



Dual temporal pathway model of emotion processing based on dynamic network reconfiguration analysis of EEG signals

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ABSTRACT

Emotion is crucial for the quality of daily life. Recent findings suggest that the cooperation and integration of multiple brain regions are essential for effective emotion processing. Additionally, network reconfiguration has been observed during various cognitive tasks. However, it remains unclear how the brain responds to different emotional categories under natural stimuli from the perspective of network reconfiguration, or whether this reconfiguration can predict subjective rating scores.

To address this question, 28 video clips were used to evoke eight distinct emotion categories, and the participants' electroencephalogram (EEG) signals were recorded. Dynamic network reconfiguration analysis was performed on brain networks extracted from band-limited EEG signals using the phase locking value (PLV) across multiple non-overlapping time windows. Robust dynamic community detection was applied to these networks, followed by quantification of integration and segregation at both node- and community-level changes. Multi-dimensional rating scores were collected for each clip. The analysis revealed that the metrics of dynamic network reconfiguration could predict subjective ratings. Specifically, longer EEG segments improved predictions for positive emotions, whereas shorter segments were more effective for negative emotions.

Our study provides empirical evidence integrating the dual-process model and the theory of constructed emotion. Based on observed spatiotemporal patterns of global integration and segregation across the brain, we propose the dual temporal pathway model for emotional processing across various emotion categories, highlighting fast and slow neural processes associated with negative and positive emotions, respectively. These findings offer valuable support for developing temporally targeted diagnostic and therapeutic strategies for emotion-related brain disorders.

1. Introduction

Emotion is a crucial component of daily life, influencing thoughts, memory, attention, and motor actions (Alves et al., 2008; Pessoa, 2018; Pessoa & McMenamin, 2017; Siqi-Liu et al., 2018). Various stimuli can trigger complex emotional responses, and the dual-process model provides insights into how emotions are processed in the brain (Fiori, 2009; Gyurak et al., 2011; Thorneycroft, 2019). One model distinguishes between lower-level intuitive processes and higher-level reflective processes, suggesting that the former resembles primitive emotional responses observed in other species, while the latter involves deliberate reasoning and cognitive evaluation (Adolphs, 2013; Thorneycroft, 2019). A complementary theory proposes two mechanisms for emotion processing: top-down and bottom-up. Bottom-up processing begins with

sensory input that triggers emotional responses, whereas top-down processing involves higher-order cognitive assessments that shape emotional reactions (Azevedo et al., 2022; Comte et al., 2016; McRae et al., 2012). Emotions can emerge from both pathways, one bottom-up, driven by sensory perception, and the other top-down, shaped by cognitive appraisals (Bago et al., 2018; McRae et al., 2012).

2. EEG research on emotions

EEG has significantly advanced our understanding of emotion. Emotion categories are typically divided into basic and complex emotions. Basic emotions represent instinctual reactions, while complex emotions involve reasoning and social cognition (Adolphs, 2013). Abstract social emotions generally require longer reaction times, whereas

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sensory summation can further prolong responses (Romanski et al., 1993). Event-related potentials (ERPs), such as N170 and P300 indicate that basic emotions like fear and sadness elicit rapid, automatic responses, whereas complex emotions like joy and inspiration engage slower, higher-order cognitive processing (Shah et al., 2018; Simić et al., 2021). Fearful stimuli, in particular, evoke fast responses, as evidenced by enhanced N1, P3, and N2 signals during early and late stages of emotional face processing (Adolphs, 2013). Furthermore, patients exhibit faster reactions to fearful faces than to happy ones, reflecting rapid, nonconscious processing (Tsuchiya et al., 2009). Neutral words are processed faster than emotionally charged ones due to sensory summation, and facial expressions are decoded more quickly than words because of differences in meaning acquisition speed (Lei et al., 2023). Fast timescales govern core emotional responses, while slower timescales reflect enduring emotional traits (Oravecz & Brick, 2019). According to the corticolimbic dual-route model, rapid emotional processing is mediated by limbic circuits, enabling pre-attentive responses (Kruithof et al., 2022; Mamoon et al., 2024). However, understanding how fast and slow neural responses correspond to different emotional categories under natural conditions remains a challenge beyond what ERP studies can reveal.

Power spectra across frequency bands of EEG signals have been instrumental in deciphering emotional states. For instance, negative clips evoke higher gamma activity compared to neutral or erotic stimuli, while fear-inducing clips show reduced gamma activity (Maffei et al., 2020). Negative emotions also evoke stronger right hemisphere activation compared to positive ones (Alfano & Cimino, 2008; Zheng & Lu, 2015). Additionally, beta-band activity is more prominent during both positive and negative emotional tasks (Ray & Cole, 1985). The frontal alpha asymmetry (FAA) biomarker reflects withdrawal motivation and emotion regulation during negative stimuli (Deng et al., 2023). Alpha and lower beta oscillations are closely linked to cortical activation in response to emotional stimuli (Codispoti et al., 2023). Alpha band suppression indicates attentional engagement, with increased alpha desynchronization reflecting deeper emotional processing during aversive stimuli (Bacigalupo & Luck, 2022). Theta-band oscillations are implicated in emotion regulation, showing stronger activity during negative memory encoding and cognitive behavioral therapy (CBT) sessions (Heinbockel et al., 2021; Micoulaud-Franchi et al., 2021). Theta oscillations also discriminate between major depressive disorder (MDD) and anxiety disorders (Zhang et al., 2022). Changes in both delta and theta bands reflect lingering emotional effects after regulation and play an essential role in empathy and pain processing (Balconi et al., 2024; Lapomarda et al., 2022).

3. Global involvement of the brain in emotion

The theory of constructed emotion argues that emotions result from global integration across multiple brain areas rather than being restricted to specific regions (Barrett, 2017). The involvement of large-scale brain networks is critical for emotion processing (Pessoa, 2018; Pessoa & McMenamin, 2017). Graph theory and complex network approaches are increasingly being applied to EEG data, revealing how functional connectivity among neural populations contributes to decoding emotional states (Jahromy et al., 2019). The dynamic mapping of interaction patterns reflects the complexity of emotions (Wang et al., 2020, 2023).

Phase alignment and coupling between brain regions create temporal windows that facilitate effective interregional communication (Zheng et al., 2019). Temporal dynamics of functional connectivity can predict multidimensional emotional experiences, with particularly strong performance in measures of arousal and dominance (Mishra et al., 2022). Integrating phase and amplitude features further improves emotion classification accuracy (Bi et al., 2024; Hu et al., 2024).

