Uncovering Emotion Correlates to Transitions in EEG Energy Landscapes

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Abstract

Wearable brain-computer interfaces (BCIs) have made it feasible to monitor brain activity for emotion recognition in real-world settings. While deep learning models achieve high classification accuracy on EEG data, they often lack interpretability, limiting their neuroscientific relevance. In this study, we present an interpretable framework for EEG-based emotion analysis rooted in energy landscape analysis. EEG signals from the DEAP dataset were standardized and binarized prior to quantification of neural state transitions. We found significant subject-specific correlations between the number of state transitions and emotional ratings of valence and arousal. Further analysis revealed that certain binary brain states, particularly complementary pairs, were among the most frequently observed and showed emotion-dependent frequency differences. Transitions between these state pairs varied across subjects, suggesting their role as local minima in the brain's dynamic landscape. Our findings demonstrate that energy landscape analysis provides an interpretable alternative to black-box models, offering insights into how brain dynamics relate to emotional experiences. This approach contributes toward building explainable affective computing systems and supports the use of neural state modeling in emotion-aware BCIs.

1 Introduction

Interpreting human emotions through neurophysiological signals has become a central challenge in affective computing and cognitive neuroscience. Among various modalities, electroencephalography (EEG) has emerged as a valuable tool for real-time monitoring of emotional states due to its high temporal resolution and non-invasive nature. With recent advances in brain-computer interface (BCI) technology, particularly in developing portable and wearable EEG systems, it has become increasingly feasible to design low-cost, low-power devices capable of continuous emotion monitoring. In the post-COVID era, where mental health disorders such as anxiety and depression have become more prevalent, such technologies can enable early detection and intervention through real-time tracking of emotional fluctuations [Wu *et al.*, 2024; Xing *et al.*, 2024].

EEG has been extensively used for studying affective states and uncovering neural correlates of emotions. Existing research indicates that emotional responses are reflected in distinct spatiotemporal patterns of brain activity, which can be captured using machine learning techniques. Numerous studies have employed EEG-based features such as power spectral density, differential entropy, and connectivity measures to classify emotions, typically within the valence-arousal dimensional framework [Liu *et al.*, 2020; Anubhav *et al.*, 2020]. In parallel, other works focus on learning spatiotemporal representations of EEG signals directly, without relying on hand-crafted features, aiming to develop computationally efficient and real-time emotion recognition frameworks [Anubhav and Fujiwara, 2023; Anubhav and Fujiwara, 2024].

Recent studies have significantly improved EEG-based emotion recognition through deep learning methods. For instance, Yin et al. (2021) proposed a graph convolutional neural network (GCNN) combined with LSTM to capture both spatial and temporal characteristics of EEG signals, attaining classification accuracies exceeding 90% for valence and arousal [Yin *et al.*, 2021]. Similarly, Ma et al. (2019) developed a residual LSTM model for multimodal emotion recognition on the DEAP dataset, demonstrating strong performance on EEG signals alone [Ma *et al.*, 2019]. Other approaches employing CNNs, LSTMs, attention mechanisms, or hybrid models have also reported high classification accuracies, often exceeding 90% under subject-dependent settings [Hasan *et al.*, 2021; Nath *et al.*, 2020; Alhalaseh and Alasasfeh, 2020; Kim and Choi, 2020; Karthiga *et al.*, 2024]. However, these models function primarily as black boxes and offer limited insights into the underlying neural mechanisms of emotional state transitions.

Despite the advances in classification accuracy, existing models fail to provide an interpretable framework for understanding how emotional states emerge and evolve over time in the brain. Specifically, no prior work has linked transitions between emotional states to the energy landscape topography derived from EEG activity. While energy landscape analysis has been applied to model brain dynamics in other neuroimaging modalities such as fMRI and fNIRS [Watanabe *et al.*, 2013; Watanabe *et al.*, 2014; Xing *et al.*, 2024;

