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RESEARCH ARTICLE

Similarities and Differences in Emotional Processing Between Children With and Without Autism Spectrum Disorder: Evidence from an Electroencephalogram Case Study

Jingying Chen[a‡], Naiqian Mao[a‡], Zhiyi Yang[a], Xiaoyu Hu[a], Dan Chen[b], Yiping Zuo[b], Tengfei Gao[a]

[a] Faculty of Artificial Intelligence in Education, Central China Normal University, Wuhan 430079, China

[b] School of Computer Science, Wuhan University, Wuhan 430072, China

Abstract Autism, also known as autism spectrum disorder (ASD), is a neurodevelopmental condition associated with differences in emotional processing and social communication. Electroencephalogram (EEG) analysis presents a unique avenue for exploring its underlying neural evolutionary mechanisms. To this end, this study explored the similarities and differences in emotional processing between children with ASD (ASD group) and those without ASD (control group) using EEG. The final analysis included 45 children: 22 with ASD (mean age = 5.29, age range: 2–8) and 23 without ASD (mean age = 4.37, age range: 2–6). EEG signals were synchronously collected during stimulation with a series of emotional videos. The *t*-tests on the collected EEG data were performed to determine any statistical differences in power spectral density, sample entropy, and differential entropy values between the groups. A functional connectivity analysis was also performed for a more comprehensive understanding. SHapley Additive exPlanations (SHAP) were applied to validate the findings, ensuring their robustness and reliability. The results showed that the ASD group exhibited reduced beta-band activity in the frontal regions and enhanced delta-band activity in the temporo–occipital areas compared to the control group. Entropy analyses revealed lower brain complexity in the ASD group. Functional connectivity results showed increased high-frequency synchronization in the ASD group but more coordinated low-frequency connectivity patterns in the control group. Moreover, the application of SHAP-based analysis with XGBoost confirmed the significance and predictive value of beta- and delta-band features in the frontal and occipital regions, providing potential biomarkers for distinct emotional processing in individuals with ASD. Overall, this study holds potential to facilitate the understanding of the neuronal mechanisms underlying emotional processing in individuals with ASD and inform the development of targeted neurotherapeutic interventions.

Keywords autism spectrum disorder, electroencephalogram, SHapley Additive exPlanations, emotional processing

1 Introduction

Autism, also known as autism spectrum disorder (ASD), is characterized by difficulties in social communication and restrictive and repetitive behaviors (American Psychiatric Association, 2013). Previous studies suggested that children with ASD often struggle with social interaction, nonverbal communication, facial emotional processing, and interpreting others' emotions (Billstedt et al., 2005; Brewer et al., 2016; Elbich & Scherf, 2017). A meta-analysis on emotion recognition abilities reported that, even after correcting for publication bias, children with ASD continue to exhibit moderate challenges in overall emotional recognition (Uljarevic & Hamilton, 2013). It further suggested that these children show significant difficulties in recognizing all basic emotions except happiness, with difficulties in recognizing fear being slightly greater than those in recognizing happiness, aligning with the findings of Lozier et al. (2014). However, some studies did not report such challenges or have only identified difficulties in recognizing specific basic emotions (Harms et al., 2010; Yeung, 2022). Several studies suggest that children with ASD sometimes show a within-group advantage, that is, the ability to

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Tengfei Gao (✉)
E-mail: tengfei.gao@ccnu.edu.cn

‡These authors contributed equally to this work and should be considered as co-first authors.

recognize the facial expressions of their autistic peers more accurately than those without ASD (Edey et al., 2016).

Children with ASD exhibit different abilities in recognizing facial emotions and processing emotions compared to those without ASD (Nuske et al., 2013). Existing theories examined the emotional–cognitive differences in ASD from various viewpoints. All agreed that the development of emotional recognition has an inherent neuronal basis and that difficulties in the relevant brain regions may be the underlying cause of the impairment (Mason & Capitanio, 2012). The perception of emotional expressions activates key emotion-related brain regions, including the amygdala, insula, and limbic system, and varies depending on age and task context. Reportedly, children with ASD show reduced activation in the fusiform face area during face-matching tasks, a brain region considered central to face detection and recognition (Pereira et al., 2019). A task-based and resting-state functional magnetic resonance imaging (fMRI) study reported reduced activation in the right posterior superior temporal sulcus and decreased intrinsic functional connectivity with the frontoparietal action observation network, both of which were found to predict individual differences in emotional recognition ability (Alaerts et al., 2014). In an fMRI study examining self-face recognition and the experience of embarrassment, children with ASD showed reduced activation in the right anterior insula, along with decreased functional connectivity between the anterior cingulate cortex and the medial prefrontal cortex (Morita et al., 2016). A meta-analysis reported that children with ASD exhibit more pronounced reductions in the activity of the amygdala and parahippocampal regions compared to those without ASD (Costa et al., 2021).

