technologies have demonstrated potential, there is insufficient integrated evidence linking specific technologies to specific mortality-related challenges while

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simultaneously considering infrastructure, privacy, affordability, energy, connectivity, scalability, interoperability, decentralization and institutional sustainability. This systematic review consequently seeks to move beyond a simple catalogue of technologies by examining their roles, limitations, complementarities and potential integration pathways for mortality reduction in Nigeria. The aim of this study is to systematically identify, classify and assess emerging sustainable technologies with potential to contribute to maternal, newborn and child mortality reduction in Nigeria, with particular attention to fog computing, federated learning, and General Artificial Intelligence technologies.

LITERATURE REVIEW

PRISIMA

The PRISMA 2020 flow diagram in figure 1 depicts the systematic process of identifying, screening, assessing and selecting studies for the review process. The initial records identified were 121 from five databases (PubMed/MEDLINE with 32 records, Scopus with 30 records, Web of Science with 25 records, ScienceDirect with 18 records, and IEEE Xplore with 16 records). Twenty-four duplicate records were removed prior to screening leaving 97 records for title and abstract screening, 39 of which were eliminated due to being out of focus for the review. Thus, 58 reports needed to be retrieved and 4 could not be retrieved, resulting in 54 full-text reports being eligible for eligibility assessment. A total of 23 were excluded after full-text assessment, either because they were not directly related to maternal, newborn or child health or mortality (9), were based on an inappropriate technology or intervention (6), insufficient relevance to Nigeria or similar low- and middle-income settings (4), insufficient empirical or review evidence (2), or represented duplicate or overlapping reports identified at the full-text stage (2). Finally, 31 studies were selected for the systematic review to serve as the evidence base to explore the potential roles, limitations, sustainability and potential mortality reducing contributions of emerging technologies such as General Artificial Intelligence, Fog Computing and Federated Learning.

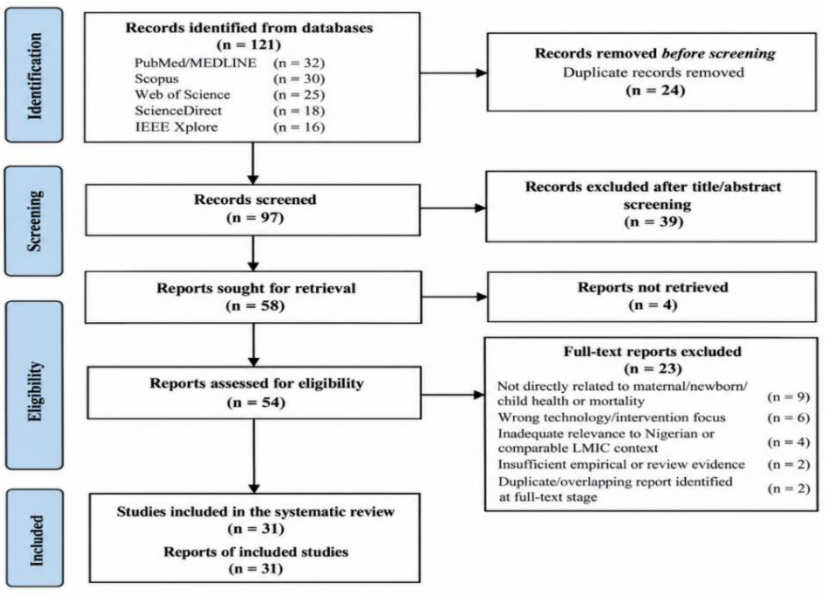


Figure1: PRISIMA Diagram of Literature Review Process

Maternal and Child Mortality in Nigeria

Chima-Oduko et al., (2026) reported based on PRISMA 2020, compiled primary studies that assessed integrated maternal, newborn and child health (MNCH) interventions in Nigeria. A total of 14 studies were included that covered a broad spectrum of geopolitical areas. Eleven indicators were used for evaluation of the effect of integrated approaches to the maternal and child health. There were three measures where there were consistent improvements (antenatal care visits, skilled birth attendants, and home visits by health

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workers) and two measures where there were mixed results (family planning and maternal mortality). The three child health indicators which had positive impacts were: tetanus protection, exclusive breastfeeding, and reduction in neonatal, infant and child mortality; while the three others were: postnatal care, immunization, antibiotic treatment for pneumonia. The barriers reported included the lack of labour (particularly female), weak supply chain, negative attitude of health workers, lack of supervision, and infrastructural problems. The study concluded that the integrated approaches can potentially minimize maternal and child mortality and improve outcomes, particularly in the context of supply side interventions (skilled providers, functional facilities, and reliable commodities) and demand side interventions (financial protection, community mobilization). Adaptation of interventions to sociocultural norms, access barriers and health system capacity can be strategies to maximize effectiveness. To continue to make progress, it is important to increase context-specific, community engaged strategies in northern and rural areas, and to mitigate ongoing health system barriers. Long-term impact and cost-effectiveness needs to be further investigated by region using strong designs.

In Lagos and Ogun States, where infrastructure, socio-cultural, financial and lack of skilled health workers present huge challenges for the reduction of maternal deaths in rural areas, Oluwole et al., (2025) reviewed the effectiveness of community-based health interventions. Relevant peer-reviewed articles, policy reports and institutional documents from 2013 to 2023 were searched and analyzed using a structured literature review approach in databases like PubMed, Scopus and ScienceDirect. The study results underscored the importance of policy changes and programmatic adaptations to improve the sustainability and effectiveness of community-based maternal health interventions. The policy implications that can be drawn from the above include: Government Funding be increased, Referral System strengthen, Workforce capacity building of healthcare workers and Community Engagement Strategies.

