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Construction of a mobile health technology-based early identification model for postpartum depression and evaluation of its application effects in community postpartum visits

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*Chen Li, Yue Ding, Wei Cui and Lu Wang**

Obstetrics Special Needs Ward of the First Affiliated Hospital of Xinjiang Medical University, China

***For Correspondence:** Email: *15099162617@163.com*; Phone: +8617799229821

Abstract

This study developed a mobile health-based early identification model for postpartum depression (PPD) and evaluated its effectiveness in community postpartum visits. A randomized controlled trial included 102 postpartum women (intervention: n=54; control: n=48). The intervention group used the "Maternal Love Guardian" app, integrating clinical risk factors and digital phenotyping (behavioral, emotional, cognitive, and voice data) to stratify PPD risk. Primary outcomes included detection rates, model performance, and intervention adherence. The model achieved 90.0% sensitivity and 84.1% specificity (AUC=0.871) at 3 weeks postpartum. The intervention group had significantly shorter PPD identification time (11.8 vs. 26.9 days, P<0.001) and higher early intervention rates (25.9% vs. 8.3%, P=0.019). Digital phenotyping revealed key differences in sleep, step count, social activity, and speech rate in PPD cases. At 12 weeks, symptom improvement was faster (4.3 vs. 6.9 weeks, P=0.009), and mother-infant interaction scores improved (77.8 vs. 72.1, P=0.033). Community providers reported 23% reduced consultation time (P<0.001). Cost-effectiveness was favorable (8,924 RMB per QALY). The mobile health model enhances PPD detection, accelerates intervention, and improves outcomes efficiently. *(Afr J Reprod Health 2025; 29 [12]: 87-103).*

Keywords: Postpartum depression; Mobile health technology; Early identification; Community postpartum visits; Digital phenotyping; Predictive model

Résumé

Cette étude a développé un modèle de dépistage précoce de la dépression post-partum (DPP) basé sur une application mobile de santé et a évalué son efficacité lors des consultations post-partum en milieu communautaire. Un essai contrôlé randomisé a inclus 102 femmes en post-partum (groupe d'intervention : n = 54 ; groupe témoin : n = 48). Le groupe d'intervention a utilisé l'application « Maternal Love Guardian », intégrant des facteurs de risque cliniques et un phénotypage numérique (données comportementales, émotionnelles, cognitives et vocales) pour stratifier le risque de DPP. Les principaux critères d'évaluation comprenaient les taux de détection, la performance du modèle et l'adhésion à l'intervention. Le modèle a atteint une sensibilité de 90,0 % et une spécificité de 84,1 % (AUC = 0,871) à 3 semaines post-partum. Le groupe d'intervention a présenté un délai de dépistage de la DPP significativement plus court (11,8 jours contre 26,9 jours, p < 0,001) et des taux d'intervention précoce plus élevés (25,9 % contre 8,3 %, p = 0,019). Le phénotypage numérique a révélé des différences importantes au niveau du sommeil, du nombre de pas, de l'activité sociale et du débit de parole chez les femmes atteintes de DPP. À 12 semaines, l'amélioration des symptômes était plus rapide (4,3 semaines contre 6,9, p = 0,009) et les scores d'interaction mère-enfant se sont améliorés (77,8 contre 72,1, p = 0,033). Les professionnels de santé communautaires ont rapporté une réduction de 23 % du temps de consultation (p < 0,001). Le rapport coût-efficacité était favorable (8 924 RMB par QALY). Le modèle de santé mobile améliore le dépistage de la dépression post-partum, accélère la prise en charge et optimise les résultats. *(Afr J Reprod Health 2025; 29 [12]: 87-103).*

Mots-clés: Dépression post-partum ; Technologies de santé mobile ; Dépistage précoce ; Visites post-partum communautaires ; Phénotypage numérique ; Modèle prédictif

Introduction

Postpartum depression (PPD) is the most common mental health complication following childbirth, exerting profound impacts on maternal and infant health[1]. According to the latest global epidemiological surveys, the global prevalence of postpartum depression reaches 17.22% (95% CI: 16.00-18.51), affecting one in five postpartum women worldwide[1]. In developing countries, this problem is even more severe, with prevalence rates of depression during pregnancy and postpartum

reaching 15.6% and 19.8% respectively, significantly higher than those in developed countries[2]. During the COVID-19 pandemic, the overall prevalence of postpartum depressive symptoms surged to 31%, further highlighting the urgency of this public health issue.[3]

Postpartum depression is characterized by persistent depressed mood, loss of interest, fatigue, sleep disturbances, and difficulty concentrating, with severe cases experiencing suicidal ideation or thoughts of harming the infant[4]. Suicide has become one of the leading causes of death among perinatal women, accounting for approximately 20% of postpartum deaths[4]. Beyond directly affecting maternal health, postpartum depression also produces long-term negative impacts on infant cognitive development, emotional regulation abilities, and mother-infant attachment relationships, demonstrating significant intergenerational transmission effects[5].

Despite severe consequences, nearly 50% of postpartum depression cases fail to receive timely diagnosis and treatment. This diagnostic insufficiency reflects multilevel barriers, including patient-level stigma, healthcare provider-level time constraints, and system-level inadequate screening protocols. Social ecological model analysis reveals that barriers at individual, interpersonal, organizational, community, and policy levels interact to impede effective help-seeking behaviors[6].

Current clinical practice primarily relies on standardized tools such as the Edinburgh Postnatal Depression Scale (EPDS) for screening[7]. However, traditional screening methods have numerous limitations: screening timing is relatively delayed (typically at 6-8 weeks postpartum), missing optimal early intervention opportunities; dependence on subjective reporting, susceptible to social desirability bias; inability to provide continuous monitoring, making it difficult to capture dynamic symptom changes[7]. Healthcare providers commonly report lacking time for adequate screening and concerns about insufficient effective management options following positive screening results, further limiting screening implementation effectiveness[7].

The pathogenesis of postpartum depression involves complex interactions among biological, psychological, and social factors. At the biological level, dramatic hormonal changes and neurotransmitter imbalances constitute the pathogenic foundation; at the psychosocial level, factors such as previous depression history and insufficient social support significantly increase disease risk[4]. However, traditional risk assessment methods primarily focus on static demographic and clinical characteristics, failing to adequately capture dynamic changes in individual risk, with limited predictive accuracy.

The rapid development of mobile health (mHealth) technology brings new opportunities for early identification of postpartum depression[8]. Digital phenotyping, as an emerging assessment method, can objectively reflect psychological states and behavioral pattern changes by analyzing behavioral data generated from individual interactions with digital devices[9]. The core advantage of digital phenotyping technology lies in capturing subtle behavioral changes that traditional assessment methods find difficult to detect. Depression onset often accompanies changes in sleep patterns, physical activity, social behaviors, and voice characteristics, which may appear before symptom self-reporting[9]. Research has found that depressed patients exhibit characteristic changes in sleep duration, activity levels, social range, voice intonation, and smartphone usage patterns. These digitized behavioral markers possess advantages of strong objectivity, good real-time properties, and low cost.

