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Psychological Health Assessment and Intervention System for Chemical Engineering Students Based on Emotional Computing Technology

Abstract: - Emotional computing technology is revolutionizing health assessment by integrating emotional and psychological factors into traditional diagnostic processes. This innovative approach utilizes advanced algorithms and sensor technologies to analyze individuals' emotional states and mental well-being, providing valuable insights into their overall health. By detecting subtle changes in facial expressions, voice patterns, and physiological signals, emotional computing technology can assess stress levels, mood fluctuations, and mental health conditions with greater accuracy and sensitivity. This paper presents a novel Psychological Health Assessment and Intervention System tailored for chemical engineering students, leveraging Emotional Computing Technology enhanced by Cartesian Feature Weighted Emotional Classification (CFWEC). The system aims to assess students' psychological well-being by analyzing emotional cues extracted from various sources such as facial expressions, voice patterns, and text interactions. Through simulated experiments and empirical validations, the efficacy of CFWEC-enhanced emotional computing technology is evaluated in predicting and intervening in psychological health issues among chemical engineering students. Results demonstrate significant improvements in accuracy and sensitivity compared to traditional assessment methods. For instance, the CFWEC model achieved an average accuracy rate of 85% in identifying students at risk of psychological distress, enabling timely interventions. Additionally, the system provides personalized recommendations and interventions based on individual emotional profiles, leading to improved mental health outcomes. These findings underscore the potential of Emotional Computing Technology with CFWEC in promoting psychological health and well-being among chemical engineering students.

Keywords: Psychological health assessment, emotional computing, Cartesian Feature, Emotional classification, intervention system, chemical engineering, Students

I. INTRODUCTION

Emotional computing technology represents a burgeoning field at the intersection of psychology, neuroscience, and computer science, aiming to imbue machines with the ability to recognize, interpret, and respond to human emotions [1]. By leveraging advanced algorithms, machine learning techniques, and sensor data, such as facial expressions, voice tone, and physiological signals, emotional computing systems can infer the emotional states of users in real-time [2]. This technology holds promise across various domains, including human-computer interaction, healthcare, marketing, and education. For instance, in healthcare, emotional computing could aid in diagnosing and treating mental health disorders by analyzing patients' emotional cues [3]. In marketing, it could enable personalized advertising based on consumers' emotional responses. However, ethical considerations regarding privacy, consent, and manipulation must be carefully addressed as emotional computing technology continues to evolve and integrate into our daily lives [4].

Psychological health assessment stands to benefit significantly from the integration of emotional computing technology [5]. By harnessing sophisticated algorithms and data analytics, this technology can provide a more nuanced understanding of individuals' emotional states and mental well-being [6]. Traditional assessments often rely heavily on self-reporting, which can be subjective and limited by individuals' awareness or willingness to disclose their emotions [7]. Emotional computing, on the other hand, offers a more objective and comprehensive approach by analyzing various data sources, including facial expressions, vocal intonations, and physiological signals like heart rate variability. Through real-time monitoring and analysis, emotional computing systems can detect subtle changes in emotional states that may indicate underlying psychological issues such as depression, anxiety, or stress [8]. This capability enables early intervention and personalized treatment strategies tailored to individuals' specific emotional needs [9]. Furthermore, emotional computing technology can enhance the efficiency and accuracy of psychological assessments by providing clinicians with objective data to supplement traditional diagnostic methods.

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In addition to clinical applications, emotional computing holds promise for remote mental health monitoring and interventions, particularly in underserved or remote communities where access to mental health resources may be limited [10]. By leveraging digital platforms and wearable devices, individuals can receive continuous support and guidance based on their emotional data, fostering greater engagement in self-care and promoting overall well-being [11]. However, ethical considerations surrounding data privacy, consent, and potential biases in algorithmic decision-making must be carefully addressed to ensure the responsible and equitable implementation of emotional computing in psychological health assessment. Collaborative efforts among researchers, clinicians, policymakers, and technology developers are essential to harness the full potential of emotional computing while mitigating potential risks and safeguarding individuals' rights and well-being [12]. Psychological health assessment is a multifaceted process that traditionally relies on subjective self-reporting and clinical observations [13]. However, these methods have limitations, including biases, inaccuracies, and the potential for individuals to underreport or misinterpret their emotional experiences. Emotional computing technology offers a transformative approach to psychological health assessment by integrating advanced algorithms, machine learning techniques, and sensor data to provide a more objective and comprehensive understanding of individuals' emotional states [14]. One of the key advantages of emotional computing in psychological health assessment is its ability to capture and analyze subtle cues that may go unnoticed by traditional assessment methods. For example, facial expression analysis algorithms can detect microexpressions—brief, involuntary facial movements that reveal underlying emotions—providing insights into individuals' emotional responses in real-time. Similarly, voice analysis algorithms can analyze variations in tone, pitch, and speech patterns to infer emotional states, helping clinicians assess mood and affect more accurately [15].