Most of this evidence has been obtained from fMRI studies. However, it is noteworthy that while fMRI provides valuable spatial information, it is limited in temporal resolution. Electroencephalogram (EEG) is a widely used method with high temporal sensitivity that enables the capture of rapid neuronal dynamics during emotional processing in children with ASD (Bosl et al., 2018). A recent study on EEG functional connectivity, oscillatory power, and broadband aperiodic activity during dynamic facial emotional processing tasks in children without ASD found that enhanced theta- and beta-band connectivity related to facial emotional processing was positively correlated with higher Social Responsiveness Scale, Second Edition scores. This suggests that children without ASD exhibiting more ASD-related traits demonstrate stronger theta- and beta-band connectivity when processing facial emotions (Hill et al., 2025). EEG in children with ASD exhibits divergent neuronal oscillatory dynamics during emotional stimulus exposure, suggestive of distinct neurocognitive mechanisms underlying their emotional processing (Peng et al., 2021).

An EEG study on emotional perception in children with ASD using auditory stimuli reported that both groups of children showed similar EEG and emotional responses to fearful sounds, characterized by increased power in the alpha band and reduced power in lower frequency bands (Portnova & Maslennikova, 2020). However, when exposed to crying and laughing sounds, children with ASD exhibited atypical EEG patterns compared to those without ASD. Similarly, Maslennikova et al. (2022) reported that while both groups exhibited comparable EEG oscillatory responses to fearful and angry prosody, there were significant group differences in the power spectral density (PSD) during the processing of sad and joyful prosody. Moreover, EEG responses to emotional prosody in the ASD group showed reduced hemispheric asymmetry compared to the control group. This research indicated that children with ASD exhibited reduced theta coherence in the right frontal region when compared to those without ASD. Taken together, these studies demonstrate that EEG oscillatory measures, particularly PSD, are highly sensitive to differences in emotional processing between two groups.

The present study employed a comprehensive analytical framework to characterize the temporal dynamics of latent neuronal features under dynamic emotional stimuli. Videos were widely used as experimental stimuli in neurophysiological experiments for emotion induction, which contained rich audiovisual information and offered realistic and vivid scenarios for evoking various human emotions in a laboratory environment. By analyzing the EEG signals of both groups when positive and negative emotions are induced, this research examined band-limited PSD, entropy-based neuronal complexity, and phase-based functional connectivity at specific brain regions and across networks. Compared to the existing studies, this research employed a more comprehensive analytical approach by proposing an interpretable machine learning model that integrates XGBoost and SHapley Additive exPlanations (SHAP) to classify children with and without ASD and analyze key features, which facilitates a mechanistic interpretation of the research outcomes through explainable AI techniques.

This study aimed at exploring the similarities and differences in emotional processing between both groups and thereby enhancing understanding of the neuronal mechanisms. We hypothesized that, under different emotional stimuli, children with ASD would exhibit distinctive characteristics in PSD, sample entropy (SE), and functional connectivity compared to those without ASD. In addition, we expected that the

application of a SHAP model based on XGBoost would yield results consistent with the group-level differences, thereby providing additional evidence for potential biomarkers relevant to distinguishing children with ASD from those without ASD.

2 Materials and Methods

2.1 | Participants

This research was authorized by the Ethics Committee of the Central China Normal University, China. Parents read the consent form and then signed on it. A total of 75 children (with and without ASD) were recruited for the study; however, not all could be included in the final analysis for two main reasons. First, the quality of EEG data collected from some children was compromised due to a lack of cooperation. After preprocessing, participants whose number of bad segments exceeded 30% of the total were excluded. As a result, 9 participants each were excluded from both ASD group and control group to ensure the reliability and accuracy of the analysis results. Second, to ensure comparability between both groups and to avoid statistical bias caused by sample size differences, given the smaller sample size of the ASD group, 12 additional participants were excluded from the control group based on the number of segments. In the end, 45 sets of valid data were included in the analysis: 22 children with ASD (mean age = 5.29, age range: 2–8) and 23 age-matched children without ASD (mean age = 4.37, age range: 2–6).

2.2 | EEG Collection and Preprocessing

An overview of the experimental paradigm, data acquisition, data preprocessing, and subsequent analytical procedures is presented in Figure 1. The experimental procedure employed emotional video clips to elicit positive and negative emotions in children, during which EEG signals were recorded and subsequently preprocessed (Figure 1(a)). The stimulus materials consisted of a positive emotional video compiled from emotional materials (total duration: 56 s), followed by a negative emotional video edited from selected clips (total duration: 131 s). Each participant completed the experiment in the separate classroom. The experimental procedure was as follows:

(1) Posture calibration: Participants sat 50–60 cm from the display screen. After explaining the requirements to the children and their guardians, they were asked to maintain fixation on a central cross.

(2) EEG preparation: With the EEG headset properly placed, baseline data collection started when participants were relaxed. Positive emotional videos were presented first, followed by negative emotional videos without asking for responses.

(3) Rest interval: A 5-min rest separated positive and negative valence trials.

(4) Emotion check: After watching each video, children were asked to verbally identify the perceived emotion to ensure they understood the emotional content.

(5) Data saving: Once the experiment concluded, EEG recordings were saved for subsequent analysis.

