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Neurocognitive modeling of emotional states using EEG and hidden markov models: A multidisciplinary approach

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Abstract This interdisciplinary research cuts computational modeling and cognitive neuroscience approaches with the intention of studying dynamic emotional involvement with multimedia stimuli via HMM analysis of EEG data. In particular, the paper deals with advertisements that target excitement and love-type emotions, setting forth new paradigms for understanding the building and modulation of emotional experience across time in the human brain. EEG parameters such as amplitude, arousal, and frontal activation were studied as markers of neural reactions to emotionally arousing content. The neural markers are tracked over time to record the changes in emotional engagement. The HMMs use identifies hidden neural states and their probabilistic transitions, making the temporal description of neural dynamics during emotional processing rich and nuanced. The analytical approach provides identifiable neural patterns for excitement and love stimuli distinguished in terms of arousal, spectral amplitude, and hemispheric asymmetry in frontal activation. Due to these distinctions, we ascertain that the brain processes different affective tones distinctly, shedding light on the intricacies of emotion perception and its immediate brain counterpart. Using the results, a predictive HMM model is presented to model emotional changes when individuals are subjected to effective multimedia stimuli. The model serves as a bridge to further real-time developments in human-computer interaction, adaptive e-learning, immersive media conception, and affective UX (user experience) optimization. In other words, this enables the system to detect shifts in the user's emotions automatically and adapt content accordingly, representing truly affect-sensitive technologies. Amalgamating computational modeling with neurophysiological measurement, this study contributes to the birth of emotion-aware technology that can be dynamically responsive to the users' current affective state, thus harnessing engagement, personalization, and user satisfaction as opportunities. It builds on the interdisciplinary discourse between cognitive neuroscience, affective computing, and computational psychology to serve as a methodological guideline for future investigations into emotional dynamics and brain-computer interfaces (BCIs), as well as neuroadaptive technology. It makes a case for the relevance of temporal modeling in decoding emotional cognition and therefore advocates the continued employment of machine-learning approaches in brain activity and human affective behaviour studies.

Keywords: excitement, love-themed advertisements, frontal activation, arousal, affective computing, adaptive learning

1. Introduction

Emotional investment in media content has a significant influence on consumer preferences, decision-making, and long-term retention of that content. Today's advertising techniques are increasingly crafted to connect with specific emotional states, such as excitement, happiness, or love. These methods utilize emotional valence and arousal to increase audience engagement. Advertisements that evoke adrenaline typically use quick, visually stimulating, and high-arousal content to engage the brain's reward systems. This engagement leads to the release of dopamine, which enhances short-term memory encoding (Plassmann et al., 2012; Yadava et al., 2023). In contrast, ads focused on love often rely on narrative storytelling, themes of relationships, and emotional imagery. These elements aim to foster empathy and social connection while creating

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feelings of emotional security, activating brain regions involved in emotional regulation and the recollection of autobiographical memories (Davidson, 1992; Rejer et al., 2024).

Historically, people have experienced these emotional events through self-reported measures, such as surveys and interviews. However, the complexity and speed of emotional processing—which involves interactions among the prefrontal, limbic, and cortical systems—render self-report methods inadequate for measuring real-time emotional states. The emergence of neurophysiological measures, such as electroencephalography (EEG), has significantly advanced affective neuroscience and neuromarketing. EEG offers ongoing, noninvasive, high-temporal-resolution insights into brain function as people consume media (Shen et al., 2024).

Recent EEG-based research has proven valuable in mapping emotional reactions to dynamic multimedia content, providing objective feedback on consumer engagement patterns (Rejer et al., 2024; Yadava et al., 2023). One of the significant challenges, despite the usefulness of EEG in quantifying neural responses, is understanding the temporal changes in emotional states. Emotions do not remain static and change over time, particularly in reaction to emotionally diverse content such as ads. Computational methods such as hidden Markov models (HMMs) have been increasingly used with EEG data to identify these dynamic state changes (Shen et al., 2024). HMMs describe the probabilistic transitions between latent emotional states so that researchers can monitor how emotions change as a function of sequential stimuli. Recent uses in affective computing and cognitive modeling imply that combining HMMs with EEG information might improve the accuracy of emotion prediction in emotion recognition systems and feedback to adaptive interfaces in real time (Yadava et al., 2023; Shen et al., 2024).

