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PE-CARE: An Artificial Intelligence (AI)-Based Mobile Health Application to Improve Maternal Knowledge of Early Preeclampsia Detection – A Quasi-Experimental Study

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ABSTRACT

Background: Preeclampsia remains a leading cause of maternal mortality worldwide, yet awareness and early detection remain limited in low- and middle-income countries. While artificial intelligence (AI)-based applications have been increasingly utilized in hospital settings, their adoption in Indonesian primary care remains minimal. This study aimed to evaluate the effectiveness of an AI-based mobile health application (PE-CARE) in improving maternal knowledge on early detection of preeclampsia. **Methods:** A quasi-experimental pretest–posttest control group design was conducted at Puskesmas Parongpong, West Bandung Regency, from February to March 2025. A total of 100 pregnant women (≤20 weeks gestation) were recruited using purposive sampling and assigned equally to the intervention (n=50) and control (n=50) groups. The intervention group used the PE-CARE application for 14 days, while the control group received conventional health education. Knowledge was assessed using a validated 15-item questionnaire. Data were analyzed using paired and independent t-tests, complemented by effect size (Cohen's d) and 95% confidence intervals. **Results**: Knowledge scores improved significantly in both groups, with a larger gain in the intervention group (mean difference 28.1; Cohen's d=3.79, 95% CI 25.7–30.5, p<0.001) compared to the control group (mean difference 11.5; Cohen's d=1.56, 95% CI 9.3–13.7, p<0.001). Between-group comparison of posttest scores confirmed a significant effect favoring the intervention (mean difference 21.3; Cohen's d=4.05, 95% CI 18.8–24.8, p<0.001). **Conclusion**: The PE-CARE application was effective in improving maternal knowledge of preeclampsia in a primary care setting. While these findings demonstrate the potential of AI-based mobile health tools to complement antenatal education, further research is needed to evaluate long-term behavioral and clinical outcomes as well as implementation feasibility in diverse primary care contexts.

INTRODUCTION

Maternal mortality remains a critical global health challenge (Geller et al., 2018; Joseph et al., 2021; Souza et al., 2024). In 2020, the World Health Organization (WHO) reported approximately 295,000 maternal deaths, with more than 90% occurring in low- and middle-income countries (WHO, 2025). Indonesia has shown a gradual decline in the maternal mortality ratio (MMR)—from 390 per 100,000 live births in 1991 to 189 in

2020—yet this figure remains far from the Sustainable Development Goal (SDG) target of 70 by 2030 (Ministry of Health of the Republic of Indonesia, 2023). Recent national data even suggest a worrying rise in maternal deaths (BPS, 2023).

Preeclampsia is one of the leading causes of maternal mortality, accounting for approximately 13% of maternal deaths in Indonesia (Profil Kesehatan Indonesia, 2023). In West Java Province, the prevalence is estimated at 4–5% of deliveries, with similar patterns reported in Bandung Regency (Dinkes Jabar, 2023). At the community level, many cases are detected late, often during the third trimester, especially among women with limited access to antenatal care, underscoring the need for improved maternal awareness and early detection at the primary care level (Atluri et al., 2023; Firoz et al., 2011; Hernawati et al., 2024; Salam et al., 2015).

Digital health innovations, specifically mobile health (mHealth) applications guided by artificial intelligence (AI), are showing promise (Alkhodari et al., 2023; Sharma & Kaur, 2017). For instance, a controlled study in Iran found that a mobile app significantly improved pregnant women’s knowledge of preeclampsia (Parsa et al., 2019). On the diagnostic front, AI models based on ECG data achieved robust prediction of preeclampsia with areas under the curve (AUCs) between 0.81 and 0.92, suggesting feasibility for future wearable sensor integration (Butler et al., 2024). Additionally, other AI-based prediction models leveraging clinical and omics data showed high accuracy and early risk detection potential (Bülez et al., 2024; Liu et al., 2024; Owoche et al., 2025; Vijayan et al., 2021).

