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Original Research

EEG Analysis of Visual Attention Under Perception of Affective Prosody in Children with Autism Spectrum Disorder

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Abstract

Background: Multiple object tracking (MOT) tasks are widely used to examine attention impairments in autism spectrum disorder (ASD); however, existing research has predominantly relied on behavioral measures and has barely incorporated physiological data, such as electroencephalography (EEG). Additionally, how cognition and emotion interact in individuals with ASD during MOT tasks remains unclear. **Methods:** In this study we addressed these gaps using a publicly available dataset containing EEG recordings and clinical measurement from 28 children with ASD and 28 typically developing (TD) individuals. Participants listened to speech recordings reflecting prosodic happiness and sadness while completing three attention-level tasks: neutral image viewing (low-attention), one-target four-disc MOT-4 (intermediate-attention), and one-target eight-disc MOT-8 (high-attention). For each participant's EEG data, we calculated the theta-beta ratio (TBR) for each channel and then extracted five EEG features: averaged TBR for all channels (allTBR), averaged TBR for channels in the frontal brain region (fTBR), averaged TBR for channels in the temporal brain region (tTBR), averaged TBR for channels in the central brain region (cTBR), and averaged TBR for channels in the parietal brain region (pTBR). Correlation analysis was also conducted to explore the association between EEG features and clinical measures. **Results:** Findings showed that: (1) the interaction effect between attentional level and emotion was significant for allTBR and tTBR; (2) Significant main effects of group were observed for all five TBR metrics (allTBR, fTBR, tTBR, cTBR, and pTBR), with the ASD group showing higher values than the TD group; (3) only tTBR showed a significant difference between happiness and sadness stimuli during the MOT-8 task after Bonferroni correction; (4) during the MOT-4 task, the TD group had higher correlations between five EEG features and clinical measures than the ASD group; and (5) the tTBR finding during the MOT-8 task suggests that emotional valence may modulate neural processing in the temporal region under high cognitive load. **Conclusions:** These findings could provide new insights into attentional impairments and cognition-emotion interactions in ASD, offering potential implications for the development of clinical intervention strategies.

Keywords: autism spectrum disorder; electroencephalography; cognition; emotions; multiple object tracking; theta-beta ratio

1. Introduction

Autism spectrum disorder (ASD) is a lifelong neurodevelopmental condition marked by persistent difficulties with social communication and interaction, coupled with restricted, repetitive patterns of behavior, interests, or activities [1]. Over the past decade, the incidence of ASD has increased significantly [2], imposing considerable economic and affective challenges on families caring for children with ASD [3]. The etiology of ASD is multifaceted, encompassing both genetic and environmental influences [4]. Despite progress in identifying the origins of ASD, difficulties in attention, social cognition, and adaptive behavior continue to be fundamental aspects of the lived experience of individuals with ASD and represent essential priorities for rigorous neuroscientific research.

Researchers have been progressively using objective measures such as electroencephalography (EEG) and eye tracking (ET) to discover aberrant patterns in fundamental areas such as joint attention [5], visual preference [6,7], and visual attention [8,9,10,11] in order to gain a better understanding of the neurocognitive foundations of ASD. Visual attention, as a fundamental filter of experience, can select a subset of incoming sensory information for further processing [8]. Although impairments in visual attention are not part of the formal diagnostic criteria, a growing body of evidence suggests that individuals with ASD exhibit pervasive difficulties in the visual attention domain [8,9,10,11,12]. Specifically, ASD subjects often struggle to adjust the size of their attentional focus or shift attention between locations and objects, particularly when stimuli are dynamic, repetitive, or socially relevant [8,9,10,11,13]. Moreover, individuals with ASD may also have lower temporal resolution of attention [14], as seen by an expanded attentional blink and a decreased capacity for temporal integration across visual, auditory, and multimodal tasks [8,9,10,11]. These findings

suggest that patients with ASD have difficulties with both dynamic and spatiotemporal attention [8,9,10,11].

Multiple object tracking (MOT) tasks have emerged as a prevalent paradigm for examining attentional functioning in ASD, as they enable the assessment of various aspects of attention, including selection, division, and sustained tracking within a single experimental framework [15]. In MOT tasks, participants must select and continuously track multiple moving targets among identical distractors. Performance is typically modulated by factors such as the number of targets, object speed, and spatial proximity between targets and distractors [8,9,10,11]. Numerous studies report impaired MOT performance in individuals with ASD [8,9,10,11]. However, nearly all prior work has relied solely on behavioral measures. It remains unclear whether physiological signals, particularly EEG, collected during MOT tasks can also reveal atypical neural signatures in ASD.

Moreover, individuals with ASD often face challenges in perspective-taking and flexible strategy use, especially in social contexts. While the diagnostic criteria for ASD emphasize two core domains (1) social communication deficits and (2) restricted/repetitive behaviors, whereas research has traditionally treated these as separate socio-emotional and cognitive domains. Yet emerging evidence suggests that emotion and cognition are highly interactive rather than modular [16,17,18,19]. For instance, while some models partition brain function into affective and cognitive systems [18], others argue that neural substrates of emotion and cognition are deeply intertwined [19,20]. This supports a shift toward integrative models that examine how cognitive control modulates the processing of social and emotional information, a gap particularly relevant in ASD research. Furthermore, cognitive control is the ability to maintain goal-directed behavior, suppress inappropriate responses, and adapt to changing demands [21], may be differentially affected in ASD when emotional context is introduced. However, the extent to which affective prosody (i.e., the emotional tone of voice) affects cognitive performance in individuals with ASD during attentionally demanding tasks such as MOT remains unknown. This lack of clarity motivates the current study, which seeks to examine the interplay between emotion and cognition in children with ASD through EEG recordings obtained during MOT tasks under different levels of attentional demand and affective auditory stimuli.

Importantly, previous behavioral and neurophysiological studies further support the presence of atypical emotion-attention interactions in ASD. Hubbard et al. [22] demonstrated that adults with ASD exhibit increased acoustic variability in emotional speech production, including greater pitch range, intensity, and duration compared to typically developing (TD) individuals, particularly in emotional contexts, suggesting altered modulation of affective expression. In addition, Gebauer et al. [23] reported that while individuals with ASD show largely typical activation of fronto-temporal and subcortical brain regions during affective prosody processing, they exhibit altered neural responses in subcortical structures such as the caudate and lower perceived emotional intensity, which was interpreted as reflecting increased attentional demands during emotion processing. Complementing these findings, recent EEG evidence indicates that emotion recognition in ASD is sensitive to sensory variability, with reduced acoustic complexity improving prosody-based emotion discrimination [24]. Together, these findings suggest that emotional processing in ASD may be characterized not by complete neural dysfunction, but by increased cognitive and attentional effort during affective evaluation.

The EEG stands out among objective neurophysiological tools to study aberrant neural activities in ASD subjects because of its relative price, ease of use, high temporal resolution, and its demonstrated sensitivity to abnormal brain activity in ASD [25,26,27]. For example, individuals with ASD frequently exhibit anomalies in their resting-state EEG [25,26,27]. Since the beginning of human EEG research [28], power spectrum analysis has been the prevailing method for studying the resting-state EEG by breaking it down into frequency bands that are associated with different brain functions [29,30]. The theta (4–7 Hz) and beta (13–30 Hz) bands are commonly used for analysis, though band definitions might differ. One important metric that has recently surfaced is the theta-beta ratio (TBR), which is widely used as a measure of attentional regulation and cognitive control [31,32,33].

Evidence links elevated TBR to attentional dysfunction: (1) individuals with attention deficit hyperactivity disorder (ADHD) show increased TBR [31]; (2) TBR modulates attentional bias toward threat-related stimuli during mind-wandering [34,35], consistent with attentional control theory [36]; and (3) TBR reflects engagement of executive functions during task performance [37,38]. Importantly, TBR has also been used to quantify cognitive load in ASD [39]. Notably, a recent study found that in autistic children, average gaze duration during social video viewing was negatively correlated with TBR. In contrast, the correlation was positive in TD children [40]. Despite these findings, the relationship between TBR and core ASD features, particularly in dynamic, ecologically relevant contexts, remains poorly understood.

Taken together, this study aimed to reveal the atypical characteristics of visual attention during the perception of affective prosody in children with ASD. For this purpose, EEG data were obtained from a publicly available dataset [41,42], which includes recordings from two MOT tasks and one international affective picture system (IAPS) task (with different attentional loads) while participants listened to affective prosodies. The EEG data were preprocessed following the procedure originally implemented by the primary authors of the dataset [41,42]. Then, we extracted

the TBR features from the EEG data. Finally, we aimed to test whether the TBR measures can reveal group differences between ASD and TD children, and to explore how these measures can be used to investigate the interaction between emotion and cognition. In order to illustrate our techniques, this study used a publicly accessible database that included EEG signals and clinical (behavioral) measures collected from 31 ASD (High-autism spectrum rating scales [ASRS]) children and 31 TD (Low-ASRS) children [41,42,43].

2. Materials and Methods

2.1 Participants

This study adopted a publicly accessible database [41,42], which was hosted at Mendeley Data (see the site http://doi.org/10.17632/spwnt8t25y.1). Participants were recruited from local schools and clinical centers in Monterrey, Mexico. According to the original dataset classification, participants were divided into high-ASRS (n = 31) and low-ASRS (n = 31) groups. The high-ASRS group included children with previously identified ASD severity level 1 or Asperger's syndrome, as reported by parents/guardians and confirmed by experienced clinicians using standardized diagnostic instruments, including DSM-5 (n = 2), Childhood Autism Spectrum Test (n = 1), Mexican Filter for Asperger's Detection (n = 17), Ángel Rivière's Autism Spectrum Inventory (n = 2), Autism Diagnostic Interview-Revised (n = 3), Autism Diagnostic Observation Schedule-2 (n = 4), Psychoeducational Profile-3 (n = 1), and Gilliam Autism Rating Scales-3 (n = 1). The low-ASRS group consisted of children without reported neurological, psychiatric, cognitive, hearing, or sensory disorders. Parents/guardians reported that these children were not taking medications affecting the central nervous system (CNS) or peripheral nervous system (PNS). In this manuscript, the high-ASRS and low-ASRS groups are referred to as the ASD and TD groups, respectively, consistent with the original dataset classification. ASRS scores were used as behavioral measures of autism-related traits and were not used as the sole criterion for group assignment. The original dataset included 62 participants (31 ASD and 31 TD). All participants completed the experimental protocol; however, six participants (three ASD and three TD) were excluded from EEG analyses due to an insufficient number of valid EEG epochs after preprocessing and artifact rejection. Therefore, the final EEG analytic sample consisted of 56 participants (28 ASD and 28 TD).

As shown in Ref. [41], this database involved the EEG data collected from children and clinical (behavioral) measures collected from their parents or legal guardians. In particular, the original dataset consists of EEG data collected from 62 children (31 in the ASD group and 31 in the TD group) across three attentional tasks while listening to affective prosodies. While, to obtain clinical (behavioral) measures, the parents or legal guardians of participating children were required to evaluate the handedness of their children, and complete the ASRS, which consists of 13 subdimensions, including social/communication (SC), unusual behaviors (UB), self-regulation (SR), total autism spectrum rating scale (total-ASRS), diagnostic and statistical manual of mental disorders (DSM-5), peer socialization (PS), adult socialization (AS), social/emotional reciprocity (SER), atypical language (AL), stereotypy (ST), behavioral rigidity (BR), sensory sensitivity (SS), and attention (AT). The total score of each subdimension was calculated.