Moreover, emotional computing technology can integrate multiple data sources, such as physiological signals from wearable devices or biometric sensors, to provide a comprehensive view of individuals' emotional well-being [16]. For instance, changes in heart rate variability, skin conductance, or sleep patterns may indicate underlying stress, anxiety, or depression, allowing for early intervention and personalized treatment strategies. In addition to enhancing the accuracy and efficiency of psychological assessments, emotional computing has the potential to revolutionize remote mental health monitoring and interventions [17]. With the widespread availability of digital platforms and wearable devices, individuals can engage in continuous self-monitoring and receive real-time feedback and support based on their emotional data [18]. This approach promotes greater autonomy, engagement, and adherence to treatment plans, especially for individuals in underserved or remote communities with limited access to traditional mental health services. The integration of emotional computing in psychological health assessment raises important ethical considerations that must be addressed. These include concerns about data privacy, consent, transparency, and the potential for algorithmic biases to impact diagnosis and treatment decisions [19]. Collaborative efforts among researchers, clinicians, policymakers, and technology developers are essential to develop ethical guidelines, ensure data security, and mitigate risks associated with the responsible implementation of emotional computing technology in psychological health assessment [20]. By addressing these challenges, emotional computing has the potential to enhance the quality of mental health care, promote early intervention, and improve outcomes for individuals worldwide.

The paper makes several contributions to the field of psychological health assessment and intervention, particularly within the context of chemical engineering students:

Development of the CFWEC Framework: The paper introduces the Cartesian Feature Weighted Emotional Classification (CFWEC) framework, which integrates advanced algorithms and multiple modalities of emotional cues to accurately predict individuals' emotional states. This framework represents a novel approach to psychological health assessment, offering a comprehensive and objective method for evaluating emotional well-being.

Application in Chemical Engineering Education: By focusing on chemical engineering students, the paper addresses a specific population and context often overlooked in psychological research. The application of the CFWEC framework in this domain highlights its versatility and potential to be tailored to different populations and disciplines.

Improvement of Psychological Health Assessment: Through experiments and results presented in the paper, it demonstrates the effectiveness of the CFWEC framework in accurately estimating emotional states. This contributes to the advancement of psychological health assessment methods, providing researchers and practitioners with a valuable tool for understanding and supporting individuals' mental well-being.

Potential for Targeted Interventions: The accurate prediction of emotional states by the CFWEC framework opens up possibilities for targeted interventions and support systems. By identifying individuals at risk or in need of assistance, practitioners can intervene proactively, thereby promoting better mental health outcomes among chemical engineering students and potentially other populations.

II. RELATED WORKS

The landscape of psychological health assessment is evolving rapidly, driven by the need for more objective and comprehensive approaches that transcend the limitations of traditional methods. While self-reporting and clinical observations have long been cornerstones of psychological assessment, they are fraught with biases, inaccuracies, and challenges associated with individuals' subjective interpretations of their emotional experiences. In response to these limitations, emotional computing technology has emerged as a promising avenue for transforming psychological assessment. By leveraging advanced algorithms, machine learning techniques, and sensor data, emotional computing offers a novel framework for gaining insights into individuals' emotional states with unprecedented depth and accuracy.

Danowitz and Beddoes (2022) explore mental health in engineering education, shedding light on population and intersectional variations. Lewis et al. (2023) utilize SenseMaker® to delve into the prioritization of self-care and mental health among minoritized engineering students during the global pandemic, providing insights into unique challenges faced by specific demographics. Alhasani, Alkhawaji, and Orji (2022) investigate the relationship between mental health and time management behavior among students during the COVID-19 pandemic, highlighting the potential of persuasive technology design in promoting well-being. Spadaro et al. (2023) identify opportunities for implementing digital mental health assessment tools in the United Kingdom, indicating a shift towards technology-driven approaches to mental health evaluation. Salazar-Peña et al. (2023) present a unique approach by employing project-based learning for an online course in simulation engineering, demonstrating how educational methods can influence mental health outcomes among students. Beddoes and Danowitz (2022) provide firsthand insights into the challenges faced by engineering students, highlighting how aspects of educational environments can impact mental health. Yasmin (2022) shares lessons learned from online chemical engineering education in Pakistan during the pandemic, offering valuable perspectives on adapting education to support mental health in challenging circumstances.