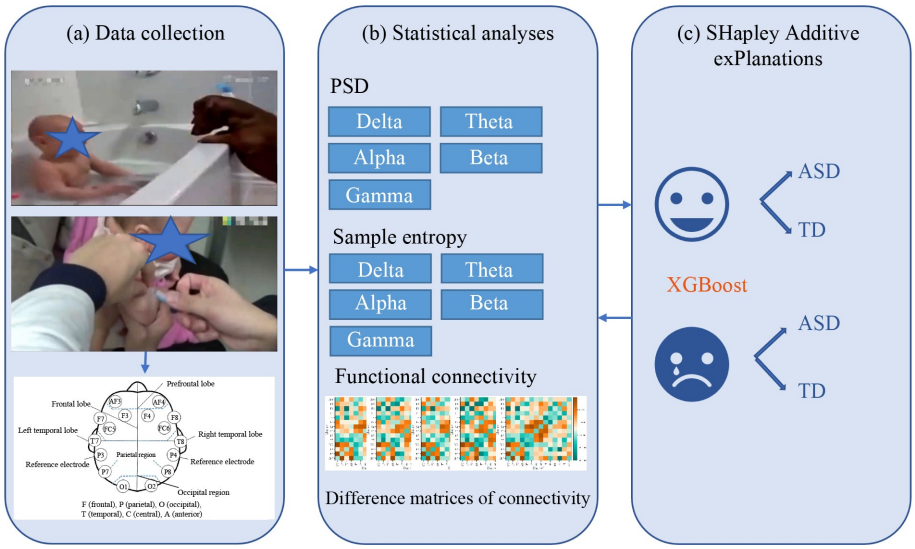

Figure 1 Experimental flow chart. (a) Data collection: Emotional video clips were used to elicit positive and negative emotions in children, during which EEG signals were recorded and subsequently preprocessed; (b) statistical analyses: Under different emotional stimuli, multiple features across five frequency bands were extracted for group-level analysis; (c) SHapley Additive exPlanations (SHAP): An XGBoost classifier was applied and SHAP was used to assess feature importance, thereby examining the contribution of EEG features. PSD: power spectral density, ASD: autism spectrum disorder, TD: typical development.

The order of video presentation was consistent across participants. By deliberately controlling the sequence of emotional stimuli, the purpose was to ensure that each participant received the negative and positive emotional stimuli in the same sequence and to minimize potential order effects interfering with the experimental results, which allows for the accuracy of the impact.

EEG signals were recorded using EMOTIV EPOC+ (a portable EEG device for scalable and contextual human brain). To effectively capture brain activity related to emotional processing, 14 EEG channels were selected (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4) from the international 10–20 system, covering key brain regions, such as the frontal, parietal, occipital, and temporal lobes (see Table 1). These electrode positions have been validated in multiple studies and are known to effectively reflect the activity of different brain regions during emotional processing (Cai et al., 2025; Fan et al., 2018).

EEG preprocessing pipeline involved applying a Finite Impulse Response bandpass filter between 1 and 60 Hz, which was then down-sampled to 128 Hz using EEGLAB's filtering functions. Subsequently, independent component analysis was performed to identify and remove artifactual components caused by eye and muscle activity. Then, all of the EEG channels were manually rechecked to reject epochs that were still contaminated by the artifacts. Finally, the continuous epochs after rejection were segmented using a sliding window with a length of 2 s and an overlap of 1 s, resulting in a total of 7,616 EEG epochs.

2.3 | Statistical Analyses

To fully explore the similarities and differences in the brain evolution characteristics between both groups under different emotional stimuli, this study extracted multiple EEG features across five frequency bands (delta [1, 4) Hz, theta [4, 6) Hz, alpha [6, 13) Hz, beta [13, 30) Hz, and gamma [30, 45] Hz) (Figure 1(b)). The data were subjected to PSD, SE, and functional connectivity analyses to investigate the neuronal underpinnings of emotional processing in children with ASD from multiple perspectives.

IBM SPSS Statistics 25 was used to perform statistical analyses, including descriptive statistics, independent-samples *t*-test, and effect size calculations. To compare the differences in EEG features related to emotional processing between ASD group and control group under different emotional stimuli, statistical comparisons of the extracted EEG features were performed. Specifically, independent-samples *t*-tests were performed on the PSD, SE, and differential entropy (DE) for each frequency band to compare EEG features between the groups under both positive and

Table 1 *t*-test results for PSD across frequency bands under positive stimuli

Frequency band	EEG channel	*F*	*p*	*t*
Delta	AF3	0.999	0.001	3.513
	F7	0.119	0.003	3.142
	T7	2.256	0.031	2.231
	P7	0.526	0.005	2.960
	O1	0.552	0.001	3.656
	O2	3.495	0.001	3.631
	P8	0.845	0.005	2.952
	T8	2.143	0.037	2.150
	FC5	0.012	0.002	3.316
	F4	1.693	0.004	3.016
	F8	0.124	0.000	3.787
	AF4	3.776	0.005	2.964
Theta	AF3	0.078	0.028	−2.271
	F3	0.031	0.015	−2.574
	FC6	0.209	0.045	−2.598
	P7	1.094	0.006	−2.911
	O1	0.137	0.007	−2.820
	F4	0.095	0.024	−2.333
	AF4	0.151	0.049	−2.025
Alpha	AF3	0.230	0.015	−2.542
	F3	0.029	0.008	−2.778
	FC5	0.098	0.045	−0.267
	T7	0.437	0.006	−2.867
	P7	2.514	0.006	−2.911
	O1	5.231	0.005	−2.985
	O2	1.335	0.004	−2.998
	P8	0.672	0.006	−2.886
	T8	0.215	0.004	−2.167
	FC6	0.110	0.009	−2.783
	F4	0.032	0.037	−2.157
	AF4	1.165	0.015	−2.543
Beta	AF3	0.235	0.004	−3.067
	F7	2.182	0.000	−3.893
	O1	0.055	0.032	−2.124
	P8	0.068	0.030	−2.248
	FC6	1.306	0.009	−2.719
	F4	0.100	0.041	−2.109
	F8	0.554	0.000	−3.841
	AF4	2.889	0.012	−2.614
Gamma	F7	1.527	0.020	−2.424
	O2	0.074	0.037	−2.155
	F8	0.076	0.013	−2.606

