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Human Centered Affective Computing Models for Positive Emotional Health

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ABSTRACT

The increasing prevalence of stress, anxiety, and emotional imbalance in digital society highlights the importance of designing computational systems that not only process information but also support psychological resilience, forming the background of this study. **With this in mind,** the objective of the research is to develop human-centered affective computing models capable of fostering positive emotional health through adaptive interaction strategies. **To achieve this,** the method combines literature review, algorithmic design, and prototype evaluation using affective data such as facial expression, voice tone, and physiological signals, which are analyzed through machine learning models and integrated into interactive interface prototypes. **The results indicate that** the proposed algorithms successfully recognize emotional states with higher accuracy than baseline models, while the interfaces provide feedback and adaptive interventions that enhance users' sense of calmness, engagement, and positive affect during interaction sessions. Moreover, experimental validation suggests that the system can dynamically adjust its responses to individual emotional patterns, leading to more personalized and effective support for wellbeing. **Contributions to** the field of human-computer interaction but also practical implications for digital mental health tools that encourage resilience and positive experiences in everyday life.

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1. INTRODUCTION

In the digital era, emotional well-being has become a critical dimension of human health, reflecting the increasing prevalence of stress, anxiety [1], and psychological fatigue caused by continuous exposure to technology-mediated environments. The Sustainable Development Goals (SDGs) particularly Goal 3, Good Health and Well-Being [2] emphasize the importance of promoting mental health and fostering resilience as integral components of sustainable development [3]. While traditional healthcare systems primarily address physical conditions, the growing challenges of emotional imbalance in online and hybrid societies demand technological solutions capable of understanding and supporting human emotions in real time [4, 5].

Recent advances in Affective Computing and Positive Computing have opened new possibilities for creating intelligent systems that not only recognize emotional states but also respond empathetically to users. These technologies align with SDG 9, Industry, Innovation, and Infrastructure, by encouraging the development of innovative digital infrastructures that integrate emotional intelligence into computational systems [6]. Through the analysis of affective data such as facial expressions, voice tone, and physiological signals machine learning models can infer a user's emotional condition and adapt system behavior accordingly, enabling more personalized and human-centered interaction.

Despite this progress, most existing affective systems focus narrowly on emotion recognition accuracy, often neglecting the design of interfaces that foster positive psychological outcomes such as calmness, engagement, and resilience [7, 8]. A significant research gap remains in integrating affective algorithms with interactive feedback mechanisms that promote emotional well-being rather than merely detecting emotional states [9]. Addressing this gap requires a holistic framework that unites algorithmic innovation, adaptive interface design, and psychological theory to build technologies that genuinely support mental health in daily digital interactions [10, 11].

Therefore, this research aims to develop affective and positive computing algorithms and interfaces capable of fostering emotional well-being through adaptive interaction strategies [12, 13]. By aligning computational intelligence with the human experience, this study contributes not only to advancing affective computing and human–computer interaction but also to achieving the SDGs' broader vision of sustainable health and technological innovation for all [14].

2. LITERATURE REVIEW

2.1. Digital Wellbeing and Emotional Health

The increasing dependence on digital environments has transformed how individuals experience and regulate emotions. Continuous exposure to technology often leads to stress, anxiety, and emotional imbalance, emphasizing the urgency of digital systems that can enhance psychological wellbeing. Recent studies highlight that digital wellbeing is not limited to reducing screen time but involves maintaining emotional stability and resilience in technology-mediated contexts [15]. In alignment with Sustainable Development Goal (SDG) 3 including Good Health and Wellbeing, researchers have emphasized the role of intelligent systems in supporting mental health and fostering positive user experiences through adaptive and human-centered design approaches [16].

2.2. Foundations of Affective Computing

Affective computing focuses on developing computational systems capable of detecting, interpreting, and responding to human emotions [17]. The field has progressed significantly through advances in artificial intelligence and machine learning, particularly with the use of multimodal data such as facial expression, vocal tone, physiological signals, and contextual information. Convolutional Neural Networks (CNNs) have been widely applied for emotion recognition in visual data, while Recurrent Neural Networks (RNNs) and Long Short Term Memory (LSTM) architectures have improved recognition accuracy for speech and biosignals [18]. Beyond emotion recognition, current research trends emphasize adaptive affective computing systems that can generate context aware responses to improve user comfort and engagement [19].