Disruptions in cooperation and communication across brain regions can lead to mental and psychological disorders (Ding et al., 2022;

Harlalka et al., 2019; Hendler et al., 2018; Kaiser et al., 2015; Vatans-ever et al., 2017). As a key metric for quantifying brain network integrity, network cohesion has been linked to emotion regulation, and its disruption has been associated with stress and attention deficit hyperactivity disorder (ADHD) (Ding et al., 2022; Young et al., 2017). Maintaining network cohesion has also been identified as a therapeutic target in interventions for preterm birth (White et al., 2014). Additionally, nodal disjointedness—a lack of coordination among network nodes—has been associated with impairments in attention and visual memory (Zhang et al., 2021). EEG is highly valuable in emotion research because of its temporal precision and ability to capture dynamic brain activity. Community detection techniques offer powerful insights into brain networks, and the investigation of dynamic community structures provides novel perspectives on the neural basis of emotions, warranting further investigation.

In summary, the dual-process model, together with complementary theories of top-down and bottom-up processing, offers a nuanced framework for understanding how the brain processes different emotional stimuli. EEG provides valuable insights into these mechanisms by capturing the temporal dynamics of neural responses across various emotion categories. However, further research is required to explore how long and short neural processes operate using segmented signals with different time windows under naturalistic emotional conditions and to predict complex emotional experiences. Our preliminary findings suggest that longer EEG segments yield better predictive performance for positive emotions, which correspond to slower emotional responses. In contrast, shorter segments are more effective in predicting ratings for negative emotions, reflecting faster emotional responses. The proposed theoretical framework, referred to as the dual temporal pathway model, is illustrated in Fig. 1.

4. The present study

Accumulating evidence highlights the unique advantage of EEG recordings in affective neuroscience. Recent studies have successfully predicted personality traits and subjective emotional ratings by integrating multimodal measurements during emotional stimulation (Hu et al., 2022; Li et al., 2020; Shui et al., 2023). While functional connectivity patterns are effective in decoding six basic emotions, their temporal dynamics remain underexplored (Liu et al., 2023). To address this gap, we propose a novel framework leveraging dynamic network reconfiguration metrics derived from time-varying functional connectivity patterns. These metrics were subsequently applied to predict standardized emotional assessment scores, with the workflow illustrated in Fig. 2.

4.1. Participants and stimuli

A total of 80 subjects participated in the study, and their EEG recordings are available as a public dataset, with approval obtained from local ethics committees (Hu et al., 2022). All participants signed an informed consent form prior to the experiment. To elicit eight discrete emotions representing a comprehensive range of emotional experiences, 28 video clips were selected following previous research (Ge et al., 2019; Hu et al., 2017; Schaefer et al., 2010). Negative emotions included anger, fear, disgust, and sadness, while positive emotions included amusement, inspiration, joy, and tenderness.

The experiment consisted of seven blocks: three for positive emotions, three for negative emotions, and one for neutral emotions. Between each pair of video clips, distraction tasks—such as solving mathematical problems—were administered to eliminate residual effects from the previous stimuli (Van Dillen & Koole, 2007). After each video clip, participants provided self-reported ratings, followed by a 30-second rest break before the next stimuli. The self-reported ratings covered 12 dimensions: anger, disgust, fear, sadness, amusement, joy, inspiration, tenderness, arousal, valence, familiarity, liking. We focused

EEG Activities in Emotion Processing

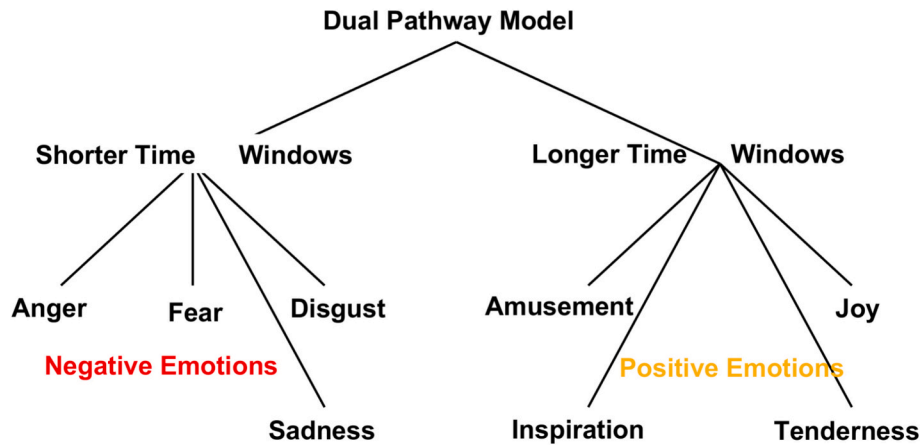


Fig. 1. The graphical representation of the dual temporal pathway model for the present study.