Notes. *F* denotes the statistic from analysis of variance, *p* is the two-tailed *p*-value, and *t* is the independent-samples *t* statistic. PSD: power spectral density, EEG: electroencephalogram.

negative emotional stimuli. Only those features that reached statistical significance were reported. The corrected p-value threshold for significance was set at 0.05 divided by the number of pairwise comparisons conducted, ensuring that the family-wise error rate was controlled. In addition, a Bonferroni correction was applied for multiple comparisons to minimize the risk of type I errors.

This study also calculated the phase locking value (PLV) to investigate the functional connectivity between different brain regions under emotional stimuli. PLV measures phase differences in EEG signals, revealing the differences in brain functional connectivity between ASD group and control group. To validate the effectiveness of EEG features, we employed the XGBoost classifier and conducted feature importance analysis using SHAP (Figure 1(c)). SHAP quantifies the contribution of each feature to the model's predictions, helping us interpret which EEG features have a significant impact on ASD-related classification tasks.

2.4 | Validation via SHAP

SHAP uses Shapley values from game theory to interpret black-box models. The resulting Shapley value of each feature quantifies its impact on predictions, allowing for precise feature quantification (Hardin & Rocke, 2004).

We performed classification between ASD group and control group (with typical development) based on EEG signals under different emotional stimuli (Figure 1(c)). Using a total of 210 features extracted from 14 EEG channels and 5 frequency bands, including PSD, SE, and DE, we employed the XGBoost classifier to accomplish the discrimination task. Next, SHAP was utilized to analyze the contribution of each feature. The results obtained were then compared with the conclusions drawn from the above statistical analysis to verify their correctness.

3 Results

3.1 | PSD Analysis

Independent-samples t-tests revealed significant differences in EEG characteristics between ASD group and control group when presented with both positive and negative emotional stimuli.

When exposed to positive emotional stimuli, ASD group exhibited a significant increase in the PSD within the delta frequency band across many EEG channels, particularly in the frontal, parietal, occipital, and temporal lobes (Table 1). Precisely, compared to the control group, the ASD group showed increased PSD in the delta frequency band at F8 (F = 0.124, t = 3.787, p < 0.001, d = 1.129, here F denoting the statistic from analysis of variance, t indicating the independent-samples t statistic, p denoting the two-tailed p-value, and d indicating Cohen's d), O1 (F = 0.552, t = 3.656, p < 0.001, d = 1.090), O2 (F = 3.495, t = 3.631, p < 0.001, d = 1.083), and T8 (F = 2.143, t = 2.150, p < 0.050, d = 0.641) electrodes. Similarly, ASD group exhibited a significant increase in the PSD within the beta frequency band in the frontal region. However, compared to the control group, beta PSD at F7 (F = 2.182, t = –3.893, p < 0.001, d = 1.145) and F8 (F = 0.554, t = –3.841, p < 0.001, d = 1.145) electrodes were significantly lower in the ASD group.

When exposed to negative emotional stimuli, ASD group exhibited significant alterations in the PSD of the beta and delta frequency bands in the frontal, temporal, and occipital lobes (Table 2). These findings suggested the presence of atypical high- and low-frequency activity patterns that could be associated with emotional processing. Compared to the control group, the beta-band PSD at T7 (F = 0.001, t = –3.346, p < 0.050, d = 0.998), T8 (F = 0.027, t = –2.569, p < 0.050, d = 0.766), and FC5 (F = 0.046, t = –2.967, p < 0.050, d = 0.885) electrodes was significantly lower and delta-band PSD at T8 (F = 1.021, t = 3.127, p < 0.050, d = 0.933) and O1 (F = 0.362, t = 3.091,

Table 2 t-test results for PSD across frequency bands under negative stimuli

Frequency band	EEG channel	F	p	t
Delta	FC5	2.356	0.024	2.343
	T7	3.230	0.004	3.035
	P7	1.183	0.009	2.734
	O1	0.362	0.003	3.091
	O2	0.959	0.011	2.662
	P8	0.465	0.007	2.841
	T8	1.021	0.003	3.127
	FC6	0.004	0.021	–2.400
	F8	0.920	0.036	2.162
Alpha	O1	0.001	0.009	–2.746
Beta	F7	0.264	0.005	–2.996
	FC5	0.046	0.005	–2.967
	T7	0.001	0.002	–3.346
	P7	1.338	0.006	–2.872
	O1	1.567	0.022	–2.368
	O2	0.457	0.013	–2.596
	P8	0.544	0.010	–2.963
	T8	0.027	0.014	–2.569
	FC6	0.004	0.021	–2.400

Notes. F denotes the statistic from analysis of variance, p is the two-tailed p-value, and t is the independent-samples t statistic. PSD: power spectral density, EEG: electroencephalogram.