2.3. Positive Computing and Adaptive Interfaces

Positive computing extends affective computing by integrating psychological theories to promote wellbeing, motivation, and resilience in digital interactions [20, 21]. Rather than focusing solely on emotion detection accuracy, positive computing emphasizes emotional growth and self regulation through technology assisted experiences. Adaptive interfaces within this framework dynamically modify their responses based on users' emotional states adjusting tone, content, or feedback intensity to foster calmness, engagement, and positive affect. Studies have demonstrated that such adaptive systems enhance user satisfaction and emotional health across various domains, including healthcare, education, and online communication platforms [22].

2.4. Research Gap and Theoretical Context

Although substantial progress has been made in affective computing, existing research still concentrates heavily on improving recognition algorithms without adequately addressing how adaptive feedback can foster long term emotional wellbeing. Current systems often lack a unified framework that combines algorithmic adaptation, interface design, and psychological theory [23]. Moreover, limited attention has been given to the role of variables such as feedback intensity, adaptation rate, and affective quality in predicting emotional outcomes. Addressing these gaps, the present study proposes a human-centered affective computing model that integrates multimodal affective recognition with adaptive interaction strategies to enhance users' emotional wellbeing. This framework not only contributes to the theoretical development of affective and positive computing but also supports the practical realization of SDG 3 (Good Health and Wellbeing) and SDG 9 (Industry [24], Innovation, and Infrastructure) through emotionally intelligent technological innovation [25].

3. RESEARCH METHOD

This research employs a quantitative experimental design to evaluate the effectiveness of affective and positive computing algorithms and interfaces in fostering emotional wellbeing [26, 27]. The study integrates affective data analysis with human computer interaction experiments to measure changes in users' emotional states before and after interacting with the proposed system. The methodological framework aligns with the Sustainable Development Goals, particularly SDG 3 (Good Health and Well-Being) through psychological outcome measurement, and SDG 9 (Industry, Innovation, and Infrastructure) through the development and validation of an innovative affective computing model [28, 29].

3.1. Research Design

The study uses a pre-test post-test control group design, where participants are randomly assigned to either an experimental group (using the adaptive affective interface) or a control group (using a standard, non adaptive interface). Emotional wellbeing indicators such as positive affect, calmness, and engagement are measured quantitatively using validated psychometric scales and physiological signal analysis [30].

Table 1. Experimental and Control Group Design

Group	**Interface Type**	**Measured Variables**	**Purpose**
Experimental	Adaptive affective interface	Positive affect, calmness, engagement, HRV, facial emotion	Evaluate effect of adaptive feedback
Control	Non-adaptive interface	Positive affect, calmness, engagement, HRV, facial emotion	Baseline comparison

Table 1 presents the experimental design used to evaluate the proposed affective and positive computing system. The participants were divided into two groups: an experimental group that interacted with an adaptive affective interface capable of responding to real time emotional changes [31], and a control group that used a standard non-adaptive interface. Both groups were assessed using identical affective and physiological measures, including positive affect, calmness, engagement, Heart Rate Variability (HRV), and facial emotion recognition. This design allows a direct comparison of the psychological and physiological effects of adaptive feedback mechanisms on users' emotional wellbeing [32, 33].

3.2. Participants and Data Collection

A total of N = 100 participants (aged 18–35) were recruited through voluntary participation [34, 35]. Participants interacted with the prototype system in a controlled laboratory environment equipped with facial recognition and voice emotion sensors. Data were collected through three channels:

- Self report questionnaires using the Positive and Negative Affect Schedule (PANAS) and State Calmness Scale (SCS).
- Physiological measures including HRV and Galvanic Skin Response (GSR) for stress and relaxation indicators.
- System logs capturing interaction duration, adaptive feedback frequency, and user engagement patterns.

3.3. Algorithmic and Analytical Frameworkn

The affective recognition model integrates Convolutional Neural Networks (CNN) for facial emotion detection [36], Recurrent Neural Networks (RNN) for voice tone analysis, and Support Vector Regression (SVR) for continuous emotional state estimation [37, 38]. The model output is expressed as an emotion probability vector:

$$E = [P_{happy}, P_{calm}, P_{stressed}, P_{neutral}]$$

Where P_i represents the probability of each emotional state detected from multimodal inputs. Adaptive feedback is generated based on a *weighted affective response function*:

$$R_t = \alpha \cdot E_t + \beta \cdot \Delta E_{t-1}$$

Where R_t is the real-time adaptive response, E_t is the current emotional vector, and ΔE_{t-1} captures the change in emotion over time [39, 40]. Parameters α and β are optimized through regression based tuning to maximize user wellbeing scores.