The MamaBase pilot programme and early findings of the implementation of the programme were described by (Afolabi et al., 2026). The pilot phase of MamaBase was a project of the Maternal Reproductive Health Research Collective (MRH Collective) in 2024. The programme aimed at tackling demand-side constraints to the utilization of maternal health services, based on a community-centred and data-informed approach and was deployed in all 20 Local Government Areas (LGAs) of Lagos State, Nigeria, which are low-income communities. The study found that MamaBase pilot was feasible for an integrated, community-based maternal health intervention in low-income urban communities. The program helped to address demand-side barriers, improve linkages to primary healthcare facilities, and integrate real-time data systems, which helped to address inequities in access and increase the use of skilled maternal care. The MamaBase experience provided valuable policy implications, programmatic insights and lessons learnt that would be valuable for policy makers, program implementers, and health stakeholders in the global context who are seeking scalable solutions to improve maternal and neonatal health outcomes in urban areas with limited resources. The global conceptual model that supports the MamaBase intervention is illustrated in figure 1. The theory of change depicts how the key elements of service delivery, community engagement and policy engagement were anticipated to lead to better maternal health service utilization and maternal outcomes.

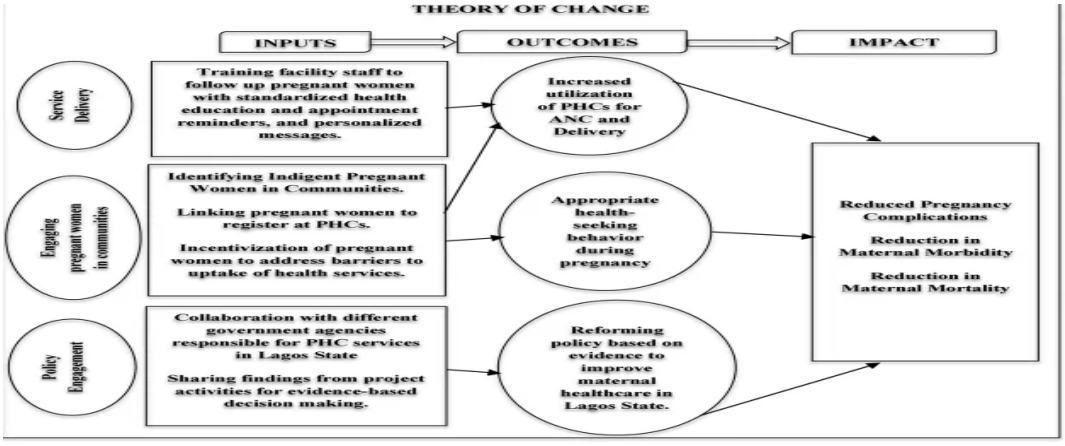


Figure 1: Mamabase Project Theory of Change (Afolabi et al., 2026)

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The major aim of (Nasir et al., 2022) was to systematically scope and map research regarding interventions, programmes or strategies to improve maternal and newborn health (MNH) in Nigeria. The information retrieved included the source and year of publication, geographical setting, study design, target population(s), type of intervention/ programme, reported outcomes and any reported facilitators or barriers.

Data analysis included descriptive numerical summaries and qualitative content analysis. In this review 80 publications were included. In most cases, interventions were in line with WHO recommendations (71%) and 50% of interventions (n=40) focused on the pregnancy and childbirth phase of the continuum of care.

Most of the programmes (n=74) examined the intermediate social determinants of maternal health related to health system factors within health facilities, with only a few interventions aimed at structural social determinants we found most MNH interventions in Nigeria were aligned with the WHO recommendations and focused on the intermediate social determinants of health within health facilities.

We identified a gap in research for interventions targeting the structural social determinants and community-based interventions, and limited research on pre-pregnancy interventions. More attention is needed to implement interventions and to assess context-specific problems beyond the health facility to move towards achieving the sustainable development goal that MNH aims to contribute to.

In an attempt to find out the perspectives, beliefs and feelings of women on the unspoken “silences” that influence the uptake of maternal health services in the South-South of Nigeria, (Ekpenyong, M. S. (2025) set out to investigate them. The study illustrated that there is not a uniform experience of barriers and facilitators.
The study revealed that stigma and public humiliation were more likely to affect Younger, less-educated women, whereas older women with multiple births often brought up inefficiencies and neglect. In the existing literature, women are studied as a unified group, which, according to the study, does not reflect the nuances of the situation; the study reinforces the demand for interventions that are context-specific, and aimed at certain groups.

The study also identified a tension between the need for and the failure to experience skilled maternal care in Nigeria, as skilled care is necessary but the experience is marred by mistreatment, failures in the system, and silence from culture. Solving these contradictions must not only be related to the infrastructure but also be linked with compassionate care, confidentiality and cultural sensitivity. These are all key components of building trust in formal health care systems and in women's experience in health care, which will be necessary to restore if women are to access health care—and access it in a way that is respectful, safe and empowering.

Mortality Reduction: Emerging Technologies.

General Artificial Intelligence

Akeju et al., 2022 explored the use of satellite communication technology (SatCom) together with the current 3G mobile networks to deliver video training (VTR) to health workers and digitize health care data. The research revealed that digital innovations, such as VTR and data digitization interventions, were provided in 62 health care facilities in Ondo State, South-West Nigeria, of which 61 did not have access to a 3G mobile network, between March 2017 and March 2019.

