

Tabular Prior-Data Fitted Networks for Objective Depression Screening with Portable EEG and ECG

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Submitted to: JMIR Mental Health
on: September 11, 2025

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Abstract

Background: Major depressive disorder (MDD) is a prevalent and debilitating psychiatric condition; however, early detection remains challenging due to reliance on subjective assessments. There is a critical need for scalable, objective tools to facilitate timely screening and intervention.

Objective: To evaluate a portable multimodal system that combines single-channel Electroencephalogram (EEG) and Electrocardiogram (ECG) for rapid assessment of depression in real-world settings, including its utility for depression screening and severity prediction.

Methods: We collected data recorded with a portable EEG-ECG system under four standardized conditions: eyes?open rest, eyes?closed rest, negative?emotion image viewing, and a structured interview. To identify the MDD biomarkers, we derived standard heart rate variability (HRV) indices from ECG and computed power spectral density (PSD) features using EEG. Besides, brain-heart coupling was quantified by calculating the correlation between EEG and ECG. A state-of-the-art tabular prior-data fitted network machine?learning model (TabPFN) was trained with leave-one-out cross-validation to (1) classify MDD versus HC using three input sets (EEG?only, ECG?only, and fused EEG and ECG) and (2) predict depression severity indexed by Hamilton Depression Rating Scale (HAMD?24) scores. Furthermore, permutation feature importance was used to interpret the contribution of PSD and HRV features.

Results: Fifty-six participants including 26 clinical diagnosed MDD and 30 healthy controls (HC) were included in this study. Relative to HC group, the MDD group showed consistent HRV alterations and disrupted brain-heart coupling, most pronounced during negative-emotion tasks, suggesting impaired central-autonomic regulation. ECG-only models demonstrated strong discrimination, while fused EEG and ECG achieved the highest cross-validated accuracy of 80.4% (area under the curve, AUC: 0.712). For severity estimation, multimodal physiological features predicted HAMD-24 ($r = 0.659$; $P < .001$). Permutation importance consistently prioritized signals from the Interview conditions and HRV reactivity between rest and task conditions.

Conclusions: These findings establish brain-heart biomarkers as a practical and objective basis for depression screening and severity prediction. The proposed portable system offers a promising step toward scalable, precise mental health assessment with potential applications in primary care and community settings.

(JMIR Preprints 11/09/2025:83931)

DOI: <https://doi.org/10.2196/preprints.83931>

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Conclusions: These findings establish brain–heart biomarkers as a practical and objective basis for depression screening and severity prediction. The proposed portable system offers a promising step toward scalable, precise mental health assessment with potential applications in primary care and community settings.

Keywords: major depressive disorder; electroencephalography; electrocardiography; heart rate variability; real-world data; brain-heart coupling; multimodal biomarker; machine learning; wearable portable electronic devices; mental health

Introduction

Major depressive disorder (MDD) is a highly prevalent and disabling psychiatric illness, characterized by persistent low mood, anhedonia, and significant impairments in daily functioning [1, 2]. Traditional depression screening and diagnostic approaches—such as clinician interviews, standardized questionnaires, and self-report scales—are widely used but remain limited by subjectivity, recall bias, and low recognition rates, especially in primary care and community settings [3-5]. In China, for example, although the lifetime prevalence of depression is about 6.9%, less than 10% of patients receive professional intervention, and many remain undiagnosed [6, 7]. Given the global burden of depression, there is an urgent need for objective, rapid, and

accurate screening tools that can facilitate early identification and intervention [8].

Recent advances in multimodal physiological monitoring and artificial intelligence have opened new avenues for objective depression screening. Approaches that integrate psychological, behavioral, and electrophysiological data—such as EEG, ECG, text, and audiovisual signals—have demonstrated improved accuracy and robustness in depression detection over unimodal methods [9-14]. Among these, electrophysiological signals are particularly promising, as they offer direct, quantitative measures of neural and autonomic function [15, 16]. Numerous studies have reported that individuals with depression exhibit abnormal EEG activity (e.g., increased amplitude or altered oscillatory patterns) and reduced heart rate variability (HRV), reflecting dysregulation in

both brain and autonomic systems [15, 17-19]. Notably, combining EEG and ECG features can capture both central and peripheral physiological alterations associated with depression, and has shown particular promise as a multimodal

biomarker [20].

However, the majority of existing research relies on laboratory-based, multi-channel EEG systems, which are often cumbersome and impractical for large-scale or real-world screening. The emergence of portable, single-channel, or dry-electrode EEG and ECG devices provides a more convenient and scalable alternative, enabling broader application beyond the lab [21-23]. Early findings suggest that even with simplified hardware, EEG and ECG signals can yield meaningful biomarkers for depression—particularly when advanced machine learning and feature selection techniques are employed [16, 22]. Despite these advances, key questions remain. Specifically, it is unclear whether portable EEG signals—with their lower spatial resolution and potential susceptibility to noise—can provide clinically meaningful diagnostic value, and whether integrating EEG and ECG features can further enhance rapid depression screening and symptom severity estimation. Moreover, most existing studies have not systematically evaluated the complementary roles of central (EEG) and autonomic (ECG) physiological signals using scalable, user-friendly wearable devices in real-world, multi-task scenarios. Addressing these uncertainties is essential for advancing objective, data-driven mental health assessment.

To address these gaps, this study introduces an innovative portable multimodal system that combines single-channel dry-electrode EEG and ECG acquisition for rapid, real-world depression assessment. Leveraging a multi-condition paradigm—including resting state, emotional stimulation, and structured interview tasks—we

systematically examine: (1) group differences in EEG and ECG features across diverse behavioral states; (2) alterations in brain–heart coupling; (3) validated the incremental and synergistic value of EEG and ECG feature fusion for MDD discrimination using cutting-edge tabular prior-data fitted network machine learning method (TabPFN) [24]; and (4) the feasibility of predicting symptom severity (Hamilton Depression Rating Scale-24, HAMD-24 scores) from multimodal physiological data. By emphasizing scalable, objective, and user-friendly technology, this work aims to clarify the unique and integrated contributions of portable EEG and ECG signals, paving the way for practical, data-driven depression screening and monitoring in real-world community and primary care settings.

Methods

Study Population

The data analyzed in this report were collected in a prospective study conducted at Hangzhou Seventh People's Hospital from June 2024 to June 2025. Patients with MDD were recruited primarily via psychiatrist referral in routine clinical care and voluntary self-referral, whereas healthy controls (HC) were recruited through posters and online advertisements. Eligibility criteria included age 16–60 years. For the MDD group, diagnosis was required to meet Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) criteria and was confirmed by a board-certified psychiatrist using the Structured Clinical Interview for DSM-5 Research Version (SCID-5-RV) within two weeks of enrollment; participants also demonstrated clinically significant depressive symptoms during screening (assessed with the 24-item Hamilton Depression Rating Scale score greater than 18 in the week prior to enrollment). HC were frequency-matched to patients on age and sex and screened with the SCID to verify

absence of current or past psychiatric disorders. In addition to the HAMD-24 for evaluating depression severity, the following validated scales were administered as part of the clinical assessment: the Pittsburgh Sleep Quality Index (18-item version, PSQI-18) to assess sleep quality; the Patient Health Questionnaire-9 (PHQ-9) for depression screening; the Generalized Anxiety Disorder-7 (GAD-7) for anxiety symptoms; the Personal and Social Performance Scale (4-

domain version, PSP-4) for social functioning; and the Symptom Checklist-90 subscales for Phobic Anxiety (SCL-90-PA) and Psychoticism (SCL-90-PS). Exclusion criteria for both groups included any history of bipolar or psychotic disorders, major neurological disease, acute medical conditions likely to affect EEG/ECG, substance use disorder within the past six months, pregnancy or breastfeeding, current suicidal intent requiring urgent care, and recent treatments with potential electrophysiological effects (e.g., electroconvulsive therapy within the past six months).

