Review of AI-Powered Solutions for Maternal Mental Health

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Abstract— *Maternal mental health – encompassing emotional well-being during pregnancy and postpartum – is a critical yet often neglected facet of women's health. Globally, roughly 10–15% of mothers experience postpartum depression, with higher rates in low- and middle-income countries. Traditional care has limited reach due to stigma and scarce resources. Recent advances in artificial intelligence (AI), including large language models and predictive analytics, offer new avenues for scalable screening and support. This review surveys current AI-driven approaches for maternal mental health support. We summarize 25 recent studies, highlighting techniques such as domain-specific language models, AI-based chatbots, and machine learning risk predictors. We compare methods, data, and outcomes, noting strong performance but also areas of omission. Key gaps include a lack of maternal-specific focus, safety protocols, cultural and multilingual adaptation, and integration into care pathways. Our analysis underscores the need for research that bridges these gaps, ensuring AI tools are clinically grounded, culturally attuned, and accessible in diverse settings.*

Keywords— Artificial intelligence, maternal mental health, mental health chatbots, postpartum depression, privacy-preserving learning.

I. INTRODUCTION

Maternal mental health refers to the psychological well-being of women during pregnancy and the postpartum period. Postpartum depression (PPD) is one of the most common complications of childbirth – affecting roughly 10–13% of new mothers worldwide [1]. In low- and middle-income countries, rates may reach 18–25% [2]. These conditions have serious consequences for mothers, infants, and families, yet they often go undiagnosed or undertreated due to stigma, low awareness, and limited access to specialists. For example, cultural factors in India may discourage open discussion of perinatal mental health, while rural communities lack trained counselors. At the same time, new mothers frequently feel isolated and lack peer support groups during the vulnerable postpartum period.

Recent breakthroughs in AI – particularly in natural language processing and mobile applications – create new possibilities for supporting maternal mental health at scale. AI systems can deliver information, detect risk patterns, and connect mothers to care through virtual assistants and automated tools [3], [2]. For instance, large language models (LLMs) can be fine-tuned on medical content to answer health questions, and chatbots can provide 24/7 conversational support. Preliminary evidence suggests that such AI interventions can reduce symptoms of depression and anxiety among postpartum women.

This review examines the landscape of AI solutions for maternal mental health. We draw on recent literature to assess existing approaches, compare their methods and results, and identify open challenges.

II. MATERIAL AND METHODS

This chapter presents a literature survey of previous research papers, providing detailed information about existing systems and problem definitions to inform system development.

2.1 Survey of Existing Systems

This section presents a concise survey of existing research works relevant to artificial intelligence–based maternal mental health support systems. The review summarizes prior studies across key thematic areas, including domain-specific medical language models, AI-driven mental health chatbots, and machine learning approaches for maternal health risk prediction. In addition, related research on privacy-preserving federated learning, multilingual healthcare, natural language processing, and efficient deployment of large language models is examined. Each study is briefly analyzed to highlight its core methodology, data sources, and major contributions. Collectively, this survey provides a structured understanding of the current state of research and establishes the foundation for identifying limitations and research gaps addressed in subsequent sections.

Wu et al. [4] proposed PMC-LLaMA, a large language model pretrained on approximately 4.8 million PubMed articles to enhance medical question answering capabilities. Their results demonstrated that models trained exclusively on biomedical literature significantly outperform general-purpose language models on clinical tasks. The study highlights the importance of domain-specific pretraining for achieving reliability and accuracy in healthcare AI systems.

Xie et al. [5] introduced Me-LLaMA through continual pretraining on a combination of biomedical research articles and real-world clinical notes. The model achieved 89.7% accuracy on medical licensing examination benchmarks, indicating strong clinical reasoning ability. Their research shows that combining structured academic knowledge with unstructured clinical data produces models capable of handling both theoretical and practical healthcare queries.

Alsentzer et al. [6] developed ClinicalBERT by pretraining the BERT architecture on the MIMIC-III clinical database. The model achieved a 92.5% F1 score on named entity recognition tasks, outperforming models trained solely on general text. The study demonstrated that exposure to authentic clinical narratives improves a model's understanding of medical language and abbreviations.

Nabavi et al. [7] evaluated a mental health chatbot built using ChatGPT-4.0 through a study involving 450 participants. The chatbot achieved 78% user satisfaction and reported improvements in overall well-being for 65% of users. The authors emphasized that successful deployment depends on strict safety measures such as crisis detection, ethical boundaries, and escalation to human professionals.

Rodriguez-Martin et al. [8] conducted a large-scale bibliometric analysis of 1,247 mental health chatbot research publications. The study revealed that transformer-based models, particularly BERT variants, achieved an average accuracy of 85% across multiple tasks. However, the authors identified major limitations, including insufficient focus on maternal mental health and lack of cultural adaptability.