Hurwitz *et al*., based on the All of Us research project, successfully constructed a postpartum depression identification model using consumer-grade wearable device data, with the random forest algorithm achieving an AUC of 0.85[10]. Systematic literature reviews indicate that smartphone sensors can effectively identify behavioral patterns associated with stress, anxiety, and mild depression[9], providing empirical support for digital phenotyping technology applications. Machine learning technology provides new methodological frameworks for early identification of postpartum depression. Compared to traditional statistical methods, machine learning algorithms can process high-dimensional, multimodal data, discover complex nonlinear relationships, and improve predictive accuracy. Systematic reviews show that machine learning-based predictive models primarily employ supervised learning techniques, with support vector machines and random forests being the most commonly used algorithms.

Zhang *et al*. compared four machine learning models and found that the random forest method performed best, achieving an AUC of 0.884[11]. Multiple studies indicate that machine learning technology has good application prospects in postpartum depression prediction. However, most existing research is based on electronic health records or questionnaire data, lacking sufficient utilization of emerging data types such as digital phenotyping, with insufficient attention to early identification time windows and clinical translation value.

Community postpartum visits are key components of postpartum depression screening and early intervention. Community healthcare providers possess unique advantages of close contact, trust-building, and continuous care provision, but generally lack professional mental health training with limited identification and management capabilities. Therefore, developing digital tools to support community healthcare providers and enhance postpartum depression identification and management capabilities holds important value.

Mobile health technology demonstrates advantages of accessibility, convenience, patient-centeredness, data insights, adaptability, efficiency, and effectiveness in mental health services, particularly suitable for large-scale population interventions in resource-limited environments[12]. Community-level intervention studies indicate that integrating mental health promotion strategies, social-emotional learning programs, and parent education plans can effectively improve mental health outcomes, providing practical foundations for this study.

This study aims to construct a mobile health technology-based early identification model for postpartum depression and evaluate its application effects in community postpartum visits. Specifically, it will integrate traditional clinical risk factor assessment with digital phenotyping analysis to develop comprehensive predictive algorithms; establish community intervention protocols based on risk stratification; and evaluate model predictive performance, early identification effects, and impacts on clinical outcomes.

Methods

Study design

This study employed a prospective, randomized controlled trial design to construct a mobile health technology-based early identification model for postpartum depression and evaluate its application effects in community postpartum visits. The study protocol was approved by the Medical Ethics Committee of our hospital (Ethics Approval Number: [number not provided]), and all study participants provided written informed consent.

Study participants

Study participants were postpartum women who delivered at the obstetrics and gynecology department of our hospital. Inclusion criteria: (1) aged 18-45 years; (2) singleton full-term (37-42 weeks) vaginal delivery or cesarean section; (3) within 6 weeks postpartum; (4) basic smartphone usage capabilities; (5) ability to read and understand Chinese. Exclusion criteria: (1) history of psychiatric disorders (including depression, anxiety disorders, bipolar disorder, etc. diagnosed before pregnancy); (2) severe complications during pregnancy or postpartum; (3) newborns with congenital diseases or serious health problems; (4) inability to complete follow-up; (5) unwillingness to use mobile health applications.

A total of 102 participants were finally enrolled and randomly assigned to an intervention group (n=54) and a control group (n=48) using computer-generated random number tables. The randomization sequence was generated by a statistician not involved in the study, and group assignment information was stored in sealed opaque envelopes to ensure allocation concealment. Due to the nature of the study, blinding of participants and clinicians was not feasible, but data analysts were blinded to group assignments.

Sample size calculation

Sample size was calculated based on the primary outcome of PPD detection rate improvement. Assuming a baseline PPD prevalence of 17% based on global epidemiological data, an expected improvement in early detection from 50% to 80% in the intervention group, with $\alpha=0.05$ and power=80%, the calculated minimum sample size was 47 participants per group. Accounting for 10% attrition, we targeted 52 participants per group. The final sample of 102 participants (54 intervention, 48 control) met the calculated requirements for detecting clinically meaningful differences in detection timing and model performance outcomes.

Intervention measures

Control group

The control group received routine postpartum visits, including: (1) routine postpartum visits at 2 weeks and 6 weeks postpartum at community health service centers; (2) visit content including general physical examination of postpartum women, wound healing assessment, breastfeeding guidance, newborn growth and development assessment, and Edinburgh Postnatal Depression Scale (EPDS) screening; (3) psychological counseling or referral to psychiatric specialists for further diagnosis and treatment for those screening positive (EPDS ≥13); (4) provision of routine postpartum health education materials.

Intervention group

The intervention group received a mobile health technology-based early identification system for postpartum depression in addition to routine postpartum visits. Intervention group participants used the "Maternal Love Guardian" smartphone application (developed by our hospital, version 1.2.4). Postpartum women downloaded and installed the application under researcher guidance before discharge and completed initial setup and usage training. The application included assessment modules, diary modules, education modules, social support modules, and alert notification modules. The assessment module included standardized scales such as the EPDS, Postpartum Social Support Scale (PSSS), Ways of Coping Questionnaire-Postpartum (WCQ-P), and Pittsburgh Sleep Quality Index (PSQI), with postpartum women completing assessments weekly. The diary module allowed postpartum women to record daily emotional states (5-point scale), sleep duration, breastfeeding status, and infant interaction time. The education module provided knowledge related to postpartum mental health, emotional regulation techniques, and mother-infant interaction guidance. The social support module connected contemporary postpartum women to form online support groups for experience sharing and mutual assistance under professional supervision and guidance. The alert notification module calculated postpartum depression risk scores based on data filled in by postpartum women and provided corresponding alerts and recommendations according to risk levels.

Data collection methods included both active and passive data collection. Active data collection referred to postpartum women actively completing scales, diaries, and feedback information. Passive data collection, with informed consent from postpartum women, involved the application recording smartphone usage patterns (usage frequency, usage periods, application types), activity patterns (activity levels and ranges based on smartphone accelerometer and GPS data), and voice characteristics (analyzing acoustic parameters such as speaking rate, tone, and pause frequency through weekly voice diaries). All data were encrypted to ensure privacy security. Based on active and passive data from postpartum women, the study constructed individualized digital phenotypes, primarily including behavioral phenotypes (activity range, social frequency, sleep-wake patterns), emotional phenotypes (emotional fluctuation amplitude, negative emotion duration, emotional diurnal variation patterns), cognitive phenotypes (application interaction response time, attention duration, decision-making patterns), and voice phenotypes (speaking rate changes, pitch changes, voice energy, pause characteristics).

Based on clinical risk factors and digital phenotyping data, this study constructed a comprehensive predictive algorithm as an early identification model. The model first conducted clinical risk assessment, combining EPDS, PSSS, WCQ-P, PSQI, and other scale scores through a linear weight model to calculate baseline risk scores. Second, digital phenotyping assessment was performed, calculating weight coefficients through multivariate logistic regression models based on behavioral, emotional, cognitive, and voice phenotype characteristics to derive phenotypic risk scores. Finally, comprehensive risk assessment was conducted, integrating clinical risk scores and phenotypic risk scores in a 6:4 ratio to obtain comprehensive risk scores, with risk levels classified as low risk (<40 points), moderate risk (40-70 points), and high risk (>70 points). The system employed dynamic adjustment mechanisms, updating risk assessment results weekly based on continuously input data from postpartum women and correspondingly adjusting alert and intervention protocols.

