MindCare: An Innovative Application for Depression Diagnosis and Treatment Support

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***Abstract*—Depression screening remains challenging due to reliance on subjective assessments and limited accessibility of mental health services. This paper presents MindCare, an integrated mobile platform combining standardized questionnaires, AI-powered therapeutic interactions, emotional journaling, and EEG-based neurophysiological assessment. The system implements a novel visual stimulation protocol using 60 emotionally evocative images from the Open Affective Standardized Image Set (OASIS) to elicit measurable neural responses. User evaluation with 7 participants demonstrated high satisfaction across all features. EEG analysis of 4 participants during emotional stimulation revealed strong correlations between frontal channel neural features and PHQ-9 depression scores. Machine learning classification achieved 97.9% accuracy in distinguishing depression status using segment-based analysis of 240 stimulus-response pairs. The integration of objective neurophysiological markers with subjective assessment tools demonstrates significant potential for enhancing digital mental health screening capabilities.**

***Index Terms*—depression screening, EEG biomarkers, mobile health applications, artificial intelligence, digital therapeutics**

I. Introduction

Depression affects over 322 million people worldwide, representing the leading cause of disability globally [1], with healthcare costs exceeding $210 billion annually in the United States [2]. Traditional assessment relies on clinical interviews and questionnaires such as the PHQ-9 [3], but suffers from subjective bias and limited accessibility [4] [5]. The global shortage of mental health professionals further restricts access to timely diagnosis [6] [7].

Existing digital mental health solutions offer promising assessment avenues, but primarily focus on single-modality approaches [8]. Popular depression screening applications such as Moodpath rely exclusively on self-reported questionnaires, lacking objective validation [9]. Current EEG-based depression detection systems typically operate in controlled laboratory settings with limited real-world applicability [10]. Large language models also demonstrate therapeutic potential through empathetic interactions, but remain isolated from comprehensive assessment frameworks [11].

This study develops an integrated platform combining multiple assessment modalities: questionnaire-based assessment, AI-powered therapist, emotional journaling, and EEG-based stimulation. Our objectives are to: (1) develop a comprehensive mobile application integrating these components; (2) evaluate user acceptance; (3) investigate correlations between EEG features and depression severity; and (4) assess EEG-based depression classification feasibility.

II. Methodology

MindCare implements a client-server architecture with Flutter-based mobile application and AWS cloud backend. The mobile app handles local data processing, user interactions, while AWS services manage user authentication, data storage (DynamoDB), and cloud analytics [12] [13]. The system integrates five core modules: assessment, emotional journaling, AI-powered virtual therapist, EEG visual stimulation and reporting, as illustrated in Figure 1.

A. Core Module Implementation

Assessment Module: Implements the validated PHQ-9 questionnaire following standard clinical protocols [3]. The backend employs DynamoDB for historical data storage with automatic timestamp indexing. Scoring algorithms calculate severity classification in real-time using weighted response values.

Virtual Therapist: Leverages Qwen-2.5-7B model with specialized therapeutic prompt engineering. API communication employs asynchronous processing with local message queuing to ensure application responsiveness during model inference. The implementation includes the technical features in Table I.

TABLE I: Key Features of the Conversational Interface

Feature	Description
Asynchronous message processing	Maintains application responsiveness during API communication
Conversation persistence	Enables message history management for continuity of care
Markdown rendering	Supports formatted therapeutic responses including structured advice and psychoeducational content
Visual status indicators	Communicates processing state to enhance user experience

Journaling Module: Implements evidence-based expressive writing protocols with structured emotional data capture [14].

