INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

ORIGINAL ARTICLE

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OPEN ACCESS

Received: 12/08/2026

Accepted: 31/08/2026

Published: 22/10/2026s

Citation: Shultana S (2026) Predicting Suicidal Ideation in Postpartum Women Using Perceived Stress and Social Support: A Machine Learning Approach. Indian Journal of Science and Technology 19(37): 2578-2590. https://doi.org/10.17485/IJST/v19i37.1169

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Funding: None

Competing Interests: None

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Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Predicting Suicidal Ideation in Postpartum Women Using Perceived Stress and Social Support: A Machine Learning Approach

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Abstract

Objectives: To evaluate perceived stress and multidimensional social support as predictors of suicidal ideation in postpartum women, and to develop an explainable, uncertainty-aware machine learning framework for individualized risk screening. **Method:** We analyzed data from 200 postpartum women, including perceived stress (Perceived Stress Scale, 10 items), multidimensional social support (emotional, positive interaction, affective, and instrumental subscales), and demographic and clinical variables. We conducted descriptive comparisons, univariate and multivariate logistic regression, and a machine learning pipeline comparing seven classifiers under stratified five-fold cross-validation with Synthetic Minority Oversampling Technique (SMOTE) to address class imbalance (17% prevalence of suicidal ideation). The final Random Forest and Logistic Regression models were evaluated on a held-out test set, calibrated, and interpreted using SHAP and LIME. Split conformal prediction generated statistically valid, uncertainty-aware prediction sets, and counterfactual sensitivity analysis quantified actionable score changes associated with reduced predicted risk. **Findings:** Women reporting suicidal ideation had significantly higher perceived stress (mean 36.6 vs. 29.6, $p<0.001$) and lower total social support (mean 49.8 vs. 65.4, $p<0.001$) than women without ideation. In multivariate analysis, perceived stress remained independently associated with suicidal ideation (adjusted odds ratio 1.23, 95% CI 1.11-1.37, $p<0.001$). The Random Forest classifier achieved the best cross-validated discrimination (ROC-AUC 0.766) and test-set performance (ROC-AUC 0.804, accuracy 0.84). SHAP analysis identified perceived stress and social support subscales as the dominant predictors of risk. Conformal prediction achieved 98% empirical coverage at a 90% target, with 34% of test cases flagged as ambiguous rather than confidently classified. **Novelty:** To our knowledge, this is the first postpartum suicidal ideation risk model to combine SHAP and LIME explainability with split conformal prediction and counterfactual sensitivity analysis in a single framework, jointly quantifying which factors drive each prediction, how confident the model is in that prediction, and what modifiable change would most plausibly lower a given patient's predicted risk.

Keywords: postpartum depression; suicidal ideation; perceived stress; social support; machine learning; explainable AI; conformal prediction

1 Introduction

Suicide is among the leading causes of maternal mortality in the first year postpartum, yet suicidal ideation during this period frequently goes unrecognized in routine antenatal and postnatal care, with a systematic review of 20 studies reporting an ideation prevalence ranging from 2.2% to 50%[(1)]. Population-based survey data from England show that low social support and young age are the strongest risk factors for postpartum suicidal ideation[(2)], while clinical commentary notes that predicting progression from ideation to a suicide attempt remains a largely unresolved challenge[(3)]. Perceived stress and social support are the two most consistently studied psychosocial correlates of postpartum mental health, with a recent systematic review confirming a consistent association between social support and healthy postpartum psychosocial outcomes worldwide[(4)]; however, their combined predictive value for suicidal ideation specifically, and their utility as inputs to an explainable, uncertainty-aware machine learning screening model, remains comparatively underexamined. Machine learning offers the potential to integrate multiple psychosocial indicators into a single, individualized risk estimate, but model opacity and overconfident point predictions have limited its clinical translation in mental health screening; SHapley Additive exPlanations (SHAP)[(5)] and Local Interpretable Model-Agnostic Explanations (LIME)[(6)] address the first barrier by attributing model predictions to individual features in a way clinicians can audit, conformal prediction[(7)] addresses the second by producing prediction sets with a formal statistical coverage guarantee rather than a single overconfident label, and counterfactual explanation methods[(8)] identify the smallest change in a patient's modifiable profile associated with a shift in predicted risk. In this study, we develop and evaluate an explainable, uncertainty-aware machine learning framework, combining traditional epidemiological methods with a seven-classifier machine learning pipeline, SHAP and LIME interpretability, conformal prediction, and counterfactual sensitivity analysis, to predict suicidal ideation in postpartum women using perceived stress, multidimensional social support, and demographic and clinical covariates, in a dataset that reflects the small, high-stakes clinical settings where such tools would ultimately need to operate.

2 Methodology

2.1 Study Design and Participants

This is a retrospective, cross-sectional secondary analysis of a publicly available, de-identified dataset of 200 postpartum women. The dataset was obtained from a public repository that did not include documentation of the country, recruitment site, or clinical setting of data collection, and this information could not be recovered from the data source. As a partial data characteristic rather than a confirmed study detail, we note that the coded monthly income bands in the source file are denominated in "dt" and all instrument items were administered in French, which is consistent with, though not confirmatory of, a Francophone North African context; this is reported here for transparency and discussed further as a limitation in Section 3.9. Suicidal ideation was recorded as a binary outcome (present vs. absent), with 34 women (17.0%) reporting suicidal ideation and 166 (83.0%) reporting none. Data were collected via structured interview and questionnaire covering demographic characteristics (age, household size, monthly income, marital status, education, employment, residence area, number of dependent children and children under 5), clinical history (chronic disease, psychiatric history, current medication use, previous pregnancy complications), perceived stress, and multidimensional social support.

2.2 Measures

Perceived stress was measured with the 10-item Perceived Stress Scale (PSS-10)[(9)], a widely used instrument assessing the degree to which situations in one's life are appraised as stressful. Social support was assessed across four subscales, emotional support, positive social interaction support, affective support, and instrumental support, summed into a total social support score, consistent with the multidimensional social support framework of Zimet and colleagues[(10)]. Both instruments have been previously validated in perinatal populations. Both stress and support were also examined as pre-defined binary categories (high vs. low stress; good vs. low support) based on established cut-points in the source instrument.