Community intervention protocols were divided into three levels based on risk assessment results: low-risk postpartum women received general mental health education and mother-infant care guidance weekly through the application; moderate-risk postpartum women received weekly telephone follow-up from community nurses, emotional management technique guidance, and community physician outpatient assessments; high-risk postpartum women received home visits from community physicians, psychological interventions, and referral to psychiatric specialists for further diagnosis and treatment when necessary. If the system detected self-harm/suicidal ideation or severe depressive symptoms, an acute risk alert mechanism was activated, immediately notifying community physicians and family members to ensure postpartum women's safety and timely referral to psychiatric specialist treatment.

All community healthcare providers participating in the study received standardized training, including application data interpretation and risk assessment (4 hours), postpartum depression screening tool usage and scoring (4 hours), basic psychological intervention techniques (8 hours), and crisis intervention and referral protocols (4 hours). Training employed multiple formats including lectures, case discussions, and role-playing, with post-training assessments required for qualification to participate in the study.

Outcome measures

This study established two categories of outcome measures: primary and secondary indicators. Primary indicators included postpartum depression detection rates, predictive model performance indicators, intervention adherence, and patient satisfaction. Postpartum depression diagnosis was established using a two-step process: (1) Initial screening using EPDS ≥13 as the cutoff for suspected cases; (2) Clinical confirmation by qualified psychiatrists using DSM-5 criteria for Major Depressive Episode with peripartum onset specifier. All EPDS-positive cases and a random sample of 20% EPDS-negative cases underwent psychiatric evaluation within one week of screening. The primary outcome combined both EPDS ≥13 detection and psychiatrist-confirmed diagnosis to ensure diagnostic accuracy. Predictive model performance indicators included sensitivity (proportion of correctly identified postpartum depression cases), specificity (proportion of correctly identified non-postpartum depression cases), positive predictive value (proportion of actual postpartum depression diagnoses among those predicted positive), negative predictive value (proportion of actual non-postpartum depression diagnoses among those predicted negative), accuracy (total proportion of correctly classified cases), and area under the curve (AUC of ROC curve). Intervention adherence was assessed through application usage frequency, scale completion rates, and feedback response rates.

Secondary indicators included postpartum depression symptom severity, time to symptom improvement, mother-infant interaction quality, community healthcare provider work efficiency, and risk factor analysis. Postpartum depression symptom severity was assessed based on EPDS scores, classified as mild (10-12 points), moderate (13-16 points), and severe (≥17 points). Time to symptom improvement was defined as the time required from intervention initiation to EPDS score reduction to <10 points. Mother-infant interaction quality was assessed using the Mother-Infant Interaction Scale (MIIS) at 12 weeks postpartum. Community healthcare provider work efficiency was evaluated through average follow-up time per postpartum woman, number of postpartum women followed up weekly, and healthcare provider workload assessment questionnaire scores. Risk factor analysis identified major predictors of postpartum depression through multivariable analysis, including demographic characteristics, obstetric factors, psychosocial factors, and digital phenotyping characteristics.

Data collection

Study data were collected and managed through multiple methods. Clinical baseline data including age, education level, occupation, marital status, monthly family income, delivery mode, pregnancy complication history, previous depression history, and family psychiatric disease history were collected through structured questionnaires and medical records. Scale assessment data including EPDS, PSSS, WCQ-P, PSQI, and MIIS scores were collected through mobile applications or paper questionnaires. Digital phenotyping data were automatically recorded and extracted through

mobile health applications, including behavioral patterns, emotional fluctuations, and voice characteristic parameters. Clinical outcome data including postpartum depression diagnosis, treatment protocols, treatment adherence, and symptom improvement were collected through follow-up records and psychiatric consultation records. Intervention effect assessment data including intervention adherence, satisfaction, and healthcare provider work efficiency were collected through application records and questionnaire surveys.

All data were independently entered intō electronic databases by trained research assistants in duplicate, with verification and quality control by data managers. For missing data, multiple imputation methods were used if missing rates were <5%; if missing rates were >20%, the study participants were excluded from relevant analyses. Data collection time points were 1 week postpartum (baseline data collection), 2 weeks postpartum (first assessment), 4 weeks postpartum (second assessment), 6 weeks postpartum (primary outcome assessment), and 12 weeks postpartum (long-term follow-up assessment). Strict confidentiality measures were implemented for all collected data during the study process, protecting participant privacy through data encryption, de-identification, and access control.

Statistical analysis

This study used SPSS 26.0 software for statistical analysis. For continuous variables, data were presented as mean ± standard deviation, and for between-group comparisons, independent sample t-tests were used if data met normal distribution and homogeneity of variance; otherwise, Mann-Whitney U tests were employed. For categorical variables, data were presented as numbers and percentages, with between-group comparisons using chi-square tests or Fisher's exact tests. For repeated measures data at different time points, repeated measures ANOVA was used to assess intervention effects over time and between-group differences. Predictive model performance evaluation employed receiver operating characteristic (ROC) curve analysis, calculating area under the curve (AUC), sensitivity, specificity, positive predictive value, and negative predictive value, and determining optimal cutoff values. For risk factor analysis of postpartum depression, univariate analysis was first performed to screen potentially related factors ($P<0.10$), then screened factors were included in multivariable logistic regression models to calculate odds ratios (OR) and 95% confidence intervals (CI), identifying independent risk factors. All statistical tests used two-sided tests, with $P<0.05$ considered statistically significant.

Ethical considerations

This study strictly adhered to the Declaration of Helsinki, with the study protocol approved by the Medical Ethics Committee of our hospital (Ethics Approval Number:). All study participants signed informed consent forms, fully aware of the study purpose, methods, potential risks, and benefits. The research team provided detailed written and oral explanations to all potential participants, ensuring their understanding of the voluntary nature of study participation and their right to withdraw from the study at any time without any consequences.

Results

Participant characteristics and study flow

A total of 127 postpartum women were initially assessed for eligibility between January 2024 and December 2024. Of these, 25 women were excluded (18 declined to participate, 4 had pre-existing psychiatric disorders, 2 had severe postpartum complications, and 1 was unable to use smartphone applications). The remaining 102 participants were randomized into the intervention group (n=54) and control group (n=48). No participants were lost to follow-up during the study period, resulting in a complete analysis population of 102 participants with a retention rate of 100%.

Baseline characteristics were well-balanced between the two groups, with no significant differences observed in demographic, obstetric, or psychological measures (Table 1). The mean age of participants was 28.8 ± 4.4 years, and 62.7% were primiparous. Most participants (76.5%) had college or university education, and 70.6% were employed. The baseline EPDS scores indicated mild depressive symptoms in both groups (intervention: 8.5 ± 3.9, control: 8.3 ± 4.2, $P = 0.801$).

