

The Association between Social Rewards and Anxiety: Links from Neurophysiological Analysis in Virtual Reality and Social Interaction Game

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Abstract

Individuals' affective experience can be intricate, influenced by various factors including monetary rewards and social factors during social interaction. However, within this array of factors, divergent evidence has been considered as potential contributors to social anxiety. To gain a better understanding of the specific factors associated with anxiety during social interaction, we combined a social interaction task with neurophysiological recordings obtained through an anxiety-elicitation task conducted in a Virtual Reality (VR) environment. Employing inter-subject representational similarity analysis (ISRSA), we explored the potential linkage between individuals' anxiety neural patterns and their affective experiences during social interaction. Our findings suggest that, after controlling for other factors, the influence of the partner's emotional cues on individuals' affective experiences is specifically linked to their neural pattern of anxiety. This indicates that the emergence of social anxiety may be particularly associated with the emotional cues provided by the social partner, rather than individuals' own reward or prediction errors during social interaction. These results provide further support for the cognitive theory of social anxiety and extend the application of VR in future cognitive and affective studies.

Keywords Affective Experience, Virtual Reality, Social Interaction, EEG, Anxiety

1 Introduction

Each individual has a unique way of experiencing and expressing mood states, which can have a wide range of effects on social behavior. Affective states and sociability shape our perceptions of the social world and how we infer social cues from others, especially during interactions. It emphasizes the benefits of positive emotions and explores how negative emotions can hinder social interactions and prosocial behavior (Dunn & Schweitzer, 2005; Stellar et al., 2015). However, affective experiences during social interaction are complex and influenced by various factors. Previous studies have identified that learning history, monetary reward, and social stimuli can all influence an individual's subjective feelings during interactions (Kao et al., 2023; Rutledge et al., 2014). Meanwhile, the emotions as social information (EASI) model suggests that individuals use others' expressed emotions to infer intentions, motivations, and relational dynamics, thereby influencing social judgments, decision-making, and behaviors(Kleef, 2009).

Anxiety plays a significant role in social contexts and adaptive responses, guiding individuals to conform to social norms, thereby influencing social interactions and emotional experiences(Gilbert, 2001). Evidence from both animals and humans consistently supports the association between anxiety and decision-making in aversive situations(Browning et al., 2015; Hein et al., 2021). Anxious individuals are characterized by overestimating the likelihood of aversive results or worrying about negative outcomes and difficulty learning the action-outcome association (see a review (Grupe & Nitschke, 2013)). Existing findings imply that clinical and subclinical (trait) anxiety can lead to higher intolerance of uncertainty and different learning rates between the volatile and stable contexts, which can impair decision-making and interferes with learning(Hein et al., 2021). Prior event related potential (ERP) study shows that socially anxious individuals often exhibit a negative-expectancy bias on social cues(Cao et al., 2015). Meanwhile, adaptation to context volatility requires the detection of change in action-outcome contingencies and the processing of surprise signals(Gagne et al., 2020). Although previous studies have investigated learning and behavioral patterns in anxious individuals, the association between individuals' idiosyncratic anxious neural activity patterns and their affective experience during real social interaction remains largely unknown.

Affective experiences during social interaction can be described using two dimensions: valence and arousal, which captured distinct but related aspects of human affect (Russell, 1980). While valence reflects the positivity or negativity of an emotional state, arousal reflects the level of activation or intensity associated with it (Feldman Barrett & Russell, 1998). Affective states can fluctuate with decisions or social interactions. For example, in the social context, people's valence and arousal could have an influence on their punitive and uncooperative choices in competitive interactions(Heffner & FeldmanHall, 2022). On the other hand, it has been demonstrated the long-lasting effect of emotions on cognition and behaviors, as well as consistent patterns of emotional expression across cultures and individuals(Ip et al., 2021; Hu et al., 2022). Having a more comprehensive understanding of the affections during social interactions requires us to know how these affective states are processed in the brain. To investigate the dynamic nature of these affective states and their underlying neural mechanisms, electroencephalography (EEG) has been emerged as a powerful tool in studying human affection. The comprehensive features of EEG, like power spectral bands, are valuable tools to study humans' affect and emotion and their interaction with behavior(Suhaimi et al., 2020). For example, it is identified EEG alpha asymmetry as a potential bio-marker for anxiety and depression(Mathersul et al., 2008; Thibodeau et al., 2006). Previous studies used resting-state EEG features as stable indicators of individuals' cognitive deficiencies(J. Wang et al., 2013; Khanna et al., 2015). There is also a recent study that used inter-trial EEG variations to predict individual differences in social tasks(Zhang et al., 2021). The cumulative evidence strongly suggested that EEG can be considered as a effective bio-marker to represent individual's affective patterns during social interaction. In addition to EEG, electrocardiogram (ECG) data also provides critical insights into the physiological underpinnings of emotional and affective experiences. ECG measures, such as heart rate variability (HRV), are closely linked to affect regulation and stress responses (Thayer & Koenig, 2019), especially some negative emotions like fear or anxiety(Garfinkel et al., 2014).

Unlike traditional methods, virtual reality (VR) techniques offers a dynamic and immersive environment that closely mirrors real-world situations, which can be considered as a more effective and ecological tool to study emotion(Faul et al., 2020; Ban˜os et al., 2006; Riva et al., 2007; Melo et al., 2022). However, the affective responses in such contexts are often nuanced and complex, making them difficult to capture using traditional analysis methods that rely on comparisons across different conditions. To address this challenge, inter-subject representational similarity analysis (ISRSA) has emerged as a powerful analytical tool in naturalistic settings (Chen et al., 2020; Finn et al., 2020; Camacho et al., 2024). This technique builds upon intersubject correlation analysis (ISC), which assesses the consistency of participants' temporal responses to a dynamic stimulus(Cohen et al., 2017; Hasson et al., 2004; Nastase et al., 2019). Our previous work identified the idiosyncratic neurophysiological pattern across individuals under negative emotions and the relationships to their sociability through VR, which suggests that sociability plays a significant role in shaping how individuals process and respond to negative emotional stimuli in VR, highlighting the importance of considering individual differences in sociability when studying emotional responses (R. Wang et al., 2022). However, further evidence needs to be provided on how the emotional responses in VR can link to real social tasks.

Thus, the current work aims to use those neural patterns under VR-induced anxiety as an idiosyncratic marker to investigate individuals' affective patterns during natural social interaction. To bridge individuals' idiosyncratic anxiety patterns and their affective patterns during social interaction, here, we employed a combination of EEG recordings and behavioral tasks to assess the impact of anxiety on social decision-making and emotional responses. Specifically, we aimed to answer the following questions. **Q1:** How does monetary reward and social reward affect social-interaction-based affective experiences? **Q2:** Which factors that affect individuals' affective experience during social interaction can be specifically associated with the emergence of anxiety? To avoid explicitly introducing the concepts or feelings of anxiety to the participants during social interaction, we first used an independent emotion-elicitation task to record participants' neural-physiological pattern of their intense anxiety under VR.

Then, using the inter-subject representational similarity analysis (ISRSA), we aim to see if individuals' anxiety neural patterns can be linked to individuals' affective experience during social interaction. We hypothesize that individuals' variation in generating different affective experiences during social interaction can be linked to their idiosyncratic anxiety neural patterns.

2 Methods

2.1 Participants

A total of 42 right-handed individuals (31 females, age range: 19 - 24 years old, mean age = 21.74 ± 2.19) were recruited from the University of Macau using an online advertisement. No participants reported a history of mental abnormalities or neurological disorders. Prior to the experiments, all participants provided informed consent. All participants were scheduled to complete three sessions of the study: 1) Participants' mentalizing and empathy abilities were measured using psychological scales before the experiment; 2) During the neurophysiological recording session, participants were required to watch the emotion-inducing video clips under VR with the EEG and electrocardiograph (ECG) recording; 3) participants were required to complete a computer-based social interaction game later online. A total of 37 individuals completed the task. 6 participants' data were excluded due to contaminated signals during emotion elicitation. A total of 31 participants were included in further analysis (21 females, mean age = 21.55 ± 2.08) All procedures reported above were approved by the local ethics committee of the University of Macau (BSERE21-APP006-ICI). The EEG and ECG data used in this study were previously reported in our earlier work, which addressed different research questions (R. Wang et al., 2022). New analyses were performed in the current study to explore distinct research questions

2.2 Experimental Tasks

2.2.1 Social Interaction Game

The social interaction game (SIG) was used to investigate participants' emotional responses and inferences from social interaction (Fig. 1a)(Deng et al., 2021). On each trial, participants would interact with a partner who made a $10 offer or not with a different emotional cue (happy vs. sad). After the interaction, participants were asked to indicate their affective state, including valence and arousal. Then they were required to make a prediction on the possibility of getting the $10 offer in the subsequent trial. In this study, each subject engaged in interactions with all three different partners (Partner 1, Partner 2, and Partner 3), representing different levels of emotional volatility (low, medium, and high). The different levels of volatility were manipulated by the partner's frequency of switching the emotional cue, where the cues and rewards were pseudo-randomly assigned (Fig. 1b). All three partners had the same probability of offering the reward given a certain emotional cue (Fig. 1c). As a within-subject study, all participants would have to complete 30 trials of interaction with each partner, which means there were 90 trials in total.

2.2.2 Naturalistic Viewing Task under VR

During the emotional recording period, VR devices were used for the video presentation to elicit an immersive anxiety experience for each participant. More specifically, before the neurophysiological recording session, experimenters would ensure the EEG cap and ECG electrodes were well placed and then asked the participants to wear the VR head-mounted display goggles (Vive Eye pro, HTC Corporation) with an adjusted focal length for each participant. To ensure the viewing environment would move along with the head for immersive, real-life experiences, we used infrared lights, accelerometry, and a gyroscope to track the head movement.

During the viewing session, three preliminary selected anxiety-inducing video clips were presented to the participants. All participants were asked to use a 4-point scale to rate their emotional arousal after the viewing task, which was done to confirm the effectiveness of the manipulation in terms of reliability and validity of the stimulus as well as participant engagement during the task. The rating was the same as the 4-point Likert scale used in the selection period.

The current naturalistic viewing paradigm was programmed by the Unity platform and communicated with the goggles using Steam VR. Meanwhile, an embedded Python script (https:// github.com/andlab-um/Emotion EEG) was used in the Unity program for sending marks to EEG and ECG recording machines for synchronization.