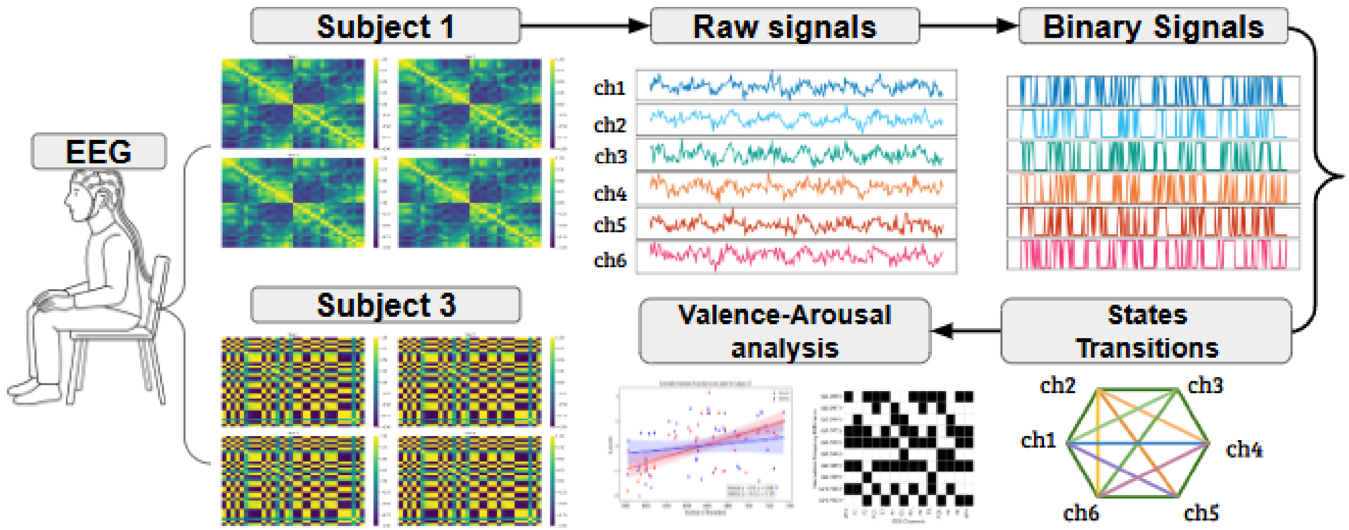


Figure 1: Overview of the proposed framework for interpretable EEG-based emotion analysis. EEG signals are recorded from multiple subjects and preprocessed to obtain raw time-series data. The signals are standardized and binarized to represent neural activity in binary state space. State transitions are computed and analyzed with valence and arousal labels. Subject-specific analyses highlight individual differences in transition-emotion correlations and dominant emotion-specific brain states.

Wu *et al.*, 2024], its potential for uncovering interpretable transitions in EEG-based emotion recognition remains unexplored. Given the importance of explainable models in mental health applications, it is critical to investigate alternative frameworks that can offer insight into the neurophysiological basis of emotions.

This study proposes an interpretable framework for EEG-based emotion recognition by leveraging energy landscape analysis to model state transitions corresponding to different emotional responses, Figure 1. We use binarized EEG activity from the DEAP dataset to construct energy landscapes and identification of metastable states. Transitions among these states are analyzed to investigate their correspondence with valence and arousal levels. Unlike traditional deep learning approaches that focus on accuracy alone, our framework provides interpretable representations of brain activity, facilitating the identification of neural biomarkers associated with emotional transitions.

The remainder of this paper is organized as follows: We present a literature review in Section 2 followed by Section 3 detailing the methodological procedures, including data preprocessing, binarization, and analysis of state transitions. Section 4 presents the experimental results, including identified metastable states and transition dynamics. Section 5 discusses the implications of the findings, limitations, and potential avenues for future work with conclusion in Section 6.

2 Related Works

2.1 Deep Learning Approaches for EEG-Based Emotion Recognition

EEG-based emotion recognition has attracted considerable research attention due to its characteristics of non-invasively capturing high-temporal-resolution brain activity. The DEAP dataset [Koelstra *et al.*, 2012] has become a benchmark for evaluating classification models of emotional dimensions such as valence and arousal. Early studies employed handcrafted features and conventional classifiers, but recent works have demonstrated that deep-learning models can substantially improve classification accuracy. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), particularly long short-term memory (LSTM) architectures, have been widely used for modeling spatiotemporal EEG patterns. Yin et al. [Yin *et al.*, 2021] introduced a hybrid model combining graph convolutional networks (GCN) with LSTM to capture spatial connectivity and temporal dynamics in EEG data, achieving over 90% accuracy on DEAP for valence and arousal. Similarly, Ma et al. [Ma *et al.*, 2019] proposed a multimodal residual LSTM (MMResLSTM) network that yielded competitive results using EEG alone.