2.2 Experimental Overview

The publicly available dataset was used to investigate the interaction between emotion and cognition in the ASD group. The experimental design consisted of three levels of attentional load (low, medium, and high) applied to both ASD and TD participants. At the same time, they listened to emotional prosodies (happiness and sadness) during attentional tasks. EEG and behavioral data, along with demographic information and clinical measures (including ASRS subscales and DSM-5 ratings), were collected from both groups, as shown in Fig. 1 (Ref. [44]). The experimental paradigm comprised six scenarios in which emotional prosodies were presented in a randomized manner. Specifically, the design combined auditory stimuli of happiness and sadness with three graded levels of attentional load to examine ASD-specific neural responses under varying cognitive-emotional demands. The attentional load conditions included: (i) a neutral picture viewing task representing low load; (ii) a MOT-4 task requiring participants to track one target among four moving objects, representing medium load; and (iii) a MOT-8 task requiring tracking of one target among eight moving objects, representing high load. Each attentional condition was paired with both emotional stimuli, resulting in six standardized experimental conditions. In all scenarios, EEG signals were recorded for each participant, along with behavioral performance measures such as tracking capacity and accuracy. Furthermore, Each MOT condition consisted of 40 trials, whereas the IAPS condition consisted of 96 images, as indicated by ×40 and ×96 in Fig. 1.

2.3 EEG Data Collection

Fig. 2 (Ref. [44]) summarizes the experimental setup. The entire experiment consisted of six scenarios across three cognitive tasks at different attentional load levels, each lasting 8 minutes. All scenarios required playing the same 24 affective prosody files, but they appeared randomly in each scenario. In each scenario, participants were required to listen to affective prosody files (happy and sad tones) while responding to three tasks: IAPS (low attentional load), one-target 4-disc MOT (MOT-4) (intermediate attentional load), and one-target 8-disc MOT (MOT-8) (high attentional load). EEG data for all three tasks were recorded in each scenario. Although the main dataset in-

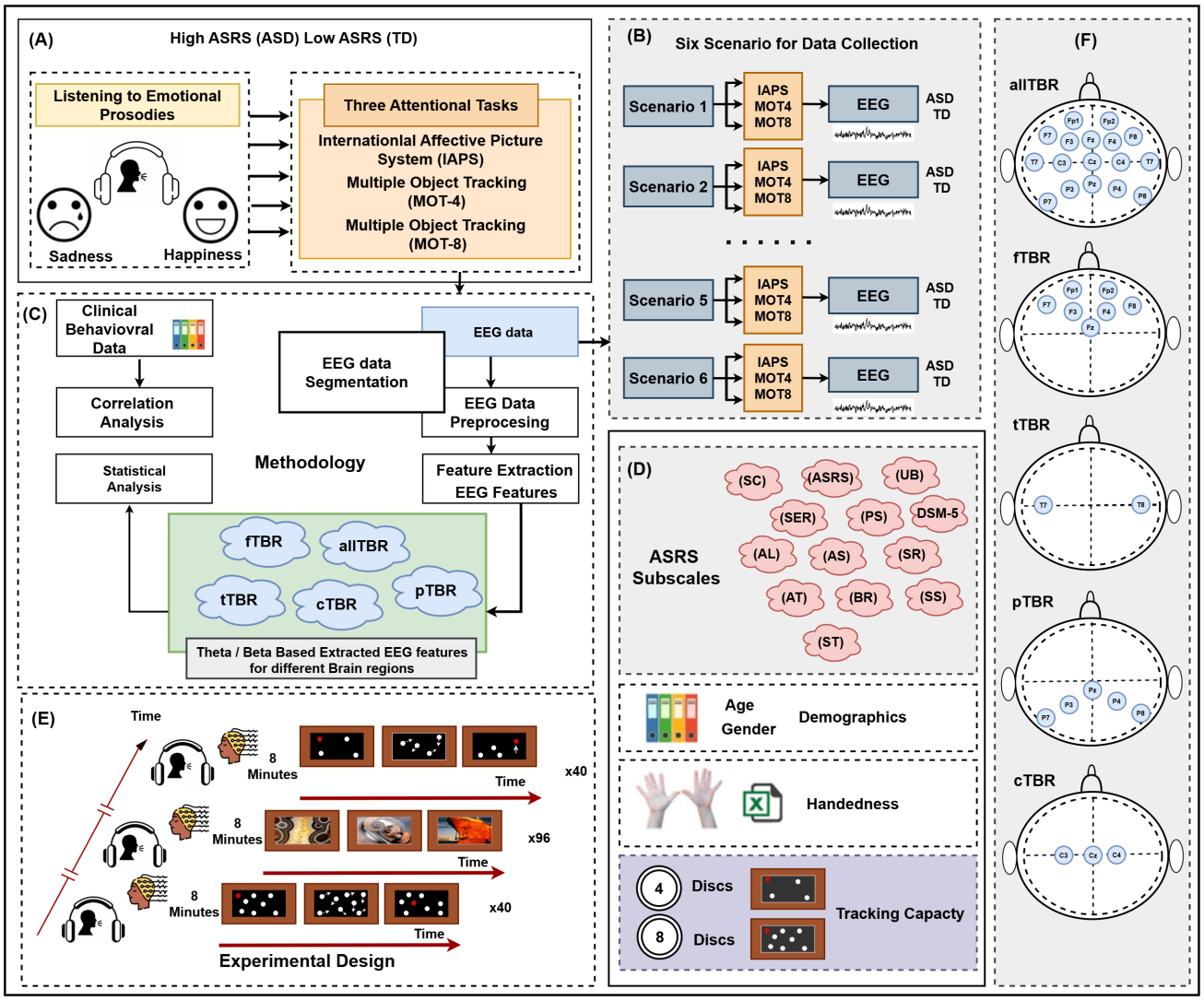

Fig. 1. Experimental framework for exploring emotion-cognition interactions in the ASD and TD participants. (A) ASD and TD groups listening to two emotional prosodies while performing three attentional tasks; (B) six experimental scenarios for EEG data collection; (C) methodology in which EEG data were preprocessed, segmented, and five TBR-based features were extracted; (D) demographic information obtained alongside the EEG data; (E) the overall experimental design (Adapted from [44]); and (F) TBR-based EEG features extracted from different brain regions. ASD, autism spectrum disorder; TD, typically developing; EEG, electroencephalography; TBR, theta-beta ratio; fTBR, frontal brain region; tTBR, temporal brain region; cTBR, central brain region; pTBR, parietal brain region; allTBR, averaged TBR for all channels; ASRS, autism spectrum rating scales; SC, social/communication; UB, unusual behaviors; SR, self-regulation; DSM-5, diagnostic and statistical manual of mental disorders; PS, peer socialization; AS, adult socialization; SER, social/emotional reciprocity; AL, atypical language; BR, behavioral rigidity; SS, sensory sensitivity; AT, attention.

cludes six scenarios utilizing 24 effective prosody files with various emotions, this study specifically focused on happiness and sadness due to their extreme differences in examining emotional responses, and could be applied to reveal cognitive activity [45] in the context of prosody during three tasks (i.e., IAPS, MOT-4, and MOT-8).

EEG data for TD children were collected using a 32-channel gUSBamp EEG amplifier system (g.tec medical engineering GmbH, Schiedlberg, Austria) with Ag/AgCl electrodes placed according to the modified international 10-20 system. EEG signals were recorded at a sampling rate of 256 Hz, with electrode impedance maintained below 5 kΩ. ASD children's data were acquired using a semi-dry mBrain Train Smarting mobi system with 24 active electrodes following the expanded 10–20 system, at 500 Hz and <10 kΩ impedance. For details on the electrode configurations used for these groups, refer to [41]. The EEG data for children with ASD were collected using 24 electrodes, while those for TD children were collected using 32 electrodes. To ensure consistency in data analysis, this study extracted EEG data from the 17 common channels (Fp1, Fp2, F7, F8, F3, Fz, F4, T7, T8, C3, Cz, C4, P7, P3, Pz,

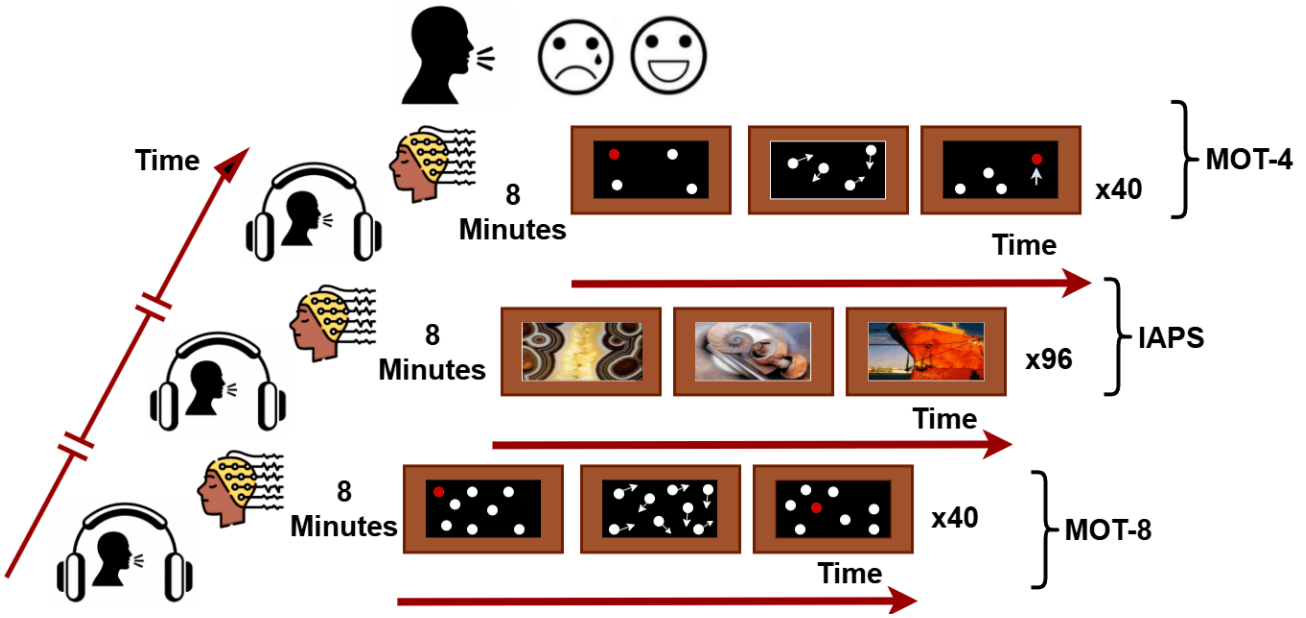

Fig. 2. Description of experimental setup. Participants performed three visual attention tasks: one-target four-disc (MOT-4; upper), neutral image viewing (IAPS; middle), and one-target eight-disc (MOT-8; bottom), while simultaneously listening to emotional prosodies (happiness and sadness) and undergoing EEG recordings. Each task was paired with both happiness and sadness emotional prosodies, resulting in six experimental scenarios. Emotional stimuli were presented in a randomized order rather than separate blocks. created with (https://draw.io). Adapt from [44].