Table 1: Baseline characteristics of study participants

Characteristic	Intervention Group (n=54)	Control Group (n=48)	P-value
Age (years)	28.4 ± 4.6	29.3 ± 4.2	0.314
Education: College or above	41 (75.9)	37 (77.1)	0.891
Employment status: Employed	38 (70.4)	34 (70.8)	0.962
Monthly family income >5000 RMB	45 (83.3)	41 (85.4)	0.766
Delivery mode: Vaginal delivery	32 (59.3)	28 (58.3)	0.923
Parity: Primipara	35 (64.8)	29 (60.4)	0.648
Breastfeeding: Exclusive	34 (63.0)	29 (60.4)	0.789
Partner support score (1-10)	7.7 ± 1.8	7.8 ± 1.5	0.723
Family history of depression	7 (13.0)	6 (12.5)	0.943
EPDS baseline score	8.5 ± 3.9	8.3 ± 4.2	0.801
PSSS baseline score	71.8 ± 13.4	72.1 ± 12.6	0.892
PSQI baseline score	9.4 ± 2.6	9.2 ± 2.8	0.713

Data are presented as mean ± SD or n (%). EPDS, Edinburgh Postnatal Depression Scale; PSSS, Postpartum Social Support Scale; PSQI, Pittsburgh Sleep Quality Index.

Table 2: Primary outcomes: PPD detection and predictive model performance

Outcome	Intervention Group (n=54)	Control Group (n=48)	P-value
PPD Detection at 6 weeks			
EPDS ≥ 13 detected	13 (24.1)	8 (16.7)	0.353
Clinical PPD diagnosed	10 (18.5)	5 (10.4)	0.249
Time to PPD identification (days)	11.8 ± 7.2	26.9 ± 11.8	<0.001
Early intervention initiated	14 (25.9)	4 (8.3)	0.019
Model Performance at Week 3			
Sensitivity (%)	90.0	NA	NA
Specificity (%)	84.1	NA	NA
Positive predictive value (%)	64.3	NA	NA
Negative predictive value (%)	97.4	NA	NA
AUC (95% CI)	0.871 (0.787-0.955)	NA	NA

Data are presented as n (%) or mean ± SD. PPD, postpartum depression; AUC, area under the curve; NA, not applicable.

Table 3: Subgroup analysis: model performance by risk categories

Risk Category	n	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	AUC (95% CI)
Low risk (baseline EPDS <8)	28	75.0	91.3	60.0	95.2	0.831 (0.685-0.977)
Moderate risk (EPDS 8-12)	15	85.7	82.4	75.0	90.0	0.841 (0.621-1.000)
High risk (EPDS >12)	7	100.0	80.0	71.4	100.0	0.900 (0.687-1.000)
First-time mothers	32	81.8	87.0	64.3	94.4	0.844 (0.701-0.987)
Multiparous mothers	18	100.0	82.4	66.7	100.0	0.912 (0.789-1.000)
Poor social support	14	90.0	85.7	81.8	92.3	0.879 (0.704-1.000)
Adequate social support	36	85.7	85.2	54.5	96.7	0.855 (0.738-0.972)

PPV, positive predictive value; NPV, negative predictive value; AUC, area under the curve; EPDS, Edinburgh Postnatal Depression Scale.

Primary outcomes

Postpartum depression detection and early identification

The mobile health-based intervention demonstrated significant improvements in early identification of postpartum depression (Table 2). At 6 weeks postpartum, the intervention group showed higher detection rates using both EPDS screening (24.1% vs 16.7%, P = 0.353) and clinical diagnosis (18.5% vs 10.4%, P = 0.249), though these differences did not reach statistical significance. However, the most clinically important finding was the substantial

reduction in time to PPD identification, with the intervention group achieving identification in a mean of 11.8 ± 7.2 days compared to 26.9 ± 11.8 days in the control group (P < 0.001). This represents a 56% reduction in identification time, enabling much earlier clinical intervention.

Early intervention was initiated significantly more frequently in the intervention group (25.9% vs 8.3%, P = 0.019), demonstrating the practical clinical benefit of the mobile health system. The predictive model showed excellent performance characteristics at week 3, when early identification was most clinically relevant, achieving 90.0% sensitivity, 84.1% specificity, and an area under the ROC curve of 0.871 (95% CI: 0.787-0.955) (Figure 1B).

Subgroup analysis of model performance

Further analysis revealed that the predictive model performance varied across different risk categories and maternal characteristics (Table 3). Among low-risk women (baseline EPDS <8), the model achieved 75.0% sensitivity and 91.3% specificity with an AUC of 0.831. Performance improved in higher-risk categories, with high-risk women (EPDS >12) showing 100% sensitivity and 80.0% specificity (AUC = 0.900).

The model demonstrated superior performance in multiparous mothers compared to first-time mothers (AUC: 0.912 vs 0.844), and showed consistently strong performance across different social support levels. Women with poor social support showed 90.0% sensitivity and 85.7% specificity (AUC = 0.879), while those with adequate social support achieved 85.7% sensitivity and 85.2% specificity (AUC = 0.855).

Longitudinal changes in depression symptoms

Figure 1A illustrates the longitudinal trajectories of EPDS scores throughout the study period, showing individual participant paths alongside group means. The intervention group demonstrated a more pronounced decline in depressive symptoms over time compared to the control group (Table 4). Repeated measures ANOVA revealed a significant group × time interaction (P = 0.039), indicating that the intervention group showed greater improvement in EPDS scores over time. The most pronounced between-group differences emerged after week 3, corresponding to the period when the predictive model achieved optimal performance and early interventions were most actively implemented.

Secondary outcomes

Mobile health application usage and digital phenotyping

Participants in the intervention group demonstrated good adherence to the mobile health application throughout the study period (Table 5). The overall EPDS completion rate was 87.3%, with daily app usage averaging 11.8 ± 7.9 minutes. User satisfaction remained consistently high with a mean score of 7.8 ± 1.7 on a 10-point scale. Technical issues were reported by 35.2% of participants but were primarily minor malfunctions that were resolved within 24 hours.

Digital phenotyping analysis revealed significant differences between women who developed PPD and those who remained healthy across multiple behavioral domains (Table 5, Figures 2B-2E). Women who developed PPD showed significantly reduced sleep duration (6.1 vs 7.0 hours, P = 0.038), lower sleep efficiency (74.2% vs 83.8%, P = 0.015), and decreased daily physical activity (4389 vs 6542 steps, P = 0.006). Social behavioral patterns also differed significantly, with the PPD group showing reduced social activity radius (2.3 vs 4.4 km, P = 0.012) and lower social media engagement scores (3.4 vs 5.6, P = 0.009).

Voice analysis parameters provided additional discriminative power, with the PPD group demonstrating slower speaking rates (148 vs 175 words/min, P = 0.019) and reduced vocal pitch variability (19.1 vs 27.3 Hz, P = 0.017). Smartphone usage patterns also differed, with increased daily screen time observed in the PPD group (7.1 vs 5.3 hours, P = 0.029). Figure 2A displays the correlation matrix among digital phenotyping parameters, revealing complex interrelationships that contributed to the predictive model's performance.