Other studies have further integrated attention mechanisms or hybrid optimization methods to enhance performance. Kim and Choi [Kim and Choi, 2020] incorporated an attention module into an LSTM framework, improving the model's ability to focus on temporally salient EEG segments. Karthiga et al. [Karthiga *et al.*, 2024] applied a meta-heuristic hybrid model combining artificial bee colony and grey wolf optimization to tune CNNs, reporting near-perfect accuracy under subject-dependent conditions. While these methods report high classification performance, they often lack interpretability, treating EEG signals as opaque inputs to black-box models.

Several studies acknowledge the trade-off between classification accuracy and explainability in affective computing systems. Liu et al. [Liu *et al.*, 2020] and Alhalaseh et al. [Alhalaseh and Alasasfeh, 2020] underscore this issue, noting that although deep models outperform classical approaches, their internal representations offer limited insight into the un-

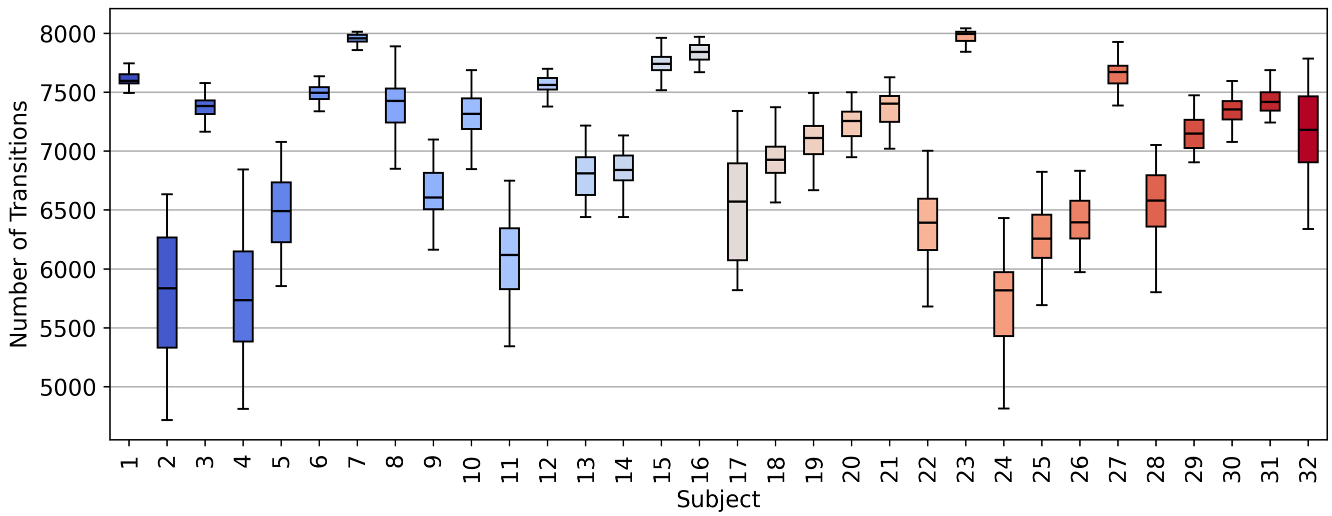


Figure 2: Distribution of number of state transitions across trials for each subject. A narrower spread suggests consistent state-switching behavior across emotional conditions, whereas a broader spread may indicate increased state stability.

derlying neurophysiological processes. As a result, there is increasing interest in methods that maintain high accuracy while providing interpretable mappings between brain activity and emotional states.

2.2 EEG-microstate and Energy Landscape Analysis

To address the need for interpretability in emotion recognition systems, several researchers have explored state-transition analyses of neural activity. These approaches assume that brain dynamics can be represented as transitions among discrete neural states and that the structure of these transitions carries meaningful information about cognitive or affective processes. In the EEG domain, Barzon et al. [Barzon *et al.*, 2024] proposed a microstate-based framework to analyze cognitive effort during a Stroop task. By computing transition costs between EEG microstates using optimal transport theory, they demonstrated that increased task difficulty corresponds to higher cognitive reconfiguration effort. This work highlights the potential of microstate dynamics as a source of interpretable neural metrics.