P4, and P8). Although the TD group's gUSBamp system recorded at 256 Hz and the ASD group's Smarting mobi recorded at 500 Hz, both were down-sampled to 256 Hz before all preprocessing and analyses. Since the TBR involves only low frequencies, the Nyquist criterion requires a minimum sampling rate of only 60 Hz to avoid aliasing [46]; our 256 Hz rate is therefore more than four times this minimum and is exceptionally safe. Furthermore, down-sampling to a common rate is a standard, routine step in EEG preprocessing pipelines [47], and it eliminates any sampling-related differences between groups. More critically, Kam et al. [48] directly compared a wet EEG system to a dry wireless system and found that resting-state spectral power in theta, alpha, and beta bands showed significant positive correlations between systems, with similar performance across both [48]. This finding has been extended to clinical populations, where Hinrichs et al. [49] reported no significant differences in absolute alpha and beta power between wet and dry systems in neurological subjects [49].

Furthermore, the use of two different EEG acquisition systems is acknowledged as a potential methodological concern due to differences in amplifier type, electrode configuration, and sampling rates. However, this dataset has been previously validated by Duville et al. [44] to address this issue. Specifically, they performed cluster-based permutation tests on resting-state EEG data and reported no significant group differences attributable to recording hardware. In addition, preprocessing procedures included harmonization of sampling rates, referencing schemes, and frequency bandwidths across groups. Finally, our analyses were restricted to the 17 shared electrodes between systems and groups (ASD vs. TD), ensuring comparability of spatial information.

2.4 EEG Data Preprocessing

The EEG data were preprocessed following the procedure originally implemented by the primary author of the dataset [44]. The EEG data were first offline average re-referenced, and then the channels' baseline means were removed. The data were processed using a Butterworth-type infinite impulse response (IIR) filter with a bandpass configuration, with an order of 6 and cut-off frequencies ranging from 0.1 Hz to 70 Hz. To eliminate the 60 Hz line noise, the clean line plug-in was used. The artefact subspace reconstruction (ASR) algorithm was used to remove high-variance spontaneous artefacts. The identification of bad channels was performed using specific criteria, including the presence of a flatline longer than 5 seconds, excessive line noise relative to the signal, or a joint log-probability of deviation from the mean exceeding 5 standard deviations. The bad channels were interpolated using the superfast spherical spline interpolation method with parameters m = 4 and n = 7 once they were identified. The subsequent step in the processing pipeline involved decomposing the signal's Independent Components using the extended infomax independent component analysis (ICA) algorithm. The ICLabel plug-in was used to eliminate constant, fixed-source artifacts. Components that had less than

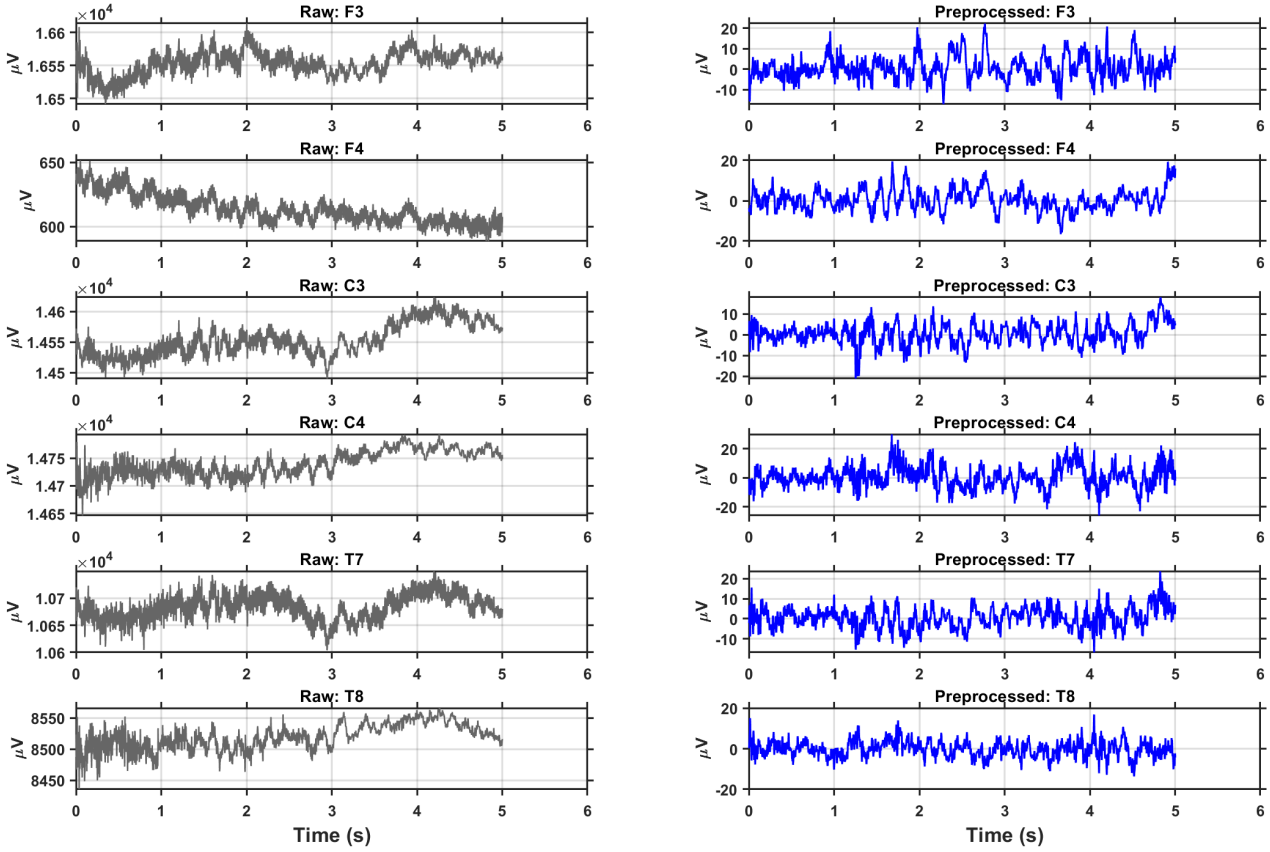

Fig. 3. Representative raw and preprocessed EEG signals from an ASD participant (Subject 1). EEG recordings obtained during the happiness condition under the MOT-8 task are shown. The displayed segment corresponds to a 5-second EEG epoch.

70% confidence in the brain category were discarded. EEG data were epoched over a 3.11 s time window (1.11 s pre-, 2 s post-stimulus). The sample rate was equalized to 256 Hz for both groups before data processing. To enhance the transparency of the preprocessing pipeline, representative EEG signal visualizations are provided in Fig. 3 and Fig. 4. Fig. 3 presents raw and preprocessed EEG signals from a subset of channels for the same subject (5 s), illustrating the effect of preprocessing. Fig. 4 shows the TBR analysis for individual EEG channels. After preprocessing, three subjects were excluded from the TD and ASD groups due to insufficient usable EEG segments during the happiness and sadness prosody events. Following artifact rejection and segment extraction, these subjects retained too few clean epochs for reliable statistical analysis. As a result, 28 subjects per group, TD (low-ASRS) and ASD (high-ASRS), remained for further analysis.

2.5 Feature Extraction of EEG Data

The power spectra of the theta (4–7 Hz) and beta (13–30 Hz) bands were first calculated for each channel, and the TBR value for each channel was then obtained by computing the ratio of the theta-to-beta power spectra. We used finite impulse response (FIR) bandpass filters with a Kaiser window to extract theta and beta frequency bands from the EEG signal. The power spectra of EEG epochs were estimated using Welch's method with a frequency resolution of 0.5 Hz and 50% overlap. Furthermore, this study extracted five EEG features, including the averaged TBR value for all set of channels (referred to as allTBR), the averaged TBR value for the channels (i.e., Fp1, Fp2, F7, F8, F3, F4, and Fz) in frontal brain region (referred to as fTBR), the averaged TBR value for the channels (i.e., T7 and T8) in temporal brain region (referred to as tTBR), the averaged TBR value for the channels (i.e., C3, C4, and Cz) in central brain region (referred to as cTBR), the averaged TBR value for the channels (P3, P4, P7, P8, and Pz) in parietal brain region (referred to as pTBR).

2.6 Topographic Map Generation

Topographic maps of the TBR were generated to visualize its spatial distribution across the scalp. For each participant, TBR was computed per channel by dividing the mean theta power by the mean beta power, averaged across trials within each emotional condition (happiness and sadness) and attentional task (IAPS, MOT-4, and MOT-8). Group-level TBR maps (ASD and TD) were derived by averaging TBR values across all participants in each group.

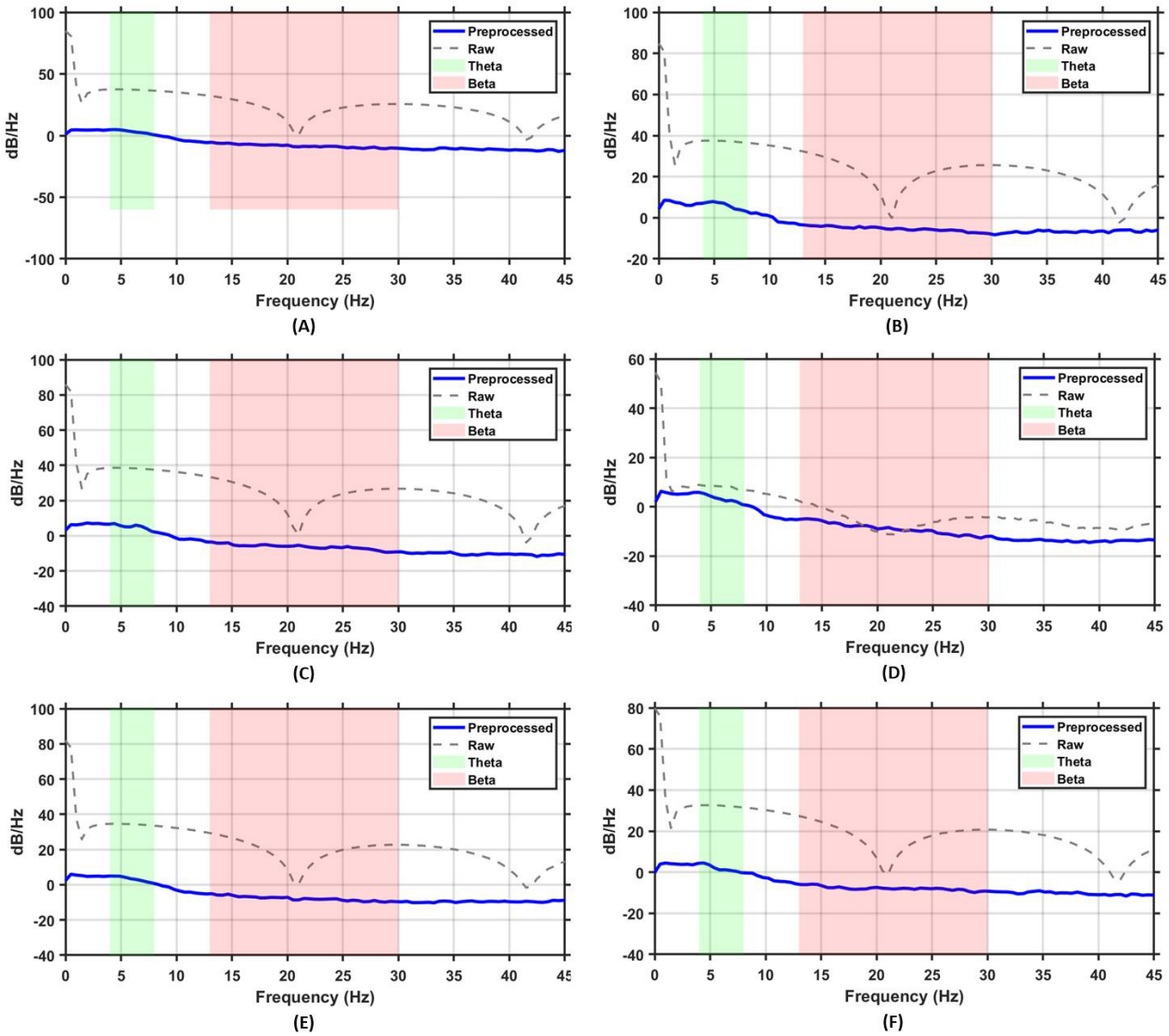

Fig. 4. Power spectral density (PSD) analysis for individual EEG channels. Panels (A–F) show the PSD curves for the C3, C4, F3, F4, T7, and T8 EEG channels, respectively. The preprocessed signal (solid blue line) is compared with the raw signal (dashed gray line). The theta (4–7 Hz) and beta (13–30 Hz) frequency bands are highlighted in green and red, respectively, representing the spectral components used for TBR calculation.

