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Postpartum Depression in Females After Pregnancy

Priyanka Kasera[1], Saamin Sosan[2], Harsh Nath[3], Jayashree M Kudari[4]

[123]Student, School of Computer Science and Information Technology, Jain (Deemed to be University), Jayanagar, Bengaluru, Karnataka, India

[4]Associate Professor, School of Computer Science and Information Technology, Jain (Deemed to be University), Jayanagar, Bengaluru, Karnataka, India.

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Abstract

Postpartum Depression (PPD) is a common mental health condition that affects many women after childbirth, leading to emotional instability, anxiety, and depression, which can impact both the mother and the child. This study brings together findings from 15 research papers to understand the prevalence, risk factors, and effective ways to manage PPD in women after delivery. The review includes systematic reviews, meta- analyses, and cohort studies published between 2021 and 2025. The findings show that factors such as antenatal depression, hormonal changes, lack of social support, previous mental health issues, and intimate partner violence play a major role in increasing the risk of PPD. Different prediction methods, including logistic regression and machine learning models like Random Forest and SVM, have been used in recent studies. Among these, logistic regression and Random Forest showed the best accuracy, ranging from 85% to 90%. Interventions like CBT, interpersonal therapy, and regular physical activity were found to be effective in managing PPD.

Keywords: *Postpartum Depression, Maternal Mental Health, Machine Learning, Risk Factors, Cognitive Behavioral Therapy*

1. Introduction

Postpartum depression (PPD) is a complex and multifaceted mental health disorder that occurs in women after giving birth. On the biological side, changes in estrogen and progesterone levels cause imbalances in serotonin and dopamine levels. PPD, characterized by feelings of sadness, fatigue, emotional instability, and hopelessness, is one of the most prevalent and underdiagnosed complications of the perinatal period. Unlike "baby blues," which affect many mothers after giving birth and disappear within two weeks, PPD lasts for months and can have serious consequences for maternal functioning, infant care, and the family in general. Anxiety, and low self- esteem, and history of previous depression, which have been cited as the strongest predictors of PPD in multiple studies [2], [6], [9]. Environmental and sociocultural factors, including marital stress, financial difficulties, gender-based violence, and lack of support, also play a role in PPD.
The World Health Organization (WHO) estimates that "one in five women in the world social support, thus exacerbating the risk [3], [4], [10]. Hence, the disorder needs to be defined by a biopsychosocial model that considers both the inner causes of the condition as well as the external factors that influence it. substantially higher levels of depressive symptoms within the first year of giving birth, though the actual prevalence of the condition varies greatly depending on cultural, economic, and diagnostic factors [1], [7].

2. Literature Survey

Oyetunji *et al.* (2021) conducted a large-scale systematic review and meta-analysis that examined the global prevalence and determinants of postpartum depression (PPD). Drawing data from over forty studies across multiple continents, the authors estimated a global PPD prevalence rate of approximately 14%, indicating significant cross- national variation. Their study identified antenatal depression, gestational diabetes, and family psychiatric history as key risk factors for postpartum depression. Using a random-effects model, the researchers accounted for variability across studies and showed how biological predispositions and pregnancy-related complications together increase the risk of PPD [1].
Tambelli, Tosto, and Favieri (2025) further examined psychiatric and psychological factors associated with PPD. Their review, based on both longitudinal and cross- sectional studies, found that antenatal depression, prior episodes of major depressive disorder, and high neuroticism were strong predictors. They also emphasized the role of cognitive vulnerabilities and poor emotional regulation, suggesting that preventive measures should begin during pregnancy rather than after childbirth [2].
Kabunga et al. (2024) highlighted regional differences

through a review of studies conducted in Uganda. They found that PPD rates were significantly higher than the global average due to socioeconomic and cultural challenges. Key factors included intimate partner violence (IPV), lack of social support, and unplanned pregnancies, with IPV nearly doubling the risk of depressive symptoms. This reflects the heightened vulnerability of women in low- and middle-income countries (LMICs) [3].

Similarly, Yetwale et al. (2025) conducted a meta- analysis in Ethiopia, focusing on suicidal ideation among pregnant and postpartum women. Their findings showed a strong link between IPV, social stigma, and suicidal thoughts, further intensified by limited access to mental health services. Cultural barriers were also identified as a major factor preventing women from seeking help [4].