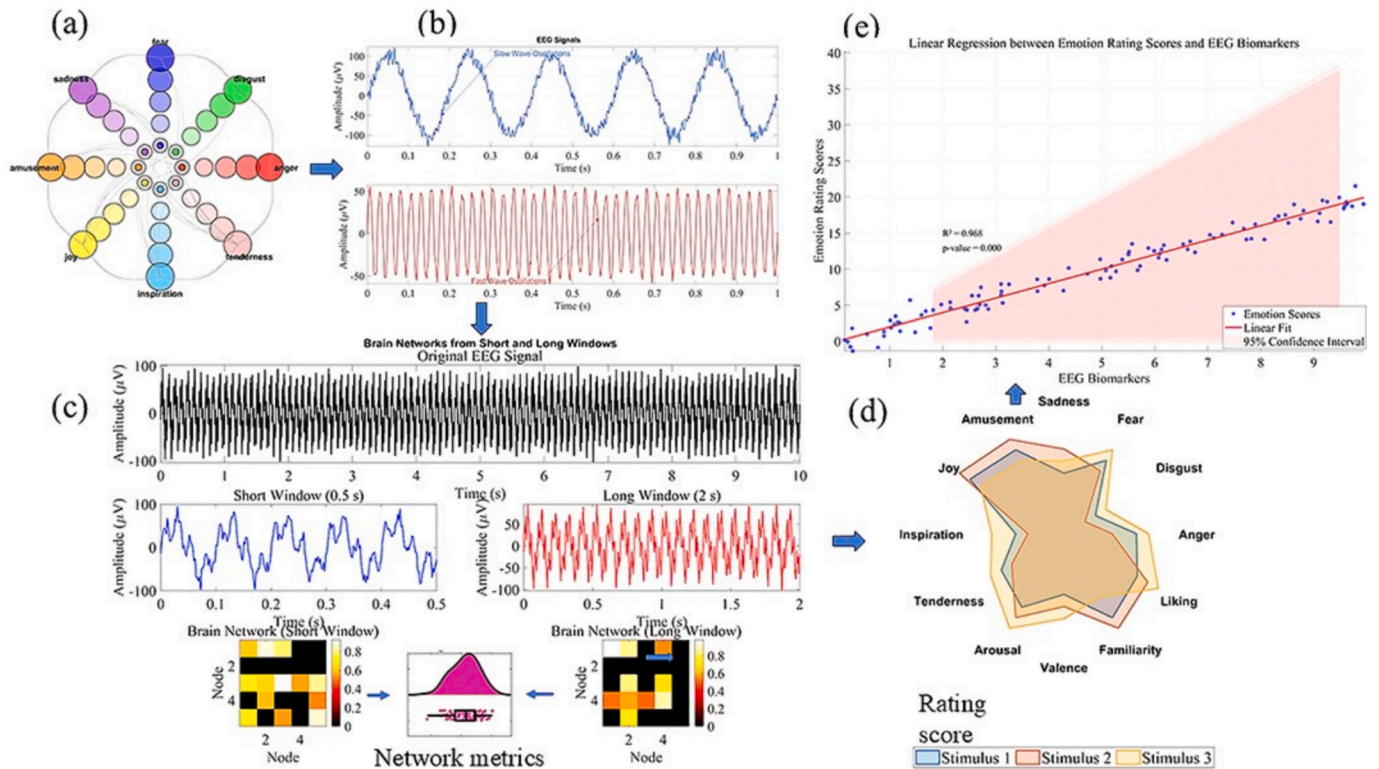


Fig. 2. Computational workflow of the present study (a) Delivery of emotional stimuli across 8 emotion categories (b) Multichannel EEG recordings with 30 channels (c) Dynamic network metric extraction from long and short sliding windows (d) multidimensional emotion rating collection (e) Regression modeling between network metrics and emotion ratings.

on the first eight emotion-specific dimensions for further analysis.

4.2. EEG recording

EEG was recorded at a sampling rate of 250 Hz using a 32-channel EEG system following the international 10–20 system (Hu et al., 2022). The last 30 s of EEG signals from 30 channels (numbered 1 to 30) were used for brain network extraction. The selected channels included the following: Fp1/2, Fz, F3/4, F7/8, FC1/2, FC5/6, Cz, C3/4, T5/4, CP1/2, CP5/6, T5/6, Pz, P3/4, PO3/4, Oz, and O1/2. Pre-processing

steps included re-referencing, artifact removal, and band-pass filtering to extract the following frequency bands: delta (0.5–3 Hz), theta (4–7 Hz), alpha (8–13 Hz), beta (14–29 Hz), and gamma (30–47 Hz). These frequency-dependent signals were segmented into non-overlapping time windows of 1, 2, 3, and 5 s for functional brain network construction.

4.3. Brain network construction

To account for volume conduction effects, functional brain networks were constructed using the phase-locking value (PLV) method, as it is an

efficient technique for functional connectivity investigation. For instance, Aydore et al. (2013), Bruña et al. (2018) and Alteriis et al. (2025) comprehensively summarize PLV as a main technique for dynamic functional connectivity investigation. Jian et al. (2017) addresses that PLV plays important role in sensorimotor rhythm (SMR) based brain computer interface (BCI). Wang et al. (2020, 2023, 2024) adopt PLV for characterizing functional integration and separation for emotion processing and emotion recognition. Reddy et al. (2021) and Ahmadi Moghadam et al. (2024) integrate PLV with deep learning techniques to develop new biomarkers for brain disorders. In this framework, each electrode corresponds to a node, and the PLV measurements between nodes formed weighted network matrices (Dimitriadis et al., 2010; He et al., 2023; Wang et al., 2020). After segmenting the signals into different time windows, time-varying brain connectivity matrices were generated, with each matrix representing the functional connectivity for a specific time window. Four non-overlapping sliding time windows (1 s, 2 s, 3 s, 5 s) were applied to characterize the time-varying properties of EEG signals. Frequency-specific functional connectivity matrices were constructed, with nodes representing EEG channels and edges quantifying phase synchronization between node pairs. Weighted adjacency matrices were generated for each time window and frequency band, providing a time-resolved representation of network dynamics. This multi-temporal approach enables the detection of both transient and sustained network interactions. This approach enabled the detection of transient and persistent network interactions, resulting in undirected, weighted brain networks.

We compared PLV with other phase-based synchronization methods, including the phase slope index (PSI), phase lag index (PSI), conjugate phase locking value (cPLV), weighted phase lag index (wPLV), to assess their performance. However, the time-varying brain networks derived from these techniques failed to support robust dynamic community detection. This failure may be due to their inability to effectively capture strong synchronous activities and dynamic changes in global synchrony, which are essential for detecting functional modules in dynamic community detection. In contrast, PLV excels in these areas because of its focus on pure phase relationships and its performance with nonstationary and time-varying EEG signals.

4.4. Dynamic community structure and temporal dynamics

Dynamic community structure analysis was employed to quantify the temporal dynamics under emotional stimuli. A key challenge was to extract robust and effective communities from time-varying brain networks. Communities were defined as subsets of nodes with more intense intra-group than inter-group connections. Modularity optimization was taken to assign community members for static networks, with multiscale grouping evaluated through varying resolution parameters (Onnela et al., 2012; Porter et al., 2009; Reichardt & Bornholdt, 2006).