To enhance comparability and highlight spatial patterns, the 17-channel TBR values were converted to Z-scores by subtracting the across-channel mean and dividing by the across-channel standard deviation within each group, condition, and task. These Z-scored TBR values were then interpolated and plotted onto a 2D scalp layout using the standard 10–20 electrode coordinates. Group differences (ASD - TD) were visualized by subtracting the Z-scored TBR topographies of the TD group from those of the ASD group.

2.7 Statistical Analysis

This study focused on five EEG features: allTBR, fTBR, tTBR, cTBR, and pTBR measured across five brain regions (all, frontal, temporal, central, parietal). The primary objective was to investigate whether and how attention levels and emotions modulate group differences (ASD vs. TD) in TBR across brain regions. Prior to statistical analysis, data were assessed for normality and homogeneity of variance to determine the suitability of parametric methods. Normality of the model residuals was assessed using the Shapiro-Wilk test, which indicated that the residuals were normally distributed ($W = 0.994$, $p = 0.238$). This was further supported by visual inspection of Q-Q plots, which showed only minor deviations in the upper tail, while the majority of residuals closely followed the expected normal distribution. To evaluate the assumptions of normality and homogeneity of variance for the parametric tests, diagnostic plots of the model residuals were examined and are presented in the **Supplementary Material** (**Supplementary Fig. 1**).

Homogeneity of variance was evaluated using Levene's test. When considering all condition combinations, the assumption was not violated ($F_{(11, 324)} = 1.720$, $p = 0.068$). However, a partially significant heterogeneity of variance was observed between subject groups ($F_{(1, 334)} = 5.161$, $p = 0.023$), indicating moderate variance inequality driven primarily by group differences. Given that the normality assumption was satisfied and a violation of homogeneity of variance was partially observed, particularly driven by between-group differences, the three-way ANOVA was applied due to its robustness under reasonably balanced designs [50,51]. To address heteroscedasticity, Welch's corrections were additionally applied for relevant between-group comparisons. Effect sizes (generalized η^2 and Cohen's d) were reported alongside p-values to support robust interpretation of results. As these assumptions were satisfied, three-way ANOVA models were conducted for each EEG feature, with emotion (happiness vs. sadness) and attentional level (low vs. intermediate vs. high) as within-subject factors, and subject type (ASD vs. TD) as a between-subject factor. Post-hoc pairwise comparisons following significant ANOVA effects were performed using t-tests, with Bonferroni correction applied within each post-hoc set to control the family-wise error rate (FWER). Main effects and interaction effects from the ANOVAs were also corrected (Bonferroni correction) for multiple comparisons. No single global alpha correction was applied across all tests, as different correction strategies were used for different test families. To address multiple comparisons in the correlation analyses, Pearson's correlations between EEG features and the 13 ASRS subscales were corrected using the Benjamini-Hochberg False Discovery Rate (FDR) procedure. Group differences in demographic and clinical variables were also examined, and these variables were corrected using the FDR correction.

Additionally, the current study included 56 children, with 28 in the ASD (Male/Female: 26/2) and 28 in the TD group (Male/Female: 8/20), as shown in Table 1. Overall, the sample comprised 34 males and 22 females. We acknowledge the substantial gender imbalance between groups, particularly the very small number of females in the ASD group, which may represent a potential confounding factor. To address this concern, we conducted additional linear mixed-effects analyses including gender and age as fixed covariates. The results showed that neither gender (corrected $p = 0.484$) nor age (corrected $p = 0.318$) had a significant effect in any model (all $p > 0.05$). Importantly, the inclusion of these covariates did not alter the pattern of results across all five EEG features, including both main effects and interaction effects reported in the original analyses. The primary analyses were conducted using repeated-measures ANOVA. Linear mixed-effects models were additionally used as a robustness check to confirm that demographic variables did not influence the observed effects.

All statistical analyses were performed using R (version 4.0.2; R Foundation for Statistical Computing, Vienna, Austria), with a nominal significance threshold set at $\alpha = 0.05$. This cross-sectional secondary analysis was reported in accordance with the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines, and the completed checklist is provided in **Supplementary Material**.

3. Results

3.1 Demographic Information of Participants

The current study included 56 children, with 28 in the ASD group (Male/Female: 26/2) and 28 in the TD group (Male/Female: 8/20), as demonstrated in Table 1. Table 1 presents a summary of the demographic characteristics, including age, gender, and overall scores across the 13 ASRS subscales. No significant difference in age was observed between the groups ($p > 0.05$). However, the ASD group demonstrated significantly higher scores across all ASRS subscales compared with the TD group ($p < 0.001$). The findings indicate increased difficulties in social communication, behavioral rigidity, sensory sensitivity, and attention within the ASD group. The TD group exhibited significantly enhanced tracking capacity ($p < 0.001$), indicating superior attentional tracking. The observed profiles align with known clinical features of ASD and further validate the ASRS as a sensitive measure for differentiating between ASD and TD populations. Regarding handedness, intergroup differences could theoretically influence motor or neural biomarkers. However, the vast majority of participants in both groups were right-handed, and handedness information was incomplete or unavailable for a subset of participants [42]; thus, this variable was excluded from subsequent analyses.

As shown in Table 1, ASRS was used to characterize behavioral and social functioning across multiple domains. The ASRS is a standardized caregiver-report measure assessing autism-related symptoms, including SC difficulties, UB, SR, SS, and AT functioning. Subscales such as PS, AS, SER, AL, and BR capture distinct aspects of social interaction and behavioral patterns, while the DSM-5 scale reflects core diagnostic features. All scores are reported as mean and standard deviation, with higher values indicating greater symptom severity or impairment. The Total ASRS score provides an overall index of autism-related traits. These measures were included to comprehensively describe the clinical profile of the ASD and TD groups and to confirm expected group differences relevant to the study's investigation of neurocognitive and attentional processes. SC reflects deficits in social interaction and communication abilities; UB capture repetitive, restricted, and atypical behavioral patterns; SR refers to difficulties in emotional and behavioral control; Peer and AS assess the ability to engage in age-appropriate social interactions; SS represents atypical responses to sensory stimuli; the AT Scale mea-

Table 1. Demographic characteristics for ASD and TD participants.

Demographics	ASD (Male/Female: 26/2)	TD (Male/Female: 8/20)	Test statistic	FDR-corrected *p*-value
Age, years	9.71 ± 1.51	10.11 ± 1.223	t = -1.067	0.290
Gender, Male/Female	[92.9%/7.1%]	[28.6%/71.4%]	X^2 = 24.257	<0.001
Social/Communication	31.68 ± 9.676	13.54 ± 9.55	t = 7.061	<0.001
Unusual Behaviors	50.36 ± 15.334	19.96 ± 11.95	t = 8.272	<0.001
Self-Regulation	35.79 ± 11.22	16.50 ± 11.50	t = 6.352	<0.001
Total-ASRS	192.54 ± 15.985	143.07 ± 23.360	t = 9.247	<0.001
DSM-5 Scale	78.64 ± 20.16	31.04 ± 17.35	t = 9.469	<0.001
Peer Socialization Scale	19.93 ± 5.64	7.39 ± 4.83	t = 8.940	<0.001
Adult Socialization Scale	9.61 ± 3.75	3.86 ± 2.99	t = 6.339	<0.001
Social/Emotional Reciprocity	23.57 ± 6.33	9.37 ± 7.24	t = 7.751	<0.001
Atypical Language Scale	11.14 ± 5.48	3.96 ± 4.62	t = 5.297	<0.001
Stereotypy Scale	11.96 ± 4.81	5.43 ± 3.82	t = 5.627	<0.001
Behavioral Rigidity Scale	19.86 ± 7.37	8.33 ± 5.20	t = 6.678	<0.001
Sensory Sensitivity Scale	10.25 ± 4.66	3.39 ± 3.33	t = 6.334	<0.001
Attentional Scale	23.18 ± 7.88	10.54 ± 7.49	t = 6.156	<0.001
Tracking Capacity	0.87 ± 0.92	2.69 ± 1.394	t = –5.761	<0.001

FDR, Benjamini-Hochberg False Discovery Rate.

sures attention-related difficulties; and TC reflects behavioral performance in the MOT task, with higher values indicating better attentional tracking ability.

3.2 Main Effect Analysis

For each EEG feature, we conducted a three-factor ANOVA to test the main effects and their interaction. The main effect analysis results were listed as follows.

3.2.1 allTBR

The main effect of Subject-type was significant [Subject-type: $F_{(1, 54)}$ = 48.85, corrected $p < 0.001$, η^2 = 0.315], but the main effects of Emotion and Attentional Level were not (all corrected $p > 0.05$). Furthermore, the interaction between Subject-type and Emotion and that between Subject-type and Attentional Level were not significant (all corrected$p > 0.05$). However, the interaction effect between Emotion and Attentional Level was significant [Emotion * Attentional Level: $F_{(2, 108)}$ = 3.130, corrected p = 0.048, η^2 = 0.001]. In contrast, the three-way interaction between Subject-type, Emotion, and Attention Level was not (all corrected $p > 0.05$).

3.2.2 fTBR

The main effect of Subject-type was significant [Subject-type: $F_{(1, 54)}$ = 35.35, corrected $p < 0.001$, η^2 = 0.251], while the main effects of Emotion and Attention Level were not (all corrected $p > 0.05$). Furthermore, the interaction between Subject-type and Emotion, that between Subject-type and Attention Level, and that between Emotion and Attention Level were not significant (all corrected $p > 0.05$). Additionally, the three-way interaction between Subject-type, Emotion, and Attention Level was not significant (all corrected $p > 0.05$).

