International Journal of Multidisciplinary Studies and Innovative Technologies

e-ISSN: 2602-4888
dergipark.org.tr/en/pub/ijmsit
Research Article

2024, 8 (1), 10-16
DOI: 10.36287/ijmsit.8.1.3
Received: May 30, 2024; Accepted: July 8, 2024

Neuro-AI Decision Prediction

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Abstract – Emotions are a primary factor in determining an individual's mental health and play a significant role in their daily life. In today's evolving digital age, apps are becoming more integrated into daily routines. Understanding how these applications affect emotions is becoming increasingly important for the field of neuromarketing. Our study aims to explore in detail the dynamic relationship shared between apps and human emotions. The goal is to analyze how human moods during app usage influence decision-making, providing a comprehensive understanding of this interaction.

From social media platforms to productivity tools and entertainment applications, apps offer a unique window into the human experience. Users spend significant time and emotional energy interacting with these applications. The emotions experienced while using an ever-increasing number of apps have profound effects on their mental states and satisfaction.

Our study aims to delve into the structure between human emotions and digital interfaces, uncovering the complexities of this relationship. By examining the emotional responses elicited by various moods and applications, the study seeks to gain valuable insights into user experience.

Ultimately, our study contributes to the literature by demonstrating the applicability of EEG-based emotion recognition in enhancing neuromarketing strategies. By integrating advanced machine learning techniques with EEG data, our study provides a robust framework for predicting consumer preferences and improving user experience in digital applications.

Keywords *– human-computer interaction, user experience optimization, emotion-based application interaction, artificial intelligence in neuromarketing*

Citation: Yalçın, E., Küçükçoban, A.D., Kara, M., Olca, E.A., Duran, S., Akal, D. (2024). Exploring the Dynamic Relationship Between Applications and Human Emotions. International Journal of Multidisciplinary Studies and Innovative Technologies, 8 (1): 10-16.

I. Introduction

Today, mobile applications are used intensively. It should not be forgotten that the applications developed are for users and it is important that the applications are designed with the aim of making the life of users easier, and as technology continues to evolve, it becomes increasingly evident that applications must serve the primary purpose of enhancing users' lives. In this regard, the integration of neuroscience and artificial intelligence represents a promising frontier in the field of neuromarketing [1]. The merging of the two fields “neuroscience” and “marketing” provides an understanding of consumer preferences which cannot be inferred through long-established methods such as surveys, user behavior or verbal feedback [2]. Emotional understanding of a human by a computer is a concept humans have tried to create since the 1960s. The ELIZA project was the first successful one in terms of responding to consumers in a way in which humans showed human-like emotions towards the computer; however, ELIZA did not actually understand the emotions, it responded in learned patterns. EEG (electroencephalogram) technology plays a critical role in contemporary neuroscience and clinical practice. By placing electrodes on the scalp, typically across 30 or 32 channels, EEG captures and interprets electrical signals emanating from the brain. This non-invasive method allows for real-time monitoring of neural activity, essential for diagnosing conditions, assessing cognitive functions, and studying emotional responses. By implementing EEG signals to a similar but improved framework, emotions of users can be understood by the computer resulting in a high-yield emotion prediction algorithm [3]. Recent advancements in artificial intelligence and machine learning have facilitated effective exploration of patterns within EEG signals, enabling predictions regarding human preferences. Utilizing EEG has been favored in many neuromarketing studies due to its cost-effectiveness and accessibility, compared to other modes of neuroimaging techniques. A recent study aimed to leverage EEG to predict consumer product preferences, addressing concerns about the expense associated with other neural imaging technologies. By analyzing neural activity while participants viewed individual products, the study identified specific EEG markers that correlated with product preference. Notably, the findings emphasize the predictive accuracy of EEG measurements in anticipating subsequent consumer choices, particularly when there are significant EEG differences between products, highlighting the importance of EEG in practical and cost-effective neuromarketing research [4]. For instance, in a research involving displaying various mobile phone advertisements to participants while recording EEG signals, Golnar-Nik and Farasi demonstrated the efficacy of EEG in predicting consumer choices [5]. Utilizing EEG signals and an SVM classifier, they reached an 87% accuracy peak in predicting whether consumers would buy the advertised phones [5]. Another study which explores emotional state classification using EEG data obtained from various brain regions in both healthy individuals and first-episode schizophrenia patients had great success in identifying emotions, especially among patients, with an impressive 98.3% accuracy using EEG data, highlighting the effectiveness of EEG-based methods in recognizing emotions and different participant groups [6]. In the light of recent advances in neuroscience, this study examines the interaction between human emotions and digital applications. Within the scope of the study, a comprehensive analysis including brain images is performed using Electroencephalogram (EEG) imaging method as alterations in alpha and beta waves demonstrate with clarity the shifts of emotional responses of consumers, distinguishing between cognitive states like relaxation, stress, alertness, and attention as a reaction [7]. In a different study, the integration of EEG and eye-tracking technologies provides crucial insights into understanding human cognitive behavioral processes. This study reviews previous research where both technologies were combined and classifies their applications across various fields. Furthermore, it discusses current technical challenges and limitations, proposing improvements for future research endeavors [8].