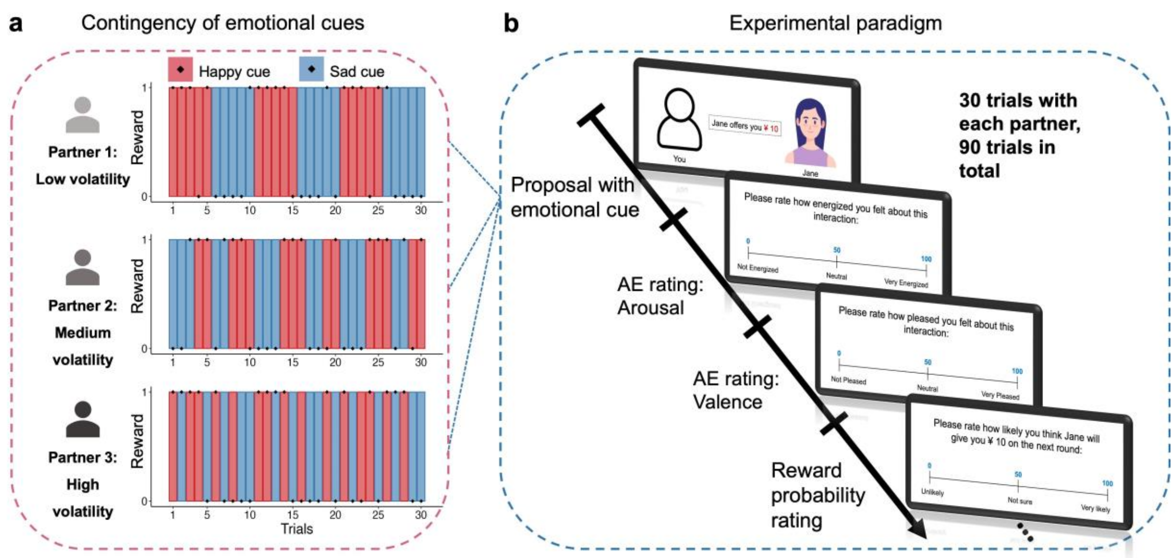

Figure 1 The behavioral paradigm of the study a) Partner's emotional cue. This study involved participants interacting with three different partners(Partner 1, Partner 2, and Partner 3) who exhibited varying levels of emotional volatility represented by their frequency of switching between happy(red bar) and sad (black bar)expressions. The diamond squares represent Reward probability, which means if there is a $10 offer in this trial (Reward = 1) or not (Reward = 0). The probability of offering the reward given a certain emotional cue was the same for all partners. The probability of getting a reward was 0.8 when the cue was happy, and the probability was 0.2 if the cue was sad. **b)** The social interaction task. Each trial included a proposal, two affective experience ratings(arousal vs. valence), and a reward probability rating. During the proposal period, participants interacted with a partner who made a $10 offer or not with different emotional expressions (happy vs. sad). After the interaction, they were asked to rate the two dimensions of their current affect state, including valence and arousal. Then they were required to predict the possibility of getting the offer in the subsequent trial. Participants would have to complete 30 trials of interaction with each partner, which means there were 90 trials in total.

2.3 Materials

2.3.1 Psychological Scales

In this study, two psychological scales, the interactive mentalizing questionnaire (IMQ) (Wu et al., 2022) and the Interpersonal Reality Index (IRI)(Davis, 1983), were administered to participants for the aim of assessing participants' mentalizing and empathy capacities. IMQ was generated based on the interactive theory of mentalizing, which consists of three subscales: inference of the mental state of others (SO: self-other), meta-cognition (SS: self-self), and meta-mentalization (OS: other-self). Meanwhile, the IRI is a widely used tool for measuring individual differences in trait empathy which consists of four domains: perspective-taking (PT), fantasy (FS), empathic concern (EC), and personal distress (PD). In this study, we specifically focused on the "SO" subscale (Wu et al., 2020) within the IMQ and the EC and PD within the IRI to support our hypothesis. Participants were required to complete these scales before the experiments.

2.3.2 Emotional Video Materials

There were three steps for stimulus selection, we first constructed a movie dataset with the following three criteria: 1) the clip lasts for around three minutes; 2) the clarity of the video content; 3) there is only one type of emotional experience can be elicited by watching each clip, which is anxiety in this case. Then we recruited 40 other participants to rate the previously selected candidates on a 4-point Likert scale(0 = not strong at all, 3 = very strong). Based on the participants' ratings, the three video clips with the highest scores were selected for later use in the experiment.

The majority of video clips were selected from movies and TV series, and detailed information on the materials was presented in supplementary 1. Besides, to investigate the neurophysiological responses of the most intense emotional feelings, we further recruited 5 volunteers (male = 3) to rate the emotional arousal. We marked a 20s excerpt that elicited the most intense emotional experiences for each video clip. Only those clips that all participants recognized were employed as the final material of the formal experiments.

Participants were also instructed to evaluate the emotional intensity of four types of negative emotions (helplessness, anxiety, anger and fear) after each viewing at the naturalistic viewing task to ensure participants' engagement during the movie viewing and validate the effectiveness of the clips in eliciting the intended emotions. Ratings were provided on a 4-point Likert scale (0 = not strong at all, 3 = very strong). In the current study, participants watched three videos selected as emotion elicitation materials. However, only two of these videos successfully elicited anxiety that was distinguishable from other negative emotions in the formal experiment. Consequently, only the neurophysiological recordings from these two videos were included in the final analysis. Video 1 was a footage from *Shock Wave 2* (96:08 – 98:50), with a scene where a bomb is about to explode. Video 2 was a footage from *L´eon: The Professional* (29:16 – 31:40), showing the scene where the girl asks the man to open the door.

2.4 ECG Data Acquisition and Preprocessing

The ECG signals were recorded using BIOPAC MP160 (BIOPAC, USA), with an acquisition sampling rate of 2000 Hz. The preprocessing of the ECG data was conducted using the Python module *Neurokit2* Makowski et al. (2021), where the raw signal was resampled to 250 Hz, and the noise was reduced using the default method embedded in *Neurolit2*. The typical feature of the ECG signal is heart rate variability (HRV), which refers to the variability of the heartbeat cycle. Here, we extracted HRV for further analysis using the *Neurolit2* function ecg rate based on the previously located cardiac peaks(R peaks) of the denoised ECG data. Then the hrv time function was utilized for HRV calculation. Two time-domain HRV features, MeanNN and SDNN, were used for further analysis, which referred to the mean and the standard deviation of the interval across cardiac peaks, respectively. According to previous literature in affective research, the time-domain features could be considered a good representation of the total variability of HR (Pham et al., 2021) .

2.5 EEG Data Acquisition and Preprocessing

The EEG recordings were conducted using the 64-channel Ag/AgCl electrodes fitted in the EEG cap (actiCap; BrainAmp; Brain Products), following the 10/20 system with the impedance of 10 kΩ or less, with a 1000 Hz sampling rate (with a 0.1 to 100 Hz bandpass filter). The EEG data were initially referenced to the mid-frontal (FCz) electrode with the ground placed at the forehead (AFz) electrode site. During the procedure, participants were instructed to minimize head and body movements.

The EEG data were preprocessed using the open-accessed EEGLAB toolbox Delorme & Makeig (2004) in MATLAB script (R2020b, The MathWorks Inc.). For the convenience of analysis, the data was firstly downsampled to 250 Hz and were filtered with a low-pass filter of 50 Hz and a high-pass filter of 1 Hz. For noise reduction, the EEGLAB *cleanrawdata* plug-in was utilized for detecting and discarding the bad channels, with a maximum flatline duration of 5 seconds, a line noise criterion of 4 SD, and a minimum acceptable correlation with nearby channels of 0.8. The removed channels were interpolated using the spherical method and were re-referenced to the average of all the channels Maffei et al. (2020).

Further, the data were corrected using the Artifact Subspace Re-construction method with the maximum acceptable windows of 0.5 seconds (SD =10) to minimize the artifacts further. To discard the artifact contributed by cardio activity, muscle movement, and ocular movement, the Independent component analysis (ICA) was conducted by the EEGLAB *runica* function. After the ICA, a semiautomatic manner was implemented to discard the artifact component using the *ICAlabel* plug-in (https://labeling.ucsd.edu/tutorial/overview) based on a component rejection threshold of 0.7 (Pion-Tonachini et al., 2019).

2.6 EEG Feature Extraction

The power spectral density (PSD) was calculated by integrating the energy within each frequency band (delta: 1–4 Hz, theta: 4–8 Hz, alpha: 8–12 Hz, beta: 12–30 Hz, and gamma: 30–45 Hz). PSD is a widely used frequency domain analysis to capture the EEG feature within each frequency subband, which was commonly used in the study of emotion (Hu et al., 2017) and affective computing (Zheng et al., 2014). To get the neurophysiological responses of capturing the most intense feelings of anxiety for the participants, we only extracted EEG features of the 20 seconds that elicited the strongest emotional experience from each original video, which were then averaged into the meantime course EEG data under VR-induced anxiety. The MNE module based on python was used to do the feature extraction (Gramfort et al., 2014). Specifically, we used the multitaper method from *mne.time frequency.psd _ multitapper* function to compute the PSD value for each channel(Sup. Fig. 2a). We then averaged the PSD values of frequency bands for later use (Sup. Fig. 2b), and obtained a data structure of 64*5*20 (channels*frequency bands*time points) for each individual.

2.7 Statistical Analysis

In this study, we first used repeated ANOVA and paired t-tests to analyze participants' self-reported affective experiences and reward expectations across varying levels of the partner's emotional volatility and emotional cues. Following this, we applied a general linear model (GLM) to predict participants' affective experiences (specifically arousal and valence) based on factors such as reward, cue, and PE from the SIG, as well as EEG features we extracted. We also fitted individual GLMs for each participant to predict their affective experiences during the SIG using the same factors (reward, cue, and PE). This approach allowed us to assess the impact of both monetary and social rewards on each participant's affective experience, which was then utilized in the calculation of intersubject similarity analysis. Spearman correlation were used in the ISRSA analysis for accessing the association across different modality of data.

2.8 Intersubject Similarity Analysis

The intersubject correlation (ISC) was used to measure the consistency of the neurophysiological responses to naturalistic stimuli across individuals (Hasson et al., 2004; Nastase et al., 2019). We did the ISC analysis on all EEG channels using Pearson correlation, which brought us 64*5 intersubject similarity matrices of the neural representation under VR-induced emotion.

The intersubject similarity analysis on sociability traits, affective experiences,PE, and model estimates was conducted using the Anna Karenina (AnnaK) method (Finn et al., 2020), which was designed for one-dimensional values that are unsuitable for correlation analysis, considering that brain responses tend to cluster for individuals at one extreme of a behavioral spectrum, while variability increases as one move towards the other end of the spectrum. More specifically, all high scorers are similar, but each low scorer is different in its own way, which may be more effective to use a metric that reflects the absolute position on the scale, such as the mean, the minimum of values from subject i and j, or the product of the mean and minimum. In this case, the AnnaK method could be an alternative to Euclidean distance, which was considered well-suited for unique uninterchangeable values(Finn et al., 2020). In a detailed explanation, the original scores were converted into ranks. Then, for every pair of scores, the distance is determined by computing the mean of the sum of the absolute positions of the corresponding ranks of each subject.