For brain networks, dynamic properties such as cohesion and disjointedness were measured as nodes change their community affiliations over time. Cohesion refers to nodes that transit from one community to another together over time, while disjointedness reflects isolated movements of nodes (Bassett, Porter, et al., 2013; Fortunato & Barthelemy, 2007; Good et al., 2010; Newman, 2018). A modular optimization algorithm has been implemented for robust dynamic community detection (Bassett, Porter, et al., 2013; Bassett, Wymbs, et al., 2013; Bickel & Chen, 2009; GÅksgens et al., 2023). Multilayer modularity maximization optimized partitions across temporally evolving network layers, where the modularity index Q is defined as follows:

$$Q = \frac{1}{2\mu} \sum_{ijl} \{ (A_{ijl} - \gamma_l P_{ijl}) \delta_{lr} + \delta_{ij} \omega_{jlr} \} \delta(g_{il}, g_{jr}) \quad (1)$$

$$\mu = \frac{1}{2} \sum_{jr} K_{jr} \quad (2)$$

$$K_{jl} = k_{jl} + c_{jl} \quad (3)$$

$$k_{jl} = \sum_i A_{ijl} \quad (4)$$

$$c_{jl} = \sum_r \omega_{jlr} \quad (5)$$

where A_{ijl} denotes the adjacency matrix of layer l , P_{ijl} represents the component for the optimization default model, γ_l controls structural resolution as parameter, g_{il} and g_{jr} represent the community assignment quantity for node i/j in layer l/r separately, and ω_{jlr} weights inter-layer connections, μ comes from the total edge weight (K_{jl}) which combines inter-layer (c_{jl}) and intra-layer strength (k_{jl}) (Bassett & Mattar, 2017; Bassett, Porter, et al., 2013; Bassett, Wymbs, et al., 2013; Onnela et al., 2012; Porter et al., 2009; Reichardt & Bornholdt, 2006). Nodes were assigned to communities through Louvain-like optimization with 100 random initializations to ensure robustness (Bickel & Chen, 2009; Fortunato & Barthelemy, 2007; GÅksgens et al., 2023; Good et al., 2010; Mucha et al., 2010; Newman, 2018).

For quality control considerations, EEG data from 74 participants were selected for further network reconfiguration analysis after robust community detection. Statistical optimization models, including an optimization null model and a post-optimization null model, were employed to ensure meaningful partitioning of the networks. Maximized modularity was the primary criterion used to partition the network into communities, ensuring that the total edge weights within communities were maximized (Brandes et al., 2007; Porter et al., 2009; Reichardt & Bornholdt, 2006). The optimization null model preserves the degree distribution while randomizing connections, whereas the post-optimization null model randomizes community labels while maintaining community size. Both models were iterated 100 times to establish significance thresholds for cohesion/disjointedness metrics (Bassett, Porter, et al., 2013; Brandes et al., 2007; Kivela et al., 2014; Porter et al., 2009; Reichardt & Bornholdt, 2006). Each time window was treated as a single layer, with time-varying community partitioning over time identified through the optimization of the multi-layer modularity quality function. As time evolved, the nodes exhibited distinct community affiliations, reflecting the temporal dynamics in the brain during emotion processing.

The derived network metrics included node and community disjointedness, node and community cohesion, node flexibility, community changes and cohesion strength. Node cohesion reflects how frequently nodes are assigned to the same community, while node disjointedness indicates how often nodes are isolated from their original communities. The cohesion matrix measures the strength of coordinated nodes transitions between communities, while the disjointedness matrix quantifies the extent to which nodes become isolated. These matrices characterize the temporal dynamics of brain network reconfiguration, with cohesive and disjoint switches quantifying node transitions between communities.

Node cohesion describes the coordinated shifts of node clusters across communities, while node disjointedness represents isolated node transitions. Node flexibility calculates the ability of nodes to switch between communities, indicating the adaptability and functional diversity of specific recording sites. These metrics were calculated over time. Community changes represent shifts in node affiliations, and community cohesion characterizes the structural stability of communities over time, while community disjointedness captures the overall fragmentation of communities within the brain network. Cohesion strength indicates the overall strength of network integration during emotional processing. These network metrics illustrate the balance

between functional integration as cohesive shifts and segregation as disjoint transitions, reflecting dynamically reconfigured neural networks during emotion processing (Fortunato & Barthelemy, 2007; Mucha et al., 2010; Bassett, Porter, et al., 2013; Bassett, Wymbs, et al., 2013; Kivelä et al., 2014; Telesford et al., 2017).

4.5. Regression analysis between network metrics and rating scores

Linear regression models were used to explore the relationship between network reconfiguration metrics and self-reported scores (Hu et al., 2022; Kuo et al., 2020; Li et al., 2020; Mattar & Bassett, 2019; Tang et al., 2021). The coefficient of determination (R^2) and p -value are used to assess the predictive power of a regression model. In the case of time-varying EEG signals, an R^2 threshold of 0.25 strikes a balance between avoiding overfitting and capturing weaker but significant relationships. The R^2 threshold of 0.25 was chosen because stricter thresholds may inadvertently exclude subtle but important changes. A threshold of FDR-corrected (False Discovery Rate) $p < 0.05$ was applied for statistical significance. The network features capture essential information from the original brain networks, and their predictive power was assessed in this study. After implementing different time window lengths, a set of network features was extracted from the robust community detection and network reconfiguration measurements of the different functional brain networks. The network metrics derived from dynamic community detection and network reconfiguration were used to predict rating scores across time windows and emotion categories.

5. Results

The results show that community disjointedness achieves strong predictive performance based on linear correlation analysis between EEG-derived network reconfiguration metrics and rating scores across all four kinds of time windows. When setting the coefficient of determination (R^2) threshold at 0.25 (equivalent to a Pearson correlation coefficient of 0.5), longer time window (5 s) exhibits stronger correlations with positive emotions, while shorter time windows (1 s) exhibit higher predictive power for negative emotions. Tables 1 and 2 present the coefficients of determination and the corresponding p -values for the 1-second and 5-second time windows, respectively. Tables 3 and 4 present these metrics for the 2-s and 3-s time windows, where

Table 1
Regression analysis with the time window length of 5 s.

Emotion	R^2	P value	Frequency band	Network metric	Channel number
Tenderness	0.316	1.85E-07	Theta	commDisjoint	11
Joy	0.269	2.18E-06	Theta	Node flexibility	27
Amusement	0.258	3.78E-06	Theta	commDisjoint	11
Joy	0.271	2.00E-06	Theta	commDisjoint	5
Joy	0.285	9.55E-07	Theta	commDisjoint	11
Joy	0.286	9.03E-07	Gamma	commDisjoint	25
Inspiration	0.306	3.13E-07	Alpha	Node disjointedness	26
Tenderness	0.252	5.11E-06	Alpha	Community changes	11
Joy	0.280	1.23E-06	Delta	Node flexibility	25
Joy	0.272	1.92E-06	Delta	Node cohesion	25
Fear	0.303	3.77E-07	Alpha	commDisjoint	14
Anger	0.355	2.18E-08	Alpha	commDisjoint	14

Table 2
Regression analysis with the time window length of 1 s.

