Adaptive Personalized Multimodal AI For Longitudinal Stress Monitoring Using EEG, HRV And EDA

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***Abstract*—Stress is a highly individualized and dynamic psychophysiological response, making reliable continuous monitoring challenging. Existing artificial intelligence approaches to stress detection have demonstrated the usefulness of physiological and neural signals, including electrodermal activity (EDA), heart rate variability (HRV), and electroencephalography (EEG). However, many existing approaches rely on population-level models or limited personalization, while longitudinal validation and adaptive modeling remain comparatively underexplored. This research proposes an adaptive, personalized AI framework for longitudinal stress monitoring by integrating complementary neural and physiological signals from EEG, HRV, and EDA. The proposed framework will initially establish an individual's baseline characteristics and subsequently identify deviations from their personal baseline rather than relying solely on generalized stress patterns across individuals. Machine learning techniques will be investigated for multimodal feature fusion and adaptive model updating as additional individual data becomes available. The study will compare the performance of conventional population-level models with personalized and progressively adaptive models using appropriate evaluation metrics. The research aims to determine whether incorporating individual baseline characteristics and continuous adaptation can improve the reliability and generalizability of stress monitoring. The proposed framework is intended as a foundation for future non-invasive, personalized, and wearable AI-based stress-monitoring systems, while addressing current challenges associated with inter-individual variability, multimodal integration, and longitudinal assessment.**

***Index Terms*—Artificial Intelligence, Machine Learning, Personalized Stress Monitoring, Multimodal Signals, EEG, Heart Rate Variability (HRV), Electrodermal Activity (EDA), Adaptive Learning.**

I. INTRODUCTION

Stress is a dynamic psychophysiological response that can vary considerably between individuals and across different situations. Reliable monitoring of stress is therefore important for understanding an individual's changing physiological state and for developing future intelligent health-monitoring technologies. Recent advances in artificial intelligence (AI) and wearable sensing have enabled automated stress detection using physiological signals collected from the human body [1]. Among the commonly investigated signals, electrodermal activity (EDA), heart-rate variability (HRV), and other physiological and neural signals have demonstrated potential for machine-learning-based stress recognition. Recent reviews indicate that EDA and cardiovascular signals are among the most frequently used modalities in wearable stress-detection research [1].

However, stress responses are not identical across individuals. Differences in physiological characteristics, baseline states, behavioral patterns, and responses to stressful situations can cause a model trained on a population to perform differently when applied to a new individual. Consequently, personalized stress-detection approaches have received increasing research attention [1]. A 2024 scoping review of personalized stress detection identified a growing body of research on wearable biosignals. It emphasized the need for user-centric, computationally practical approaches suitable for real-world applications [1].

Multimodal sensing provides an opportunity to address some of these limitations by combining complementary information from different physiological and neural sources. EDA reflects changes associated with sympathetic nervous system activity, while HRV provides information related to cardiovascular autonomic regulation. Electroencephalography (EEG), in contrast, provides information about brain electrical activity. Combining these signals can provide a broader representation of stress-related responses than relying on a single modality [2]. However, multimodal systems introduce challenges related to feature integration, dimensionality, inter-individual variability, and model generalization.

Personalization alone, however, may not be sufficient for continuous stress monitoring. An individual's physiological baseline can change over time, meaning that a model calibrated at one point may not remain equally effective as additional observations become available. Recent research has therefore begun investigating adaptive personalized stress-detection frameworks in which a generalized model can be adapted to individual users using physiological data [3]. For example, adaptive approaches using PPG and EDA have been proposed to address domain differences among users and improve personalized stress detection [3].

Despite these developments, there remains a need to systematically investigate the combined effect of multimodal sensing, individual baseline modeling, and progressive adaptation. Existing literature contains studies addressing personalized stress detection, multimodal physiological sensing, and adaptive modeling, but these research directions are often investigated separately or with different signal combinations and evaluation protocols. The 2024 scoping review also highlights limitations related to dataset representativeness, data quality, and the need for user-centric AI approaches [1].

