AI-Driven Approaches for Maternal Health Risk Prediction, Gestational Diabetes Detection, and Postpartum Depression Screening: A Literature Survey

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***Abstract*—*Pregnancy-related complications such as gestational diabetes mellitus (GDM), hypertension, anaemia and postpartum depression (PPD) remain significant contributors to maternal morbidity and mortality, particularly in rural and resource-limited settings. This paper surveys recent literature on the application of Artificial Intelligence (AI), Machine Learning (ML), Explainable AI (XAI) and Natural Language Processing (NLP) to maternal healthcare, covering twenty studies published between 2021 and 2026. The reviewed work is organised into four themes: general maternal-risk classification, GDM prediction, PPD detection, and maternal-health dataset creation. Across these themes, a consistent pattern emerges — most systems solve one problem in isolation, provide little transparency behind their predictions, stop at prediction without offering actionable follow-up, and are validated on data that does not represent rural or low-resource populations. Based on these findings, the paper argues for an integrated, explainable and recommendation-driven maternal-health platform, motivating the design of the proposed system, MaaSuraksha.*

Keywords*—*Maternal Health, Machine Learning, Gestational Diabetes Mellitus, Postpartum Depression, Explainable AI, Natural Language Processing, Risk Prediction

I. INTRODUCTION

Maternal health remains one of the clearest indicators of a healthcare system's reach and quality, and pregnancy-related complications continue to be a major cause of death and illness worldwide, with the burden falling hardest on rural and underserved populations. Conditions such as gestational diabetes, hypertension, anaemia and postpartum depression are frequently missed until they become severe, largely because specialist care, diagnostic infrastructure and continuous monitoring are not consistently available in these settings.

Over the past several years, AI and ML techniques have opened up new possibilities for predictive healthcare — identifying at-risk patients from routine clinical data well before complications manifest. In parallel, NLP methods have shown promise in picking up early signs of psychological conditions such as PPD from journal entries, questionnaire responses and clinical notes. A substantial body of research now exists across these individual problems, but comparatively little work looks at maternal risk prediction, GDM detection and PPD screening as parts of one connected system.

This paper surveys that literature with two goals: first, to summarise how AI, ML, XAI and NLP have been applied to maternal healthcare in recent years; and second, to identify the gaps that remain, as a basis for the design of an integrated maternal-health platform, MaaSuraksha, that this survey ultimately motivates.

II. BACKGROUND

A. Maternal Health Risk Prediction

Maternal risk prediction refers to identifying, ahead of time, which pregnant women are likely to experience complications during pregnancy or childbirth. Models typically classify patients using clinical inputs such as blood pressure, blood glucose, BMI, heart rate, age and obstetric history.

B. Gestational Diabetes Mellitus (GDM)

GDM is a form of elevated blood glucose that develops during pregnancy. Left unmanaged, it increases risk for both mother and child, making early prediction and dietary or clinical management important.

C. Postpartum Depression (PPD)

PPD is a mood disorder that can follow childbirth, characterised by persistent sadness, anxiety and loss of interest in daily activities. Because its symptoms can be mistaken for normal post-delivery fatigue, early and continuous screening is particularly important.

D. Machine Learning, XAI and NLP in Healthcare

Algorithms such as Random Forest, XGBoost, Logistic Regression, Support Vector Machines and Artificial Neural Networks are the most common choices in this literature for classification tasks. Explainable AI methods — chiefly SHAP and LIME — are increasingly layered on top of these models to show which input factors drove a given prediction, which matters for clinical trust. NLP techniques, meanwhile, are applied to free-text inputs such as mood journals to support mental-health screening.

III. RELATED WORK

A. Maternal Health Risk Prediction Models

A major strand of research treats maternal risk prediction as a multi-class classification problem, sorting patients by risk level from clinical indicators. Dey et al. [1] applied Random Forest, XGBoost and stacked ensembling to this task and reported 87.2% accuracy, though on a dataset drawn from a fairly narrow geographic region. Al-Azazi et al. [2] compared multiple algorithms for the same problem and reached close to 91% accuracy with their best-performing model. Al-Zahrani and Alharthi [3] took an ensemble route, blending Gradient Boosting, Random Forest and XGBoost, and found the combined model outperformed any single classifier, although it was validated on a comparatively small dataset.