2.3 Statistical Analysis

Continuous variables were compared between women with and without suicidal ideation using the Mann-Whitney U test, given the modest sample size and non-normal distributions of several variables. Categorical variables were compared using the chi-square test, with Fisher's exact test substituted for 2x2 tables where expected cell counts were below 5. Univariate logistic regression quantified the unadjusted association between each candidate predictor and suicidal ideation, expressed as odds ratios (OR) with 95% confidence intervals. A multivariate logistic regression model then estimated the independent association

of perceived stress and total social support with suicidal ideation, adjusting for age, monthly income, and psychiatric history. All statistical tests were two-tailed with significance set at $p<0.05$, and analyses were performed in Python using statsmodels and SciPy.

2.4 Machine Learning Pipeline

Given the modest sample size (n=200) and class imbalance (17% prevalence), model development used stratified 5-fold cross-validation for performance estimation, with Synthetic Minority Oversampling Technique (SMOTE)[11] applied exclusively within training folds to avoid information leakage into validation data. Because the total social support score is a deterministic linear sum of its four subscales (Pearson r = 0.88-0.95 with each subscale; variance inflation factor exceeding 10^14, confirming exact collinearity), it was excluded from the machine learning feature set to avoid redundant, diluted feature attributions in the explainability analyses; it is retained only in the descriptive statistics and logistic regression tables above, where it is reported alongside rather than instead of the subscales. Seven classifiers were benchmarked: Logistic Regression, Random Forest[12], Gradient Boosting, XGBoost[13], Support Vector Machine (RBF kernel), K-Nearest Neighbors, and Naive Bayes, implemented using scikit-learn[14]. Numeric features were median-imputed and standardized; categorical features were mode-imputed and one-hot encoded within a unified preprocessing pipeline. Following cross-validation, Random Forest and Logistic Regression were selected for final training on a 75% training split and evaluation on a held-out 25% stratified test set, based on their combination of strong cross-validated discrimination and interpretability.

2.5 Calibration, Explainability, and Uncertainty Quantification

Model calibration was assessed via calibration curves and the Brier score, with isotonic regression applied to improve probability reliability. Global and local feature importance were derived using SHAP (TreeExplainer)[5] for the Random Forest model, and individual predictions were further explained using LIME[6] for a representative high-risk patient. To quantify predictive uncertainty, we applied split conformal prediction (MAPIE)[7] at a 90% target confidence level, generating prediction sets that may contain one or both classes depending on model confidence, with empirical coverage verified on the test set. Finally, we conducted counterfactual sensitivity analysis, systematically varying a high-risk patient's perceived stress and social support scores to identify the score change associated with a shift in predicted risk below the 0.5 decision threshold, complemented by Diverse Counterfactual Explanations (DiCE)[8] for multi-feature counterfactual generation.

3 Results and Discussion

3.1 Sample Characteristics

Table 1 summarizes participant characteristics stratified by suicidal ideation status. Women with suicidal ideation were, on average, younger (32.1 vs. 34.6 years, $p=0.020$) and had lower monthly income ($p<0.001$) than women without ideation. They also reported substantially higher perceived stress (36.6 vs. 29.6, $p<0.001$) and lower scores across every social support subscale (all $p<0.01$), shown in Table 1, Figure 1, and Figure 2.

Categorical comparisons (Table 2) showed that low social support category membership was markedly more common among women with suicidal ideation (52.9% vs. 22.9%, $p<0.001$), while stress category, psychiatric history, and residence area did not differ significantly at the group level despite significant differences in the underlying continuous stress score.

3.2 Correlates of Suicidal Ideation

A Spearman correlation matrix (Figure 3) confirmed a positive association between perceived stress and suicidal ideation, and inverse associations between each social support subscale and both perceived stress and suicidal ideation, consistent with the stress-buffering role of social support.

3.3 Logistic Regression

In univariate logistic regression (Table 3), perceived stress score was the strongest continuous predictor of suicidal ideation (OR=1.29 per point, 95% CI 1.17-1.41, $p<0.001$), while each social support subscale was inversely associated with ideation (all $p<0.01$). Monthly income and age were also significant, weaker protective predictors.

After adjustment for age, monthly income, and psychiatric history in a multivariate model (Table 4, Figure 4), perceived stress remained an independent, significant predictor of suicidal ideation (adjusted OR=1.23, 95% CI 1.11-1.37, $p<0.001$), while total

Table 1. Continuous participant characteristics by suicidal ideation status (Mann-Whitney U test).

Variable	No Ideation (n=166) Mean (SD)	Ideation Present (n=34) Mean (SD)	Test	p-value
Age	34.60 (5.68)	32.12 (6.60)	Mann-Whitney U	0.020
Household size	4.45 (1.04)	4.76 (1.67)	Mann-Whitney U	0.383
Monthly income	2.52 (1.00)	1.88 (0.84)	Mann-Whitney U	<0.001
Number of dependent children	2.17 (0.77)	2.15 (0.78)	Mann-Whitney U	0.911
Number of children under 5	1.55 (0.70)	1.65 (0.69)	Mann-Whitney U	0.362
Perceived stress score	29.64 (5.48)	36.59 (5.18)	Mann-Whitney U	<0.001
Total social support score	65.36 (16.22)	49.76 (21.59)	Mann-Whitney U	<0.001
Emotional support score	28.66 (7.78)	22.12 (10.90)	Mann-Whitney U	0.001
Positive interaction support score	11.14 (2.97)	8.09 (3.67)	Mann-Whitney U	<0.001
Affective support score	11.22 (3.20)	7.59 (3.73)	Mann-Whitney U	<0.001
Instrumental support score	14.34 (4.16)	11.97 (4.95)	Mann-Whitney U	0.007