Therefore, this research proposes an adaptive personalized multimodal AI framework for stress monitoring using EEG, HRV, and EDA signals. The proposed approach first establishes an individual's baseline characteristics and then investigates whether progressively incorporating additional individual observations can improve stress prediction. The study compares a conventional generalized model with personalized and adaptive personalized models using multimodal features. The objective is to determine whether personalization and model adaptation can improve stress-monitoring performance while providing a foundation for future non-invasive and wearable AI-based applications.

II. LITERATURE REVIEW

A. Personalized Stress Detection

Bolpagni *et al.* presented a scoping review of personalized stress detection using wearable biosignals and analyzed the increasing use of individual-specific approaches for stress monitoring. The review highlighted the importance of physiological variability between individuals and identified challenges related to dataset representativeness, data quality, computational efficiency, and real-world deployment [1].

Rodríguez-Arce *et al.* investigated anxiety and stress recognition in academic environments using physiological features and machine-learning techniques. Their study demonstrates the potential of physiological measurements for automated stress recognition and highlights the importance of considering individual physiological responses in stress-monitoring systems [4].

B. Multimodal Stress Detection

Multimodal stress-detection approaches combine information from multiple physiological signals to obtain a more comprehensive representation of stress-related responses. Abdelfattah *et al.* investigated machine-learning and deep-learning approaches using multimodal physiological data and demonstrated the potential of combining complementary physiological information for automated stress detection [2].

The SWELL-KW dataset has also been used extensively for stress and workload recognition using physiological and behavioral information. The dataset includes measurements such as heart rate variability and skin conductance collected under different working conditions, providing a basis for investigating stress-related physiological responses [5].

Although multimodal approaches can improve information availability, combining multiple signal types also introduces challenges involving feature dimensionality, synchronization, inter-individual variability, and model generalization.

C. Adaptive and Personalized Stress Detection

Adaptive modeling extends personalization by allowing a model to incorporate additional information from an individual after initial calibration. Xu *et al.* proposed an adaptive wearable stress-detection framework using photoplethysmography (PPG) and electrodermal activity (EDA), in which a generalized model is adapted to individual users using user-specific information [3].

This approach demonstrates the potential of progressive model adaptation to address differences among users. However, the framework primarily considers PPG and EDA signals, whereas the present research investigates the combination of EEG, HRV, and EDA.

D. Multimodal Dataset for Stress Research

Bussolan *et al.* introduced the MultiPhysio-HRC dataset, which contains synchronized multimodal physiological and neural measurements, including EEG, ECG, EDA, respiration, and other signals collected during cognitive, virtual-reality, and human–robot collaboration tasks [6]. The dataset also includes questionnaire-based measurements that can support stress and cognitive-load analysis.

The availability of EEG, ECG, and EDA measurements makes this dataset suitable for investigating multimodal stress-monitoring approaches. In the present study, EEG features together with HRV-derived and EDA features are used to investigate generalized, personalized, and adaptive personalized stress-monitoring models.

E. Summary of Existing Research

The reviewed literature demonstrates that personalized stress detection, multimodal physiological sensing, and adaptive stress modeling are established in research directions. However, these approaches have generally been investigated using different signal combinations, datasets, personalization strategies, and evaluation protocols. Therefore, further investigation is required to determine whether progressively incorporating individual-specific information into a multimodal model using EEG, HRV, and EDA can improve stress-monitoring performance compared with conventional population-level modeling.

Table I. COMPARISON OF RELATED STUDIES

Study	Signals/ Modalities	Personalization	Adaptation	Main Focus
Bolpagni *et al.* [1]	Wearable biosignals	Yes	Not the main focus	Review of personalized stress detection
Abdelfattah *et al.* [2]	Multimodal physiological signals	Not the main focus	No	ML/DL-based stress detection
Xu *et al.* [3]	PPG + EDA	Yes	Yes	Adaptive wearable stress detection
Rodríguez-Arce *et al.* [4]	Physiological features	Not the main focus	No	Stress and anxiety recognition in academic environments
SWELL-KW [5]	HRV, skin conductance, behavioral data	Not the main focus	No	Stress and workload recognition
MultiPhysio-HRC [6]	EEG, ECG, EDA, RESP, EMG, audio, facial AUs	Dataset support	Not the main focus	Multimodal dataset for stress, cognitive load and affect
This study	EEG+ HRV +EDA	Yes	Yes	Comparison of generalized, personalized, and adaptive personalized models

III. RESEARCH GAP

Although previous studies have demonstrated the effectiveness of artificial intelligence for stress detection, several limitations remain. Existing research has explored personalized stress detection using wearable biosignals, multimodal stress recognition using physiological signals, and adaptive approaches for adjusting models to individual users. However, these research directions are often evaluated separately and use different signal combinations, datasets, personalization strategies, and evaluation protocols.