Explainability has increasingly been folded into this line of work. Hossain et al. [4] paired Gradient Boosting with both LIME and SHAP so that each risk classification came with a traceable explanation. Moreira et al. [5] examined machine learning more broadly across pregnancy and childbirth risk management and concluded that AI-assisted tools

meaningfully support earlier problem identification, while Mahmud et al. [6] pushed predictive accuracy further with a deep hybrid model, at the cost of considerably higher computational overhead. Islam et al. [7] compared several algorithms on clinical health indicators and found ensemble methods consistently ahead of individual classifiers, and Osei et al. [8], reviewing 39 studies that used electronic medical records for maternal-risk prediction, observed that very few of these models make it into actual clinical deployment despite encouraging results on paper.

B. Gestational Diabetes Prediction

A second cluster of studies narrows in on GDM specifically. Huang et al. [9] focused on first-trimester prediction and reached an AUC of 0.83 with XGBoost — a strong result given how early the prediction window is. Kumari et al. [10] combined SHAP with XGBoost for interpretable GDM prediction from clinical markers, though their work stopped short of offering any downstream recommendation component. Xiao et al. [11] applied similar techniques specifically to an Asian population, using BMI, age and glucose to predict GDM effectively within that group, while Chen et al. [12] built an XGBoost-based GDM model that performed strongly, reinforcing XGBoost's standing as a dependable choice for this class of problem. Ye et al. [13], in a meta-analysis spanning multiple GDM-prediction studies, concluded that machine-learning approaches consistently outperform traditional statistical methods for this task.

C. Postpartum Depression Detection

PPD detection research has largely relied on either static questionnaire data or free-text mood entries analysed through NLP. Akter et al. [14], in a scoping review, found Random Forest to be the most frequently used algorithm for PPD prediction and noted that continuous, NLP-based monitoring is still relatively underexplored. Park et al. [15] took a more ambitious approach, combining NLP with large language models for real-time PPD screening, though their model relied heavily on synthetic rather than real-world data. Anand et al. [16] compared several ML models and found Logistic Regression performed best, but only within a Korean population, which limits how broadly the result generalises. Zhang et al. [17] combined XGBoost and LASSO with SHAP for an interpretable depression-prediction model validated on hospital-sourced records, while Kim et al. [18] tested six algorithms alongside various feature-selection techniques to identify the strongest predictors of PPD, without building in real-time monitoring capability. Aziz et al. [19], reviewing the broader ML literature on PPD prediction, were optimistic about AI's potential for both early detection and ongoing mental-health tracking.

D. Maternal Health Datasets

Underpinning much of this research is the availability of usable datasets. Rahman et al. [20] contributed a sizeable maternal-health dataset — over six thousand records collected via IoT devices — intended less as a working prediction system and more as groundwork for future models.

IV. COMPARATIVE ANALYSIS

Table I summarises how the surveyed literature compares against the design goals of the proposed system, MaaSuraksha, across the capabilities most relevant to an integrated maternal-healthcare platform.

Parameter	Existing Studies	MaaSuraksha
Maternal Risk Prediction	Yes	Yes
GDM Prediction	Yes	Yes
PPD Screening	Yes	Yes
Explainable AI	Limited	Yes
Personalised Diet Plan	Rare	Yes
Integrated Platform	No	Yes
Rural Healthcare Focus	Limited	Yes
Real-Time Monitoring	Limited	Yes

TABLE I. COMPARATIVE ANALYSIS OF EXISTING LITERATURE VS. PROPOSED SYSTEM

V. RESEARCH GAPS

Reading across the twenty studies surveyed, six recurring gaps stand out.