Ethical Considerations

The study protocol was approved by the Ethics Committee of Hangzhou Seventh People's Hospital. Written informed consent was obtained from all participants.

Experimental Paradigm

This study adopted a case-control group design. Eligible participants underwent synchronous multimodal data acquisition with portable EEG (iFocus, Niantong Intelligence, single-channel forehead patch) and ECG (VV-330, VivaLNK, portable electrode sticker) devices. Data were collected under a series of experimental conditions, including resting states (eyes open and eyes closed), negative emotional picture viewing, structured clinical interviews, as well as completion of self-assessment and clinician-rated questionnaires. All experimental

procedures were completed in a single session in Figure 1.

Specifically, ECG recording was initiated first, with a five-minute stabilization period before commencing EEG recording. Experimental presentation and data synchronization were managed by using PsychoPy (v2023.2.3) and LabRecorder software on a Huawei Matebook 14 laptop (2160×1440 resolution, 60Hz refresh rate). Absolute time stamps were recorded at the onset and conclusion of each experimental task. The experimental sequence comprised four conditions: (i) Eyes Open Resting State (EO), during which participants fixated on a central point on the screen for 5 minutes with eyes open; (ii) Negative Emotion Picture Viewing (Neg), where participants viewed 150 negative emotional facial images representing five emotion categories (sadness, anger, surprise, fear, disgust; 2 seconds per image; gender-balanced), selected from the Chinese Facial Affective Picture System (CFAPS; [25]), for approximately 5 minutes; (iii) Eyes Closed Resting State (EC), in which participants rested with eyes closed for 5 minutes; and (iv) Clinical Interview (Interview), where participants responded to 12 key questions related to depressive symptoms (e.g., sleep quality, work interest over the past two weeks), adapted from Zou et al. [9]. Upon completion of these conditions, participants filled out standardized self-assessment and clinician-rated scales. EEG recording was terminated at the end of the final experimental condition, while ECG recording continued for an additional five minutes after EEG termination to ensure the acquisition of stable HRV data.

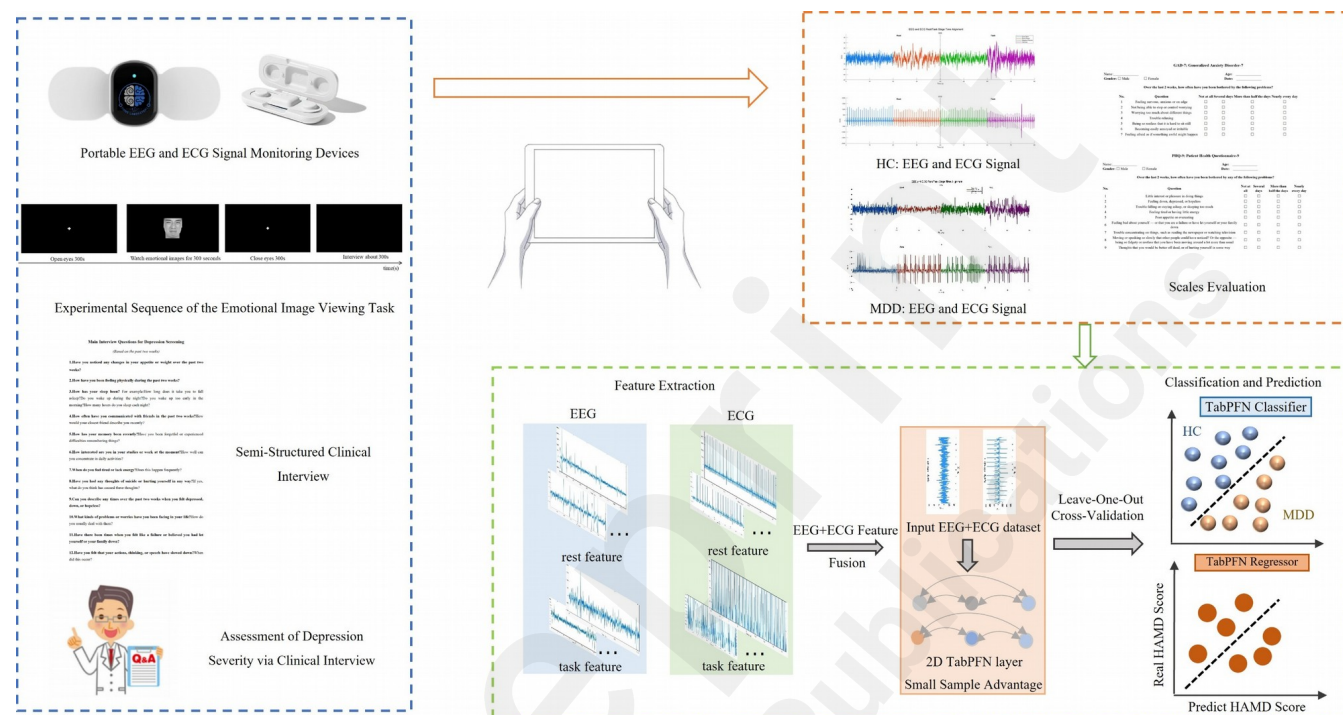
EEG and ECG Data Acquisition and Preprocessing

Single-channel EEG was recorded with a wearable forehead patch (iFocus, dry electrode) placed over the frontal region per manufacturer

guidance (sampling rate 500 Hz). Simultaneous ECG was collected via a chest sticker device (VV-330, 128 Hz; voltage range ± 8.677 mV; heart-rate range 40–300 bpm; 1 bpm resolution)

meeting relevant medical device standards. Participants sat comfortably in a quiet, temperature-controlled room. Multimodal synchronization used LabRecorder event

Figure 1. Experimental Framework Overview. The study protocol consisted of the following steps. First, Participants wore a portable EEG-ECG device and completed four sequential conditions: (i) 5-minute resting state with eyes open (EO); (ii) Viewing negative emotional stimuli (Neg); (iii) 5-minute resting state with eyes closed (EC); (iv) Structured clinical interview assessing depression (12 key questions) (Interview). After data acquisition, acquired signals were preprocessed (e.g., noise removal, artifact correction) and subjected to feature extraction. Then EEG and ECG features were integrated to construct a composite biomarker and a machine learning classifier was employed for objective depression assessment.



markers written to the EEG stream; each task onset (four conditions: EO, Neg, EC, Interview) was aligned to the nearest ECG timestamp. Raw EEG was saved in XDF; ECG in CSV. Initial quality control involved visual inspection to exclude segments with excessive noise or artifacts.