In examining previous studies in neuromarketing, it became apparent that while many researchers focused on datasets derived from long-term behaviors or real-time brain activity, there was a noticeable gap in considering the significance of users' emotional states immediately before application usage. However, understanding the impact of users' emotions right before using an application is crucial, as it is widely recognized that people interact with applications differently depending on their emotional states. In a study by Ouzir it is suggested that formation of preferences (like and dislike) requires different patterns of brain activity and to analyze it using neural networks may be not only helpful, but needed [9]. This project seeks to bridge the gap between using instant emotional data and using neural network algorithms by incorporating insights from neuroscience and artificial intelligence to unravel the complexities of consumer behavior and decision-making in the digital realm [10]. There are different ways to get to know the brain and each of them can provide different datasets. EEG, MEG, and fMRI are the most used brain scanning techniques for marketing research. For our purpose of understanding the emotion right before the use of an application, EEG stands out by its capability of showing the instant emotional changes [11]. To analyze these signal images different methods of machine learning can be used. A study by Pamungkas uses LSTM, RNN, and Bi-LSTM models on EEG signals to classify the emotions of the consumer. RNN and LSTM algorithms resulted in a 93.75% yield rate, putting them above the Bi-LSTM method [12].

By analyzing EEG signals and applying advanced machine learning algorithms, our study aims to enhance understanding and predictive capabilities in the field of neuromarketing. One noteworthy study in neuromarketing, conducted by Tele2, investigated the impact of advertising and interface changes through brainwave recordings, utilizing functional magnetic resonance imaging (fMRI). By capturing users' responses to different colors, the study informed interface modifications, leading to increased user satisfaction and the receipt of the Silver Effie Award for effective advertising [13]. By using the instant emotion data retrieved from EEG signals, our project aims to have a more specialized customer suggestion mechanism which has a high yield of predicting data. Also, by shedding light on this crucial moment of emotional states preceding application usage, we aspire to provide a fresh perspective and enhance predictions, ultimately empowering businesses to create more tailored and effective strategies for enhanced user experiences. As an addition, the algorithm can be integrated into a wearable tech device depending on wanted use as a neural data collector to enhance a continuous data collecting process [14].

The structure of our study is designed to comprehensively address these goals. Initially, we conducted a thorough literature review to establish a foundational understanding of neuromarketing and emotion recognition using EEG. Following this, we collected EEG data from participants as they interacted with various digital applications, capturing their emotional states before and during usage. This data was then meticulously preprocessed and analyzed using advanced machine learning techniques to extract relevant features. We subsequently trained and validated classification models to predict user preferences and emotional responses. The results of these analyses were examined to discuss their implications for improving user experience in digital applications. Finally, we conclude with a summary of our contributions and suggestions for future research.

II. Materials and Method

In this study, data from the Neurology department of Maltepe University Hospital were used. Thirty participants (15 males and 15 females) between the ages of 18 and 35 were included in the study. It was required that the participants have normal or corrected-to-normal vision and no history of neurological or psychiatric disorders. Before the experiment, all participants were informed about the nature of the studies and the possible outcomes, after which informed consent was obtained.