- No single integrated system – maternal-risk prediction, GDM detection and PPD screening are almost always tackled as separate problems, with no platform combining all three.
- Limited explainability – a majority of the models reviewed operate as black boxes, offering a score without a reason.
- No actionable follow-up – prediction is typically where these studies stop, with few translating a risk score into diet plans, alerts or referral guidance.
- Urban and developed-country bias – most datasets originate from urban hospitals or developed-country populations, limiting relevance to rural, low-resource contexts.
- Static, one-time mental-health screening – PPD studies largely rely on a single questionnaire rather than continuous tracking over time.
- Limited real-world deployment – a large share of the reviewed models remain confined to academic evaluation and are not implemented as usable healthcare applications.

VI. DISCUSSION: TOWARDS AN INTEGRATED SYSTEM

The gaps identified above motivate the design of MaaSuraksha, an AI-powered maternal-health platform intended to bring maternal-risk prediction, GDM detection and PPD screening together in one place. The proposed system uses XGBoost for risk and GDM classification, SHAP for explainability, and an NLP-based sentiment pipeline for continuous PPD monitoring through mood-journal entries, closing the loop with automatically generated diet plans, alerts and referral recommendations. Unlike most of the systems reviewed here, it is designed from the outset for rural and resource-constrained healthcare delivery, aiming to move beyond isolated prediction toward a deployable, preventive-care tool for healthcare workers and doctors.

VII. PROPOSED SYSTEM ARCHITECTURE

Building on the gaps identified above, this section presents the proposed architecture of MaaSuraksha. As shown in Fig.

1, the system is organised as a layered stack, with a Patient / ASHA Worker / Doctor / Administrator interface at the top, feeding into an Authentication & Security Layer that provides secure login, role-based access control (RBAC), bcrypt password hashing and TLS encryption. Authenticated requests then pass through a Data Collection Module, which gathers clinical and lifestyle data, reports and questionnaires, followed by a Data Pre-processing Module that performs data cleaning, handling of missing values and normalisation. The pre-processed data is routed to three parallel prediction modules — a Maternal Risk Prediction Module and a GDM Detection Module, both built on XGBoost, and a PPD Screening Module built on a DistilBERT-based NLP pipeline. Outputs from all three modules feed into an Explainable AI Module using SHAP, so that every prediction is accompanied by a traceable explanation rather than a bare score. This feeds a Recommendation Engine that converts the risk level and its explanation into concrete suggestions and alerts, which are persisted in a Database Layer built on MongoDB Atlas and surfaced through role-specific Dashboards & Reports for patients, doctors and administrators. This layered design directly addresses the integration, explainability and actionable-follow-up gaps identified in Section V.