Raw EEG and ECG were imported and preprocessed with custom MATLAB R2021a scripts. ECG timestamps were converted to UTC datetime (e.g., 2024-11-13T10:54:55.562Z $\rightarrow$ 2024-11-13 10:54:55.562) for precise alignment with EEG event markers. EEG preprocessing (EEGLAB v2024.2) applied a 1–30 Hz bandpass filter to remove slow drift and high-frequency noise, followed by event-based segmentation into the four conditions (EO, Neg, EC, Interview). ECG preprocessing computed

inter-beat intervals (IBIs) and excluded those exceeding ± 3 SD from the local mean per standard HRV guidelines. Multimodal synchronization used absolute condition timestamps from EEG events, matching each to the nearest ECG timestamp to minimize time difference, achieving ≤ 10 ms alignment error. All steps (filtering, outlier removal, segmentation, synchronization) were applied uniformly across participants and groups. The result was synchronized, condition-segmented EEG and ECG data ready for feature extraction and analysis.

Feature Extraction and Fusion

EEG and ECG features were extracted separately and then

concatenated for multimodal modeling. EEG

Feature Extraction: Preprocessed data were imported into FieldTrip (release 20240110). Four conditions (EO, Neg, EC, Interview) were segmented into consecutive non-overlapping 1 s epochs. Power spectral density (1–30 Hz) was computed per epoch using multitaper mtmfft (Hanning taper, 2 Hz spectral smoothing, zero-padded to 2 s). Epoch PSDs were averaged within each condition at every frequency, yielding 59 frequency-bin means per condition for statistical group comparisons (independent-sample t-tests per bin). A single mean 1–30 Hz PSD value per condition (4 total EEG features) was retained for further statistical analysis and machine learning.

ECG Feature Extraction: R peaks were detected via maximal overlap discrete wavelet transform (MODWT) (to level 5), reconstructing scales 3–5, squaring the signal, applying an adaptive 80th-percentile threshold plus a 0.4 s refractory period. Inter-beat intervals (IBIs, seconds) were derived; outliers (± 3 SD) were removed. Time-domain metrics: mean heart rate (BPM), Standard Deviation of NN intervals (SDNN), Percentage of successive NN intervals that differ by more than 50 ms (PNN50), Root Mean Square of Successive Differences (RMSSD), Standard Deviation of Successive Differences (SDSD). Frequency-domain (Welch: 256-point window, 50% overlap, 512-point FFT): very low frequency (VLF: 0.003–0.04 Hz), low frequency (LF: 0.04–0.15 Hz), and high frequency (HF: 0.15–0.4 Hz); features: LF, HF, LF/HF ratio. Static ECG set: 8 metrics $\times$ 4 conditions = 32. Dynamic reactivity: for Neg and Interview relative to EO and EC, absolute changes (task – rest) and ratios (task/rest) across four pairings (EO $\rightarrow$ Neg, EO $\rightarrow$ Interview, EC $\rightarrow$ Neg, EC $\rightarrow$ Interview): $8 \times 2 \times 4 = 64$ features. Fusion produced 100 features (EEG 4 + static ECG 32 + dynamic ECG 64) spanning resting, task, and autonomic reactivity for classification and severity prediction. Feature-

level fusion combined EEG (4 mean PSD features) with ECG metrics (32 static HRV + 64 dynamic change/ratio features) = 100 features per subject, covering resting (EO, EC) and task (Neg, Interview) stages. EEG PSD, HRV, and engineered ECG reactivity (absolute changes, ratios) capture baseline and stimulus-evoked dynamics for predictive modeling exploiting complementary brain–cardiac signals.

Statistical Analysis

All statistical analyses were conducted using MATLAB. For EEG data, independent-sample t-tests were performed at each frequency point within the 1–30 Hz range to assess group differences in PSD between HC and MDD. In addition, for each participant and experimental conditions, the mean PSD across the entire frequency band was calculated, and group differences in these mean values were evaluated using independent-sample t-tests. For HRV features—including BPM, RMSSD, SDNN, SDSD, PNN50, LF, HF, and LF/HF ratio— independent-sample t-tests were performed to compare HC and MDD within each of the four experimental conditions. To assess the relationships between EEG and ECG metrics, as well as the associations between resting and task conditions, Spearman correlation coefficients were calculated between corresponding features (e.g., mean PSD and HRV parameters) across subjects within each group. Group differences in Spearman correlation coefficients between EEG-ECG and resting-task conditions were further assessed using Fisher's z-tests. To control for multiple comparisons, p-values from Fisher's z-tests were adjusted using the Bonferroni correction within each set of four conditions combinations. All statistical tests were two-tailed, and significance was set at $P < .05$ after Multiple Comparison correction.

Classification and Regression

To systematically evaluate the discriminative and predictive power of EEG, ECG, and their multimodal combination features, we developed an integrated machine learning pipeline based on the scikit-learn framework and the TabPFN model [24]. TabPFN (“Tabular Prior-Data Fitted Network”) is a transformer-based model specifically designed for tabular data, capable of both classification and regression. Unlike traditional approaches, TabPFN is trained in a meta-learning fashion: it simulates millions of synthetic tasks with diverse data distributions, thereby learning a Bayesian prior over a wide range of tabular problems. At inference time, TabPFN processes the entire training set and a test point as context, outputting the predictive posterior in a single forward pass without the need for fine-tuning or retraining. This design enables fast, well-calibrated, and robust predictions. We adopted TabPFN due to its state-of-the-art performance, particularly in scenarios with limited sample sizes—a common challenge in biomedical and neuroimaging research. Prior studies have demonstrated that TabPFN outperforms both classical machine learning algorithms and modern deep learning architectures on small-sample tabular datasets for both classification and regression tasks. Its meta-learned prior facilitates effective generalization and uncertainty estimation even with very limited data, making it especially well-suited for our experimental setting.

We evaluated discriminative performance of three feature subsets—EEG only (4 mean PSD features), ECG only (static HRV + dynamic change/ratio features), and fused multimodal (100 total)—using leave-one-out cross-validation (LOOCV) at the subject level to maximize data utilization and reduce variance in performance estimation. In each LOOCV iteration, a TabPFN classifier was trained on $N-1$ subjects for a given subset and applied to the held-out subject. Predicted class probabilities

from all folds were pooled to compute accuracy, precision, recall, F1 score, and to generate a global ROC curve and area under the curve (AUC). Uncertainty was quantified as the standard deviation (SD) estimated via nonparametric bootstrap over subjects (1,000 resamples), recomputing each metric per resamples. Metric distributions and comparative performance across feature subsets were visualized with bar plots and the aggregated ROC, enabling direct assessment of the incremental value of ECG dynamics and multimodal fusion relative to unimodal baselines. For HAMD score prediction we applied the same LOOCV protocol with the TabPFN regressor, aggregating fold-wise outputs to obtain mean absolute error (MAE), root mean squared error (RMSE), coefficient of determination (R^2), Pearson correlation r , and associated p-value; scatter plots (predicted vs true) illustrated calibration and dispersion. A broad random hyperparameter search over TabPFN configuration variants (e.g., internal prior/task parameters) repeated LOOCV per setting; the top five (ranked by Pearson r) were compared to assess robustness and parameter sensitivity before selecting the final model.