A major challenge in stress monitoring is inter-individual variability, where physiological responses to similar stressful conditions can differ considerably between individuals. Population-level models may therefore fail to represent an individual's normal physiological characteristics effectively. Personalized approaches address this issue by incorporating individual-specific information, but a static personalized model may become less effective when the individual's physiological state changes over time.

Furthermore, although adaptive stress-detection approaches have been investigated, there is a comparatively limited systematic evaluation of progressive personalization using combined neural and physiological signals. In particular, the effect of progressively incorporating individual information into a multimodal model using EEG, HRV, and EDA requires further investigation.

Therefore, the research gap addressed in this study is the need to systematically compare generalized, personalized, and adaptive personalized multimodal stress-monitoring approaches using complementary neural and physiological features. The study investigates whether establishing an individual's baseline and progressively adapting the model using additional individual observations can improve stress-monitoring performance compared with conventional population-level modeling.

IV. PROBLEM STATEMENT

Conventional AI-based stress-detection systems often rely on generalized patterns learned from multiple individuals. However, physiological and neural responses to stress can vary substantially between individuals, which may reduce the effectiveness of a single generalized model when applied to a new user. Personalized models can address this issue by learning individual-specific characteristics, but static personalization may not adequately account for changes in an individual's physiological baseline as additional observations become available.

Therefore, there is a need for a stress-monitoring approach that can combine complementary neural and physiological information while also considering individual variability and progressive changes in personal physiological patterns. The problem addressed in this research is to determine whether an adaptive personalized multimodal AI approach using EEG, HRV, and EDA signals can provide improved stress-monitoring performance compared with conventional generalized and non-adaptive personalized approaches.

V. OBJECTIVES

The main objectives of this research are:

1. To develop a multimodal stress-monitoring approach by integrating EEG, HRV, and EDA features for AI-based stress classification.
2. To establish an individual-specific baseline by analyzing the normal physiological and neural characteristics of each participant.
3. To develop and evaluate a personalized stress-monitoring model that incorporates participant-specific observations to improve stress prediction.
4. To investigate an adaptive personalized approach that progressively updates the model as additional individual observations become available.
5. To compare generalized, personalized, and adaptive personalized models using performance measures such as accuracy, precision, recall, and macro F1-score.

VI. PROPOSED METHODOLOGY

A. Overall Approach

The proposed research follows a multimodal and personalized machine-learning approach for stress monitoring. EEG, HRV, and EDA features are integrated to represent complementary neural and physiological responses associated with stress. The methodology consists of data preparation, multimodal feature integration, stress-label generation, feature preprocessing, model development, personalization, adaptive model updating, and performance evaluation.

B. Dataset

The study uses the MultiPhysio-HRC dataset, a multimodal physiological dataset containing signals collected during different cognitive, virtual-reality, and human–robot collaboration tasks. The dataset provides EEG, ECG, EDA, respiration, EMG, and other modalities along with questionnaire-based measurements.

For this study, the analysis is restricted to EEG, HRV-derived, and EDA features. The EEG features are obtained from the provided EEG feature file, while HRV and EDA features are obtained from the physiological feature file. Stress labels are derived using the available STAI-based measurements.

C. Multimodal Feature Preparation

The selected modalities provide complementary information:

- EEG: represents neural activity associated with different frequency bands and entropy-related characteristics.

- HRV: represents variations in cardiac activity and provides information related to autonomic regulation.
- EDA: represents changes in electrodermal activity associated with physiological arousal.

The extracted EEG, HRV, and EDA features are aggregated and combined according to participant, task, and repetition information to construct a unified multimodal representation.

