

Maternal Healthcare Monitoring Using Artificial Intelligence and Internet of Things: A Comprehensive Review

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ABSTRACT

Maternal healthcare monitoring has emerged as a critical research domain due to the persistent challenges of maternal and fetal morbidity, limited access to continuous prenatal care, and the growing demand for timely, data-driven clinical decision-making. Recent advances in Artificial Intelligence (AI) and the Internet of Things (IoT) have enabled intelligent, real-time, and non-invasive maternal monitoring solutions, particularly for high-risk and resource-constrained settings. This systematic literature review aims to comprehensively examine state of the art AI and IoT based maternal healthcare monitoring systems, identify prevailing research themes, and highlight technological trends and gaps. The review was conducted following the PRISMA protocol, utilizing two major scientific databases Web of Science and Scopus. An advanced search strategy employing the keywords “maternal,” “monitoring,” “AI,” and “IoT” was applied, with studies limited to publications between 2018 and 2025. After identification, screening, eligibility assessment, and quality evaluation, a total of 26 primary studies were included for in depth analysis. The findings were systematically classified into three dominant themes: (1) IoT based wearable sensing for maternal fetal monitoring, focusing on real time physiological data acquisition; (2) AI driven prediction and decision support in smart maternal care, emphasizing machine learning models for risk assessment and early complication detection; and (3) remote prenatal care platforms, system architectures, and rural health enablement, highlighting telemedicine-oriented solutions for underserved populations. Numerical analysis indicates a substantial increase in integrated AI IoT frameworks, with over half of the studies proposing predictive or decision-support capabilities. Despite notable progress, challenges remain regarding data reliability, interoperability, scalability, and clinical validation. This review provides structured insights into current research directions and serves as a foundation for future developments toward reliable, intelligent, and accessible maternal healthcare monitoring systems.

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1. INTRODUCTION

The integration of Artificial Intelligence (AI) and the Internet of Things (IoT) in maternal healthcare monitoring has revolutionized the way healthcare providers manage and monitor pregnancies, particularly high-risk ones. IoT sensors

are employed to collect vital maternal and fetal data such as temperature, blood pressure, oxygen saturation, heart rate, and fetal heart rate. This data is then stored on cloud platforms for continuous monitoring and predictive analysis using advanced AI algorithms. For instance, a study proposed the use of an optimized single-dimensional Convolutional Neural Network

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(1D-OCNN) to classify and predict emergencies for both mother and fetus, demonstrating superior performance in terms of accuracy, precision, recall, and F1-score compared to other learning algorithms [1]. Similarly, another study suggested the use of a Gated Recurrent Unit (GRU) for improved categorization and forecasting of emergencies, further validating the efficacy of AI and IoT in maternal and fetal monitoring [2].

The application of AI in maternal healthcare extends beyond mere data collection and monitoring. Explainable AI (XAI) models have been developed to enhance transparency and effectiveness in AI-driven healthcare solutions. These models analyze collected data to identify risk factors and generate actionable insights, thereby empowering healthcare providers to make informed decisions and implement timely interventions. For example, an IoMT system integrated with an XAI-based deep learning model achieved an accuracy of 80% for patient risk prediction and 92.6% for regional risk prediction, providing interpretable explanations that aid in decision-making [3]. Additionally, AI-driven clinical decision support systems (CDSSs) are being used to predict glucose trends and provide tailored treatments for pregnant women with diabetes, facilitating real-time adjustments and reducing complications for both mother and fetus [4].

The convergence of IoT and AI has also led to the development of comprehensive maternal health monitoring systems that utilize various sensors and platforms to provide continuous monitoring and analysis. For instance, a Fetal Health Monitoring System employing Raspberry Pi and Django server technology collects real-time data related to the expectant mother's health, ensuring prompt identification of abnormalities and improving the overall patient experience [5]. Another study proposed a novel approach using IoT-based deep learning architecture to detect fetal QRS complex from abdominal ECG signals, enhancing the accuracy of fetal heart rate monitoring [6]. These systems not only provide personalized advice and early danger detection but also optimize pregnancy management by offering valuable insights to both patients and healthcare professionals.

Despite significant advancements, the implementation of AI and IoT in maternal healthcare faces challenges such as data security, cost-effectiveness, and maintaining the patient-provider relationship. However, the potential benefits are substantial, particularly in resource-constrained environments. For example, an AI-based system using natural language processing (NLP) for decision support has been developed to improve maternal care by providing educational information and personalized monitoring results through an interactive chatbot system [7]. This system has shown promise in improving maternal care, especially in areas with limited healthcare resources. Furthermore, the integration of wearable technologies and mobile health applications facilitates continuous monitoring and self-management, extending quality care to underserved populations and reducing the need for frequent in-person visits [4], [8].

Figure 1 presents a concept map that frames maternal healthcare monitoring as an integrated ecosystem driven by smart healthcare innovations, IoT technologies, and artificial intelligence. The map highlights how continuous monitoring and digital partograms enable real-time assessment of maternal conditions, supported by IoT sensors, microcontroller boards, and scalable IoT architectures that

interoperate with hospital information systems. In parallel, AI-driven learning systems enhance diagnosis, prediction, and clinical decision-making, particularly for pregnancy management and fetal monitoring. Collectively, these interconnected components illustrate a shift toward intelligent, data-driven, and interoperable maternal healthcare solutions that improve monitoring accuracy, enable early risk detection, and support proactive, personalized care throughout pregnancy, ultimately strengthening maternal and fetal health outcomes.