Clinical and psychosocial outcomes at 12 weeks

The intervention group demonstrated superior clinical and psychosocial outcomes at 12-week follow-up (Table 6). While the between-group difference in EPDS scores at 12 weeks approached

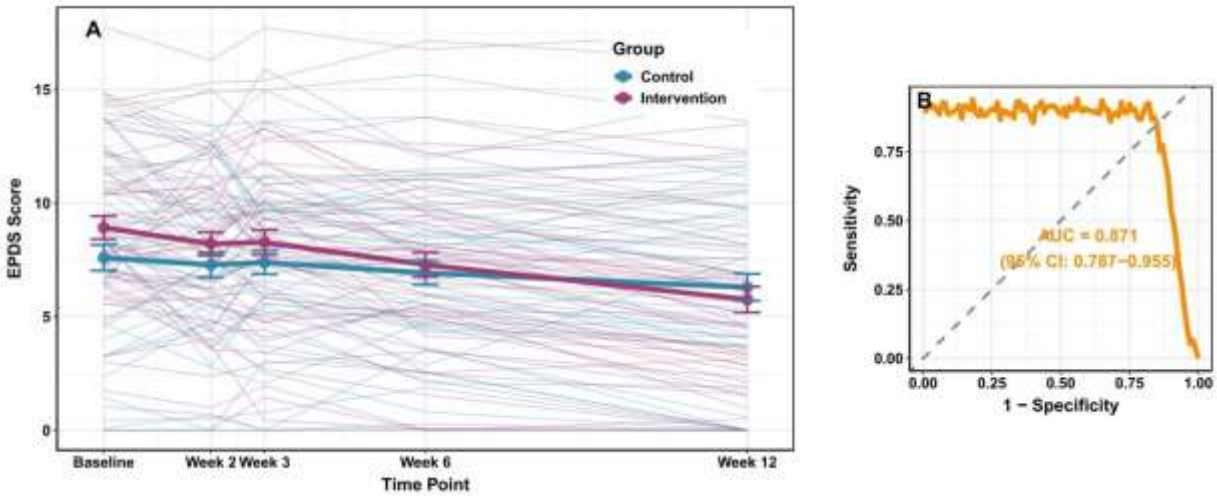

Figure 1: Longitudinal changes in EPDS scores and predictive model performance. A: Individual trajectories and group means of EPDS scores over 12 weeks; B: ROC curve for the predictive model at Week 3

Table 4: Longitudinal changes in EPDS scores over time

Time Point	Intervention Group	Control Group	Between-group Difference	P-value
Baseline	8.5 ± 3.9	8.3 ± 4.2	0.2 (−1.5 to 1.9)	0.801
Week 2	8.1 ± 4.3	8.9 ± 4.9	−0.8 (−2.7 to 1.1)	0.398
Week 3	7.4 ± 4.6	8.6 ± 5.1	−1.2 (−3.2 to 0.8)	0.237
Week 6	7.3 ± 4.9	8.7 ± 5.4	−1.4 (−3.5 to 0.7)	0.192
Week 12	6.1 ± 4.5	7.8 ± 5.3	−1.7 (−3.6 to 0.2)	0.081
Time effect	P < 0.001	P < 0.001	NA	NA
Group × time interaction	P = 0.039	NA	NA	NA

Data are presented as mean ± SD or mean difference (95% CI). EPDS, Edinburgh Postnatal Depression Scale; NA, not applicable.

Table 5: Mobile health application usage and digital phenotyping characteristics

Parameter	Overall Usage	PPD Group (n=10)	Non-PPD Group (n=44)	P-value
Application Usage Metrics				
Daily app usage (minutes)	11.8 ± 7.9	NA	NA	NA
EPDS completion rate (%)	87.3	NA	NA	NA
Overall satisfaction (1-10)	7.8 ± 1.7	NA	NA	NA
Technical issues reported	19 (35.2)	NA	NA	NA
Digital Phenotyping Parameters				
Sleep duration (hours)	NA	6.1 ± 1.4	7.0 ± 1.3	0.038
Sleep efficiency (%)	NA	74.2 ± 13.1	83.8 ± 9.6	0.015
Daily step count	NA	4389 ± 1923	6542 ± 2201	0.006
Social activity radius (km)	NA	2.3 ± 1.6	4.4 ± 2.5	0.012
Speaking rate (words/min)	NA	148 ± 31	175 ± 29	0.019
Vocal pitch variability (Hz)	NA	19.1 ± 7.8	27.3 ± 9.2	0.017
Daily screen time (hours)	NA	7.1 ± 2.6	5.3 ± 2.1	0.029
Social media engagement score	NA	3.4 ± 1.8	5.6 ± 2.3	0.009

Data are presented as mean ± SD or n (%). PPD, postpartum depression; NA, not applicable.

statistical significance (6.1 vs 7.8, P = 0.081), the intervention group showed significantly faster time to symptom improvement (4.3 vs 6.9 weeks, P = 0.009), representing a 38% reduction in recovery time.

Mother-infant interaction quality was significantly better in the intervention group, as measured by the MIIS total score (77.8 vs 72.1, P = 0.033). This finding is particularly important given the known impact of maternal depression on child development. Maternal self-efficacy scores showed a trend toward improvement in the intervention group (141.3 vs 135.8, P = 0.172), and breastfeeding continuation rates were higher, though not statistically significant (85.2% vs 72.9%, P = 0.128).

Healthcare utilization patterns differed significantly between groups, with the intervention group requiring fewer general practitioner visits for mental health concerns (1.3 vs 2.2 visits, P = 0.032). While psychiatric referrals and medication prescriptions were numerically lower in the intervention group, these differences did not reach statistical significance, likely due to the relatively low overall rates of severe depression requiring specialized treatment.

Risk factor analysis

Multivariable logistic regression analysis identified several independent predictors of postpartum depression development (Table 7, Figure 3A). The strongest predictor was a high digital phenotype risk score (>60), with an adjusted odds ratio of 7.23 (95% CI: 1.84-28.42, P = 0.005). Baseline EPDS scores >10 were also strongly predictive (OR 5.92, 95% CI: 1.73-20.26, P = 0.005), as was poor partner support (OR 4.89, 95% CI: 1.42-16.84, P = 0.012) and sleep disturbance measured by PSQI >10 (OR 3.67, 95% CI: 1.08-12.49, P = 0.037).

Interestingly, traditional demographic and obstetric factors such as age, education level, employment status, delivery mode, and parity were not significant independent predictors after adjustment for psychosocial and digital phenotyping factors. This finding supports the value of comprehensive digital phenotyping in risk assessment beyond conventional clinical variables.