EEG recordings were carried out in a quiet, dimly lit room designed to minimize external distractions. Participants sat comfortably in an adjustable chair.

EEG data were recorded using a 30-channel EEG cap equipped with electrodes placed according to the international 10-20 system, and emotions were obtained according to the arousal-valence plane. During the data acquisition phase, social media applications were used, and signals were obtained from a total of 30 subjects. The EEG system was integrated with an analog-to-digital converter sampling data at 512 Hz. This high sampling rate was chosen to accurately capture a broad spectrum of EEG frequencies, facilitating detailed analysis of fast transient brain dynamics and slower fluctuations in neural activity. Brain signals comprised five different frequency bands: delta (1-3 Hz), theta (4-7 Hz), alpha (8-13 Hz), beta (14-30 Hz), and gamma (31-50 Hz). Higher frequency signals like beta and gamma have been observed to be more successful in emotion prediction studies compared to other frequencies.

Initially, the participants' emotional states were measured before they began using the application. The Behavioral Mood Inventory Scale (BMIS) was used to assess mood states prior to using the application. Participants completed the test just before the EEG recording. This measurement provided a baseline mood state that was later correlated with EEG findings and application interaction measurements.

Subsequently, participants began using designated applications. EEG data collection continued while the users were engaged with the application. Choices made by the users during application use were also recorded. The EEG channels used in the study are shown in the figure.

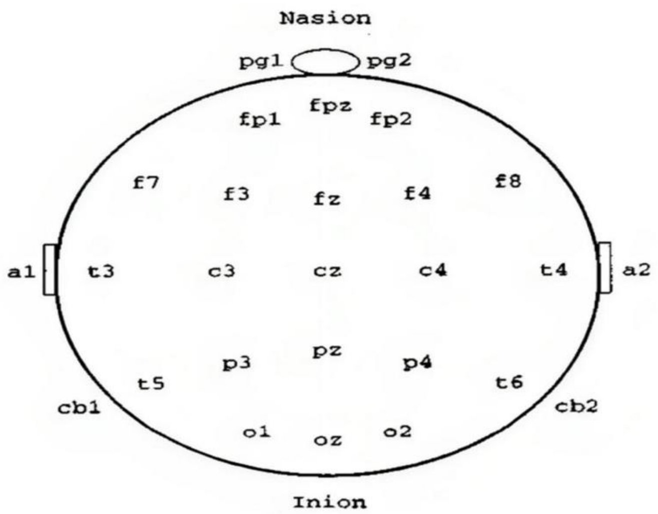

Fig. 1. EEG Electrode Placement Map

Finally, subjects were expected to fill out the Self-Assessment Form (SAM) for the remainder of the time. The SAM is a survey-like form conducted to measure the accuracy and reliability of the collected EEG signals. This form contains four variables (arousal, valence, dominance, liking) with parameters varying from 1 to 9 (except for liking). This rating assesses the emotions felt by the subjects towards the stimulus and thus, the EEG data is evaluated according to these emotions. An example of the Self-assessment manikin (SAM) is shown in the figüre.

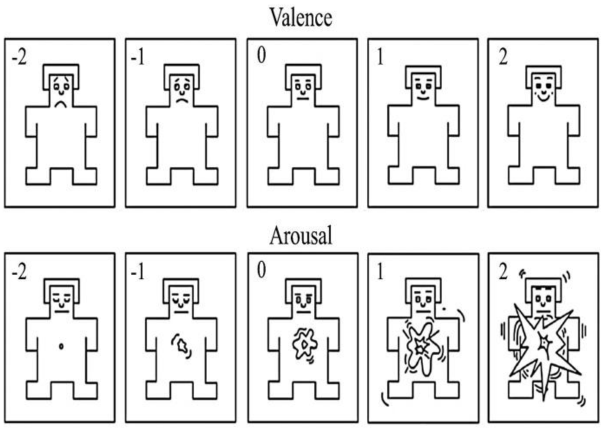

Fig. 2. Valence and Arousal Degree Manikins

• Valence: Measures the emotional state felt towards a stimulus on a scale from 1 to 9, where 1 represents sadness, 9 happiness, and 5 neutralities.