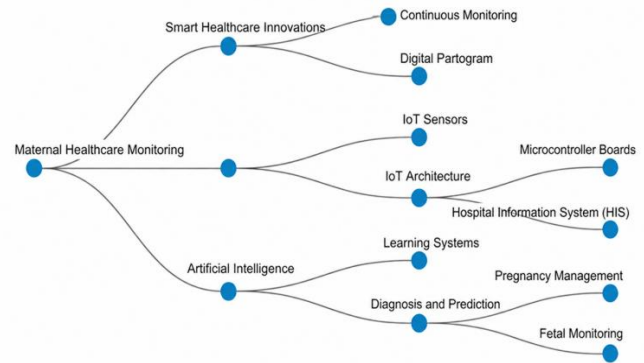


Fig. 1. Conceptual Framework of AI and IoT-Based Maternal Healthcare Monitoring

In conclusion, the amalgamation of AI and IoT in maternal healthcare monitoring offers a practical and efficient solution for managing high-risk pregnancies and improving maternal and fetal outcomes. By leveraging advanced AI algorithms and IoT sensors, healthcare providers can continuously monitor vital signs, predict emergencies, and implement timely interventions. While challenges remain, the ongoing development and refinement of these technologies hold great promise for enhancing maternal healthcare and reducing complications during pregnancy.

2. RESEARCH QUESTION

Research questions constitute the conceptual backbone of a systematic literature review (SLR), as they establish the analytical focus and methodological trajectory of the entire review process. Clearly articulated research questions delineate the scope of inquiry, guiding the identification, inclusion, and exclusion of relevant studies while ensuring alignment with the central research objectives. By defining precise boundaries, well-formulated research questions enable a comprehensive and systematic literature search that captures all pertinent evidence addressing the core dimensions of the topic. This structured approach reduces the likelihood of selection bias and supports a balanced and exhaustive synthesis of existing knowledge.

Moreover, research questions provide an organizing framework for data extraction, thematic classification, and comparative analysis, facilitating meaningful interpretation and integration of findings across diverse studies. Their clarity also enhances analytical precision, preventing conceptual ambiguity and ensuring that the review remains focused on specific, actionable issues. Importantly, explicit research questions strengthen the transparency and reproducibility of the review process, allowing subsequent researchers to

replicate, validate, or extend the findings. Ultimately, research questions ensure coherence between the review methodology and its intended outcomes, whether the objective is to map the state of the art, identify research gaps, assess methodological trends, or evaluate the effectiveness of emerging approaches.

The specification of research questions (RQs) represents critical activity during the planning phase of an SLR and remains the most influential component of the review, as it drives all subsequent methodological decisions [9]. Given that the objective of this SLR is to systematically identify, analyze, and synthesize the state of the art in the targeted research domain, a structured framework was required to support rigorous question formulation. Accordingly, the PICo framework originally proposed by [10] as a mnemonic approach for developing research questions in qualitative and exploratory studies was adopted. PICo comprises three key elements: Population, Interest, and Context. Applying this framework enables the decomposition of complex research aims into well-defined conceptual components, thereby ensuring precision, relevance, and methodological consistency. The use of PICo facilitates a focused literature search strategy and supports systematic evidence synthesis by aligning research questions with the underlying characteristics of the reviewed studies. Based on this framework, three research questions were formulated in this study, as presented below:

- 1) *In pregnant women (including high risk pregnancies), how effective are IoT enabled wearable sensing systems for continuous maternal fetal monitoring, within home and community based remote care contexts, in improving monitoring accuracy, usability, and early detection of abnormal maternal or fetal conditions?*
- 2) *For pregnant women, how do AI driven prediction and decision support approaches using IoT and/or clinical data perform within smart maternal care settings, in terms of predictive validity, interpretability, timeliness of alerts, and clinical usefulness for risk stratification and early intervention?*
- 3) *Among pregnant women and maternal healthcare providers, how do remote prenatal care platforms and system architectures integrating IoT and AI enabled monitoring function in rural and low resource contexts, particularly regarding accessibility, connectivity resilience, data security/privacy, interoperability and impact on continuity and quality of antenatal care?*

3. MATERIAL AND METHODS

This study adopts the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, a globally recognized standard for conducting systematic literature reviews that ensures methodological transparency, completeness, and reproducibility, as established by Page et al., [11]. Adherence to PRISMA guidelines enhances the scientific rigour of the review process by providing a structured protocol for the systematic identification, screening, and selection of relevant studies. By emphasizing the inclusion of high-quality and randomized studies, the framework effectively mitigates selection bias and strengthens the evidential robustness of the review outcomes. Accordingly,

two authoritative databases Web of Science and Scopus were selected due to their extensive coverage, indexing quality, and reliability in scholarly research.