$p < 0.050$, $d = 0.922$) electrodes was significantly higher in the ASD group. Overall, the results suggested that, when exposed to negative emotional stimuli, children with ASD exhibited relatively reduced high-frequency activity in the frontal and temporal lobes, accompanied by increased low-frequency activity.

In addition to the most prominent differences described above, significant group differences were also observed in other frequency bands and at specific electrode positions. These findings indicate that the observed variations in brain electrical activity are not isolated but rather indicate broad neurological differences related to how the brain processes emotions in children with ASD compared to those without ASD.

3.2 | Entropy Analysis

The analysis showed a significant difference in SE values between ASD and control groups in the medium- and high-frequency bands. When exposed to positive and negative emotional stimuli, significant differences in the entropy values of frontal regions FC6 ($F = 0.310$, $t = -2.149$, $p < 0.050$, $d = 0.641$) and F3 ($F = 0.050$, $t = -2.125$, $p < 0.050$, $d = 0.634$) in the alpha frequency band were observed (Tables 3 and 4). When children feel happy, their brains normally exhibit heightened activity, particularly in areas of cognition and attention, resulting in elevated EEG activity. However, here, when the ASD group was exposed to positive emotional stimuli, the entropy value at high frequency in the occipital lobe O2 ($F = 0.039$, $t = -2.207$, $p < 0.050$, $d = 0.658$) and the frontal lobe FC6 ($F = 0.005$, $t = -2.197$, $p < 0.050$, $d = 0.634$) were significantly low. These findings suggest that children with ASD have a lower entropy value than those without ASD, implying that the reduced complexity and randomness in brain activity could be due to insufficient brain development.

A comparison of DE values of both groups when exposed to two emotional stimuli showed differences in the low- and high-frequency band entropy values (Tables 5 and 6). Under positive emotional stimuli, significant differences between the groups were observed in the frontal lobe regions, particularly in AF3 ($F = 1.541$, $t = 2.190$, $p < 0.050$, $d = 0.653$) and FC6 ($F = 0.005$, $t = 2.468$, $p < 0.050$, $d = 0.736$). Similarly, significant differences were observed between the groups under negative emotional stimuli (e.g., AF4, $F = 0.804$, $t = 2.607$, $p < 0.050$, $d = 0.777$). According to a previous study, the entropy value of EEG signals in children with ASD is often lower than that in neurotypical children (Kang et al., 2019). In this study, the entropy value of the frontal lobe in both groups inside the delta frequency band was considerably elevated compared to that of the control group under the two emotional stimuli. DE value in the beta frequency band of the ASD group was markedly lower than that of the control group. Significant differences in gamma frequency band entropy value were seen in the frontal and temporal lobes of both groups solely under positive emotional stimuli.

Table 3 *t*-test results for SE across frequency bands under positive stimuli

Frequency band	EEG channel	*F*	*p*	*t*
Alpha	P7	0.284	0.013	−2.582
	FC6	0.310	0.037	−2.149
Beta	F4	0.509	0.041	−2.110
	FC6	0.005	0.033	−2.197
Gamma	O2	0.039	0.033	−2.207

Notes. *F* denotes the statistic from analysis of variance, *p* is the two-tailed *p*-value, and *t* is the independent-samples *t* statistic. SE: sample entropy, EEG: electroencephalogram.

Table 4 *t*-test results for SE across frequency bands under negative stimuli

Frequency band	EEG channel	*F*	*p*	*t*
Alpha	F3	0.050	0.039	−2.125

Notes. *F* denotes the statistic from analysis of variance, *p* is the two-tailed *p*-value, and *t* is the independent-samples *t* statistic. SE: sample entropy, EEG: electroencephalogram.

Table 5 *t*-test results for DE across frequency bands under positive stimuli

Frequency band	EEG channel	*F*	*p*	*t*
Delta	AF3	1.541	0.034	2.190
	F7	0.470	0.032	2.214
	T7	2.095	0.011	2.600
	P7	2.643	0.017	2.493
	FC6	0.005	0.018	2.468
Beta	FC5	0.843	0.001	−3.546
	FC6	0.006	0.004	−3.020
Gamma	T7	1.338	0.048	−2.038
	F8	0.392	0.030	2.240

Notes. *F* denotes the statistic from analysis of variance, *p* is the two-tailed *p*-value, and *t* is the independent-samples *t* statistic. DE: differential entropy, EEG: electroencephalogram.

Table 6 *t*-test results for DE across frequency bands under negative stimuli

Frequency band	EEG channel	*F*	*p*	*t*
Delta	AF3	0.000	0.006	2.881
	AF4	0.804	0.013	2.607
Beta	F7	5.519	0.048	2.033
	FC5	0.491	0.003	−3.115

Notes. *F* denotes the statistic from analysis of variance, *p* is the two-tailed *p*-value, and *t* is the independent-samples *t* statistic. DE: differential entropy, EEG: electroencephalogram.