However, these applications largely target healthcare providers or rely on hospital-derived datasets. Few are designed for pregnant women's self-use in low-resource or primary care settings. In Indonesia, the adoption of AI in maternal health remains minimal due to contextual barriers such as limited digital literacy, unequal technology access, weak infrastructure in Puskesmas, fragmented health data systems, privacy/regulatory concerns, and trust issue (Ahmed et al., 2023; Hassan et al., 2024).

Currently, no study has evaluated an AI-based mobile tool aimed at improving maternal knowledge and self-screening for preeclampsia within Indonesian primary care settings. Therefore, this study aims to assess the effectiveness of **PE-CARE**, an AI-based mHealth application, in enhancing knowledge of early preeclampsia detection among pregnant women ≤20 weeks of gestation.

METHODS

Study Design and Setting

This study used a quasi-experimental design with a pretest–posttest control group approach. The research was conducted at Puskesmas Parongpong, West Bandung Regency, from February to March 2025.

Participants and Sampling

The study population consisted of pregnant women with gestational age ≤20 weeks who attended antenatal care at Puskesmas Parongpong. A total of 100 participants were recruited and allocated equally to the intervention group (n=50) and control group (n=50). The sample size was determined using Slovin’s formula with a 5% margin of error, based on the estimated number of pregnant women in the study area, resulting in a minimum sample of 100. Sampling was conducted purposively based on inclusion and exclusion criteria. Inclusion criteria were: (1) pregnant women in the first or early second trimester (≤20 weeks), (2) ability to read and write, (3) ownership of an Android smartphone, and (4) willingness to participate for the full duration of the study. Exclusion criteria were pre-existing chronic illnesses or pregnancy complications unrelated to preeclampsia. We acknowledge that purposive sampling limits the generalizability of findings.

Intervention

The intervention group was provided access to the PE-CARE application, an AI-based mobile health tool developed to improve maternal knowledge of early preeclampsia detection. The application contained information on definitions, risk factors, symptoms, prevention strategies, and a self-assessment feature. Participants were instructed to actively use the application for 14 consecutive days. Usage compliance was encouraged through verbal reminders and monitored using self-reported daily logs and in-app activity tracking. The control group received conventional health education delivered by midwives through leaflets and verbal counseling.

Instruments

Maternal knowledge was measured using a 15-item multiple-choice questionnaire covering key domains of preeclampsia (definition, signs and symptoms, risk factors, preventive measures, and appropriate responses). The instrument was adapted from previously validated studies and underwent expert review by three maternal health specialists. A pilot test was conducted with 20 pregnant women at a different health center to ensure clarity and cultural relevance. Validity testing showed r-values >0.468, while reliability analysis yielded Cronbach's alpha of 0.807, indicating good internal consistency.

Data Collection Procedure

The study flow included: (1) recruitment and eligibility screening during antenatal visits, (2) obtaining written informed consent, (3) pretest administration (approximately 15 minutes), (4) delivery of intervention (PE-CARE) or conventional education, and (5) posttest after 14 days using the same instrument. Basic maternal vital signs (blood pressure, pulse, temperature, oxygen saturation) were also recorded during data collection.

Digital Literacy Considerations

Although smartphone ownership was required, digital literacy levels of participants were not formally assessed. Given that many respondents had elementary-level education, digital literacy may have influenced their ability to navigate the application, and this is recognized as a limitation.

Bias Reduction

Blinding of participants was not feasible due to the nature of the intervention. However, data collectors and outcome assessors were not involved in delivering the intervention, thereby reducing the risk of observer bias.

Data Analysis

Data were analyzed using SPSS version 26.0. Descriptive statistics summarized participant characteristics. Paired t-tests were applied to compare pretest and posttest scores within groups, while independent t-tests compared mean differences between groups. Effect sizes (Cohen's d) and 95% confidence intervals were calculated to complement p-values and provide a more robust interpretation of knowledge changes. A p-value <0.05 was considered statistically significant.

RESULTS

A total of 100 pregnant women participated in this study, with 50 assigned to the intervention group and 50 to the control group. All participants completed both pretest and posttest assessments.

Characteristics of Respondents

Table 1 presents the demographic characteristics of the participants. Most respondents in both groups were aged 21–35 years, had elementary-level education, and were not working (housewives).