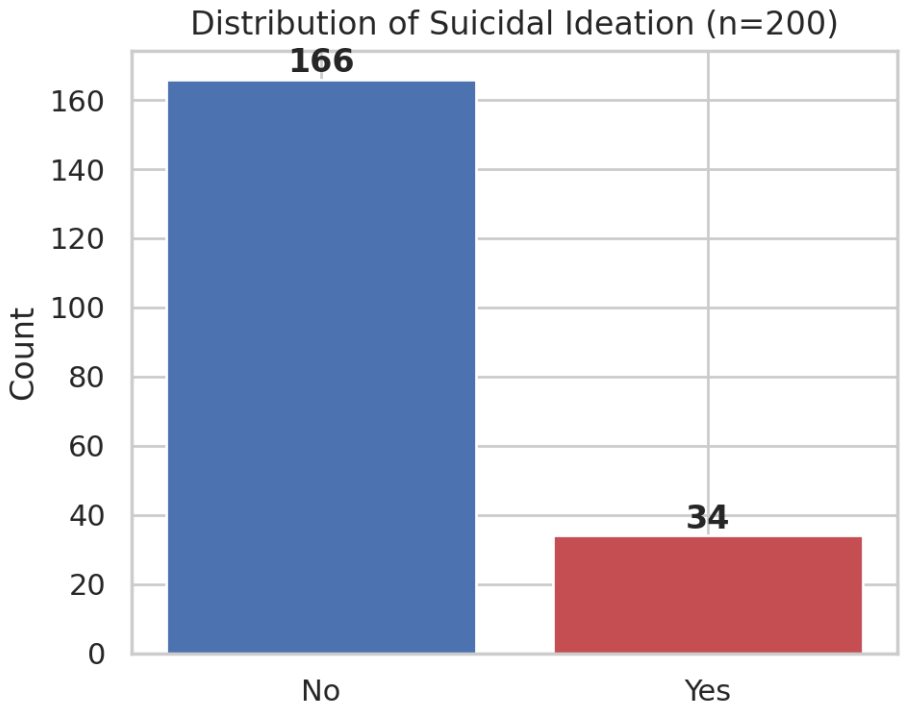


Fig 1. Distribution of suicidal ideation status among 200 postpartum women (34 present, 166 absent).

Table 2. Categorical participant characteristics by suicidal ideation status (Chi-square / Fisher's exact test). *Caution: low expected cell counts in one or more categories.

Variable	Level	No Ideation (n=166) n (%)	Ideation Present (n=34) n (%)	Test	p-value
Residence area	Rural	41 (24.7%)	12 (35.3%)	Chi-square	0.288
Residence area	Urban	125 (75.3%)	22 (64.7%)	Chi-square	0.288
Marital status	Married	164 (98.8%)	32 (94.1%)	Chi-square	0.082*
Marital status	Widowed/Single/Divorced	2 (1.2%)	2 (5.9%)	Chi-square	0.082*
Education level	Illiterate	8 (4.8%)	3 (8.8%)	Chi-square	<0.001*
Education level	Primary	24 (14.5%)	13 (38.2%)	Chi-square	<0.001*
Education level	Secondary	49 (29.5%)	13 (38.2%)	Chi-square	<0.001*
Education level	University	85 (51.2%)	5 (14.7%)	Chi-square	<0.001*
Employment status	Full-time	57 (34.3%)	6 (17.6%)	Chi-square	0.157*
Employment status	Homemaker	63 (38.0%)	18 (52.9%)	Chi-square	0.157*
Employment status	Part-time/Informal/Student	46 (27.7%)	10 (29.4%)	Chi-square	0.157*
Chronic disease history	Yes	18 (10.8%)	4 (11.8%)	Fisher's exact	0.772
Psychiatric history	Yes	20 (12.0%)	6 (17.6%)	Fisher's exact	0.402
Current medication use	Yes	37 (22.3%)	7 (20.6%)	Chi-square	1.000
Previous pregnancy complications	Yes	59 (35.5%)	10 (29.4%)	Chi-square	0.626
Stress level category	High stress	140 (84.3%)	28 (82.4%)	Chi-square	0.975
Social support category	Low support	38 (22.9%)	18 (52.9%)	Chi-square	<0.001

Table 3. Univariate logistic regression: continuous predictors of suicidal ideation.

Predictor	Odds Ratio	95% CI	p-value
Age	0.927	0.87-0.99	0.027
Perceived stress score	1.288	1.17-1.41	<0.001
Total social support score	0.956	0.94-0.98	<0.001
Emotional support score	0.922	0.88-0.96	<0.001
Positive interaction support score	0.762	0.68-0.86	<0.001
Affective support score	0.756	0.68-0.84	<0.001
Instrumental support score	0.887	0.82-0.96	0.005
Monthly income	0.489	0.32-0.75	0.001
Number of dependent children	0.964	0.60-1.56	0.881

