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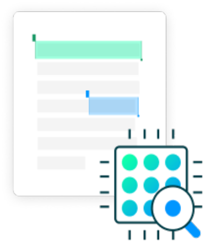

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# Personalized Mental Health Mood Analytics Engines: A Literature Review

**I. Introduction**

As mental health is becoming more popular, more focus is placed on individualized interventions and c predictors of mental health. In this present literature review, the recent studies of the Personalized Mental Health Mood Analytics Engine and the current trends, issues and opportunities of the said field will be reviewed.

**II. History of AI in mental healthcare**

Finally, Jin et al. [20] is a study which do provide a profound insight of AI usage in one mental health context. Because of the availability of the extensive datasets across the modalities, AI, especially, ML techniques have been found to have a very good potential. The authors point out that in regard to this, DL methodologies have attracted quite the attention as their performance outperforms classical ML in many mental health employment cases.

**III. Personalized Mood Analytics Engines**

**A. User Centricity and Experience**

Schueller et al. [1] have shown that users use mood related applications to track changes in their state, rather than to outright control such activities. The study therefore draws attention to the utility of features suited for promoting self awareness and visual feedback of affective patterns, which are key ingredients of analytical engines. Overdijk et al. [2] discussedDesigning mood self tracking opportunities, whereas the user's views on affective self tracking is the subject of Seth, Mussel, Cramer, and Bos [13]. In their study, with 46 participants, they observed some peculiarities of preferences and concerns around sharing mood data. It proposed the use of tangibles, in the form of innovative design techniques such as, and the integration of such into the bespoke mood analytics engines to increase the experience of using them.

**B. Integration of mental health expertise**

In [3], Branco et al. described an interaction design analysis that required people with mental health issue. The analysis reads out some of the issues that they discover and it suggests that mental health experts could be involved in the building of mood analytical engines. As a result, in this approach, the tools ensure not only capturing the mood but suggesting recommendations based on the user's mood.

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Based on existing works, those by Ginige and van Cuylenburg [4] developed an emotion tracking application powered by AI, that recommends personalized suggestions to the user in a low mood. The system achieves 98.46% accuracy in emotion detection and shows the promise of AI on building highly accurate and tuned mood analytics engines. And these engines can also learn adaptive behaviors to individual emotional patterns, and provide tailored interventions.

In a proactive emotion tracker, Asif et al. [5] involved a novel BERT model, which takes depressive text from the social media and web browsing data. This system achieves a 93%

test accuracy, and integrates physiological signals from wearables, to completely analyze the user's emotional state. The importance of such integration is all the more crucial in order to develop personalized mood analytics engines which can provide a holistic view of the user mental health.

**B. Machine Learning Techniques for Personalization**

Shah and collaborators [6] use machine learning to generate personalized predictions of depressed mood using data from wearables and neurocognitive sampling. And they found that each individual best-fit model varied, emphasizing the need for personalized, ML' guided approaches in mood analytics engines. However, this allows the engines to accommodate individual and unique emotional needs of each user.

In [7], Alslaity and Orji conducted a systematic review of the machine learning techniques used in emotion detection and sentiment analysis. It also noted that the most common supervised learning approaches were Support Vector Machine (SVM) and Naïve Bayes (NB). The importance of standardized datasets and excavation to non textual data sources for personalization were emphasized in mood analytics engines.

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Facial emotion recognition (FER) systems have recently made tremendous advances in their accuracy and efficiency due to recent advancements in deep learning. Huang et al. (2023) used a CNN with squeeze and excitation network and residual neural network to perform FER tasks. In their study, they found that facial landmarks around the nose and mouth are key facial landmarks for neural networks estimating emotion. Using transfer learning between datasets [8], they reached high accuracy rates.

Facial expression recognition was applied to a CNN-10 model, which can easily detect spatial features, manage translation invariance, and interpret expressive feature representations, as demonstrated by Dada et al. (2023). On multiple datasets such as CK+, FER-2013, and JAFFE [9], even better results were achieved compared to other architectures such as VGG 19 and Inception V 3, getting accuracy of 99.9%, 84.3% and 95.4% respectively.

Cîrneanu et al. (2023) review the state-of-the art neural network architectures for emotion recognition and recommend CNNs as their architectures featuring computational efficiency and their capability of extracting features. Also, they stated potential applications of these models in healthcare, education or security [10].

**D. Conventional Machine Learning for Real-Time Emotion Detection**

The conventional machine learning techniques were used by Bhattacharya et al. [16] to develop an Android application for real time mood detection and prediction. The potential for near real time emotion analysis with mobile devices is demonstrated by their work, which may be of great value for building personal mood analytics engines. Nine conventional learning methods are studied, and it is found that, in terms of precison, recall, F1 score, and accuracy, random forest, decision tree, and complement naive Bayes classifiers marginally outperform other classifiers.