Specifically, if there are a total of n subjects, the distance between subject i and subject j is calculated using the equation presented below (eq.(1)):

$$D_{\mathrm{ij}} = mean(\frac{ranl\,(i)+rank(j)}{n_{subs}})$$

where D stands for the distance between subject i and subject j. The distance was calculated for each pair of subjects to get the ISM.

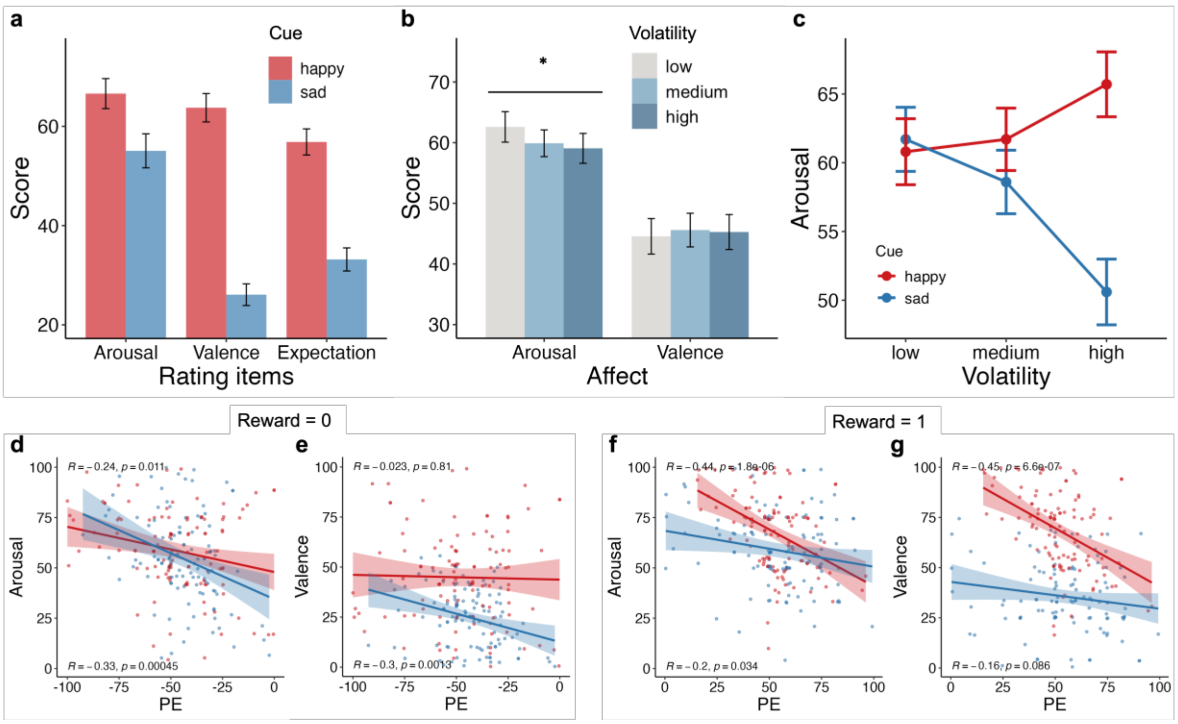

Figure 2 Behavioral results General behavioral analysis across the the manipulated conditions and participants' responses. **a)** Arousal, valence and the reward expectation were all significantly higher when the social partner facial cue was happy compared to the sad cue. **b)** Participant's arousal ratings are significantly higher in the low volatility condition compares to the high volatility condition. Volatility plays non-significant role in the ratings of valence across conditions.**c)** There is a significant moderating role of volatility on cue predicting arousal. **d)-g)**3-way interaction of PE's effect on valence and arousal in different levels of cue and reward.

3 Results

3.1 Monetary rewards and Social Rewards can Affect Affective Experience

3.1.1 The effect of cue, reward, and volatility on affective experience

We first examined the effect of cue on the measurements of affective experience and reward expectations. The paired sample t-test suggested that all three measurements (arousal, valence and reward expectation) were significantly higher in the trials where the social partner presented a happy cue (arousal: $t = 2.05, p < 0.05$, valence: $t = 7.35, p < 0.001$, expectation: $t = 7.75, p < 0.001$, Fig. 2 a). Besides, social partner's reward offer on the current trial also plays a significant role on participants' affective experience(arousal: $t = 7.08, p < 0.001$, valence: $t = 12.116, p < 0.001$). To examine the role of social partner's emotional volatility, we used repeated measures ANOVA to see the potential differences across different emotional volatility conditions.Results showed that there was a significant effect of volatility on arousal ($F = 3.11, p < 0.05$, Fig. 2 b). To further investigate the differences across conditions, we did a post-hoc t-test to compare the arousal score of each volatility condition. Results showed that participant's arousal ratings are significantly higher in the low volatility condition compares to the high volatility condition($t = 2.24, p < 0.05$, Fig. 2 b left). Volatility plays a non-significant role in the ratings of valence across conditions.

We also examined the relationship between affective experience and prediction error (PE = Reward - Prediction) in facing different cues. According to the Pearson correlation analysis, it was observed that both arousal and valence exhibit a negative correlation with prediction error (PE), regardless of whether the participant's cue is happy or sad (Sup. Fig. 3). To better understand the results, we calculated the absolute value of PE using the same analysis. The absolute PE negatively correlates with arousal and valence only when the partner presented a happy cue(Sup. Fig. 4).

3.1.2 Both Arousal and Valence can be Predicted by Reward, Cue and PE across Conditions of Volatility

Table 1 Arousal can be predicted by reward, cue and PE across conditions of volatility

Model 1 Prediction of Arousal

Arousal ~ β_1PE + β_2Cue + β_3Reward + β_4Volatility + β_5Cue*Volatilit + β_6Reward*Cue + β_6Reward*PE+ β_7PE*Cue + β_8Reward*PE*Cue + ε

Variable	Std. Est.	SE	t	p
PE	-1.400	0.12	-4.588	0.182
Cue:				
1 – 0	0.426	7.849	0.997	0.319
Reward:				
1 – 0	2.142	8.11	5.397	<0.001***
Volatility:				
1 – 0	-0.198	3.239	-1.278	0.202
2 – 0	-0.501	3.515	-2.989	0.003***
Cue * Volatility:				
(1 – 0) * (1 – 0)	0.255	4.614	1.158	0.247
(1 – 0) * (2 – 0)	0.799	5.054	3.228	<0.001***
Reward * Cue:				
(1 – 0) * (1 – 0)	0.444	11.963	0.993	0.321
Reward * PE:				
(1 – 0) * PE	0.691	0.147	1.854	0.064
Cue * PE:				
(1 – 0) * PE	0.687	0.15	1.804	0.072
Reward * Cue * PE:				
(1 – 0) * (1 – 0) * PE	-1.581	0.208	-3.001	0.003**

Std. Est. refers to the standardized estimates of the predictors,
SE refers to the standard error of the estimates (the same below).

We then fitted the regression models to investigate how the monetary factors (monetary reward and PE) and the social factors (cue and volatility) affect participants' valence and arousal during social interaction. Results revealed that, the reward for the current trial was a positive contributor for the prediction for both arousal ($\beta = 43.766, t = 5.397, p < 0.001$, see Table 1) and valence ($\beta = 32.639, t = 4.211, p < 0.001$, see Table 2). Regarding the effect of cue and PE, there was significant main effect of cue ($\beta = 27.01, t = 3.603, p < 0.001$) and PE ($\beta = -0.291, t = -2.53, p < 0.05$) on valence, but not arousal.

Regarding the effect of volatility, results showed significant interaction effect between volatility and cue on arousal. Volatility played a divergent effect on arousal when facing different social partner's emotional cue.(interaction β = 16.316,t = 5.054,p < 0.001, see Table 2). Individuals had higher arousal scores in the high volatility condition compared to the low when the partner's cue was happy, but had lower arousal scores when facing the sad cue as the social partner changed the emotional cues more frequently. (Fig. 2 c)

We have also observed the interaction effect across the effect of reward and PE in both arousal(β = −0.624,t = −3.001,p < 0.01, see Table 1) and valence(β = −0.696,t = −3.504,p < 0.001, see Table 2). PE had a stronger negative effect on valence when the emotional cue and reward offer of the social partner were congruent (Fig. 2 e, g). The effect of PE on arousal also shared a weaker but similar pattern (Fig. 2 d, f).

3.2 Anxiety EEG features can Predict Affective Experience During Social Interaction

We take the individuals' affective experiences and the neurophysiological responses under VR-induced anxiety together to investigate how people's EEG features can predict their real-life behavior. We firstly examined the effect of emotion elicitation in VR. Repeated ANOVA were used to investigate if

Table 2 Valence can be predicted by reward, cue and PE across conditions of volatility

Model2: Prediction of valence

Valence ~ β_1PE + β_2Cue + β_3Reward + β_4Volatility + β_5Cue*Volatility + β_6Reward*Cue + β_6Reward*PE + β_7PE*Cue + β_8Reward*PE*Cue + ε

Variable	Std. Est.	SE	t	p
pe	-0.621	0.115	-2.53	0.012*
cue:				
1 – 0	1.118	7.497	3.603	<0.001***
reward:				
1 – 0	1.331	7.751	4.211	<0.001***
Volatility:				
1 – 0	0.094	3.085	0.761	0.447
2 – 0	-0.058	3.351	-0.429	0.668
Volatility * cue:				
(1 – 0) * (1 – 0)	-0.045	4.408	-0.252	0.801
(2 – 0) * (1 – 0)	0.280	4.825	1.444	0.149
PE * cue:				
PE * (1 – 0)	0.454	0.143	1.482	0.139
reward * cue:				
(1 – 0) * (1 – 0)	1.047	11.434	2.5	0.013*
reward * PE:				
(1 – 0) * PE	0.260	0.14	0.869	0.385
reward * cue * PE:				
(1 – 0) * (1 – 0) * PE	-1.485	0.199	-3.504	<0.001***

the films can elicit the certain emotion of anxiety rather than other negative emotions ($F = 19.8, p < 0.001$, Sup. Fig. 5). The Tukey's post hoc test results showed that the anxiety induced from the video was differentiated from emotion of anger ($t = 5.14, p < 0.001$) and fear ($t = 3.86, p < 0.01$).