Beyond EEG, energy landscape analysis has been extensively applied to fMRI and fNIRS data[Watanabe *et al.*, 2013]. Kang et al. [Kang *et al.*, 2019] used a pairwise maximum entropy model to estimate energy landscapes from resting-state fMRI signals. They found that brain state transitions are organized around hub configurations, with the default mode network (DMN) mediating between distinct cognitive states. Similarly, Xing et al. [Xing *et al.*, 2024] applied this framework to study Alzheimer's disease, finding that patients exhibited altered dwell times and transition frequencies, which correlated with cognitive impairment. Wu et al. [Wu *et al.*, 2024] extended this methodology to fNIRS data in clinical populations. By constructing energy landscapes from cognitive task recordings, they showed that individuals with depression displayed more metastable states and shallower attractor basins. These quantitative features served as both interpretable markers of neurodynamics and effective discriminators between clinical and control groups.

Although energy landscape models have demonstrated success in characterizing brain dynamics across modalities, their application to EEG-based emotion recognition remains largely unexplored. To our knowledge, no existing study has linked emotional state transitions in EEG to energy landscape topology. This gap highlights the need for frameworks combining the predictive power of state-of-the-art classification algorithms with principled analyses of state-based affect behaviors.

3 Methods

3.1 Dataset Description

This study utilizes the DEAP dataset [Koelstra *et al.*, 2012], a benchmark resource for emotion analysis using physiological signals. The dataset consists of 32 participants undergoing 40 trials wherein one-minute music videos were presented to evoke emotional responses. During each trial, 32-channel EEG signals were recorded, which were later downsampled to a sampling rate of 128 Hz. The dataset authors preprocessed all EEG data to remove ocular artifacts and line noise through independent component analysis and bandpass filtering (0.5–45 Hz)[1].

3.2 Proposed Framework

We propose an interpretable analysis of EEG signals based on the state transitions derived from binarized EEG activity and analysis modeled using energy landscape analysis. The following methodological steps were followed to ensure consistency and computational tractability.

[1]http://eecs.qmul.ac.uk/mmv/datasets/deap/readme.html

Data Preparation

First, the EEG signals were standardized for each subject and trial individually by subtracting the mean and dividing by the standard deviation. The standardized signals were then binarized: positive values were set to 1 and non-positive values to 0. This transformation enabled the conversion of continuous EEG data into discrete binary state vectors suitable for energy-based modeling. Due to the exponential increase in computational complexity with the number of EEG channels in pairwise maximum entropy models, we restricted the analysis to a subset of 14 channels. These correspond to the configuration of the Emotiv Epoc headset, a commercially available wearable EEG device. This subset selection allows our framework to remain computationally efficient while remaining applicable in mobile and real-world settings, where portable EEG hardware is typically constrained in channel count.

We computed pairwise correlations between channel activity across trials to understand the subject-wise consistency and variability in EEG dynamics. The analysis revealed moderate to strong intra-subject consistency but significant inter-subject variability, highlighting the necessity to evaluate the energy landscape features under subject-dependent and subject-independent protocols. This comparative strategy enables the investigation of the trade-off between personalized emotion modeling and generalizable affective decoding.

State-Transition Analysis

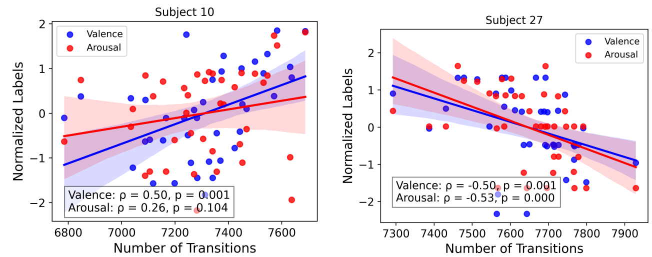
We then quantified the number of state transitions for each trial and grouped them by subject. Figure 2 shows the distribution of transition counts across subjects. For some subjects, transitions are tightly concentrated across all trials, indicating consistent dynamic reconfiguration of brain states in response to emotional stimuli. In contrast, other subjects exhibit a wider spread in transition counts, which may reflect heterogeneous affective responses or the stabilization of neural dynamics into quasi-attractor states with limited transitions.

In the next section, we will explore the correlations between the number of transitions and subjective valence and arousal ratings. This analysis will examine whether the dynamic properties of EEG state transitions are predictive of emotional dimensions and can offer interpretable insights into affective brain dynamics.