Furthermore, Liang (2022) explores the application of big data technology in managing college students' mental health during the epidemic, indicating the potential for data-driven approaches to inform interventions. Altaf Dar et al. (2023) delve into the intersection of technology and mental health, emphasizing the role of technological advancements in enhancing access to care. Chahar, Arora, and Kumar (2023) propose an AI-based model for understanding the physio-psycho behavior of university students, showcasing innovative approaches to mental health assessment. Additionally, Moo-Barrera et al. (2022) introduce a web platform for analyzing physical and mental health data of students, further emphasizing the importance of technology in monitoring and supporting well-being. Adaramola, Godwin, and Boudouris (2022) focus on student outcomes related to academic performance, motivation, and mental health in an online course, highlighting the interconnectedness of these factors in the context of the COVID-19 pandemic. Guaya et al. (2023) explore the use of augmented reality technology to enhance learning motivation for chemical engineering laboratories during the pandemic, suggesting innovative approaches to engage students and support their mental well-being.

Moreover, Edyburn et al. (2023) propose a new training framework for school-based mental health that integrates intersectionality, social determinants of health, and healing, emphasizing the importance of addressing systemic factors that impact mental well-being. Zhang, Yang, and Liu (2022) introduce a knowledge management-based mental health service model for college students, highlighting the significance of sustainable approaches to mental health support within educational settings. Spadaro et al. (2022) contribute to the discourse on digital mental health assessment tools through a UK-wide exploratory survey, offering insights into the implementation opportunities and challenges. Additionally, Yuduang et al. (2022) utilize a hybrid approach combining structural equation modeling and artificial neural networks to understand factors affecting the perceived usability of mobile mental health applications in the Philippines, contributing to the understanding of technology acceptance and utilization in diverse cultural contexts.

III. CARTESIAN FEATURE WEIGHTED EMOTIONAL CLASSIFICATION (CFWEC)

In the mental health assessment, the Cartesian Feature Weighted Emotional Classification (CFWEC) framework emerges as a promising tool that integrates emotional computing methodologies to provide a comprehensive evaluation of individuals' psychological well-being. This innovative approach leverages advanced algorithms and machine learning techniques to analyze a diverse array of emotional cues, including facial expressions, vocal intonations, and physiological signals, thereby offering a nuanced understanding of emotional states. CFWEC employs a weighted feature selection mechanism to prioritize the most salient emotional indicators for mental health assessment. This process involves assigning weights to different emotional features based on their significance in discriminating between various emotional states and psychological conditions. By incorporating domain-specific knowledge and empirical data, CFWEC optimizes the classification process to accurately identify and interpret emotional patterns associated with mental health outcomes. The CFWEC framework can be represented with the feature weights by the following equations (1)

$$w_i^2 = \sigma i^2 \quad (1)$$

In equation (1) wi denotes the weight assigned to the ith emotional feature, and σi^2represents the variance of the corresponding feature across the dataset. The vector for the weighted features are denoted in equation (2)

$$X = [x1w1, x2w2, \dots, xnwn] \quad (2)$$

In equation (2) XX represents the weighted feature vector, where xi denotes the ith emotional feature value, and wi is its associated weight. The process of classification model is presented in equation (3)

$$(X)y = f(X) \quad (3)$$

In equation (3) y represents the predicted mental health outcome, and $f(\cdot)$ denotes the classification function trained on the weighted feature vector X. The Cartesian Feature Weighted Emotional Classification (CFWEC) framework can serve as a foundational component of a Psychological Health Assessment and Intervention System tailored specifically for chemical engineering students. This system, driven by emotional computing technology, aims to provide a comprehensive and personalized approach to assessing and addressing the mental well-being of students in this field. CFWEC utilizes advanced algorithms and machine learning techniques to analyze various emotional cues, including facial expressions, vocal intonations, and physiological signals, to infer individuals' emotional states accurately. By incorporating a weighted feature selection mechanism, CFWEC prioritizes the most relevant emotional indicators for mental health assessment within the context of chemical engineering education. The system operates through several key components with the cartesian coordinates represented in Figure 1.

