



Individual variation in the neurophysiological representation of negative emotions in virtual reality is shaped by sociability

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ABSTRACT

Negative emotions play a dominant role in daily human life, and mentalizing and empathy are also basic sociability in social life. However, little is known regards the neurophysiological pattern of negative experiences in immersive environments and how people with different sociabilities respond to the negative emotional stimuli at behavioral and neural levels. The present study investigated the neurophysiological representation of negative affective experiences and whether such variations are associated with one's sociability. To address this question, we examined four types of negative emotions that frequently occurred in real life: angry, anxious, fearful, and helpless. We combined naturalistic neuroimaging under virtual reality, multimodal neurophysiological recording, and behavioral measures. Inter-subject representational similarity analysis was conducted to capture the individual differences in the neurophysiological representations of negative emotional experiences. The behavioral and neurophysiological indices revealed that although the emotion ratings were uniquely different, a similar electroencephalography response pattern across these negative emotions was found over the parieto-occipital electrodes. Furthermore, the neurophysiological representations indeed reflected interpersonal variations regarding mentalizing and empathic abilities. Our findings yielded a common pattern of neurophysiological responses toward different negative affective experiences in VR. Moreover, the current results indicate the potential of taking a sociability perspective for understanding the interpersonal variations in the neurophysiological representation of emotion.

1. Introduction

Emotion plays a dominant role in daily human social function (Tyng et al., 2017; Keltner and Kring, 1998; Cacioppo and Gardner, 1999), and humans spend most of their time pursuing positive emotional experiences or avoiding negative ones (Delgado et al., 2009). From the fundamental level (Ekman and Davidson, 1994), researchers have been dedicated to examining the nature and classification of emotion and understanding emotion from the basic perceptual and cognitive perspective (Adolphs, 2002; Kragel and LaBar, 2016). The basic emotion theory holds that certain emotions are unique, indivisible experiences that are innate and universal across cultures (e.g., anger, disgust, fear, happiness, sadness, and surprise) (Russell et al., 2017). Furthermore, evidence shows that emotional categories can be mapped onto certain biological and psychological domains and connected with distinct neurophysiological representations (Ekman and Cordaro, 2011; Tracy and Randles, 2011). However, there is a large inter-individual difference between social groups, or in emotion production, even when the same emotional stimuli are presented (Hu et al., 2021). Particu-

larly, for negative emotions, there is an argument that they are more salient in the cognitive process and exhibit larger individual variations (Adolphs, 2002; Tyng et al., 2017). One study shows that negative emotional experiences synchronize neural activities across subjects, which further promotes social interaction (Nummenmaa et al., 2012). Specifically, those negative feelings or emotions that frequently occurred in real life (e.g., angry, anxious, fearful, and helpless), and influence our normal functioning and social life (Feldman Barrett and Russell, 1998; Nezlek and Kuppens, 2008). Since there are various negative feelings in real life, an interesting question is raised, as to whether variations in negative emotional representations are associated with human behavioral and neurophysiological responses in real-world settings.

In addition to emotion, mentalizing and empathy are closely linked to social interaction (Majdandžić et al., 2016; Hooker et al., 2008), which also constitute individual differences. Mentalizing is essential for social function, and optimal social decision-making and responses are highly dependent on the accurate perception and prediction of the emotional states of others (Frith and Frith, 2006). Especially in aversive conditions, from inferring the negative feelings of others from witnessing

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their suffering or distress, empathy and prosocial behaviors would be produced, such as altruistic behaviors (Batson et al., 1987). In this process, mentalizing is a critical ability, especially during social interactions (Wu et al., 2020). Wu et al. developed a measure for different mentalizing components in social interaction: self-self mentalizing, other-self mentalizing, and self-other mentalizing (Wu et al., 2022). Empathy, negative emotion recognition, and sharing require self-other mentalizing first, and people would show instinct prosocial willingness if the perceived agent is vulnerable. Furthermore, mentalizing and empathy are conceptually related in terms of social cognitive processes and social functioning, while evidence from social neuroscience has revealed a distinct neural network that supports these constructs. Specifically, mentalizing has been recognized as a socio-cognitive process (Singer and Tusche, 2014). In the mentalizing process, the temporal-parietal junction (TPJ), superior temporal sulcus (STS), temporal pole (TP), posterior cingulate cortex (PCC), and medial prefrontal cortex (MPFC) are mainly involved in inferring the thoughts, actions, and intentions of others (Kanske et al., 2015; Schurz et al., 2021; Bzdok et al., 2012). Empathy focuses on the socio-affective process (Singer and Tusche, 2014). A distinct brain network that consists of the anterior insula (AI), anterior cingulate cortex (ACC), and dorsolateral prefrontal cortex (DLPFC) supports the understanding and the sharing of the affective states of others (Preckel et al., 2018; Kanske et al., 2015; Singer and Lamm, 2009).

Meanwhile, large individual differences have been found in mentalizing ability and trait empathy (Davis, 1983a, 1983b; Kliemann and Adolphs, 2018; Li et al., 2022). Previous studies have shown that people with similar personality traits may produce similar understating and neurophysiological responses toward social stimuli (van Baar et al., 2021; Bacha-Trams et al., 2018). While on the other hand, these variations in personality and sociability may also significantly induce great variations of negative emotion perception and representation in the social context (Chen et al., 2020; Gruskin et al., 2020). Therefore, it is of interest to further investigate whether mentalizing and trait empathy contributes to the variations in negative emotional representations and their association with neurophysiological responses.

In the last few decades, multiple neuroimaging methods and psychophysiological recording methods have been used to study emotional responses. Most of the neuroscience studies utilized functional magnetic resonance imaging (fMRI) and electroencephalography (EEG) as neural signals that respond to different emotional states. For example, fMRI studies have examined and summarized the neural substrate that represents emotion and generates and regulates emotional response (Sievers et al., 2021; Wager et al., 2008a, 2008b; McRae et al., 2008). These studies significantly advance our understanding of the emotion-related neural mechanism. Apart from fMRI, EEG has also been widely used in different emotional states (Nummenmaa et al., 2012; Hu et al., 2017; Ding et al., 2018). Meanwhile, in addition to the activity of the central nervous system (CNS), the autonomic nervous system (ANS) indices are also involved in emotional responses, including skin conductance level (SCL), heart rate (HR), and heart rate variability (HRV) (Fernández et al., 2012; Quintana et al., 2012), as summarized by Kreibitz (2010). When it comes to decoding others' emotional states, psychophysiological and neural responses are almost irrepressibly engaged in computing. Individuals share extensive similarities with others in their neural responses to emotions and also show individual differences in physiological and neural responses to emotional stimuli (Nguyen et al., 2019; Pérez et al., 2021).

However, most previous emotion research employed static emotional facial expressions, emotional arousing scenes, or objects to probe the psychophysiological and neural responses. To provide ecologically valid, realistic, and dynamic negative emotional experiences to individuals, it is necessary to utilize the emerging method of naturalistic neuroimaging to study the corresponding brain states. Specifically, in contrast to conventional highly-controlled tasks, a natural neural response to dynamic stimuli is induced by naturalistic paradigms such as movie viewing or narrative listening (Chang et al., 2021; Gruskin et al., 2020).

Previous studies indicated that movie viewing would robustly induce functional brain states (van der Meer et al., 2020; Tan et al., 2022). Evidence shows that emotion-driven attention effects are more prominent in naturalistic settings (Kulke and Pasqualetto, 2022), which further suggests the utility of the naturalistic paradigm in affective research.

In addition to utilizing various naturalistic materials, virtual reality (VR) techniques are also emerging in the fields of cognitive and affective science. Previous studies have revealed that VR elicits emotions more efficiently than the classical methods (Baños et al., 2006; Riva et al., 2007). Such an advantage especially benefits negative emotion elicitation, where VR offers an immersive multisensory environment that facilitates reliable emotions. Therefore, VR provides a new solution for improving ecological validity (Susindar et al., 2019). Negative emotions such as fear, anger, and helplessness are difficult to induce in standard laboratory settings. For example, one recent study used VR for fear conditioning (Faul et al., 2020), and another also combined EEG and VR to decode emotional arousal (Hofmann et al., 2021). Existing evidence showed mixed results on whether there are larger individual variations in negative emotions, which may have two limitations: (1) the approach to elicit natural negative emotions, and (2) the simultaneous validity of the body or brain signals. Thus, it is plausible and promising to leverage VR as a platform for the naturalistic paradigm and provide subjects with dynamic negative experiences in an immersive way.

Nevertheless, given the complex nature of human emotion, sociability, and the method of naturalistic neuroimaging, how can we examine and quantify the shared response and individual variations in negative feelings, from behavioral to neurophysiological response? The inter-subject representational similarity analysis (IS-RSA) (Finn et al., 2020; Nguyen et al., 2019), with the second-order statistical akin to RSA, can cast a new light on this issue. By leveraging IS-RSA, the neurophysiological representation of the individual differences in behavioral traits can be obtained by associating the similarity matrices of different modalities. In the last decade, IS-RSA has been used to explore the neural representations that reflect interpersonal variation in narrative interpretation (Nguyen et al., 2019), affective experiences (Chen et al., 2020), trait paranoia (Finn et al., 2018), and even moral decisions (van Baar et al., 2019). Thus, we used the IS-RSA to explore how individual differences in mentalizing and sociability impact the inter-individual variations among the negative emotions in the VR experience.