To interpret model behavior, permutation feature importance was computed: for classification via decreases in accuracy, F1, and AUC when shuffling each feature; for regression via increases in RMSE and decreases in R^2 and r . This yielded ranked importance profiles highlighting influential EEG PSD summaries, static HRV indices, and engineered dynamic ECG reactivity metrics, and demonstrated the added predictive value of integrating neural and autonomic information in a unified multimodal representation.

Results

Fifty-six participants were enrolled in this study,

comprising 30 healthy controls (HC) and 26 MDD. Demographic and clinical characteristics of the participants are summarized in Table 1.

Table 1. Demographic information and scale data

	HC (n =30)	MDD (n=26)	P
Demographic			
Age ^a (years)	23.2±7.4 ^g	27.46±13.19	=.142
Gender ^b (F/M)	15/15	15/11	=.565
Scales			
PSQI-18 ^c	3.87±2.13	11.7±3.78	<.001
PHQ-9 ^d	3.30±2.55	15.8±5.94	<.001
GAD-7 ^e	2.60±2.43	10.5±4.67	<.001
PSP-4 ^f	95.6±2.22	61.2±12	<.001
SCL-90-PA ^g	8.17±2.26	13.6±6.83	<.001
SCL-90-PS ^h	11.7±2.38	23±9.19	<.001
HAMD-24 ⁱ	-	24.36±4.57	-

^{a,c,d,e,f,g,h}Independent sample two-tailed t test.
^bTwo tailed chi square test.
^cPSQI-18: Pittsburgh Sleep Quality Index-18-item.
^dPHQ-9: Patient Health Questionnaire-9.
^eGAD-7: Generalized Anxiety Disorder-7.
^fPSP-4: Personal and Social Performance Scale-4.
^gSCL-90-PA: Symptom Checklist-90 subscales for Phobic Anxiety.
^hSCL-90-PS: Symptom Checklist-90 subscales for Psychoticism.
ⁱHAMD-24: Hamilton Depression Rating Scale-24.
^gData is represented in mean and standard deviation.

Group Differences in EEG PSD and ECG HRV

EEG PSD: No significant differences in EEG PSD values were observed between the HC and MDD groups across the 1–30 Hz frequency range during the EO, EC, and Neg conditions. In the Interview condition, however, significant differences were detected at the 2.5 Hz ($p = .049$) and 3.0 Hz ($P = .033$) frequency points. The overall group differences in EEG PSD values yielded non-significant mean P -values for each condition (EO: 0.362, EC: 0.682, Neg: 0.423, Interview: 0.186). ECG HRV: HRV indices are summarized in Table 2. The MDD group exhibited significantly higher BPM than the HC group during the whole experiment (EO, EC, Neg, Interview). Conversely, the HC group showed higher values for SDNN, PNN50, and LF, with significant differences observed in both resting and interview conditions (SDNN: $P = .043$ and $<.001$; PNN50: $P = .03$ and $<.001$;

LF: $P = .025$ and $.017$). Post hoc tests consistently indicated $HC > MDD$ for these HRV measures, whereas BPM was consistently higher in the MDD group.

Table 2. Heart rate variability differences between MDD and HC

	HC (n=30)	MDD (n=26)	P
BPM^d			
EO ^a	73.93±6.18 ^h	81.99±10.71	<.001
EC ^b	74.02±7	81.85±10.24	=.0014
Neg ^c	75.31±6.54	93±9.77	<.001
Interview	76.93±6.39	86.28±9.28	<.001
SDNN^e			
EO	52.36±18.63	41.26±21.47	=.043
Interview	67.42±26.37	52.16±28.16	<.001
PNN50^f			
EO	19.03±15.46	10.14±14.29	=.03
Interview	20.42±14.32	11.04±14.2	<.001
LF^g			
EO	639.92±498.67	371.04±345.8	=.025
EC	705.68±460.63	418.67±403.2	=.017

^aEO: eyes open.
^bEC: eyes close.
^cNeg: negative emotion pictures.
^dBPM: Beats Per Minute.
^eSDNN: Standard Deviation of NN intervals.
^fPNN50: Percentage of successive NN intervals that differ by more than 50 ms.
^gLF: Low Frequency power.
^hData is represented in mean and standard deviation

Brain-Heart and Rest-Task Correlation Analysis

To assess the coupling between neural and cardiac activity, Spearman correlation analyses were conducted between EEG PSD and ECG BPM across the four experimental conditions. As summarized in Figure 2, MDD group consistently exhibited stronger brain–heart correlations compared to HC group. For display, we overlaid Theil–Sen (median-based, outlier-robust) regression lines. In each condition, the line's slope matched the direction of the corresponding Spearman correlation. Specifically, no significant group differences were found in the EO resting state (the correlation was -0.211 in HC and 0.261 in MDD, Figure 2 (a)) and in the EC resting state (-0.122 for HC and 0.346 for MDD, Figure 2 (b)). Notably, during the Neg task state, the

brain–heart association was significantly higher in the MDD group ($r = 0.441$) than in the HC group ($r = -0.283$, $P = .028$) (Figure 2 (c)). In the Interview task state, a trend toward greater coupling was also observed in MDD (HC: $r = -0.429$, MDD: $r = 0.241$, $P = .052$) (Figure 2 (d)). These results indicate that individuals with MDD exhibit enhanced neural–cardiac coupling, particularly under emotional or social challenge

Figure 2. PSD–ECG BPM correlation analysis in MDD and HC groups across all four conditions: (a) EO; (b) EC; (c) Neg; (d) Interview. There is a significant difference between groups under the Neg condition after multiple comparison correction.