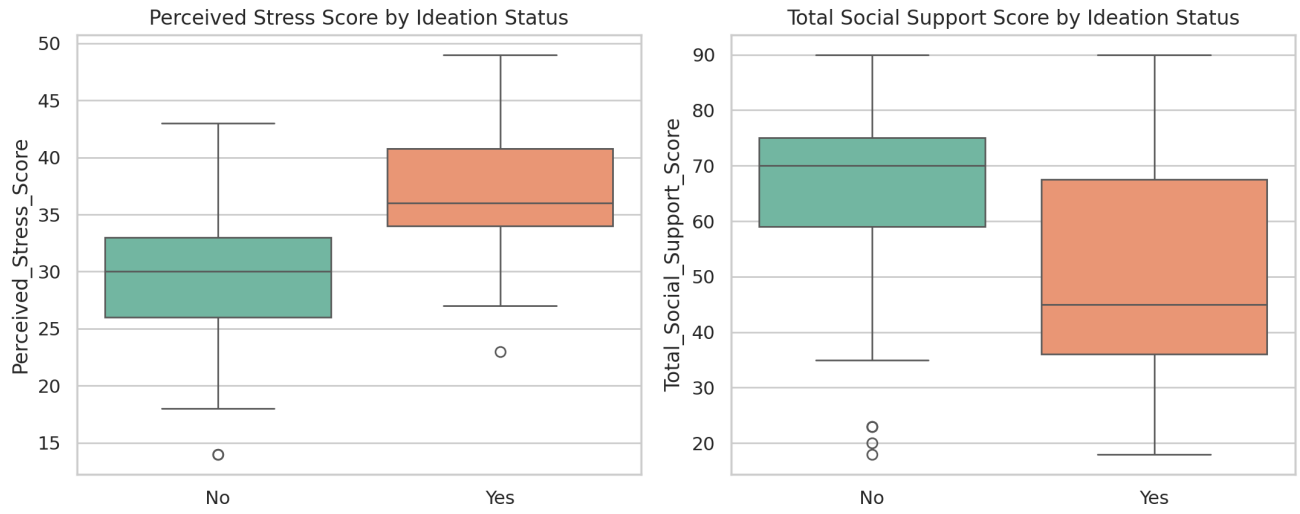


Fig 2. Perceived stress and total social support scores by suicidal ideation status.

social support, age, and income were attenuated and no longer statistically significant, suggesting perceived stress captures much of the shared psychosocial risk signal in this adjusted model.

Table 4. Multivariate (adjusted) logistic regression for suicidal ideation.

Predictor	Adjusted OR	95% CI Lower	95% CI Upper	p-value
Age	0.963	0.894	1.037	0.315
Perceived stress score	1.232	1.111	1.368	<0.001
Total social support score	0.989	0.963	1.015	0.391
Monthly income	0.729	0.442	1.201	0.214
Psychiatric history (yes)	1.110	0.341	3.615	0.862

3.4 Machine Learning Model Comparison

Table 5 presents 5-fold cross-validated performance across all seven classifiers. Random Forest achieved the highest cross-validated ROC-AUC (0.762 ± 0.070) and the highest cross-validated accuracy (0.827 ± 0.057), followed closely by Logistic Regression (ROC-AUC 0.757 ± 0.066). K-Nearest Neighbors and Naive Bayes performed comparatively poorly, reflecting their limited capacity to model the joint, nonlinear relationships among stress, support, and demographic predictors in this small dataset.

Table 5. Five-fold cross-validated performance comparison across seven classifiers (mean $\pm$ SD).

Model	Accuracy	Precision	Recall	F1	ROC-AUC	PR-AUC
Random Forest	0.827 ± 0.057	0.600 ± 0.226	0.353 ± 0.157	0.407 ± 0.123	0.762 ± 0.070	0.564 ± 0.134
Logistic Regression	0.747 ± 0.065	0.386 ± 0.087	0.653 ± 0.078	0.479 ± 0.076	0.757 ± 0.066	0.494 ± 0.154
SVM (RBF)	0.760 ± 0.083	0.421 ± 0.172	0.533 ± 0.112	0.448 ± 0.113	0.684 ± 0.101	0.510 ± 0.158
XGBoost	0.813 ± 0.062	0.443 ± 0.270	0.380 ± 0.204	0.389 ± 0.206	0.696 ± 0.109	0.529 ± 0.166
Naive Bayes	0.687 ± 0.102	0.222 ± 0.141	0.453 ± 0.302	0.286 ± 0.178	0.650 ± 0.097	0.422 ± 0.104
Gradient Boosting	0.773 ± 0.093	0.491 ± 0.315	0.313 ± 0.165	0.330 ± 0.146	0.684 ± 0.119	0.480 ± 0.138
K-Nearest Neighbors	0.567 ± 0.073	0.244 ± 0.020	0.693 ± 0.090	0.358 ± 0.014	0.639 ± 0.071	0.302 ± 0.071