3.3 | Functional Connectivity Analysis

PLV assesses the degree of phase synchronization between signals by calculating the phase differences. The connectivity differences between ASD group and control group when exposed to negative and positive emotional stimuli are illustrated in Figure 2. Each matrix illustrates the between-group differences in PLV. The rows and columns correspond to EEG electrode positions, and the color values indicate the magnitude and direction of the differences. Warm colors represent stronger phase synchronization in ASD group relative to the control group, whereas cool colors indicate stronger phase synchronization in the control group relative to ASD group. The matrices are displayed separately under negative and positive emotional stimuli across five frequency bands, highlighting emotion- and frequency-specific differences in functional connectivity.

Under negative emotional stimuli, ASD group showed greater coherence and phase synchronization in the low-frequency bands, particularly the delta, theta, and alpha frequency bands. Based on this, we infer that there is a more stable phase relationship between brain regions in the control group, further suggesting more coordinated and synchronized neuronal activities in different brain regions within the same group. This

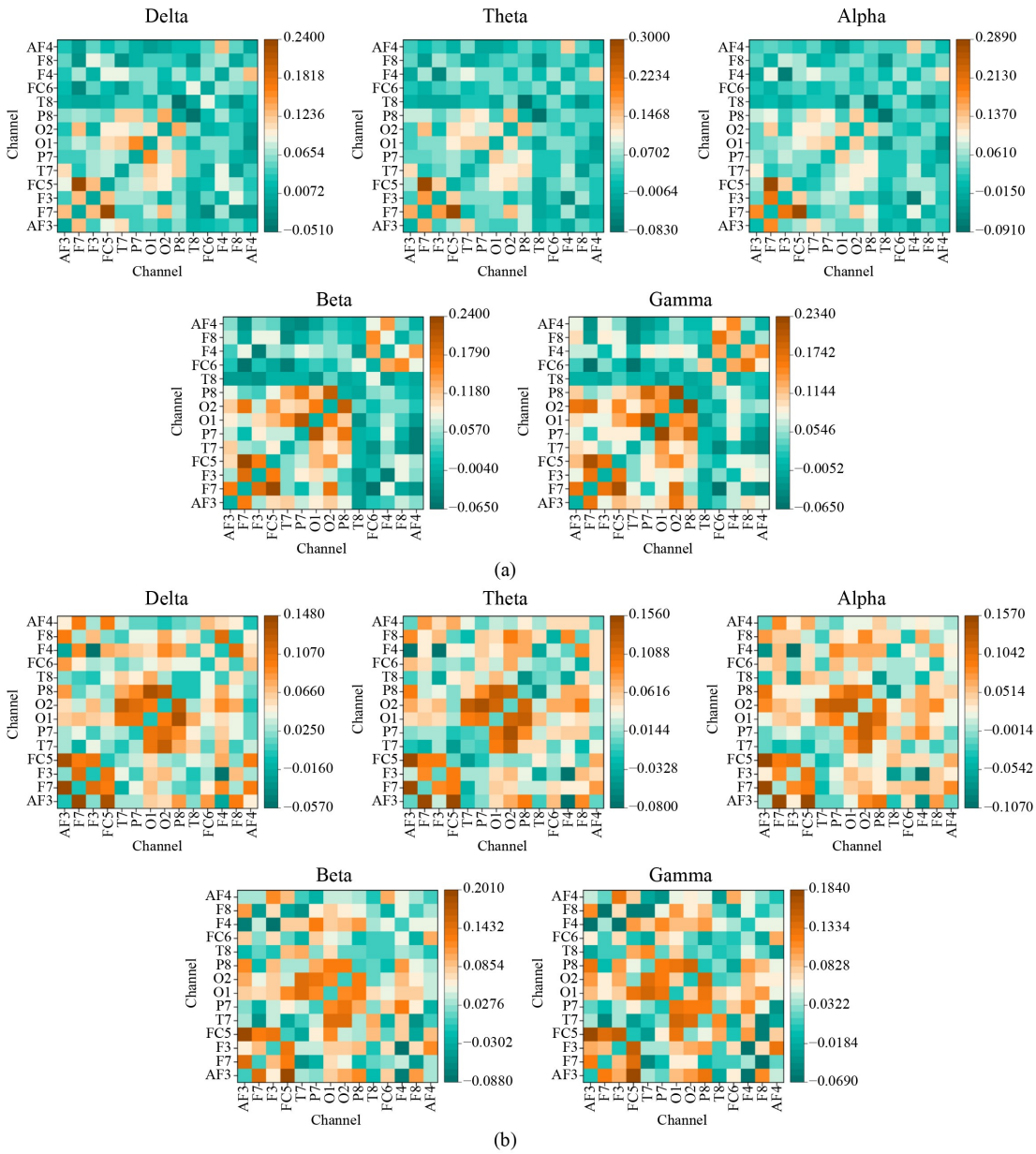

Figure 2 Difference matrices of connectivity between autism spectrum disorder group and control group under (a) negative and (b) positive emotional stimuli across five frequency bands.

increased stability leads to a more consistent and ordered transmission of information within the brain, which is a fundamental aspect of healthy brain function. In the beta and gamma frequency bands, ASD group exhibited stronger phase synchronization between different brain regions, indicating a propensity for coordinated neuronal activity in this frequency range. This may be related to the unique neuronal mechanisms in children with ASD concerning emotional processing, perception, or attention. Under positive emotional stimuli, ASD group exhibited stronger phase synchronization than the control group. This suggests that children with ASD exhibit stronger phase synchronization in different frequency bands in the brain network, highlighting their distinct neural connectivity patterns when experiencing positive emotions.