The PRISMA methodology is structured into four sequential phases: identification, screening, eligibility, and data abstraction. During the identification phase, comprehensive database searches are conducted to capture all potentially relevant studies. The screening phase applies predefined inclusion and exclusion criteria to remove irrelevant or low-quality records. Subsequently, the eligibility phase involves an in-depth assessment of the remaining studies to ensure full compliance with the selection criteria. Finally, the data abstraction phase focuses on systematically extracting and synthesizing key information from the included studies. This rigorous, stepwise approach ensures methodological consistency and credibility, enabling the derivation of reliable insights that can effectively inform future research directions and evidence-based practice.

3.1 Identification

According to the PRISMA framework, the Identification stage provides the methodological basis for a transparent and systematic literature review. In this study, Scopus and Web of Science (WoS) as presented in Table 1 were selected due to their comprehensive coverage of high impact, peer reviewed journals and their strong credibility in medical and artificial intelligence research. Using the keywords, a total of 512 records were identified, including 395 from Scopus and 117 from WoS. The higher number of records retrieved from Scopus reflects its broader indexing of interdisciplinary and applied AI research, whereas WoS offers more selective coverage of well-established and highly cited journals. The combined use of both databases reduces database-specific bias and improves search completeness.

Table 1. The search string

Scopus	TITLE-ABS-KEY (("maternal" OR "mother" OR "pregnancy" OR "antenatal" OR "postnatal") AND ("monitoring" OR "tracking" OR "surveillance" OR "assessment" OR "evaluation") AND ("IoT" OR "Internet of Things" OR "connected devices" OR "smart devices" OR "wearable technology")) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2023) OR LIMIT-TO (PUBYEAR , 2024) OR LIMIT-TO (PUBYEAR , 2025))
	Date of Access: Jan 2026
WoS	("maternal" OR "mother" OR "pregnancy" OR "antenatal" OR "postnatal") AND ("monitoring" OR "tracking" OR "surveillance" OR "assessment" OR "evaluation") AND ("IoT" OR "Internet of Things" OR "connected devices" OR "smart devices" OR "wearable technology") (Topic) and 2025 or 2024 or 2023 or 2022 or 2021 or 2020 or 2018 or 2019 (Publication Years) and 2025 or 2024 or 2023 or 2021 or 2022 or 2020 or 2019 or 2018 (Publications Years) and Article (Document Types) and English
	Date of Access: Jan 2026

The substantial number of identified records indicates strong and growing scholarly interest in AI and IoT-based maternal healthcare monitoring, justifying the relevance of the selected keywords. However, this volume also necessitates a structured screening process to remove duplicates, irrelevant

studies, and low-quality publications. Limiting the search to Scopus and WoS enhances the methodological rigor and reliability of the review, as both databases apply strict quality and citation standards. Overall, the Identification stage provides a robust and defensible starting point for subsequent PRISMA phases and ensures that the review is grounded in credible, high-impact literature.

3.2 Screening

During the screening stage of the PRISMA process, the initial 512 records identified from Scopus and Web of Science were systematically evaluated against predefined inclusion and exclusion criteria as depicted in Table 2. As a result of this screening, 309 records were excluded due to non-compliance with the study criteria, including non-English publications, articles published before 2018, and document types such as conference papers, books, review articles, and papers in press. This step was essential to ensure temporal relevance, methodological consistency, and alignment with high impact journal standards, particularly for an evidence based review focusing on recent advances in AI-driven maternal healthcare monitoring.

Following this refinement, 203 records were retained for further consideration, comprising 133 articles from Scopus and 70 articles from Web of Science. Subsequently, a duplicate checking process was conducted to eliminate overlapping records across the two databases, resulting in the removal of 57 duplicate articles. This careful screening process significantly improved the quality and relevance of the dataset by retaining only original, recent, and peer reviewed research articles. Overall, the screening stage effectively narrowed the literature to a focused and high-quality corpus, providing a robust foundation for the eligibility assessment and in-depth analysis in subsequent PRISMA phases.

Table 2. The selection criterion is search

Criterion	Inclusion	Exclusion
Language	English	Non-english
Timeline	2018 - 2025	< 2018
Literature Type	Journal (Article)	Conference, Book, Review
Publication Stage	Final	In Press
Subject Area	Computer Science, Engineering and Health Professions	Besides Computer Science, Engineering and Health Professions

3.3 Eligibility

At the eligibility stage of the PRISMA process, 146 articles that passed the screening phase were assessed through full text evaluation to determine their relevance and suitability for inclusion. This step enabled a detailed examination of each study's scope, objectives, and methodological alignment with the review focus. Following this assessment, 117 articles were excluded for well defined reasons, including being outside the research scope, having titles with limited relevance, abstracts that did not address the review objectives, or the absence of accessible full-text versions. Applying these criteria ensured consistency and prevented the inclusion of studies that could dilute the analytical focus of the review.

The exclusions at this stage emphasize the importance of full text assessment in enhancing the rigor and validity of

systematic reviews. Studies that appear relevant at the abstract level may lack sufficient methodological depth or conceptual relevance when examined in detail. Moreover, excluding articles without full text access is necessary to support transparency, reproducibility, and critical appraisal. Overall, the eligibility stage effectively refined the literature corpus, ensuring that only methodologically sound and thematically aligned studies progressed to the final inclusion phase, thereby strengthening the credibility and reliability of the review findings.