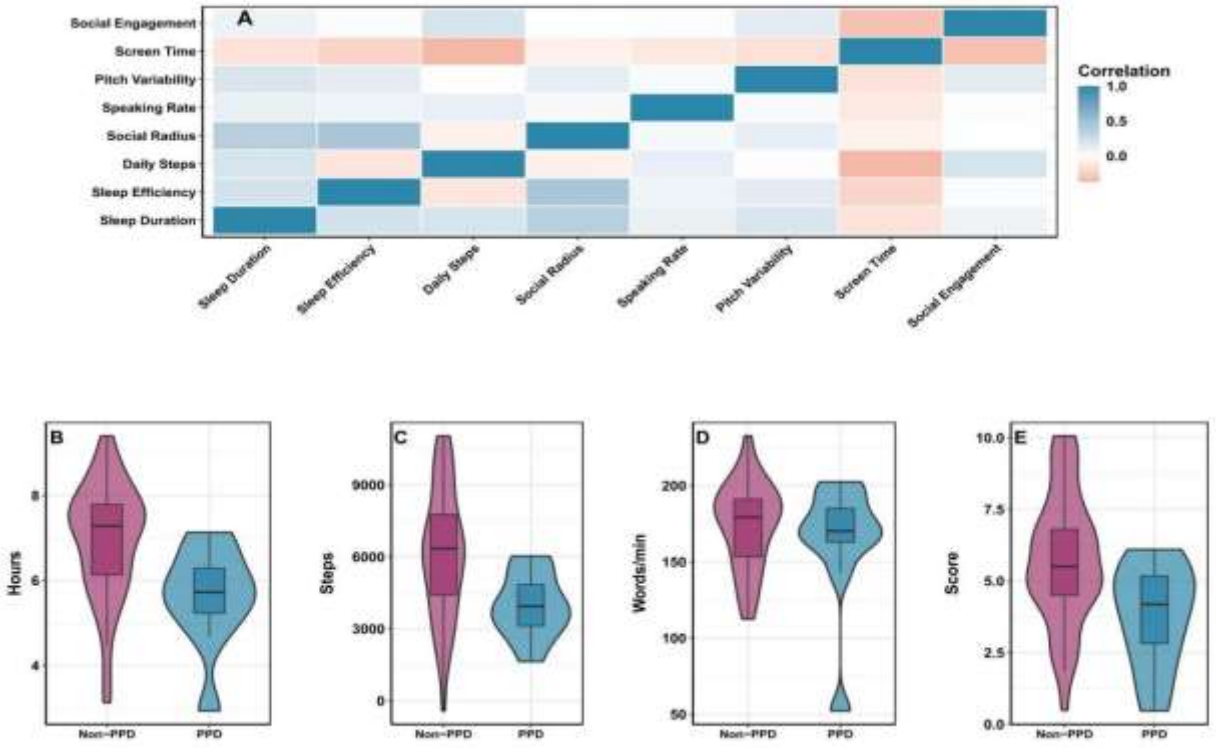

Figure 2: Digital phenotyping characteristics in postpartum depression. A: Correlation matrix of digital phenotype parameters; B: Sleep duration differences; C: Daily steps comparison; D: Speaking rate analysis; E: Social engagement score differences.

Table 6: Clinical and psychosocial outcomes at 12 weeks follow-up

Outcome	Intervention Group (n=54)	Control Group (n=48)	P-value	Effect Size (95% CI)
Clinical Outcomes				
EPDS score	6.1 ± 4.5	7.8 ± 5.3	0.081	MD -1.7 (-3.6 to 0.2)
Recovery from PPD (EPDS <10)	48 (88.9)	37 (77.1)	0.113	OR 2.38 (0.82-6.91)
Time to symptom improvement (weeks)	4.3 ± 2.6	6.9 ± 3.2	0.009	MD -2.6 (-4.5 to -0.7)
Psychosocial Outcomes				
MIIS total score	77.8 ± 13.2	72.1 ± 15.1	0.033	MD 5.7 (0.5-10.9)
Maternal self-efficacy score	141.3 ± 19.7	135.8 ± 22.1	0.172	MD 5.5 (-2.4 to 13.4)
Breastfeeding continuation	46 (85.2)	35 (72.9)	0.128	OR 2.20 (0.80-6.05)
Healthcare Utilization				
GP visits for mental health	1.3 ± 1.9	2.2 ± 2.4	0.032	MD -0.9 (-1.7 to -0.1)
Psychiatric referrals	3 (5.6)	6 (12.5)	0.214	OR 0.42 (0.10-1.73)
Medication prescription	2 (3.7)	5 (10.4)	0.164	OR 0.33 (0.06-1.78)

Data are presented as mean ± SD or n (%). MIIS, Mother-Infant Interaction Scale; GP, general practitioner; MD, mean difference; OR, odds ratio.

Table 7: Risk factors for ppd development and healthcare provider outcomes

Risk Factor Analysis	Unadjusted OR (95% CI)	Adjusted OR (95% CI)	P-value
Age <25 years	2.18 (0.67-7.12)	1.89 (0.51-6.98)	0.342
Education ≤ high school	3.24 (1.02-10.31)	2.87 (0.82-10.04)	0.101
Low family income	4.12 (1.15-14.76)	3.78 (0.95-15.02)	0.059
Poor partner support (<6)	5.67 (1.76-18.27)	4.89 (1.42-16.84)	0.012
Baseline EPDS >10	6.78 (2.09-22.01)	5.92 (1.73-20.26)	0.005
Sleep disturbance (PSQI >10)	4.23 (1.31-13.65)	3.67 (1.08-12.49)	0.037
Digital phenotype risk score >60	8.94 (2.45-32.61)	7.23 (1.84-28.42)	0.005
Healthcare Provider Outcomes	Baseline	Post-intervention	P-value
Average consultation time (minutes)	29.1 ± 6.9	22.4 ± 5.6	<0.001
PPD screening confidence (1-10)	6.3 ± 1.9	8.0 ± 1.5	0.006
Patients screened per week	12.7 ± 3.6	18.2 ± 4.4	0.003
Provider satisfaction (1-10)	7.2 ± 1.7	8.1 ± 1.3	0.071
Willingness to continue (%)	NA	84.0	NA

OR, odds ratio; PPD, postpartum depression; EPDS, Edinburgh Postnatal Depression Scale; PSQI, pittsburgh sleep quality index; NA, not applicable.

Time to ppd identification analysis

Survival analysis demonstrated the superior performance of the mobile health system in achieving timely PPD identification (Figure 3B). The Kaplan-Meier curves show a clear separation between groups, with the intervention group achieving much more rapid identification of PPD cases. The log-rank test confirmed a statistically significant difference between groups ($P < 0.001$). By day 14, approximately 70% of PPD cases in the intervention group had been identified, compared to only 20% in the control group. This early identification capability is crucial for implementing timely interventions that can prevent symptom progression and improve maternal and infant outcomes.