Then we included the EEG PSD features into the behavioral model to find possible connections (Sup. Fig. 2. 5 scalp regions were selected for the regression. AF3, AF7, F1, F3, F5, F7, FC3, and FC5 were selected as the left frontal channels. AF4, AF8, F2, F4, F6, F8, FC4, and FC6 were selected as the right frontal channels. FC1, FC2, C1, Cz, C2, and CPz were selected as the central channels. CP3, CP5, P1, P3, P5, P7, PO3, and PO7 were selected as the left parietal channels. CP4, CP6, P2, P4, P6, P8, PO4, and PO8 were selected as the right parietal channels (Sup. Fig. 6). Results showed that the EEG features had divergent patterns of contribution to arousal and valence. With the other factors controlled, EEG features had a generally significant contribution to arousal with no interaction effect of cue (see table 3), whereas the EEG features had few significant main effects on valence during the interaction, but significant interaction effect of cue and the Anxiety EEG features were detected (see table 4, only interaction terms of EEG features was included, see Supplementary for the full table). Specifically, the interaction term of cue and frontal features of both sides were all significant contributors in the model predicting valence controlling for the main effect of PE, cue, reward and volatility.

3.3 Individual Variation during the Interaction can be Explained by Similarities of Sociability Traits Neurophysiological Responses under VR

To address the second question **(Q2)** concerning the role of anxiety during social interaction, we first used the IS-RSA method to see the relationship across the intersubject similarity matrices (ISM) of the affective experiences and PE for each participant and their psychometric sociability scores using Pearson correlation (Fig.3 a, lower path). For the analysis of trait empathy, results showed that the similarity of the absolute value of PE was positively correlated with both empathetic concern (EC) ($r = 0.119, p < 0.01$) and personal distress (PD) ($r = 0.119, p < 0.01$). The similarity of valence was positively correlated with EC ($r = 0.191, p < 0.001$), and the similarity of PE was positively correlated with PD ($r = 0.091, p < 0.05$). Regarding the connection across individuals' affective experiences and

Table 3 Arousal can be predicted by the VR-induced anxious EEG features controlling for Cue, PE, and Volatility

Model 3: Prediction of arousal using the EEG features				
Arousal ~ β_1PE + β_2Cue + β_3Reward + β_4Volatility + $\Sigma_{i=5}^{29}\beta_i$ EEG features + ε				
Variable	Std. Est.	SE	t	p
PE	-0.403	0.0472	-8.54	<0.001***
Cue 1 – 0	0.306	1.5279	4.31	<0.001***
Reward 1 – 0	1.074	4.9209	4.69	<0.001***
Volatility (1 – 0)	-0.098	1.8729	-1.12	0.262
Volatility (2 – 0)	-0.168	1.8617	-1.94	0.053
alpha lF	1.063	5.6481	1.74	0.082
alpha rF	-8.618	10.1897	-7.88	<0.001***
alpha c	4.333	6.2851	4.82	<0.001***
alpha lP	-5.150	8.3083	-5.28	<0.001***
alpha rP	8.231	10.5158	6.41	<0.001***
beta lF	-11.371	11.1299	-8.54	<0.001***
beta rF	6.124	9.3862	5.66	<0.001***
beta c	4.391	7.5305	4.58	<0.001***
beta lP	12.322	13.3471	8.02	<0.001***
beta rP	-9.795	11.6637	-7.52	<0.001***

delta _lF	3.221	4.9317	8.36	<0.001***
delta _rF	-6.247	8.7665	-8.72	<0.001***
delta _c	0.835	5.1619	1.81	0.071
delta _lP	2.608	8.0789	4.38	<0.001***
delta _rP	-0.869	7.3127	-1.41	0.160
gamma lF	11.972	9.1202	9.45	<0.001***
gamma rF	-7.063	6.9139	-7.71	<0.001***
gamma c	-1.405	4.5303	-3.11	0.002**
gamma lP	-4.651	4.8849	-8.35	<0.001***
gamma rP	1.790	3.6684	5.11	<0.001***
theta lF	-2.444	6.5006	-5.19	<0.001***
theta rF	9.146	14.7262	8.02	<0.001***
theta c	-3.229	9.169	-3.61	<0.001***
theta lP	-2.109	10.9978	-2.54	0.012**
theta rP	-2.850	12.8625	-2.66	0.008**

their mentalizing ability, results also showed that the estimates of both arousal ($r = 0.430, p < 0.001$) and valence ($r = 0.167, p < 0.001$) were connected with the self-other mentalizing ability (SO).

To further investigate the role of emotional volatility of the social partner during the interaction, we fitted two separate regression models on different levels of the partner's volatility (low vs. high). Repeated ANOVA indicated that there is no significant difference between the model estimates on valence between two volatility conditions (Fig.3 d-f). However, the data distribution patterns indicated that there might be a considerable variation among participants regarding the role played by reward, cue and PE on arousal and valence. To further investigate the role of anxiety during social interaction and the individual differences across those processes, we used IS-RSA to identify the possible source of those variations across individuals (Fig. 3 a, upper path).

Following our hypothesis, the anxiety neural similarity can explain the individual variation in arousal models during social interaction, especially in the estimates of cue predicting arousal and valence (Fig. 4, Fig. 5). For the results of arousal, the correlations were stronger in the high volatility condition compared to the low volatility condition. The most salient association was found in the beta band activity of anxiety with the effect of the cue on arousal in the high volatility condition. Salient electrodes were globally correlated with the estimates of cue, including FT10 ($r = 0.194, p < 0.01$), AF7 ($r = 0.140, p < 0.01$), and F1 ($r = 0.125, p < 0.01$) of the frontal channels, C3 ($r = 0.169, p < 0.01$), CP3 ($r = 0.198, p < 0.01$), and C1 ($r = 0.165, p < 0.01$) of the central channels, and P7 ($r = 0.174, p < 0.01$), P4 ($r = 0.156, p < 0.01$), and Pz ($r = 0.166, p < 0.01$) of the parietal channels.

Table 4 Valence can be predicted by the VR-induced anxious EEG feature controlling for Cue, PE, and volatility

Model 4: Prediction of valence using the EEG features
Valence ~ β_1PE + β_2Cue + β_3Reward + β_4Volatility +$\Sigma_{i=5}^{30}\beta_i$ EEG features $\Sigma_{i=31}^{45}\beta_i$ EEG features*Cue + ε

Variable	Std. Est.	SE	t	p
PE	-0.084	0.0469	-0.8496	0.396
Cue: 1 – 0	1.077	103.3259	7.1383	<0.001***
Reward: 1 – 0	0.829	4.8842	4.3023	<0.001***
Volatility: (1 – 0)	0.029	1.8384	0.3932	0.694
Volatility: (2 – 0)	0.021	1.8232	0.2975	0.766
alpha lF * cue	2.274	11.0854	2.2335	0.026*
alpha rF * cue	-9.179	19.715	-5.105	<0.001***
alpha c * cue	5.024	12.2856	3.3534	<0.001***

alpha lP * cue	-8.669	16.214	-5.3485	<0.001***
alpha rP * cue	9.797	20.5946	4.5748	<0.001***
beta lF * cue	-14.381	21.842	-6.4795	<0.001***
beta rF * cue	10.130	18.4246	5.6271	<0.001***
beta c * cue	2.994	14.5633	1.8956	0.059
beta lP * cue	14.814	26.0866	5.805	<0.001***
beta rP * cue	-10.640	22.7116	-4.9299	<0.001***
delta lF * cue	3.680	9.5158	5.8361	<0.001***
delta rF * cue	-5.082	16.8453	-4.3468	<0.001***
delta c * cue	0.104	10.0844	0.1362	0.892
delta lP * cue	1.976	15.8157	1.9961	0.047*
delta rP * cue	-1.092	14.3241	-1.0629	0.289
gamma lF * cue	14.826	17.8478	7.0479	<0.001***
gamma rF * cue	-10.926	13.5652	-7.1572	<0.001***
gamma c * cue	-0.241	8.7762	-0.3237	0.746
gamma lP * cue	-5.426	9.5271	-5.8883	<0.001***
gamma rP * cue	1.490	7.1464	2.5677	0.011*
theta lF * cue	-3.321	12.5807	-4.2957	<0.001***
theta rF * cue	7.345	28.2883	3.9544	<0.001***
theta c * cue	-1.760	17.8452	-1.1901	0.235
theta lP * cue	0.036	21.3951	0.0264	0.979
theta rP * cue	-4.108	25.1124	-2.3086	0.022*

About the valence model estimates(Fig. 5), the correlation topography displayed a stronger significant correlation pattern compared to the estimation of arousal. The major association was found in the theta, alpha, and gamma of the frontal channels, and the global beta band activity of anxiety with the effect of cue on arousal in both low and high volatility conditions. Specifically, the saliently significant channels includes Fp1 (low: $r = 0.217, p < 0.01$; high: $r = 0.150, p < 0.01$), FT9 (low: $r = 0.190, p < 0.01$; high: $r = 0.178, p < 0.01$), and FT8 (low: $r = 0.142, p < 0.01$; high: $r = 0.117, p < 0.05$) in the theta band; Fp1(low: $r = 0.192, p < 0.01$; high: $r = 0.205, p < 0.001$), FC5 (low: $r = 0.151, p < 0.01$; high: $r = 0.198, p < 0.001$), and AF7 (low: $r = 0.181, p < 0.01$; high: $r = 0.200, p < 0.001$) in the alpha band; and C1 (low: $r = 0.195, p < 0.01$; high: $r = 0.167, p < 0.001$), P2 (low: $r = 0.191, p < 0.01$; high: $r = 0.203, p < 0.001$), and FC2 (low: $r = 0.181, p < 0.01$; high: $r = 0.200, p < 0.001$) in the beta band. To further investigate the relationship between the similarity in physiological responses to anxiety and the similarity in affective experience patterns during social interaction, we calculated the mean interval between cardiac peaks as the HRV feature (HRVm). We then assessed the similarity between each pair of participants by measuring the distance between their respective HRV features (Fig. S7 a). Based on the ISRSA results of individuals' HRVm features and behavioral estimates, the significantly positive Spearman correlations were only found with the cue estimates on arousal in the