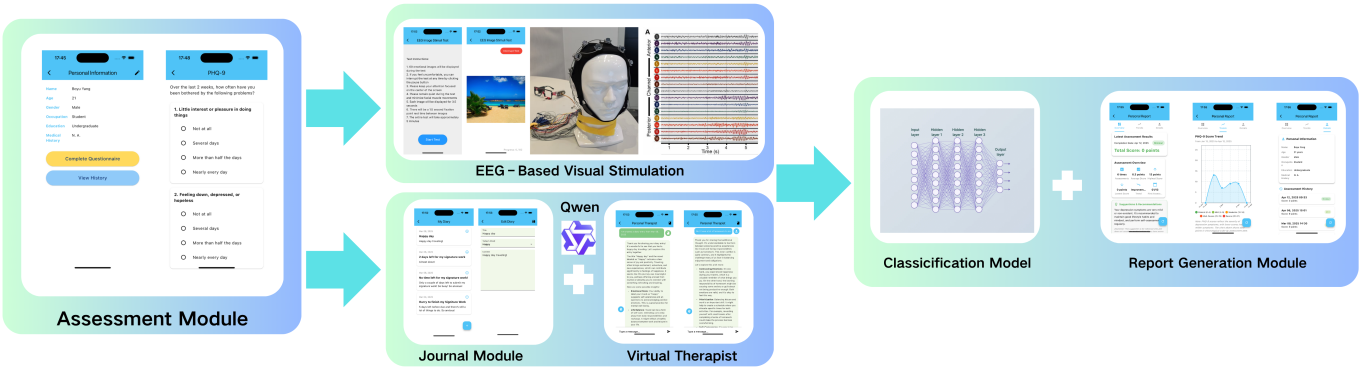


Fig. 1: MindCare system workflow showing integrated modular architecture. Users progress through Assessment (PHQ-9), Journal, and Virtual Therapist modules. EEG Visual Stimulation provides neurophysiological data for machine learning classification, with all data converging in the Report Generation Module.

The system employs real-time data validation and automatic cloud synchronization. Emotional state classification uses predefined categorical mapping for quantitative trend analysis.

EEG Stimulation Protocol: Presents 60 carefully selected OASIS images alternating between high and low emotional valence [15]. Each stimulus displays for 3.5 seconds with 1.5-second inter-stimulus intervals, totaling 5 minutes with precise timestamp recording for external EEG synchronization.

Report Generation Module: Synthesizes assessment data through multi-layered analytics including summary overviews, temporal trend visualization via interactive time-series representations, and comprehensive profile integration. Statistical techniques include descriptive analysis, linear regression for symptom trajectories, and severity threshold categorization based on validated clinical standards.

B. User Interface and Interaction Flow

The MindCare application guides users through a structured mental health assessment workflow designed for intuitive navigation and clinical validity. Users enter through a streamlined onboarding process requiring only essential demographic information, with the main dashboard displaying five module cards in recommended sequence. The PHQ-9 assessment presents questions with clear 4-point scale labels, allowing backward navigation with response persistence to prevent data loss. Upon completion, immediate visual feedback presents severity classification using color coding (green=minimal, yellow=mild, orange=moderate, red=severe) accompanied by contextual explanations. The therapeutic chat interface provides familiar messaging experience with differentiated message styling, enabling users to initiate conversations through free text and share journal entries directly with the virtual therapist for contextual discussions. The journaling experience follows a three-step process beginning with optional title creation, followed by emoji-based mood selection for immediate emotional validation, and a free-text area with subtle prompts to encourage meaningful reflection. EEG testing begins with clear preparation instructions, using a prominent "Start Testing" button to initiate full-screen mode with minimal interface elements. Progress indication (image X/60) appears briefly without causing distraction, while inter-stimulus fixation crosses maintain attention between emotional stimuli. The reporting interface presents summary cards with key metrics and actionable insights, complemented by trend visualization for quick visual assessment of progress direction.

C. Data Collection

Participants were recruited from Duke Kunshan University through questionnaire-based screening. A total of 7 students (4 males, 3 females) aged 18-25 years participated in the study. All participants provided informed consent before engaging in any experimental procedures. The protocol included 20-minute app exploration followed by EEG recording for 4 participants using OpenBCI Cyton + Daisy with standard 10-20 electrode placement.

EEG signals were recorded at 125 Hz using OpenBCI GUI software. Participants viewed 60 alternating high and low emotional valence images (30 each). Application logs provided precise timing synchronization between stimulus presentation and EEG recording.

Following completion of both experimental phases, participants completed a comprehensive questionnaire addressing multiple dimensions of the application experience. The assessment instrument included both demographic information (gender and age group) and a series of experience ratings using 5-point Likert scales.

D. Data Processing

Raw EEG data were bandpass filtered (1-50 Hz, 5th order Butterworth) and segmented into epochs from -0.2 to 3.5 seconds relative to stimulus onset, with baseline correction applied to the pre-stimulus interval.