Emotion	R^2	P value	Frequency band	Network metric	Channel number
Anger	0.302	3.86E-07	Alpha	commDisjoint	4
Sadness	0.397	1.81E-09	Alpha	commDisjoint	4
Disgust	0.379	5.26E-09	Alpha	commDisjoint	4
Fear	0.403	1.21E-09	Alpha	commDisjoint	4
Fear	0.737	1.45E-22	Beta	commDisjoint	5
Fear	0.558	2.20E-14	Beta	commDisjoint	25
Fear	0.371	8.53E-09	Beta	commDisjoint	29
Sadness	0.373	7.74E-09	Beta	commDisjoint	29
Disgust	0.689	6.39E-20	Beta	commDisjoint	5
Disgust	0.530	2.05E-13	Beta	commDisjoint	25
Disgust	0.295	5.63E-07	Beta	commDisjoint	29
Anger	0.627	4.54E-17	Beta	commDisjoint	5
Anger	0.471	1.42E-11	Beta	commDisjoint	25
Anger	0.270	2.08E-06	Beta	commDisjoint	29
Anger	0.257	3.95E-06	Theta	commDisjoint	4
Anger	0.276	1.54E-06	Theta	commDisjoint	7
Anger	0.374	7.32E-09	Theta	commDisjoint	24
Sadness	0.425	3.15E-10	Theta	commDisjoint	4
Sadness	0.271	1.98E-06	Theta	commDisjoint	19
Sadness	0.328	9.47E-08	Theta	commDisjoint	20
Sadness	0.478	9.41E-12	Theta	commDisjoint	24
Fear	0.486	5.33E-12	Theta	commDisjoint	4
Fear	0.264	2.79E-06	Theta	commDisjoint	19
Fear	0.331	8.21E-08	Theta	commDisjoint	20
Fear	0.479	8.44E-12	Theta	commDisjoint	24
Disgust	0.629	3.83E-17	Theta	commDisjoint	4
Disgust	0.319	1.57E-07	Theta	commDisjoint	20
Disgust	0.385	3.57E-09	Theta	commDisjoint	24
Fear	0.347	3.36E-08	Delta	commDisjoint	3
Fear	0.486	5.33E-12	Delta	commDisjoint	29
Sadness	0.342	4.25E-08	Delta	commDisjoint	3
Sadness	0.425	3.15E-10	Delta	commDisjoint	29
Disgust	0.277	1.44E-06	Delta	commDisjoint	3
Disgust	0.451	5.91E-11	Delta	commDisjoint	13
Disgust	0.629	3.83E-17	Delta	commDisjoint	29
Anger	0.256	4.28E-06	Delta	commDisjoint	3

(continued on next page)

Table 2 (continued)

Emotion	R ²	P value	Frequency band	Network metric	Channel number
Anger	0.344	3.88E-08	Delta	commDisjoint	13
Anger	0.257	3.95E-06	Delta	commDisjoint	29
Inspiration	0.380	4.93E-09	Delta	commDisjoint	9
Tenderness	0.288	8.21E-07	Alpha	commDisjoint	21

Table 3

Regression analysis with the time window length of 2 s.

Emotion	R ²	P value	Frequency band	Network metric	Channel number
Joy	0.262133	3.12E-06	Alpha	commDisjoint	4
Joy	0.264904	2.71E-06	Alpha	commDisjoint	25
Joy	0.33842	5.46E-08	Theta	commDisjoint	3
Joy	0.279704	1.27E-06	Beta	commDisjoint	25
Anger	0.277727	1.41E-06	Gamma	Strength cohesion	2
Anger	0.405702	1.06E-09	Theta	commDisjoint	12
Anger	0.281096	1.18E-06	Theta	commDisjoint	23
Anger	0.413117	6.66E-10	Theta	commDisjoint	25
Anger	0.455005	4.43E-11	Beta	commDisjoint	25
Fear	0.451852	5.47E-11	Delta	commDisjoint	2
Fear	0.26169	3.19E-06	Delta	commDisjoint	21
Fear	0.394886	2.05E-09	Theta	commDisjoint	12
Fear	0.268256	2.29E-06	Theta	commDisjoint	20
Fear	0.352311	2.50E-08	Theta	commDisjoint	23
Fear	0.322409	1.32E-07	Theta	commDisjoint	25
Fear	0.39986	1.51E-09	Beta	commDisjoint	25
Fear	0.259823	3.51E-06	Gamma	Node disjointedness	26
Sadness	0.253636	4.79E-06	Gamma	commDisjoint	11
Sadness	0.269141	2.19E-06	Delta	commDisjoint	2
Sadness	0.483254	6.33E-12	Theta	commDisjoint	12
Sadness	0.430481	2.22E-10	Theta	commDisjoint	23
Sadness	0.25529	4.41E-06	Gamma	Node disjointedness	26
Disgust	0.26814	2.30E-06	Gamma	Node disjointedness	26
Disgust	0.26145	3.23E-06	Gamma	commDisjoint	11
Disgust	0.33396	7.00E-08	Delta	commDisjoint	2
Disgust	0.26126	3.26E-06	Delta	commCohesion	15
Disgust	0.50973	9.29E-13	Theta	commDisjoint	12
Disgust	0.41322	6.62E-10	Theta	commDisjoint	23

‘commDisjoint’ is defined as the abbreviation for community disjointedness, ‘commCohesion’ as the abbreviation for ‘community cohesion’ metrics, and the electrode number from 1 to 30 represents Fp 1/2, Fz, F3/4, F7/8, FC 1/2, FC 5/6, Cz, C 3/4, T3/4, CP 1/2, CP 5/6, T5/6, Pz, P3/4, PO 3/4, Oz, O1/2 separately.

All EEG frequency bands contributed to capturing dynamic community structures, while theta band EEG oscillations showed superior performance in predicting rating scores. Among the recording sites, almost all EEG channels contributed to the involvement of dynamic community structure, with frontal lobe, parietal lobe and occipital lobes playing important roles in it. Specifically, Fp 2, F3, FC 6, CP 6, P3, P4, PO 3 and O1 are more prominent than other channels.