Li et al. (2025) examined the role of medical conditions by studying the association between allergic rhinitis and PPD. Their analysis showed that allergic rhinitis could independently predict PPD, suggesting a link between immune system dysfunction and mental health. Their model achieved an accuracy of 87%, highlighting a significant connection between biological and psychological factors [5].

Cameron et al. (2021) extended this research to include fathers, conducting a systematic review and meta- analysis on postpartum depression among men. This study showed that paternal depression tends to co- occur with maternal PPD, and this is attributed to relational strain, role conflict, and psychosocial factors. The meta-analysis study, which included data from different parts of the world, showed that poor marital relationship and maternal depressive symptoms are major risk factors for paternal mood disorders. This indicates the need to apply a family- centered approach to mental health care during the perinatal period [6].

Gupta (2024) made a notable contribution to the topic by publishing a narrative review on PPD, including epidemiological patterns, risk factors, and cultural differences. This study indicated that mental illness and PPD are culturally taboo and that mental health care frameworks and tools developed and used in high-income countries are not applicable to LMIC due to resource and cultural constraints. The author suggested that non-clinical stakeholders should be involved in mental health care during the perinatal period [7].

Li et al. (2023) examined the role of cognitive behavioral therapy (CBT) in treating postpartum depression through a systematic review. Their study covered both face-to-face and online CBT approaches and found strong evidence that CBT helps reduce symptoms and prevent relapse. Randomized trials showed about a 40% improvement among women receiving CBT. However, the review also pointed out gaps such as limited cross-cultural validation and lack of long-term follow-up data. Despite these limitations, the overall findings confirmed the effectiveness of CBT across different formats [8].

Ji et al. (2025) provided a comprehensive overview of postpartum depression, covering its causes, diagnosis, and treatment. They emphasized the need for a combined approach that includes medication, psychotherapy, and social support. The study also highlighted biological indicators such as cortisol imbalance and inflammatory markers, along with the growing use of artificial intelligence and machine learning for early prediction and screening of PPD [9].

Some studies have focused on specific vulnerable groups. A 2024 review in *Prevention Science* examined psychosocial interventions among teenage mothers and found a clear reduction in depressive symptoms after structured counselling and mentorship programs. The results suggested that such interventions can be as effective as medication, especially in settings with limited resources [10].

Similarly, Nguyen and Pengpid (2025) explored prevention strategies for women at risk of developing PPD. Their review found that mindfulness-based therapy and educational programs were effective in reducing anxiety. They emphasized that early preventive efforts during pregnancy are more beneficial than focusing only on treatment after symptoms appear [11].

Physical activity has also been shown to play an important role. Jani-Suresh et al. (2025) reviewed multiple studies and found that activities such as walking, yoga, and aerobic exercise help reduce depressive symptoms in pregnant and postpartum women. Although these interventions showed good results, maintaining long-term participation remained a challenge. The authors recommended including physical activity in postnatal care programs [12].

Zhang et al. (2024) further compared different exercise-based interventions and found that aerobic exercises were the most effective, followed by yoga and strength training. Their study used advanced statistical methods to ensure reliable and consistent results across different studies [13].

Technology-based interventions are also gaining importance. Zhou et al. (2022) studied telemedicine approaches such as mobile apps, online CBT, and virtual counselling. Their findings showed improvements in depression symptoms and overall maternal functioning, especially for women in rural areas. However, issues like limited access to technology, data privacy, and user engagement were identified as challenges [14].

Motofelea et al. (2025) examined screening tools used for detecting postpartum depression, including the EPDS and PHQ-9. These tools showed high reliability, but the authors pointed out the need for more culturally sensitive approaches, as standard scoring methods may not be suitable for all populations [15].

Overall, these studies show that postpartum depression is influenced by a combination of biological, psychological, and social factors. Effective

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interventions need to consider these different aspects, along with cultural and socioeconomic conditions. Recent developments in digital tools and predictive models also suggest a shift toward more personalized approaches in maternal mental health care.

3. Methodology

This study uses a systematic narrative review approach to examine and bring together recent research on postpartum depression (PPD) published between 2021 and 2025. The main purpose is to understand global trends, identify key risk factors, and review different treatment approaches. In doing so, the study considers both traditional research methods as well as newer approaches involving computational models to provide a more complete understanding of the topic.