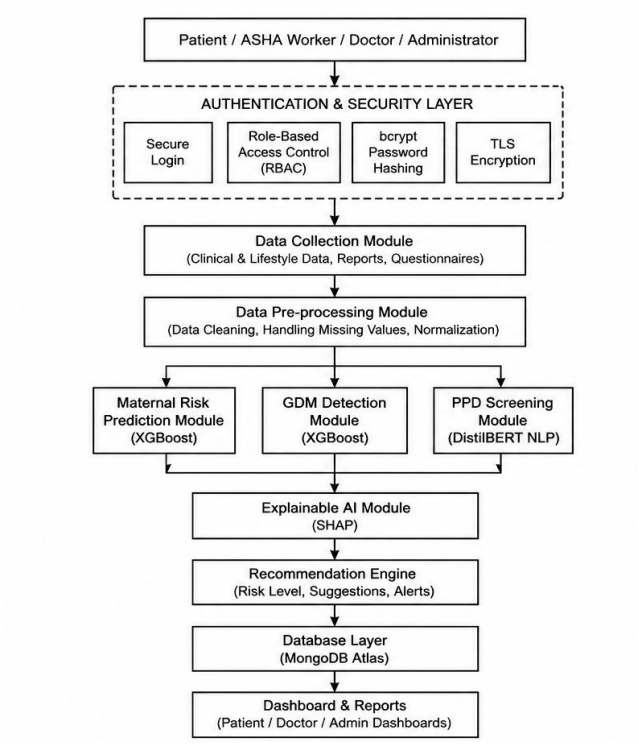


Fig. 1. Proposed System Architecture of MaaSuraksha

VIII. PROPOSED METHODOLOGY

Fig. 2 sets out the operational methodology that implements the architecture of Fig. 1 as a sequential pipeline. The process begins with user registration and login, followed by authentication and security verification through credential checks and RBAC. Data collection then gathers demographics, clinical data, lifestyle information, lab reports and questionnaire responses, after which a data validation step performs consistency checks and handles missing values, and a data pre-processing step carries out cleaning, normalisation and encoding. Relevant clinical and behavioural features are then selected or extracted before being passed to the three AI prediction modules — Maternal Risk Prediction and GDM Detection, both using XGBoost, and PPD Screening using DistilBERT-based NLP — running in parallel. Predictions from these modules are passed through an explainability step driven by SHAP, which generates feature-importance explanations, before a recommendation-generation step produces the risk level along with treatment or lifestyle suggestions and alerts. These outputs are then delivered through the doctor dashboard and patient alerts and reports, and finally the results are written back to the MongoDB Atlas database, completing the cycle from data intake to actionable, explainable output.

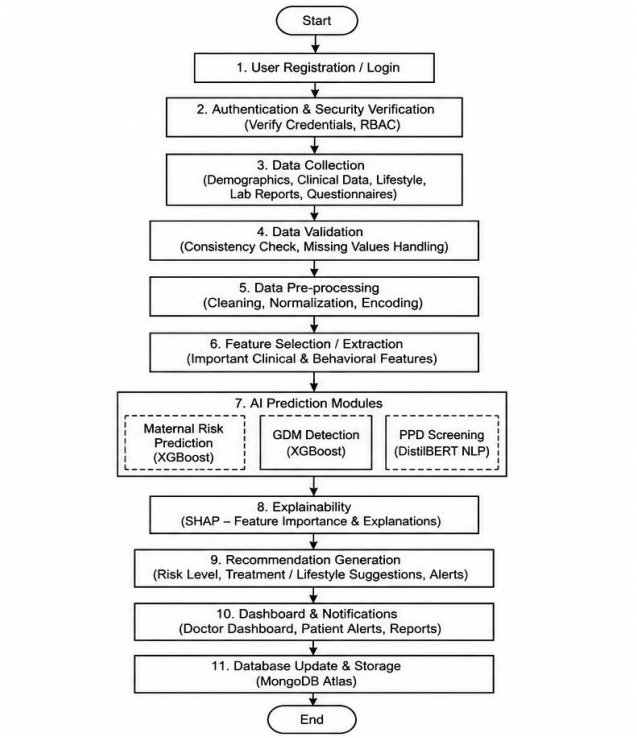


Fig. 2. Proposed Methodology of MaaSuraksha

IX. CONCLUSION

This survey reviewed twenty recent studies on AI-driven maternal healthcare, spanning maternal-risk prediction, GDM detection, PPD screening and dataset development. While individual techniques — particularly XGBoost-based classification and SHAP-based explainability — have matured considerably, the literature as a whole remains fragmented: most systems address a single complication, offer limited transparency, stop short of actionable guidance, and are validated on data that under-represents rural populations. These findings support the case for an integrated, explainable and recommendation-driven platform such as MaaSuraksha, which brings these capabilities together with a specific focus on underserved healthcare settings.

REFERENCES

[1] S. K. Dey, A. Rahman, U. R. Siddiqi, and A. Howlader, "Maternal health risk prediction with machine learning methods," PLoS ONE, vol. 19, no. 1, p. e0296307, Jan. 2024.

[2] R. Al-Azazi, H. Al-Rashidi, and M. Al-Enezi, "Predicting maternal risk level using machine learning models," Scientific Reports, vol. 14, no. 1, p. 3892, Feb. 2024.