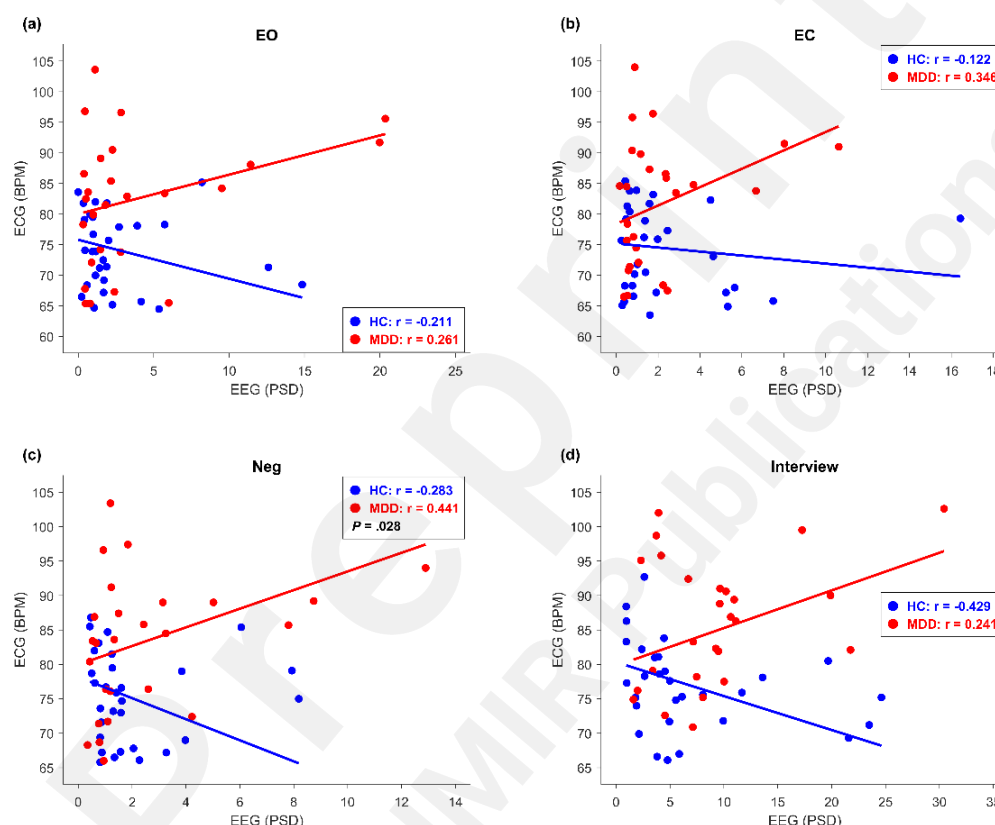


Figure 3. Rest–Task ECG BPM correlation analysis in MDD and HC groups across all four conditions: (a) EO; (b) EC; (c) Neg; (d) Interview. There is a significant difference between groups under the Neg condition after multiple comparison correction.

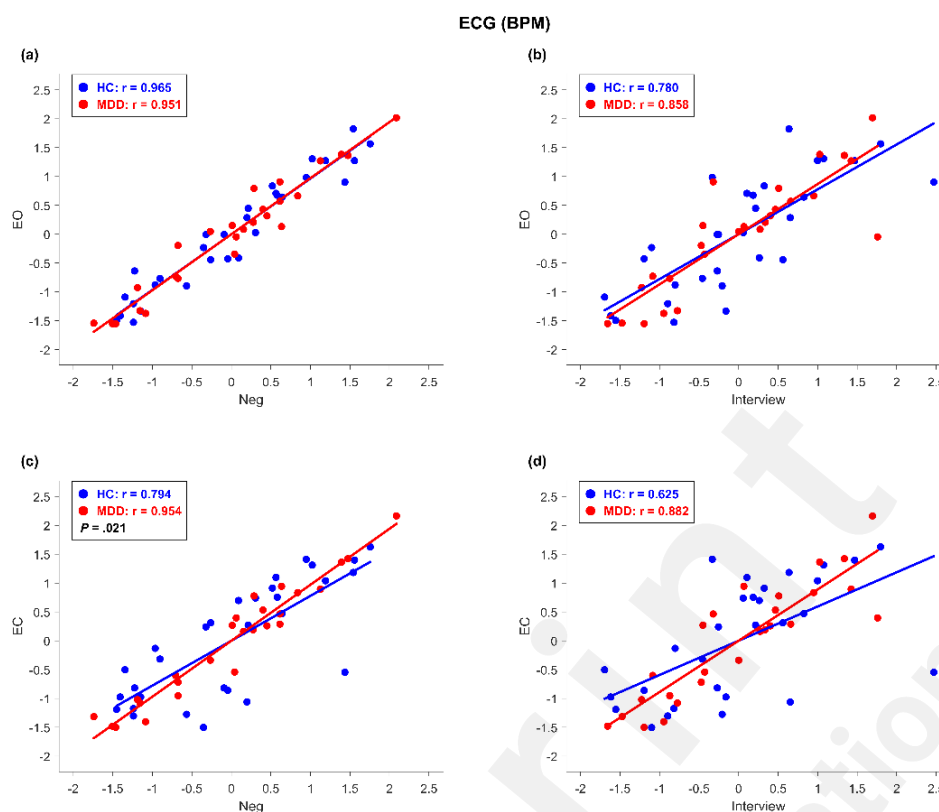


Figure 4. MDD classification and feature importance. (a) Metrics (accuracy, precision, recall, F1-score) for TabPFN classification using EEG features, ECG features, and the combined feature set. (b) ROC curves of TabPFN models trained on EEG-only (AUC = 0.487), ECG-only (AUC = 0.669), and combined EEG+ECG features (AUC = 0.712). (c) Permutation feature importance for the combined model, quantified as the drop in accuracy when each feature is shuffled (top 10 shown). Top three features: Interview_ECG_BPM, Interview_EEG, and Interview_vs_RestEC_PNN50_ratio.