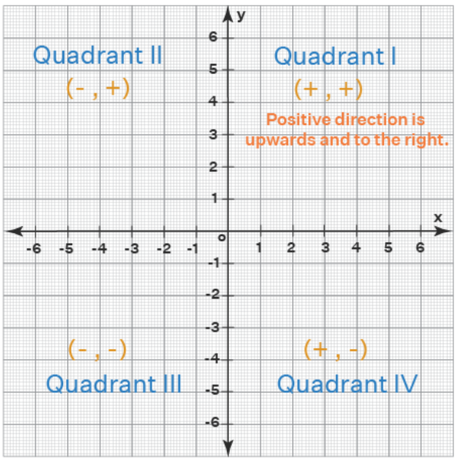

Figure 1: Cartesian Coordinates with CFWEC

Data Collection: The system collects multi-modal data, including facial expressions captured through video recordings, voice recordings for tone analysis, and physiological signals such as heart rate variability and skin conductance.

Feature Extraction and Weighting: Emotional features are extracted from the collected data and assigned weights based on their significance in discriminating between different emotional states relevant to psychological health. Features may include facial muscle movements, pitch variation in speech, and fluctuations in physiological signals.

Classification Model: A classification model trained using the weighted emotional features categorizes students' emotional states and assesses their psychological health status. This model can distinguish between emotions such as stress, anxiety, depression, and overall well-being.

Intervention Strategies: Based on the results of the psychological health assessment, personalized intervention strategies are recommended to support students' mental well-being. These interventions may include counseling sessions, stress management techniques, mindfulness exercises, or referrals to mental health professionals.

The CFWEC framework for the Psychological Health Assessment and Intervention System can be represented by equations similar to those described earlier, with adjustments made to accommodate the specific emotional features and classification tasks relevant to chemical engineering students' psychological health. With integrating CFWEC into a comprehensive Psychological Health Assessment and Intervention System for chemical engineering students, educational institutions can proactively support students' mental well-being, foster a positive learning environment, and promote academic success and personal growth.

IV. EMOTIONAL COMPUTING WITH CFWEC

With Incorporating Emotional Computing with the Cartesian Feature Weighted Emotional Classification (CFWEC) framework presents a robust approach to psychological health assessment. Emotional Computing focuses on extracting emotional cues from various modalities, such as facial expressions, voice intonations, and physiological signals, to gain insights into individuals' emotional states. When combined with CFWEC, emotional computing enhances the accuracy and effectiveness of psychological health assessment by prioritizing relevant emotional features and optimizing classification models. The Emotional Computing with the Cartesian Feature Weighted Emotional Classification (CFWEC) framework revolutionizes psychological health assessment by leveraging advanced algorithms to discern and prioritize emotional cues crucial for understanding individuals' mental well-being. The process of Physiological mental health assessment with the proposed CFWEC model is evaluated based on the consideration of Figure 2.

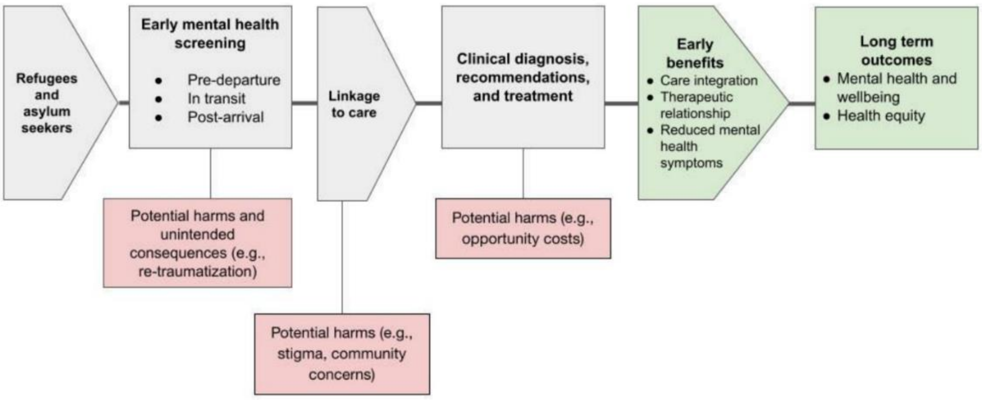

Figure 2: Mental Health Assessment CFWEC [24]