It is found out that community disjointedness is more sensitive in predicting rating scores compared to other network metrics. Another remarkable network metric is node disjointedness. Community disjointedness describes how often nodes within a community change independently as the community splits or merges, while node disjointedness indicates whether the node moves from one community to another independently within a time window. That is, both node and community disjointedness quantify whether nodes or communities remain consistently disconnected from their neighbors. From the

perspective of temporal dynamics, the excellent performance of both node and community disjointedness illustrates the critical local and global network segregation for emotion processing. Moreover, other network metrics such node flexibility/disjointedness/cohesion as well as community changes could predict the evaluation results to some extent, indicating the efficiency of the dynamic community structure in capturing the temporal characteristics associated with different emotion categories.

When the length of the time windows varies, the multilayer brain network alters which affects the produced network reconfiguration metrics. To illustrate later, the four positive emotions are grouped as ‘positive’, and the four negative emotions are grouped as ‘negative’. With respect to the discrete emotion categories, the ratio of positive to negative successful predictions increases as the length of the time window increases. Tables 1 to 4 illustrate the trend of more predicted positive rating scores as the time window lengths increases. The results clearly indicate that positive emotions are better predicted with longer length of time windows, while negative emotions show improved performance with shorter time windows. Fig. 3 illustrates the differences between these two groups using node disjointedness and community disjointedness measurements under the 2-second time window, as these metrics are superior at predicting emotion ratings.

6. Discussion

6.1. Constructed theory and the dual pathway model of emotion

This study employs a multilayer network approach to investigate the dynamic reorganization of functional connectivity in the brain. Band-limited EEG signals were segmented into temporally non-overlapping windows, with each window representing a distinct layer in the multilayer architecture. Within this framework, functional network modules were identified through multilayer modularity optimization, where the quality function of the community structure of each layer was statistically validated against a null model accounting for random connections. A Louvain-based optimization algorithm was implemented to maximize the multilayer modular quality function, generating time-resolved community partitions that capture transient module reorganization during emotion processing. Then, an EEG-based dynamic network reconfiguration framework is applied for depicting emotion processing, featuring the proposed dual temporal pathway model.

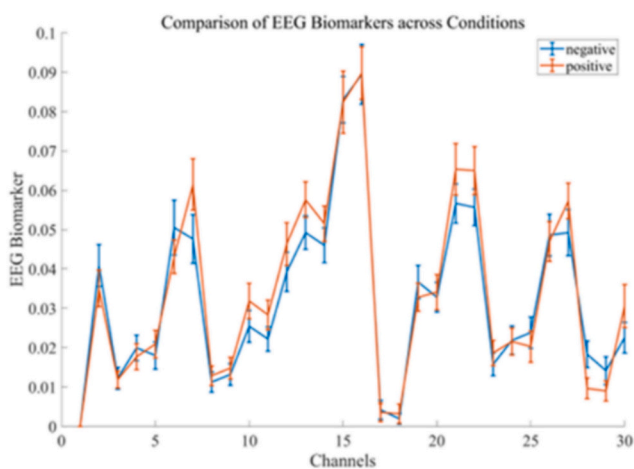
Dynamic network reconfiguration profiling was conducted on time-resolved EEG-derived network slices spanning multiple temporal scales. The proposed analytical framework bypasses the stationary assumptions inherent in conventional EEG analyses through time-resolved quantification of network reconfiguration dynamics. Self-reported emotional ratings were integrated with topological metrics of nodal and modular reconfiguration to compute coefficients of regression (R²). Notably, community-level and nodal disjointedness indices demonstrated superior predictive performance compared to alternative metrics in predicting emotional ratings for both positive and negative emotions (FDR corrected $p < 0.05$). These findings suggest that the brain employs distinct adaptive coping strategies, manifested through its capability for flexible network reconfiguration in response to diverse emotional stimuli. The observed spatiotemporal patterns of global integration and segregation in the brain provide empirical support for the neurobiological underpinnings of the theory of constructed emotion, particularly regarding the dynamic coordination of large-scale neural assemblies during affective processing (Barrett, 2017).

Consistent with the theory of constructed emotion, emotion involves coordinated interactions across distributed multiple brain areas including parietal and occipital lobes (Barrett, 2017). Through multi-temporal analysis of dynamic community cohesion and disjointedness in EEG-derived network slices, we demonstrate that longer time windows, reflecting sustained integration, are more effective at predicting positive emotions, whereas shorter windows, capturing rapid neural

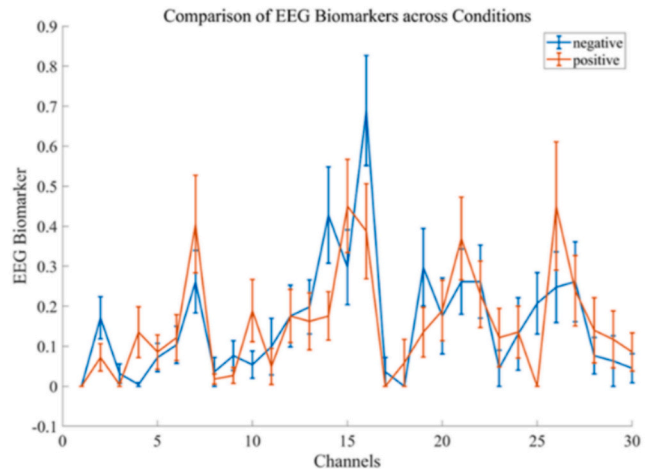
Table 4

Regression analysis with the time window length of 3 s.