3.4 Data Abstraction and Analysis

An integrative analytical approach was adopted as a core assessment strategy to systematically examine and synthesise evidence derived from diverse research designs, including qualitative methodologies. The primary objective of this process was to identify salient themes and subthemes relevant to the scope of the study. Data collection constituted the initial phase of theme development, during which 29 selected publications were rigorously reviewed, as illustrated in Figure 2, to extract statements and findings pertinent to the study objectives. Each study was critically examined with respect to its methodological approach and reported outcomes, ensuring a comprehensive understanding of the existing evidence base.

Theme construction was subsequently conducted through iterative collaboration among the author and co-authors, with themes derived inductively from the analysed evidence and contextualised within the study framework. Throughout the analysis, an audit log was systematically maintained to document analytical decisions, emerging interpretations, unresolved issues, and reflective insights, thereby enhancing transparency and methodological rigor. To ensure consistency and credibility, the identified themes were cross compared to detect potential discrepancies in interpretation. Any conceptual disagreements were resolved through consensus-based discussion among the authors, reinforcing the robustness and reliability of the thematic development process.

3.4.1 Quality of Appraisal

According to the methodological guidelines established by Kitchenham and Charters [9], the quality of the selected primary studies must be systematically evaluated to enable rigorous and quantitative comparison. Accordingly, this study adopts the quality assessment framework proposed by Anas Abouzahra et al. [12], which comprises six well-defined quality assessment (QA) criteria for the systematic literature review. Each criterion is evaluated using a three-level scoring scheme: "Yes" (Y), assigned a score of 1 when the criterion is fully satisfied; "Partly" (P), assigned a score of 0.5 when the criterion is partially met with identifiable limitations; and "No" (N), assigned a score of 0 when the criterion is not satisfied. This structured scoring mechanism ensures objectivity, transparency and comparability across the included studies.

- 1) *Is the purpose of the study clearly stated?*
- 2) *Is the interest and the usefulness of the work clearly presented?*
- 3) *Is the study methodology clearly established?*
- 4) *Are the concepts of the approach clearly defined?*
- 5) *Is the work compared and measured with other similar work?*
- 6) *Are the limitations of the work clearly mentioned?*

Each study is independently evaluated by multiple domain experts against the defined quality assessment criteria, after which the individual scores are aggregated to compute an overall quality score. To qualify for inclusion in the subsequent stage of the review process, a study must achieve a cumulative score of at least 3.0 (50%), based on the combined assessments of the three experts. This predefined threshold serves to enforce a minimum quality benchmark, ensuring that only methodologically sound and sufficiently robust studies are retained for further analysis. To complement the methodological QA, three supplementary engineering dimensions were considered in the technical discussion: hardware prototype readiness, experimental validation rigor and real-time reliability. These dimensions provide an engineering perspective on the maturity, validation and operational feasibility of the reviewed systems without altering the original QA1-QA6 scoring criteria or the predefined inclusion threshold.

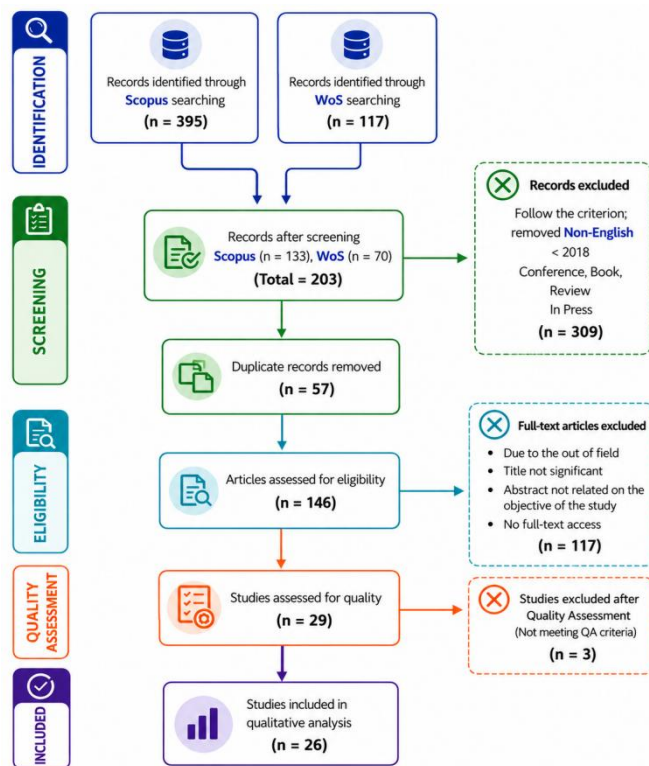


Fig. 2. Flow diagram of the proposed searching study [13]

4. RESULT AND FINDING

Table 3 presents the results of the quality assessment for the 29 primary studies (PS1–PS29) included in this review. Overall, the findings indicate that most of the selected studies demonstrate moderate to high methodological quality, with most articles achieving percentage scores above 60%. Several studies (e.g., PS3, PS5, PS14, PS15, PS18, PS22, PS25, and PS29) attained scores exceeding 80%, reflecting clearly stated research objectives, well-established methodologies, clearly defined concepts, and, in some cases, comparative evaluation with related work. Studies scoring between 60% and 79% generally fulfilled the core quality criteria but showed partial shortcomings, most related to limited comparative analysis (QA5) or the absence of explicitly stated limitations (QA6). Conversely, a small number of studies (PS7, PS10 and PS11) recorded percentage scores below 50%, primarily due to

insufficient methodological detail, weak conceptual clarity, and the lack of comparison with existing approaches. In accordance with the predefined quality threshold, all studies with assessment scores below 50% were excluded from further analysis, ensuring that the subsequent stages of the systematic literature review are based only on studies that meet the minimum required quality standard. From an engineering perspective, the retained studies were also considered in terms of hardware prototype readiness, experimental validation rigor and real-time reliability. These dimensions complement the methodological QA by emphasizing the practical implementation and operational feasibility of maternal healthcare monitoring systems.