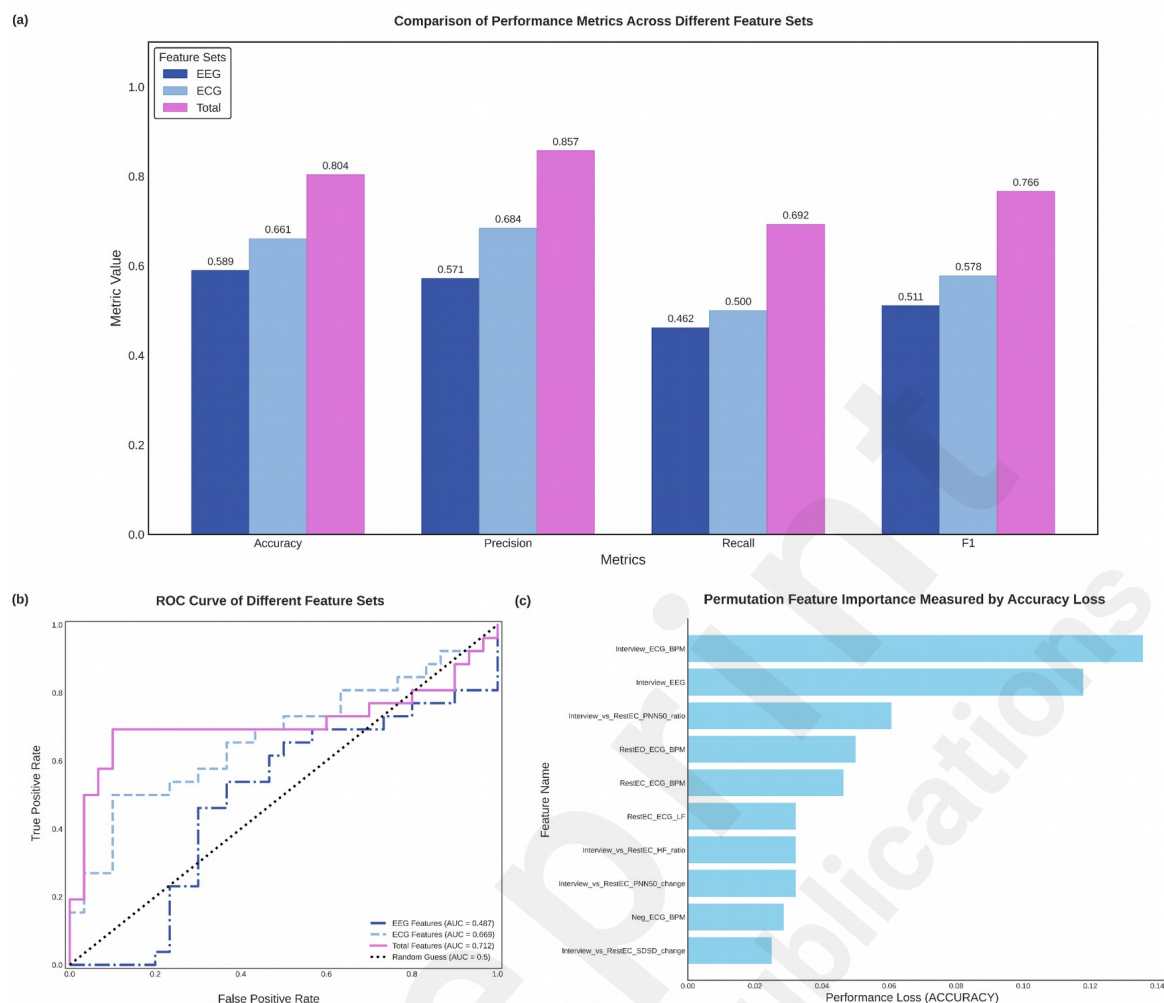
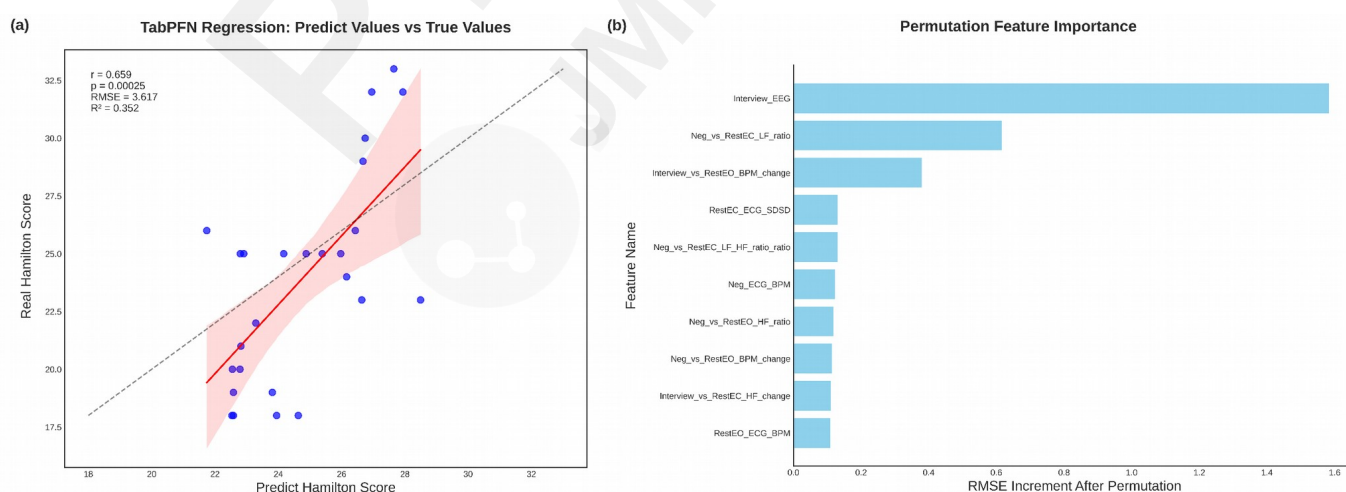


Figure 5. Depression severity prediction with TabPFN regression. (a) Scatter plot showing the relationship between predicted and actual HAMD-24 scores using the optimal TabPFN regression model. The red line represents the linear fit with 95% confidence interval. (b) Top 10 features ranked by permutation importance, as measured by the increment in RMSE after feature permutation. Top three features: Interview_EEG, Neg_vs_RestEC_LF_ratio and Interview_vs_RestEO_BPM_change.



consistently demonstrated higher BPM correlations between rest and task than the HC group. For the Neg versus EC comparison, the

correlation between BPM was significantly higher in the MDD group (HC: $r = 0.794$, MDD: $r = 0.954$, Bonferroni-corrected $P = .021$)

(Figure 3 (c)). For the Interview versus EC comparison, a trend toward significance was also observed (HC: $r = 0.625$, MDD: $r = 0.882$, corrected $P = .085$) (Figure 3 (d)). In contrast, for Neg versus EO and Interview versus EO, no significant group differences were found (Neg vs EO: HC: $r = 0.965$, MDD: $r = 0.951$; Interview vs EO: HC: $r = 0.780$, MDD: $r = 0.858$) (Figure 3 (a), (b)). These results indicate that individuals with MDD exhibit greater consistency in BPM dynamics across resting and task states, particularly when transitioning from eyes-closed rest to emotionally challenging conditions.

Classification Performance and Feature Importance

The classification performance of different feature sets—EEG, ECG, and the combined features—was systematically evaluated using the TabPFN classifier with leave-one-out cross-validation. As shown in Figure 4 (a), in terms of detailed metrics, ECG features achieved an average accuracy of 66.1% (SD 6.3%), precision of 0.684 (SD 0.11), recall of 0.5 (SD 0.1), and F1-score of 0.578 (SD 0.09). The EEG feature set demonstrated lower performance, with an accuracy of 58.9% (SD 6.5%). Notably, combining EEG and ECG features resulted in the best classification results, with an average accuracy of 80.4% (SD 5.4%), precision of 0.857 (SD 0.08), recall of 0.692 (SD 0.09), and F1-score of 0.766 (SD 0.07). As shown in Figure 4 (b), the ROC curve illustrates that the ECG feature set outperformed EEG features, achieving an AUC of 0.669 (SD 0.07) compared to 0.487 (SD 0.08) for EEG. The combined EEG and ECG feature set (Total) yielded the highest overall performance, with an AUC of 0.712 (SD 0.08). These findings indicate that multimodal feature fusion provides complementary information, enhancing classification robustness and discriminative power compared to single-

modality inputs. As shown in Figure 4 (c), permutation feature importance analysis identified BPM during the interview condition as the most influential feature, followed by EEG features from the same condition. Additionally, dynamic ECG features, such as the ratio and change of PNN50 and BPM between rest and interview states, ranked highly. This suggests that both cardiac and neural activity during the interview, as well as dynamic autonomic reactivity, are critical for distinguishing between groups in the classification model.