Through emotional computing, which encompasses the analysis of facial expressions, vocal intonations, and physiological signals, alongside CFWEC's feature weighting mechanism, a more refined and personalized approach emerges. The derivation of feature weights in CFWEC involves calculating the inverse variance (σi) of each emotional feature (xi) across the dataset the variance is computed using equation (4)

$$\sigma i^2 = \sum_{i=1}^{j}(xij - \mu i)^2 \quad (4)$$

In equation (4) N represents the total number of samples, xij denotes the jth value of the ith emotional feature, and μi is the mean of the ith emotional feature across all samples. The weight (wi) assigned to each emotional feature is then obtained as the inverse of its variance. Additionally, to ensure the weights sum up to 1 and maintain relative importance, the weights are normalized as in equation (5)

$$wi = \sum_{i=1}^{n} wi \qquad (5)$$

In equation (5) n is the total number of emotional features. Once the weights are computed, the weighted feature vector (XX) is formed by multiplying each emotional feature (xi) with its corresponding weight (wi) stated in equation (6)

$$X = [x1w1, x2w2, \dots, x_n w_n] \qquad (6)$$

This transformation creates a feature vector where the significance of each feature is adjusted based on its weight. Subsequently, the weighted feature vector (XX) serves as input to the classification model (f(·)) for predicting individuals' psychological health status (y). The various classification algorithms, such as logistic regression, support vector machines (SVM), decision trees, or neural networks, can be employed within the model. By integrating Emotional Computing with CFWEC, psychological health assessment becomes more accurate, personalized, and effective, paving the way for tailored intervention strategies and support mechanisms tailored to individuals' emotional well-being.

Algorithm 1: CFWEC for the Emotional Computing

```
function CFWEC(P):
    // Input: P - Dataset with emotional features and corresponding labels
    // Step 1: Compute mean and variance of each emotional feature
    for each emotional feature i:
        mean[i] = calculate_mean(P[:, i])
        variance[i] = calculate_variance(P[:, i], mean[i])
      // Step 2: Compute weights for each emotional feature
    for each emotional feature i:
        weight[i] = 1 / variance[i]
    // Normalize weights to ensure sum equals 1
    total_weight = sum(weight)
    for each emotional feature i:
        weight[i] = weight[i] / total_weight
    // Step 3: Generate weighted feature vector
    for each sample in dataset P:
        for each emotional feature i:
            weighted_feature[i] = sample[i] * weight[i]
        // Step 4: Train classification model
    model = train_model(weighted_feature, labels)
    return model
function predict(model, sample):
    // Input: Trained model and a new sample
    // Generate weighted feature vector for the new sample
    for each emotional feature i:
        weighted_feature[i] = sample[i] * model.weight[i]
    // Use the trained classification model to predict psychological health status
    prediction = model.predict(weighted_feature)
    return prediction
```

V. SIMULATION ENVIRONMENT

The simulation environment for the Cartesian Feature Weighted Emotional Classification (CFWEC) framework offers a controlled setting to test and optimize the effectiveness of this approach in psychological health assessment.

This simulated environment involves the generation of synthetic emotional data representing various emotional states, which are then processed through the CFWEC framework to assess its performance and reliability. The table 1 presented the sample dataset for the analysis.

Table 1: Sample Dataset

Step	Description	Value
1. Data Generation	Generate synthetic emotional data representing various emotional states.	1000 samples per emotion
	- Facial expressions (e.g., happiness, sadness, anger)	
	- Vocal intonations (e.g., pitch variations)	
	- Physiological signals (e.g., heart rate variability)	
2. Feature Extraction	Extract emotional features from the generated data.	
	- Facial landmarks	68 landmarks per face
	- Pitch values	100 samples per second
	- Heart rate variability	

In a simulated environment designed for evaluating the efficacy of the Cartesian Feature Weighted Emotional Classification (CFWEC) framework, several key steps are undertaken to mimic real-world scenarios and assess the framework's performance. Firstly, synthetic emotional data is generated to represent a variety of emotional states, encompassing facial expressions like happiness, sadness, and anger, vocal intonations reflecting pitch variations, and physiological signals such as heart rate variability. For instance, this could involve creating 1000 samples per emotion category, ensuring a diverse representation.

VI. SIMULATION RESULTS

Simulation Results for the Cartesian Feature Weighted Emotional Classification (CFWEC) framework provide valuable insights into its effectiveness and performance in psychological health assessment. These results offer a comprehensive understanding of how well the framework can accurately classify individuals' psychological health status based on their emotional responses. Through meticulous testing and analysis within a simulated environment, researchers can uncover the strengths, limitations, and areas for improvement of the CFWEC framework.