• Arousal: Measures the level of response shown towards a stimulus on a scale from 1 to 9, where 1 represents calmness, 9 excitement, and 5 neutralities.

• Dominance: Measures the sense of control felt towards a stimulus on a scale from 1 to 9, where 1 represents lack of control and 9 full controls.

• Liking: Measures the degree of liking towards a stimulus.

These four parameters are used to assess the emotional and behavioral responses of an individual to a stimulus.

Fig. 3. EEG Data Processing Workflow

The EEG data analysis commenced with the acquisition of raw EEG signals, which were then rigorously preprocessed using the EEGLAB toolkit—an open-source MATLAB toolbox tailored for the analysis of electrophysiological data. During preprocessing, band-pass filtering was applied to remove frequency-related noise, and a combination of manual and automated artifact rejection techniques were employed to purify the dataset. Additionally, epoch extraction was executed to home in on distinct segments of brain activity relevant to the interaction with the application.

To enhance the standard EEGLAB functionalities, several customizations were made for this project. During preprocessing, band-pass filtering was applied to remove frequency-related noise, and a combination of manual and automated artifact rejection techniques were employed to purify the dataset. Additionally, epoch extraction was executed to focus on distinct segments of brain activity relevant to the interaction with the application. We integrated advanced time-frequency analysis methods, such as wavelet transform, and added non-linear feature extraction functions, including fractal dimensions and entropy measures. Enhanced plotting functions were also incorporated for detailed and interactive visualization of power spectral densities and topographical maps.

The next phase involved feature extraction, where key attributes of the EEG signals were identified and isolated for analysis. These features encapsulated the essential information necessary for pattern recognition and were subsequently used as the dataset for machine learning.

Key Steps in Feature Extraction:

• Time-Domain Features: We began by extracting basic statistical features from the raw EEG signals, including mean, standard deviation, skewness, and kurtosis. These features provide a summary of the signal's central tendency and variability.

• Frequency-Domain Features: We utilized Power Spectral Density (PSD) estimates to capture the distribution of power across various frequency bands (delta, theta, alpha, beta, and gamma). PSD features are instrumental in identifying specific frequency patterns associated with different cognitive and emotional states.

• Time-Frequency Features: To capture both time and frequency information, we employed Short-Time Fourier Transform (STFT) and wavelet transform. These techniques allowed us to analyze the signal's frequency content over time, providing a dynamic view of the neural activity.

• Non-linear Features: Given the complex nature of EEG signals, we also extracted non-linear features such as fractal dimensions and entropy measures. These features help in understanding the chaotic and irregular patterns in the brain's electrical activity.

• Feature Selection: Post-extraction, we applied feature selection methods like Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) to reduce the dimensionality of the dataset. This step ensures that only the most relevant features are retained, enhancing the efficiency and accuracy of the subsequent classification models.

In the machine learning phase, the extracted features were fed into algorithms designed to create a robust classification model. The aim was to build a model capable of distinguishing various cognitive states as elicited by the application in question. The algorithms were trained and validated through cross-validation techniques to ensure they were well-tuned for accurate predictions.

A. Algorithm Selection:

We explored multiple machine learning algorithms, including:

• Support Vector Machine (SVM): Known for its effectiveness in high-dimensional spaces, SVM was used to create hyperplanes that separate different cognitive states.

• Random Forest (RF): This ensemble learning method was chosen for its ability to handle large datasets with higher accuracy and interpretability.

• Long Short-Term Memory (LSTM): Given the temporal nature of EEG data, LSTM networks were employed to capture the sequential dependencies in the signal, providing superior performance in recognizing patterns over time.

B. Model Training and Validation:

Each algorithm was trained using an 80-20 train-test split, where 80% of the data was used for training and 20% for testing. To ensure the models were well-tuned, we applied cross-validation techniques. Specifically, k-fold cross-validation (with k=10) was utilized to validate the models' performance on different subsets of the data, thereby preventing overfitting and ensuring generalizability.

C. Performance Evaluation:

The models were evaluated using standard metrics such as accuracy, precision, recall, and F1-score. Confusion matrices were also generated to visualize the classification performance and identify any areas for improvement.