4 Results

The DEAP dataset provides emotion annotations on a scale of 1 to 9 along two continuous dimensions: valence and arousal. To ensure that inter-subject differences in rating tendencies do not bias the analysis, we independently standardized the valence and arousal labels for each subject. This normalization step maps the emotional ratings for each subject to a zero-centered distribution, facilitating fair comparison across trials and individuals.

To evaluate the association between EEG transition dynamics and emotional states, we performed subject-wise Spearman correlation analyses between the number of state transitions and normalized valence and arousal scores across the 40 trials. The rationale behind this approach is that the frequency of transitions between metastable states may reflect the brain's affective reactivity or flexibility under emotional stimulation.



(a) Subject 10 (b) Subject 27

Figure 3: Regression between number of transitions and normalized valence/arousal ratings.

Figure 3a and Figure 3b illustrate representative regression plots for Subject 10 and Subject 27, respectively. For Subject 10, a strong positive correlation was observed between valence and number of transitions ($\rho = 0.50$, $p = 0.001$), suggesting that higher valence (positive emotions) are associated with greater neural state switching. In contrast, for Subject 27, both valence and arousal show significant negative correlations with the number of transitions ($\rho = -0.50$, $p = 0.001$ for valence; $\rho = -0.53$, $p < 0.001$ for arousal), indicating that lower affective ratings coincide with more frequent state changes.

When aggregating trials across all subjects and performing a global regression analysis, no significant relationship was found between the number of transitions and either valence or arousal (Figure 4). The correlation coefficients were $\rho = 0.04$ ($p = 0.175$) for valence and $\rho = 0.01$ ($p = 0.608$) for arousal. These results suggest that while transition-emotion relationships may exist at an individual level, they do not generalize across the entire population.

Table 1 summarizes spearman correlation coefficients and p-values between the number of transitions and emotion dimensions for all 32 subjects. Subjects 10, 16, 17, and 27 exhibit statistically significant correlations in at least one emotional dimension. Subject 3 and Subject 5 also showed a significant correlation with arousal. However, the direction and strength of these correlations vary substantially across subjects, further supporting the notion of individualized neural-affective coupling.

These results demonstrate that the number of metastable state transitions derived from energy landscape analysis carries information relevant to emotional experience, particularly at the individual level. However, the heterogeneity of correlation direction across subjects suggests that emotional correlates of brain dynamics are likely subject-specific. Therefore, in future prediction models, we should incorporate transition metrics for affective computing and devise mechanisms for personalization to account for inter-subject variability.