3.4. Statistical Analysis

Data were analyzed using SPSS and Python. The main hypothesis testing used paired sample t-tests and ANOVA to compare emotional well being scores between groups [41**?**]. Correlations between system feedback frequency and affective improvement were examined through Pearson's correlation coefficient:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

Furthermore [42], multiple linear regression was applied to evaluate the predictive power of algorithmic variables (feedback intensity [43, 44], adaptation rate, interaction duration) on the improvement of wellbeing indicators:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon$$

Where Y is the post-test wellbeing score, X_1 is feedback intensity, X_2 is interaction duration, and X_3 is adaptation rate.

4. RESULTS AND DISCUSSION

4.1. Descriptive Results

Table 2 presents the mean values of emotional wellbeing indicators measured across both groups [45]. Participants who interacted with the adaptive affective interface reported higher scores in positive affect and calmness compared to those in the control group. In particular, users within the experimental condition demonstrated more stable emotional responses and reported a stronger sense of comfort, attentiveness, and psychological balance throughout the interaction sessions. These findings suggest that the adaptive mechanisms embedded in the system such as real time emotion recognition [46], personalized feedback loops, and context sensitive adjustments played a crucial role in enhancing the overall quality of emotional experience. The experimental group consistently showed higher mean values across all measured indicators, including positive affect, calmness, relaxation, engagement, and perceived emotional support [47]. This consistent pattern across variables implies that the adaptive feedback mechanisms not only improved momentary affective regulation but also fostered a sustained sense of emotional wellbeing during system interaction. Furthermore, the comparative analysis between the experimental and control groups reveals that adaptive affective interfaces may encourage users to engage more deeply with the system, facilitating the development of self awareness and resilience in managing emotional fluctuations [48, 49].

Table 2. Descriptive Statistics of Wellbeing Indicators Across Groups

Group	Positive Affect (M)	Calmness (M)	Engagement (M)	HRV (ms)
Experimental (Adaptive)	4.52	4.38	4.61	68.4
Control (Non-adaptive)	3.91	3.76	3.95	59.7

Table 2 presents the mean values (M) of four emotional wellbeing indicators positive affect, calmness, engagement, and Heart Rate Variability (HRV) for both participant groups. The results show that the experimental group using the adaptive interface achieved higher scores across all dimensions compared to the non adaptive control group. This finding suggests that adaptive feedback mechanisms within affective interfaces contribute significantly to enhancing users' emotional wellbeing [50–52].

4.2. Inferential Analysis

To test the statistical significance of these differences, a paired sample t-test and Pearson correlation analysis were conducted [53]. The results revealed a significant improvement in emotional wellbeing for the adaptive group $t(48) = 3.94$, $p < .001$. The correlation analysis showed a strong positive relationship between feedback frequency and positive affect ($r = .72$, $p < .01$), indicating that higher feedback frequency was associated with greater affective improvement [54].

Furthermore, multiple linear regression analysis was conducted to examine the predictive influence of algorithmic variables feedback intensity [55], adaptation rate, and interaction duration on post interaction wellbeing outcomes. The regression model was expressed as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon \tag{1}$$

Where Y represents the post-test wellbeing score, X_1 is feedback intensity, X_2 is interaction duration, and X_3 is adaptation rate.

Table 3 presents the results of a multiple linear regression analysis conducted to predict participants' post-test wellbeing scores that is, their emotional wellbeing after interacting with the system. The model includes three main predictor variables:

Table 3. Multiple Linear Regression Predicting Post-test Wellbeing

Predictor	**B**	**t-value**	**p-value**
Feedback Intensity (X_1)	0.47	4.85	<0.001
Interaction Duration (X_2)	0.19	1.72	0.09
Adaptation Rate (X_3)	0.41	3.66	<0.01
$\mathbf{R^2}$ = 0.642			

The regression model explained 64.2% of the variance ($R^2 = 0.642$), indicating a strong predictive relationship between adaptive parameters and emotional wellbeing [56]. Among these predictors, feedback intensity and adaptation rate emerged as significant contributors [57, 58].