With the adoption of Theory of Change model as depicted in figure 2, the study found out that four project outcomes which were achieved at end-line evaluation were sustained 12 months after project closedown namely: staff motivation and satisfaction; increased staff confidence to perform healthcare roles; improved standard of healthcare delivery; and increased adoption of eHealth innovations beyond the health sector.

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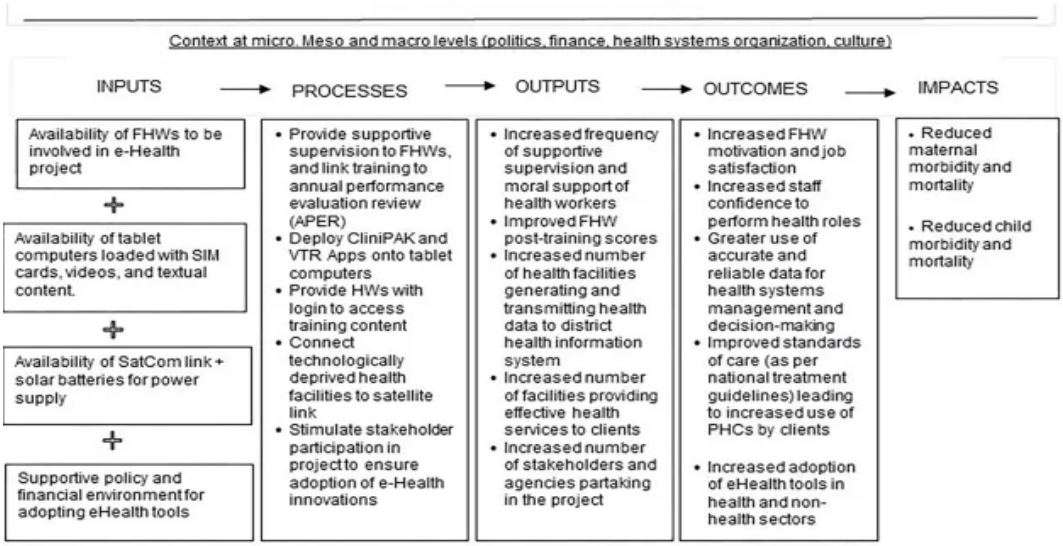


Figure 2: Theory of Change Model for eHealth Project in Nigeria (Akeju et al., 2022)

The use of AI-driven models is transforming MCH care, allowing for accurate and timely forecasting of a range of health conditions all pertinent to public health. The models use information from other sources to help estimate other complications, including pre-eclampsia, gestational diabetes, birth disorders, and more, based on maternal characteristics, lab tests and prenatal imaging from prior pregnancies (Victor, 2025). AI models have been consistently outperforming traditional models. They are currently not widely used in practice due to small datasets, "black-box" algorithms, and poor reporting practices (Correia,et al., 2025). AI-powered solutions show potential in medical diagnostics, risk prediction, providing automation, improving accuracy, and enabling personalized medicine. Yet there are issues that need to be addressed when it comes to acquiring knowledge of the data, transparency of the algorithms, and ethical concerns for clinical application, and those concerns must be resolved for it to be a safe and efficient tool for clinical use. We need to take these challenges seriously to fully make use of the amazing advances in the field of artificial intelligence (AI) that can be brought to this critical area of public health and fetal health (Kalyan et al., 2025). In a study titled "The potential of digital innovations such as mHealth, Artificial Intelligence (AI), blockchain, and gamification in the improvement of maternal and child health (MCH) in Nigeria," (Yahaya et al., 2025) discussed the potential of these digital innovations in enhancing maternal and child health (MCH) in Nigeria. It examined its ability to improve access, delivery and engagement in health care and its challenges to implementation. The study also recommended policies for sustainable and equitable integration of these technologies into Nigeria's MCH system.

In Africa and other low- and middle-income countries (LMIC), Digital MCH has been steadily growing. Unfortunately, the role has been underutilized, since interventions do not necessarily involve communities in a timely and inclusive way in the design of interventions. (Till et al., 2023) identified a number of opportunities and sociotechnical challenges associated with digital MCH in LMIC, including increased ability to reach people with low literacy levels using custom-developed culturally appropriate apps, and improved availability of mobile data and of smartphones and wearable technologies. They also highlighted issues of barriers like over-reliance on text-based communication and challenges that MCH research and design face when informing and translating to policy. A similar study was conducted by (Ssegujja et al., 2025) which developed a conceptual framework that delineates the current state of the e-service delivery, highlighting the existing domains, and proposing a desired state that integrates the potential e-services.

Fog Computing

Fog computing is the new emerging distributed computing technology in which the computing, storage and communication services are situated between IoT devices and cloud computing. Healthcare use of this architecture allows health data to be processed near where it is created, minimizing latency, network usage, and reliance on ongoing cloud connectivity. This is especially important in maternal, newborn and child

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health care as physiological information can be processed quickly, enabling early detection of potentially dangerous situations (Jeyaraman et al., 2024). By enabling the local processing layer for connected medical devices, the use of fog computing can enhance maternal and child-health monitoring in the context of IoT. The physiology information like the blood pressure, heart rate, temperature, oxygen saturation and other physiological information can be collected continuously using the maternal monitoring devices, wearable sensor devices and neonatal devices, which can be preprocessed by the fog nodes located near the monitoring device. In healthcare, where timely data analysis and responses are crucial, fog computing can enable more responsive action at the local level by allowing for the processing of data at the edge of the network rather than sending it to a remote cloud server (Navakauskas & Kazlauskas, 2023).