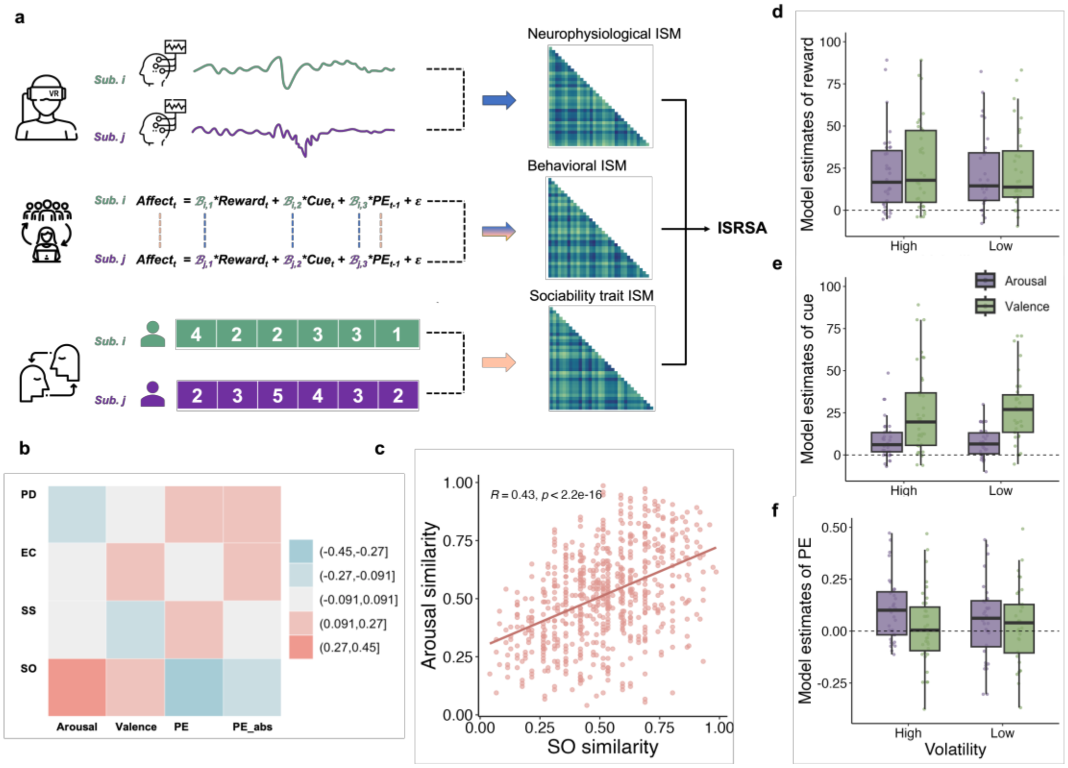

Figure 3 The flowchart of the IS-RSA in the current study. a) inter-subject similarity matrices(ISM) were calculated for three modalities of measurements. (1) Neurophysiological ISM under VR-induced anxiety, where 64 channels *5 frequency bands, 320 matrices in total for the EEG features, and 1 matrice of hrvm features for the ECG; (2) Behavioral measure estimates ISM and behavioral model estimates ISM. We calculated the arousal, valence, PE, and absolute PE, total 4 matrices. For behavioral model estimates, there are 2 predictors (Cue vs. PE)*2 respondents(Arousal vs. Valence)*2 volatility level (high vs. low), 8 matrices in total; and (3) Trait measurement, mentalizing (SO: self-other) and empathy (empathic concern, EC; and personal distress, PD), 3 matrices in total. After getting all the matrices, we did the Spearman correlation analysis for each Neurophysiological ISM with each behavioral model estimates ISM (blue arrow) to see the association between individual's anxiety pattern and affective patterns during social interaction. Spearman correlation analysis was also performed for each behavioral measures ISM with each sociability ISM (pink arrow) to see the association between individual's sociability and affective responses during social interaction. **b)** the correlation matrix represents the Pearson correlation results across the similarities on affective experience and PE RSMs and the sociability trait RSMs. **c)** The most salient correlation between the sociability similarities and the similarities on affective experience and PE during the SIG. Participant's similarity on SO is significantly positively correlated with the individual's similarity on their arousal levels during the task. **d)** Model estimates of reward on affective experience (AE) for each individual. **e)** Model estimates of cue on affective experience for each individual. **f)** Model estimates of PE on AE for each individual.

high volatility condition ($r = 0.112, p < 0.01$, Fig. S7 d) and the cue estimates on valence in the low volatility condition ($r = 0.114, p < 0.01$, Fig. S7 e), which is in line with the EEG results that only the effect of the cue on affective experience was associated with the anxiety neuralphysiological patterns.

4 Discussions and Conclusions

The complex nature of individuals' affective experiences during social interaction is subject to various factors that influence their manifestation. Through our empirical findings from the social interaction task, it has become evident that these experiences are influenced by critical factors like monetary rewards and learning accuracy. Our results also aligns with the previous hypothesis that individuals'

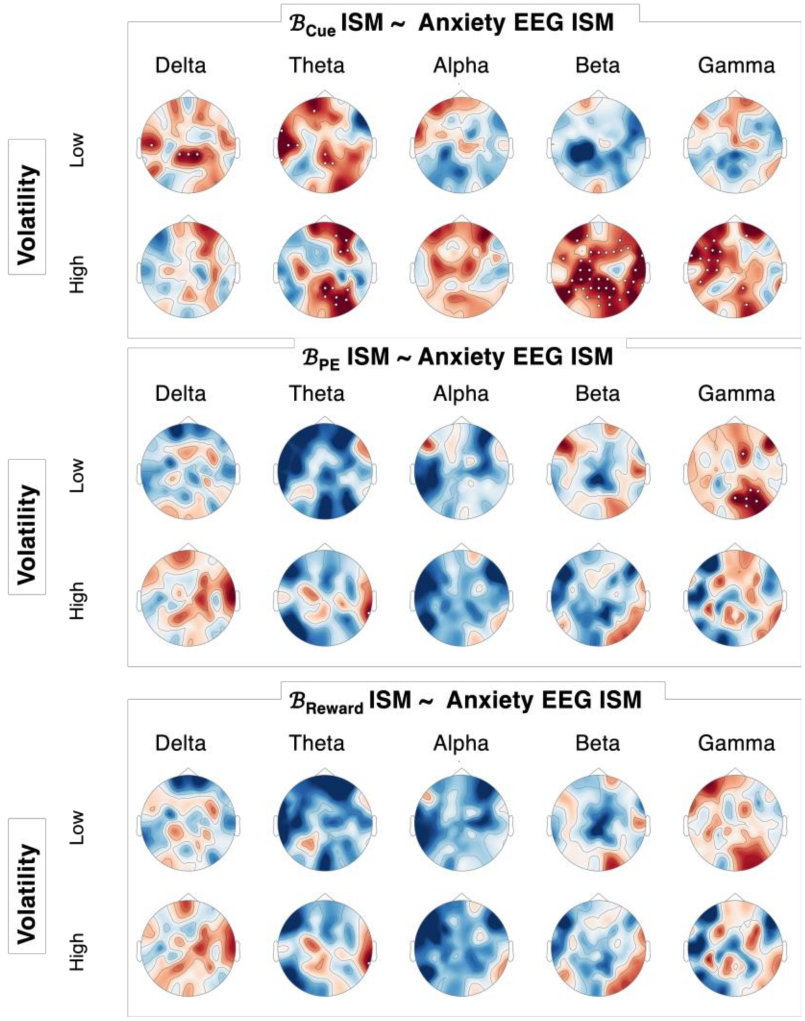

Figure 4 EEG topographies representing the IS-RSA results between arousal estimates and the EEG similarity of five frequency bands. Results mainly showed that an individual's similarity in the Theta, Beta, and Gamma EEG frequencies during anxiety was significantly correlated with the effect of social partner's cue on individual's arousal in the high volatility condition.

neural recordings under anxiety can be considered as an idiosyncratic neural fingerprint for each individual that can be associated with their affective experience during social interaction.Furthermore, social factors such as the emotional cues and emotional volatility of an individual's partner play a significant role in shaping affective experiences. Meanwhile, controlling for other factors, the effect of a partner's emotional cue on individuals' affective experience can be specifically linked to their neural pattern of anxiety. This suggests that the anxiety component during social interaction might be specifically associated with the partner's emotional cue, rather than their own reward or PE during social interaction.

In the present study, we created a framework to explore the association between individuals' neural responses of anxiety in a VR environment and their affective experiences during subsequent social interactions. The VR-induced EEG features of anxiety can be considered as stable features of individuals, which captured their neural pattern of anxiety. As such, this approach provides a valid alternative to the conventional self-report measurements of anxiety during social interactions, allowing the study of

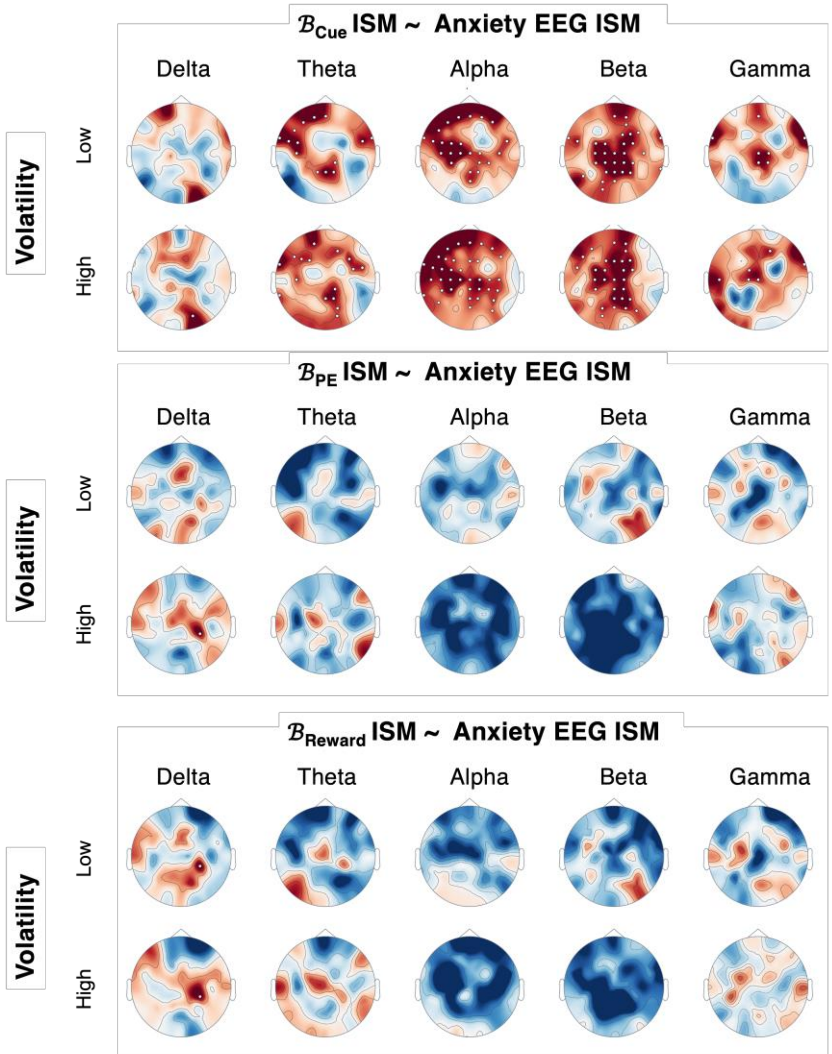

Figure 5 EEG topographies representing the IS-RSA results between valence estimates and the EEG similarity of five frequency bands. Results mainly showed that individual's similarity in the Theta, Beta, and Gamma EEG frequencies during anxiety was significantly correlated with the effect of the social partner's cue on the individual's arousal in both low and high-volatility conditions.

individuals' affective experiences while interacting with social partners without explicitly introducing the anxiety to the participants.