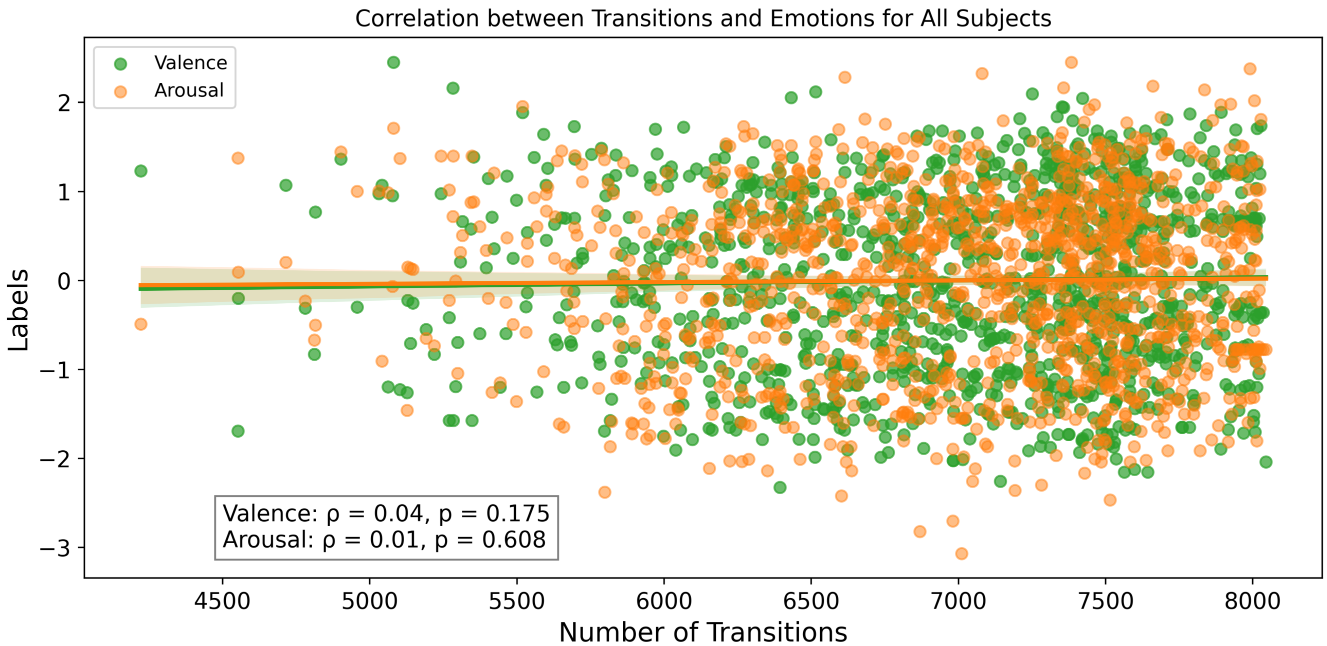


Figure 4: Correlation between number of transitions and normalized valence/arousal across all subjects. No significant associations were observed at the group level.

Subject	**Valence** ρ **(p)**	**Arousal** ρ **(p)**	**Significance**
1	0.17 (0.289)	0.18 (0.268)	–
3	-0.10 (0.528)	**0.32 (0.047)**	Arousal
5	0.19 (0.243)	**0.38 (0.015)**	Arousal
6	**-0.31 (0.048)**	0.06 (0.707)	Valence
10	**0.50 (0.001)**	0.26 (0.104)	Valence
11	**-0.44 (0.004)**	0.20 (0.214)	Valence
16	0.23 (0.145)	**0.42 (0.007)**	Arousal
17	0.23 (0.149)	**0.54 (0.000)**	Arousal
27	**-0.50 (0.001)**	**-0.53 (0.000)**	**Both**
32	**0.42 (0.006)**	-0.05 (0.736)	Valence

Table 1: Summary of subject-level Spearman correlations.

5 Discussion

This study proposes interpretable correlates of investigating EEG-based emotion dynamics, specifically the number and structure of state transitions. Our subject-wise analyses revealed that the number of transitions in brain states is significantly associated with emotional ratings. Notably, both positive and negative correlations were observed, highlighting individual-specific trajectories of emotional dynamics in the energy landscape. However, no consistent relationship emerged when aggregated at the population level, suggesting a high degree of inter-subject variability.

To interpret these results further, we investigated whether specific brain states are more prevalent for certain emotions. We compared the most frequent states in trials labeled with high vs low valence and similarly for arousal. The resulting heatmaps (Figure 6a, 6b) depict the top 10 most discriminative brain states ranked by their normalized frequency difference.

These visualizations show that many prominent states occur in complementary pairs, i.e., state configurations that are binary inverses of one another. This observation suggests the existence of opposing or mutually exclusive neural activation patterns tied to emotional polarity, possibly reflecting transitions between antagonistic neural regimes (e.g., approach vs. withdrawal circuits). The recurring presence of these complementary states implies that they represent local minima in the brain's energy landscape attractor-like states that are recurrent across different emotions.

To investigate this further, we analyzed the frequency of transitions between these complementary state pairs across all subjects and compared them for high vs. low valence and arousal conditions. As shown in Figure 5, the difference in mean complement transitions varies considerably across subjects. Positive values denote more frequent transitions during positive (valence = 1 or arousal=1) trials, while negative values indicate predominance during low-value emotion trials (valence = 0 or arousal = 0). Statistical significance markers indicate subjects where these differences were found significant using a t-test.

These findings emphasize that complementary state transitions are among the most common transitions observed across trials, suggesting their structural relevance within the energy landscape. The variability in their association with emotion labels across subjects highlights the need for personalized interpretation. Nonetheless, the observation that emotion-relevant trials consistently recruit such state pairs supports their interpretive value as potential neurodynamic biomarkers. Future work involving detailed topological analysis of the energy surface (e.g., basin stability, saddle paths) may uncover the latent neural mechanisms underlying these recur-