The proportions of connectivity corresponding to the five frequency bands are illustrated in Figure 3. Under negative and positive emotional stimuli, children with ASD exhibit a higher proportion than those with typical development in all five frequency bands, suggesting more enduring brain network connections.

3.4 | SHAP

XGBoost was used as a classification model, and the model's stability and generalization ability were evaluated through 5-fold cross-validation. Under negative emotional stimuli, the model achieved an accuracy of 0.7857, an F1 score of 0.7273, and an area under the curve (AUC) of 0.7143, indicating that the model performed well in terms of accuracy and F1 score. Under positive emotional stimuli, the model demonstrated satisfactory performance, with an accuracy of 0.7857, a recall of 0.8571, an F1 score of 0.8000, and an AUC of 0.7143. To enhance the model's credibility and interpretability, we employed SHAP analysis to explain its prediction process and visualized the contribution of different features to the model's predictions through SHAP summary plots.

Figure 4(a) presents the SHAP-based feature importance ranking under positive emotional stimuli. Delta DE (O1) was the most important feature, accounting for 27.0% of the overall feature importance. Features including delta SE (P7), delta PSD (FC6), and delta DE (FC6) also showed significant contributions, accounting for 7.9%, 7.8%, and 7.6% of the feature importance, respectively. Theta DE (F3) and beta DE (FC5) also play meaningful roles in the XGBoost, with contribution rates of 9.1% and 7.3%, respectively. SHAP feature impact and summary plots suggest that the model's decisions are primarily influenced by delta band features, particularly delta DE (O1), while other features from alpha, theta, and gamma bands provide additional supporting contributions.

SHAP summary plot depicting feature importance and the direction of feature influence is shown in Figure 4(b). Gamma PSD (FC6) is the most important feature, accounting for 9.0% of the overall feature importance. It has a significant impact on the XGBoost's predictions, with higher feature values being associated with stronger prediction outcomes. Beta PSD (T8) and delta PSD (T8) also show significant contributions, accounting for 4.0% and 7.3%, respectively, and these features have a relatively consistent impact. Moreover, features including alpha SE (F7), delta DE (AF3), and gamma PSD (T8) play a moderate role in the decision-making process, with contribution rates ranging from 4.0% to 6.0%. The plot indicates that features with higher importance are generally related to the power spectra of the gamma and beta frequency bands, which may suggest their significance in processing negative emotional stimuli.

SHAP analysis under positive emotional stimuli revealed that the top-ranked features, including delta DE (FC6), beta DE (FC5), and theta PSD (F3), were largely consistent with the features identified as significant in the statistical tests. Under negative

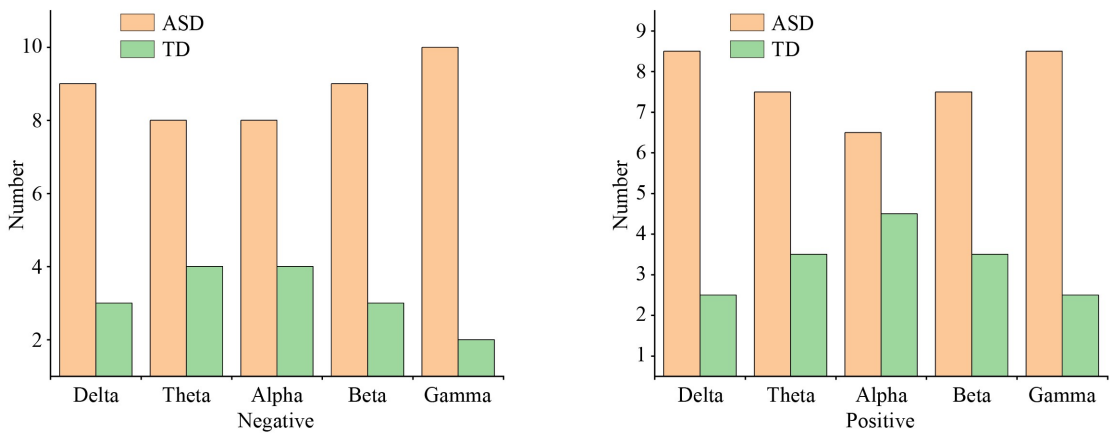

Figure 3 Bar chart of the proportion of connectivity. ASD: autism spectrum disorder, TD: typical development.

Figure 4 Feature importance ranking via SHAP. (a) Feature importance ranking of positive stimuli; (b) feature importance ranking of negative stimuli. SHAP: SHapley Additive exPlanations, PSD: power spectral density, SE: sample entropy, DE: differential entropy.

emotional stimuli, the SHAP analysis indicated that delta PSD (T8), beta DE (FC5), and delta DE (AF3) were generally consistent with the features identified as significant in the statistical tests. This overlap suggests that the features showing significant group differences also have substantial predictive contributions in the model. This consistency between statistical and machine learning approaches strengthens the argument that these EEG features may serve as potential biomarkers for distinguishing between autistic and non-autistic groups under emotional stimuli. Moreover, SHAP analysis provides deeper insights into how these features

contribute to model predictions, elucidating their role in emotional processing and supporting their potential role as biomarkers of ASD-related neural differences in emotional contexts.