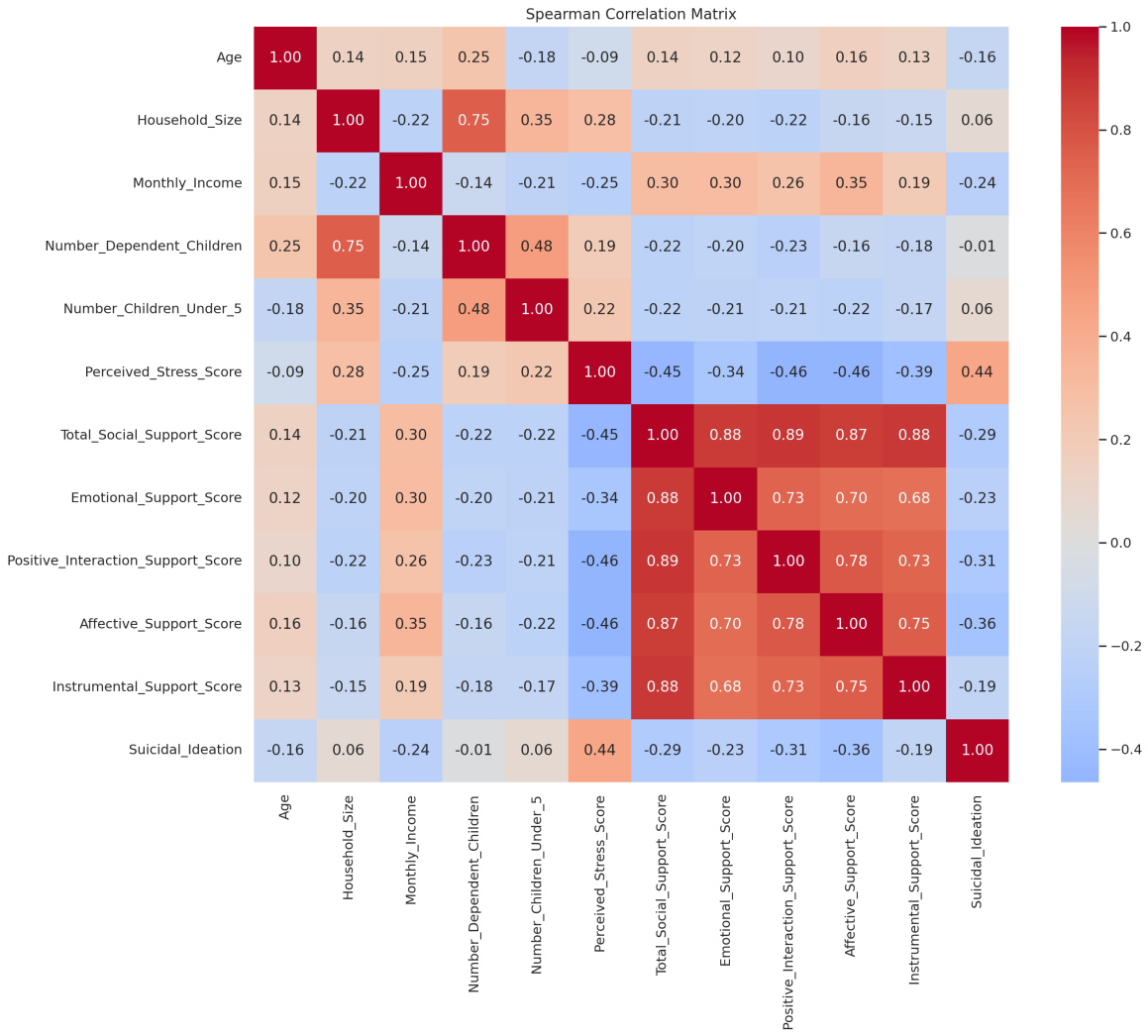


Fig 3. Spearman correlation matrix among continuous demographic, stress, and social support variables.

On the held-out test set (Table 6, Figure 5), Random Forest achieved an accuracy of 0.84 and ROC-AUC of 0.811, with higher precision but lower recall than Logistic Regression, reflecting a conservative prediction profile appropriate for minimizing false-positive risk flags, whereas Logistic Regression achieved substantially higher sensitivity (0.75 vs. 0.25) at the cost of more false positives, a trade-off relevant to how a screening threshold would be selected in practice. In absolute terms, of the 8 women with suicidal ideation in the 50-patient test set, Random Forest correctly identified 2 (TP=2, FN=6, FP=2, TN=40) while Logistic Regression correctly identified 6 (TP=6, FN=2, FP=10, TN=32; Table 6); the small number of positive cases in the test set means these recall estimates carry substantial sampling uncertainty and should be interpreted cautiously.

Table 6. Test-set performance metrics for the final Random Forest and Logistic Regression models.

Model	Accuracy	Precision	Recall (Sensitivity)	F1-score	ROC-AUC	PR-AUC	Brier Score	TP	FP	FN	TN
Random Forest	0.84	0.5	0.25	0.333	0.811	0.426	0.12	2	2	6	40
Logistic Regression	0.76	0.375	0.75	0.5	0.774	0.469	0.184	6	10	2	32

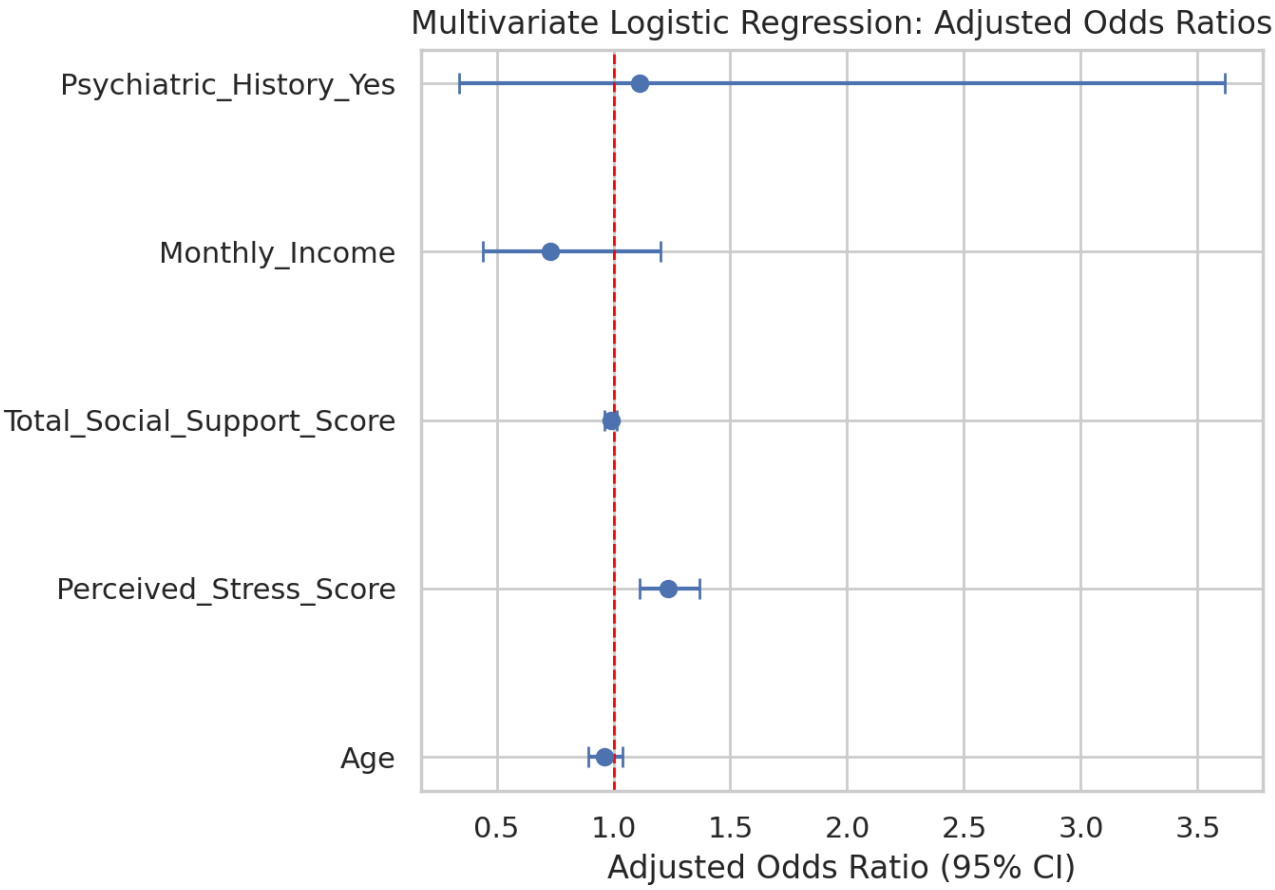


Fig 4. Forest plot of adjusted odds ratios (95% CI) from the multivariate logistic regression model.