Prediction of HAMD Scores Using Physiological Features

We leveraged advanced feature engineering and state-of-the-art machine learning methods to predict individual HAMD-24 scores from multimodal physiological data. Static and dynamic features were extracted from both EEG and ECG signals, including engineered variables capturing state-dependent changes across resting and emotional conditions. This comprehensive multimodal feature set enabled effective modeling of both neural and autonomic reactivity relevant to depression severity. For regression analysis, we employed the TabPFN Regressor, systematically optimizing its configuration via random hyperparameter search. Model performance was robustly evaluated using LOOCV, maximizing utilization of our limited sample size and reducing bias. The optimal TabPFN model achieved a Pearson correlation of $r = 0.659$ ($P = 0.00025$) between predicted and true HAMD-24 scores, with an RMSE of 3.617 and R^2 of 0.352 (see Figure 5 (a)). Permutation feature importance (measured as the increase in RMSE when shuffling a feature) yielded a ranked list of predictors (Figure 5(b)). The top three features were: Interview_EEG, Neg_vs_RestEC_LF_ratio, and

Interview_vs_RestEO_BPM_change.

Discussion

Principal findings

Using a portable single-channel EEG–ECG system across four conditions (EO, EC, Neg, Interview) and subject-level LOOCV with TabPFN, we found the expected cardiac autonomic pattern in MDD (higher heart rate, reduced HRV) and altered brain–heart coupling. For screening and prediction, multimodal fusion outperformed unimodal inputs (accuracy = 80.4%, AUC = 0.712) and multimodal physiological features predicted HAM-D-24 ($r = 0.659$; $P < .001$). Below we discuss the main findings, limitations, and future research.

Brain–Heart Coupling Across Groups

In this study, group differences in both central (EEG-PSD) and peripheral (ECG-HRV) physiological indices were assessed between HC and MDD. Contrary to some previous reports, we didn't find significant differences in EEG PSD values between two groups during the EO, EC, and Neg conditions. Notably, significant group differences were observed only at two low-frequency points (2.5 Hz and 3.0 Hz) in the interview condition, suggesting that MDD-related neural oscillatory changes may be context-dependent and most evident during emotionally salient or interactive conditions. While prior studies reported increased EEG amplitude in depression [26], [27], [28], our results indicate these effects are not generalized but rather localized. The lack of broad EEG PSD differences supports the notion that cortical alterations in MDD may be subtle or restricted to specific states, in line with findings of heterogeneity in EEG profiles among depressed individuals [28], [29]. In terms of cardiac autonomic function, our findings further

confirmed that individuals with depression had significantly higher heart rates and reduced heart rate variability, including lower SDNN, PNN50, and LF measures, across multiple conditions. These results are in line with previous literature demonstrating decreased HRV and parasympathetic activity in MDD [30], [31], which is considered an important biomarker of impaired autonomic flexibility and increased cardiovascular risk.

Notably, our brain–heart correlation analysis revealed that patients with MDD consistently exhibited stronger coupling between EEG PSD and heart rate compared to HC across all experimental conditions. This effect was particularly prominent during the Neg and Interview task states, where the MDD group showed moderate positive associations while HCs displayed weak or even negative correlations. Specifically, during the Neg task, the brain–heart association was significantly higher in the MDD group ($r = 0.441$) relative to the HC group ($r = -0.283$), and a similar trend was observed during the Interview condition (HC: $r = -0.429$, MDD: $r = 0.241$, $P = 0.052$). These findings suggest an enhanced, and potentially maladaptive, neural–cardiac interplay in MDD under emotional and social challenge, aligning with recent evidence that depression is linked to altered central–autonomic network function and increased rigidity in brain–body coupling [32].

We extended the brain–heart analysis to the HRV HF component and related it to EEG PSD within each condition using Spearman's r , and compared groups with Fisher's z (Bonferroni-corrected across the four conditions). A clear group divergence emerged only during the Neg condition: HC showed a positive brain–heart coupling ($r = 0.484$), whereas MDD showed a weak inverse association ($r = -0.184$), yielding a significant between-group difference (corrected $P = 0.047$). In the remaining conditions the

group differences were not significant: EO (HC: $r = 0.139$; MDD: $r = -0.205$), EC (HC: $r = 0.099$; MDD: $r = 0.041$), and Interview (HC: $r = 0.192$; MDD: $r = -0.004$). Importantly, under negative emotional stimulation, the correlation between ECG HRV and EEG PSD was significantly lower in MDD compared to HC, indicating a blunted integration between central neural activity and cardiac autonomic function. This reduced synchrony during emotional challenge may underlie the emotional dysregulation and impaired physiological adaptability characteristic of depression. Such a pattern is consistent with previous studies reporting attenuated brain–autonomic coupling in affective disorders under stress or negative affective contexts [33]. Together, these results suggest that altered brain–heart coupling in depression encompasses multiple facets of cardiac autonomic regulation, not just BPM. In addition, our rest–task correlation analysis showed that individuals with MDD displayed higher consistency in heart rate dynamics between resting (EC) and task states (Neg and Interview) compared to HCs, reflecting reduced physiological flexibility.

This aligns with prior studies indicating that depression is associated with less adaptive cardiovascular responses to emotional or stressful stimuli, particularly under negative stimulation [34], and a blunted autonomic reactivity as evidenced by reduced HRV [35]. In summary, our results provide convergent evidence that MDD increased BPM, reduced HRV, and enhanced brain–heart coupling across several physiological domains. These alterations likely reflect the interplay between dysfunctional neural regulation and impaired autonomic flexibility that underlies depressive symptomatology.

Depression Screening and Prediction

Our findings demonstrate that the integration of multimodal physiological features, specifically EEG and ECG, substantially enhances the accuracy and robustness of depression classification. Consistent with previous studies, ECG-derived features alone displayed greater and more stable discriminative power than EEG features, likely reflecting the central role of autonomic nervous system dysregulation as a biomarker for MDD [28], [36], [37]. As shown in Figure 4 (b), the ECG feature set achieved higher AUC values than the EEG set, reinforcing the notion that HRV alterations are reliably associated with depressive states. Notably, our results further reveal that combining EEG and ECG features in a multimodal framework led to the highest overall classification performance with the combined feature set achieving an average accuracy of 0.804 and AUC of 0.712. This finding supports a growing body of evidence that multimodal integration offers complementary information and more effectively captures the complex, heterogeneous manifestations of depression than unimodal approaches [12], [20].

Permutation feature importance analysis (Figure 4 (c)) further clarified that BPM during the interview stage was the most influential feature for classification, closely followed by EEG features from the same stage. Several dynamic ECG features, representing changes or ratios of PNN50 and BPM between rest and task states, also ranked highly. This highlights the critical roles of both interview-specific cardiac and neural activity, as well as dynamic autonomic reactivity, in distinguishing between groups in the classification model. The relatively lower performance of EEG features may be partially attributed to the limitations of single-channel, dry-electrode EEG acquisition, which is more susceptible to noise and lower signal quality compared to conventional multi-channel, wet electrode systems [38]. These results

underscore the importance of rigorous feature engineering and noise mitigation when utilizing wearable EEG technologies in clinical applications. Overall, our study demonstrates that both the selection of physiological features and the strategy for their integration are pivotal for the effectiveness of machine learning approaches in depression detection. Continued advances in multimodal data fusion, robust feature engineering, and thorough validation will be essential for developing reliable and generalizable screening tools.