To our knowledge, rare research has investigated the experiences with ANS and CNS responses to negative emotions experienced in a naturalistic context. Based on the variety of negative emotions and emerging methods of naturalistic neuroimaging, the current study aimed to: (1) reveal the common neurophysiological responses to negative emotional experiences, and further (2) examine the relationship between the individual difference in mentalizing ability, trait empathy, and neurophysiological representation of negative emotional experiences. To probe the nature of emotional experiences systematically, we used VR to elicit emotional experiences, combined with the multi-modal neurophysiological recordings from both the ANS and CNS. Our first hypothesis is that, under different negative emotional experiences, people would produce similar or shared responses from behavioral to neurophysiological levels. Based on the shared responses, we further hypothesized that the individual variations in mentalizing ability and empathy would be associated and reflected by the similarity of EEG and ECG responses. The structure of the current study is illustrated in Fig. 1.

2. Methods

2.1. Participants

There were 42 right-handed students (31 female, age range: 19–24, mean age = 21.74 ± 2.19 years) from the University of Macau recruited through an online recruitment advertisement. No participants had a history of mental health or neurological disorders. All participants signed an informed consent form before the experiments. This

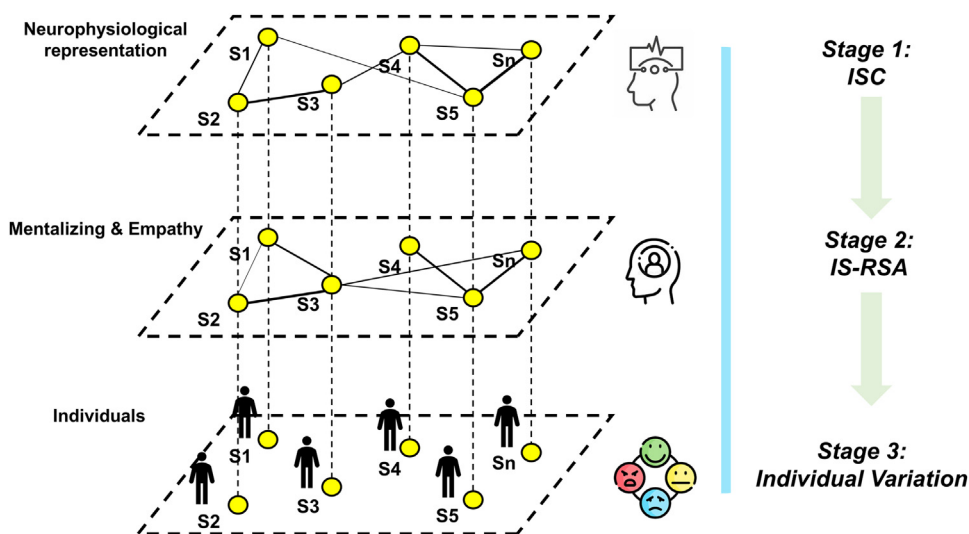


Fig. 1. Illustration of the structure of the current study. The current study combined neural recording, physiological and behavioral measurements to probe the individual variations of the neurophysiological representation of negative emotion. The first stage of analysis is the intersubject correlation (ISC) analysis, which aimed to construct the intersubject similarity matrices of neurophysiological representation and sociability. Furthermore, based on the ISC analysis, the second stage analysis was the intersubject representational similarity analysis (IS-RSA), which bridged the neurophysiological representation and sociability to examine the individual variations. Note: ISC = intersubject correlation, IS-RSA = intersubject representational similarity analysis.

study was approved by the local ethics committee of the University of Macau (BSERE21-APP006-ICI).

2.2. Psychological scales

Participants were required to complete two psychological scales before experiments. Based on our hypothesis, we used the interactive mentalizing questionnaire (IMQ) (Wu et al., 2022) and the interpersonal reactivity index (IRI) (Davis, 1983b) to measure the capacity for mentalizing and empathy. The IMQ scale was constructed based on the interactive theory of mentalizing and divided into three subscales: inference of the mental state of others (SO: self-other), meta-cognition (SS: self-self), and meta-mentalizing (OS: other-self). Meanwhile, the IRI scale, which is widely used to measure individual differences in trait empathy and consists of four domains: (1) perspective taking (PT) which scale assesses the tendency to spontaneously adopt the psychological point of view of others; (2) fantasy (FS) which tends to transpose themselves imaginatively into the feelings and actions of fictitious characters; (3) empathic concern (EC) scale which assesses “other-oriented” feelings of sympathy and concern for unfortunate others; (4) personal distress (PD) scale which measuring “self-oriented” feeling of personal anxiety and tense interpersonal settings. In particular, to support the hypothesis, the “SO” subscale within the IMQ and the EC IRI were mainly addressed in this study. In addition, the PT within the IRI was included in the analysis as a complementary measure of sociability.

2.3. Emotional video materials

Twelve video clips were selected that aimed to induce four target negative emotion states: angry, anxious, fearful, and helpless. We also included three happy video clips as a control condition.

For materials selection, we first constructed a dataset of movies as candidates for the further formal experiment. We then recruited 40 participants through an online advertisement to select movie clips for the experiment from the dataset; there were three criteria for selection: (1) the duration being about 3 min long; (2) the clip to be easy to understand and not needing supplementary explanation; (3) the clip should elicit single dominant emotional experiences. They were also required to rate the emotional intensity of the clips and give the score on a 4-point Likert scale (0 = not strong at all - 3 = very strong). For each emotion condition (angry, anxious, fearful, helpless, and happy), the top three clips with the highest rating score were selected for the experiment. These emotional video clips were mainly selected from movies and series, and the source of the movies was included in the supplementary information.

Furthermore, to confirm the emotional elicitation, we also recruited another five individuals (3 males and 2 females) to rate the negative emotional arousal and annotate the excerpts of 20 s that elicited the most intense emotional experiences. Only the clips and annotations that were recognized by all volunteers were used in the formal experiments. This is because we aimed to analyze the neurophysiological response when participants experience the most intense or strong emotional feeling.

2.4. Naturalistic viewing task under VR & experimental setup

We displayed all the video clips under VR to elicit immersive emotional experiences. In the formal experiment, participants were first instructed to be seated and wear the EEG electrodes and attached the ECG electrodes before wearing the VR head-mounted display goggles (Vive Eye pro, HTC Corporation) (Fig. S1 B). The experimenter then adjusted the focal length of the goggles and the position of the headphone to ensure that the participants had a clear view of the virtual environment and could hear the sound. During the experiment, the head movements were tracked with infrared lights, accelerometry, and gyroscope to make sure that the playing environment would move along with the head for immersive experiences. The ECG and EEG data were collected simultaneously from all subjects (Fig. 2).

In the experiment, the fifteen video clips were presented to the participants, and the viewing sequence was identical for all participants. Specifically, after viewing each video clip, participants were instructed to report their emotional arousal ratings based on a 4-point scale. The participant would have a rest for at least 30 s before watching the next video to recover to the baseline state and minimize the intertwined emotions. This procedure was adopted following the common practice of affective research leveraged EEG and naturalistic viewing (Masood and Farooq, 2021; Hu et al., 2021; Hofmann et al., 2021). In the case where 30 s was not long enough, participants would have a longer rest until they perceived themselves as ready for the next video.

The 3-dimensional VR playing environment was programmed on the Unity platform, which is a powerful integrated platform for 3D and VR development. The Unity platform communicated with the goggles employing Steam VR. In terms of the playing environment in the current study, a curved screen was built in the virtual environment with an immersive surrounding experience during movie viewing (Fig. S1. A). During the formal experiment, all movie clips were projected onto a built curved screen with high resolution. In the formal experiment, to minimize the interference of light, the playing environment was completely dark except for the curved screen. Meanwhile, it is also noteworthy that