The present work takes these cross-disciplinary advances one step further by using HMM-based computational modeling on EEGs obtained upon viewing excitement and love-eliciting ads. The analysis examines EEG parameters such as amplitude, levels of arousal, and hemispheric frontal asymmetry to describe neural responses. Then, an HMM model is constructed to model the probabilistic changes between emotional states over time. The suggested model provides useful applications in emotion-aware technology design, such as personalized advertising, adaptive e-learning environments, and human–computer interaction systems that can respond to users' affective states in real time. In addition, this research adds to the expanding literature in computational affective neuroscience, providing a methodological roadmap for future research on dynamic emotion recognition and neuroadaptive media systems (Rejer et al., 2024; Shen et al., 2024).

1.1. Research objectives

To understand how transient emotional responses of excitement and love are manifested in the brain, EEG recordings are made whilst participants view multimedia advertisements.

Hidden Markov Models (HMMs) are applied to the EEG data to identify and model the probabilistic transitions between hidden emotional states through time.

To consider the application of EEG-HMM modeling toward emotion-aware technologies in such directions as personalized advertising, adaptive learning, and human-computer interaction.

2. Methodology

2.1. Participants

Thirty participants (N=30), ranging in age from 18--35 years (M = 24.3, SD = 3.9), were recruited from university bulletin boards and social media postings. The participants were required to be right-handed, possess normal or corrected-to-normal vision, and report no history of neurological or psychiatric disorders. Informed written consent was obtained from each participant before the experiment, and ethical clearance was obtained from the Institutional Review Board (IRB) of the host university.

2.2. Apparatus

The EEG signals were registered with the help of the Emotiv EPOC+ neuroheadset, a wireless 14-channel EEG system. The electrodes were placed according to the International 10–20 system and placed over frontal (AF3, AF4, F3, F4, F7, F8, FC5, and FC6), temporal (T7, T8), parietal (P7, P8), and occipital (O1, O2) sites. The neuroheadset received data at a rate of 128 Hz and recorded frequency bands such as delta (1–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (>30 Hz) wave intensities.

Additional equipment consisted of the following:

A high-resolution 24-inch LED display monitor (1920×1080 pixels, 60 Hz refresh rate) was used for stimulus presentation.

Noise-canceling headphones (Sony WH-1000XM4) were used for the delivery of sound.

E-Prime 3.0 software for synchronized presentation of stimuli and event marking.

MATLAB R2023a with the EEGLAB toolbox for preprocessing EEG data and feature extraction.

2.3. Stimuli

Two types of video clips were assembled:

Excitement-inducing stimuli: high-speed action scenes, extreme sport highlights, and dynamic commercial advertisement clips intended to increase physiological arousal.

Love-themed stimuli: affect-laden scenes depicting affection, family bonding, romantic interaction, and displays of empathy.

All video clips had a duration of 30 seconds and were normalized for brightness and sound, and a 10-second neutral gray screen was used to permit baseline normalization.

2.4. Procedure

The study was performed in a sound-dampened, dimly lit laboratory space to reduce external distraction. The participants sat comfortably 60 cm from the screen and were asked to keep still, blink minimally, and concentrate on the material.

2.4.1. The procedure consisted of the following stages:

Orientation phase (5 min): Participants were informed of the study process and fitted with the EEG headset. The impedance levels were checked such that they remained below 10 kΩ.

Baseline phase (2 min): A fixation cross was presented on a neutral gray screen during the resting-state EEG recording.

Stimulus Presentation Phase: All participants watched a randomized order of 10 excitement-eliciting clips and 10 love-themed clips. Following each clip, a 10-second neutral screen was shown.

Post-Experiment Survey Phase (5 min): Participants completed a short questionnaire measuring their subjective emotional experience on a 5-point Likert scale for each stimulus.