Table 3. Performance of quality assessment for the 29 primary studies (PS1-PS29).

PS	QA						Total Mark	Percentage (%)
	1	2	3	4	5	6		
PS1 [14]	Y	Y	Y	Y	P	N	4.5	75.00
PS2 [15]	Y	Y	Y	Y	N	P	4.5	75.00
PS3 [16]	Y	Y	Y	Y	Y	N	5.0	83.33
PS4 [17]	Y	Y	P	Y	P	N	4.5	75.00
PS5 [18]	Y	Y	Y	P	Y	P	5.0	83.33
PS6 [19]	Y	Y	P	Y	N	N	4.0	66.67
PS7 [20]	Y	P	P	P	N	N	2.5	41.67
PS8 [21]	Y	Y	P	Y	N	N	4.0	66.67
PS9 [2]	Y	Y	P	P	Y	N	4.0	66.67
PS10 [22]	Y	P	N	P	N	N	2.5	41.67
PS11 [23]	Y	P	N	P	N	N	2.0	33.33
PS12 [24]	Y	Y	Y	Y	P	N	4.5	75.00
PS13 [25]	Y	Y	Y	Y	P	N	4.5	75.00
PS14 [26]	Y	Y	Y	Y	Y	N	5.0	83.33
PS15 [1]	Y	Y	Y	Y	Y	N	5.0	83.33
PS16 [27]	Y	Y	Y	Y	P	N	4.5	75.00
PS17 [28]	Y	P	P	P	N	N	3.0	50.00
PS18 [29]	Y	Y	Y	Y	Y	P	5.5	91.67
PS19 [30]	Y	Y	Y	Y	P	N	4.5	75.00
PS20 [31]	Y	Y	Y	Y	N	N	4.0	66.67
PS21 [32]	Y	P	P	P	N	N	3.0	50.00
PS22 [33]	Y	Y	Y	Y	Y	N	5.0	83.33
PS23 [34]	Y	P	Y	P	Y	N	4.0	66.67
PS24 [35]	Y	Y	P	Y	N	N	3.5	58.33
PS25 [36]	Y	Y	Y	Y	P	P	5.0	83.33
PS26 [37]	Y	Y	Y	Y	N	N	4.0	66.67
PS27 [38]	Y	P	P	P	N	N	3.0	50.00
PS28 [39]	Y	Y	P	Y	N	P	4.0	66.67
PS29 [40]	Y	Y	Y	Y	P	P	5.0	83.33

4.1 IoT Based Wearable Sensing for Maternal Fetal Monitoring

IoT based wearable sensing for maternal fetal monitoring is reported as clinically meaningful when measurement quality, continuity, and decision support are addressed together, rather than treating sensing and analytics as separate components. Across smartwatch or multi-sensor platforms, the most consistent finding is that combining routinely measurable maternal vitals with machine learning improves triage of pregnancy risk and supports earlier escalation pathways in low resource or low access contexts. A smartwatch-oriented approach links systolic, diastolic blood pressure and glucose with risk stratification and shows that hybrid classifiers can reach high discriminative performance while also translating outputs into clinically interpretable action thresholds for hypertension, hyperglycaemia, and tachycardia [14]. System level studies extend this idea from “single episode screening” toward sustained monitoring, showing feasibility for months long acquisition of wearable photoplethysmography with acceptable energy behaviour and data reliability, and highlighting that integration into routine care pathways is a central constraint, not an optional feature [36]. For high-risk scenarios, integrated architectures measure maternal temperature, oxygen saturation, heart rate, blood pressure, and fetal heart rate, then apply deep learning for multi-class emergency prediction; reported outcomes suggest that adding edge or fog processing can maintain accuracy while managing heterogeneous data streams and supporting timely alerts [33]. Comparable IoT cloud pipelines, when paired with optimized sequence or convolutional models, report improvements in classification of maternal fetal emergencies using larger datasets and multi-model benchmarking, reinforcing that performance gains usually come from careful model optimization rather than sensor count alone [1], [2]. Taken together, the evidence indicates that wearable maternal monitoring benefits most from: (i) a small set of high-yield physiological indicators, (ii) interpretable escalation rules aligned to obstetric practice, and (iii) validated end-to-end data pathways covering acquisition, transmission, storage, and prediction [14], [33], [36].