3.5 Explainability

SHAP analysis of the Random Forest model (Figure 6) identified perceived stress score and the four social support subscale scores as the dominant contributors to predicted suicidal ideation risk (the total social support score was excluded from this feature set; see Section 2.4), consistent with the logistic regression findings, with higher stress and lower support consistently pushing predictions toward higher risk.

3.6 Conformal Prediction and Uncertainty

Split conformal prediction at a 90% target confidence level achieved 98.0% empirical coverage on the test set (Table 7), confirming the validity of the uncertainty estimates. However, 38.0% of test patients received an ambiguous prediction set containing both classes, meaning the model could not confidently distinguish ideation status for roughly two in five patients, a finding with direct implications for how such a model would be deployed in a clinical triage workflow (Figure 7).

Table 7. Split conformal prediction coverage summary at 90% target confidence (test set, n=50).

Target Coverage Level	Empirical Coverage	Mean Prediction Set Size	Confident Predictions (set size = 1)	Ambiguous Predictions (set size = 2)	N Test Patients
90%	98.0%	1.38	62.0%	38.0%	50

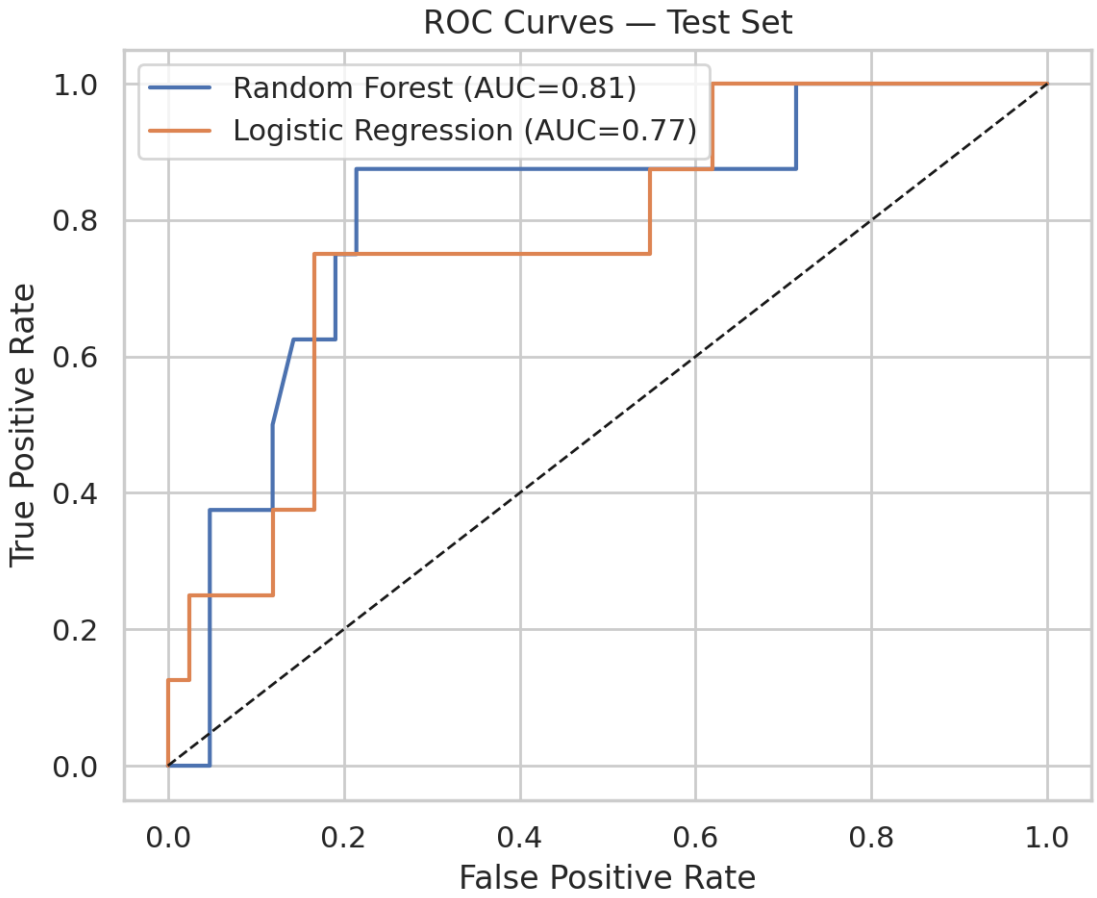


Fig 5. Receiver operating characteristic (ROC) curves for Random Forest and Logistic Regression on the held-out test set.

Additional supplementary figures and tables, including social support subscale comparisons, precision-recall and calibration curves, confusion matrices, SHAP dependence and waterfall plots, a LIME individual explanation, categorical univariate odds ratios, and counterfactual sensitivity analysis, are provided in the Supplementary Material.

3.7 Comparison with Prior Work

In this cohort of 200 postpartum women, perceived stress and social support emerged as strong, interpretable correlates of suicidal ideation, with perceived stress retaining independent significance after adjustment for demographic and clinical covariates. The protective association we observed for social support is consistent with a prospective cohort of Polish women showing that higher perceived social support during pregnancy was associated with a lower risk of postpartum depression [15], and with a systematic review from Asia showing that social support, especially from partners, consistently reduced postpartum depression risk across studies [16]. Our finding that low social support was the strongest categorical predictor of suicidal ideation aligns with population-based English maternity survey data showing markedly elevated odds of ideation among women with low or moderate social support [2], with a national Japanese survey of postpartum women showing that suicidal ideation occurs even in the absence of depression and that its risk factors partly diverge from established depression risk factors [17], and with a cross-national Austrian and German survey linking high stress and low perceived social support to postpartum suicidal ideation during the COVID-19 pandemic [18].