3.2.3 tTBR

The main effects of Subject-type were significant [Subject-type: $F_{(1, 54)}$ = 33.823, corrected $p < 0.001$, η^2 = 0.220]; whereas the main effect of Emotion was not significant [Emotion: $F_{(1, 54)}$ = 3.952, p = 0.052, η^2 = 0.068], but the main effect of Attention Level was not (corrected $p > 0.05$). Additionally, the interaction between Subject-type and that between Emotion and Attention Level were significant [Subject-type * Emotion: $F_{(1, 54)}$ = 5.557, corrected p = 0.022, η^2 = 0.002; Emotion * Attention Level: $F_{(2, 108)}$ = 4.022, corrected p = 0.021, η^2 = 0.003], but the interaction between Subject-type and Attention Level was not (corrected $p > 0.05$). Furthermore, the three-way interaction between Subject-type, Emotion, and Attention Level was not significant (all corrected $p > 0.05$).

3.2.4 cTBR

The main effect of Subject-type was significant [Subject-type: $F_{(1, 54)}$ = 60.527, corrected $p < 0.001$, η^2 = 0.375], while the main effects of Emotion and Attention Level were not (all corrected $p > 0.05$). Furthermore, the interaction between Subject-type and Emotion, that between Subject-type and Attention Level, and that between Emotion and Attention Level were all not significant (all corrected $p > 0.05$). Additionally, the three-way interaction between Subject-type, Emotion, and Attention Level was not significant (all corrected $p > 0.05$)

3.2.5 pTBR

The main effect of Subject-type was significant [Subject-type: $F_{(1, 54)}$ = 57.476, $p < 0.001$, η^2 = 0.345], while the main effects of Emotion and Attention Level were not (all corrected $p > 0.05$). Additionally, the interaction between Subject-type and Emotion, that between Subject-type

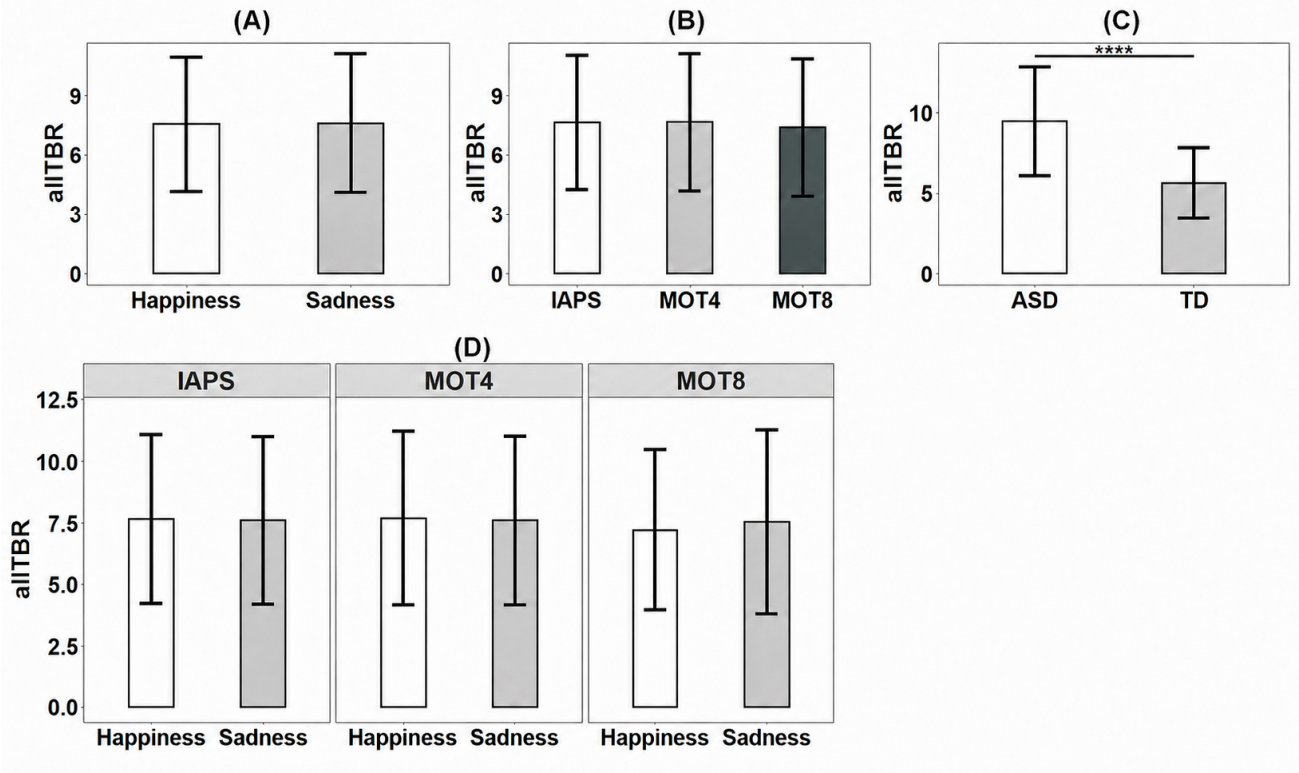

Fig. 5. Post-hoc analysis of the allTBR. (A) Difference between emotions; (B) Differences among attention levels (IAPS, MOT-4, MOT-8); (C) Difference between the ASD and TD groups; (D) Comparison of neural responses between happiness and sadness conditions across different attentional task levels. Error bars represent the standard error of the mean (SEM). ****: $p < 0.0001$.

and Attention Level, and that between Emotion and Attention Level were all not significant (all corrected $p > 0.05$). Furthermore, the three-way interaction between Subject-type, Emotion, and Attention Level was not significant (all corrected $p > 0.05$).

3.3 Post-hoc Multiple Comparison

For those EEG features with significant main effect of Subject-type, we further conducted post-hoc multiple comparisons. Figs. 5,6,7,8,9 summarized our results, and main results were listed as follows.

3.3.1 allTBR

As shown in Fig. 5A, allTBR values did not show significant difference between happiness and sadness prosody (corrected $p = 0.407$). Similarly, as shown in Fig. 5B, allTBR values did not show significant difference between different Attentional Levels for IAPS vs. MOT-4: (corrected $p = 0.936$); IAPS vs. MOT-8: (corrected $p = 0.329$); and MOT-4 vs. MOT-8: (corrected $p = 0.460$). However, as shown in Fig. 5C, ASD children had higher allTBR values than TD children and show significant group (ASD vs. TD) difference [$t_{(54)} = 6.99$, corrected $p < 0.001$, Cohen's $d = 1.87$]. Furthermore, as shown in Fig. 5D, allTBR values did not differ significantly between happiness and sadness prosodies for the IAPS ($p = 0.632$) and MOT-4 ($p = 0.428$) tasks and did not differ significantly for the MOT-8 high-attentional task after Bonferroni correction [$t_{(55)} = -2.381$, raw $p = 0.021$, Bonferroni-adjusted $p = 0.063$, Cohen's $d = -0.318$].

3.3.2 fTBR

As shown in Fig. 6A, fTBR values did not show a significant difference between happiness and sadness emotional prosodies (corrected $p = 0.837$). Similarly, as shown in Fig. 6B, fTBR values did not show significant differences between different Attentional Levels for IAPS vs. MOT-4: (corrected $p = 0.957$); IAPS vs. MOT-8: (corrected $p = 0.292$); and MOT-4 vs. MOT-8: (corrected $p = 0.493$). However, as shown in Fig. 6C, ASD children had higher fTBR values than TD children and showed a significant group (ASD vs. TD) difference [$t_{(54)} = 5.950$, corrected $p < 0.001$, Cohen's $d = 1.59$]. Furthermore, as shown in Fig. 6D, fTBR values did not show a significant difference between happiness and sadness emotional prosodies for the IAPS (low), MOT-4 (intermediate), and MOT-8 (high) attentional tasks IAPS: (corrected $p = 0.507$); MOT-4: (corrected $p = 0.351$); and MOT-8: (corrected $p = 0.060$).

3.3.3 tTBR

As shown in Fig. 7A, tTBR values did not show a significant difference between happiness and sadness affec-

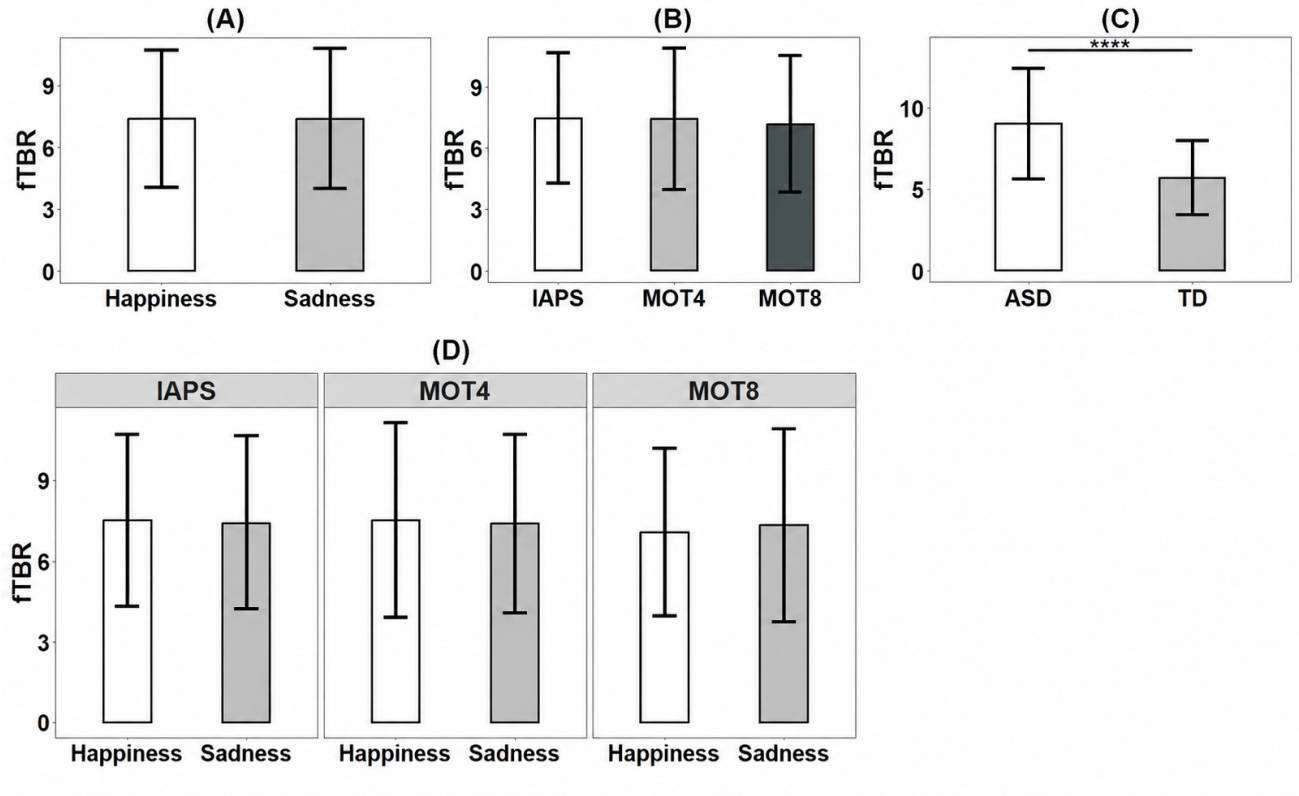

Fig. 6. Post-hoc analysis of the fTBR. (A) Difference between emotions; (B) Differences among attention levels (IAPS, MOT-4, MOT-8); (C) Difference between the ASD and TD groups; (D) Comparison of neural responses between happiness and sadness conditions across different attentional task levels. Error bars represent the standard error of the mean (SEM). ****: $p < 0.0001$.

tive prosodies (corrected $p = 0.069$). Similarly, as shown in Fig. 7B, tTBR values did not show a significant difference between different Attentional Levels for IAPS vs. MOT-4: (corrected $p = 0.499$); IAPS vs. MOT-8: (corrected $p = 0.301$); and MOT-4 vs. MOT-8: (corrected $p = 0.121$). However, as shown in Fig. 7C, ASD children had higher tTBR values than TD children and show significant group (ASD vs. TD) difference [$t_{(54)} = 5.82$, corrected $p < 0.001$, Cohen's $d = 1.550$]. Furthermore, as shown in Fig. 7D, tTBR values did not differ significantly between happiness and sadness prosodies during the IAPS ($p = 0.760$) or MOT-4 ($p = 0.947$) tasks. However, the difference remained significant during the MOT-8 task after Bonferroni correction, [$t_{(55)} = -2.711$, raw $p = 0.009$, Bonferroni-adjusted $p = 0.027$, Cohen's $d = -0.362$], as demonstrated in Fig. 7D.