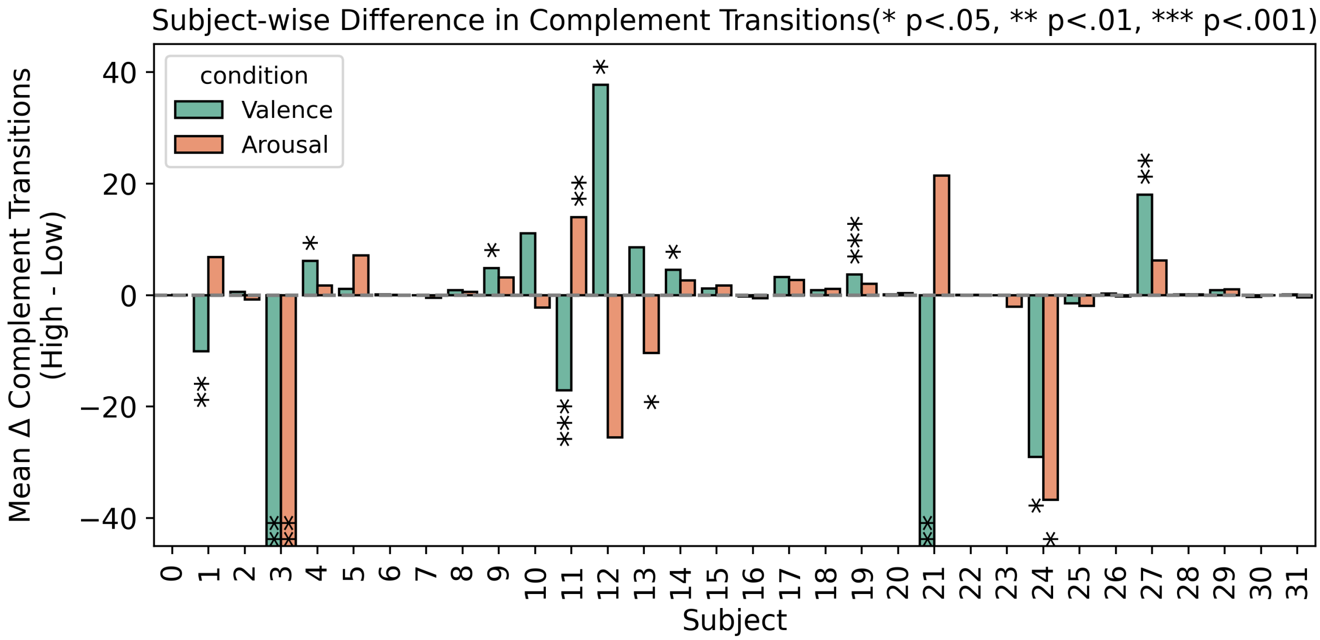


Figure 5: Subject-wise difference in mean transitions between complementary states under high vs. low valence/arousal conditions. Asterisks indicate statistical significance (* $p < .05$, ** $p < .01$, *** $p < .001$).

rent transitions.

Existing EEG-based emotion recognition models primarily employ deep learning architectures that optimize for predictive accuracy but offer limited interpretability [Yin *et al.*, 2021; Ma *et al.*, 2019; Kim and Choi, 2020]. These models do not explain how dynamic brain activity patterns evolve across emotional conditions. By contrast, our study adopts an energy landscape perspective rooted in statistical physics, offering a mechanistic interpretation of emotional states as stable or metastable configurations and transitions as quantifiable dynamical events. Prior work has applied energy landscapes to fMRI and fNIRS [Kang *et al.*, 2019; Xing *et al.*, 2024], but not to EEG-based emotion recognition.

By linking the number of neural state transitions and the structure of energy basins to emotion dimensions, our work provides a pathway for interpretable emotion decoding grounded in neurodynamics. Moreover, our identification of emotion-specific and complementary states aligns with findings from microstate and attractor landscape theories in cognitive neuroscience, where specific brain states reflect functional processing.

5.1 Limitations

Despite the promising findings, this study has several limitations. First, the results depend on the binarization method applied to EEG signals. Artifacts or signal noise could alter the binary configurations and the inferred energy landscapes. Therefore, more robust binarization techniques should be explored to enhance reliability. Second, the trial duration in DEAP is limited to one minute, potentially restricting the range of state transitions that can be empirically observed. Therefore, exploring longer EEG recordings would further enable observing slower or less frequent transitions that may be crucial for emotional processing.