3.1 Research Design

The study used a mixed approach that combined a systematic literature review with experimental data analysis. The review helped identify key factors linked to postpartum depression, while the data analysis tested how well machine learning models could predict it.

3.2 Dataset Description

A structured dataset of about 14,000 records was used for the analysis. Each entry represented one individual case and included details on demographic, reproductive, and psychosocial factors. The outcome variable was binary, indicating whether postpartum depression was present or not. The predictor variables covered age, working status, family type, history of miscarriage, interpersonal relationships, and socioeconomic conditions.

3.3 Data Preprocessing

The data was first cleaned by handling missing values and correcting inconsistencies in categorical entries. Qualitative variables were then converted into numerical form so they could be used for model training. The dataset was split into training and testing sets in an 80:20 ratio. Wherever necessary, scaling was applied to keep the variables on a consistent scale.

3.4 Model Implementation

Three supervised classification models were used in the study.:

- Logistic Regression
- Support Vector Machine
- Random Forest

Each model was trained on the same training data and tested on the same dataset so that the results could be compared fairly.

A. Data Sources and Search Strategy Relevant studies on postpartum depression were gathered from widely used academic databases such as PubMed, ScienceDirect, Scopus, and Google Scholar. To narrow down the search, different keywords like “postpartum depression,” “maternal mental health,” “risk factors,” “cognitive behavioral therapy,” “machine learning,” and “telemedicine interventions” were combined using Boolean operators. Initially, 176 articles were obtained, which were filtered by using inclusion and exclusion criteria.

To establish the reliability of literature, it has been ensured that only journal articles published during January 2021 and May 2025 and reviewed by renowned journals have been used. Conference papers and publications not written in English have been excluded.

Appropriate literature has been filtered by using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol. After three stages of literature refinement, 15 studies were used for a detailed review.

B. Inclusion and Exclusion Criteria The inclusion criteria focused on:

i. Studies that directly addressed the prevalence, risk factors, or treatment of postpartum depression.

ii. Research that employed quantitative, qualitative, or mixed methods with clear methodology.

iii. Papers that used statistical or computational algorithms (e.g., logistic regression, random forest, or network meta-analysis) to assess PPD determinants.

iv. Interventional studies using cognitive- behavioral, psychosocial, or physical activity- based approaches for prevention or treatment.

Exclusion criteria included:

- Articles focused solely on antenatal depression without postpartum follow-up.
- Reviews lacking empirical or quantitative analysis.
- Case studies without generalized data.

C. Data Extraction and Synthesis

From each selected study, data on author, publication year, country or region, sample size, methodology design, and key findings were extracted. A data extraction matrix was created to ensure consistency in data extraction and facilitate cross-study comparisons. The data extraction matrix included data on the study's results, significant predictors (psychological, biological, or social factors), and intervention outcomes.

Thematic and comparative analysis synthesis was employed in this study. First, thematic synthesis was conducted by organizing the studies according to thematic domains: epidemiological trends, psychosocial factors, biological factors, and intervention outcomes. Second, comparative synthesis was conducted to reveal similarities and differences in the data from diverse populations and methodologies.

D. Analytical and Computational Frameworks Another significant methodological aspect of the research was the incorporation of computational and statistical modeling techniques that authors employed in their respective studies. Some of the identified predictive models that the authors employed in the studies included:

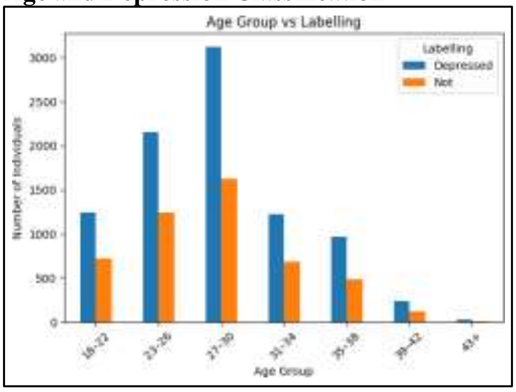
- Logistic Regression: This technique was employed by Li et al. (2025) in developing nomogram models that predict PPD using physiological and demographic parameters. The technique showed a significant level of prediction accuracy of approximately 87%. This makes it one of the most robust techniques in the prediction of PPD.
- Random Forest: The technique has been employed in studies that integrated datasets from biological, psychological, and social factors to classify at-risk women with high levels of accuracy (85- 90%). The technique is significant in handling multidimensional variables without linearity assumptions.
- Support Vector Machine (SVM): The technique has been employed in comparative studies to classify depressed individuals from non-depressed individuals with moderate levels of accuracy (~82%), depending on the quality of features.
- Network Meta-Analysis: Implemented by the authors in Zhang et al. (2024) to study non-pharmacological interventions. This type of analysis integrated results from numerous randomized trials and identified aerobic exercise as the most effective intervention.
- Random Effects Model: Utilized by the authors in Oyetunji et al. (2021) and Ji et al. (2025) to calculate the global prevalence and heterogeneity. The performance of all models was evaluated based on the accuracy, sensitivity, and specificity measures. The Logistic Regression and Random Forest models were found to be performing better in all cases in relation to predicting risks.