### E. Speech Emotion Recognition

In a systematic review of speech emotion recognition (SER) using machine learning, Madanian et al. [17] have shown. Finally, they emphasized the leading role of data augmentation with respect to balancing and scarcity of data problems in SER. It also highlighted the great potential of ensemble-model architectures to significantly improve SER performance. Transforming audio signals to spectrograms and normalizing feature is found capable of improving SER and diminishing impact of diversity of speakers in recognition.

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In Balliu et al. [21], they showed how digital behavioral phenotypes, passively and continuously logged to a smartphone, can be used to predict depressive mood. With cubic spline interpolation and idiographic models, the study attains high prediction accuracy of depression severity up to three weeks in advance ($R2 \geq 80\%$). This research demonstrates the ability to quantify high quality longitudinal mood assessments and predict symptom severity weeks in advance from passively collected digital behavioral data in a clinical population.

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Self predictions of mood were investigated by Totterdell et al [22]. However, just over 10% of the varience in daily mood was explained by the reliably associated participants' predictions, and their patterns of prediction were not significantly related to their subsequent moods. Interestingly, lowering of mood across the morning hours was only predicted by hassles when it was not expected to improve, even after controlling for expectations of improvement. Based on this, self predictions of mood could trigger moods regulating and improving processes, which could be vitally important to consider when designing personalized mood analytics engines.

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In their work, Cho et al. [24] studied using machine learning and passive digital phenotypes based on circadian rhythm, to predict circadian rhythm based mood in patients with mood disorder. This study collected various digital log data through wearable devices and smartphone apps over 2 years period. The implications of their results are that passive data pertaining to circadian rhythms could be used for mood prediction, in clinical settings. The approach is in line with the increasing research into the use of digital technologies for mental health monitoring and intervention..

### G. ECG-Based Emotion Analysis

A method for emotion analysis and prediction was proposed by Xie Ying [25] using ECG signal acquisition. It outlines a comprehensive ECG signal acquisition, denoising, feature analysis extraction and emotion classification. We additionally provide a contribution to the growing body of work on physiological signal based emotion recognition, by demonstrating the potential of ECG signals to accurately recognize emotion. It lays down a baseline for comparing other emotion analysis techniques, and adds further theoretical foundations for emotion analysis using physiological signals.

**H. Spatio-Temporal Attention for Mood Prediction**

Narayana et al. [26] presents a new way for predicting emotion by learning emotion changes in a spatio temporal attentional basis. According to their study, it could differentiate between emotions and moods in terms of temporal aspect of mood prediction. Spatial and temporal attention mechanisms and parallel and sequential arrangements of them were explored by the researchers in order to improve mood prediction performance. They find that emotion change information is intrinsically beneficial to prediction of mood, and show that sequential and parallel spatial temporal attention modules facilitate further improvements in prediction performance. Taking the application of state of the art machine learning techniques to the challenge of mood prediction to a whole new level, this work is a major advancement.

**V. Novel Implementation: Neural Network-Based Mood Prediction**

**A. Methodology and Implementation**

Building upon the existing research in mood prediction, we implemented a neural network-based approach using a Multi-Layer Perceptron (MLP) regressor. The implementation considers multiple factors that influence daily mood, including:

- Sleep quality
- Stress levels
- Physical activity
- Temporal patterns (day of week)

The model architecture incorporates several key design choices:

1. Feature Engineering
    - Cyclical encoding for day of week using sine and costal transformations
    - Feature normalization using MinMaxScaler
    - Careful handling of temporal dependencies
2. Neural Network Architecture
    - Two hidden layers (10 and 5 neurons respectively)
    - Maximum iteration limit of 1000 epochs
    - Consistent random state for reproducibility

B. Performance and Results The model demonstrated robust performance in mood prediction:

- Mean Absolute Error (MAE): 0.58

- Root Mean Square Error (RMSE): 0.67
- $R^2$ Score: 0.86

Notably, the model substantially outperformed the baseline prediction (using mean value) with a baseline MAE of 1.47, representing a 60.5% improvement in prediction accuracy. This significant performance differential demonstrates the effectiveness of the neural network approach in capturing complex relationships between input features and mood outcomes.

The high $R^2$ score of 0.86 indicates that the model explains 86% of the variance in mood predictions, suggesting strong predictive capability. The relatively low MAE and RMSE values further support the model's precision in predicting mood states.