Our regression findings support the premise that compact physiological signals carry clinically meaningful information about depressive symptom burden. In particular, the prominence of interview-epoch EEG power and autonomic reactivity features (eg, LF changes from negative affect to resting EC, as well as BPM reactivity) suggests that state-dependent, socially salient and emotionally evocative contexts expose variance in central–autonomic control that is tightly coupled to symptom severity. This pattern is consistent with models positing altered central–autonomic network function and blunted or dysregulated physiological adaptation in depression, and aligns with evidence that multimodal physiology can serve as an objective complement to rating scales [39]. Practically, these results indicate that brief, scripted tasks may be more informative than resting-only paradigms for severity tracking, and that brain–heart fusion features—rather than either modality alone—yield the most informative signal. Overall, our results indicate that optimized multimodal physiological models, particularly those sensitive to both neural and autonomic dynamics during emotionally salient conditions, have substantial potential to supplement traditional depression assessment tools.

Clinical Relevance and Impact

Portable multimodal electroencephalogram

EEG-ECG assessment provides specific incremental clinical value for MDD by addressing three persistent gaps in first-line testing: reliance on subjective self-report, variability in interviewer expertise, and lack of concurrent cardiometabolic risk stratification [40]. Within a brief screening system, it generates an objective physiological fingerprint integrating autonomic dysregulation and state-dependent brain–heart coupling. This allows for (i) early flagging of high-risk individuals whose questionnaire scores are marginal or ambiguous due to limited insight; (ii) dual screening for depression and elevated cardiovascular risk, given the prognostic relevance of reduced HRV ([30], [31]); (iii) improved diagnostic specificity through task-evoked (resting to Neg or Interview) responses and coupling patterns, distinguishing pathological rigidity from normative arousal and reducing false positives driven by nonspecific self-reported affect; and (iv) objective baseline plus longitudinal follow-up—once a minimal clinically important change threshold is established, recalculation of the fusion score can indicate potential for non-response, relapse risk, or persistent physiological burden despite symptom improvement. This approach does not replace the clinical interview, but rather serves as a decision-making aid [41], introducing quantifiable, reproducible physiological measures to reduce subjective bias and support equitable, data-driven management in primary care, psychiatry, and preventive cardiology.

This compact, minute-by-minute workflow—single-channel dry EEG paired with a standard ECG—could be deployed with minimal training, easy setup, and good fit for busy clinics, community screenings, and resource-limited settings. Short, structured tasks (EO, EC, Neg, Interview) can be standardized or semi-automated, enabling scale without specialized electrophysiology staff. The same architecture

could also support hybrid telemedicine models: for example, an initial ~20-minute in-clinic screen for community programs; for those flagged as higher risk, a week of at-home monitoring with a portable device to enrich the signal; and a brief follow-up task to check whether “physiological resilience” improves before versus after an intervention—steps that would enhance ecological validity and personalization [42]. With secure cloud aggregation, a brain–heart index could feed a centralized risk dashboard for proactive outreach, stepped-care escalation, and relapse monitoring. By combining mental-health risk detection with cardiometabolic vigilance on a single portable platform—something rating scales alone rarely provide—this approach aligns with precision, measurement-based care and has the potential to speed early intervention, reduce missed or delayed diagnoses, and lower downstream healthcare burden through integrated, physiology-informed decisions.

Limitations

Several limitations that should be considered when interpreting the results. First, the sample size was relatively limited and drawn from a experimental paradigms to include cognitive, social, and real-world tasks may provide deeper insight into the dynamic nature of brain–heart coupling in depression. Finally, integrating additional data modalities—such as behavioral, genetic, and self-report measures—and leveraging advanced machine learning and explainable AI techniques could further improve predictive accuracy and support clinical translation [12], [13].

Conclusions

In conclusion, this study demonstrates that combining portable neural and cardiac

single center, which may restrict the generalizability of the findings and increase the risk of overfitting in the applied machine learning models [43], [44]. Second, the EEG data relied on a single-channel dry electrode system. Although this approach enhances comfort and practicality, it may compromise signal quality and spatial resolution, making the extracted EEG features less robust compared to those from traditional multi-channel wet electrode systems [38]. Third, the cross-sectional design—with possible medication comorbidity influences and limited symptom-subtype characterization—may mask condition- or subtype-specific patterns.

Future research should address these limitations by recruiting larger and more diverse participant samples, ideally across multiple sites, to enhance the external validity and reliability of the results. Methodologically, future studies should implement more rigorous validation frameworks, such as nested cross-validation and external test sets, to minimize information leakage and provide more accurate estimates of model generalizability. In addition, expanding the range of

physiological signals—along with their dynamic interactions—provides a robust and objective approach for both detecting depression and quantifying its severity. Multimodal feature fusion significantly enhances predictive accuracy, underscoring the value of brain–heart biomarkers in mental health assessment. These findings lay the foundation for developing practical, AI-driven tools for depression screening and monitoring, and highlight the need for further validation in broader clinical populations.

Funding

This work was supported by STI2030-Major Projects (2022ZD0212400), National Natural Science Foundation of China (82371453, 32271078), Key R&D Program of Zhejiang [2024C03006, 2024SSYS0017], Hangzhou Biomedical and Health Industry Special Projects for Science and Technology (2021WJCY240), Fundamental Research Funds for the Central Universities (2023ZFJH01-01, 2024ZFJH01-01, 226-2024-00207) and Double first-class project of central finance (112100*1942225R1/004).

Data Availability

The datasets generated during and analyzed in this study are available from the corresponding author on reasonable request.

Authors' Contributions

XRG and HTJ Proposed the theme idea and main framework; MFN mainly assisted in editing the experimental procedures; ALD and PW mainly collected data from the depression group; ZMZ and MTC mainly collected data from the healthy group; XRG, XYL, ZMZ, and KXC conducted statistical analysis and machine learning; XRG wrote the main manuscript text; HTJ, ZDC and LYC mainly revised the manuscript. All authors reviewed the manuscript.

Conflicts of Interest

None declared.

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Abbreviations

MDD: major depressive disorder
HAMD-24: Hamilton Depression Rating Scale-24
HC: healthy controls
EEG: electroencephalogram
ECG: electrocardiogram
EO: eyes open resting state
Neg: negative emotion picture viewing
EC: eyes closed resting state
Interview: structured clinical interview
PSD: power spectral density
HRV: heart rate variability
BPM: beats per minute.
SDNN: standard deviation of NN intervals
PNN50: percentage of successive NN intervals that differ by more than 50 ms
RMSSD: root mean square of successive differences
SDSD: standard deviation of successive differences
LF: low frequency power
HF: high frequency power
AUC: area under the curve
RMSE: root mean squared error
R²: coefficient of determination
LOOCV: leave-one-out cross-validation
TabPFN: tabular prior-data fitted network