Emotion	R^2	P value	Frequency band	Network metric	Channel number
Tenderness	0.272564	1.84E-06	Gamma	Node disjointedness	11
Amusement	0.315689	1.90E-07	Gamma	commDisjoint	8
Amusement	0.395471	1.98E-09	Gamma	commDisjoint	11
Amusement	0.290753	7.17E-07	Delta	nodeDisjoint	9
Amusement	0.395471	1.98E-09	Alpha	commDisjoint	24
Inspiration	0.261157	3.28E-06	Beta	nodecohesion	25
Inspiration	0.252428	5.08E-06	Alpha	commDisjoint	7
Inspiration	0.393307	2.25E-09	Gamma	commDisjoint	8
Inspiration	0.270885	2.00E-06	Gamma	commDisjoint	28
Joy	0.265382	2.65E-06	Beta	commDisjoint	19
Joy	0.291454	6.91E-07	Beta	commDisjoint	25
Joy	0.28157	1.16E-06	Theta	commDisjoint	4
Joy	0.338079	5.56E-08	Delta	nodeDisjoint	30
Disgust	0.44444	8.94E-11	Alpha	commDisjoint	26
Disgust	0.50688	1.15E-12	Theta	commDisjoint	2
Disgust	0.34616	3.54E-08	Theta	commDisjoint	24
Disgust	0.61953	9.20E-17	Delta	Node disjointedness	14
Disgust	0.30263	3.83E-07	Delta	Node disjointedness	26
Disgust	0.32357	1.24E-07	Delta	Node disjointedness	29
Disgust	0.27705	1.46E-06	Beta	commDisjoint	21
Fear	0.65365	3.05E-18	Delta	Node disjointedness	14
Fear	0.2657	2.61E-06	Delta	Node disjointedness	16
Fear	0.38633	3.43E-09	Delta	Node disjointedness	29
Fear	0.26016	3.45E-06	Beta	commDisjoint	30
Fear	0.38116	4.67E-09	Alpha	commDisjoint	20
Fear	0.3633	1.33E-08	Alpha	commDisjoint	26
Fear	0.4252	3.11E-10	Theta	commDisjoint	2
Fear	0.28905	7.84E-07	Theta	commDisjoint	8
Fear	0.45836	3.53E-11	Theta	commDisjoint	24
Sadness	0.51022	8.96E-13	Theta	commDisjoint	2
Sadness	0.25447	4.59E-06	Theta	commDisjoint	6
Sadness	0.33133	8.09E-08	Theta	commDisjoint	24
Sadness	0.62099	8.00E-17	Delta	nodeDisjoint	14
Sadness	0.26385	2.86E-06	Beta	commDisjoint	21
Sadness	0.44022	1.18E-10	Alpha	commDisjoint	26
Anger	0.43513	1.64E-10	Delta	Node disjointedness	14
Anger	0.28347	1.05E-06	Delta	Node disjointedness	29
Anger	0.46141	2.87E-11	Beta	commDisjoint	21
Anger	0.30675	3.08E-07	Alpha	commDisjoint	20
Anger	0.33822	5.52E-08	Alpha	commDisjoint	26
Anger	0.37363	7.28E-09	Theta	commDisjoint	2



(a) Network metrics of node disjointedness



(b) Network metrics of community disjointedness

Fig. 3. Network metrics for negative and positive emotions where x-axis represents is the electrode number (a) network metric of node disjointedness (b) network metrics of community disjointedness.

dynamics, are more closely associated with negative emotions. This temporal specificity resolves ambiguities in classical dual-process models by directly linking temporal EEG features to emotion processing, thereby advancing beyond the generalized fast and slow processes

outlined in dual-process theory (Adolphs, 2013; Bellini-Leite, 2022; Evans, 2008; Fiori, 2009; Gyurak et al., 2011; Thorneycroft, 2019). This distinction highlights differential neural mechanisms for persistent versus transient emotional processing. Our study provides the first

empirical evidence integrating theory of constructed emotion and the dual process model of emotion. Crucially, we demonstrate that temporal scale selection constitutes a fundamental methodological determinant in emotion prediction architectures, establishing quantitative linkage between neural dynamics and subjective emotional experience. The integration of dynamic network reconfiguration metrics with self-reported ratings establishes a mechanistic perspective for emotion processing, delineating structure-function relationships between emotion categories and whole-brain network reconfiguration dynamics across optimized temporal scales.

Our proposed dual temporal pathway model distinguishes between slow, sustained processing associated with positive emotional states and fast, transient processing linked to negative affective responses. This temporal dissociation finds mechanistic support in computational frameworks such as the thalamic-cortical model of fear processing, where rapid thalamic filtering precedes cortical interpretation through temporally staggered pathways (Armony et al., 1997). The extended temporal summation facilitated by the slower kinetics of NMDA receptors, further enhances the concurrent fast and slow processing of information in the brain (Armony et al., 1997). Neurocomputational evidence from spiking neuron models reveals how balanced inhibitory and excitatory dynamics mediate temporally specialized emotional processing (Murakoshi & Saito, 2009).

Through their dynamic interaction, complementary fast, resource-efficient automatic processes and slower, resource-intensive controlled processes jointly support adaptive emotion regulation, manifesting in our proposed dual-temporal process architecture (Tugade, 2010). Contemporary frameworks extend this dichotomy by incorporating both explicit and implicit regulatory mechanisms (Gyurak et al., 2011) and thalamocortical system interactions (LeDoux & Pine, 2016). Oscillatory dynamics further instantiate this temporal specialization, where γ -aminobutyric acid type A (GABA_A) interneurons with different kinetics generate mixed gamma-theta cross-frequency coupling (Desroches et al., 2022; Keeley et al., 2017). The fast-acting limbic system may mediate the rapid, pre-attentive processing of impulsive aggression stimuli (Kruithof et al., 2022; Mamoon et al., 2024). One problem with the dual-route hypothesis is the lack of quantitative evidence to support its claims regarding emotion processing (Lowe et al., 2009).

Stimulus characteristics modulate processing speeds, evidenced by faster facial expression processing versus lexical stimuli (Schacht & Sommer, 2009). Fearful body language is processed faster than happy or neutral postures, reflecting automatic defensive responses in the brain (Botta et al., 2021). The previous dual-processing theory posits the coexistence of intuitive, unconscious processes and deliberate, analytical ones in cognition (Adolphs, 2013; Evans, 2008; Fiori, 2009; Gyurak et al., 2011; Thorncroft, 2019). Building on dual system theory, the fast-acting limbic system facilitates the rapid, pre-attentive processing of impulsive aggression stimuli (Kruithof et al., 2022; Mamoon et al., 2024). Meanwhile, reaction times increase under extremely negative (EN) conditions, accompanied by impaired cognitive performance and enhanced frontal-to-occipital connectivity, suggesting that greater priority and cognitive resources are allocated to EN stimuli than to neutral ones (Yang et al., 2023). Later, Kahneman extended the dual process framework to emotion, proposing a two-factor model comprising physical arousal and cognitive labeling (Kennedy & Bugjska, 2010; Ye et al., 2023). Evidence suggests that the social engagement system processes emotional signals automatically, with certain regulatory mechanisms operating subconsciously (Ye et al., 2023). Event-related alterations in the sensorimotor cortex further differentiate responses to dynamic emotional facial expressions (Charidza & Gillmeister, 2022). According to these studies, it appears that our brain responds to negative stimuli more quickly than to other types of stimuli.