In terms of maternal health care, fog computing can facilitate the continuous monitoring of pregnant women in hospitals, primary healthcare centres and community-based areas. Fog nodes can be used locally to collect data from IoT devices, to conduct basic analysis and detect any abnormal measurements that need to be addressed, while the cloud can be used to keep the patient's longitudinal records and conduct more complex analysis. Such a distributed setup is possible to minimize delays in the communication of information from the detection of maternal risk to health workers (Jeyaraman et al., 2024). Fog computing can also play a role in monitoring neonatal and child health, as it can help to process data in real time from connected medical devices. Fog nodes can locally analyze the measurements received from newborns that need to be monitored using connected physiological sensors and prioritize the measurements that are likely out of normal ranges for healthcare professionals. One of the significant applications that have been identified in the recent systematic reviews of fog computing in healthcare is real-time monitoring and decision making (Jeyaraman et al., 2024).

A major drawback of traditional cloud-based healthcare systems is that a significant amount of health information can have to pass through from healthcare devices to distant servers before analysis can take place. This can have a negative impact on communication, higher bandwidth needs, and can cause exposure in the event of poor network connections. Fog computing overcomes this drawback by processing the data near the data source and running certain analytics there, while keeping the cloud as the top layer where extensive data is stored and processed. (Navakauskas & Kazlauskas, 2023) The connectivity can be intermittent, especially in healthcare settings where quick responses are needed, and this feature is crucial. Fog nodes can also continue to perform selected processing functions in the local healthcare environment right where it is, rather than having to communicate with a remote cloud platform, making every healthcare decision. This means that fog computing can help ensure operational resilience while still enabling essential data to be updated to the central systems when they are available (Jeyaraman et al., 2024). Fog computing is another of the key infrastructures for incorporating Artificial Intelligence in maternal and child health care. Although more computing intensive models can stay in the cloud, AI models used at the fog nodes can process selected information generated by IoT devices locally to detect, classify and predict potential risks in the early stages. The combination of AI and fog computing is seen as one of the most significant paths with potential for implementation in real-time healthcare applications (Navakauskas & Kazlauskas, 2023). Another significant chance is the combination of fog computing and Federated Learning (FL). Fog nodes can offer local aggregation and computational assistance, while federated learning allows healthcare institutions or distributed computing nodes to work together to create machine-learning models without having to share raw patient records with a central repository. Tripathy et al. (2024) showed how fog can be integrated with federated-learning architecture for healthcare applications and how the combination of both technologies can reduce the communication latency and energy consumption in such resource-constrained applications.

The synergy of IoT, fog computing, federated learning and AI thus opens an intriguing technological route for maternal and child-health systems. They can be used to produce patient data, fog nodes to process information near the patient, federated learning to develop models collaboratively without sharing raw data with central entities, and AI to convert the information into predictive and decision-making outputs. This integrated arrangement is the next step in the evolution of individual technologies and is moving towards a distributed intelligent healthcare architecture (Tripathy et al., 2024). But fog computing can't be seen as a panacea for maternal and neonatal or child death. More recent systematic reviews have confirmed

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interoperability, scalability, security and privacy as still existing issues in healthcare fog-computing environments, whereas also more recent research has stressed the importance of implementing adequate security mechanisms all along the IoT, edge, fog and cloud layers. Such restrictions are especially relevant for designing systems that handle sensitive information about maternal and child health (Jeyaraman et al., 2024; Shahrour et al., 2026).

Federated Learning

Federated Learning (FL) is a new distributed AI (DAI) technique that can be used to train machine-learning models across several healthcare institutions without opening up the raw healthcare data and sharing it with a central server. Instead, the participating institutions train models based on data locally available and send out the parameters of models selected for aggregation or their updated versions. This is especially applicable to maternal, newborn and child health care, as the clinical information is extremely sensitive and is shared between hospitals, primary health care centres and other healthcare institutions. The promise for FL in mortality reduction is that it could allow healthcare organizations to learn from each other from patient populations spread across a geographic area. Conventional centralised machine learning models need data to be brought together before the models can be trained, with potential data sharing privacy and security concerns, ethical issues, and institutional challenges. An alternative is federated learning, where institutions can keep their own data in their local servers and supply elements to the creation of a shared predictive model (Nguyen et al., 2024).

FL can help develop models that predict complications and adverse maternal outcomes in maternal health. Models can be trained together at hospitals and/or primary healthcare facilities, with information like maternal demographic characteristics, clinical history, laboratory results, vital signs and observations related to pregnancy and labour, without routinely sharing individual patient records. This may enhance the capacity for AI systems to identify risk patterns between various populations while keeping local control over sensitive health data. FL can also contribute to new-born and child health services, such as the ability for distributed institutions to create a model for identifying a child's risk of early onset of health problems. Data already gathered at the point of care including neonatal observations, lab measurements, physiological data, treatment information and other clinical variables can be used to train the model without leaving the healthcare facility. This kind of partnership can be beneficial because the model might not be well-represented by data from a single institution, as they may not fully reflect the diversity of patient populations and treatment practices of other institutions. One of its greatest merits with FL is the potential to enhance the diversity and overall generalizability of healthcare AI systems. A model that is developed collaboratively at multiple health care systems might reflect more demographic, geographical and clinical diversity than one developed at a single health care system. There are still many challenges in federated models that need to be carefully studied and addressed, such as the variation of performance across different datasets, the possibility of generalization to new healthcare settings, and the necessity for robust validation procedures.While federated models hold promise, they must be thoroughly validated, and distinct differences in data sets can impact model performance, as well as the capacity to apply the resulting model to fresh healthcare settings (Yang et al., 2025).