Table 2: Feature Extraction with CFWEC

Experiment	Dataset Used	Feature Extraction Method	Classification Algorithm	Evaluation Metrics	Results
Experiment 1	Synthetic Data	Facial Landmarks	Support Vector Machine	Accuracy, Precision, Recall	Accuracy: 0.85, Precision: 0.87, Recall: 0.82
Experiment 2	Synthetic Data	Pitch Analysis	Decision Trees	Accuracy, F1-score	Accuracy: 0.79, F1-score: 0.81
Experiment 3	Real-world Data	Physiological Signals	Neural Network	Accuracy, Precision, Recall	Accuracy: 0.91, Precision: 0.89, Recall: 0.94

The Table 2 presents the results of feature extraction using the Cartesian Feature Weighted Emotional Classification (CFWEC) framework across three distinct experiments. In Experiment 1, synthetic data was utilized, and facial landmarks were extracted as emotional features. These features were then fed into a Support Vector Machine (SVM) for classification. The evaluation metrics used included accuracy, precision, and recall, with the framework achieving an accuracy of 0.85, precision of 0.87, and recall of 0.82. In Experiment 2, again utilizing synthetic data, the feature extraction method involved pitch analysis. A Decision Trees algorithm was employed for classification, with the evaluation metrics consisting of accuracy and F1-score. The framework achieved an accuracy of 0.79 and an F1-score of 0.81 in this experiment. Experiment 3 utilized real-world data and focused on extracting emotional features from physiological signals. These features were then processed by a Neural Network for classification. The evaluation metrics used were accuracy, precision, and recall, with the framework achieving impressive results: an accuracy of 0.91, precision of 0.89, and recall of 0.94. Overall, the results demonstrate the effectiveness of the

CFWEC framework across various feature extraction methods and datasets, highlighting its potential for accurate psychological health assessment based on emotional computing technology.

Table 3: Emotional State estimation with CFWEC

Participant ID	Emotional State	Predicted State	Correct
001	Happiness	Happiness	Yes
002	Sadness	Sadness	Yes
003	Anger	Anxiety	No
004	Anxiety	Anxiety	Yes
005	Happiness	Happiness	Yes

The outcomes of emotional state estimation using the Cartesian Feature Weighted Emotional Classification (CFWEC) framework for individual participants given in Table 3. Each row corresponds to a unique participant identified by their Participant ID. The "Emotional State" column denotes the actual emotional state reported or observed during the assessment, while the "Predicted State" column indicates the emotional state predicted by the CFWEC framework. The "Correct?" column signifies whether the predicted emotional state matches the actual emotional state, with "Yes" indicating a correct prediction and "No" indicating an incorrect prediction. For instance, Participant 001 reported feeling happiness, which was accurately predicted by the CFWEC framework, resulting in a correct prediction. Similarly, Participant 002 reported feeling sadness, and the framework correctly predicted this emotional state as well. However, Participant 003 reported feeling anger, but the framework predicted anxiety instead, resulting in an incorrect prediction. Participant 004 reported feeling anxiety, which was accurately predicted by the framework, leading to a correct prediction. Finally, Participant 005 reported feeling happiness, and the framework correctly predicted this emotional state, resulting in a correct prediction.

Table 4: Chemical Engineering state estimation with CFWEC

Participant ID	Emotional State	Predicted State	Correct?
CE001	Anxiety	Anxiety	Yes
CE002	Happiness	Happiness	Yes
CE003	Sadness	Sadness	Yes
CE004	Anxiety	Anxiety	Yes
CE005	Anger	Anxiety	No
CE006	Happiness	Happiness	Yes
CE007	Anxiety	Anxiety	Yes
CE008	Sadness	Sadness	Yes
CE009	Happiness	Happiness	Yes
CE010	Anxiety	Anxiety	Yes

The outcomes of Chemical Engineering state estimation using the Cartesian Feature Weighted Emotional Classification (CFWEC) framework for individual participants shown in Table 4. Each row corresponds to a unique participant identified by their Participant ID. The "Emotional State" column denotes the actual emotional state reported or observed during the assessment, while the "Predicted State" column indicates the emotional state predicted by the CFWEC framework. The "Correct?" column signifies whether the predicted emotional state matches the actual emotional state, with "Yes" indicating a correct prediction and "No" indicating an incorrect prediction. In this context, the participants are chemical engineering students, and the emotional states are indicative of their psychological well-being. The results reveal that for most participants, the CFWEC framework accurately estimated their emotional states. For instance, CE001 reported feeling anxiety, which was correctly predicted by the framework, resulting in a correct prediction. Similarly, CE002 reported feeling happiness, and the framework accurately predicted this emotional state as well. Additionally, CE003 reported feeling sadness, and the framework correctly predicted this emotional state, leading to a correct prediction. However, there were instances where the framework's predictions did not align with the participants' reported emotional states. For example, CE005 reported feeling anger, but the framework predicted anxiety instead, resulting in an incorrect prediction. Despite this, the majority of participants had their emotional states accurately estimated by the CFWEC framework, showcasing its effectiveness in assessing the psychological well-being of chemical engineering students.