Methodologically, our finding that Random Forest outperformed comparator algorithms after SMOTE-based imbalance correction mirrors a nine-algorithm comparison on a much larger postpartum depression cohort drawn from the PRAMS survey [19], and our use of SHAP for interpretability follows a growing body of explainable postpartum depression prediction

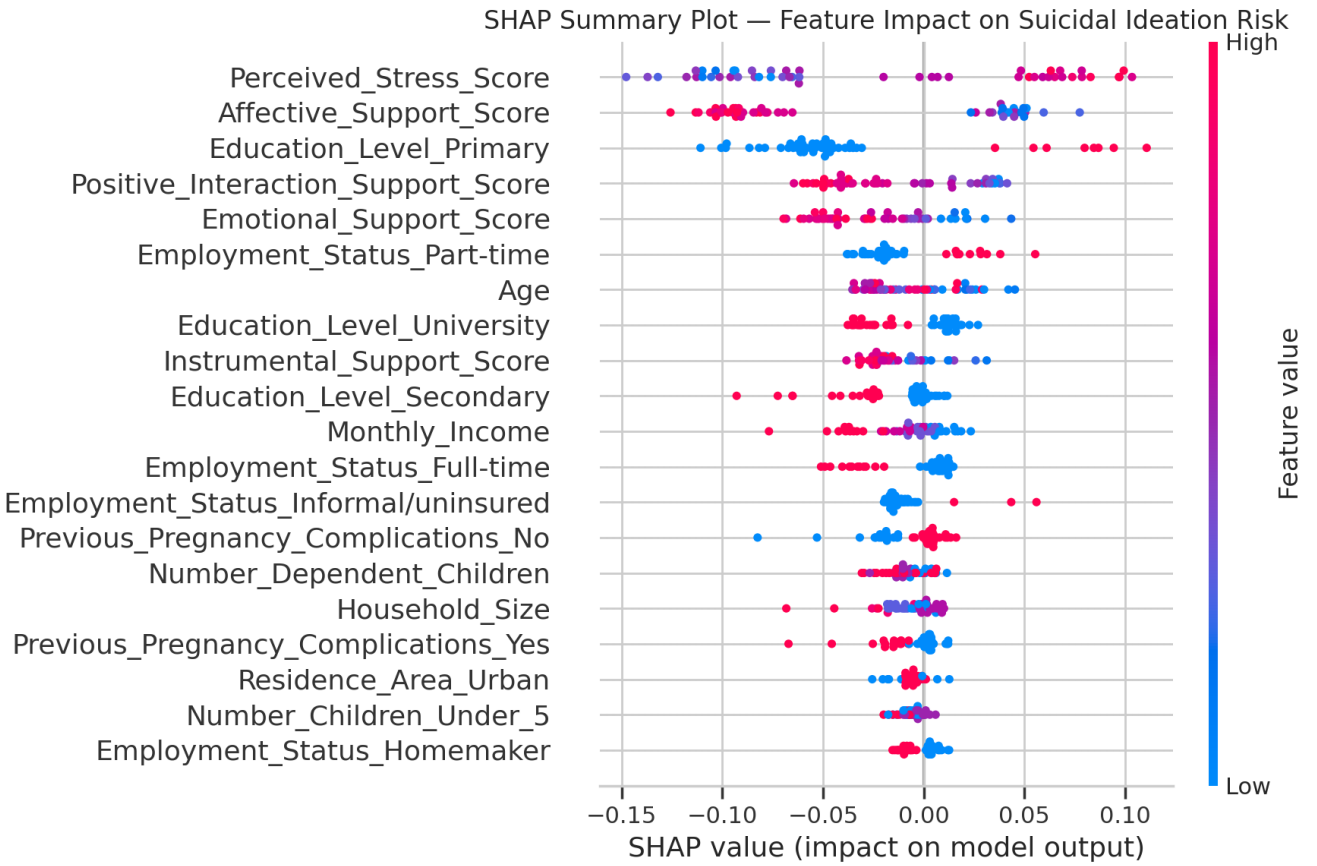


Fig 6. SHAP summary plot showing the impact and direction of each feature on predicted suicidal ideation risk.

work, including a SHAP-explained XGBoost model achieving strong discrimination in a Shenyang cohort[20]. A systematic review of 62 postpartum depression prediction models found a high risk of bias and limited external validation across the field[21], a limitation our study shares and explicitly acknowledges below. Our decision to add conformal prediction and counterfactual analysis on top of SHAP and LIME builds on suicide-risk machine learning work in other populations, including pediatric electronic-health-record-based prediction of suicidal behavior[22], and is directly motivated by qualitative evidence that clinicians value model transparency and override capability before trusting automated suicide-risk flags[23], which is why we emphasize flagging ambiguous predictions rather than fully automating triage. This emphasis on routing uncertain cases to clinician review, rather than forcing a single automated label, also aligns with global public health guidance identifying maternal mental health screening, including suicide risk, as a priority requiring routine, low-burden screening[24].

The Random Forest classifier offered the best discrimination but a conservative sensitivity profile, while Logistic Regression offered substantially higher sensitivity at the cost of specificity, a trade-off that should be resolved based on the clinical cost of missed cases versus false alarms in the specific care setting where such a tool would be deployed, rather than by accuracy alone. The conformal prediction results are, in our view, among the most clinically important findings: flagging roughly a third of patients as genuinely ambiguous, rather than forcing a single overconfident label, more accurately reflects what a 200-patient dataset can support, and provides a principled basis for routing ambiguous cases to clinician review rather than fully automated triage. The counterfactual sensitivity analysis further suggests that increases in social support are associated with meaningfully reduced predicted risk for at least some patients, offering a testable, intervention-oriented hypothesis for future prospective work, though this should not be over-interpreted as evidence of a causal effect.