The technology is also highly relevant to the Nigerian healthcare context where health information can be dispersed across tertiary-level hospitals, secondary-level hospitals, primary health centres and community-based health programmes. Federated learning may enable these institutions to collaborate on creating AI without creating a single entity housing all maternal and child-health records. While FL does not render privacy and security problems entirely extinct, it could establish crucial balance between the requirement for bigger datasets for AI development and the institution's requirement to preserve privacy and institutional control over sensitive information. While the raw patient data stay within individual institutions, information included in the model updates may be able to be exploited by means of sophisticated inference, reconstruction or poisoning attacks. Federated learning alone should not be considered as a privacy solution; there is still a need for other protocols for authentication, secure communication, privacy protection, model monitoring, and governance to ensure the effective deployment of this technology. Data Heterogeneity is another significant challenge. Healthcare organizations might employ various EHR systems, coding,

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measurement, and data formats, which can make effectively combining the contributions of these different systems difficult within a single federated learning process. Differences in information representation between these institutions can have a significant impact on the performance of models in federated learning for heterogeneous healthcare data, necessitating customised learning and aggregation methods (Zhang et al., 2024). Another important consideration for the implementation of FL in resource-limited healthcare settings is the computational and communication needs. While the need for participation institutions to have adequate computing power and network connectivity to train local models and share updates on these models, this could be scaled down through the use of edge or fog computing. With the aid of a fog-enabled federated-learning architecture, local healthcare nodes can undertake data processing and model-training tasks near the patient, which can result in a more distributed and responsive AI infrastructure (Tripathy et al., 2024). One of the most interesting use cases for the proposed study is the connection of fog computing to FL, as they solve complementary issues. Continuous maternal, newborn and child-health data can be gathered by IoT devices, fog nodes can process data locally and help local model training, FL can coordinate learning among participating healthcare facilities, and cloud computing can offer large-scale storage and computational resources. The collaboratively built models can then be used to build risk-prediction and clinical decision-support tools for healthcare professionals that can be done with the help of AI.

Sustainability of Emerging Technologies

- The sustainability of new technologies in maternal, newborn and child health means that they can provide sustained health benefits at a sustainable cost, available to all, sustainable, and environmentally friendly over time. Sustainability requires energy, infrastructure needs, connection, data management, interoperability, human resources, scalability and institutional acceptance beyond technical performance. A digital-health intervention must thus be sustainable and adaptable to the financial, technological and environmental constraints of the health care system in which it is implemented (Berger et al., 2025).

- The fog computing concept has significant potential to be sustainable in the healthcare industry since it involves a decentralized approach of distributing computing and storage between end-user devices and centralized cloud computing resources. Fog computing processes selected health data near the point of generation, which can result in less data being sent, faster response times, and reduced reliance on constant communication between distant cloud servers. These are especially important for maternal and child-health facilities where connectivity and network reliability can fluctuate (Jeyaraman et al., 2024). For the economy, maybe fog computing can de-incentivize some communication and cloud-processing needs: Data can be filtered, aggregated and analyzed local to the community before only what's needed is sent to central systems. This can be advantageous for healthcare institutions that have a stream of data coming from IoT sensors which monitor patients. Yet, for sustainable implementation, costs of fog nodes, gateways, sensors and networking equipment acquisition, powering, upgrading and maintenance must be taken into account.

- Although energy usage is not a critical factor, it is still important because of the extra computational devices added to healthcare environments. The energy consumption of distributed servers, gateways, sensors and networking equipment needs to be calculated throughout the system life cycle, although processing can reduce the energy use associated with communications. Studies of fog-based healthcare have shown that the effective deployment of fog-based aggregation can lower communication latency and energy use in resource-limited IoT healthcare applications (Tripathy et al., 2024). By avoiding the need for continuous Internet connectivity, fog computing can also help ensure the operational sustainability of the system. If the ability to communicate with a remote cloud-based platform is temporarily lost, selected monitoring and analytical functions can continue locally, and information will be synced when the connectivity is restored. This can be helpful in the context of maternal and child-health facilities with poor infrastructure in their communities, but it does not address security, interoperability and maintenance as implementation criteria.

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- Beyond this, Federated Learning provides another angle of sustainability, enabling hospitals to partner up without the need to often share their original patient data with a central repository. This can increase the level of privacy, governance and institutional challenges of centralised data pooling but still enable distributed healthcare facilities to help feed into a shared intelligence system. Federated learning has emerged as a promising method to leverage distributed health data while keeping data custodians in control.Federated learning is a recent research area that has identified as an approach to use health data that is distributed across different sites while still maintaining control for the data custodians (Eden et al., 2025). The economic and infrastructural sustainability of federated learning, however, relies on the computational and communication demands it places on the healthcare facilities involved. Local model training needs compute resources and repeated sharing of model updates needs network connectivity and communication capacity. The above could be challenging for healthcare facilities in Nigeria that may be limited in their digital infrastructure, which could leave lightweight models, efficient communication protocols and the proper aggregation strategies to consider.