4.1 Individuals' Affective Feeling can be Influenced by both Monetary Reward and Social Reward

In social interactions, individuals can learn from emotional feedback that may consist of both positive and negative experiences, each having the potential to influence their affective state. It has also been established that both monetary and social rewards are powerful drivers of individuals' subjective feelings. Through exposure to these stimuli, individuals gain insight into the responses of others and are further influenced by how these responses make them feel.(Izuma et al., 2008; Pessiglione et al., 2008). While there are common neural responses in the striatum to both social and monetary rewards, some differences have been observed. For example, Izuma et al. (2008) observe a slightly stronger response to social rewards in the ventral striatum compared to monetary rewards, indicating some level of divergence in processing in the role played by the two kinds of rewards(Izuma et al., 2008). Within the dimension of monetary factors, PE also played a critical role in predicting affective experience, aligning with the previous study suggesting that the process of learning contributes a lot to momentary subjective well-being compared to the immediate experience of reward (Blain & Rutledge, 2020; Rutledge et al., 2014).

Meanwhile, the effect of the partner's emotional volatility, or stability, presented a divergent pattern of effect on arousal when facing different social partner's emotional cues. In the high volatility condition, the arousal ratings were notably lower when participants were presented with the sad cue and significantly higher when the cue was happy. These results suggested that the presented cue has a larger effect when the social environment is unpredictable. Previous studies already found that new information will be of higher weight when individuals perceived an increase in environmental uncertainty(Behrens et al., 2007; Browning et al., 2015; Aylward et al., 2019; Lamba et al., 2020). Meanwhile, people in an anxious state will exhibit impaired adaptive learning on the contingency volatility(Gagne et al., 2020; Lamba et al., 2020). These results can be considered as an extension of the previous studies, which suggest that new information not only has more weight on their decision-making processes but also on their affective experiences. Generally, our results were consistent with the previous studies that both monetary (reward, and RPE) and social factors (partner's cue, and partner's emotional volatility) can affect the affective experiences in social interaction(Kao et al., 2023; Rutledge et al., 2014).

4.2 Affective Experience during Social Interaction can be Predicted by Individuals' Anxious EEG Features

Arousal and valence track different aspects of affective experience in social interaction(FeldmanHall & Heffner, 2022). Our results suggested that arousal can specifically track the partners' emotional volatility in social reward contingencies. Controlling for the monetary and social rewards, the results also suggested that extracted anxiety EEG features presented different contribution patterns on arousal and valence. With the other factors controlled, anxiety EEG features significantly contributed to arousal during the social context.

Anxiety manifests differently across individuals, typically characterized by heightened arousal and negatively skewed valence (FeldmanHall & Heffner, 2022; Grupe & Nitschke, 2013; Kashdan & Roberts, 2007). In our study, participants displayed consistently high arousal during the social interaction game, largely independent of the partners' emotional cues. However, valence ratings showed clear variability, with higher ratings for happy cues and significantly lower ratings for sad cues. This indicates that negative social rewards can trigger anxiety and other negative emotions, highlighting the impact of emotional cues on affective experiences during social interactions. These findings are consistent with previous evidence that social rewards strongly influence affective states during social engagement (Heffner & FeldmanHall, 2022; Bhanji & Delgado, 2014; D. Wang et al., 2020).

Divergent directions of EEG contributions were also detected from the regression models. The early studies revealed greater left frontal activation during positive affective states, while the right frontal region showed greater activation during negative affective states (Davidson, 1992; Tomarken et al., 1992; Coan & Allen, 2004). More recent studies have further shown that frontal EEG asymmetry is not only a stable indicator of affective style but also a dynamic marker of emotional processing in various contexts(Allen et al., 2017; Koller-Schlaud et al., 2020; Neuhaus et al., 2023).

Meanwhile, prior studies detected that individuals with greater resting-state left frontal activation demonstrated higher positive and lower negative affect levels, indicating a positive affective style. In contrast, those with greater resting-state right frontal activation exhibited lower positive and higher negative affect levels, exhibiting a negative affective style(WHEELER et al., 2007). Studies above suggested that the left and right frontal activities are sensitive to different directions of individual affective experience. Consistent with the previous findings, we also detected a divergent direction of contribution on the arousal of the anxiety frontal EEG features in all five frequency bands, which suggested that the task-free anxiety patterns in the left and right front channels also encoded different affective components.

4.3 The Emergence of Anxiety during Social Interaction Might be Specifically Associated with Social Reward instead of Monetary Reward

Our findings indicate that individuals who shared similar neural patterns during VR-induced anxiety also shared a similar effect of cue on their affective experience during social interaction. However, this pattern was not observed when it comes to the effect of PE and reward, which constitute the monetary factors in our prediction model. Previous studies have identified the role of both monetary reward and social reward in individual's affective experience during decision making(Sanfey et al., 2003; Kao et al., 2023; Rutledge et al., 2014). Building upon this, the current results further advances this understanding by revealing a specific association between the emergence of anxiety and social rewards within the mixed components of affective experience.

The ISRSA results demonstrate a positive correlation between the similarity of individuals' anxietyrelated neural patterns and the similarity of their affective responses to social cues. Specifically, widely significant correlation patterns between the anxiety EEG features and the effect of the cue on valence in both low and high-volatility conditions, which suggests that valence might not be as sensitive to the stability of contextual cues as arousal. The prediction of cues on valence can be globally associated with the anxiety pattern of theta, alpha, beta, and gamma band frequencies. But the global significant correlation was only found in the beta band frequency and the prediction of the cue on arousal. Prior research indicates that the majority of negative emotions are aligned with the negative valence dimension, which can be more effectively discriminated by their variation in the intensity of arousal levels (Heffner & FeldmanHall, 2022; Kashdan & Roberts, 2007). This is also in line with previous MEG and intracranial EEG research that beta band activity is closely linked to negative emotions, including fear and anxiety(Schneider et al., 2018; Lee et al., 2024). Given these insights, our results further indicate that beta band EEG features may serve as a reliable neural marker for anxiety. This marker can detect the influence of cues on both arousal and valence during social interactions, providing a more nuanced understanding of the neural mechanisms underlying anxiety in the social context.

This finding underscores the unique influence of social rewards on anxiety, which can distinguish it from the impact of monetary rewards in decision-making scenarios. This results may put further evidence to support the cognitive perspective regarding the emergence of anxiety. From a cognitive perspective, this result supports the idea that social anxiety is rooted in negative thought patterns and cognitive biases that individuals experience during social interactions(Beck, 1979; Beck & Dozois, 2011). These biases include selective attention to perceived threats, overestimation of the probability and severity of negative social outcomes, and biased interpretation of ambiguous social cues. Cognitive biases reinforce and maintain anxious thoughts and feelings for socially anxious individuals(Clark & Beck, 2010; Beck, 1979).

Understanding how anxiety developed in the social context is important for the detection and intervention of social anxiety symptoms. Anxiety merged during social interaction can have a negative effect on social functioning (Stein & Stein, 2008; Clark & Beck, 2010). Taking the cognitive perspective, individuals prone to anxiety often have negatively biased beliefs, which can increase the likelihood of making erroneous judgments (Beck, 1979; Clark & Beck, 2010). Meanwhile, anxiety has been characterized as intolerance of uncertainty(Bishop, 2007; Aylward et al., 2019), which echoes studies identified that impaired adaptive learning abilities were prevalent in anxious individuals(Lamba et al., 2020; Hein et al., 2021).

4.4 Implications on Anxiety Detection and VR

Our findings suggest a noteworthy distinction between the impact of social and monetary rewards on individuals' affective experiences during social interaction, particularly with their correlation with neural responses under anxiety. This underscores the unique role that social interactions play in shaping individuals' emotional experiences, which emphasises the importance of social rewards in affective studies.

This results contribute to the understanding of affective experiences during social interaction, and also hold implications for the computational aspects of human affection, particularly in the context of anxiety. The distinctive correlation between social rewards and neural responses under anxiety highlights a critical avenue for the development of computational models that aim to capture and predict emotional states in individuals during social interactions. The emphasis on social rewards as a significant factor influencing anxiety-related neural patterns can be important for creating more advanced and context-aware computational models. The field of affective computing has seen prevalent applications in sensing and interpreting human emotions(Cambria et al., 2017; Saxena et al., 2020). Integrating these findings into computational frameworks can enhance the accuracy and reliability of algorithms designed to detect and understand anxiety in real-time, especially within the dynamic and complex context of social interactions.

The unique insights from our study also includes the potential use of VR as a powerful tool in the study of human affection, specifically anxiety. Creating more intuitive and immersive VR environments may serve as a controlled and ecologically valid platform to study human affective experience. Our study provides a novel dataset using VR as emotion stimuli for the recording of individuals' neural fingerprint of strong emotional experience. Existing dataset combining VR and EEG on studying human emotion is still rare. Limited previous datasets predominantly focused on positive and negative emotions(Yu et al., 2022), our current study uniquely focuses on anxiety, which can serve as a valuable supplement to the existing literature. This promotes the use of VR in affective computing research, providing a unique opportunity to bridge the gap between controlled experimental settings and realworld social interactions.

4.5 Limitations, and Future Direction

The present study, while offering valuable insights, has certain limitations that need consideration in future research endeavors. First and foremost, a more effective validation of the brain-behavior association could be achieved by incorporating neural recordings during the course of social interactions. The acquisition of such data promises a holistic understanding of the findings while lending credence to the conclusions of the study. Drawing inspiration from previous literature, two viable paths could be pursued: enhancing the statistical power through an increased sample size or zeroing in on specificities that augment effect sizes Gratton et al. (2022). To further consolidate the association between anxiety-related neural responses and an individual's affective experience during social interaction, it is imperative that future research explores diverse strategies to bolster the reliability of brain-behavior correlations. Another aspect worth exploring involves the temporal dynamics of EEG features during social interaction tasks, which may shed light on the emergence and proliferation of social anxiety. In lieu of solely focusing on frequency features, the temporal analysis can potentially demystify the subtle distinctions among varying affective experiences during social engagements. By incorporating this approach, we can strive to unravel the complexities accompanying social anxiety and its tangible manifestation in real-time social interactions.

Take together, individuals' affective experience during social interaction can be predicted by both monetary reward and social reward. Specifically, both arousal and valence can be predicted by reward, cue, and PE across conditions of partner's emotional volatility, where arousal is more sensitive to the partner's emotional volatility. Affective experience during social interaction can be predicted by individuals' anxious EEG features, where a moderating effect of cue on the prediction of valence was observed. Individuals who shared similar neural patterns during VR-induced anxiety shared a similar effect of cue on their affective Controlling for other factors, social reward holds a unique contribution to the anxiety component of individuals' mixed affective experience.

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Competing interests

The authors declare that they have no competing financial interests.

Data and Code Availability

The analytic scripts of the current study are available on the GitHub at https://github.com/andlab -um/VR-EEG-Social-Anxiety .