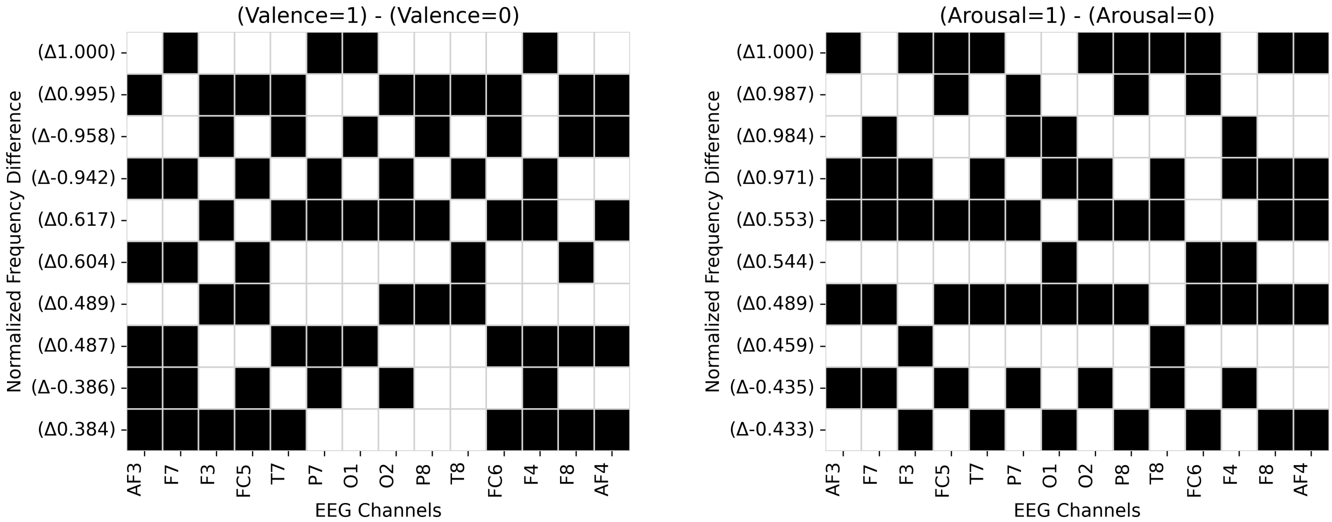
5.2 Future Work

Future studies can address these limitations by employing signal processing pipelines that compute spectral band power features (e.g., alpha, beta bands) before binarization. Band-specific features are widely used in cognitive neuroscience and may enhance both interpretability and robustness to noise. Furthermore, detailed energy landscape metrics such as basin depth, transition entropy, or attractor proximity could be computed to model individual differences in emotion dynamics. Finally, coupling the energy landscape framework with deep learning classifiers could yield hybrid models that retain interpretability while achieving high classification accuracy.

6 Conclusion

With the increasing adoption of wearable BCIs, interpretable models of brain activity have vast potential for reliable and personalized emotion monitoring and prediction. This study presents an interpretable approach to EEG-based emotion recognition rooted in energy landscape analysis to characterize transitions among brain states associated with different emotions. By quantifying the frequency and structure of these state transitions, we demonstrated how individual differences in neural dynamics relate to subjective experiences of valence and arousal.

The subject-wise correlation analysis revealed that the number of transitions between neural states is significantly



(a) Valence

(b) Arousal.

Figure 6: Top 10 most discriminative brain states for valence and arousal. Each row corresponds to a state, black indicating an active EEG channel, and the normalized frequency difference is annotated on the y-axis.

associated with emotional ratings in several individuals. However, no consistent trend was observed at the population level. By analyzing high-frequency emotion-specific states and their complementary counterparts, we identified candidate brain states that recur across emotional trials. The prevalence of transitions between complementary states and their emotion-specific dependency further supports the hypothesis that these states represent meaningful structures in the brain's energy landscape.

By integrating empirical EEG data with a physics-based modeling approach, this research addresses a critical gap in the literature: the lack of interpretability in deep learning-based emotion recognition systems. Our findings suggest that energy landscape dynamics offer a viable path toward identifying neural biomarkers of affective processing, particularly when analyzed in a subject-specific manner.

Nevertheless, the current analysis may suffer from limitations in the use of binarization methods and trial duration. Thus, in future work, we will explore more robust spectral feature-based transformations and investigate topological properties of energy landscapes in greater depth. By doing so, we aim to bridge the divide between high-performance emotion classification and interpretable EEG modeling, thereby advancing the development of explainable affective brain-computer interfaces.

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