For fetal status assessment, findings concentrate on replacing inconvenient manual counting and clinic bound tests with wearable detection of movement, cardiac activity, and uterine activity that remains robust to posture, motion artifacts, and real-world use. Movement focused devices show that sensor fusion and feature optimization can separate fetal from non fetal motion with practical latency for continuous use; accelerometer or gyroscope wearables demonstrate strong sensitivity and sustained operation on a single charge, with performance boosted by feature selection and tuned gradient boosting [16]. Belt based designs using thin film pressure sensors extend movement monitoring to quantify kick intensity, frequency, and spatial location over the abdomen, enabling longitudinal trend tracking and home monitoring, while also adding contextual measures such as maternal position and temperature to support interpretation [17]. Cardiac signal acquisition remains a dominant fetal well-being route: wearable abdominal ECG systems report high fetal QRS extraction accuracy using combined adaptive thresholding and source separation methods, and show resilience across multiple maternal postures, suggesting suitability for home fetal heart rate monitoring when signal conditioning is adequate [30]. Alternative modalities

demonstrate that clinically comparable fetal heart rate and uterine contraction assessment can be achieved through remote fetal phonocardiography and electrohysterography with a wearable wireless prototype validated against standard clinical devices, supporting rural or low access service models [26]. Uterine activity monitoring advances further via algorithms derived from maternal cardiac related signals embedded into a wearable remote device; comparative studies report markedly higher sensitivity than conventional external tocodynamometry in intrapartum settings, indicating improved detection reliability for telehealth workflows [29]. Earlier wearable systems and data modules also emphasize the importance of textile electrodes, mobile applications, and secure transmission so that home-collected fetal heart rate traces can be reviewed remotely with clinically usable tools and without data loss, reinforcing that usability and hospital system integration are as pivotal as algorithm choice [30], [39], [40]. From an engineering perspective, these findings demonstrate that sensor placement and physical coupling, together with signal-conditioning approaches such as adaptive thresholding and source separation, are important for maintaining signal quality under maternal movement and posture variations. However, detailed reporting of parameters such as analog front-end (AFE) configuration, quantitative signal-to-noise ratio (SNR) and sampling rate should be considered when comparing hardware performance and reproducibility.

Synthesis across the abstracts indicates a converging design pattern: wearable sensing must be paired with dependable connectivity, secure storage, and validated analytics that can operate under motion, diverse postures, and long wear times. Reported results repeatedly associate higher diagnostic performance with optimization of feature pipelines and model tuning, while practical deployment depends on energy efficiency, latency, and data integrity rather than accuracy alone [16], [33], [36]. Architectures that balance cloud services with local or fog computation are presented to handle multi rate streams and reduce alert delay, but continued emphasis is placed on clinical validation against reference devices and specialist judgement to ensure that wearable outputs remain medically actionable [26], [29], [33]. Security and interoperability appear as recurring constraints: systems proposing cloud-centric monitoring and mobile transmission modules highlight the need for secure linkage to electronic records and dependable real time visualization without perturbing hospital networks [2] [40]. Overall, the theme supports an evidence based conclusion that IoT based wearable sensing can expand maternal fetal surveillance from episodic clinic testing to continuous home monitoring, if sensor placement guidance, signal-acquisition quality, artifact mitigation, appropriate sampling, energy budgeting and end-to-end validation are treated as core requirements rather than implementation details [14], [36], [39].

4.2 AI Driven Prediction and Decision Support in Smart Maternal Care

AI driven prediction and decision support in smart maternal care is increasingly framed as a response to delayed recognition of complications and delayed access to timely treatment, where continuous sensing and automated risk scoring can convert routine physiological measurements into earlier clinical action. In hypertensive disorders, the real time preeclampsia watch concept integrates IoT biosensing with

cloud processing and a machine learning risk model that triggers alerts when risk rises, emphasizing early diagnosis as a practical pathway to improved outcomes [18]. A related direction uses trimester attributes and remote monitoring to estimate infant mortality risk, where classification outputs are positioned as decision support for targeted follow-up in settings with limited specialist access [34]. Beyond single-condition prediction, a deep learning pipeline for ambulatory maternal fetal monitoring applies feature extraction across multiple physiological indicators like heart rate, oxygen saturation, blood pressure, and uterine tone and proposes multi outcome classification to support broader triage rather than one-risk-at-a-time screening [32]. Across these studies, a shared finding is that decision support becomes more actionable when alerts are tied to continuous measurement and when prediction is embedded within an end-to-end monitoring workflow, rather than delivered as a standalone model output [18], [32], [34].