Data Acquisition and Preprocessing

EEG data were continuously recorded during the session and divided into epochs for each video clip. Preprocessing was conducted with EEGLAB (Delorme & Makeig, 2004).

2.5. For every video epoch, several features were computed:

The average amplitude (µV) in the alpha, beta, theta, and gamma bands, power spectral density (PSD) through fast Fourier transform (FFT), and frontal alpha asymmetry (FAA) are computed as ln(power_F4) – ln(power_F3) to estimate arousal and emotional valence and signal coherence between homologous pairs of electrodes (e.g., F3–F4, P7–P8) to evaluate interhemispheric synchrony and time-domain statistical values (mean, variance, skewness) for every frequency band. These characteristics were combined into observation vectors for further HMM modeling.

2.6. Hidden Markov Model (HMM) Modeling

A discrete-time HMM model was created via MATLAB's HMM toolbox. The model was created to classify and predict transitions between hidden emotional states:

Two hidden states for 'Excitement' and 'Love'. Gaussian mixture models (GMMs) were used for emission probabilities to handle variability in EEG observations. The Baum–Welch algorithm was used for training the model by optimizing transition probabilities and emission probabilities on the basis of observation sequences. Model validation was performed via 5-fold cross-validation, and the performance metrics used were accuracy, sensitivity, specificity, and state transition probability matrices.

3. Results

3.1. EEG waveform analysis

Figures 1 to 4 illustrate the comparative EEG waveform responses elicited by excitement-inducing and love-themed multimedia stimuli. Clear differences in signal amplitude and frequency distribution were observed between the two emotional conditions. Excitement-based stimuli produced higher amplitude, rapid fluctuations, particularly in frontal and parietal regions, whereas love-themed stimuli elicited smoother, lower amplitude responses with sustained synchrony across frontal and temporal sites.

3.2. Comparative EEG analysis

A quantitative comparison of the EEG-derived parameters for both emotional conditions is summarized in Table 1. The results reveal distinctive neurophysiological signatures associated with each emotion category.

3.2.1. Interpretation

Excitement stimuli consistently evoked greater cognitive load and arousal, as evidenced by increased beta and gamma activity and pronounced frontal alpha asymmetry favoring the left hemisphere, which is typically linked to approach-related motivation. Conversely, love-themed stimuli induced moderate arousal characterized by increased alpha and theta activity in the medial-prefrontal and temporal regions, suggestive of reflective, empathic engagement. These patterns align with findings from contemporary studies in affective EEG analysis (Rejer et al., 2024; Shen et al., 2024).