**VI. Applications and Ethical Considerations**

**A. Mental Health Monitoring and Intervention**

In Cummins et al. [18], the authors looked into the use of AI in detecting mood disorders in particular, in this case, depression and bipolar. Mobile and wearable technology coupled along with AI analysis was shown to be a promising way to bring objective markers of these conditions. The authors highlight the benefits to using AI based technologies in clinical psychology practice, and describe sources of data, particularly information streams which can be collected via mobile technologies.

**B. Ethical Implications and User Perceptions**

In their qualitative analysis of emotion AI use in U.S. adults' mental healthcare, Roemmich et al. [19] suggest emotion AI is well-received by the U.S. public if it is designed to be used to complement the support of a human therapist. The study found both the positive and negative. 'We believe that emotion AI has potential to help with mental healthcare assessment, diagnosis, and treatment, and also to aid information disclosure and discrimination of self harm,' they explained. But they also flagged that AI inferences might be misused, inaccurate assessments, and fewer opportunities for patient-provider interaction. According to the authors, emotion AI use in mental healthcare may constitute an insufficient techno solution susceptible to exacerbating diverse challenges and — potentially — to impart distributive, procedural, and interactional injustices.

**VII. Challenges and Future Directions**

**A. Data Quality and Diversity**

Pandey et al. (2022) emphasized the challenge of recognizing facial emotions across different cultures, ages, and environments. They highlighted the importance of diverse and representative datasets for training robust FER models [11].

**B. Multi-Modal Approaches**

According to Ballesteros et al. (2022) it is possible to improve recognition of emotion by combining the computer vision algorithms with psychological theories of emotion.

Furthermore, they suggested the need for additional training (with different images and with other algorithms) to distinguish between closely related emotional patterns [12].

**C. Real-Time Processing and Mobile Applications**

Based on conventional machine learning techniques, Bhattacharya et al. (2022) developed an Android application for the real time mood detection and prediction. This work showcased how near real time emotion could be performed on mobile devices and could be very beneficial for personal user analytics engines [13].

**D. Ethical Considerations and User Privacy**

The implementation of emtion AI in the mental healthcare is pointed out that there is need of careful consideration of ethical implications and users' privacy by Roemmich et al. [19]. Future work should create frameworks for the use of responsible AI as it relates to privacy of the user and equitable access to mental health services.

**E. Methodological and Quality Flaws**

In the use of AI in mental health research, Tornero Costa et al. [23] conducted a systematic review of methodological and quality flaws. Distribution of AI applications towards mental health categories are not evenly spread. Lack of reporting data preprocessing and preparation steps. No assessment of model suitability compared. Blow by previous model. Models lack of external validation. Lack of reporting of how strategies for adjusting hyperparameters and model explainability are actually carried out. Lack of International collaboration and data sharing.

Few of methodological and quality flaws in the use of AI in mental health research. They identified several significant shortcomings, including:

- Unbalanced distribution of AI applications across mental health categories
- Poor reporting of data preprocessing and preparation steps
- Lack of assessment of model suitability before comparison
- Limited external validation of models
- Insufficient reporting of strategies for adjusting hyperparameters and model explainability
- Lack of international collaboration and data sharing

These findings show that there's a need for improvement in the methodological rigor and transparency in using AI for mental health research.

**VIII. Conclusion and Future Directions**

The reviewed literature suggested a great progress in personalized mental health mood analytics engines integrating the deep learning techniques and data that are accumulated through using the smartphones.

- Towards developing multi modal approaches that combine facial, textual, speech, and physiological data for better emotion recognition.
- To improve real time processing capabilities for mobile and edge devices.
- This addresses the privacy concerns while keeping usability and effectiveness coming up.
- On the applications of transfer learning, fine tuning techniques that can adapt models from common source population or contexts to specific ones.
- Applying attention mechanisms and other cutting edge deep learning architectures to examine their effect on more advanced feature extraction, and their effects on classification task performance.
- Formation of ethical frameworks and guidelines for managing the use of emotion AI that is responsible in mental healthcare settings.
- Strengthening methodological rigor and transparency for applying AI to mental health.

As the field continues to evolve, these advancements hold the potential to significantly improve mental health support and intervention strategies through personalized mood analytics engines. Future research should focus on developing more robust, adaptable, and ethically sound systems that can effectively recognize and respond to human emotions across diverse populations and contexts. Our implementation contributes to the growing body of work in personalized mood analytics by demonstrating the effectiveness of neural network-based approaches in mood prediction. With an $R^2$ score of 0.86 and a 60.5% improvement over baseline predictions, our results support the viability of machine learning approaches in mood prediction. These findings suggest several promising directions for future research:

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