3.3.4 cTBR

As shown in Fig. 8A, cTBR values did not show a significant difference between happiness and sadness affective prosodies (corrected $p = 0.642$). Similarly, as shown in Fig. 8B, cTBR values did not show a significant difference between different Attentional Levels for IAPS vs. MOT-4: (corrected $p = 0.866$); IAPS vs. MOT-8: (corrected $p = 0.196$); and MOT-4 vs. MOT-8: (corrected $p = 0.466$). However, as shown in Fig. 8C, ASD children had higher cTBR values than TD children and showed a significant group (ASD vs. TD) difference [$t_{(54)} = 7.780$, corrected $p < 0.001$, Cohen's $d = 2.08$]. Furthermore, as shown in Fig. 8D, cTBR values did not show a significant difference between happiness and sadness emotional prosodies for the IAPS (low), MOT-4 (intermediate), and MOT-8 (high) attentional tasks IAPS: (corrected $p = 0.866$); MOT-4: (corrected $p = 0.627$); and MOT-8 task: (corrected $p = 0.110$).

3.3.5 pTBR

As shown in Fig. 9A, pTBR values did not show significant difference between happiness and sadness emotional prosodies (corrected $p = 0.321$). Similarly, as shown in Fig. 9B, pTBR values did not show a significant difference between different Attentional Levels for IAPS vs. MOT-4: (corrected $p = 0.976$); IAPS vs. MOT-8: (corrected $p = 0.583$); and MOT-4 vs. MOT-8: (corrected $p = 0.661$). However, as shown in Fig. 9C, ASD children had higher pTBR values than TD children and showed a significant group (ASD vs. TD) difference [$t_{(54)} = 7.580$, corrected $p < 0.001$, Cohen's $d = 2.03$]. Furthermore, as shown in Fig. 9D, pTBR values did not differ significantly between happiness and sadness prosodies during the IAPS ($p = 0.806$) or MOT-4 ($p = 0.559$) tasks. The difference during the MOT-8 task was also nonsignificant after Bonferroni correction, [$t_{(55)} = -2.280$, raw $p = 0.026$, Bonferroni-adjusted $p = 0.078$, Cohen's $d = -0.305$].

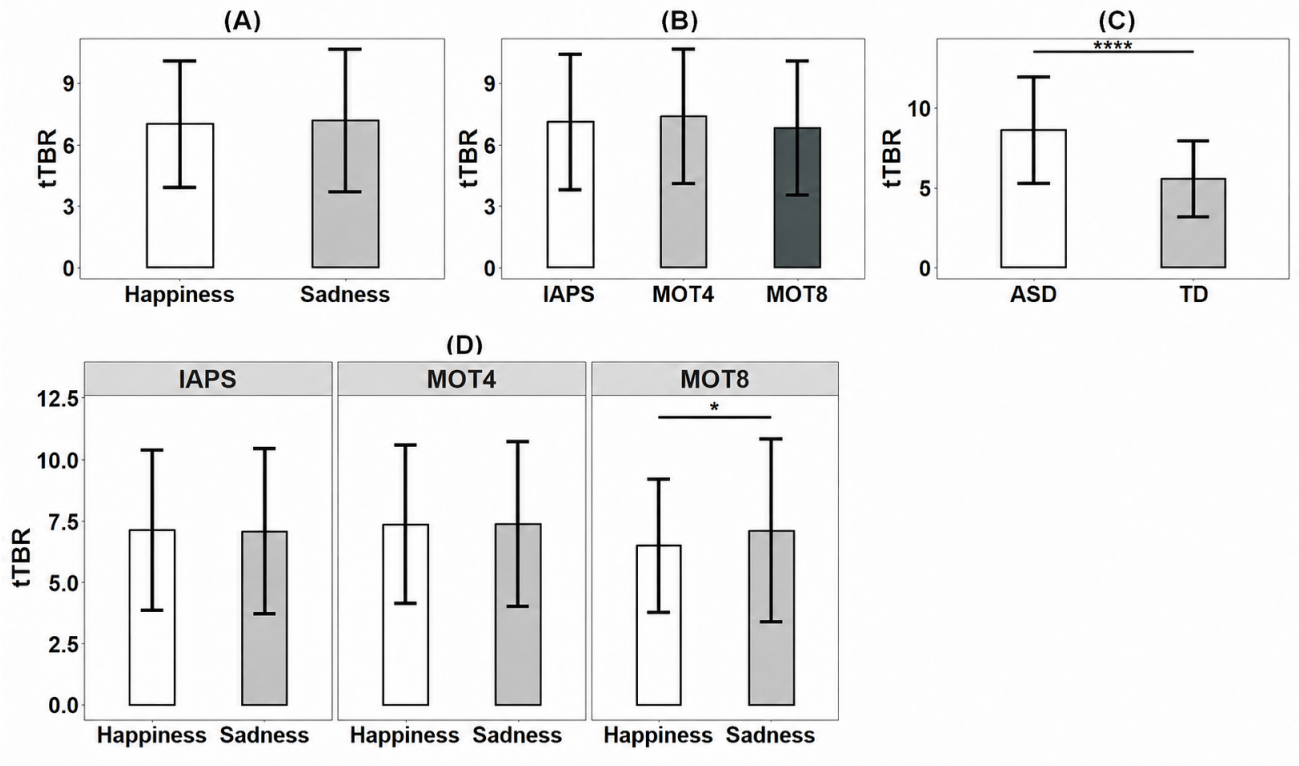

Fig. 7. Post-hoc analysis of the tTBR. (A) Difference between emotions; (B) Differences among attention levels (IAPS, MOT-4, MOT-8); (C) Difference between the ASD and TD groups; (D) Comparison of neural responses between happiness and sadness conditions across different attentional task levels. Error bars represent the standard error of the mean (SEM). *: $p < 0.05$; ****: $p < 0.0001$.

3.4 Correlation Between EEG Features and Clinical Metrics

We examined the correlations between five EEG features (i.e., allTBR, fTBR, tTBR, cTBR, and pTBR) and clinical metrics (i.e., scores on the 13 ASRS subscales) in both groups (ASD and TD) across three tasks with varying attentional demands (Neutral image-viewing task (IAPS task), One-target 4-disc MOT task (MOT-4 task), and One-target 8-disc MOT task (MOT-8 task)), while participants (ASD and TD groups) listened to happiness and sadness prosody. The significant correlation analysis results are summarized in Table 2 and in Fig. 10. The significant correlations are stated as follows: (1) In the MOT-4 attentional load condition, while ASD subjects listened to emotional prosody of happiness, a significant positive correlation was found between cTBR and the BR subscale ($r = 0.378$, corrected $p = 0.047$). (2) In the MOT-4 attentional condition while listening to sadness prosody for TD subjects, a significant negative correlation was found between cTBR and the ASRS total score ($r = –0.408$, corrected $p = 0.035$). (3) In the MOT-4 attentional condition while listening to sadness prosody for TD subjects, a significant negative correlation was found between allTBR and the PS subscale ($r = –0.405$, corrected $p = 0.036$). (4) In the MOT-4 attentional condition, while listening to sadness prosody for TD subjects, a significant negative correlation was found between fTBR and the PS subscale ($r = –0.415$, corrected $p = 0.031$). (5) In the MOT-4 attentional condition while listening to sadness prosody for TD subjects, a significant negative correlation was found between fTBR and the BR subscale ($r = –0.417$, corrected $p = 0.031$). (6) In the MOT-4 attentional condition while listening to sadness prosody for TD subjects, a significant negative correlation was found between pTBR and the BR subscale ($r = –0.426$, corrected $p = 0.027$). (7) In the MOT-4 attentional condition while listening to sadness prosody for TD subjects, a significant negative correlation was found between cTBR and the BR subscale ($r = –0.426$, corrected $p = 0.027$). While listening to sadness and happiness prosody in IAPS, MOT-4, and MOT-8 conditions for ASD and TD, no other significant correlations emerged (all corrected $p > 0.05$).

3.5 Topographic Maps

In this study, we employed topographic maps to visualize the spatial distribution of TBR power across the scalp, highlighting Z-scored power values for TBR, condition, and cognitive task as shown in Fig. 11. To illustrate the differences in EEG activity between the ASD and TD groups, we calculated the mean power for each attentional task using the set of all channels, averaging the signals across trials, and focusing on the emotional conditions. Subsequently, Z-scoring was applied to standardize