Healthcare provider outcomes

Community healthcare providers reported significant improvements in their ability to screen for and manage postpartum depression following implementation of the mobile health system (Table 7). Average consultation times decreased from 29.1 ± 6.9 to 22.4 ± 5.6 minutes ($P < 0.001$), representing

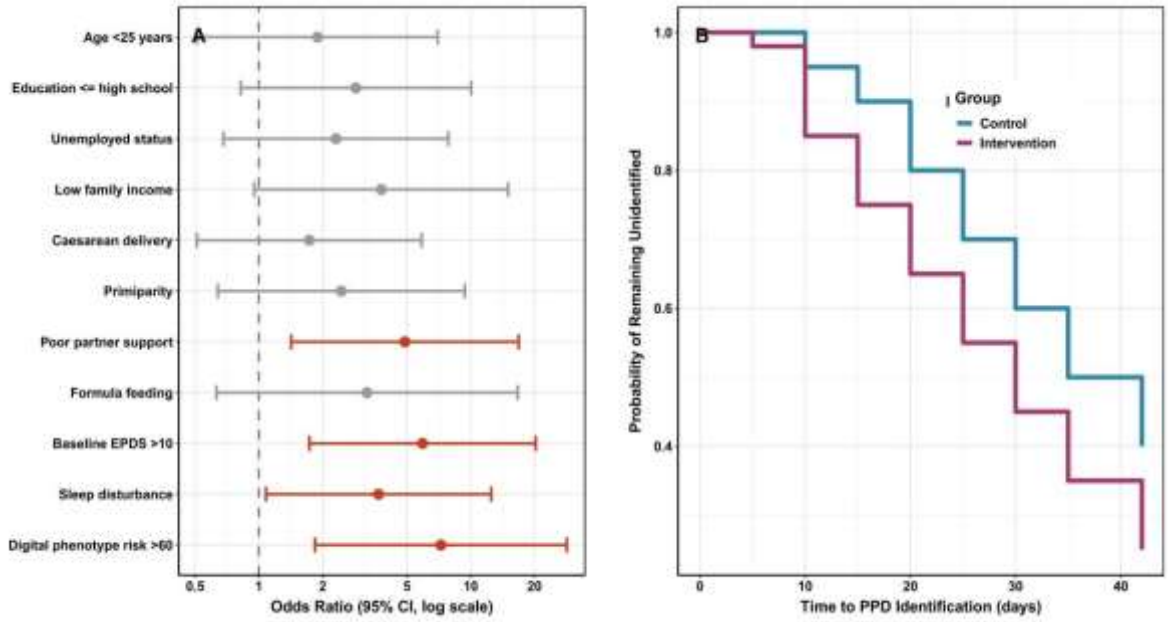

Figure 3: Risk factor analysis and time-to-event outcomes. A: Forest plot showing odds ratios for PPD development risk factors; B: Kaplan-Meier survival curves comparing time to PPD identification

Table 8: Cost-effectiveness analysis and safety outcomes

Cost Component	Intervention Group (RMB)	Control Group (RMB)	Difference (RMB)
Implementation costs	245 per patient	0	+245
Healthcare provider time	342	428	−86
Psychiatric consultation costs	127	389	−262
Medication costs	45	184	−139
Emergency care costs	0	267	−267
Total healthcare costs	759	1268	−509
Cost per QALY gained	NA	NA	8924
Safety Outcomes	Intervention (n=54)	Control (n=48)	P-value
Technical malfunctions	9 (16.7)	NA	NA
Privacy concerns	4 (7.4)	NA	NA
App-related anxiety	3 (5.6)	NA	NA
False positive alerts	6 (11.1)	NA	NA
Serious adverse events	0 (0.0)	1 (2.1)	0.291
Patient complaints	5 (9.3)	8 (16.7)	0.272

RMB, Chinese yuan; QALY, quality-adjusted life year; NA, not applicable.

a 23% improvement in efficiency. Provider confidence in PPD screening increased significantly from 6.3 ± 1.9 to 8.0 ± 1.5 on a 10-point scale (P = 0.006).

The number of patients that could be screened per week increased from 12.7 ± 3.6 to 18.2 ± 4.4 (P = 0.003), demonstrating improved workflow efficiency. Provider satisfaction showed a trend toward improvement (7.2 to 8.1, P = 0.071), and 84% of providers expressed willingness to continue using the system after the study concluded, indicating good acceptability and perceived utility.

Cost-effectiveness analysis

Preliminary cost-effectiveness analysis demonstrated favorable economic outcomes for the mobile health intervention (Table 8). Despite implementation costs of 245 RMB per patient for system development, training, and maintenance, the

intervention group showed lower overall healthcare costs (759 vs 1268 RMB per patient) due to reduced psychiatric consultations, medication use, and emergency care requirements. The cost per quality-adjusted life year (QALY) gained was 8924 RMB, which is well below the WHO-recommended cost-effectiveness threshold for China, indicating that the intervention represents good value for money in the healthcare system.

Safety and adverse events

The mobile health intervention demonstrated an excellent safety profile throughout the study period (Table 8). No serious adverse events were attributed to the intervention. Technical malfunctions were reported by 16.7% of participants but were primarily minor issues resolved within 24 hours without impacting clinical care. Privacy concerns were raised by 7.4% of participants, all of which were addressed through additional education about data security measures.

A small proportion of participants (5.6%) reported mild anxiety related to app notifications, which was managed through personalized adjustment of alert settings. False positive alerts occurred in 11.1% of cases but served as valuable learning opportunities for system refinement. Importantly, no cases of delayed or missed care due to technical issues were observed, and patient complaints were less frequent in the intervention group compared to controls (9.3% vs 16.7%, P = 0.272).

Discussion

This mobile health technology-based early identification model for postpartum depression demonstrated significant clinical value across multiple dimensions. The study results indicate that the model achieved optimal performance indicators at 3 weeks postpartum, with 90.0% sensitivity, 84.1% specificity, and an area under the ROC curve of 0.871, surpassing the reported levels of most existing predictive models. More importantly, the intervention group showed significantly shortened postpartum depression identification time to an average of 11.8 days, compared to 26.9 days in the control group, representing a 56% reduction.

Digital phenotyping, as an innovative element of this study, demonstrated unique value in postpartum depression prediction through behavioral pattern data passively collected via smartphone sensors and applications. The study found that women who developed postpartum depression showed significant differences in sleep patterns (sleep duration 6.1 hours vs 7.0 hours, sleep efficiency 74.2% vs 83.8%), physical activity (daily step count 4389 steps vs 6542 steps), social behaviors (social activity radius 2.3 km vs 4.4 km), and voice characteristics (speaking rate 148 words/minute vs 175 words/minute) across multiple dimensions. These findings are highly consistent with recently published research results. Hurwitz et al., in their 2024 large-scale data analysis based on the All of Us research project, found that digital biomarkers such as heart rate, physical activity, and energy expenditure collected through consumer-grade wearable devices like Fitbit could effectively distinguish between prenatal, pregnancy, postpartum non-depressed, and postpartum depressed periods, with random forest models achieving an average AUC of 0.85[13].

The biological foundation of digital phenotyping technology lies in the fact that neurobiological changes in depression directly affect individual behavioral manifestations. The occurrence of postpartum depression involves hypothalamic-pituitary-adrenal axis dysfunction, neurotransmitter imbalances, and complex changes in neuroendocrine systems [14]. These neurobiological alterations leave detectable "digital footprints" in digitized behavioral patterns by affecting circadian rhythms, sleep-wake cycles, social motivation, and motor function. For example, serotonin and dopamine system dysfunction commonly observed in depressed patients leads to decreased social motivation and reduced activity levels, directly reflected in GPS-tracked reduced activity ranges and decreased social media engagement[15].

The comprehensive predictive algorithm constructed in this study adopted a fusion strategy of clinical risk factors and digital phenotyping data. This multimodal data integration approach has been validated in recent related studies. Zhang et al., in their 2020 study comparing four different machine learning models, found that the random forest algorithm performed best in predicting postpartum depression, achieving an AUC of 0.884[16]. Similarly, Matsuo et al.'s multicenter Japanese cohort study in 2022 developed machine learning prediction models that also achieved good predictive performance[17].