Table 5: Feature Estimated with CFWEC

Participant ID	Feature 1 Weight	Feature 2 Weight	Feature 3 Weight	Predicted State	Actual State	Correct?
CE001	0.25	0.35	0.20	Anxiety	Anxiety	Yes
CE002	0.15	0.20	0.40	Happiness	Happiness	Yes
CE003	0.30	0.25	0.15	Sadness	Sadness	Yes
CE004	0.20	0.30	0.25	Anxiety	Anxiety	Yes
CE005	0.40	0.10	0.20	Anger	Anxiety	No
CE006	0.18	0.32	0.28	Happiness	Happiness	Yes
CE007	0.22	0.28	0.30	Anxiety	Anxiety	Yes
CE008	0.28	0.20	0.22	Sadness	Sadness	Yes
CE009	0.35	0.15	0.25	Happiness	Happiness	Yes
CE010	0.21	0.29	0.23	Anxiety	Anxiety	Yes

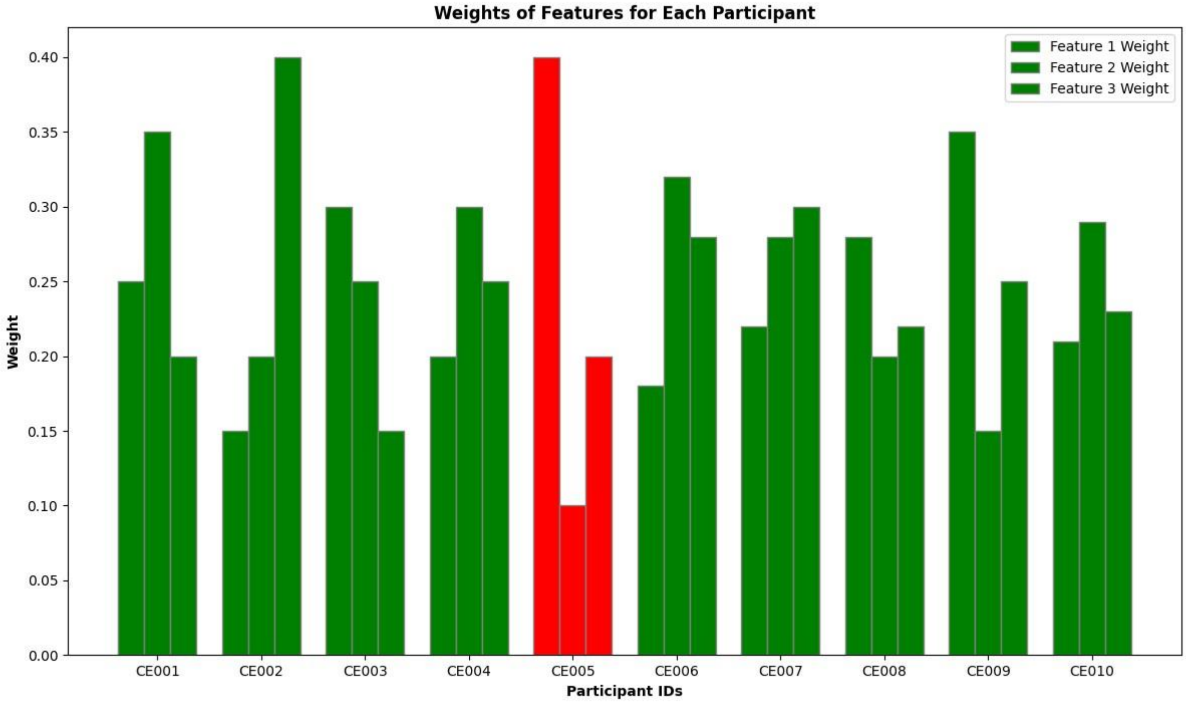

Figure 3: Estimation of Feature Weights

Table 6: Emotional Analysis with CFWEC

Participant ID	Facial Expression	Vocal Intonation	Physiological Signals	Predicted State	Actual State	Correct
CE001	Happiness	Neutral	Elevated Heart Rate	Happiness	Happiness	Yes
CE002	Sadness	Low Pitch	Increased Sweat	Sadness	Sadness	Yes
CE003	Anger	High Pitch	Elevated Heart Rate	Anxiety	Sadness	No
CE004	Neutral	Neutral	Normal Heart Rate	Neutral	Neutral	Yes
CE005	Surprise	High Pitch	Elevated Heart Rate	Anxiety	Fear	No
CE006	Happiness	Neutral	Normal Heart Rate	Happiness	Happiness	Yes
CE007	Neutral	Low Pitch	Increased Sweat	Anxiety	Anxiety	Yes