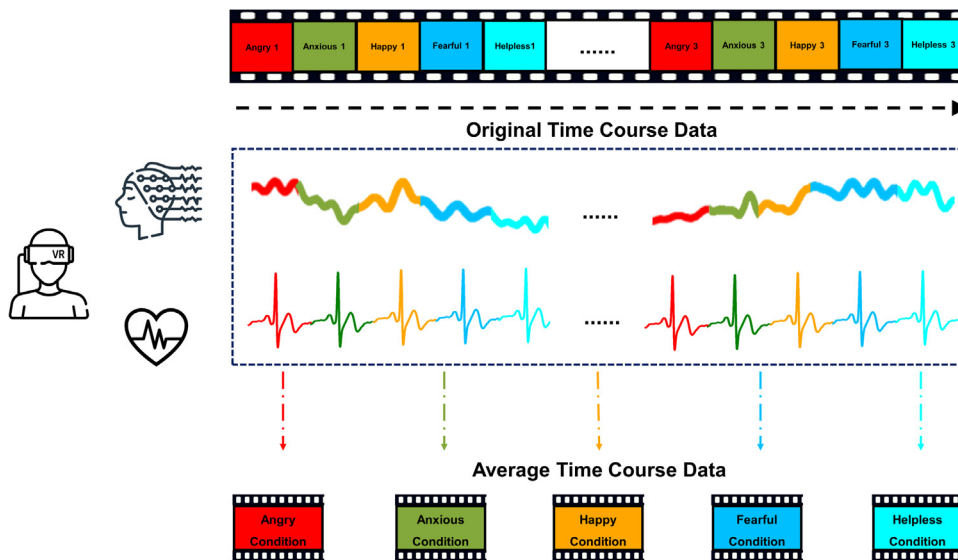


Fig. 2. Naturalistic viewing task and extraction of time course data. All participants watched the video clips in the same playing sequence in the VR. Specifically, there were three clips within each emotion condition. EEG and ECG data were acquired simultaneously from all subjects and the original time course data were obtained. Furthermore, for each video clip, only the 20 s that elicited the most intense emotional experiences was extracted from the original data; and these time course data of 20 s were averaged within each emotion condition. This procedure was conducted for all emotion conditions and both EEG and ECG data.

we used an embedded Python script (https://github.com/andlab-um/Emotion_EEG) in the Unity program for sending marks to the EEG and ECG hardware for synchronization.

2.5. Emotion rating

All participants were instructed to evaluate the emotional intensity of the four types of negative emotion after each view. This intensity score aims to: (1) ensure their engagement in the movie viewing and (2) prove the reliability of the clips with regards to emotion elicitation. This rating was also based on a 4-point Likert scale (0 = not strong at all - 3 = very strong). To further confirm that the selected videos evoked the target emotion at the behavioral level among all participants, all scores were compared within each negative emotion category. Specifically, the repeated measure analysis of variance (rmANOVA) and post-hoc paired *t*-test were used to examine the differences in the intensity score.

2.6. ECG recording and processing

The ECG signals were obtained using BIOPAC MP160 (BIOPAC, USA), with an acquisition sampling rate of 2000 Hz. For data processing, the Python package *Neurokit2* (Makowski et al., 2021) was used to conduct the data preprocessing and feature extraction.

The raw ECG signal was first resampled to 250 Hz, and the signal noise was removed by employing the default *Neurokit2* method, which was followed by the location of the cardiac peaks. After preprocessing the ECG signal and cardiac peaks' location, the function *ecg_rate* was used to compute the heart rate based on the peaks of the cleaned ECG data. As for HRV calculation, the indices of the cardiac peaks (R peaks) derived from the cleaned ECG data were utilized to calculate the HRV features through the function *hrv_time* in *Neurokit2* package.

In the current study, the HRV features in the time domain were used for further ISC and IS-RSA analysis. Specifically, two time-domain features were used: (1) the mean of the interval between cardiac peaks (RR interval: MeanNN), (2) and the standard deviation of the interval between cardiac peaks (SD of RR interval: SDNN). The time-domain features can reflect the total variability of HR, which are commonly reported as physiological indices in affective and psychological research (Pham et al., 2021). In detail, researchers have used time-domain features to examine the distinction between happy and sad emotional states (Shi et al., 2017). Time-domain features have been used in machine learning algorithms for emotion recognition (Guo et al., 2016; Valderas et al., 2015).

2.7. EEG recording

EEG signals were acquired from 64-channel Ag/AgCl electrodes (actiCap, BrainAmp; Brain Products) placed on the scalp of the participants following the 10/20 system with the impedance of 10 k Ω or less. The neural electrical activity was recorded with a bandpass of 0.01–100 Hz and a sampling rate of 1000 Hz. An electrode placed on the forehead (AFz) was used as the ground and another electrode placed on the mid-frontal (FCz) was used as the reference during the recording. Participants were instructed to minimize their head and body movements during the whole experimental procedure.

2.8. EEG data preprocessing

The EEG data were preprocessed offline by using the EEGLAB toolbox (Delorme and Makeig, 2004). Data was first downsampled to 250 Hz for further analysis, then filtered with a high-pass filter of 1 Hz, and a low-pass 50 Hz filter (Hu et al., 2017, 2021; Winkler et al., 2015). Furthermore, *cleanrawdata* plug-in of EEGLAB was used for bad channel detection and removal. As for the detailed parameters setting, the maximum flatline duration was set to 5 s, the line noise criterion was set to 4 standard deviations, and the minimum acceptable correlation with nearby channels was set to 0.8 (Mullen et al., 2015; Chen et al., 2022). After the bad channel removal, all the removed channels were interpolated by using the spherical method. Then, all the channels were referenced to the average reference (Maffei et al., 2020).

To further minimize the artifacts, the Artifact Subspace Reconstruction (ASR) method was used to correct data instead of removing the bad artifacts of data, with the maximum acceptable 0.5 s windows set to 10 standard deviations. Independent component analysis (ICA) was implemented by using the *runica* function in EEGLAB to remove the artifact caused by ocular movement, cardio activity, and muscle movement. After running the ICA, we used a semiautomatic method to remove the artifact component. In detail, we mainly used the *ICAlabel* plug-in (<https://labeling.ucsd.edu/tutorial/overview>) to remove the artifacts based on a threshold for rejecting the component, which is above 0.7 for both the muscle and ocular artifacts (Pion-Tonachini et al., 2019).

2.9. Intersubject correlation

To reveal the shared neurophysiological response pattern across participants and examine the reliability of the complex naturalistic stimuli, we first conducted ISC analysis. It is noteworthy that for each video clip,

only the 20 s that elicited the most intense emotional experiences were extracted from the original data. These time course data of 20 s were averaged within each emotion condition to obtain mean time-course data. This procedure was conducted for all emotion conditions and both EEG and ECG data (Fig. 2).

First, to calculate the behavioral similarity and capture the similarity in both high and low scores, we adopted the Anna Karenina (AnnK) method (Finn et al., 2020). The “Anna Karenina method” is a method that calculates the behavioral similarity. Particularly for behavioral measures, data are often one-dimensional, and the AnnK method computes the distance between two scores. In detail, the AnnK method first transfers the original scores into ranks, then, for each pair of the scores, the distance is calculated as the mean of the sum of the absolute positions of the ranks. For example, if we have n subjects in total, for subject i and subject j , the distance is calculated as demonstrated in the following equation:

$$\text{distance} = \text{mean} \left(\frac{\text{rank}(i) + \text{rank}(j)}{n_{\text{subs}}} \right)$$

After obtaining the distance between each pair of subjects, a pairwise subject-by-subject intersubject behavioral similarity matrix was obtained.

Second, for the EEG signal feature extraction and ISC analysis, we mainly examined the PSD features of the five frequency bands: delta (1–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (30–45 Hz). In affective research, PSD is a commonly used feature to probe the neural correlate of emotion (Hu et al., 2017; Dmochowski et al., 2012) and affective computing (Zheng et al., 2014; Kroup et al., 2011). In the current study, the function `mne.time_frequency.psd_multitaper` of MNE (Gramfort et al., 2014) was leveraged to compute the PSD value by using the multitaper method. After obtaining the PSD values, the PSD values within each respective frequency band were averaged. Therefore, for each participant, the data structure would be $64 \times 5 \times 20$ (channels*frequency bands*time points) for each emotion condition. Furthermore, the similarity of the PSD values was computed using Pearson’s correlation between each pair of subjects and bootstrapping, following the common practice of ISC analysis (Hasson et al., 2004). This practice was looped through all EEG channels and frequency bands, which yielded 320 (64 channels*5 frequency bands) subject-by-subject similarity matrices for each emotion condition.

Lastly, the ECG ISC analysis was conducted based on the HR and HRV extracted from the original ECG data. As for HR ISC analysis, which was similar to the ISC analysis for the PSD values. Specifically, Pearson’s correlation was used to calculate the similarity of HR values between each pair of subjects within each emotion condition and obtain the pairwise subject-by-subject similarity matrix. For the HRV ISC analysis, since the data are one-dimensional scalars, the AnnK method was used to calculate the pairwise similarity matrix for each emotion condition.

2.10. Intersubject representational similarity analysis

IS-RSA was further implemented to identify both the neural activity and physiological arousal that were significantly related to distinct aspects of sociability. The IS-RSA makes a further step based on the ISC, which aims to explore the interrelation between the similarity of neurophysiological responses and the behavioral profile or psychometric score. The theoretical consideration is aligned with the current hypothesis, that participants with similar regard to the mentalizing ability and empathy trait would manifest similar neurophysiological responses towards negative emotional experiences.