4 Discussion and Conclusions

This study aimed at determining the similarities and differences in emotional processing between children with and without ASD under different emotional stimuli, with a focus on elucidating the underlying neuronal mechanisms. Unlike previous studies, this study integrated PSD, SE, and functional connectivity analyses with interpretable machine learning methods to investigate the neuronal underpinnings of emotional processing in children with ASD from multiple perspectives. The findings showed significant differences in EEG spectral features between ASD group and control group when presented with positive and negative emotional stimuli. Precisely, reduced beta-band activity in the frontal regions and enhanced delta-band activity in the temporo–occipital areas were observed in the ASD group. Beta-band activity is typically associated with attentional resource allocation, executive control, and emotional regulation (Nayak & Tsai, 2022), whereas delta-band activity is an important neuronal marker of emotional arousal and perceptual processing. Increased theta and delta power is often associated with emotional arousal (Gkintoni et al., 2025).

Entropy analyses indicated lower complexity and randomness of EEG signals in the ASD group, particularly in the frontal and occipital lobes, suggesting atypical developmental patterns in emotional processing (Tenev et al., 2025). Functional connectivity results complemented these findings, pointing to a pattern of stronger high-frequency phase synchronization in ASD group but more coherent low-frequency connectivity in the control group, suggesting distinct network coordination patterns (Reiter et al., 2019; Supekar et al., 2013). Finally, SHAP-based feature analyses confirmed that delta- and beta-band features, especially those from frontal and occipital regions, were both statistically significant and predictive of atypical emotional processing in the ASD group, supporting their role as potential biomarkers.

On the one hand, previous studies have demonstrated that EEG activity in the beta band is closely related to emotional regulation. Beta-band activity is suppressed during the viewing of high-arousal images (Schubring & Schupp, 2021). In addition, resting-state EEG studies using deep learning have shown that beta power can distinguish children who frequently use cognitive reappraisal and expressive suppression from those who rarely employ these strategies (Aydın, 2023). These findings demonstrate the crucial role beta power plays in the emotional regulation process. Likewise, in the present study, the reduced beta power observed in the ASD group may signal challenges with prefrontal executive control and emotional regulation rather than typical regulatory responses (May & Kana, 2020). On the other hand, delta-band activity in EEG signals has been associated with emotional arousal and perceptual processing. During the processing of emotional stimuli, delta-band activity increases with the level of emotional arousal regardless of emotional valence (Mesa-Gresa et al., 2024). The increased delta-band activity observed in the ASD group may suggest atypical patterns in emotional arousal and perceptual processing, in line with the findings of Tseng et al. (2016).

This study found that entropy values in the ASD group were generally lower than those in the control group, with reduced complexity observed particularly in the frontal and temporal lobes. These findings suggest that the EEG signals in children with ASD are more regular and less complex, in line with the findings of Kang et al. (2019). In addition, the functional connectivity results showed that the control group exhibited more stable phase synchronization in the low-frequency bands, which facilitated efficient information transmission across brain networks. In contrast, ASD group demonstrated stronger phase synchronization in the high-frequency bands, which reflect compensatory or adaptive mechanisms during the processing of emotional stimuli (Cai et al., 2025).

Overall, these findings indicate significant neurophysiological distinctions in EEG between children with and without ASD across emotional stimuli and atypical functional connectivity patterns in the former may contribute to their emotional processing differences. This study applied SHAP framework to enhance model interpretability, identifying key factors that contribute to ASD-related classification across emotional stimuli and validating the results of prior comparative analyses. The identified EEG biomarkers have the potential to advance the understanding of ASD-related neural mechanisms and to inform supportive educational and therapeutic strategies.

In conclusion, this study contributes to a more comprehensive understanding of the neuronal correlates of emotional processing in children with ASD. The evidence obtained suggests that atypical high- and low-frequency PSD, reduced neuronal complexity, and differences in functional connectivity patterns could serve as potential neural indicators of atypical emotional processing in ASD group. It also provides insights into the design of targeted educational and therapeutic interventions aimed at enhancing emotional regulation skills in children with ASD. However, this study still has four limitations which should be acknowledged. First, the sample size is relatively small, and future research should seek to replicate these findings in larger cohorts. Second, the study

examined only two types of emotions, and future work should incorporate neutral stimuli as a baseline condition to allow clearer comparisons with emotional stimuli. Third, the individual variability is difficult to control. Future studies should incorporate standardized assessment tools, such as the Autism Diagnostic Observation Schedule, to stratify participants with ASD according to symptom severity. Fourth, this study employed a 14-channel EEG system, which has limited spatial resolution, restricting the ability to pinpoint the exact location of neural activity. Future work should employ high-density EEG systems with more channels to achieve higher spatial resolution and thereby validate and extend the current findings.

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Data Availability Statements The authors confirm that all data generated or analyzed during this study are included in this published article.

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