Unlike prior studies on the temporal dynamics of emotions, which have primarily focused on processes such as onset, duration and resurgence, or explored afterward frameworks like anticipation, crisis, and aftermath (Desmidt et al., 2014; Waugh et al., 2015), our EEG-based

network reconfiguration analysis reveals, for the first time, the multi-temporal scale characteristics of emotion processing based on quantitative evidence. This framework advances beyond previous temporal models focused on emotion phasing (Waugh et al., 2015) or crisis dynamics (Desmidt et al., 2014) by providing a temporal hierarchical network reconfiguration paradigm. The dynamic architecture of the dual temporal pathway model offers a new perspective on the mechanisms of emotional processing and paves the way for temporally targeted psychotherapeutic interventions.

6.2. The involvement of emotion in brain disorders and its clinical implications

Abnormal network dynamics are linked to mood disorders. Temporally precise EEG recordings reveal how dynamic brain networks encode emotional states. For instance, dynamic functional connectivity (dFC) improves characterization of bipolar disorder (Zhang et al., 2024), and elevated emotion network connectivity correlates with depression variability (Kelley et al., 2023). Multi-layer network analysis identifies compensatory reorganization in pathological conditions (Li et al., 2025). These findings support the “communication-through-coherence” theory, where low-frequency phase synchronization facilitates interregional communication during aversive stimuli (Lei et al., 2023). Neuroendocrine factors like cortisol awakening response further modulate neural resource redistribution, suggesting network flexibility as a biomarker for emotion regulation deficits (Zeng et al., 2024).

Disordered time perception is another neural biomarker in neuropsychiatric disorders, including time blindness and time lockdown. Disrupted temporal integration is often associated with impaired cognitive structures that hinder the ability to solve counting problems in mathematics (Rubia et al., 1997). Several studies have investigated abnormal time perception in anxiety disorders (Teixeira et al., 2013). Disordered temporal dynamics in interregional communications are linked to cognitive deficits (Zheng et al., 2017). The loss of the capability to allocate resources for sustained neural oscillations leads to the absence of ‘positive’ emotional experiences. As proposed by our dual temporal pathway model, shorter time windows are necessary for capturing negative emotion fluctuations (e.g., fear, sadness), while longer windows are required to predict positive emotions, aligning with subjective time perception distortions (Droit-Volet et al., 2013). Emotion is a key factor that influences temporal distortion while its underlying mechanism remain unclear (Lake, 2016). During our daily life experience, we tend to be more easily attracted by negative information, while feeling happy or positive becomes increasing difficult, with more individuals becoming more prone to feelings of depression. Our proposed dual temporal pathway for emotion processing may provide an explanation for this trend and offer new avenues for further clinical strategy. This study suggests that prolonged time windows for positive emotions may accelerate subjective time perception as time flies, aligning with observed neural integration patterns. The critical role of distinct temporal patterns for information processing dynamics warrants further study.

Previous studies emphasize the identification of neurocircuits and frequency components for advancing therapeutic intervention, while recent research highlights the significance of dynamic behavior in the brain (Alves et al., 2008; Deng et al., 2020; Morawetz et al., 2020; Palomero-Gallagher & Amunts, 2022; Stanković & Nešić, 2020). In our study, theta-band EEG oscillations play a crucial role in the distinct temporal patterns of information processing across different emotion categories. This finding aligns with previous studies which highlight the importance of theta oscillations in efficient emotion processing (Balconi et al., 2024; Heinbockel et al., 2021; Lapomarda et al., 2022; Micoulaud-Franchi et al., 2021; Zhang et al., 2022; Zheng et al., 2019). The data-driven framework outperforms both purely objective neural measurements and subjective behavioral assessments. This temporal aspect of information processing expands upon the previous dual-process model

of cognition and emotion.

6.3. Limitations and future research

Despite the contributions of this study, several limitations must be addressed in future research. First, the sample consists solely of college students, which may limit the generalizability of the findings; a more diverse population would be necessary to ensure broader applicability. Further investigations using more publicly available EEG datasets are needed before drawing definitive conclusions. Second, the influence of individual differences on the selection of optimal time windows warrants further investigation to explore how personalized time windows might enhance predictive models. Third, future research should consider a wider range of emotional categories, such as anxiety and depression to clarify disorder-specific mechanisms, given their strong association with psychological disorders. Fourth, multiple techniques are available for functional brain network extraction, including the wavelet coherence and cross frequency coupling. Future research should compare these network extraction techniques to evaluate their relative effectiveness. Finally, the limited spatial resolution of EEG necessitates integration with other techniques to enhance spatial localization of dysfunctional circuits, such as functional magnetic resonance imaging (fMRI) or magnetoencephalography (MEG), to provide a more comprehensive understanding of spatiotemporal brain dynamics.

7. Conclusion

The study proposes the dual temporal pathway model of emotion, which differentiates between slow, sustained and fast, transient emotional processing across distinct emotional categories. By applying network reconfiguration analysis, this research deepens our understanding of the multi-temporal neural dynamics underlying emotions, which have the potential to influence future diagnostic and therapeutic strategies for affective disorders. The adoption of dynamic network analysis offers a comprehensive view of the temporal aspects of emotional processing, while opening avenues for exploring its clinical applications. In conclusion, our findings advance the growing body of research on the spatiotemporal dynamics of brain networks during emotional processing. These insights not only refine mechanistic models of emotion processing but also highlight the translational potential of dynamic network reconfiguration as a biomarker for neuromodulation interventions.

CRedit authorship contribution statement

Yan He: Writing – original draft, Visualization, Funding acquisition, Conceptualization. **Yuan Liang:** Data curation, Conceptualization. **Ling Tong:** Investigation, Data curation. **Yujie Cui:** Conceptualization. **Hao Yan:** Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The code for robust community detection and community cohesion is available from the following website: <http://commdetect.weebly.com/>. The EEG dataset is available from Tsinghua Cloud (<https://cloud.tsinghua.edu.cn/d/3d176032a5a545c1b927/>).

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