After the ISC analysis, we obtained the intersubject similarity matrices (ISM) for all of the features, including PSD values, ECG features, and psychometric summary score (left side of Fig. 3). ISM is an essential component in IS-RSA, the shape of which is $n(\text{subs}) \times n(\text{subs})$, and each cell in ISM represents the similarity between two subjects. Therefore,

for both neurophysiological response and sociability, ISM reflects the overall similarity between any two of the subjects, and further analysis will link these ISM together to probe the individual variation.

In detail, we used the non-parametric Mantel permutation test (Mantel, 1967) to compute the similarity between the lower triangular matrix of the neurophysiological ISM and behavioral ISM. Specifically, both the rows and columns of the ISM were randomly shuffled and permuted, and Spearman rank correlation was used to compute the correlation between the two matrices. We permuted 10,000 times and obtained the null distribution of the ranked correlation, after which the observed correlation parameters were compared with this null distribution to obtain the p -value.

The above-mentioned operation was looped separately for both EEG-behavior and ECG-behavior analysis as shown in Fig. 3. As for EEG-behavior analysis, the Mantel test was looped across all channels and frequency bands on the lower triangle of behavioral ISM and upper triangle of PSD values ISM. This procedure yielded 320 similarity values (64 channels \times 5 frequency bands) for each emotion condition. Furthermore, this would produce five sets of similarity topoplots (64 channels) that demonstrate the spatial distribution of representational similarity within each emotion condition (upper part of Fig. 3). Finally, the permuted p -values were thresholded using the false-discovery rate (FDR) (Benjamini-Hochberg procedure (Benjamini and Hochberg, 1995)) across all channels against multiple comparison. For ECG-behavior analysis, we also used the Mantel test to generate the correlation between the lower triangle of behavioral ISM and the upper triangle of the ECG features ISM (lower part of Fig. 3).

3. Results

3.1. Emotion rating

Generally, as expected, these emotional film clips in VR that aimed to elicit one certain emotion indeed showed the highest ratings in the target emotion category (Figure 0.4). There was a statistically significant emotion intensity rating score in all emotion condition: (1) Angry condition ($F = 28.37, p < 0.000$), (2) Anxious condition ($F = 20.73, p < 0.000$), (3) Fearful condition ($F = 98.48, p < 0.000$), (4) Helpless condition ($F = 56.77, p < 0.000$). The Fig. 4 visualize the post-hoc paired t -test results. These preliminary emotion rating score results demonstrate that the elicitation of negative emotion in VR was successful, suggesting a distinction across these negative emotions.

3.2. Intersubject correlation analysis

3.2.1. Neural representation similarity of emotional experiences

After calculating the intersubject similarity of the neural representation within different frequency bands of the five discrete emotions, we were able to examine the overall similarity or correlation. The results revealed that the frequency band produced higher intersubject similarity and delineated the common spatial neural response pattern using topography.

First, we calculated the overall similarity value that averaged across all channels within each frequency band. When participants watched the angry videos, the highest mean ISC was produced within the theta and alpha band (0.0736 and 0.0742, respectively). As for the anxious condition, the theta (mean ISC = 0.0814) and beta (mean ISC = 0.0722) bands produced higher overall ISC than the other bands. Interestingly, in terms of the fearful condition, we observed a strikingly prominent ISC within the gamma band (mean ISC = 0.1335). For helpless emotional experiences, the beta band gave rise to the highest ISC (mean ISC = 0.0651). Finally, for the happy condition, the highest ISC values were observed at the theta (mean ISC = 0.0738) and gamma (mean ISC = 0.0790) bands.

Second, after obtaining the intersubject similarity matrices for each electrode, we calculated the mean similarity value by averaging the up-

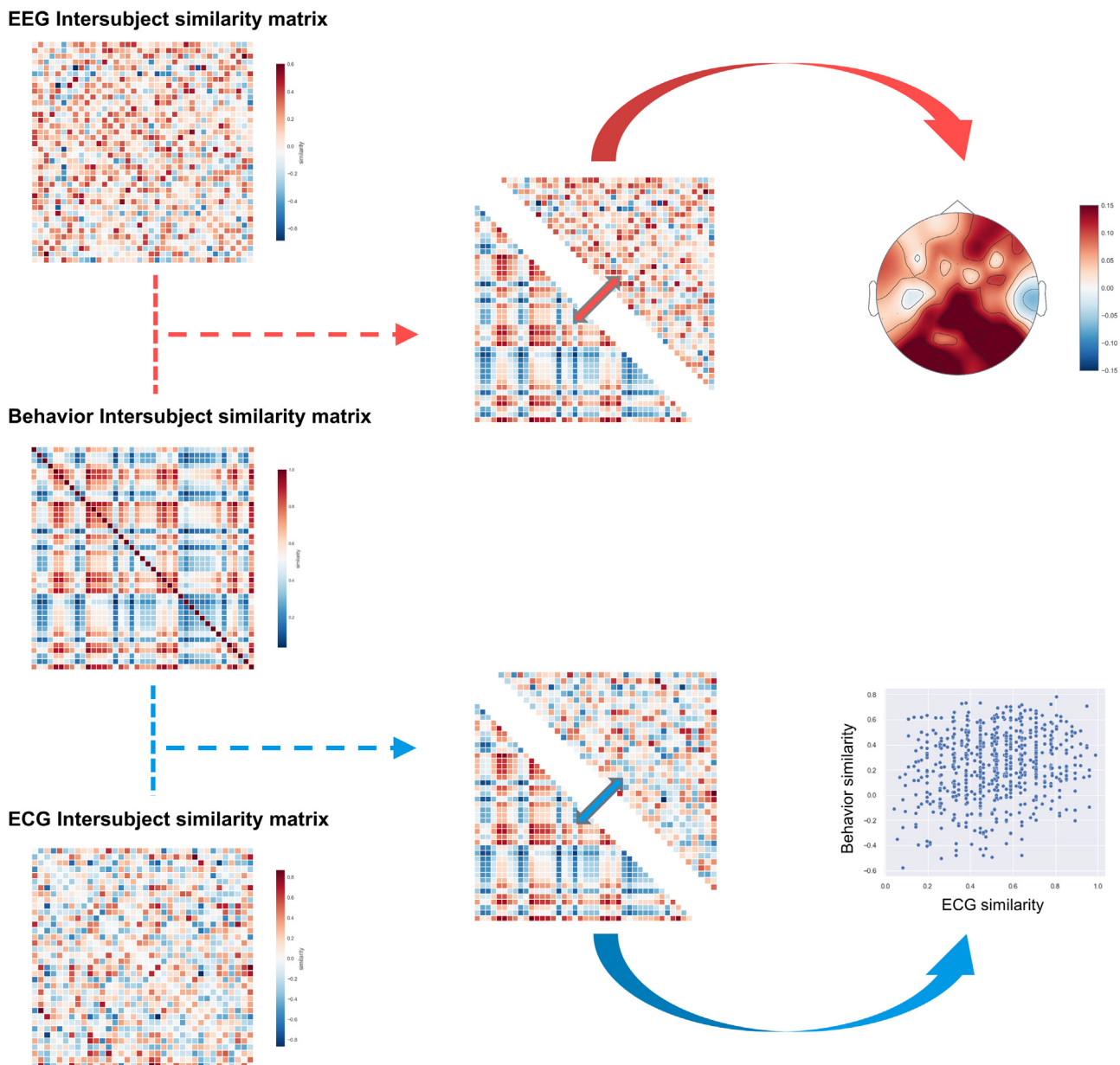


Fig. 3. Flowchart of the intersubject representational similarity analysis (IS-RSA). We had intersubject similarity matrices (ISM) for three modalities of data: (1) behavioral measures; (2) physiological data (ECG); and (3) EEG data. The upper part demonstrates the EEG-behavior IS-RSA: Spearman's rank correlation was employed to compute the similarity between the lower triangle of behavior ISM and the upper triangle of EEG ISM, and this practice was looped for all electrodes to generate the topoplots. While the lower part describes the ECG-behavior IS-RSA: the similarity between the lower triangle of behavior ISM and the upper triangle of ECG ISM was computed by Spearman's rank correlation.

per triangle matrix, and the mean similarity value was used to plot the similarity topography. Interestingly, after delineating the whole sets of intersubject similarity topographies, we were able to reveal the neural representation pattern of these discrete negative emotions as shown in Fig. 5. We found that for angry condition, the highest ISC value was observed at the occipital and posterior parietal regions within the relatively lower frequency band of theta and alpha. Anxious experiences are linked to a more pronounced ISC over the frontal and occipital region within the theta band, and a higher ISC at the central-parietal region within the beta band. As for the fearful condition, we observed an interesting dominant highest ISC value located at the frontal, right temporal-parietal, and occipital region within the gamma band. The highest ISC value for helplessness was mainly found at the occipital and central-parietal region; happy experiences showed a higher ISC at both the posterior and frontal regions.

These topographies suggested the reliability of these emotional experiences, and indicated that different cognitive processes were involved in producing and representing various negative emotional experiences. In addition, the ISC results demonstrated a common neural response across distinct negative affective experiences. Consistent with our first hypothesis, both emotion rating scores and ISC results suggested that both the specificity and the sharing of emotional responses.