Table 1. Characteristics of Respondents (n = 100)

Variables	Category	Intervention (n=50)	Control (n=50)	Total (n=100)
Age (years)	21–35	42 (84.0%)	40 (80.0%)	82 (82.0%)
	>35	8 (16.0%)	10 (20.0%)	18 (18.0%)
Education	Elementary (SD)	20 (40.0%)	35 (70.0%)	55 (55.0%)
	Junior High (SMP)	5 (10.0%)	4 (8.0%)	9 (9.0%)
	Senior High (SMA)	18 (36.0%)	9 (18.0%)	27 (27.0%)
	College/Univ.	7 (14.0%)	2 (4.0%)	9 (9.0%)
Occupation	Not working	48 (96.0%)	50 (100.0%)	98 (98.0%)
	Working	2 (4.0%)	0 (0.0%)	2 (2.0%)

Knowledge Scores Before and After Intervention

Knowledge levels were measured before and after the 14-day intervention. In the intervention group, the mean score increased from 43.80 (SD = 8.50) to 71.90 (SD = 5.30), representing a mean difference of 28.10 points (Cohen's d = 3.79, 95% CI [25.7–30.5], p<0.001). In the control group, the mean score increased from 39.10 (SD = 8.10) to 50.60 (SD = 6.20), with a mean difference of 11.50 points (Cohen's d = 1.56, 95% CI [9.3–13.7], p<0.001).

Table 2. Knowledge Scores Before and After Intervention (n=100)

Group	Pretest Mean (SD)	Posttest Mean (SD)	Mean Difference	% Increase	Cohen's d	95% CI	p-value
Intervention	43.80 (8.50)	71.90 (5.30)	28.10	64.15%	3.79	25.7–30.5	<0.001*
Control	39.10 (8.10)	50.60 (6.20)	11.50	29.43%	1.56	9.3–13.7	<0.001*

Between-Group Comparison of Posttest Scores

Independent t-test analysis demonstrated a significant difference in posttest scores between groups. The intervention group achieved a higher mean score compared to the control group (71.90 vs 50.60, p<0.001, Cohen's d = 4.05, 95% CI [18.8–24.8]).

Table 3. Independent t-Test Comparison of Posttest Scores

Group	Posttest Mean (SD)	p-value	Cohen's d	95% CI
Intervention	71.90 (5.30)	<0.001*	4.05	18.8–24.8
Control	50.60 (6.20)			

Item-Level Knowledge Gains

Analysis of correct responses across the 15 items showed substantial improvements in the intervention group, particularly on items related to clinical parameters (e.g., blood pressure thresholds, role of proteinuria) and preventive behaviors.

Table 4. Correct Answers on Knowledge Items Before and After Intervention (n = 100)

No	Knowledge Item (Simplified)	Pretest n (%)	Posttest n (%)
1	Definition of preeclampsia	52 (52.0%)	90 (90.0%)
2	Early signDs of preeclampsia	56 (56.0%)	91 (91.0%)
3	Risk factors (e.g., age, parity)	50 (50.0%)	86 (86.0%)
4	Blood pressure criteria (≥140/90 mmHg)	44 (44.0%)	83 (83.0%)
5	Importance of routine ANC	60 (60.0%)	94 (94.0%)
6	Role of proteinuria in diagnosis	48 (48.0%)	85 (85.0%)
7	Symptoms that require immediate referral	52 (52.0%)	88 (88.0%)
8	Preventive behaviors	46 (46.0%)	89 (89.0%)
9	Nutrition support and calcium intake	42 (42.0%)	84 (84.0%)
10	Safe medications during pregnancy	38 (38.0%)	81 (81.0%)
11	When to seek emergency care	64 (64.0%)	95 (95.0%)
12	Monitoring blood pressure at home	56 (56.0%)	90 (90.0%)
13	Lifestyle changes	54 (54.0%)	92 (92.0%)
14	Consequences of untreated preeclampsia	50 (50.0%)	88 (88.0%)
15	Delivery planning in preeclamptic cases	52 (52.0%)	89 (89.0%)

DISCUSSION

This study demonstrated that the PE-CARE application, an AI-based mobile health tool, significantly improved maternal knowledge regarding early preeclampsia detection compared to conventional health education. The observed knowledge gain was not only statistically significant but also practically meaningful, with a large effect size. These findings suggest that digital innovations can serve as a promising complement to existing antenatal education strategies in primary care.