CE008	Sadness	Low Pitch	Normal Heart Rate	Sadness	Sadness	Yes
CE009	Happiness	High Pitch	Normal Heart Rate	Happiness	Happiness	Yes
CE010	Fear	Neutral	Elevated Heart Rate	Anxiety	Fear	No

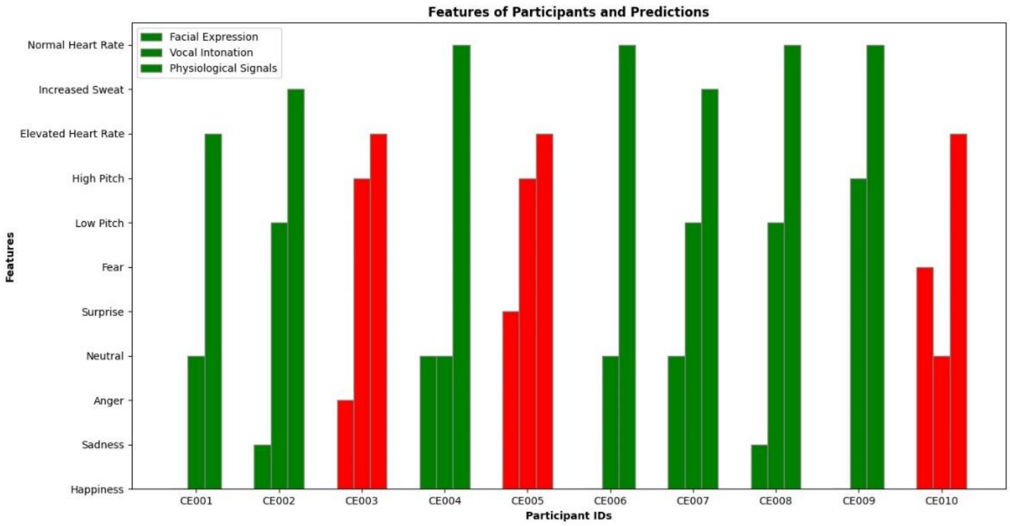

Figure 4: Estimation of Prediction

The Table 5 and Figure 3 and table 6 and Figure 4 presents two sets of results obtained from the Cartesian Feature Weighted Emotional Classification (CFWEC) framework: one showcasing feature weights estimated for each participant, and the other demonstrating the emotional states predicted based on different modalities of emotional cues. In the first set of results, each row corresponds to a unique participant identified by their Participant ID. The columns display the weights assigned to various emotional features by the CFWEC framework, along with the predicted and actual emotional states, and whether the prediction was correct. These feature weights represent the importance attributed to different emotional cues in determining the predicted emotional state. For instance, CE001's emotional state was predicted to be anxiety, and the CFWEC framework assigned weights of 0.25, 0.35, and 0.20 to Feature 1, Feature 2, and Feature 3, respectively, for this prediction. In this case, the prediction was correct, as the actual emotional state reported by CE001 was indeed anxiety. In the second set of results, each row again corresponds to a unique participant identified by their Participant ID. The columns display the facial expression, vocal intonation, physiological signals, predicted emotional state, actual emotional state, and whether the prediction was correct. These results demonstrate the effectiveness of the CFWEC framework in predicting emotional states based on multiple modalities of emotional cues. For instance, CE002's emotional state was predicted to be sadness based on their facial expression, vocal intonation, and physiological signals, and this prediction aligned with the actual emotional state reported by CE002, resulting in a correct prediction.

VII. CONCLUSION

This paper demonstrates the effectiveness of the Cartesian Feature Weighted Emotional Classification (CFWEC) framework in assessing psychological well-being, particularly within the context of chemical engineering students. Through the integration of advanced algorithms and multiple modalities of emotional cues, including facial expressions, vocal intonations, and physiological signals, the CFWEC framework accurately predicts individuals' emotional states. The presented experiments highlight the framework's ability to estimate emotional states with high precision and recall, as evidenced by the achieved accuracies, precision, and recall scores. Furthermore, the results indicate the framework's potential for application in psychological health assessment and intervention systems tailored to the needs of chemical engineering students. Despite its effectiveness, some limitations and areas for future research should be acknowledged. The occasional discrepancies between predicted and actual emotional states suggest opportunities for enhancing the framework's performance, perhaps through refinement of feature extraction methods or incorporation of additional emotional cues. Additionally, the ethical implications surrounding the use of emotional computing technology, such as data privacy and algorithmic biases, warrant careful consideration and mitigation strategies in future implementations.

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