From the perspective of analytics design, the abstracts indicate two dominant strategies: supervised classification for explicit clinical endpoints (such as preeclampsia risk or mortality risk) and unsupervised or representation driven learning for pattern discovery and robust prediction under noisy, large-scale data. For pre-eclampsia, comparative evaluation across multiple algorithms shows that a Naïve Bayes model can provide strong identification of at risk pregnancies in the tested setting, and the key reported contribution is practical integration of this predictor into an IoT watch that securely captures vitals and transmits data for near real time inference and alerting [18]. For mortality risk, a two class SVM is reported with strong discriminatory performance on a large cohort, and risk associations are highlighted for maternal age and short inter pregnancy intervals, positioning these variables as decision-support features for risk counselling and targeted monitoring [34]. In a different analytic frame, a miscarriage prediction platform is presented as a big data IoT architecture that merges sensor data, mobile phone data, and patient updated app inputs, then applies K means clustering with validation methods to produce well separated risk groupings; clinical decision support is described as clinician-facing monitoring of cluster outputs, while behavioural advice is routed to the pregnant individual via the app [24]. The ambulatory monitoring approach using DCGAN further suggests that deep generative classification can be used as a predictive mechanism for simultaneous maternal fetal health status categories, with linear and nonlinear feature measures proposed to handle multi format and multi rate streams [32]. Collectively, the reported findings imply that decision support quality depends not only on algorithm selection, but also on data fusion across modalities and on validation strategies that demonstrate stable partitions or strong discrimination in realistic data conditions [18], [24], [32], [34]. From an engineering perspective, AI model evaluation should also consider computational complexity, memory footprint and inference requirements, particularly for deployment on resource-constrained microcontrollers. These factors influence whether a model can support real-time Edge or TinyML implementation within wearable and IoT-based maternal monitoring systems. Therefore, model selection should balance predictive performance with computational and memory constraints to support practical embedded deployment.

A further layer of decision support appears in AI driven interpretation of imaging data, where fetal brain abnormality detection is positioned as automated classification to expand access to developmental assessment and reduce reliance on manual interpretation alone. The CNN-based DFBA pipeline reports improved accuracy through preprocessing and data augmentation on fetal MRI scans, and evaluation metrics are presented to support reliability of classification outcomes for abnormality detection. Although imaging differs from wearable vital-sign monitoring, the abstract aligns with the same theme: predictive outputs are intended to guide earlier clinical attention and optimize resource use, particularly when IoT enabled delivery is used to simplify access to results [25]. When combined with sensor driven prediction for hypertensive complications, miscarriage risk clustering, and mortality risk estimation, an integrated picture emerges in which smart maternal care decision support is moving toward multi source risk intelligence: continuous vitals for acute or subacute deterioration [18], longitudinal demographic and obstetric attributes for population level stratification [34], high volume behavioural and real time factors for early deviation detection [24] and imaging based classification for fetal developmental surveillance [25]. The remaining technical emphasis across abstracts is implementation realism: secure capture, cloud integration, scalable storage, and clinically usable alerting or monitoring interfaces are treated as essential elements, because prediction without operational delivery offers limited clinical value [18], [24], [32].

4.3 Remote Prenatal Care Platforms, Architecture and Rural Health Enablement

Remote prenatal care platforms in smart maternal health are often presented as an ecosystem problem, where sensing, communication, clinical workflow, and patient self-management must align to reduce unnecessary travel and improve timely care. A cloud-centric IoT platform perspective highlights how wearable devices can connect pregnant women and obstetric units through home monitoring of indicators such as fetal heart rate, blood glucose, and blood pressure, with an expected benefit of reduced workload for clinical staff and improved care efficiency through coordinated monitoring and management modes [35]. A broader IT-ecosystem model reinforces that platform value increases when services are integrated across stakeholders (pregnant women, clinicians, and healthcare systems) with semantically enriched e-health components, and when both web and mobile interfaces are validated in realistic usage; acceptance-oriented results indicate that usability and perceived usefulness can be high enough to support expansion beyond pilots [37]. Application-layer work adds operational details by proposing a mobile health product with real-time biomedical monitoring, dual alerting (manual and automatic), and personalized recommendations across patient and physician views; usability and load-test findings suggest that responsiveness and scalability under concurrent access are central for remote prenatal platforms that may face peak usage [15]. A complementary synthesis of influencing factors and IoT adoption argues that remote prenatal enablement is not only a device issue, but also a patient-centric approach shaped by individual characteristics, social determinants, and environmental context; this framing supports platform designs that combine monitoring with awareness and proactive self-care, especially when risk detection must happen earlier than facility arrival [21]. Across these contributions, the platform

theme converges on modular architectures that join wearable sensing, mobile interfaces, and hospital-facing services, while emphasizing user acceptance, scalability, and practical monitoring modes as determinants of real deployment [15], [21], [35].

Rural health enablement in the abstracts is strongly linked to reducing delays in labor-related decisions and expanding basic prenatal surveillance where frequent clinic access is limited. A rural-focused IoT-enabled system for early labor progress detection reports high accuracy for labor onset identification and high reliability for fetal heartbeat monitoring, with low alert latency enabling faster notification to medical teams, positioned as a practical approach for women living far from facilities [19]. A related labor monitoring design proposes a sensing belt, mobile-phone edge service, and IoT platform connected to hospitals to guide admission timing for low-risk primigravidas; classification outputs are structured into actionable categories (deferred, optional, recommended admission) and the AI components are reported as lightweight, indicating a design priority for home use with constrained device resources [27]. For routine prenatal parameters, a low-cost remote monitoring kit integrates multiple biosensors (heart rate, SpO₂, pressure, temperature, and a load cell proxy for fetal weight) with Arduino-based acquisition and a cloud channel for visualization; abnormal vitals trigger local alerts via a buzzer, reflecting an emphasis on immediate household-level signaling when connectivity or response time is uncertain [28]. These device-oriented studies share a common pattern: remote monitoring becomes meaningful when it supports concrete decisions such as when to travel, when to contact clinicians, and when abnormal signals require urgent attention, rather than only collecting data for later review [19], [28]. In parallel, an applications and taxonomy view supports rural enablement by mapping factors that shape pregnancy outcomes and by listing IoT sensors and device options, providing a conceptual bridge between rural constraints and the selection of measurable parameters for remote platforms [21].