3.2.2. Physiological representation similarity of emotional experiences

Meanwhile, shared responses across participants were also found in the psychophysiological responses, where we mainly focused on the ECG-related features of HR and HRV. First, regarding the mean ISC of HR, angry (mean ISC = 0.0222), anxiety (mean ISC = 0.0154), fear (mean ISC = 0.0462), helpless (mean ISC = 0.0496), happy (mean ISC = 0.3669). Second, in terms of HRV, the mean ISC was calculated

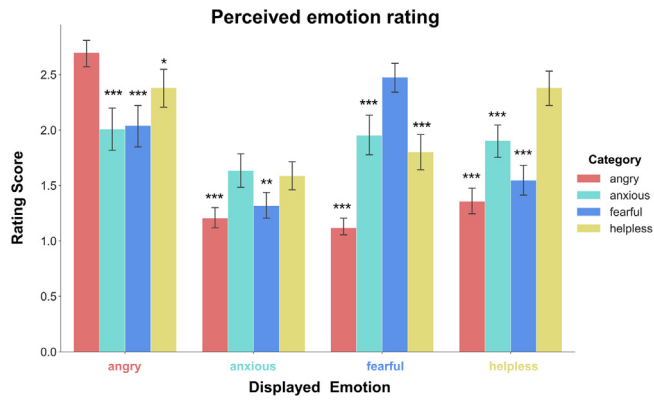


Fig. 4. Results of the emotion intensity rating score. For each type of negative emotion, all participants were required to evaluate the emotional intensity in all categories. This barplot suggests that the rating scores were highest regarding the displayed emotion in each negative emotion condition. Asterisk indicates statistical significance for post-hoc paired *t*-test, with *** indicates $p < 0.001$, ** indicates $p < 0.01$.

as following, angry (mean ISC = 0.5138), anxiety (mean ISC = 0.5131), fear (mean ISC = 0.5135), helpless (mean ISC = 0.5128), and happy (mean ISC = 0.5121). All similarity matrices of the ECG features are presented in the supplementary information (Fig. S1).

3.3. Intersubject representational similarity analysis

3.3.1. Different mentalizing abilities were associated with distinct neurophysiological patterns

Overall, the similar ability of self-other mentalizing was found to be associated with similar and distinct neural responses for different negative emotional experiences, the topography plots are shown in Fig. 6. It is also noteworthy that the statistics were reported in the main text only for the representative electrodes within the significant clusters, the detailed statistics are provided in the supplementary materials (see supplementary information Tables S1–S4) Fig. 7.

For angry emotional experiences, in the theta band, the correlation was prominent at the electrodes TP8, and TP10 ($r = 0.13$, $p = 0.01$; $r = 0.11$, $p = 0.02$, respectively) at right temporal-parietal junction. As for the beta band, the effect was pronounced at the electrodes located at the left prefrontal region, which included F7, AF7, and FT7 ($r = 0.17$, $p < 0.01$; $r = 0.12$, $p = 0.016$; $r = 0.14$, $p < 0.01$, respectively). For the

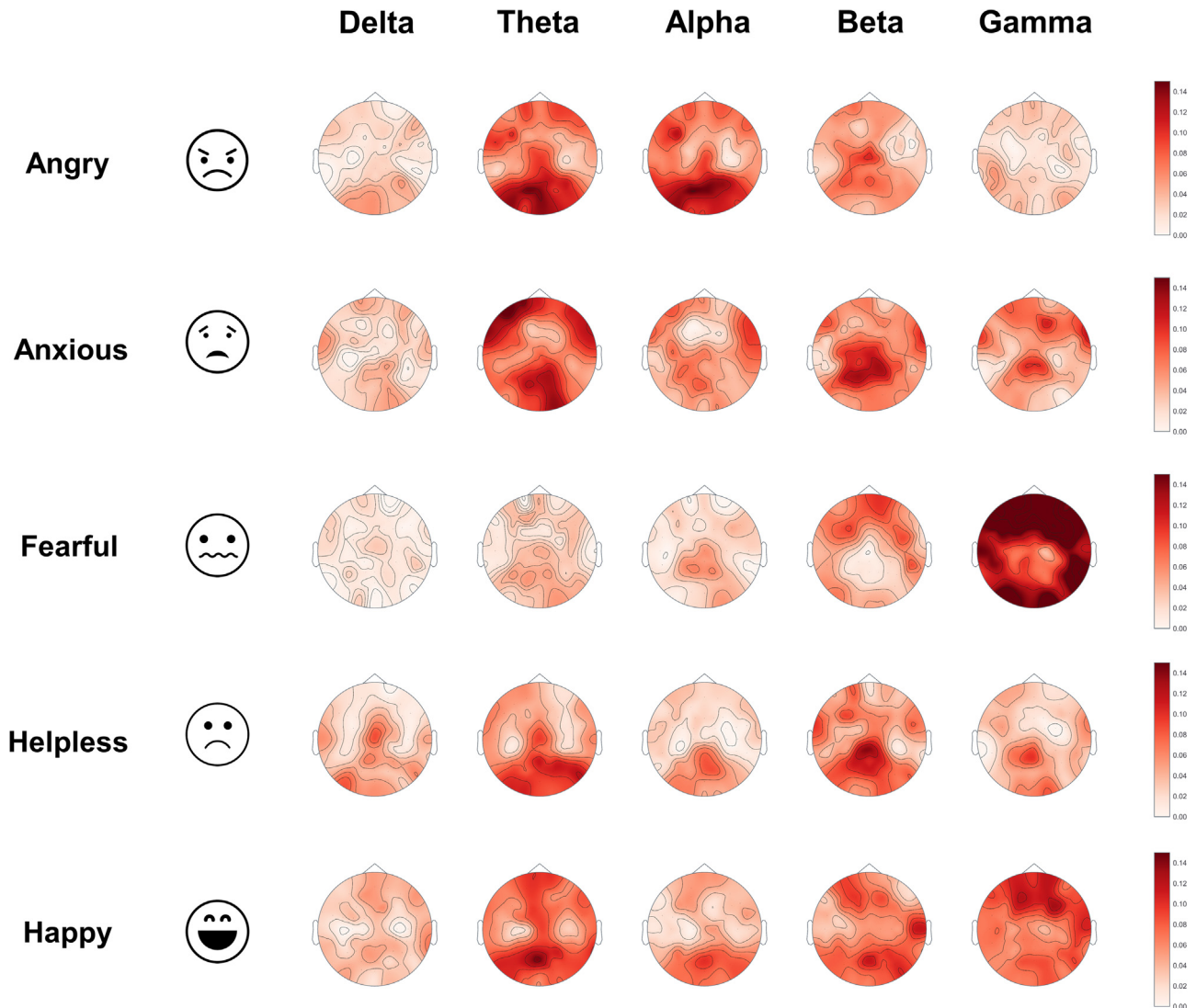


Fig. 5. Intersubject correlation of neural representation. Topographies of the intersubject similarity of neural representation within different frequency bands is shown. The spatial distribution of these topographies was quite similar across emotions.