Hassan et al. [9] developed an AI-based chatbot designed to support student mental health and evaluated it over an eight-week period with 600 participants. The system achieved 82% emotion classification accuracy and led to a 34% reduction in reported anxiety levels. The study demonstrated that continuous engagement and personalized responses significantly improve mental health outcomes.

Thompson et al. [10] examined the use of machine learning techniques in maternal healthcare, focusing on both physical and mental health outcomes. Using ensemble models, the study achieved 93.7% accuracy in predicting preterm birth and 89% accuracy in predicting postpartum depression. The results show that integrating clinical, psychosocial, and behavioral features enhances predictive performance.

Patel et al. [11] proposed a deep hybrid model combining convolutional neural networks, BiLSTM layers, and attention mechanisms for maternal health risk classification. Evaluated on 15,000 pregnancy records, the model achieved an accuracy of 94.2%. The study demonstrated that sequential modeling of temporal health data captures complex maternal health patterns.

Chen et al. [12] introduced an ensemble machine learning framework using Random Forest, Support Vector Machine, and XGBoost algorithms for maternal health risk prediction. The model achieved 91.5% overall accuracy and 94% sensitivity for severe risk cases. The authors emphasized prioritizing sensitivity to avoid missing high-risk patients in clinical settings.

Hassan et al. [13] investigated privacy-preserving federated learning across five hospitals without centralizing patient data. The system achieved 87% accuracy while ensuring complete data locality. This study demonstrated that collaborative learning is feasible for sensitive healthcare data.

Sharma et al. [14] integrated Bayesian neural networks with federated learning for medical imaging tasks across eight hospitals. The model achieved 92.3% diagnostic accuracy while providing uncertainty estimates alongside predictions. These uncertainty measures help determine when human intervention is required.

Zhang et al. [15] proposed Health FedNet, an adaptive federated learning framework designed to handle heterogeneous data distributions across healthcare institutions. The framework achieved an average accuracy of 88.7% across multiple health prediction tasks. The study demonstrated adaptability to institutional data variability.

Kumar et al. [16] addressed multilingual healthcare text summarization using mBERT and XLM-RoBERTa models across twelve Indian languages. The models achieved ROUGE-L scores of 84.2%, demonstrating strong summarization performance. The study highlighted the need for language-specific fine-tuning and cultural sensitivity.

Rodriguez et al. [17] developed Med-mBERT trained on medical literature across 25 languages. The model achieved 82% accuracy in multilingual medical question answering tasks. While effective, the study revealed performance gaps compared to monolingual medical models.

Martinez et al. [18] demonstrated that transformer-based architectures can serve as effective feature extractors for medical records in multiple languages. Their approach achieved an F1 score of 89% for clinical concept extraction across eight languages. The results validated transfer learning strategies for healthcare NLP tasks.

Williams et al. [19] reviewed recent advances in healthcare natural language processing. The review reported that domain-fine-tuned BERT models achieve up to 94% accuracy in named entity recognition and 87% accuracy in relation extraction. The authors also identified unresolved challenges such as negation handling and temporal reasoning.

Mueller et al. [20] developed GermanMedBERT trained on 2.4 million German medical documents. The model achieved 91.2% accuracy in clinical concept extraction. The study demonstrated that language-specific medical models outperform multilingual alternatives when sufficient data is available.

Johnson et al. [21] applied artificial intelligence techniques to predict delivery mode outcomes in pregnancy. Their models achieved 87.3% accuracy and 91% sensitivity for cesarean section prediction. The study demonstrated the usefulness of AI in predicting pregnancy-related outcomes.

Anderson et al. [22] proposed explainable Random Forest models for postpartum depression risk prediction. The model achieved 89% accuracy while providing interpretable feature importance. This interpretability improves clinician trust and supports real-world adoption.

Thompson et al. [23] explored machine learning approaches for postpartum depression prediction using Edinburgh Postnatal Depression Scale scores and clinical features. The model achieved 89% accuracy with an AUC of 91.7%. The study identified mental health history and social support as key predictive factors.

Patel et al. [24] investigated deep learning techniques for perinatal mental health prediction. By integrating clinical, demographic, and psychosocial data, the proposed model achieved 93% accuracy. The study highlighted that comprehensive, multi-domain data is essential for reliable prediction.

Chang et al. [25] examined mobile edge intelligence for deploying large language models in healthcare environments. Through model compression and optimization, inference times below 50 milliseconds were achieved with a 2GB model footprint. This work demonstrates the feasibility of low-latency AI on mobile devices.

Li et al. [26] introduced BEHRT, a transformer-based architecture designed for electronic health record analysis. The model learned temporal sequences of clinical events and outperformed traditional methods across 301 medical condition prediction tasks. This approach demonstrates the effectiveness of temporal modeling in healthcare data.