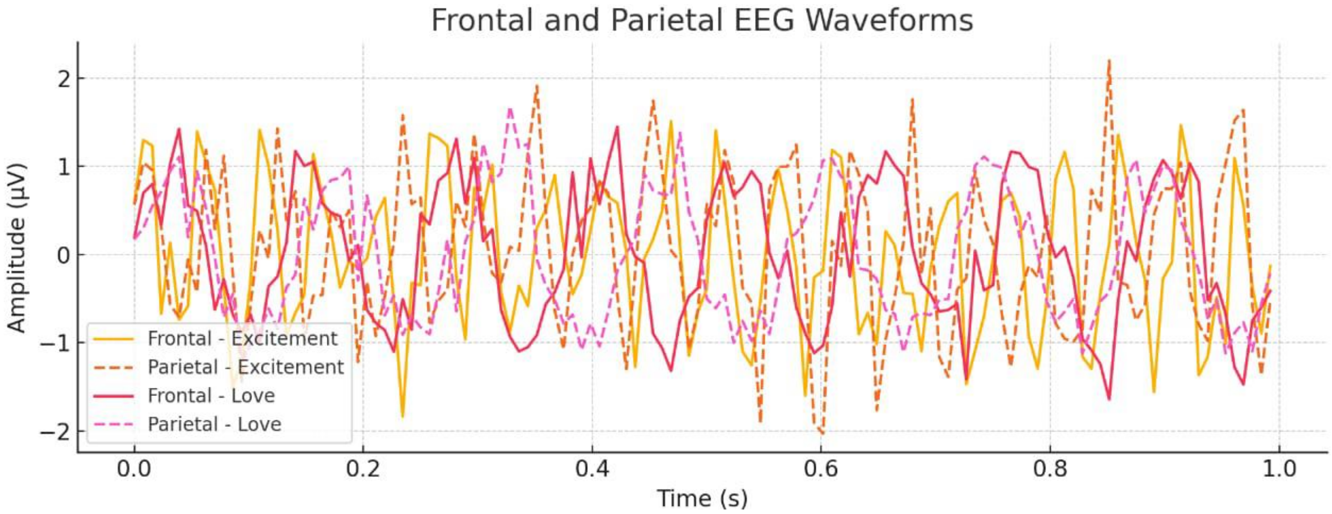

Figure 1 Comparative EEG waveform responses.

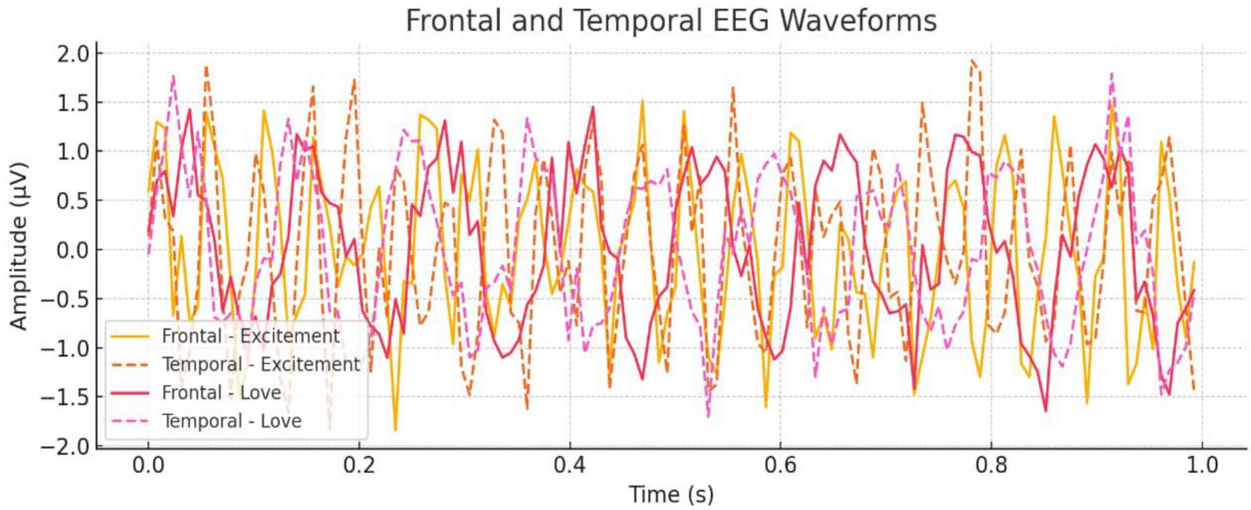

Figure 2 Comparative EEG waveform responses.