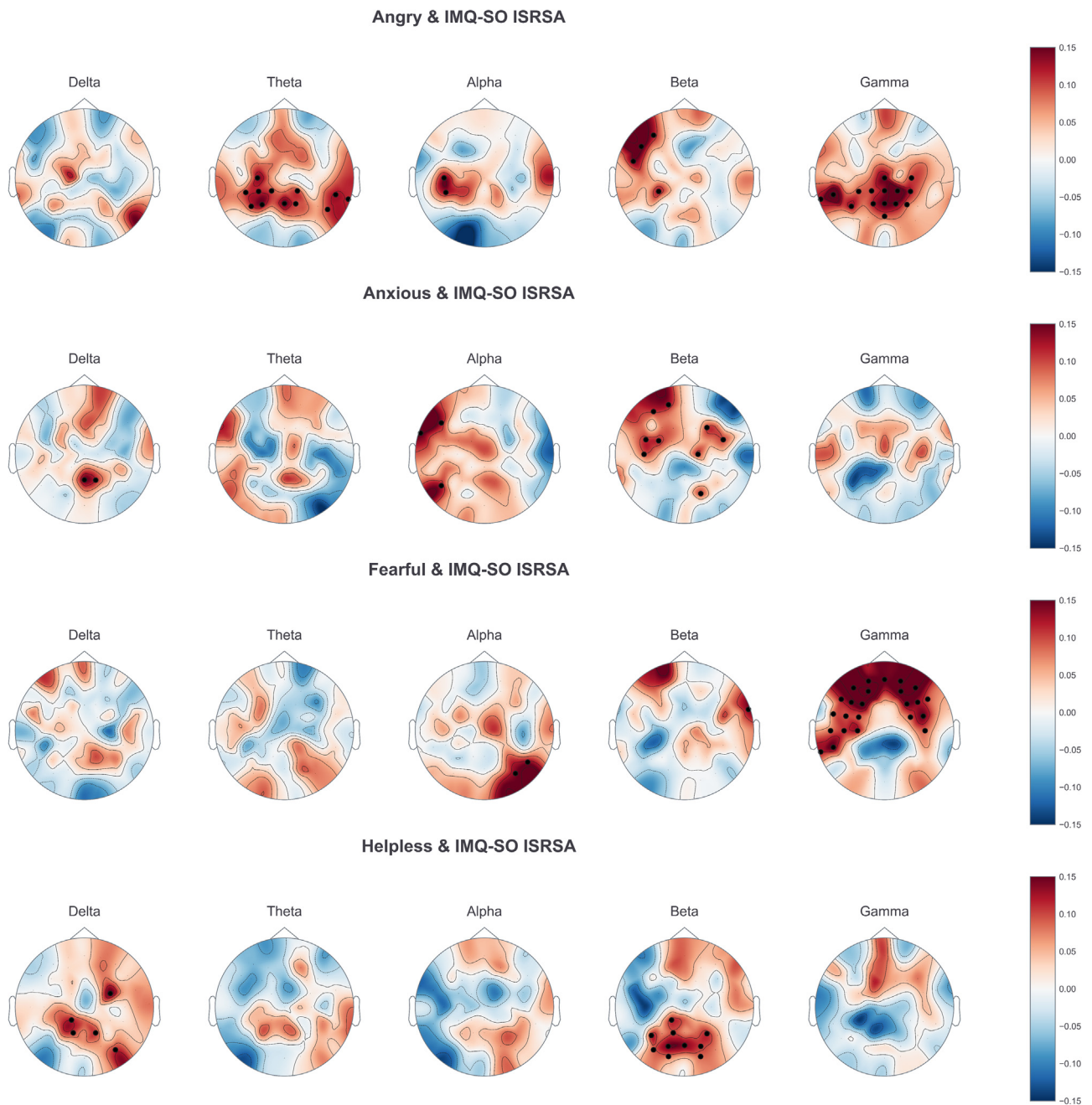


Fig. 6. IS-RSA results regard mentalizing ability. Topographies of the IS-RSA between neural similarity and mentalizing similarity within different frequency bands. Black dots in the topographies indicate the significant electrodes that survive the FDR correction in the permutation test. IMQ-SO = self-other mentalizing in the interactive mentalizing questionnaire.

gamma band, the correlation was prominent at central-parietal and left temporal-parietal region. The central-parietal cluster mainly consisted of electrodes Cz, CPz, Pz ($r = 0.14, p < 0.01$; $r = 0.14, p < 0.01$; $r = 0.15, p < 0.01$, respectively). While the left temporal-parietal regions include TP7 and TP9 ($r = 0.21, p < 0.01$; $r = 0.13, p < 0.01$, respectively). As for anxious emotion, in the alpha band, the correlation was prominent at the F7, FT9 ($r = 0.12, p = 0.018$; $r = 0.16, p = 0.012$, respectively) within the left frontal region, and the P7 ($r = 0.12, p = 0.018$) at the left temporal-parietal region. With respect to beta band, the result showed that the correlation was also prominent at the left frontal-central region, including Fp1, FC3 ($r = 0.12, p = 0.025$; $r = 0.11, p = 0.037$, respectively); and F4 ($r = 0.1, p = 0.040$) at the right frontal-central region.

Regarding fearful experiences, we found a pronounced correlation at the right parietal-occipital region, particularly at P8 and PO8 ($r = 0.13, p = 0.015$; $r = 0.14, p < 0.01$, respectively) within the alpha band. Interestingly, in gamma band, a strikingly pronounced association was found at the whole frontal region, such as at AF3 ($r = 0.25, p < 0.01$), AF4 ($r = 0.18, p < 0.01$), AF7 ($r = 0.21, p < 0.01$), and AF8 ($r = 0.19, p < 0.01$).

With regards the helpless experiences, the self-other mentalizing ability variation was distinctly mapped to neural representation at the parietal-occipital region within the beta band, which was remarkable at POz, PO3, and PO4 ($r = 0.14, p < 0.01$; $r = 0.15, p < 0.01$; and $r = 0.11, p = 0.017$, respectively).

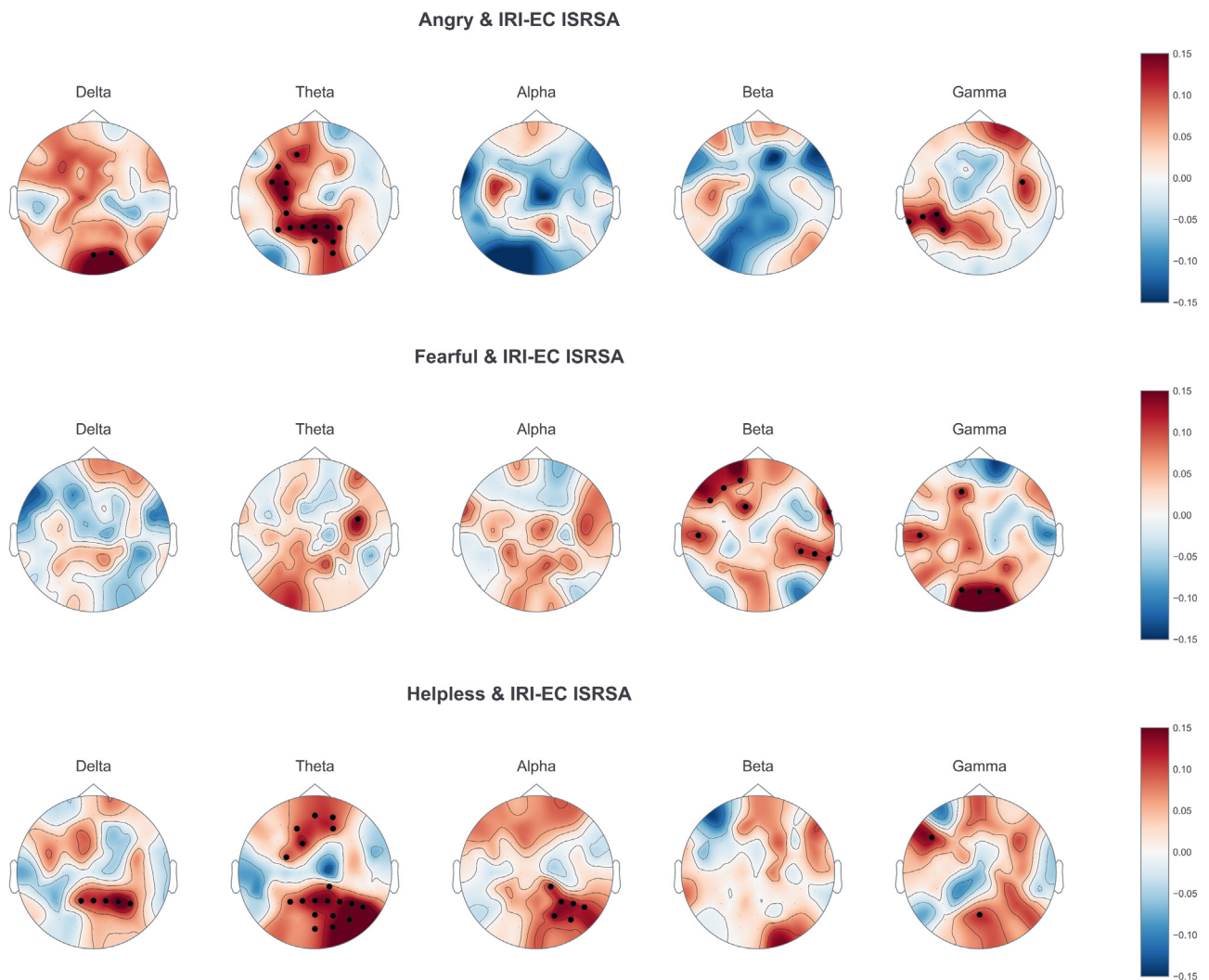


Fig. 7. IS-RSA results regarding empathic concern. Topographies of the IS-RSA between neural similarity and IRI-EC similarity within different frequency bands. Black dots in the topographies indicate the significant electrodes that survive the FDR correction in the permutation test. IRI-EC = Interpersonal Reactivity Index's Empathic Concern.

Interestingly, after performing the matrix permutation between the physiological similarity matrices and the self-other mentalizing score similarity matrices, it is revealed that the individual difference in HRV was closely associated with the mentalizing ability for self-other inference (Specifically, the result showed that under angry emotion ($r = 0.34$, $p < 0.001$); under anxiety ($r = 0.26$, $p < 0.001$); under fear condition ($r = 0.36$, $p < 0.001$); under helpless condition ($r = 0.29$, $p < 0.001$); and under happy condition ($r = 0.34$, $p < 0.001$)).

Additionally, the detailed statistical results of the IS-RSA between neurophysiological responses and perspective taking (Tables S8–S10), and the corresponding topoplots (Fig. S3) are included in the supplementary information.

In summary, this series of results indicated how interpersonal variations in mentalizing ability were captured by the responses to negative affective experiences from both the CNS and ANS.