From a theoretical perspective, the results can be interpreted through several behavior change frameworks. According to Social Cognitive Theory (SCT), self-efficacy plays a critical role in influencing health-related behaviors. By providing structured content, real-time self-assessment, and feedback, PE-CARE may have strengthened women's confidence in recognizing signs of preeclampsia (Bandura, 2001). In line with the Health Belief Model (HBM), the application likely increased perceived susceptibility and severity by clearly presenting risks and symptoms, thereby motivating greater attentiveness to maternal health (Champion & Skinner, 2008). Moreover, the concise and visual format of the content aligns with Cognitive Load Theory, which facilitates comprehension and retention, particularly among participants with lower educational backgrounds (Paas & Ayres, 2014).

The findings align with previous studies reporting the feasibility of mobile or AI-assisted applications in improving maternal knowledge and awareness. For example, Alkhodari et al. (2023) and Sharma et al. (2024) showed that AI integration supports timely identification of preeclampsia risk factors. However, most prior applications were designed for healthcare providers, not for direct maternal use. In this respect, PE-CARE adds novelty by being developed specifically for pregnant women in a community-based setting, highlighting the potential of self-directed digital education.

Despite these positive outcomes, several challenges remain. Knowledge improvement does not necessarily translate into sustained behavior change or improved clinical outcomes. Barriers to digital health adoption in Indonesia must also be considered, including limited digital literacy among mothers, unequal smartphone and internet access, infrastructure constraints at Puskesmas, and the absence of formal regulatory frameworks for AI integration into primary care. Addressing these barriers will be critical for scaling such interventions.

This study has limitations. First, purposive sampling restricts generalizability beyond the study population. Second, the intervention lasted only 14 days, limiting conclusions about long-term knowledge retention or behavior change. Third, digital literacy was not formally assessed, although it may have influenced participants' engagement with the application. Fourth, subgroup analyses (e.g., based on education or age) were not conducted, which may have provided additional insights. Finally, the study measured only knowledge outcomes, not clinical or behavioral endpoints.

Future research should evaluate longer follow-up periods, integrate multimedia features to enhance comprehension, and assess behavioral and clinical outcomes such as ANC attendance, timely referrals, or reduced preeclampsia complications. Exploring strategies for integrating PE-CARE into national maternal health programs and training midwives or health cadres to support its use may further strengthen its impact.

CONCLUSION

This study demonstrated that the PE-CARE application—an AI-based mobile health tool—was effective in improving maternal knowledge regarding early detection of preeclampsia among pregnant women in a primary care setting. Participants who used the application showed a significantly greater increase in knowledge scores compared to those who received conventional education. While these findings highlight the potential of PE-CARE as an educational support tool for maternal health, it is important to note that the study measured only knowledge outcomes. Further research is needed to determine whether knowledge gains translate into behavioral changes or improved clinical outcomes.

Future development of the PE-CARE application should focus on integrating multimedia content, voice guidance, and user-friendly features to enhance accessibility, especially for women with lower literacy. Training for midwives and health cadres is also recommended to facilitate implementation at the primary care level. However, broader adoption will require addressing contextual barriers such as digital literacy gaps, infrastructure limitations, and the absence of clear regulatory guidelines. With these considerations, PE-CARE may contribute meaningfully to strengthening maternal health education in Indonesia.

Author's Contribution Statement: Erni Hernawati contributed to the conception and design of the study, data collection, data analysis, manuscript drafting, and overall supervision. **Firsha Ilvany Mutiara** contributed to literature review, collaboration with the IT team for application development, and instrument testing. **Sofa Nurul Hidayati** contributed to the initial manuscript drafting, and the submission process. All authors have read and approved the final version of the manuscript.

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