References

Allen, J. J. B., Keune, P. M., Sch¨onenberg, M., & Nusslock, R. (2017, December). Frontal eeg alpha asymmetry and emotion: From neural underpinnings and methodological considerations to psychopathology and social cognition. *Psychophysiology*, *55*(1). Retrieved from http://dx.doi .org/10.1111/psyp.13028 doi: 10.1111/psyp.13028

Aylward, J., Valton, V., Ahn, W.-Y., Bond, R. L., Dayan, P., Roiser, J. P., & Robinson, O. J. (2019, June). Altered learning under uncertainty in unmedicated mood and anxiety disorders. *Nature Human Behaviour*, *3*(10), 1116–1123. Retrieved from https://doi.org/10.1038/s41562 -019-0628-0 doi: 10.1038/s41562-019-0628-0

Ban˜os, R. M., Lian˜o, V., Botella, C., Alcan˜iz, M., Guerrero, B., & Rey, B. (2006). Changing induced moods via virtual reality. In *International conference on persuasive technology* (pp. 7–15).

Beck, A. T. (1979). *Cognitive therapy of depression*. Guilford press.

Beck, A. T., & Dozois, D. J. (2011, February). Cognitive therapy: Current status and future directions. *Annual Review of Medicine*, *62*(1), 397–409. Retrieved from https://doi.org/10.1146/annurev -med-052209-100032 doi: 10.1146/annurev-med-052209-100032

Behrens, T. E. J., Woolrich, M. W., Walton, M. E., & Rushworth, M. F. S. (2007, August). Learning the value of information in an uncertain world. *Nature Neuroscience*, *10*(9), 1214–1221. Retrieved from https://doi.org/10.1038/nn1954 doi: 10.1038/nn1954

Bhanji, J., & Delgado, M. (2014). *The social brain and reward: Social information processing in the human striatum. wires cognitive science, 5 (1), 61–73.*

Bishop, S. J. (2007, July). Neurocognitive mechanisms of anxiety: an integrative account. *Trends in Cognitive Sciences*, *11*(7), 307–316. Retrieved from https://doi.org/10.1016/j.tics.2007.05 .008 doi: 10.1016/j.tics.2007.05.008

Blain, B., & Rutledge, R. B. (2020, November). Momentary subjective well-being depends on learning and not reward. *eLife*, *9*. Retrieved from https://doi.org/10.7554/elife.57977 doi: 10.7554/ elife.57977

Browning, M., Behrens, T. E., Jocham, G., O'Reilly, J. X., & Bishop, S. J. (2015, March). Anxious individuals have difficulty learning the causal statistics of aversive environments. *Nature Neuroscience*, *18*(4), 590–596. Retrieved from https://doi.org/10.1038/nn.3961 doi: 10.1038/nn.3961

Camacho, M. C., Balser, D. H., Furtado, E. J., Rogers, C. E., Schwarzlose, R. F., Sylvester, C. M., & Barch, D. M. (2024). Higher intersubject variability in neural response to narrative social stimuli among youth with higher social anxiety. *Journal of the American Academy of Child & Adolescent Psychiatry*, *63*(5), 549–560.

Cambria, E., Das, D., Bandyopadhyay, S., & Feraco, A. (2017). Affective computing and sentiment analysis. *A practical guide to sentiment analysis*, 1–10.

Cao, J., Gu, R., Bi, X., Zhu, X., & Wu, H. (2015). Unexpected acceptance? patients with social anxiety disorder manifest their social expectancy in erps during social feedback processing. *Frontiers in psychology*, *6*, 1745.

Chen, P.-H. A., Jolly, E., Cheong, J. H., & Chang, L. J. (2020). Intersubject representational similarity analysis reveals individual variations in affective experience when watching erotic movies. *NeuroImage*, *216*, 116851.

Clark, D. A., & Beck, A. T. (2010, September). Cognitive theory and therapy of anxiety and depression: Convergence with neurobiological findings. *Trends in Cognitive Sciences*, *14*(9), 418–424. Retrieved from https://doi.org/10.1016/j.tics.2010.06.007 doi: 10.1016/j.tics.2010.06.007

Coan, J. A., & Allen, J. J. (2004). Frontal eeg asymmetry as a moderator and mediator of emotion. *Biological psychology*, *67*(1-2), 7–50.

Cohen, J. D., Daw, N., Engelhardt, B., Hasson, U., Li, K., Niv, Y., ... others (2017). Computational approaches to fmri analysis. *Nature neuroscience*, *20*(3), 304–313.

Davidson, R. J. (1992, September). Anterior cerebral asymmetry and the nature of emotion. *Brain and Cognition*, *20*(1), 125–151. Retrieved from https://doi.org/10.1016/0278-2626(92)90065-t doi: 10.1016/0278-2626(92)90065-t

Davis, M. H. (1983, January). Measuring individual differences in empathy: Evidence for a multidimensional approach. *Journal of Personality and Social Psychology*, *44*(1), 113–126. Retrieved from https://doi.org/10.1037/0022-3514.44.1.113 doi: 10.1037/0022-3514.44.1.113

Delorme, A., & Makeig, S. (2004, March). EEGLAB: an open source toolbox for analysis of singletrial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, *134*(1), 9–21. Retrieved from https://doi.org/10.1016/j.jneumeth.2003.10.009 doi: 10.1016/j.jneumeth.2003.10.009

Deng, W., Heffner, J., & FeldmanHall, O. (2021). *Emotions and learning about social partners.* (Poster presented at Brown Univeristy)

Dunn, J. R., & Schweitzer, M. E. (2005). Feeling and believing: The influence of emotion on trust. *Journal of Personality and Social Psychology*, *88*(5), 736–748. Retrieved from https://doi.org/10.1037/0022-3514.88.5.736

Faul, L., Stjepanovi´c, D., Stivers, J. M., Stewart, G. W., Graner, J. L., Morey, R. A., & LaBar, K. S. (2020). Proximal threats promote enhanced acquisition and persistence of reactive fear-learning circuits. *Proceedings of the National Academy of Sciences*, *117*(28), 16678–16689.

Feldman Barrett, L., & Russell, J. A. (1998). Independence and bipolarity in the structure of current affect. *Journal of personality and social psychology*, *74*(4), 967.

FeldmanHall, O., & Heffner, J. (2022, December). A generalizable framework for assessing the role of emotion during choice. *American Psychologist*, *77*(9), 1017–1029. Retrieved from https://doi.org/10.1037/amp0001108 doi: 10.1037/amp0001108

Finn, E. S., Glerean, E., Khojandi, A. Y., Nielson, D., Molfese, P. J., Handwerker, D. A., & Bandettini, P. A. (2020, July). Idiosynchrony: From shared responses to individual differences during naturalistic neuroimaging. *NeuroImage*, *215*, 116828. Retrieved from https://doi.org/10.1016/j.neuroimage.2020.116828 doi: 10.1016/j.neuroimage.2020.116828

Gagne, C., Zika, O., Dayan, P., & Bishop, S. J. (2020, December). Impaired adaptation of learning to contingency volatility in internalizing psychopathology. *eLife*, *9*. Retrieved from https://doi.org/10.7554/elife.61387 doi: 10.7554/elife.61387

Garfinkel, S. N., Minati, L., Gray, M. A., Seth, A. K., Dolan, R. J., & Critchley, H. D. (2014). Fear from the heart: sensitivity to fear stimuli depends on individual heartbeats. *Journal of Neuroscience*, *34*(19), 6573–6582.

Gilbert, P. (2001, December). EVOLUTION AND SOCIAL ANXIETY: The role of attraction, social competition, and social hierarchies. , *24*(4), 723–751. Retrieved from https://doi.org/10.1016/ s0193-953x(05)70260-4 doi: 10.1016/s0193-953x(05)70260-4

Gramfort, A., Luessi, M., Larson, E., Engemann, D. A., Strohmeier, D., Brodbeck, C., ... H¨am¨al¨ainen, M. S. (2014, February). MNE software for processing MEG and EEG data. *NeuroImage*, *86*, 446–460. Retrieved from https://doi.org/10.1016/j.neuroimage.2013.10.027 doi: 10.1016/j.neuroimage.2013.10.027

Gratton, C., Nelson, S. M., & Gordon, E. M. (2022, May). Brain-behavior correlations: Two paths toward reliability. *Neuron*, *110*(9), 1446–1449. Retrieved from https://doi.org/10.1016/j.neuron.2022.04.018 doi: 10.1016/j.neuron.2022.04.018

Grupe, D. W., & Nitschke, J. B. (2013, June). Uncertainty and anticipation in anxiety: an integrated neurobiological and psychological perspective. *Nature Reviews Neuroscience*, *14*(7), 488–501. Retrieved from https://doi.org/10.1038/nrn3524 doi: 10.1038/nrn3524

Hasson, U., Nir, Y., Levy, I., Fuhrmann, G., & Malach, R. (2004, March). Intersubject synchronization of cortical activity during natural vision. *Science*, *303*(5664), 1634–1640. Retrieved from https://doi.org/10.1126/science.1089506 doi: 10.1126/science.1089506

Heffner, J., & FeldmanHall, O. (2022, March). A probabilistic map of emotional experiences during competitive social interactions. *Nature Communications*, *13*(1). Retrieved from https://doi.org/10.1038/s41467-022-29372-8 doi: 10.1038/s41467-022-29372-8

Hein, T. P., de Fockert, J., & Ruiz, M. H. (2021, January). State anxiety biases estimates of uncertainty and impairs reward learning in volatile environments. *NeuroImage*, *224*, 117424. Retrieved from https://doi.org/10.1016/j.neuroimage.2020.117424 doi: 10.1016/j.neuroimage.2020.117424

Hu, X., Wang, F., & Zhang, D. (2022, February). Similar brains blend emotion in similar ways: Neural representations of individual difference in emotion profiles. *NeuroImage*, *247*, 118819. Retrieved from https://doi.org/10.1016/j.neuroimage.2021.118819 doi: 10.1016/j.neuroimage.2021.118819

Hu, X., Yu, J., Song, M., Yu, C., Wang, F., Sun, P., ... Zhang, D. (2017, January). EEG correlates of ten positive emotions. *Frontiers in Human Neuroscience*, *11*. Retrieved from https://doi.org/10.3389/fnhum.2017.00026 doi: 10.3389/fnhum.2017.00026

Ip, K. I., Miller, A. L., Karasawa, M., Hirabayashi, H., Kazama, M., Wang, L., ... Tardif, T. (2021, January). Emotion expression and regulation in three cultures: Chinese, japanese, and american preschoolers' reactions to disappointment. *Journal of Experimental Child Psychology*, *201*, 104972. Retrieved from https://doi.org/10.1016/j.jecp.2020.104972 doi: 10.1016/j.jecp.2020.104972

Izuma, K., Saito, D. N., & Sadato, N. (2008, April). Processing of social and monetary rewards in the human striatum. *Neuron*, *58*(2), 284–294. Retrieved from https://doi.org/10.1016/ j.neuron.2008.03.020 doi: 10.1016/j.neuron.2008.03.020

Kao, C.-H., Feng, G. W., Hur, J. K., Jarvis, H., & Rutledge, R. B. (2023, February). Computational models of subjective feelings in psychiatry. *Neuroscience &amp Biobehavioral Reviews*, *145*, 105008. Retrieved from https://doi.org/10.1016/j.neubiorev.2022.105008 doi: 10.1016/j.neubiorev .2022.105008

Kashdan, T. B., & Roberts, J. E. (2007, January). Social anxiety, depressive symptoms, and post-event rumination: Affective consequences and social contextual influences. *Journal of Anxiety Disorders*, *21*(3), 284–301. Retrieved from https://doi.org/10.1016/j.janxdis.2006.05.009 doi: 10 .1016/j.janxdis.2006.05.009

Khanna, A., Pascual-Leone, A., Michel, C. M., & Farzan, F. (2015). Microstates in resting-state eeg: current status and future directions. *Neuroscience & Biobehavioral Reviews*, *49*, 105–113.