[3] A. M. Al-Zahrani and M. A. Alharthi, "Ensemble machine learning framework for predicting maternal health risk (QEML-MHRC)," IEEE Access, vol. 12, pp. 14207–14219, Feb. 2024.

[4] M. R. Hossain, M. Islam, and T. Ahmed, "Explainable AI based maternal health risk prediction using gradient boosting with LIME and SHAP," Computers in Biology and Medicine, vol. 163, p. 107238, Sep. 2023.

[5] A. Moreira, R. Santos, and L. Silva, "Machine learning for pregnancy and childbirth risk management," Journal of Biomedical Informatics, vol. 143, p. 104407, Jul. 2023.

[6] N. Mahmud, J. Islam, K. Setu, and M. Islam, "Deep hybrid model for maternal health risk classification," Healthcare Analytics, vol. 3, p. 100142, Jul. 2023.

[7] M. A. Islam, S. Akter, M. S. Hossen, S. A. Keya, S. A. Tisha, and S. Hossain, "Early prediction of maternal health risk factors using machine learning," in Proc. 2nd Int. Conf. on Intelligent Technologies (CONIT), Hubli, India, 2023.

[8] D. Osei, K. Agyemang, and N. Mensah, "Machine learning models to predict maternal morbidity from electronic medical records: A scoping review," JAMIA Open, vol. 8, no. 2, p. ooab032, Jun. 2025.

[9] Z. Huang, Y. Wei, X. Yang, et al., "Prediction of gestational diabetes mellitus at first trimester using machine learning," Frontiers in Endocrinology, vol. 15, p. 1348236, Apr. 2024.

[10] R. Kumari, R. Kumar, and M. Nishad, "Explainable AI-driven gestational diabetes prediction using clinical markers," Diagnostics, vol. 14, no. 6, p. 621, Mar. 2024.

[11] T. Xiao, R. Jiang, Y. Liu, et al., "Prediction of gestational diabetes mellitus in Asian women using machine learning," BMC Pregnancy and Childbirth, vol. 23, no. 1, p. 432, Jun. 2023.

[12] K. Chen, H. Xiong, Y. Zhang, et al., "Prediction model for gestational diabetes mellitus using XGBoost algorithm," Frontiers in Endocrinology, vol. 14, p. 1105538, Mar. 2023.

[13] L. Ye, Y. Cao, X. Li, et al., "Machine learning prediction models for gestational diabetes mellitus: A meta-analysis," Diabetes Research and Clinical Practice, vol. 190, p. 109990, Aug. 2022.

[14] F. Akter, S. Hossain, M. N. Islam, et al., "AI for detecting and predicting postpartum depression: A scoping review," npj Digital Medicine, vol. 9, no. 1, p. 12, Jan. 2026.

[15] S. Park, H. Cho, and J. Yoon, "Detecting and explaining postpartum depression in real-time with generative AI," IEEE Journal of Biomedical and Health Informatics, vol. 29, no. 4, pp. 1023–1034, Apr. 2025.

[16] C. Anand, R. Kumar, and P. Sharma, "Predictive analysis of postpartum depression using machine learning," Applied Sciences, vol. 15, no. 3, p. 1284, Feb. 2025.

[17] W. Zhang, L. Chen, X. Wang, et al., "Interpretable machine learning model for predicting postpartum depression," Journal of Psychiatric Research, vol. 181, pp. 45–54, Jan. 2025.

[18] J. Kim, H. Park, and S. Lee, "Prediction of postpartum depression: Development and validation of machine learning models," Journal of Affective Disorders, vol. 368, pp. 123–132, Jan. 2025.

[19] S. Aziz, S. Ahmed, and M. Asif, "Machine learning methods for predicting postpartum depression: A scoping review," JMIR Mental Health, vol. 8, no. 6, p. e29838, Jun. 2021.

[20] M. Rahman, T. Islam, and A. Roy, "Comprehensive maternal health risk dataset from IoT systems," Data in Brief, vol. 52, p. 110987, Feb. 2026.