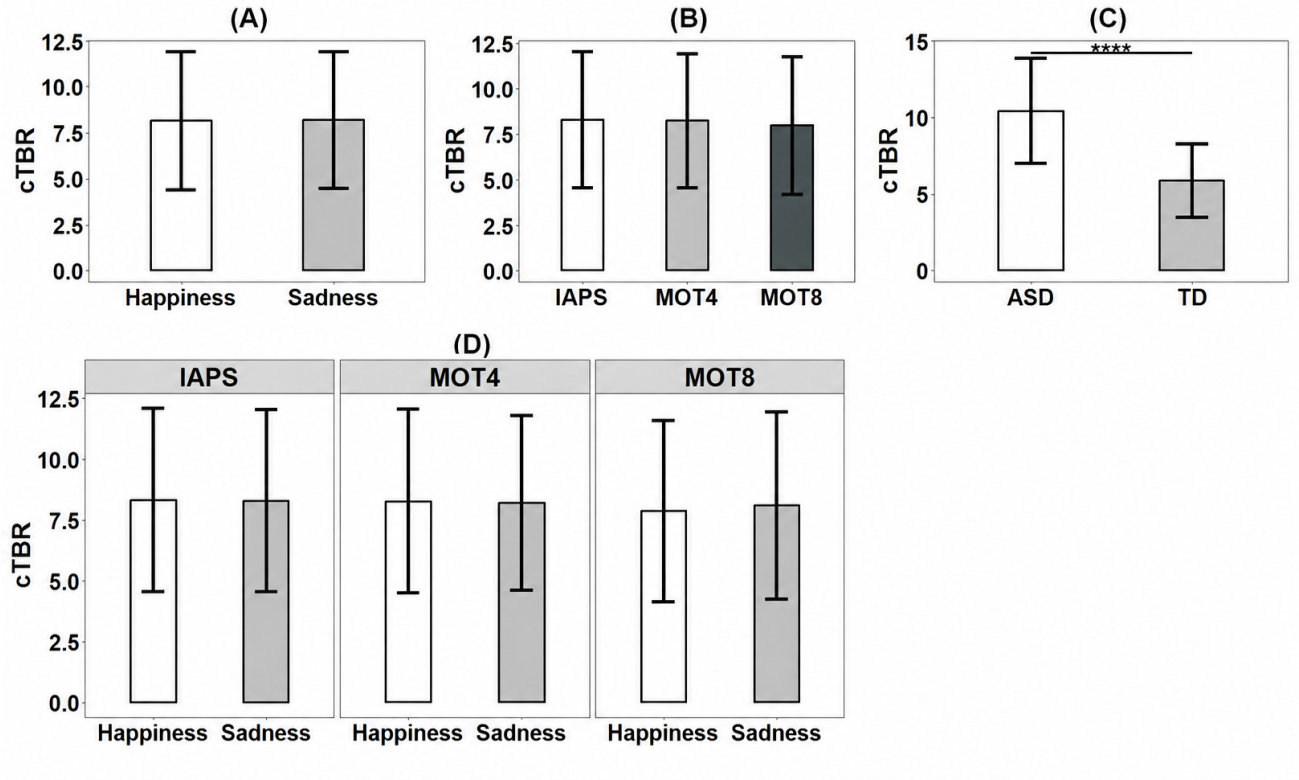

Fig. 8. Post-hoc analysis of the cTBR. (A) Difference between emotions; (B) Differences among attention levels (IAPS, MOT-4, MOT-8); (C) Difference between the ASD and TD groups; (D) Comparison of neural responses between happiness and sadness conditions across different attentional task levels. Error bars represent the standard error of the mean (SEM). ****: $p < 0.0001$.

Table 2. Correlation analysis results for EEG features and ASRS subscales.

Condition/Prosody/Group	Features	ASRS scales	Pearson correlation *r*	95% CI Lower	95% CI Upper	FDR-corrected *p*-value	N
MOT-4 Happiness (ASD)	cTBR	BR	0.378	0.005	0.658	0.047	28
MOT-4 Sadness (TD)	cTBR	Total-ASRS	–0.408	–0.682	–0.033	0.035	28
MOT-4 Sadness (TD)	allTBR	PS	–0.405	–0.680	–0.029	0.036	28
MOT-4 Sadness (TD)	fTBR	PS	–0.415	–0.687	–0.042	0.031	28
MOT-4 Sadness (TD)	fTBR	BR	–0.417	–0.688	–0.044	0.031	28
MOT-4 Sadness (TD)	pTBR	BR	–0.426	–0.694	–0.055	0.027	28
MOT-4 Sadness (TD)	cTBR	BR	–0.426	–0.694	–0.055	0.027	28

the data, enabling a meaningful comparison between the two groups. The variations in brain activity were represented through Z-scored means for each channel, clearly illustrating regions of notable difference as depicted in Fig. 11.

4. Discussion

Several studies have widely used MOT tasks to assess attentional functions in ASD and have revealed that individuals with ASD exhibit impaired performance on these tasks [8,9,10,11]. Thus far, however, most studies on the MOT tasks have focused solely on behavioral responses. It remains unclear whether the EEG signals during MOT tasks can also be adopted to uncover the atypical features in the ASD population. Furthermore, due to the interaction between emotion and cognition, it is currently unclear what changes occur in the EEG features of individuals with ASD during MOT tasks with different attentional loads while listening to different affective prosodies. In particular, this study suggested using TBR to quantify the cognitive load in ASD and revealed the relationship between TBR and core features of ASD [52]. More importantly, this study aimed to test whether this measure (i.e., TBR) can be used to investigate the interaction between emotion and cognition. To illustrate our techniques, this study used a publicly accessible database and yielded four main findings: First, attentional load level and emotional valence exerted a significant interactive modulatory effect on neural activity in the temporal lobe. Second, only under the high-load MOT-8 condition did the temporal lobe exhibit statistically significant differences in neural responses to happy versus sad emotional auditory stimuli. Third, under the medium-load MOT-4

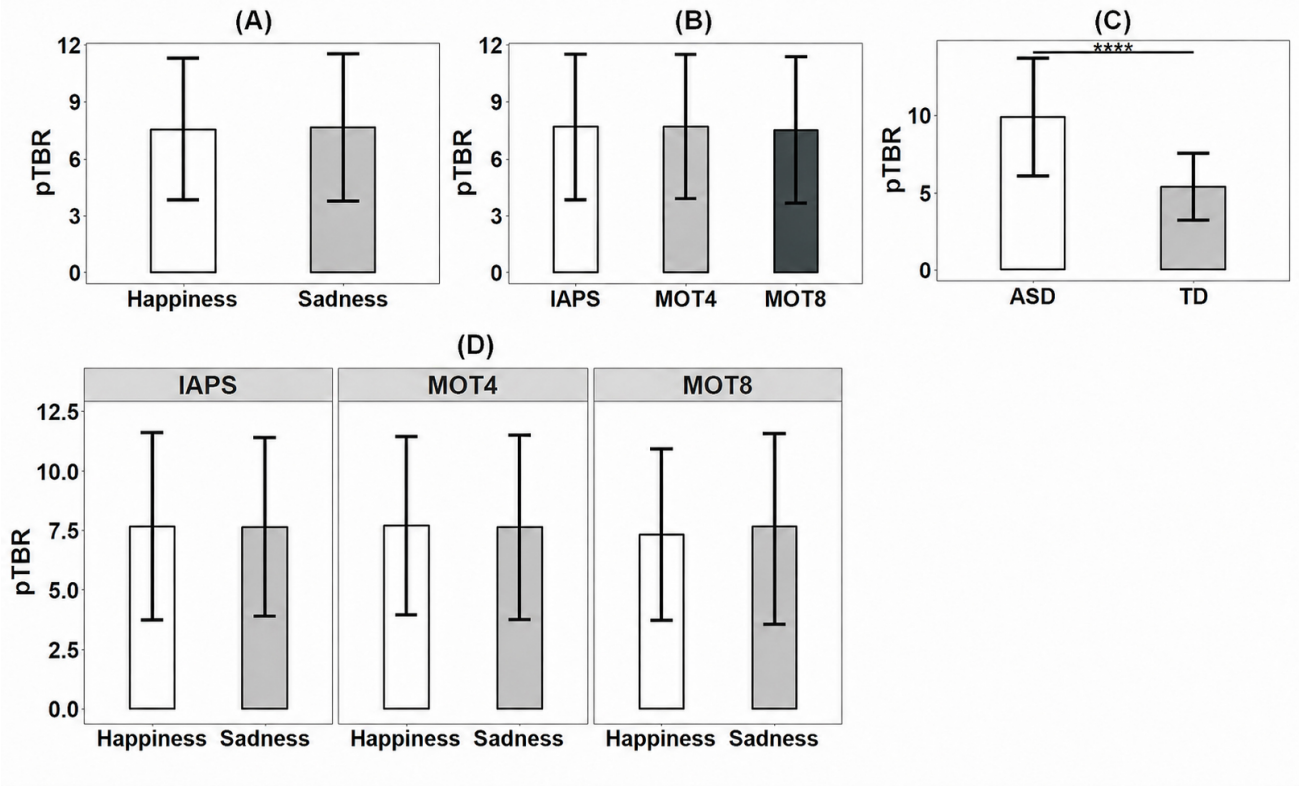

Fig. 9. Post-hoc analysis of the pTBR. (A) Difference between emotions; (B) Differences among attention levels (IAPS, MOT-4, MOT-8); (C) Difference between the ASD and TD groups; (D) Comparison of neural responses between happiness and sadness conditions across different attentional task levels. Error bars represent the standard error of the mean (SEM). ****: $p < 0.0001$.

condition, the correlation between EEG features and clinical measures was significantly stronger in the TD group than in the ASD group. Fourth, only under the high-load MOT-8 condition did the ASD group show significant differences in neural processing of happiness versus sadness emotional prosody in the temporal region, suggesting that emotional valence modulates neural processing under high cognitive load. The present findings are consistent with previous literature indicating atypical processing of affective prosody and emotion-related attentional demands in individuals with ASD. For example, Duville et al. [24] showed that emotion recognition from prosody in ASD is modulated by sensory variability, with improved performance under reduced acoustic complexity, suggesting an interaction between sensory processing and higher-order cognitive demands in emotion-attention processing. Hubbard et al. [22] reported that adults with ASD exhibit increased acoustic variability in emotional speech production, including greater pitch range, intensity, and duration compared to TD individuals, particularly in emotional contexts. These differences also contributed to perceptions of reduced naturalness in ASD speech, suggesting altered modulation of emotional expression. In contrast, Gebauer et al. [23] found that while individuals with ASD show largely typical activation of fronto-temporal and subcortical regions during affective prosody processing, they exhibit increased activation in regions such as the right caudate and report lower perceived emotional intensity, which was interpreted as reflecting increased attentional demands during emotion processing.

4.1 Interaction Between Cognition and Emotion

The present findings provide evidence that emotional context modulates attentional processing in a load-dependent manner, particularly within temporal brain regions. Specifically, significant interactions between emotion and attentional load were observed for allTBR and tTBR. These results suggest that emotion-cognition interactions in ASD are not uniformly impaired but are dynamically influenced by task demands and neural resource allocation. This pattern is consistent with prior research indicating that temporal lobe structures play a critical role in integrating emotional and cognitive information (e.g., Kim et al. [20]; Gebauer et al. [23]). Moreover, the observed differences between ASD and TD groups support the notion that individuals with ASD engage distinct neural mechanisms when processing emotionally salient stimuli, potentially reflecting increased cognitive effort or altered attentional allocation. Together, these findings align with previous work [24] suggesting that emotion-attention interactions are mediated by task complexity and are particularly sensitive to neural dynamics in temporal regions.