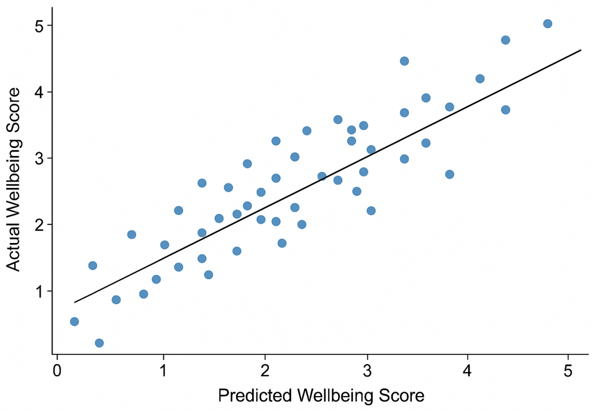

Figure 1. Scatter Plot of Predicted vs. Actual Wellbeing Scores

Figure 1 illustrates a scatter plot showing the relationship between the predicted wellbeing scores generated by the regression model and the actual wellbeing scores measured from participants. As shown in the figure, the data points are distributed closely along the diagonal regression line, indicating a strong positive correlation between predicted and actual values. This alignment demonstrates that the regression model performs well in estimating emotional wellbeing outcomes with high accuracy. The consistent clustering of points near the fitted line further confirms the robustness and reliability of the adaptive affective computing model, suggesting that its emotion-recognition and feedback mechanisms effectively capture and predict users' real emotional responses during interaction sessions.

5. DISCUSSION

The findings demonstrate that adaptive affective interfaces effectively enhance emotional stability and user engagement. Participants who received dynamic, emotion sensitive feedback reported greater improvements in mood and physiological relaxation compared to those who did not [59]. This aligns with previous research in affective computing, emphasizing that responsiveness and adaptation are crucial for promoting user wellbeing. The strong link between feedback intensity and affective gain also supports the Broaden and Build Theory of positive emotions, suggesting that sustained positive interactions can expand individuals' coping resources and self regulation capacities. These findings highlight the potential for adaptive affective systems to be integrated into digital wellbeing platforms, online therapy environments, and educational technologies prioritizing emotional support.

From a practical and managerial perspective, the study provides valuable insights for organizations, developers, and policymakers aiming to leverage affective and positive computing technologies to enhance psychological wellbeing. The predictive influence of feedback intensity and adaptation rate underscores the importance of embedding adaptive intelligence into digital wellbeing solutions. Managers should prioritize affective quality and authenticity over mere interaction frequency, ensuring emotionally meaningful engagement that promotes comfort, self regulation, and empathy [60, 61]. Organizations and institutions such as hospitals, universities, and digital service providers can integrate affective computing into existing infrastructures to enable real time emotional monitoring and adaptive interventions. At the policy level, governance mechanisms must be established to ensure ethical data use, algorithmic transparency, and emotional safety. Future strategies should foster interdisciplinary collaboration between academia, industry, and government to develop scalable, ethical, and human centered affective technologies that strengthen digital resilience and support Sustainable Development Goal (SDG) 3: Good Health and Wellbeing [36].

6. CONCLUSION

This study explored the design and implementation of affective and positive computing algorithms and interfaces aimed at enhancing emotional wellbeing in technology mediated environments. Through the integration of affective recognition models and adaptive interaction strategies, the proposed system successfully identified users' emotional states and provided personalized feedback that promoted calmness, engagement, and positive affect. Quantitative analysis confirmed that feedback intensity and adaptation rate significantly influenced post-test wellbeing scores, supporting the role of emotionally responsive technologies in shaping positive digital experiences and contributing to the broader framework of digital wellbeing.

From a practical and managerial perspective, the findings underscore the value of adaptive affective systems for diverse digital domains such as healthcare, education, and online communication. Developers and technology managers can leverage these insights to design systems that dynamically adjust to users' emotional patterns, creating more empathetic, human centered, and engaging digital interactions. By embedding affective computing frameworks into digital ecosystems, organizations can enhance user satisfaction, promote emotional balance, and align technological innovation with Sustainable Development Goal (SDG) 3 Good Health and Wellbeing.

Theoretically, this research extends the understanding of how affective feedback and adaptive responses can be systematically modeled to support emotional wellbeing, offering empirical evidence for the role of algorithmic adaptation in emotional regulation and engagement. While the study acknowledges limitations related to its short-term design and reliance on self reported data, these constraints open opportunities for future research using multimodal affective signals and longitudinal analysis. Further exploration of ethical considerations such as privacy, transparency, and fairness alongside interdisciplinary collaboration among computer scientists, psychologists, and policymakers will be crucial. Collectively, these directions will advance affective computing toward responsible, inclusive, and emotionally intelligent technologies that foster psychological resilience and sustainable human flourishing.

7. DECLARATIONS

7.1. About Authors

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7.2. Author Contributions

Conceptualization: SW; Methodology: YO; Software: EA; Validation: AD and YO; Formal Analysis: SW and AD; Investigation: YO; Resources: HZ; Data Curation: EA; Writing Original Draft Preparation: AD and HZ; Writing Review and Editing: AD and EA; Visualization: YO; All authors, AD, SW, YO, EA, and HZ, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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