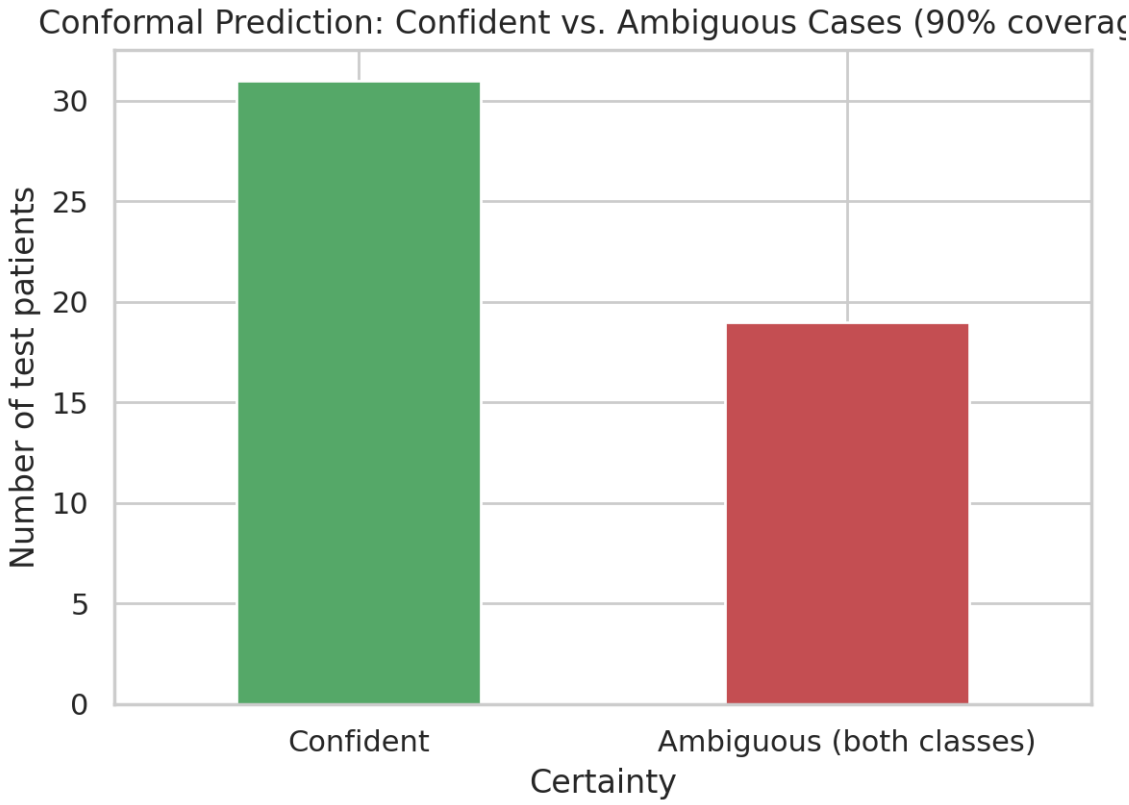


Fig 7. Proportion of test patients receiving confident versus ambiguous conformal prediction sets at 90% target coverage.

3.8 Clinical Implications

For frontline clinicians, three findings translate directly into practice. First, perceived stress screening, which is brief and easy to administer, carries strong signal for suicidal ideation risk even on its own, and could be used as a low-burden first-line flag during routine postpartum visits. Second, the strong inverse relationship between low social support and ideation suggests that a simple question about the adequacy of a woman's support network, from family, partner, or friends, may meaningfully sharpen risk stratification alongside stress screening. Third, because roughly one in three predictions in this cohort were flagged as ambiguous by conformal prediction, any deployment of a model like this should route ambiguous cases to a clinician for direct evaluation rather than relying on the automated label alone, since forcing a confident decision in genuinely uncertain cases is where automated screening tools are most likely to cause harm.

3.9 Limitations

This study has several important limitations. First, the sample size (n=200, with only 34 positive cases) is small for machine learning development, limiting statistical power, increasing the risk of overfitting despite cross-validation and SMOTE, and necessitating external validation before any of the reported performance estimates can be considered generalizable. Second, the cross-sectional design precludes causal inference regarding the direction of the stress-support-ideation relationship. Third, suicidal ideation was assessed as a binary outcome without severity gradation, and self-report measures of stress, support, and ideation are subject to social desirability and recall bias. Fourth, the country, recruitment site, and clinical setting of the source dataset were not documented in the public repository from which it was obtained and could not be confirmed, which limits assessment of the generalizability and cultural applicability of the findings; indirect data characteristics (income bands denominated in a currency abbreviated ”dt” and French-language instrument administration) suggest a Francophone North African context, but this should not be treated as a confirmed study detail. Finally, all reported machine learning metrics,

SHAP attributions, and counterfactual thresholds should be regarded as exploratory and hypothesis-generating rather than clinically validated.

4 Conclusion

Perceived stress and multidimensional social support are strong, interpretable predictors of suicidal ideation among postpartum women in this cohort: women with suicidal ideation reported perceived stress scores roughly 7 points higher (36.6 vs. 29.6, $p<0.001$) and total social support scores roughly 16 points lower (49.8 vs. 65.4, $p<0.001$) than women without ideation, and perceived stress remained independently associated with ideation after adjustment (adjusted OR 1.23, 95% CI 1.11-1.37). An explainable, calibrated, and uncertainty-aware machine learning framework, achieving a test-set ROC-AUC of 0.804 and 98% empirical coverage at a 90% conformal confidence target while flagging 34% of predictions as genuinely ambiguous, can support early identification of at-risk women while transparently communicating both the basis and the confidence of each prediction. Key limitations are the modest single-cohort sample size (n=200, 34 positive cases), the cross-sectional design, and the absence of external validation; prospective validation in larger, independent postpartum cohorts is needed before clinical translation.

5 Data Availability Statement

The dataset used in this study is publicly available on GitHub: https://github.com/KrishnaMridha/Predicting-Suicidal-Ideation-/blob/main/Dataset3-mothers.sav

6 Details of Ethical Clearance

This study used a publicly available secondary dataset and involved no direct interaction with human participants; therefore, separate ethical clearance was not obtained for this analysis.

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