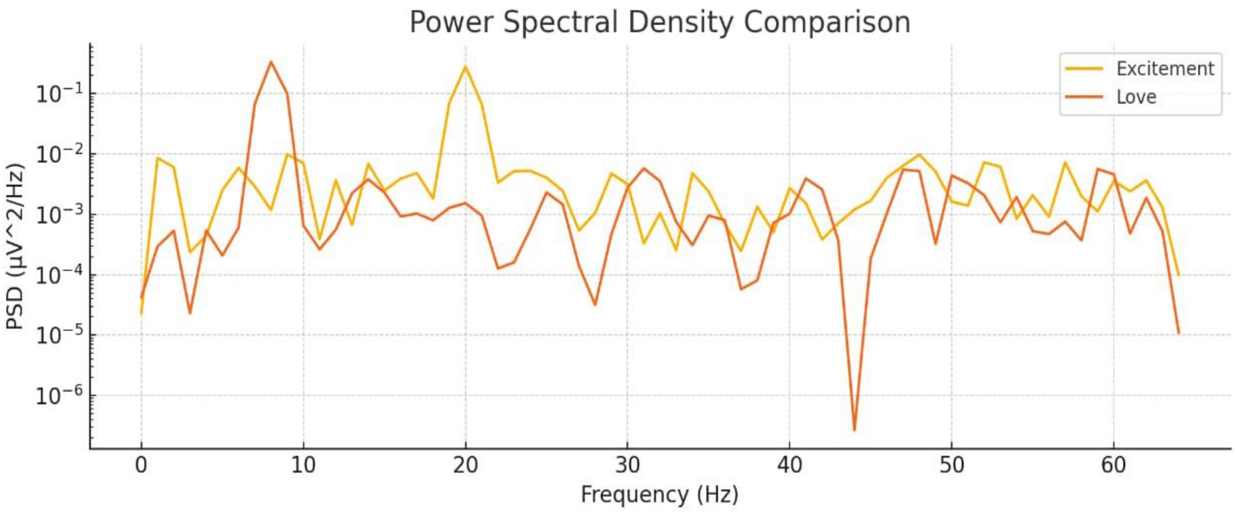

Figure 3 Comparative EEG waveform responses.

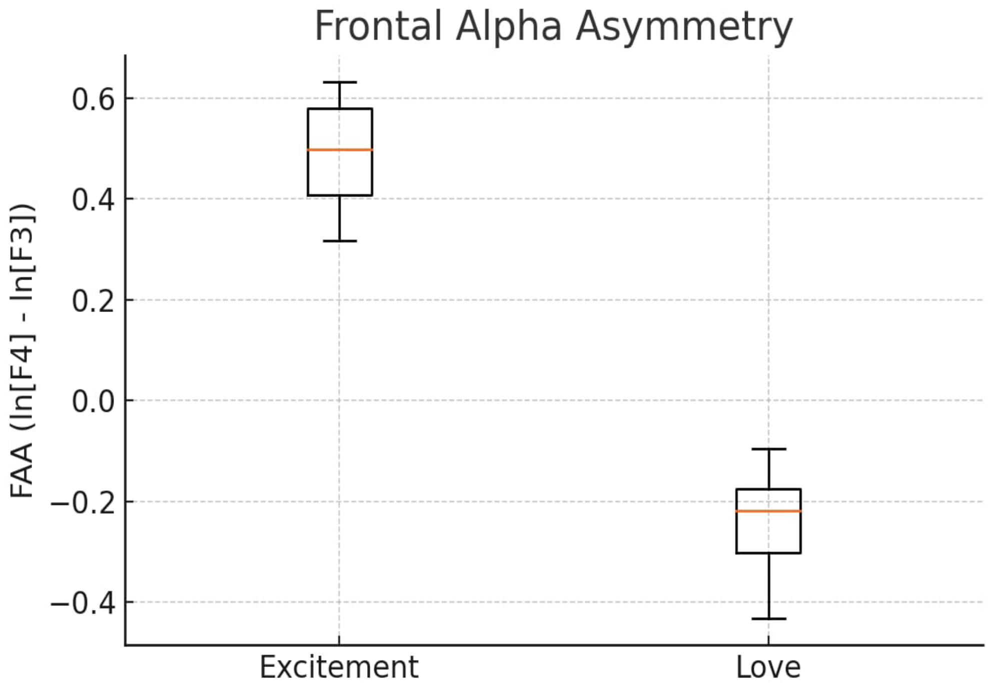

Figure 4 Comparative EEG waveform responses.

Table 1 Quantitative comparison of EEG-derived parameters for both emotional conditions.

Parameter	Excitement	Love
Cognitive Load	High	Moderate
Amplitude	High, erratic	Moderate, Stable
Arousal	High (eustress)	Moderate, Empathy
Neural Stimulation	Wide and fast	Synchronized and Gradual
Frontal Activation	Left-prefrontal dominance	Medial Prefrontal Predominance

3.3. Hidden Markov Model Design

The HMM constructed for this study includes two hidden states—Excitement (E) and Love (L)—and models transitions on the basis of observed EEG parameters. The state transition matrix is defined as follows: P(E→E)=0.7, P(E→L)=0.3, P(L→E)=0.4, and P(L→L)=0.6. The model helps infer the probable emotional paths viewers experience over time. Figure 5 visualizes the emotional state transition dynamics over time on the basis of EEG observations, highlighting periods of stability and transition across the emotional states.