D. Stress Label Generation

Following the subject-specific classification procedure used in the MultiPhysio-HRC dataset [6], STAI-based measurements are used to derive participant-specific stress categories. For each participant, the mean and standard deviation of the available STAI scores is calculated. The stress levels are then categorized into Low, Medium, and High using participant-specific thresholds:

$$Low : STAI < \mu - \frac{\delta}{2}$$

$$Medium : \mu - \frac{\delta}{2} \leq STAI \leq \mu + \frac{\delta}{2}$$

$$High : STAI > \mu + \frac{\delta}{2}$$

Where μ represents the participant's mean STAI score and δ represents the corresponding standard deviation. This subject-specific thresholding accounts for differences in reported stress levels between participants [6].

E. Data Preprocessing

The combined dataset is examined for missing values, infinite values, and constant or unusable features. Invalid or unusable features are removed, while missing numerical values are handled using median imputation.

For the final machine-learning evaluation, imputation and feature selection are fitted using only the training data to reduce the possibility of data leakage

F. Feature Selection

Because the multimodal dataset contains a relatively large number of EEG, HRV, and EDA features, feature selection is performed before model training. Mutual-information-based feature selection is used to identify features that provide useful information about stress classes.

Feature selection is performed separately within the training portion of each evaluation procedure so that information from unseen participants is not used during model development.

G. Generalized Model

The generalized model represents the conventional population-level approach. A machine-learning model is trained using data from multiple participants and evaluated on an unseen participant.

Random Forest is initially used as the baseline classifier because it can model nonlinear relationships and can handle heterogeneous multimodal features.

The generalized model establishes the baseline performance against which personalized approaches are compared.

H. Personalized Model

The personalized model incorporates observations from the target participant before predicting their later observations. Initial observations are used to learn participant-specific characteristics and establish a personal model.

In the experimental evaluation, earlier repetitions are used as calibration data, while subsequent observations are reserved for testing. This allows the model to be evaluated on data that were not used during personalization.

I. Adaptive Personalized Model

The adaptive model extends the personalized approach by allowing the model to incorporate newly available labeled observations over time.

The process follows:

Initial personal observations → Personal model → New observation → Model update → Later prediction

This allows the model to progressively adjust to changes in the individual's physiological and neural patterns rather than relying on a fixed baseline.

J. Performance Evaluation

The generalized, personalized, and adaptive personalized approaches are evaluated using:

- Accuracy
- Precision
- Recall

- Macro F1-score
- Confusion matrix

Macro F1-score is given particular importance because the study involves three stress categories: Low, Medium, and High.

The final comparison uses the same participants and future observations for the three approaches to provide a fair evaluation of whether personalization and adaptation improve stress-monitoring performance.

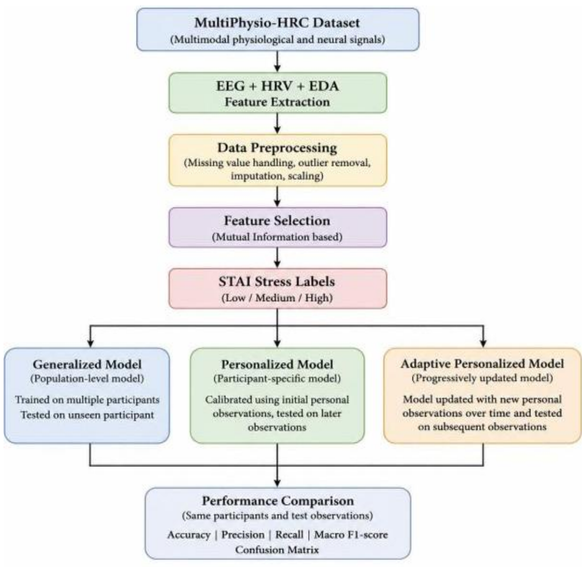

Fig. 1. Proposed methodology for adaptive personalized multimodal stress monitoring.

VII. EXPERIMENTAL DESIGN

The experimental design is developed to evaluate whether incorporating participant-specific information and progressively updating the model can improve multimodal stress classification. Three approaches are considered: a generalized population-level model, a personalized model, and an adaptive personalized model.