- Federated learning is also tied to sustainability as it may involve significant computational demands for model training as a distributed process among the participating institutions. However, the advantages gained in terms of the environment by not having to perform large-scale, centralised data transfers can be mitigated somewhat by repeated local training and communication if the federation isn't well designed. Energy efficiency is highlighted as an important design consideration for recent research on GFL and incorporating sustainability into the architecture and operation of federated AI systems (Thakur et al., 2025). Another sustainability challenge is data heterogeneity, due to the use of different information systems, clinical terminologies, data formats and measurement procedures by the healthcare institutions. A federated model therefore has to allow for differences between the participating datasets, which must not force all the institutions to overhaul their current information systems. Some recent studies in the healthcare field highlight the challenges of heterogeneous data, efficient data communication, privacy, model performance, and system scalability that remain in the practical implementation of federated learning (Madathil et al., 2025).

- AI can be applied to maternal and child health to facilitate risk prediction, clinical decision support, patient monitoring, and optimal resource allocation, and to enable early detection of potentially harmful health conditions. AI can aid in the more effective allocation of healthcare resources such as staff, equipment, and time, through more focused interventions. But the sustainability of AI should be evaluated based on its computational and environmental demands, not all AI applications are sustainable. As AI models become more complex and are trained and deployed, the environmental impact of AI in healthcare is growing and gaining significant attention. Energy is used for data centres, specialized hardware and regular model execution, and the manufacturing and recycling processes for computer components could add to environmental issues. AI's requirements for energy use have led to a recent push for energy-efficient models, green computing practices, the use of renewable energy, and lifecycle assessment as key elements of sustainable AI deployment (Ueda et al., 2024).

- Lightweight, computationally efficient AI models can help enhance sustainability in resource-limited healthcare settings. New techniques like model compression, efficient architectures, adaptive computation and low-power edge deployment can employ a reduction in computational load without compromising clinically relevant performance. An AI system's dimensions like energy usage, latency, accuracy, computational complexity, and cost are connected and should all be taken into account when evaluating an AI system (Alzahrani et al., 2025). The usefulness of models in changing healthcare conditions, patient populations and clinical practice is another factor in AI sustainability. Models developed with external data sets might need to be adapted before they can be used to get good predictions for Nigerian mothers, newborns and children, and poorly maintained models may lose their predictive value over time as health services change. Sustainability of AI, therefore, needs to be continuously validated, monitored, updated, supervised and reinforced by institutional capacity, and not be considered as a one-off technological task.

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Integrated Sustainability of Fog Computing, Federated Learning and AI

The sustainability potential of the three technologies becomes more significant when they are considered as complementary components of an integrated architecture. IoT devices can collect maternal, newborn and child-health information, fog computing can process time-sensitive data locally, federated learning can coordinate collaborative model development across healthcare institutions, and AI can transform the resulting information into predictive and decision-support outputs. Such integration can distribute computational workloads according to their urgency, resource requirements and privacy sensitivity. The combination of fog computing and federated learning can also address some of the limitations of conventional cloud-based AI. Fog nodes can provide local computational support for healthcare facilities, while federated learning can coordinate model training without requiring routine transfer of raw patient information to a central location. Experimental research on fog-enabled federated healthcare systems has demonstrated potential improvements in communication latency and energy efficiency, suggesting that the combination deserves further investigation in resource-constrained healthcare environments (Tripathy et al., 2024).

For Nigeria, the sustainability of this integrated architecture should be assessed according to local infrastructure and institutional realities. Important considerations include electricity availability, internet connectivity, hardware affordability, technical skills, maintenance capacity, data-protection requirements, interoperability and the ability of healthcare institutions to operate and update the technology over extended periods. Sustainability should therefore be evaluated not only by whether a system produces accurate predictions but also by whether healthcare institutions can realistically operate, maintain and scale it. Environmental sustainability should likewise form part of the assessment because digital transformation can produce both environmental benefits and environmental costs. Digital technologies may reduce patient travel, improve resource allocation and support more efficient healthcare processes, but they can simultaneously increase electricity consumption, hardware demand and electronic waste. Recent digital-health research consequently recommends lifecycle assessment and broader environmental evaluation rather than measuring sustainability only through immediate operational efficiency (Berger et al., 2025).

Summary of Reviewed Literature

For Nigeria, the importance of fog computing lies in its potential to provide an intermediate technological layer between resource-constrained healthcare devices and centralized cloud infrastructure. A Nigerian maternal and child-health architecture could therefore use IoT devices for data acquisition, fog nodes for local processing and rapid alerts, federated learning for collaborative privacy-preserving analytics, cloud computing for large-scale storage and advanced computation, and AI for prediction and clinical decision support. Such an architecture provides a technological basis for investigating whether emerging digital technologies can be adapted to the connectivity, infrastructure, privacy and resource constraints of Nigerian healthcare environments. Tables 1 present summaries of the reviewed studies on the application of emerging technologies to maternal and child health. It highlights the technologies investigated, major study contributions and findings, identified limitations, and their relevance to mortality reduction in Nigeria. The table provides a comparative overview of the existing evidence and helps identify research gaps that support the need for integrated, sustainable technology-driven approaches to maternal and child healthcare.