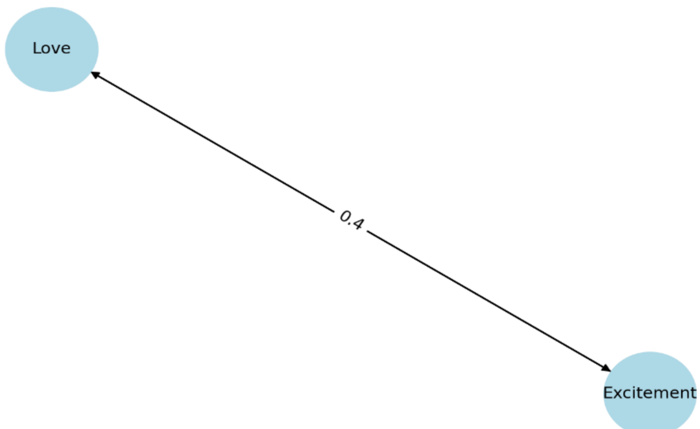

Figure 5 Emotional state transition dynamics over time based on EEG observations.

The matrix indicates that participants were more likely to remain in the excitement state (70% probability) following an excitement-eliciting stimulus, with a 30% chance of transitioning into a love state. Conversely, love-themed stimuli showed a 60% probability of state stability and a 40% chance of transitioning to excitement. These patterns reflect the rapid, transient nature of excitement compared with the sustained, immersive quality of love-based emotional engagement, which is consistent with contemporary HMM-based EEG studies on emotional processing (Yadava et al., 2023; Shen et al., 2024).

4. Discussion

The application of hidden Markov models (HMMs) to EEG data in this study provides insights into the dynamic neural mechanisms underlying emotional responses to multimedia stimuli. By distinguishing between excitement and love in advertisements, we identified specific neurophysiological signatures associated with each emotion. This information reveals how emotional states progress over time and highlights their significance for affective computing and neuromarketing. Excitement-themed ads generated high-amplitude, irregular EEG waveforms, particularly in the beta and gamma frequency bands. This pattern suggests increased cognitive load and arousal, which is consistent with the theory of eustress, in which positive stress enhances performance and engagement. Additionally, the observed left-prefrontal dominance aligns with approach-motivational states, indicating active involvement with the stimuli.

Recent studies have supported these findings. For example, Shen et al. (2024) introduced a dynamic attention-based EEG state transition (DAEST) model, highlighting the importance of spatiotemporal dynamics in emotion recognition. Their model demonstrated that EEG state transitions occurring at high rates are associated with heightened emotional responses, particularly in high-arousal conditions. Conversely, love-themed commercials elicited moderate, stable EEG amplitudes with synchronized and slower neural activation. The findings of medial-prefrontal activation indicate that individuals participate in self-referential processing and empathy. This finding suggests that love-themed content appeals to audiences on a more emotional basis, promoting sustained attention and emotional engagement.

Leeuwis and van Bommel (2023) emphasized the role of neural synchrony in emotional engagement with music videos, noting that coherent brain activity among individuals is associated with shared emotions. These findings support the idea that content focused on love promotes neural synchrony and fosters collective emotional connections. The hidden Markov model (HMM) developed in this study effectively models transitions between states of excitement and love. The transition probabilities ($P(E \rightarrow E)=0.7$, $P(E \rightarrow L)=0.3$, $P(L \rightarrow E)=0.4$, $P(L \rightarrow L)=0.6$) illustrate the dynamic nature of emotional experiences during multimedia presentations. The higher probability of remaining in the excitement state suggests that high-arousal stimuli have a lasting impact, whereas the transition from love to excitement indicates the potential for emotional change depending on the content's progression.