Channels 1, 6, 7, and 8 were selected based on their correspondence to frontal-central brain regions, which are associated with emotional processing and depression-related neural activity [10].

Time-domain features (mean, standard deviation, peak-to-peak amplitude, skewness, kurtosis) and frequency-domain features (power spectral density using Welch's method) were extracted from each channel. Spectral power was computed for five frequency bands: delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-45 Hz).

Reactivity metrics were calculated between high and low emotional valence conditions, including band power ratios and amplitude differences.

E. Statistical Analysis

Participants were categorized into higher (PHQ-9 $\geq$ 10) and lower (PHQ-9 $<$ 10) depression groups. Pearson correlations were computed between EEG features and PHQ-9 scores. To address limited sample size, a segment-based approach treated each stimulus-response pair as an independent sample, expanding the dataset from 4 participants to 240 stimulus-specific observations while preserving the participant-depression score relationship. Machine learning classification was performed using time-domain and frequency-domain features from channels 1, 6, 7, and 8, with separate analyses for high and low emotional valence stimuli. Cross-validation ensured robust performance evaluation.

Table II presents the structure of features and labels used in the classification analysis.

TABLE II: Machine Learning Training Structure

Component	Type	Description
Features	Time-domain	Std dev, mean, peak-to-peak from CH 1,6,7,8[a]
	Frequency	Power in 5 bands[b]
	Stimulus	High/low valence separation
Labels	High dep.	PHQ-9 $\geq$ 10
	Low dep.	PHQ-9 $<$ 10

[a] Includes max and min values.
[b] Delta, theta, alpha, beta, gamma.

III. RESULTS

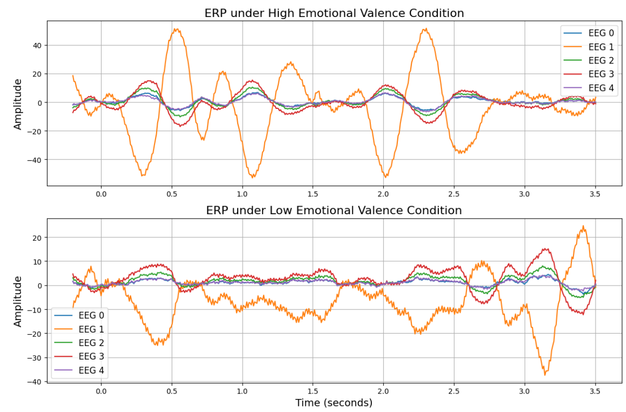
A. User Experience

User satisfaction ratings were consistently high across all evaluated features, with average scores ranging from 4.0 to 4.4 on the 5-point Likert scale. The AI therapist interaction received the highest rating (4.4), while core application features including overall impression, registration, assessments, and therapeutic benefit were rated at 4.1. The journal feature received a rating of 4.0. These results indicate high user acceptance and satisfaction with the MindCare application across all evaluated dimensions.

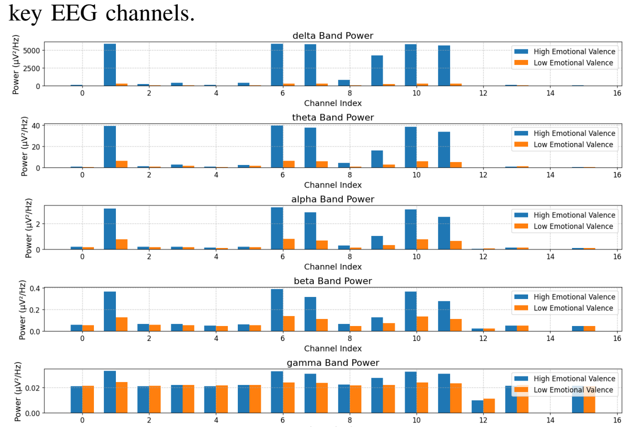
B. Neurophysiological Responses

The analysis of EEG data collected during the visual stimulation protocol revealed distinct patterns of neural activity in response to emotional stimuli. Event-related potential (ERP) analysis showed clear differences in neural responses between high and low emotional valence conditions, with high emotional valence stimuli eliciting stronger amplitude variations compared to low emotional valence stimuli, particularly in frontal channels. This different response was most pronounced between 0.5 and 2.5 seconds post-stimulus, suggesting sustained emotional processing during stimulus presentation.