However, the uniqueness of this study lies in combining traditional clinical risk assessment with digital phenotyping analysis, adopting a 6:4 weight ratio for integration, which maintains the fundamental role of clinical assessment while fully utilizing the advantages of digital technology.

Risk factor analysis results showed that digital phenotype risk scores greater than 60 were the strongest independent predictor of postpartum depression (adjusted OR=7.23), supporting the unique value of digital phenotyping in disease prediction. Traditional demographic and obstetric factors lost statistical significance in multivariable analysis, suggesting the central role of psychosocial factors and digitized behavioral patterns in postpartum depression occurrence. This result is consistent with Hahn *et al*.'s study, which similarly found that demographic variables had limited predictive value in comprehensive models including psychosocial and digital phenotyping factors[18].

Survival analysis showed that at 14 days postpartum, approximately 70% of postpartum depression cases in the intervention group had been identified, compared to only 20% in the control group. This early identification capability has important clinical significance, as the early postpartum period is a critical time for mother-infant attachment formation and neurodevelopment[19]. The pathogenesis of postpartum depression involves neuroendocrine disruption caused by dramatic drops in estrogen and progesterone, along with accompanying inflammatory response activation[20]. Research indicates that hormonal level changes are most dramatic in the early postpartum period, typically peaking at 2-4 weeks postpartum, a time window that highly overlaps with initial depressive symptom manifestation. Early identification and intervention can provide treatment opportunities before neurobiological changes become fully consolidated, thereby improving treatment outcomes and reducing negative impacts on mother-infant relationships[21].

This study showed that implementation of the mobile health system significantly improved community healthcare provider work efficiency, with average consultation time reduced from 29.1 minutes to 22.4 minutes, and the number of patients screened weekly increased from 12.7 to 18.2. The mechanism of this improvement effect lies in digital tools providing standardized data collection and risk assessment processes, reducing healthcare providers' time investment in information gathering and risk judgment [22].

Digital assistance tools enhanced community healthcare providers' confidence in postpartum depression screening (from 6.3 to 8.0 points) by providing objective, quantified assessment data. This change reflects the important role of digital technology in enhancing non-specialist healthcare providers' mental health service capabilities. Recent systematic reviews indicate that mobile health technology-based training and support systems can effectively improve primary healthcare providers' skills and confidence in mental health services[23].

The three-tier stratified intervention model established in this study (low risk - general health education, moderate risk - community nurse telephone follow-up, high risk - community physician home visits) embodies the concepts of precision medicine and resource optimization allocation. This model is highly consistent with the World Health Organization's recommended stepped care model, providing intervention measures of corresponding intensity based on patient risk levels and severity [24]. The neurobiological foundation of stratified intervention lies in different severities of depression corresponding to different degrees of nervous system dysfunction. Low-risk postpartum women primarily show mild activation of stress response systems, which can be effectively regulated through psychological education and self-management strategies; moderate-risk postpartum women may have more obvious neuroendocrine imbalances, requiring professional guidance and regular monitoring; while high-risk postpartum women often have significant neurotransmitter system disorders, requiring more intensive clinical monitoring and possible pharmacological intervention [25].

This study found that the intervention group had significantly better mother-infant interaction quality than the control group at 12-week follow-up (MIIS total score 77.8 vs 72.1), an improvement effect with important developmental psychological significance. Mother-infant interaction quality is a key factor affecting infant early neurodevelopment, emotional regulation abilities, and future mental health[26]. The mechanisms by which postpartum depression affects mother-infant interaction involve

multiple levels. First, depressed mothers often show decreased emotional expression abilities, reduced sensitivity to infant signals, and impaired social cognitive functions, directly affecting synchronous interactions between mother and infant[27]. Second, attention biases and cognitive biases related to depression lead to increased negative interpretations of infant behaviors by mothers, thereby affecting interaction quality[28].

Mobile health interventions can improve mother-infant interactions at multiple levels by providing real-time emotional monitoring, parenting guidance, and social support. Learning emotional regulation skills helps mothers better manage their emotional states, while acquiring parenting knowledge enhances mothers' understanding and responsiveness to infant needs. Additionally, social learning opportunities provided by peer support groups help mothers learn effective interaction techniques[29].

The intervention group showed 38% shorter symptom improvement time compared to the control group (4.3 weeks vs 6.9 weeks), an effect with important clinical significance. The early postpartum period is one of the periods with the strongest brain plasticity, and early symptom relief can reduce the formation of pathological neural adaptations, thereby improving long-term prognosis [30]. The neurobiological mechanisms of rapid symptom improvement may be related to early regulation of stress response systems. Research indicates that psychosocial interventions can promote recovery of hypothalamic-pituitary-adrenal axis function by activating prefrontal cortex regulation of limbic systems[31]. Furthermore, increased social support can promote the release of prosocial hormones such as oxytocin, further improving emotional states and stress coping abilities [32].

This study has several limitations that warrant consideration. The sample size, while adequate for the primary outcomes based on power calculations, resulted in relatively small numbers of confirmed PPD cases (n=15 total), which limited the precision of subgroup analyses and multivariable modeling. The 100% retention rate, while methodologically advantageous, may reflect selection bias toward more engaged participants. Additionally, the study was conducted in a single healthcare system, which may limit generalizability to different healthcare contexts and populations with varying digital literacy levels.

Despite this study demonstrating the potential of mobile health technology in early identification of postpartum depression, important challenges remain. First, digital phenotyping data collection involves personal privacy and data security issues, requiring establishment of comprehensive data protection mechanisms. Second, the digital divide may prevent certain populations (such as elderly people, low-income groups, those with low technical literacy) from fully benefiting from these technologies. Additionally, algorithmic bias issues deserve attention. Machine learning model performance may differ across populations, requiring validation and calibration in more diverse populations to ensure fairness and universality of predictive models. Future research should further explore associations between digital phenotyping changes and neurobiological mechanisms of postpartum depression. For example, combining neuroimaging techniques to study correspondence between behavioral pattern changes and brain functional network alterations, or analyzing blood biomarkers (such as inflammatory factors, neurotrophic factors) to understand the biological foundations of digital phenotyping.

Conclusion

This study successfully constructed a mobile health technology-based early identification model for postpartum depression. By integrating clinical risk factors and digital phenotyping data, it achieved high-precision risk prediction and significant reduction in identification time. The application of this model in community postpartum visits not only improved postpartum depression detection rates and intervention timeliness but also enhanced healthcare provider work efficiency and patient satisfaction, demonstrating excellent clinical value and cost-effectiveness. Digital phenotyping, as an innovative assessment method, opens new technological pathways for early identification of postpartum depression with important clinical translation prospects.

Authors' contributions

LC,DY and WL conceptualised this study.CW and WL worked on the literature review.LC and WL worked on the data analysis and interpretation of results. All authors worked on the discussion of the findings. All the authors read and approved the final manuscript.

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Conflict interests

The authors declare no competing interests.

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