3.3.2. Different trait of empathy is associated with distinct neurophysiological patterns

As for the association between the individual difference of trait empathy and neurophysiological representation, the results also demonstrated recognizable mapping between these similarity matrices. Concerning the variation of EC that aims to inspect the ability of sympathy and concern for the suffering of others, different variation patterns

were revealed regarding the diverse negative emotional experiences in the current study. The detailed statistics regarding the significant electrodes can be found in the supplementary materials (see supplementary information Tables S5–S7).

Specifically, as for angry emotion, we found a significant similarity at the occipital region within delta band, Oz and O2 ($r = 0.13$, $p = 0.015$; $r = 0.14$, $p = 0.012$, respectively). While within the theta band, the variation was also reflected at the left central region and parietal region, with highest similarity found at Pz, P1, P2 ($r = 0.19$, $p < 0.01$; $r = 0.15$, $p < 0.01$; $r = 0.18$, $p < 0.01$, respectively), and FC3, C3 ($r = 0.13$, $p < 0.01$; $r = 0.15$, $p < 0.01$, respectively). Furthermore, for the gamma band, the similarity was centered at the left temporal-parietal region, which include CP5, TP7, and TP9 ($r = 0.15$, $p = 0.01$; $r = 0.12$, $p = 0.028$; $r = 0.14$, $p = 0.01$, respectively).

Regards the fearful condition, the correlation was pronounced at the left prefrontal region, and the right central-parietal region within the beta band. In detail, the similarity was found at Fp1, AF7, and F7 ($r = 0.11$, $p = 0.026$; $r = 0.10$, $p = 0.036$; and $r = 0.10$, $p = 0.041$, respectively), and CP6, TP8, and TP10 ($r = 0.11$, $p = 0.026$; $r = 0.11$, $p = 0.026$; and $r = 0.11$, $p = 0.026$, respectively). Interestingly, we also found a prominent similarity at the occipital region within the gamma band, which was remarkable at Oz, O1, and O2 ($r = 0.16$, $p < 0.01$; $r = 0.12$, $p = 0.01$; and $r = 0.14$, $p < 0.01$, respectively).

While against the helpless condition, it was shown that the neural dynamics at the left parietal region and central frontal region were captured by the variation in the EC score. In detail, within the delta band, the highest similarity was found at P4 and P6 ($r = 0.16$, $p < 0.01$; $r = 0.14$, $p < 0.01$, respectively). For the theta band, the electrodes that produced prominent correlation were P6, P8, and PO8 ($r = 0.17$, $p < 0.01$; $r = 0.17$, $p < 0.01$; $r = 0.18$, $p < 0.01$, respectively); while for the alpha band, we found similarity at the P4 and PO4 ($r = 0.13$, $p = 0.012$; $r = 0.13$, $p = 0.012$, respectively).

However, the results did not show a significant association between the physiological similarity matrices and the EC similarity matrix. In summary, this part of the findings further elaborates our hypothesis, that individual differences in EC are also reflected in neural responses.

In addition, the intersubject representational similarity effects were also compared between gender groups, the topoplots of the exploratory results were included in the supplementary information (Figs. S4 and S5). However, the biased sex ratio in the current study may hinder such gender difference effects, which will be addressed in the limitation section.

4. Discussion

Considering the complex nature of emotional experiences and sociability, the present study aimed to characterize the common and distinct neurophysiological representation of negative emotional experiences. To test our hypotheses, we mainly examined: (1) the intersubject similarity of neurophysiological responses, and (2) whether the individual differences in sociability could be reflected in neurophysiological responses. Our findings demonstrated that the negative emotional experiences exhibit shared neural and physiological responses across subjects. Furthermore, rather than common responses, the neural responses would capture the interpersonal variations in sociability. These behavioral variations also significantly influence the psychophysiological responses to negative emotional experiences. Overall, the observed individual differences in sociability and neurophysiological representation support the involvement of social cognition in individualized emotional processing. These findings can advance our understanding regarding the prediction of individual differences in human emotional experiences.

4.1. Shared neurophysiological representation in negative emotional experiences

Indeed, negative emotions are essential for survival (Buss, 1995), and guide selective attention, memory, and adaptive decision-making. Given the cultural variations of negative emotion in previous studies (Matsumoto, 1989), it is also noteworthy that the results could be attributed to the limitation of emotional stimuli or elicitation methods. Therefore, we used VR to elicit more realistic emotional experiences and simultaneously record signals from both the CNS and ANS while watching emotional videos. In addition to providing broad evidence of the distinctions of different emotions, but we also focused on individual variability. We separate the behavioral measures (ratings of perceived emotion intensity, and sociability scales) and neurophysiological response, with the hypothesis that each individual's model of perceived emotion similarity would predict their similarity in neurophysiological responses, which may be subject to one's sociability.

In detail, at the behavioral level, it is observed that most videos evoked higher arousal regards the displayed emotion category. The rating results indicate clear distinctions across these negative emotions. For the neurophysiological responses, we have found consistent prominent intersubject similarity across different negative emotions in the parieto-occipital regions and frontal regions. In a word, the neural results demonstrate a relatively general intersubject synchronization pattern rather than distinction. More specifically, previous studies indicated that intersubject neural synchronization serves as an elementary predictive

coding, learning, and conscious processing of stimuli in the social context (Nummenmaa et al., 2018). Although we did not track back the EEG to the source brain region, the gradient of parieto-occipital region has been shown topologically mapped to emotion encoding (Lettieri et al., 2019). Therefore, the current results provide evidence for a common neural pattern that supports various negative emotional experiences.

4.2. Distinctive pattern of fear

Interestingly, especially for the fearful emotional experiences, we revealed a distinct interpersonal similarity within the gamma band in the frontal and occipital regions. Threat or dangerous stimuli are the most salient cue to our survival, which would induce a series of physiological responses and neural computation (Levy and Schiller, 2021). Previous EEG studies on fear have demonstrated the role of the gamma activity over the prefrontal regions in fear emotion encoding, expression, and recall (Mueller et al., 2014; Maffei et al., 2020). Meanwhile, in addition to the frontal region, another EEG study has shown an increase of gamma activity over the visual cortex during fear learning (Santos-Mayo et al., 2022). In the current study, the stimulus was immersive emotional videos that were identical to all subjects, and the subjects would encode different emotional and contextual cues, and a series of perceptual and cognitive processes would involve. Therefore, the current result extended the previous finding and advances our understanding of the common fear responses shared across individuals. Furthermore, we also found a co-occurrence of higher gamma-band intersubject similarity over the frontal and occipital electrodes. It is reasonable to speculate that the visual system and high-order cognitive system would interact frequently during the fear experiences. Specific to physiological interpersonal similarity, a recent interesting study (Pérez et al., 2021) revealed that narrative stimuli synchronize the HR across subjects, and this synchronization was modulated by the attention process. Thus, it is reasonable to infer that humans may give rise to similar conscious processing of the complex social and affective stimuli, which would modulate the physiological arousal and fluctuations and produce interpersonal similarity. Moreover, this physiological similarity was consistent with the neural similarity, that both modalities index the reactive perceptual and cognitive processes of the negative emotional stimuli. These shared responses further our understanding of how the CNS and ANS coordinated during negative emotional experiences and future studies can investigate whether there were fewer variations in fearful experiences across individuals.

4.3. Self-other mentalizing ability and emotional neurophysiological response

The mentalizing ability is an essential ability that enables us to read the mind of others, infer their mental states, and further share the emotions of others (Wu et al., 2022, 2020). In particular, the self-other mentalizing ability that we addressed in the current study plays a key role in the mind-inference process. Consistent with our hypothesis, the results indeed demonstrate that the individual variation in self-other mentalizing ability score modulates the EEG activities of several key regions within the 'social brain' (Adolphs, 2009), which further supports the view that emotional information processing is modulated by complex social cognition. Generally, when summarizing the result together, it is revealed that the regions that could reflect the behavioral variation include the prefrontal cortex (PFC), temporal-parietal junction (TPJ), posterior superior temporal sulcus (pSTS), and the posterior central region where the precuneus and posterior cingulate cortex (PCC) are located. These brain regions have been recognized as the key nodes within the neural network for interactive mentalizing, especially related to the self-other first-order mentalizing process (Wu et al., 2020).