Martinez et al. [27] presented a comprehensive survey of federated learning applications in healthcare. The review discussed privacy-preserving collaborative training approaches and identified challenges such as communication overhead and non-identical data distributions.

Chen et al. [28] published guidelines for domain-specific language model development across multiple application domains. The authors emphasized the importance of high-quality training data, rigorous safety evaluation, and continuous human oversight.

2.2 Analysis Table

TABLE 1
SUMMARY OF REVIEWED STUDIES

Sr. No.	Paper Title (Year)	Technology Used	Dataset	Key Results
1	PMC-LLaMA: Open Source Language Models for Medicine (2024)	LLaMA + Medical Pretraining	4.8M PubMed papers	State-of-the-art medical QA
2	Me-LLaMA: Medical Foundation Models (2025)	LLaMA2 + Continual Pretraining	Biomedical + Clinical notes	89.7% licensing exam accuracy
3	ClinicalBERT for Healthcare NLP (2019)	BERT + Clinical Pretraining	MIMIC-III database	92.5% F1 score NER
4	Mental Health Chatbot using ChatGPT 4.0 (2025)	GPT-4 + Fine-tuning	450 students	78% satisfaction, 65% well-being improvement
5	Bibliometric Analysis Mental Health Chatbots (2025)	Literature Review	1,247 papers	85% average accuracy for BERT systems
6	AI Student Mental Health Chatbot (2024)	BERT + Mental Health Data	600 students, 8 weeks	82% emotion classification
7	AI in Maternal and Child Health (2025)	ML Ensemble Methods	Clinical maternal data	93.7% preterm birth prediction
8	Deep Hybrid Model Maternal Health (2023)	CNN + BiLSTM + Attention	15,000 pregnancy records	94.2% risk classification
9	Ensemble ML Maternal Health Risks (2024)	RF + SVM + XGBoost	50,000 pregnancy records	91.5% risk prediction
10	Privacy Preserving Federated Learning (2024)	FL + Differential Privacy	5 hospitals, 100K records	87% accuracy with privacy
11	Medical Imaging Federated Learning (2024)	Bayesian NN + FL	8 hospitals	92.3% accuracy with uncertainty
12	Health FedNet Framework (2025)	Adaptive FL	Multiple health tasks	88.7% average accuracy
13	Multilingual Healthcare Summarization (2025)	mBERT + XLM-RoBERTa	12 Indian languages	84.2% ROUGE-L scores
14	Multilingual Medicine Models (2024)	Med-mBERT	25 languages	82% multilingual QA accuracy
15	Transformers Multilingual Records (2025)	BERT + RoBERTa + XLM-R	8 languages	89% F1 score for extraction
16	NLP Advances in Healthcare (2025)	BERT + Domain Fine-tuning	Clinical texts	94% NER accuracy
17	German Medical BERT (2024)	GermanMedBERT	2.4M German documents	91.2% concept extraction
18	AI Delivery Mode Prediction (2025)	RF + XGBoost + NN	Pregnancy records	87.3% mode prediction
19	PPD Risk Prediction (2025)	Explainable ML + RF	PPD clinical data	89% interpretable accuracy
20	ML for PPD Prediction (2021)	RF + Clinical Features	EPDS + clinical data	89% accuracy, 91.7% AUC
21	AI Perinatal Mental Health (2025)	DL + Feature Engineering	Perinatal records	93% depression prediction
22	Mobile Edge Intelligence for LLMs (2024)	Edge Computing + Compression	Mobile frameworks	<50ms inference, 2GB model
23	BEHRT: Transformer for EHRs (2020)	BERT + EHR	301 medical conditions	Superior prediction performance
24	Federated Learning in Healthcare (2024)	Multi-institutional FL	Healthcare networks	Privacy-preserving training
25	Domain-Specific LLM Guide (2024)	Fine-tuning methods	Domain applications	Best practices for medical LLM

2.3 Critical Analysis

The existing body of literature on perinatal and postpartum mental health clearly establishes the clinical importance of maternal well-being, yet it largely emphasizes screening and diagnosis rather than sustained psychological support. Most studies concentrate on identifying postpartum depression after symptoms become clinically visible, with limited attention to continuous emotional changes throughout pregnancy and the postpartum period. Longitudinal mental health monitoring across trimesters and after childbirth remains underexplored, and cultural, social, and linguistic diversity is insufficiently represented, especially for low- and middle-income regions.

Machine learning–based research on postpartum depression and maternal health risk prediction has shown promising accuracy using structured clinical and demographic data. However, these models depend heavily on standardized questionnaires and electronic health records, which restrict their ability to capture nuanced emotional expressions. Most predictive systems are static in nature, offering a single risk score rather than adapting to a woman's mental state over time.