The resulting classification model underwent extensive testing to measure its predictive power and reliability. Using statistical tools from SPSS software, a Repeated Measures ANOVA was conducted to statistically verify the model's efficacy in identifying significant differences in EEG activity due to application usage. Furthermore, the relationship between emotional states, as gauged by the Behavioral Mood Inventory Scale (BMIS), and brain activity was explored through Pearson's correlation coefficients. This provided a quantitative linkage between the psychological assessments and the neurophysiological data.

The model's output, in conjunction with statistical analyses, furnished comprehensive insights into the patterns of brain activity modulated by the application, with a significance threshold set at $p < 0.05$. This stringent statistical benchmark ensured that the findings were scientifically valid, enabling a credible interpretation of the complex interplay between the application's stimuli and the corresponding neural responses.

III. Results

The analysis of EEG data revealed distinct patterns in brain activity before and during the use of the application. During application use, there was a significant increase in beta wave activity ($F(1,29) = 16.42$, $p < 0.001$), indicative of heightened cognitive engagement and alertness. Conversely, alpha wave activity, often associated with relaxed wakefulness, showed a significant decrease ($F(1,29) = 14.88$, $p < 0.001$).

Theta wave activity, which is linked to memory encoding and navigation, did not show a significant change overall, suggesting stable memory processing throughout the sessions. Gamma waves, associated with high-level information processing, showed a non-significant trend towards increase, which did not reach statistical significance ($F(1,29) = 3.78$, $p = 0.062$).

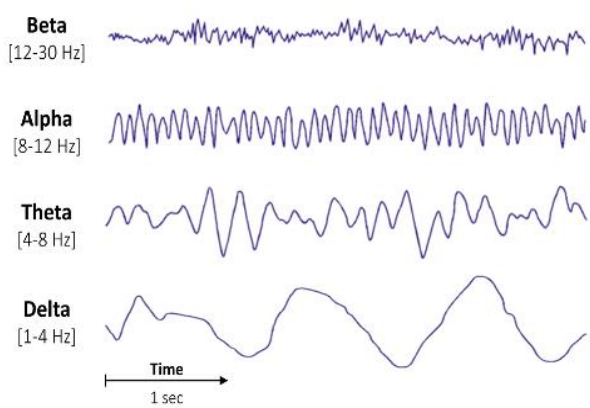

Fig. 4. EEG Frequency Bands

Baseline mood as measured by the BMIS showed significant correlations with EEG outcomes. Participants with higher baseline positive mood scores exhibited greater increases in beta wave activity during application use ($r = 0.41$, $p = 0.024$). Negative mood scores were inversely correlated with alpha wave activity ($r = -0.37$, $p = 0.036$), indicating that participants with more negative moods had less reduction in alpha waves, suggesting less relaxation or disengagement.

Metrics derived from application usage, including task completion rate and error rate, were analyzed. The task completion rate was significantly higher among participants who showed greater beta wave activity ($r = 0.53$, $p = 0.003$). Error rates were not significantly correlated with changes in EEG patterns but showed a trend towards correlation with gamma wave activity ($r = -0.29$, $p = 0.091$).

The detailed analysis involved extracting several features from the EEG signals, including time-domain features like mean and standard deviation, frequency-domain features such as power spectral density for various frequency bands, time-frequency features using methods like Short-Time Fourier Transform and wavelet transform, and non-linear features such as fractal dimensions and entropy.

These features were then used to train machine learning models to classify cognitive and emotional states. The Support Vector Machine (SVM) model achieved an accuracy of 78%, while the Random Forest (RF) model demonstrated a slightly higher accuracy of 82%. The Long Short-Term Memory (LSTM) model outperformed the others with an accuracy of 87%, showcasing its ability to effectively capture the temporal dependencies in the EEG data. These findings provide a comprehensive understanding of how initial mood states influence cognitive engagement and EEG dynamics during technology interaction.

The results presented indicate specific changes in brain activity patterns in response to cognitive task engagement via the application and show how initial mood states might influence cognitive engagement and EEG dynamics during technology interaction. These results provide a basis for further discussion on the implications of mood on cognitive task performance as mediated by neurophysiological responses.