Kleef, G. A. V. (2009, June). How emotions regulate social life. *Current Directions in Psychological Science*, *18*(3), 184–188. Retrieved from https://doi.org/10.1111/j.1467-8721.2009.01633.x doi: 10.1111/j.1467-8721.2009.01633.x

Koller-Schlaud, K., Str¨ohle, A., B¨arwolf, E., Behr, J., & Rentzsch, J. (2020). Eeg frontal asymmetry and theta power in unipolar and bipolar depression. *Journal of affective disorders*, *276*, 501–510.

Lamba, A., Frank, M. J., & FeldmanHall, O. (2020, April). Anxiety impedes adaptive social learning under uncertainty. *Psychological Science*, *31*(5), 592–603. Retrieved from https://doi.org/10.1177/0956797620910993 doi: 10.1177/0956797620910993

Lee, A. M., Sturm, V., Dawes, H., Krystal, A. D., & Chang, E. (2024). Human anterior insular cortex encodes multiple electrophysiological representations of anxiety-related behaviors. *bioRxiv*, 2024–03.

Maffei, A., Polver, S., Spironelli, C., & Angrilli, A. (2020, August). EEG gamma activity to emotional movies in individuals with high traits of primary "successful" psychopathy. *Brain and Cognition*, *143*, 105599. Retrieved from https://doi.org/10.1016/j.bandc.2020.105599 doi: 10.1016/j.bandc.2020.105599

Makowski, D., Pham, T., Lau, Z. J., Brammer, J. C., Lespinasse, F., Pham, H., ... Chen, S. H. A. (2021, February). NeuroKit2: A python toolbox for neurophysiological signal processing. *Behavior Research Methods*, *53*(4), 1689–1696. Retrieved from https://doi.org/10.3758/ s13428-020-01516-y doi: 10.3758/s13428-020-01516-y

Mathersul, D., Williams, L. M., Hopkinson, P. J., & Kemp, A. H. (2008). Investigating models of affect: Relationships among EEG alpha asymmetry, depression, and anxiety. *Emotion*, *8*(4), 560–572. Retrieved from https://doi.org/10.1037/a0012811 doi: 10.1037/a0012811

Melo, M., Goncalves, G., Monteiro, P., Coelho, H., Vasconcelos-Raposo, J., & Bessa, M. (2022, February). Do multisensory stimuli benefit the virtual reality experience? a systematic review. *IEEE Transactions on Visualization and Computer Graphics*, *28*(2), 1428–1442. Retrieved from https://doi.org/10.1109/tvcg.2020.3010088 doi: 10.1109/tvcg.2020.3010088

Nastase, S. A., Gazzola, V., Hasson, U., & Keysers, C. (2019, May). *Measuring shared responses across subjects using intersubject correlation.* Oxford University Press (OUP). Retrieved from https://doi.org/10.1093/scan/nsz037 doi: 10.1093/scan/nsz037

Neuhaus, E., Santhosh, M., Kresse, A., Aylward, E., Bernier, R., Bookheimer, S., ... others (2023). Frontal eeg alpha asymmetry in youth with autism: Sex differences and social–emotional correlates. *Autism Research*, *16*(12), 2364–2377.

Pessiglione, M., Petrovic, P., Daunizeau, J., Palminteri, S., Dolan, R. J., & Frith, C. D. (2008, August). Subliminal instrumental conditioning demonstrated in the human brain. *Neuron*, *59*(4), 561–567. Retrieved from https://doi.org/10.1016/j.neuron.2008.07.005 doi: 10.1016/j.neuron.2008.07 .005

Pham, T., Lau, Z. J., Chen, S. H. A., & Makowski, D. (2021, June). Heart rate variability in psychology: A review of HRV indices and an analysis tutorial. *Sensors*, *21*(12), 3998. Retrieved from https://doi.org/10.3390/s21123998 doi: 10.3390/s21123998

Pion-Tonachini, L., Kreutz-Delgado, K., & Makeig, S. (2019, September). ICLabel: An automated electroencephalographic independent component classifier, dataset, and website. *NeuroImage*, *198*, 181–197. Retrieved from https://doi.org/10.1016/j.neuroimage.2019.05.026 doi: 10.1016/j.neuroimage.2019.05.026

Riva, G., Mantovani, F., Capideville, C. S., Preziosa, A., Morganti, F., Villani, D., ... Alcan˜iz, M. (2007). Affective interactions using virtual reality: the link between presence and emotions. *Cyberpsychology & behavior*, *10*(1), 45–56.

Russell, J. A. (1980). A circumplex model of affect. *Journal of personality and social psychology*, *39*(6), 1161.

Rutledge, R. B., Skandali, N., Dayan, P., & Dolan, R. J. (2014, August). A computational and neural model of momentary subjective well-being. *Proceedings of the National Academy of Sciences*, *111*(33), 12252–12257. Retrieved from https://doi.org/10.1073/pnas.1407535111 doi: 10 .1073/pnas.1407535111

Sanfey, A. G., Rilling, J. K., Aronson, J. A., Nystrom, L. E., & Cohen, J. D. (2003). The neural basis of economic decision-making in the ultimatum game. *Science*, *300*(5626), 1755–1758.

Saxena, A., Khanna, A., & Gupta, D. (2020). Emotion recognition and detection methods: A comprehensive survey. *Journal of Artificial Intelligence and Systems*, *2*(1), 53–79.

Schneider, T. R., Hipp, J. F., Domnick, C., Carl, C., Bu¨chel, C., & Engel, A. K. (2018). Modulation of neuronal oscillatory activity in the beta-and gamma-band is associated with current individual anxiety levels. *NeuroImage*, *178*, 423–434.

Stein, M. B., & Stein, D. J. (2008, March). Social anxiety disorder. *The Lancet*, *371*(9618), 1115–1125. Retrieved from https://doi.org/10.1016/s0140-6736(08)60488-2 doi: 10.1016/s0140-6736(08) 60488-2

Stellar, J. E., Cohen, A., Oveis, C., & Keltner, D. (2015, April). Affective and physiological responses to the suffering of others: Compassion and vagal activity. *Journal of Personality and Social Psychology*, *108*(4), 572–585. Retrieved from https://doi.org/10.1037/pspi0000010 doi: 10.1037/pspi0000010

Suhaimi, N. S., Mountstephens, J., & Teo, J. (2020, September). EEG-based emotion recognition: A state-of-the-art review of current trends and opportunities. *Computational Intelligence and Neuroscience*, *2020*, 1–19. Retrieved from https://doi.org/10.1155/2020/8875426 doi: 10.1155/2020/8875426

Thayer, J. F., & Koenig, J. (2019). Resting cerebral blood flow and ethnic differences in heart rate variability: links to self-reports of affect and affect regulation. *Neuroimage*, *202*, 116154.

Thibodeau, R., Jorgensen, R. S., & Kim, S. (2006). Depression, anxiety, and resting frontal eeg asymmetry: a meta-analytic review. *Journal of abnormal psychology*, *115*(4), 715.

Tomarken, A. J., Davidson, R. J., Wheeler, R. E., & Kinney, L. (1992, September). Psychometric properties of resting anterior EEG asymmetry: Temporal stability and internal consistency. *Psychophysiology*, *29*(5), 576–592. Retrieved from https://doi.org/10.1111/j.1469-8986.1992.tb02034.x doi: 10.1111/j.1469-8986.1992.tb02034.x

Wang, D., Liu, T., & Shi, J. (2020). Neural dynamic responses of monetary and social reward processes in adolescents. *Frontiers in Human Neuroscience*, *14*, 141.

Wang, J., Barstein, J., Ethridge, L. E., Mosconi, M. W., Takarae, Y., & Sweeney, J. A. (2013). Resting state eeg abnormalities in autism spectrum disorders. *Journal of neurodevelopmental disorders*, *5*, 1–14.

Wang, R., Yu, R., Tian, Y., & Wu, H. (2022, November). Individual variation in the neurophysiological representation of negative emotions in virtual reality is shaped by sociability. *NeuroImage*, *263*, 119596. Retrieved from https://doi.org/10.1016/j.neuroimage.2022.119596 doi: 10.1016/ j.neuroimage.2022.119596

WHEELER, R. E., DAVIDSON, R. J., & TOMARKEN, A. J. (2007, January). Frontal brain asymmetry and emotional reactivity: A biological substrate of affective style. *Psychophysiology*, *30*(1), 82–89. Retrieved from https://doi.org/10.1111/j.1469-8986.1993.tb03207.x doi: 10.1111/j.1469-8986.1993.tb03207.x

Wu, H., Fung, B. J., & Mobbs, D. (2022, February). Mentalizing during social interaction: The development and validation of the interactive mentalizing questionnaire. *Frontiers in Psychology*, *12*. Retrieved from https://doi.org/10.3389/fpsyg.2021.791835 doi: 10.3389/fpsyg.2021.791835

Yu, M., Xiao, S., Hua, M., Wang, H., Chen, X., Tian, F., & Li, Y. (2022). Eeg-based emotion recognition in an immersive virtual reality environment: From local activity to brain network features. *Biomedical Signal Processing and Control*, *72*, 103349.

Zhang, H., Zhang, K., Zhang, Z., Zhao, M., Liu, Q., Luo, W., & Wu, H. (2021). Inter-trial variations in eeg predict the individual differences in social tasks. *bioRxiv*, 2021–10.

Zheng, W.-L., Dong, B.-N., & Lu, B.-L. (2014, August). Multimodal emotion recognition using EEG and eye tracking data. In *2014 36th annual international conference of the IEEE engineering in medicine and biology society.* IEEE. Retrieved from https://doi.org/10.1109/embc.2014.6944757 doi: 10.1109/embc.2014.6944757