E. Quality Assessment
To ensure the reliability and validity of the data, the Joanna Briggs Institute (JBI) Critical Appraisal Checklist has been employed to assess the quality of the studies included in the review. The quality of each study has been assessed based on eight parameters, and only those studies that are found to be of high or moderate quality are included in the review.

F. Ethical Considerations
Since the study is a systematic review of existing literature, no human data collection is involved in the study. However, ethical considerations are ensured in the study by appropriately crediting all sources, maintaining data integrity, and adhering to the principles of responsible academic research.

4. Exploratory Data Analysis

Age and Depression Classification

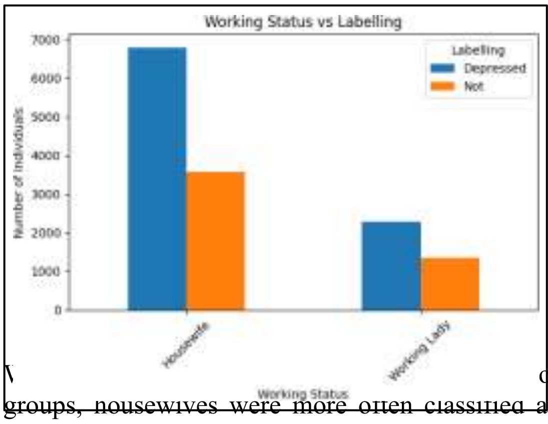


Analysis of age distribution showed variability in depression classification across different age groups. This suggests that maternal age may influence psychological vulnerability during the postpartum period. Younger and older age groups exhibited different prevalence patterns, indicating that age- related life circumstances may affect emotional resilience.

Labelling	**Depressed**	**Not**
Age Group		
18-22	1240	722
23-26	2159	1245
27-30	3119	1623
31-34	1220	686
35-38	968	482
39-42	242	118
43+	32	12

Working Status and Depression

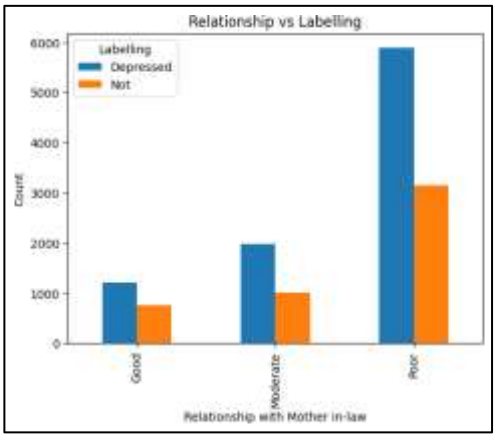
Previous Miscarriage History



W[illegible] occupational groups, housewives were more often classified as depressed than women who were employed. This may indicate that having a regular routine, interacting with others, and financial independence factors often linked with employment can have a positive effect on emotional well-being.

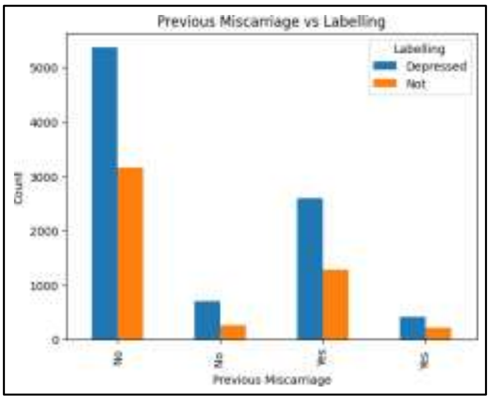
Labelling	**Depressed**	**Not**
Working Status		
Housewife	6795	3573
Working Lady	2283	1357

Relationship with Mother-in-law and Depression



Women who reported a poor relationship with their mother-in-law were more likely to show signs of depression than those who described their relationship as moderate or positive. This points to how important a supportive family environment is for a mother's mental well-being.