A. Generalized Model Evaluation

The generalized model represents a conventional population-level stress-detection approach. Data from multiple participants are used for model training, while observations from an unseen participant are used for testing. Leave-One-Participant-Out (LOPO) evaluation is used so that observations from the same participant do not simultaneously occur in both training and testing sets. This provides a more realistic assessment of how a generalized model performs when applied to an individual not previously observed during training.

B. Personalized Model Evaluation

The personalized model is designed to learn participant-specific characteristics before making predictions on later observations. For the experimental evaluation, repetitions 1–3 are used as the initial calibration period, while repetitions 4–5 are reserved for later evaluation. The model is trained using the participant's initial observations and subsequently evaluated using later observations from the same participant.

C. Adaptive Personalized Model Evaluation

The adaptive model extends the personalized approach by incorporating newly available observations during the monitoring process. Repetitions 1–3 are initially used for participant-specific calibration. Repetition 4 is then incorporated as additional information for updating the personalized model, and the updated model is evaluated on repetition 5. This design allows the study to examine whether progressively incorporating individual information improves prediction of performance.

D. Fair Model Comparison

To provide a fair comparison between the three approaches, the final evaluation uses participants who have the required sequence of observations for all three approaches.

The same future observations are used as the final test data for the compared models. Performance is evaluated using accuracy, precision, recall, and macro F1-score.

VIII. RESULTS AND DISCUSSION

A. Overall Model Performance

The three approaches were evaluated using the same set of 29 participants and 50 final test observations from repetition 5.

The generalized model was trained using calibration observations from other participants, while the personalized model was trained using repetitions 1–3 of the target participants.

For the adaptive approach, repetitions 1–3 were initially used for personalization and repetition 4 was subsequently incorporated before predicting repetition 5. The resulting performance comparison is presented in Table II.

Table II. PERFORMANCE COMPARISON OF THE THREE APPROACHES

Model	Accuracy	Precision	Recall	Macro F1-score
Generalized Model	46.00%	51.14%	44.63%	45.69%
Personalized Model	36.00%	35.70%	36.32%	35.45%

B. Discussion

The results show that the adaptive personalized model achieved the highest overall accuracy and macro F1-score, with an accuracy of 48.00% and a macro F1-score of 48.14%. The generalized model achieved an accuracy of 46.00% and a macro F1-score of 45.69%, while the static personalized model achieved lower performance with an accuracy of 36.00% and a macro F1-score of 35.45%.

Compared with the generalized model, the adaptive personalized approach improved the macro F1-score by approximately 2.45 percentage points. This indicates that incorporating additional participant-specific observations can provide useful information for adapting the model to individual patterns.

The lower performance of the static personalized model suggests that using only the initial participant-specific observations may not always be sufficient to represent later stress-related patterns. In contrast, the adaptive approach incorporates an additional observation period before the final prediction, allowing the model to update its learned representation.

Although the improvement over the generalized model is relatively modest, the result supports the importance of progressive adaptation rather than relying solely on a fixed personal baseline. Further experiments with larger participant populations and longer longitudinal observations are required to determine the robustness and statistical significance of this improvement.

C. Confusion Matrix

The confusion matrices for the generalized, personalized, and adaptive personalized models are presented in Fig. 2. The matrices show the distribution of actual and predicted stress levels across the Low, Medium, and High categories.