Table 1: Summary of Reviewed Literature

Author(s) & Year	Study Focus	Main Contribution / Findings	Key Limitation / Gap
Nasir et al. (2022)	Systematic scoping review of interventions/programmes/strategies for maternal and newborn health in Nigeria.	80 publications; most interventions aligned with WHO recommendations and focused on pregnancy/childbirth and facility-level	Limited structural, community-based and pre-pregnancy interventions; need for context-specific implementation

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		determinants.	beyond facilities.
Ekpenyong (2025)	Examined women's beliefs, experiences and barriers affecting maternal healthcare utilisation in South-South Nigeria.	Identified stigma, mistreatment, systemic failures, cultural silences and differences across demographic groups.	Infrastructure alone is insufficient; respectful, confidential and culturally sensitive care is required.
Akeju et al. (2022)	Evaluated video training and healthcare-data digitisation using satellite communication and 3G networks in 62 Ondo State facilities.	Reported sustained improvements in staff motivation, confidence, healthcare delivery and adoption of eHealth innovations.	Connectivity limitations remained relevant because most facilities lacked 3G access.
Victor (2025)	Reviewed AI-driven approaches for maternal and child health forecasting and prediction.	AI models can estimate risks including pre-eclampsia, gestational diabetes and birth disorders using clinical and imaging data.	Need for appropriate datasets and clinical translation.
Correia et al. (2025)	Scoping review of AI-driven approaches to personalised maternal and fetal health.	Identified potential for prediction, diagnostics and personalised medicine.	Limited dataset diversity, black-box models and inconsistent reporting hinder clinical adoption.
Kalyan et al. (2025)	Discussed AI applications in obstetric and fetal health.	AI offers automation, improved accuracy and potential personalised medicine.	Data availability, algorithmic transparency and ethical considerations remain barriers.
Yahaya et al. (2025)	Examined digital innovations for improving maternal and child health in Nigeria.	Identified potential to improve access, healthcare delivery and engagement and provided policy recommendations.	Sustainable and equitable implementation remains necessary.
Till et al. (2023)	Cross-disciplinary scoping review of digital health technologies for maternal and child health in Africa and other LMICs.	Highlighted mobile data, smartphones, wearables and culturally appropriate applications as opportunities.	Community involvement, text dependence and translation of research into policy remain challenges.
Ssegujja et al. (2025)	Developed a conceptual framework describing the current and desired state of maternal electronic service delivery.	Proposed integration of potential e-services into maternal healthcare.	Need to translate fragmented e-services into an integrated delivery framework.
Jeyaraman et al. (2024)	Reviewed applications of fog computing in healthcare.	Fog places computing, storage and communication closer to healthcare data sources, supporting real-time processing.	Interoperability, scalability, security and privacy remain challenges.

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Navakauskas & Kazlauskas (2023)	Systematic review of fog computing in healthcare.	Emphasised local processing, reduced latency and reduced dependence on remote cloud connectivity.	Implementation requires suitable infrastructure and integration with existing systems.
Tripathy et al. (2024)	Proposed/assessed a federated-learning-enabled healthcare analytics approach over a fog-computing platform.	Reported potential improvements in communication latency and energy consumption.	Requires adequate distributed computing, communication and security mechanisms.
Shahrour et al. (2026)	Systematic review of security and privacy challenges in healthcare IoT systems using cloud, edge and fog computing.	Identified security and privacy challenges across distributed healthcare computing layers.	Need for robust security mechanisms across IoT, edge, fog and cloud.
Nguyen et al. (2024)	Systematic review of federated learning for healthcare and future research directions.	Positions FL as a method for collaborative learning without centralising raw healthcare data.	Privacy, communication, heterogeneous data and implementation challenges remain.
Yang et al. (2024)	Discussed healthcare federated-learning applications and implementation challenges.	Supports collaborative AI while reducing the need for centralised raw-data pooling.	Requires attention to communication, privacy, heterogeneity and clinical validation.
Zhang et al. (2024)	Examined federated learning under heterogeneous healthcare data conditions.	Shows that differences in data representation can affect federated model performance.	Requires specialised learning and aggregation strategies.
Gooty et al. (2024)	Reviewed federated machine learning in healthcare and its clinical applications/technical architecture.	Identified FL as a potential approach to decentralised healthcare AI.	Much of the evidence remains proof-of-concept, with concerns around heterogeneity, communication, privacy and clinical translation.
Eden et al. (2025)	Scoping review of governance of federated learning in healthcare.	Examined governance requirements for privacy-preserving collaborative AI.	FL does not eliminate privacy/security risks; governance and technical safeguards remain necessary.
Thakur et al. (2025)	Examined energy- and environmentally-aware federated learning.	Positions energy efficiency as a design objective for distributed AI.	Distributed training and communication can increase computational energy demand.
Madathil et al. (2025)	Comprehensive survey of healthcare FL applications, systems and future directions.	Highlights healthcare applications and technical requirements of FL.	Data heterogeneity, communication efficiency, privacy,