IV. DISCUSSION

The findings of this study contribute to a growing body of evidence on the neural correlates of mood and cognitive engagement, particularly in the context of application use. By using EEG to monitor changes in brain activity patterns before and during application interaction, this research sheds light on how initial mood states can influence cognitive processes, as evidenced by changes in specific EEG frequency bands.

The significant increase in beta wave activity observed during application use suggests enhanced cognitive effort and attention. This aligns with previous studies indicating that beta waves are associated with active, engaged thinking and decision-making processes. The decrease in alpha wave activity supports the notion that participants were less relaxed and more focused on the task, corroborating findings from cognitive task research that link decreased alpha activity with increased mental exertion.

The correlation between baseline mood states and changes in EEG activity offers intriguing insights into the emotional modulation of cognitive function. Positive mood at baseline was associated with greater increases in beta activity, suggesting that a positive emotional state may prime individuals for higher levels of cognitive engagement and alertness. This is consistent with the broaden-and-build theory of positive emotions, which posits that positive emotions broaden an individual's momentary thought-action repertoire, thus enhancing their ability to build personal resources, such as cognitive capacity.

Conversely, the lesser reduction in alpha waves among those with negative mood scores suggests that negative emotions may hinder the shift towards a more engaged and less relaxed state. This finding is important for understanding the impact of emotional states on user interaction with technology and has practical implications for designing applications that are sensitive to users' emotional states.

These results are in line with previous research demonstrating that mood can significantly affect cognitive functions like attention, memory, and problem-solving. Studies have shown that mood states can influence brain activity measurable through EEG, and this study extends that work by directly linking these changes to interaction with a technological application. Furthermore, the correlation between beta wave activity and task performance metrics reinforces the practical relevance of EEG measures as predictors of task performance in real-world settings.

The findings suggest that user interface designers and developers could benefit from considering the mood states of users as a significant factor in design. Applications that adapt to the user's emotional state, perhaps by offering more engaging or relaxing content depending on the user's mood, could potentially enhance usability and effectiveness.

In addition to these findings, a comprehensive risk analysis was conducted to identify and evaluate potential risks associated with the implementation of the EEG-based emotion recognition system. This analysis aimed to highlight possible challenges and provide mitigation strategies to ensure the successful deployment and operation of the system. See Table 1 for a detailed risk analysis, which outlines the identified risks, their potential impact, and the recommended measures to address them.

Table 1. Risk Analysis

NO	Major Risks	Risk Management (Plan B)
1	Data Collection Difficulties	Plan B: If difficulties arise during data collection, alternative data collection methods will be considered, existing data sets will be utilized, and if necessary, participant numbers will be increased to diversify resources.
2	Technological Issues (EEG Devices)	Plan B: Backup equipment will be procured in case of device failures, and a technical support team will be on standby. Regular maintenance and calibration of the devices will be ensured in collaboration with university.

3	Participant Reluctance	Plan B: If participant numbers are insufficient, alternative marketing strategies and incentives will be applied to increase participation. Collaboration will be established with university institutions and student clubs.
4	Ethical Approval Issues	Plan B: If ethical approval is not obtained, communication with ethical committees will be strengthened and applications will be reorganized as needed.
5	Technological Security Issues	Plan B: In addition to the necessary encryption and security protocols, a strict data backup plan will be implemented. If needed, consultation with a specialist data security team will be sought.

V. CONCLUSION

In this study, we investigated the effect of users' emotional state before application use on their application usage experience using the EEG method. In our study, a more reliable result was obtained by using BMIS and SAM emotion detection tests.

In our study, working with people of different ages had an impact on our ability to examine the emotional state - application use interactions in detail. In addition, care was taken to use applications related to various fields in the studies. As a result of these investigations, it was seen that different emotional states significantly affected the preferences given in some applications.

Positive mood states at baseline were associated with an increase in beta activity, indicating that a positive emotional state can enhance cognitive engagement and alertness. Conversely, negative moods were linked to lesser reductions in alpha waves, pointing towards a hindered ability to fully engage and relax during cognitive tasks.