Labelling	**Depressed**	**Not**
Relationship		
Good	1218	764
Moderate	1974	1019
Poor	5886	3147

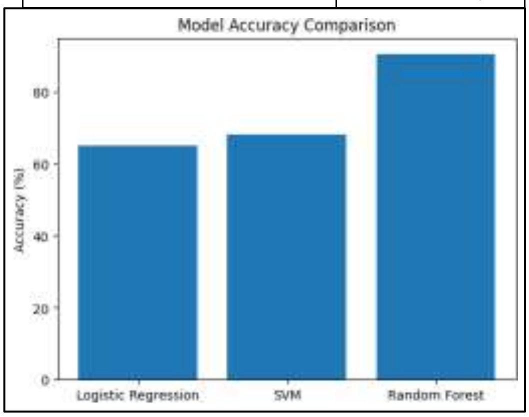


Women who had experienced a miscarriage in the past were more often classified as depressed. This suggests that earlier pregnancy complications may make women more emotionally vulnerable and increase the risk of psychological distress in later pregnancies.

Labelling	**Depressed**	**Not**
Previous Miscarriage		
No	5365	3160
No	703	269
Yes	2600	1277
Yes	410	224

5. Model Performance Results Accuracy Comparison

Model	**Accuracy**
Logistic Regression	65%
SVM	68%
Random Forest	90.36%



Among the models tested, Random Forest gave the best prediction accuracy, while Logistic Regression and SVM showed moderate performance.

Feature Importance

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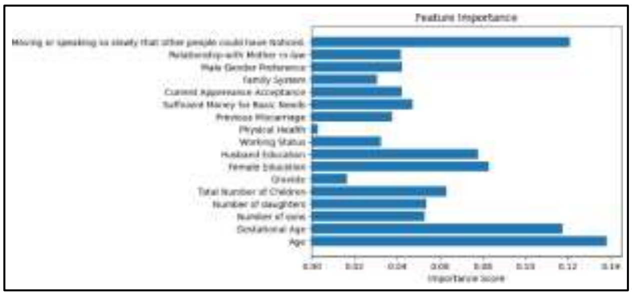

The feature importance analysis showed that some psychosocial factors had a stronger influence on predictions than others. This suggests that postpartum depression does not arise from a single cause, but rather from a combination of several interacting factors.

6. Discussion

Comparing the models shows that nonlinear methods perform better than linear ones for predicting postpartum depression. Logistic Regression is limited by its assumption of linear relationships, and although SVM performed slightly better, it still fell short of Random Forest.

The stronger performance of Random Forest suggests that postpartum depression is influenced by a combination of demographic, emotional, and social factors, rather than a single cause, which aligns with existing research.

7. Conclusion

Postpartum depression remains a complex and widely seen maternal mental health condition influenced by a mix of biological, psychological, and environmental factors. Across studies, antenatal depression, prior mental health history, and limited social support consistently emerge as key predictors. Other factors such as medical conditions, intimate partner violence, and financial stress further increase the risk, especially in low- and middle-income settings. These findings show that postpartum depression is shaped by context and requires both clinical and community-based responses.

Despite growing research, there are still gaps. Many studies focus on specific regions, making it difficult to apply findings globally. There is also a need for more long-term and multidisciplinary research that considers biological, social, and cultural aspects together. In addition, fathers and caregivers are often overlooked, highlighting the need for a more inclusive, family-centered approach. Addressing postpartum depression therefore requires a combined effort involving healthcare, psychological support, policy, and technology. Early screening, along with culturally appropriate interventions, can help reduce its impact on mothers and families.

This study also shows that machine learning can support early identification of postpartum depression risk. By using demographic and psychosocial factors, predictive models can help identify at-risk individuals at an early stage. Among the models tested, Random Forest achieved the highest accuracy, making it the most suitable for this purpose.

Overall, these findings highlight the value of data- driven approaches in maternal healthcare. Such models can assist healthcare providers in identifying high-risk cases and taking timely action. Future work can focus on larger datasets, additional variables, and improved screening systems to strengthen early detection and prevention.

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