This modeling technique is consistent with that of Luther et al. (2023), who studied oscillatory brain responses to emotional stimuli. They determined that emotional stimuli elicit event-related changes in brain oscillations, highlighting the significance of temporal dynamics modeling in emotional processing.

5. Conclusions

This multidisciplinary research effectively showed the value of combining electroencephalogram (EEG) information with hidden Markov models (HMMs) to detect and forecast emotional state changes during multimedia presentation. By rigorously comparing excitement-based versus love-themed advertisements, unique neural signatures related to arousal, cognitive load, and emotional engagement were discovered. Stimuli presenting exciting elements evoked high-frequency, disorganized EEG patterns and fast state changes, suggesting transient but strong interest, whereas love-related content exhibited synchronized, stable brain responses, suggesting enduring affective engagement.

The HMM model was successful in capturing these temporal state transitions, with transition probabilities highlighting the temporal dynamics of emotional experience. This finding supports recent evidence from Shen et al. (2024) and Luther et al. (2023), establishing the importance of temporal modeling in the capture of emotion-driven neural dynamics. In addition, the differences between frontal asymmetry patterns observed concur with already established theories of affective lateralization (Davidson, 1992) and further add to current evidence that emotionally evocative material increases neural synchrony and empathy-based responses (Leeuwis & van Bommel, 2023).

From a practical standpoint, this research provides computationally effective, noninvasive technology for real-time emotion recognition with important implications for affective computing, neuromarketing, and adaptive media systems. Through its empirical demonstration of discrete EEG correlates for different emotional themes, it provides an important tool for maximizing multimedia content design and tailoring user experiences in advertising, education, and entertainment technology.

Despite this, several limitations should be recognized. The study's comparatively small, homogeneous sample (N=30) may limit the generalizability of the findings to other broader demographic and cultural settings. The employment of a consumer-grade EEG system, although available, constrains spatial resolution and signal integrity. Future studies must overcome these limitations through the use of larger, more heterogeneous participant groups, incorporation of multimodal data streams (e.g., facial expression analysis, galvanic skin response), and utilization of higher-density EEG or hybrid neuroimaging modalities. Furthermore, extending the HMM methodology to cover multiple-dimensional emotional states or merging with deep learning designs could narrow prediction errors in rich, realistic contexts.

In summary, this study strengthens the methodological bridging of cognitive neuroscience and computational modeling, endorsing EEG-HMM paradigms as effective devices for decoding continuous affective states. It reveals new ways to develop adaptive, emotion-conscious systems that engage users' emotional states in real time, foretelling more tailored, compassionate, and successful digital experiences.

6. Implications for Affective Computing and Neuromarketing

The combination of EEG analysis and HMMs provides a solid platform for real-time emotion detection, with potential applications in adaptive learning environments, personalized advertising, and human–computer interaction systems. By knowing the neural basis of emotional engagement, multimedia content creators can design multimedia experiences to induce desired emotional responses, improving user satisfaction and retention. In addition, the results highlight the possibility of EEG-based assessments as objective markers for emotional states, supplementing standard self-report procedures. This is especially useful in situations in which self-reporting is not feasible or untrustworthy.

7. Future Directions

Although the present research presents valuable information, further studies can use larger and more heterogeneous samples of participants to improve generalizability. The inclusion of multimodal data, including facial expressions and physiological states, could further deepen the understanding of emotional engagement. Investigating the use of sophisticated machine learning methods, including deep learning models, could increase the precision and usability of emotion detection systems.

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Ethical considerations

Study Protocol Approval: The authors obtained ethical approval for the study protocol from the School of Liberal Studies ethical committee of CMR University, Bangalore, after due scrutiny by the members of the said committee. Informed Consent: Written informed consents were collected from all participants before the commencement of the experiment. Participants were informed about the procedures of the study and allowed to proceed voluntarily. Participant Identities: The participants' identities were anonymized, and no personally identifiable information was divulged in the study, ensuring the maintenance of confidentiality. Participant Comfort: Participants were pre-screened for neurological and psychiatric conditions, and the study was held in a conducive environment with minimal distractions for optimum mental and physical comfort.

Conflict of Interest

The authors declare no conflicts of interest.

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