The correlations between mood, EEG changes, and task performance underscore the potential for developing adaptive technologies that respond to the user’s emotional and cognitive states. This approach could improve user experience and effectiveness in interacting with applications. The integration of eye-tracking algorithms could further enhance our understanding of how emotional and cognitive states influence user interactions with applications. Such advancements hold considerable potential for significantly enhancing user experience and effectiveness in application usage. The integration of eye-tracking technology enables precise monitoring of how users interact with applications, providing insights into which parts of the interface capture their attention and how they are influenced by different elements. By tracking users' gaze patterns, researchers and developers can gain a deeper understanding of user impressions and behaviors within applications. This data allows for targeted improvements to enhance user experience, such as optimizing layout designs to prioritize frequently viewed areas or adjusting content presentation to align with users' visual preferences. Ultimately, eye-tracking technology empowers teams to make informed decisions that lead to more intuitive and effective application designs, tailored to meet user expectations and preferences.

ACKNOWLEDGMENT

We extend our deepest gratitude to Maltepe University for providing the academic environment and resources that made this research possible. Their unwavering support and commitment to fostering scientific inquiry have been invaluable.

Our heartfelt thanks also go to the Hospital of Maltepe University. The hospital's staff and facilities played a pivotal role in the data collection phase of our study, offering not just their equipment but also their expertise, which was crucial for the precise recording and interpretation of EEG data.

Special appreciation is directed to Hülya Özdilek, whose guidance and insight have greatly enriched this work. Her dedication and profound knowledge in the field have not only facilitated the research process but have also provided a model of academic excellence to which we aspire.

The collaboration and support we received from all parties at Maltepe University and its hospital have been integral to the success of our study. We are honored to have had the opportunity to conduct our research within such an esteemed institution and with distinguished individuals who are as passionate about advancing knowledge as we are.

Supplementary Materials

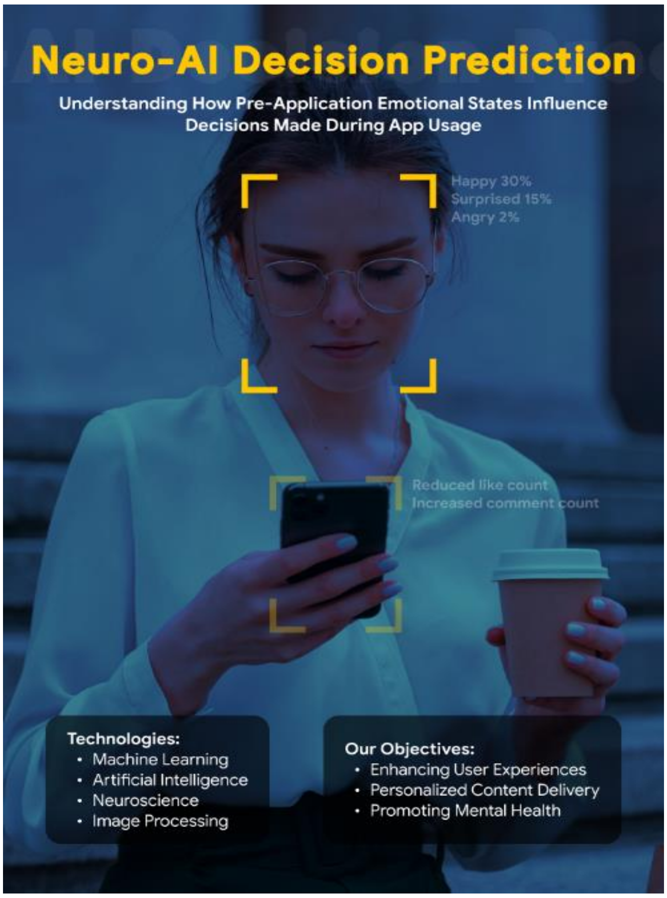

Figure 5: Neuro-AI Decision Prediction Poster

In addition to the comprehensive findings reported in this research, the poster below shows the Neuro-AI Decision Prediction study's primary aims, technology, and preliminary outcomes. This poster was created to convey the substance of our study in a clear and visually appealing manner.

Authors' Contributions

The authors' contributions to the paper are equal.

Statement of Conflicts of Interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The authors declare that this study complies with Research and Publication Ethics

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