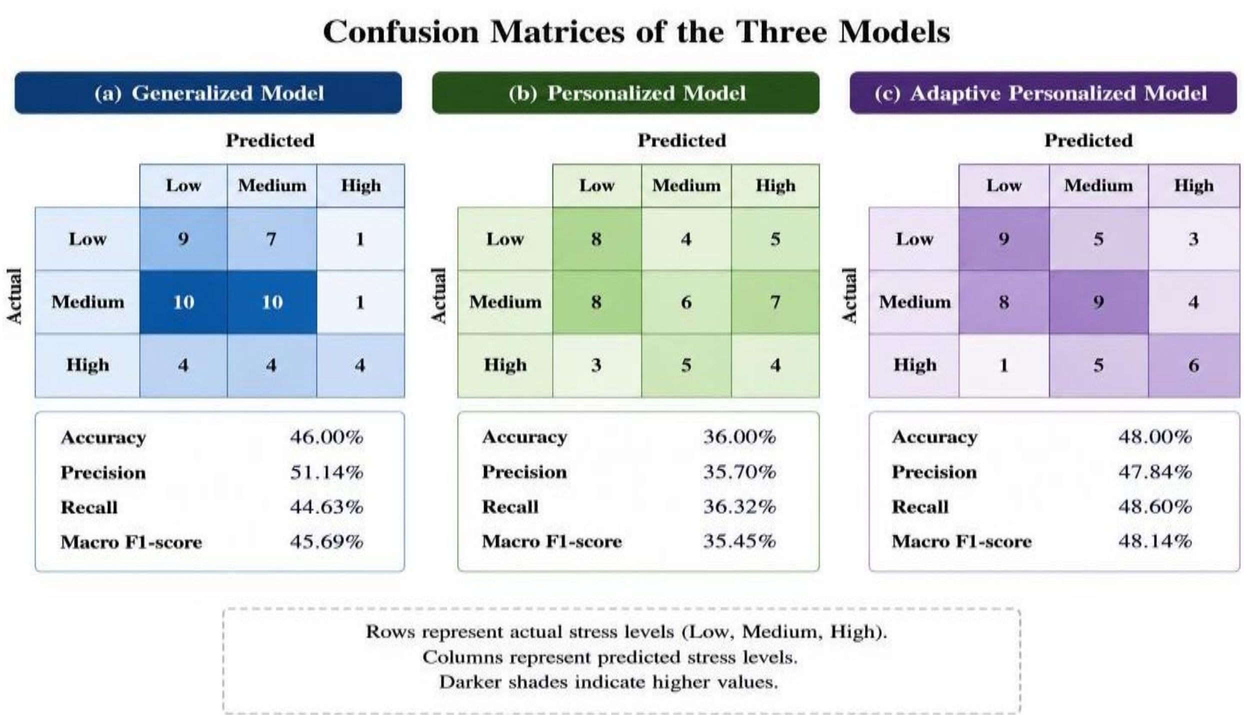

Fig. 2. Confusion matrices and performance metrics of the three models evaluated on the same 29 participants and 50 test observations (Repetition 5).

The adaptive model correctly identified 6 of the 12 high-stress observations, compared with 4 for the generalized model and 4 for the static personalized model.

IX. CONCLUSION

This study investigated an adaptive personalized multimodal artificial intelligence approach for longitudinal stress monitoring using EEG, HRV, and EDA features. The research addressed the limitations of conventional population-level stress-detection models by considering individual physiological and neural characteristics and their changes over time.

Three approaches were investigated: a generalized model, a personalized model, and an adaptive personalized model. The experimental framework used participant-specific observations for calibration and subsequently evaluated stress prediction on later observations. The results of the matched evaluation showed that the adaptive personalized model achieved the highest accuracy and macro F1-score among the three approaches, indicating the potential benefit of incorporating additional individual observations during model adaptation.

The findings also indicate that a static personalized model does not necessarily provide better performance than a generalized model in every situation. This suggests that personalization should be considered an evolving process rather than only as a one-time calibration step. Progressive adaptation may provide a more suitable approach for longitudinal stress monitoring because individual physiological patterns can change over time.

Overall, the study demonstrates the potential of combining neural and physiological information with personalized and adaptive machine-learning strategies for stress monitoring. The proposed framework provides a foundation for future development of individualized, non-invasive, and continuous AI-based stress-monitoring systems.

X. FUTURE SCOPE

Future work can extend this research in several directions. First, the proposed approach can be evaluated using a larger and more diverse participant population to improve the generalizability of the findings. Second, longer longitudinal observations can be used to investigate how individual physiological baselines change over extended periods. Third, additional machine-learning and deep-learning techniques can be investigated for multimodal feature fusion and adaptive model updating. Further research can also explore real-time implementation of wearable devices using computationally efficient models. Finally, privacy-preserving and personalized learning techniques can be investigated to enable continuous stress monitoring while reducing the need to transfer sensitive physiological data.

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