Architectural discussions further emphasize that remote prenatal platforms must manage latency, energy limits, and reliability while maintaining clinically usable recommendations and end-to-end trust in data flow. Fog computing is proposed as a processing layer that complements wearables by analyzing physiological time-series closer to the data source, addressing limitations in wearable computation/energy and reducing cloud-induced latency; validation on real participants and high recommendation accuracy highlight the feasibility of rule-based analytics combined with fog support for timely interpretation [31]. Edge intelligence for labor progress monitoring similarly places classification on a mobile phone, indicating that decision support can be delivered locally while still keeping a hospital-connected IoT platform for clinician input, which is important when admission timing must be decided promptly [27]. From an engineering perspective, Edge, Fog and Cloud architectures involve different trade-offs in latency, computational resources, connectivity and energy consumption. Edge processing supports low-latency local decisions, Fog provides intermediate processing closer to the data source, while Cloud offers greater computational and storage capacity but relies more on network connectivity. Therefore, architecture selection should consider the processing and communication requirements of continuous maternal monitoring. Similarly,

the selection of communication protocols such as BLE, LoRaWAN and cellular IoT should consider engineering trade-offs in communication range, bandwidth, latency, network dependency and energy or battery requirements for continuous maternal monitoring. Rural alerting performance is also reported as a measurable system outcome, where short transmission delay and automated notification are treated as core safety properties for remote regions, not optional optimizations [19]. At the platform and service level, scalability and usability evidence from a mobile monitoring application suggests that remote prenatal care is likely to require load-tested infrastructures and intuitive navigation to support repeated use by both patient and physician groups [15], while ecosystem evaluation outcomes indicate that perceived quality and usefulness can support broader adoption when stakeholders observe tangible communication and coordination benefits [37]. Overall, the abstracts describe a layered blueprint for rural health enablement: wearable or home kits for capture, edge/fog layers for timely interpretation, cloud services for persistence and clinician access, and user-facing applications for guidance and workflow integration [15], [19], [27], [31], [37].

5. CONCLUSION

This systematic literature review was conducted to synthesize and critically examine recent research on maternal healthcare monitoring using Artificial Intelligence and the Internet of Things, with a specific focus on studies published between 2018 and 2025 and indexed in Web of Science and Scopus. The review followed the PRISMA protocol and applied rigorous inclusion, exclusion, and quality assessment criteria, resulting in the selection of 26 primary studies for qualitative analysis. The purpose of the review was to address three central research questions concerning the effectiveness of IoT enabled wearable sensing for maternal fetal monitoring, the role of AI-driven prediction and decision support in smart maternal care, and the performance of remote prenatal care platforms in rural and low resource contexts. By systematically organizing and evaluating the existing evidence, this study aimed to bridge fragmented knowledge across engineering, computer science, and healthcare domains, while providing a structured understanding of how integrated AI and IoT solutions are reshaping maternal healthcare monitoring.

The synthesis of findings revealed three dominant and interrelated research themes. First, IoT based wearable sensing systems were consistently reported as effective tools for continuous, non-invasive monitoring of maternal and fetal physiological parameters, particularly when combined with reliable data transmission and clinically interpretable analytics. Second, AI driven prediction and decision support approaches demonstrated growing maturity, with machine learning and deep learning models increasingly embedded into end-to-end monitoring workflows to support early risk detection, triage, and personalized care. These systems showed a clear shift from isolated algorithmic performance toward integrated decision-support mechanisms aligned with clinical processes. Third, remote prenatal care platforms and system architectures highlighted the potential of AI IoT ecosystems to improve accessibility, continuity of care, and timely intervention, especially in rural and resource

constrained environments. Across these themes, common methodological trends included cloud and edge assisted architectures, multimodal data fusion, and an emphasis on usability, scalability, and alert timeliness. Collectively, these findings indicate a transition from episodic, clinic-based monitoring toward continuous, data driven, and patient centred maternal healthcare models.

This review contributes to the field by providing a consolidated thematic framework that integrates sensing technologies, intelligent analytics, and service level architectures into a coherent perspective on smart maternal healthcare. By systematically categorizing existing studies into wearable sensing, AI based decision support, and remote care enablement, the review clarifies how technological components interact across the maternal care continuum. The synthesis also highlights practical implications for healthcare practice and policy, including the potential for earlier detection of complications, reduced burden on healthcare facilities, and improved care delivery for underserved populations. At the same time, several limitations were identified, including reliance on two databases, restriction to English language publications, and variability in clinical validation and the real world deployment across studies. Future research should prioritize large scale clinical trials, standardized evaluation metrics, interoperability with hospital information systems, and ethical considerations related to data security and privacy. In closing, this review underscores the importance of systematic evidence synthesis in rapidly evolving interdisciplinary fields, where structured reviews play a critical role in guiding theory development, informing practice, and shaping future empirical research toward safer, more effective, and more equitable maternal healthcare monitoring systems.

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