Complementary spectral analysis revealed frequency-specific differences in neural activity across emotional valence conditions. The distribution of power across frequency bands showed notably higher power in delta and theta bands during high emotional valence stimuli compared to low emotional valence stimuli. This pattern was particularly evident in channels 1, 6, and 7, suggesting these electrode locations may be most sensitive to emotional content. As illustrated in Figure 2, both temporal dynamics and frequency characteristics demonstrate consistent patterns of enhanced neural activity in response to high emotional valence stimuli.



(a) Event-related potentials showing differential neural responses to high versus low emotional valence stimuli across key EEG channels.



(b) Frequency band power distribution comparing neural oscillatory activity between high and low emotional valence conditions.

Fig. 2: Neurophysiological responses to emotional stimuli: (a) temporal dynamics through event-related potentials and (b) frequency-domain analysis of neural oscillatory activity.

C. Depression Correlations

The correlation analysis between EEG features and PHQ-9 depression scores yielded several significant relationships. Figure 3 presents the correlation heatmap highlighting the strongest associations between neural features and depression severity. Standard deviation measures from channels 1, 6, and 7 showed particularly strong correlations with PHQ-9 scores (r = 0.87, 0.77, and 0.67, respectively), suggesting that variability in neural response may be a sensitive marker of depression severity.

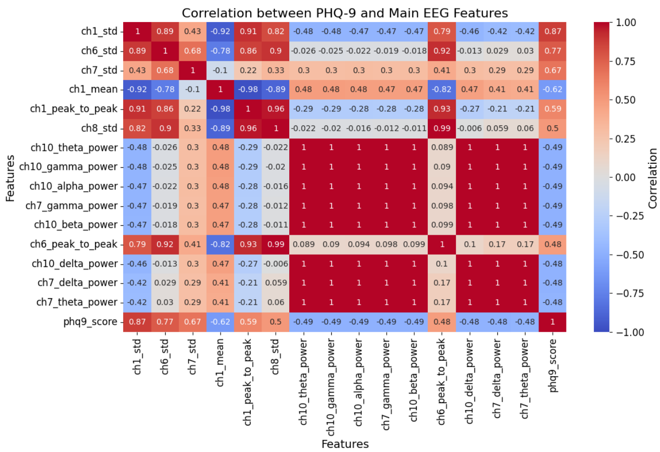


Fig. 3: Correlation heatmap displaying relationships between EEG features and PHQ-9 depression scores.

D. Classification Performance

The machine learning analysis demonstrated the feasibility of using EEG responses to emotional stimuli for depression screening. The classification model achieved remarkable accuracy in distinguishing between participants with higher and lower depression symptoms. Figure 4 shows the confusion matrix for this classification, with minimal misclassification errors.

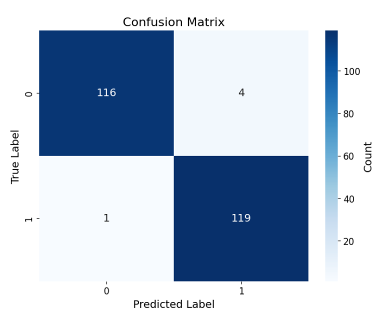


Fig. 4: Confusion matrix for depression classification model showing high accuracy in distinguishing between high and low depression groups.

Separate analyses for high and low emotional valence stimuli indicated that both stimulus types provided valuable information for depression classification. The models achieved 95.8% accuracy using high emotional valence stimuli and 96.7% accuracy using low emotional valence stimuli. This suggests that the MindCare application's visual stimulation protocol effectively captures depression-relevant neural markers regardless of stimulus emotional content, though with slightly better performance for low emotional valence stimuli.

IV. Conclusion

MindCare successfully demonstrates the integration of subjective assessment tools with objective neurophysiological markers for comprehensive depression screening. The platform addresses critical limitations of existing digital mental health solutions by combining validated questionnaires, AI-powered therapy, structured journaling, and EEG-based assessment within a single, user-friendly interface.

The strong correlations between frontal EEG features and clinical depression scores, combined with high classification accuracy, support the incorporation of neural biomarkers into digital mental health tools. While the limited sample size (n=4 for EEG analysis) requires validation through larger studies, this integrated approach demonstrates significant potential for enhancing both the accuracy and accessibility of depression screening while providing continuous therapeutic support.

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