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			model performance and scalability remain challenges.
Ueda et al. (2024)	Reviewed climate change and AI in healthcare.	Highlights the environmental footprint of healthcare AI and recommendations for sustainable deployment.	Energy, hardware and computational requirements must be considered.
Alzahrani et al. (2025)	Systematic review and evaluation of sustainable AI algorithms and techniques in healthcare.	Connects sustainability with energy use, latency, accuracy, computational complexity and cost.	Need for computationally efficient AI suitable for healthcare environments.
Berger et al. (2025)	Scoping review linking digital health with ecological sustainability and planetary health.	Frames sustainability around environmental effects, resource use and digital-health impacts.	Digital technologies can have both environmental benefits and costs.
Chima-Oduko et al. (2026)	Systematic review of integrated MNCH strategies and interventions in Nigeria.	Found improvements in several maternal and child-health indicators, including skilled birth attendance and reductions in neonatal/infant/child mortality.	Labour shortages, weak supply chains, poor supervision and infrastructure problems remain.
Oluwole et al. (2025)	Systematic review of community-based interventions in rural Lagos and Ogun States.	Identified infrastructure, sociocultural, financial and workforce barriers and policy needs.	Need for funding, stronger referral systems, workforce capacity and community engagement.
Afolabi et al. (2026)	Described the MamaBase pilot programme in low-income communities across Lagos State.	Demonstrated feasibility of a community-centred, data-driven maternal-health intervention and strengthened links to primary healthcare.	Scalability and long-term effectiveness require further assessment.
Lee et al. (2016)	Systematic review and meta-analysis of mHealth interventions for maternal, newborn and child health in LMICs.	Examined applications including antenatal care, health education and treatment adherence.	Evidence for direct mortality outcomes varies across interventions.
Amoakoh-Coleman et al. (2016)	Examined mobile-health applications relevant to maternal healthcare.	Supports mobile communication, information provision and healthcare engagement.	Implementation and evidence of mortality effects vary by context.
Ettaloui et al. (2024)	Systematic literature review of blockchain-based electronic health records.	Identified potential for secure data exchange, privacy, transparency and data integrity.	Scalability, performance, interoperability, regulation and resource consumption remain concerns.
Mouradian et al. (2018)	Comprehensive survey of fog computing and related research	Established the role of fog as an intermediate	Architectural, security, resource-

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	challenges.	distributed-computing paradigm between devices and cloud.	management and scalability challenges.
Yousefpour et al. (2019)	Survey of fog computing and related edge-computing paradigms.	Explained distributed processing closer to data sources and major fog-computing use cases.	Resource management, security, orchestration and scalability issues.
Greco et al. (2020)	Reviewed trends in IoT-based healthcare solutions and movement of AI toward the edge.	Identified edge intelligence as a way to support distributed healthcare analytics.	Cloud response time, availability, privacy and security motivate edge/fog approaches.

Research Gaps

The literature therefore suggests a progression from cloud-based healthcare to IoT-enabled healthcare to fog healthcare to General AI-enabled fog healthcare to federated-learning-enabled fog healthcare. The important gap for this study is to determine whether this technological progression has been sufficiently examined specifically in relation to maternal, newborn and child mortality in Nigeria, and whether the proposed combination is sustainable under Nigerian conditions of connectivity, electricity availability, healthcare infrastructure, affordability, data governance and technical capacity.

FUTURE DIRECTIONS AND RECOMMENDATIONS

- The Healthcare field must prioritize the creation of large, diverse, open-access datasets, mandate transparent, explainable model architectures, and establish robust ethical and regulatory frameworks. By addressing these challenges, AI can become an integral, equitable, and trustworthy component of Obstetric care worldwide.
- Exploring how technology-driven frameworks, especially those centered on mobile platforms, can integrate potential e-services to enhance maternal healthcare delivery. Bridging this gap holds the promise of revolutionizing maternal healthcare, making it more accessible and effective for women in need worldwide.
- Despite these opportunities, the application of FL to mortality reduction should not be assumed to produce direct reductions in maternal, neonatal or child deaths. Its contribution is more appropriately understood as an enabling mechanism through which healthcare data from multiple locations can support earlier risk identification, predictive analytics and evidence-based decision-making. The effectiveness of such an approach will ultimately depend on data quality, model accuracy, clinical validation, infrastructure, healthcare-worker acceptance, governance and the ability of healthcare institutions to translate predictions into timely interventions.
- Within this systematic review, Federated Learning is therefore examined as an emerging technology that can potentially overcome some of the data-sharing and privacy limitations associated with conventional AI in maternal and child healthcare. Particular attention should be given to its capacity to support collaborative learning across Nigerian healthcare institutions, its compatibility with fog and edge computing, its ability to accommodate heterogeneous datasets and its sustainability under different levels of technological infrastructure. The resulting assessment can help determine whether FL provides a practical component of an integrated digital architecture for improving maternal, newborn and child-health outcomes in Nigeria.

- Within this systematic review, sustainability therefore provides a basis for framework for evaluating fog computing, federated learning and artificial intelligence as emerging technologies for maternal, newborn and child health. The assessment should consider their clinical usefulness alongside affordability, energy efficiency, connectivity, privacy, computational requirements, interoperability,

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scalability, maintainability and environmental impact. This approach is important for determining whether these technologies can move beyond experimental applications towards sustainable digital-health systems capable of supporting long-term improvements in maternal, newborn and child-health outcomes in Nigeria.

CONCLUSION

Emerging technologies provide significant opportunities to strengthen maternal and child healthcare and contribute to mortality reduction in Nigeria. AI, IoT, mHealth, telemedicine, fog computing, and federated learning can support early risk detection, continuous monitoring, improved access to care, and data-driven clinical decision-making. However, their long-term effectiveness depends on addressing challenges related to affordability, connectivity, privacy, cybersecurity, interoperability, maintenance, energy consumption, and institutional capacity. An integrated IoT–fog–federated learning–AI architecture therefore offers a promising direction for developing sustainable and context-sensitive healthcare solutions. Its successful implementation will require appropriate infrastructure, skilled personnel, effective governance, continuous evaluation, and alignment with Nigeria's healthcare needs.

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