A recent interesting EEG study has proposed an "emotion profile" view to probing the individual difference in emotion conceptualization

and neural representation (Hu et al., 2021). They found that the variation of the negative emotion profile was associated with neural activity within the delta and theta band, which is consistent with the current results. Thus, it is possible that the revealed neural variation in delta and theta band could be due to the involvement of people's different conceptualizations of the emotional scenario. Emotional conceptualization has been recognized as an important component of the mentalizing framework (Wu et al., 2020; Kliemann and Adolphs, 2018; Frith and Frith, 2006). Therefore, individual variation in mentalizing ability would be closely associated with differences in emotional conceptualization and lead to the variance of neural response. Furthermore, with regards to social cognition, there is a growing body of evidence linking EEG frequency-domain features to sociability and related dysfunction. In detail, the EEG activity in the alpha and beta band has long been recognized to reflect the response of the mirror neuron system (MNS) and involve in sophisticated social perception and mentalization (Perry et al., 2010; Pineda and Hecht, 2009; Ménoret et al., 2014). Dysfunction of the MNS is indicated by abnormal EEG activity within the alpha band in the autism group (Oberman et al., 2005). Therefore, the alpha and beta variation found in the current study would hint at individual differences in terms of social information processing (Pineda and Hecht, 2009; Ménoret et al., 2014) and lead to different mind inference and emotional responses. As for the socio-affective process, another EEG study documented that the beta coherence between frontal and posterior regions was linked to social-emotional coordination (Reiser et al., 2012). This finding may further demonstrate the role of beta-band activity in emotional information processing in social scenarios. In summary, the neural activity of the alpha and beta bands may be a promising neural signature of social functioning (Tognoli et al., 2007).

Surprisingly, we found that posterior central region EEG activity within several frequency bands was associated with mentalizing ability across negative emotions. Given the functional role of precuneus/PCC self-referential and self-attribution process in social cognition (Pettrini et al., 2014), a possible interpretation is the different levels of involvement in the social scenarios. Specifically, individuals with different mentalizing abilities would attend to or involve the third-person perspective differentially, which would induce interpersonal variation regarding EEG activities. Furthermore, it was revealed that the effect between EEG and PT is also prominent at the central region. And previous literature has documented that the neural activity at central-parietal regions is closely related to perspective taking in a pain judgments task (Li and Han, 2010). Another insightful EEG study that examines the neural mechanism of self-disclosure process have also found that central region actively involved in self-relevance, perspective talking process, and also the processing of emotional words (Fields and Kuperberg, 2012).

Regarding the relationship between psychophysiological signals and behavior, we found a prominent association between HRV and mentalizing ability. In terms of social cognition and functioning, HRV has been found to be influenced by the types of social interaction and socio-affective information (Shahrestani et al., 2015). Furthermore, studies on social dysfunction found that HRV features decreased in the social anxiety group (Gaebler et al., 2013) and the autism group (Dijkhuis et al., 2019) in social tasks. While for emotion processing, it has been shown that HRV features were positively correlated with emotion recognition performance (Quintana et al., 2012). HRV has also been recognized as related to emotional regulation (Appelhans and Luecken, 2006; Xiu et al., 2016). Therefore, the current finding of an HRV-mentalizing association may indicate that similar cardiac activities reflected similar socio-affective processing and regulation. This is consistent with our assumption that different mentalizing abilities relate to different physiological responses. In a word, as suggested by Petrocchi and Cheli (2019), HRV is closely associated with the social brain, which is also a promising measure that reflects the individual difference in the socio-affective process.

4.4. Empathic concern and emotional neurophysiological response

Except for mentalizing, another essential sociability that empathized in the current study is empathy, which was measured by the dimension of EC in the IRI. Unlike the first-order self-other mentalizing ability that we discussed above, the EC is more focused on the prosocial concern or the motivation to share and improve the experiences of the social agents (Zaki and Ochsner, 2012). Specifically, in our results, the variation regards EC correlated with the neural response variation over the parieto-occipital region, temporal-parietal region, and frontal regions. In detail, it is shown that the association between EC variation on neural response is the most prominent over parieto-occipital region. A recent study found that individuals with high empathy showed stronger activation over parieto-occipital region while watching social interactions (Hamada et al., 2022). Our results extended this finding that the parieto-occipital region may be associated with the manifestation of negative affective experience. Furthermore, the result implied that individuals with higher EC scores would pay more attention to the dynamic social stimuli and mind inference. Another study indicated that the temporal-parietal region is associated with emotion encoding (Hu et al., 2021; Lettieri et al., 2019) and empathy (Zaki and Ochsner, 2012). Meanwhile, it has been mentioned that the effect over parieto-occipital would reflect the differential attention process. Therefore, we can speculate that individuals who differ in EC may also differentially encode the valence and arousal of affective experience differentially. Meanwhile, the frontal region is also a key node in the empathy network, especially in the ventromedial prefrontal region (Shamay-Tsoory et al., 2009; Singer and Klimecki, 2014). Especially in the helpless condition, we found similar theta band neural activity over medial frontal region associated with similar empathic concern. Helplessness has been proven to induce empathy and promote altruistic behaviors (Klimecki et al., 2016). It is appropriate to infer that the high-order social cognitive understanding implemented within the frontal region is involved in producing negative affective experiences. Such individual differences in this process could be explained by the different levels of empathic concern.

4.5. Strengths and limitations

The strengths of the present study include the following: (1) using the natural stimuli for emotion elicitation; (2) immersive elicitation in VR; and (3) capturing the individual differences using IS-RSA. Probing the 'social brain' in real-world is one of the major aims of social neuroscience. It is undeniable that the emotional experience in real-life settings is multisensory, perceptually complicated, continuously changing, and intertwined with a series of social cognition processes. Fortunately, with the rapid development of VR and naturalistic neuroimaging, social neuroscientists can provide participants with dynamic and interactive social and affective scenarios to probe the corresponding neurocognitive mechanism in a more 'realistic' manner. Echo with the complex perceptual and cognitive nature of real-world affective experience, our results of both ISC and IS-RSA provided evidence correspondingly. Specifically, the shared EEG response over the parieto-occipital and frontal region revealed the involvement of stimuli evoked activity, self-related emotional processing, and reasoning. And previous studies have shown the role of parietal region in emotional experience (Lettieri et al., 2019). Moreover, the modulation of behavioral variation on EEG response further demonstrates that several key nodes in the 'social brain' network were activated in these immersive emotional experiences. This evidence suggests that the findings based on static and controlled experiments could be generalized and extended to more dynamic and realistic experimental settings. Therefore, utilizing VR in neuroscience research would allow researchers to reliably capture the distinct neural mechanism in realistic settings.

Several limitations should be addressed. First, the moderate sample size of 42 subjects and the relatively biased sex ratio and age range in this within-subjects manipulation study may limit the generation of

comprehensive negative emotions profiles. Future studies should employ a larger sample size and comparable sex ratios to examine the reliability of the effect. Interestingly, regarding aging and social cognition, previous researchers have found that aging is related to mentalizing performance, prosocial behaviors, and empathy (Reiter et al., 2017). At the behavioral level, the socio-cognitive abilities were relatively impaired in the old age group (Henry et al., 2013), while the socio-affective abilities were still intact (Richter and Kunzmann, 2011) and emotional empathy was even greater in the old age group (Sze et al., 2012). At the neural level, it has also been documented that the neural circuit of empathy would change along with the aging process (Chen et al., 2014). Therefore, it would be interesting to examine how aging-related changes in sociability associated neurophysiological representation of negative emotions in a social context.

The second limitation relates to the results that although we found a prominent correlation between the similarity matrices of different modalities, the temporal information was overlooked. Specifically, it remains unclear whether the similarity changes through IS-RSA. Future studies could propose a larger sample size and a new analysis method that can discover the dynamic similarities based on multi-modality data. Although we did not have a specific hypothesis concerning the contribution of each frequency band to the individual variation of emotion representation, the current study has indicated the strong potential of decomposing neural time series into different frequency bands for probing the social brain.

Finally, the current passive viewing paradigm does not allow participants to implement real prosocial behaviors to release the negative states of other social agents, and there was no neutral condition or data acquired from a non-VR environment for comparison. Future studies could address these comparisons and further examine the utility of VR in socio-affective research. Meanwhile, it is promising and reasonable to construct 'realistic' negative social scenarios and examine empathy behaviors and decision-making in future work. Developing in this topic promises to benefit multiple fields, while more specific natural studies measuring emotion experience variations and its linking with individual differences are needed.

5. Conclusion

In summary, the current study first demonstrated how negative emotional experiences synchronize with neurophysiological responses. Based on this interpersonal similarity, we further examined how mentalizing ability and trait empathy modulate the representations of negative emotional experiences systematically and manifest individual variations. Meanwhile, we demonstrated the utility and reliability of VR in social affective neuroscience research, which deserves more attention in future studies. This work helps to disentangle long-history questions regarding the category and relevance of different negative emotions and their link with neurophysiological responses and one's sociability.

Data and code availability statement

The data used in this manuscript is not available due to privacy issues. The code used in this manuscript is available on GitHub (https://github.com/andlab-um/Emotion_Neurophysio_IS-RSA).

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Declaration of Competing Interest

All authors declare no competing interests to disclose.

Credit authorship contribution statement

Ruian Wang: Conceptualization, Methodology, Software, Data curation, Formal analysis, Visualization, Writing – review & editing. **Runquan Yu:** Methodology, Data curation, Writing – review & editing. **Yan Tian:** Methodology, Data curation, Writing – review & editing. **Haiyan Wu:** Conceptualization, Methodology, Visualization, Writing – review & editing, Supervision, Funding acquisition.

Data Availability

I have shared the link to code at Attach File step.

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Supplementary materials

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