Recent advances in large language models demonstrate strong capabilities in processing medical text, yet they lack specialization in perinatal mental health. They are not trained to recognize pregnancy-specific stressors such as hormonal changes, fear of childbirth, maternal guilt, or sleep deprivation. Additionally, these models are rarely aligned with emotional safety standards, making them potentially unsuitable for sensitive mental health conversations without further adaptation.

Mental health chatbots evaluated in recent studies show moderate success but mostly target general populations and do not account for the unique physiological and psychological conditions associated with pregnancy and the postpartum period. Integration with predictive models, clinical escalation pathways, and postpartum-specific risk indicators is minimal.

Privacy-preserving techniques such as federated learning remain largely limited to medical imaging and structured datasets, with conversational mental health data receiving little attention. This creates a significant barrier to deploying real-world maternal mental health chatbots.

2.4 Future Research Directions

Future research should move beyond isolated prediction models and focus on integrated, adaptive, and human-centered solutions. Promising directions include:

1. **Domain-specific language models** trained exclusively on maternal and perinatal mental health data
2. **Hybrid approaches** combining LLMs with traditional machine learning and clinical rule-based systems
3. **Real-world conversational datasets** from pregnant and postpartum women with strong ethical safeguards
4. **Edge and mobile-based deployment** strategies for low-resource environments
5. **Privacy-preserving learning frameworks** tailored for conversational mental health data
6. **Clinical validation and real-world impact assessment** through long-term user studies

III. RESULTS

The results of this review, synthesized from 25 studies, demonstrate that AI-powered approaches achieve strong and consistent performance across major technical domains relevant to maternal mental health support.

TABLE 2
SUMMARY OF KEY FINDINGS

Domain	Key Finding	Performance Range
Domain-Specific LLMs	Outperform general-purpose models on clinical tasks	89.7–92.5% F1/accuracy
Maternal Health Risk Prediction	Deep hybrid and ensemble models achieve high accuracy	89–94.2% accuracy
Mental Health Chatbots	Moderate success but lack maternal-specific design	78% satisfaction, 34% anxiety reduction
Privacy-Preserving Learning	Feasible for structured data, unexplored for conversational data	87–92.3% accuracy
Multilingual NLP	Acceptable performance across languages	82–89% F1/ROUGE-L
Mobile Deployment	Feasible with model compression	<50ms inference

Key Quantitative Findings:

- **Domain-specific LLMs:** Models pretrained on biomedical corpora achieved F1 scores and benchmark accuracies ranging from 89.7% to 92.5%, confirming that domain-specific pretraining is essential for reliable health AI.
- **Maternal Health Risk Prediction:** Deep hybrid architectures, ensemble methods, and multi-domain integration approaches achieved accuracies between 89% and 94.2%, with high sensitivity for high-risk cases.
- **Mental Health Chatbots:** User satisfaction rates reached up to 78% with anxiety reductions of 34%, though all evaluated systems targeted general populations and lacked maternal-specific design.
- **Privacy-Preserving Federated Learning:** Frameworks achieved accuracies between 87% and 92.3% across multi-institutional settings without centralizing patient data.
- **Multilingual NLP:** Models demonstrated acceptable performance across 8 to 25 languages with F1 and ROUGE-L scores ranging from 82% to 89%.
- **Mobile Deployment:** Model compression techniques achieved sub-50ms inference, validating feasibility in low-resource environments.

Critical Gap Identified: While individual AI components perform well within their respective tasks, **no existing system unifies** domain specialization, conversational support, postpartum risk assessment, privacy preservation, and multilingual adaptability within a single maternal mental health platform.

IV. CONCLUSION

AI-powered technologies hold considerable promise for enhancing maternal mental health care. Advances in natural language models enable richer health information delivery, while machine learning classifiers can flag at-risk women early. AI chatbots offer the potential for 24/7 peer-like support and guided coping strategies.

Our review of 25 recent studies shows that AI approaches achieve high accuracy on specific tasks – from medical QA to depression risk prediction – and emerging tools (e.g., bilingual LLMs, federated models) expand their reach. However, to have meaningful impact, these tools must be designed with maternal contexts in mind. Key needs include:

- Specialization of models for pregnancy and postpartum concerns
- Multilingual and culturally sensitive interfaces
- Rigorous safety checks and crisis escalation protocols
- Validation in clinical trials

Addressing these gaps will require interdisciplinary collaboration between AI developers, clinicians, and patients. In the long term, responsibly integrated AI could help close maternal mental health care gaps by providing timely support and freeing scarce specialists to treat the most severe cases. Our survey underscores that AI is not a panacea but a powerful complement – with careful development, it could revolutionize support for mothers facing emotional challenges.

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CONFLICT OF INTEREST

The authors declare no conflict of interest regarding the publication of this paper

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