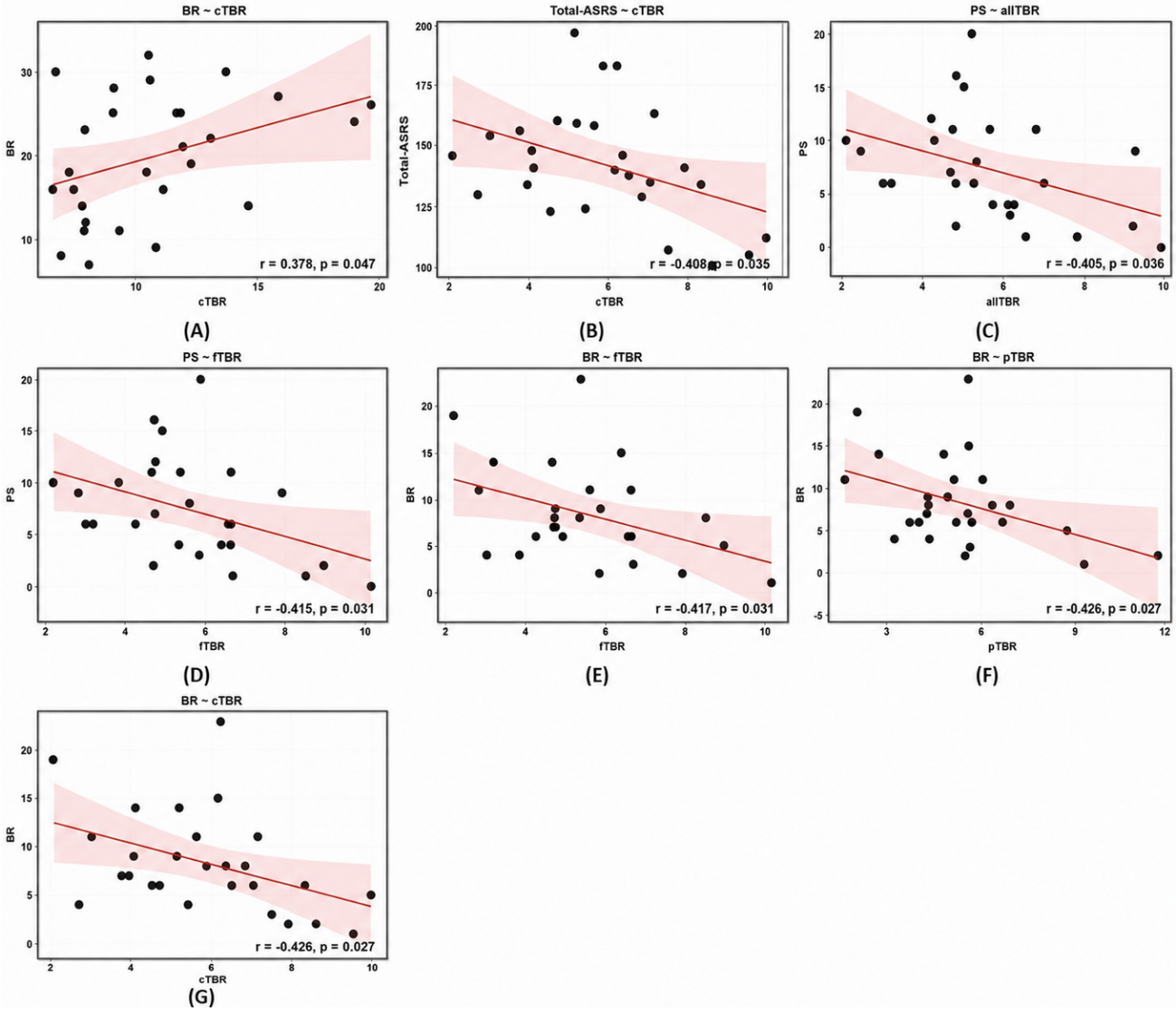

Fig. 10. Correlation analysis plots for EEG features and ASRS subscales. Correlation plots illustrate the relationships between EEG-derived features and ASRS measures: (A) MOT-4 Happiness (ASD), cTBR vs. BR; (B) MOT-4 Sadness (TD), cTBR vs. Total-ASRS score; (C) MOT-4 Sadness (TD), allTBR vs. PS; (D) MOT-4 Sadness (TD), fTBR vs. PS; (E) MOT-4 Sadness (TD), fTBR vs. BR; (F) MOT-4 Sadness (TD), pTBR vs. BR; and (G) MOT-4 Sadness (TD), cTBR vs. BR. Pearson correlation coefficients (r) and Benjamini–Hochberg FDR-adjusted p-values are displayed for each significant correlation. Detailed statistical results, including effective sample sizes, are provided in Table 2.

4.2 Group Differences Between the ASD and TD Groups

Our study also found that the ASD group had higher allTBR and tTBR values than the TD group. This is consistent with previous studies on EEG activity during social and nonsocial videos in clinical trials for children with ASD. For instance, Isaev et al. [40] found that, for the TD group, increased theta power during the social stimulus and a log-ratio (Social vs. Toys) were associated with increased preference for social videos. Increases in theta power have been implicated in the allocation of greater attentional and cognitive resources [53]. Furthermore, Portnova et al. [45] used auditory nonverbal emotional stimuli (crying, laughter, and neutral) and found that children with ASD had a higher P100 amplitude and a lower N200 amplitude for all types of sounds, and a higher P270 amplitude in response to neutral phonemes. Our findings reveal critical differences in the TBR measure between children with ASD and their TD peers, underscoring TBR's potential as a biomarker for attentional and emotional processing. There has been evidence for the use of TBR as a biomarker for attention-deficit hyperactivity disorder (ADHD), but the exact neural basis of the TBR is still poorly understood [54]. However, to our knowledge, no prior research has investigated TBR as a measure of the brain's response to emotional stimuli, such as happiness and sadness. Interestingly, it is estimated that 37%–85% of the ASD population has comorbid

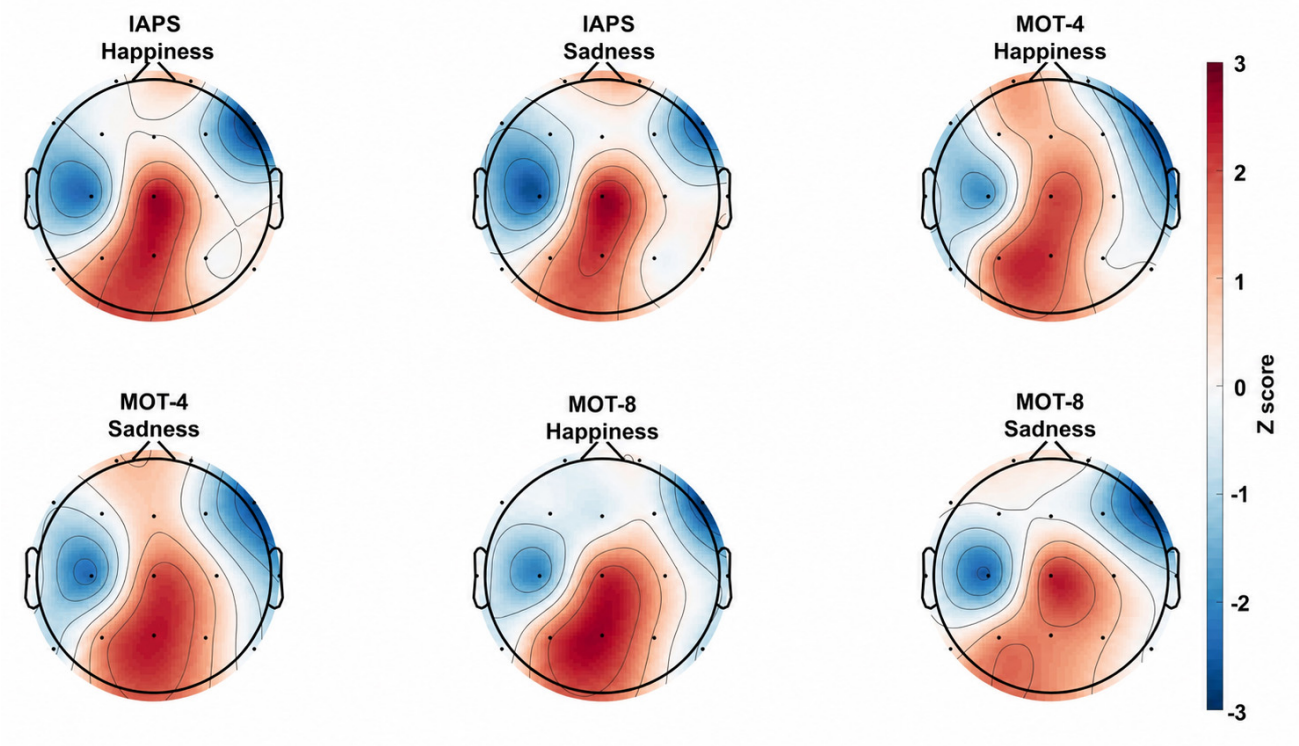

Fig. 11. Topographic distribution of z-scored TBR differences between ASD and TD groups (ASD minus TD). Topographic maps illustrate the standardized differences in TBR between the ASD and TD groups during the IAPS, MOT-4, and MOT-8 tasks under happiness and sadness emotional prosody conditions. The maps represent the difference between the within-group channel-wise Z-scores calculated as ASD minus TD across the 17 common EEG channels. Positive Z-scores (red/yellow colors) indicate higher relative standardized spatial TBR values in the ASD group compared with the TD group, whereas negative Z-scores (blue colors) indicate lower relative standardized spatial TBR values in the ASD group compared with the TD group.

ADHD [55]. While both disorders involve disruptions in attention, individuals with ADHD show more pronounced deficits in sustained attention than those with ASD [56,57]. Since TBR is atypical in both ADHD and ASD, we may be probing attentional brain circuitry that is commonly disrupted in both disorders. Hence, in this work, we also used TBR to examine the similarities and differences in brain function between ASD and TD participants.

4.3 Difference Between Different Emotional Stimuli

A significant difference between happiness and sadness stimuli was observed only in tTBR during the high-load MOT-8 task after Bonferroni correction, but not during tasks with low or moderate attentional demands. This suggests that neural differentiation of emotional stimuli may depend on cognitive load, with more pronounced effects emerging under higher task demands, which is consistent with Duville et al. [24], who showed that emotion recognition from prosody in ASD is modulated by sensory variability, with improved performance under reduced acoustic complexity, indicating an interaction between sensory processing and higher-order cognitive demands in emotion-attention processing.

4.4 Topographic Map Group Differences

In addition to the high TBR observed in ASD participants, our topographic maps (Fig. 11) reveal a spatially dissociative pattern, with higher relative standardized spatial TBR values in frontal and central regions in the ASD group compared with the TD group. Prior work has similarly emphasized the spatial heterogeneity of oscillatory dynamics in ASD. For example, Wang et al. [58], used resting-state EEG and reported excessively long-distance connections in the frontal region, temporal region, parietal region, and frontal-occipital region. In contrast, studies using eyes-closed resting-state protocols Murias et al. [59] found elevated theta band activity in the ASD group, particularly in the frontal and temporal regions. Our finding of higher relative standardized spatial TBR values in frontal and central regions underlines this regional specificity. This interpretation aligns with evidence of increased frontal-central TBR coherence in ASD [58], suggesting early-emerging and regionally distinct network alterations. Together, these results emphasize the importance of considering both spatial and frequency-specific patterns when examining the neurophysiological correlates of ASD.

4.5 Correlation of EEG Characteristics With Clinical Metrics

This study examined the correlations between five EEG features (i.e., allTBR, fTBR, tTBR, cTBR, and pTBR) and clinical metrics (i.e., measures of 13 ASRS subscales) for both groups (i.e., ASD and TD) across three tasks with different attentional levels. We interestingly found that: (1) there were no significant correlation between five EEG features and clinical metrics for the ASD and TD groups in MOT-8 task; (2) For the ASD group, BR was significantly correlated with several EEG features for ASD and TD groups (MOT-4) during listening to happiness prosodies, but there were no significant correlation between other pairs in other cases; (3) BR appears to capture distinct aspects of social interaction and behavioral patterns, suggesting that its relationship with EEG-derived attentional indices is both context- and task-dependent.

4.6 Atypical Features of ASD Individuals

The current study showed some interesting, atypical features of individuals with ASD. Taken together, this study identified several atypical neurophysiological characteristics in children with ASD, including elevated allTBR, pTBR, and tTBR values and reduced correlations between EEG features and clinical measures compared with TD children. These findings suggest potential differences in attentional control and emotion-cognition processing in ASD. While TBR has been widely studied as a biomarker in ADHD [31], its role in ASD remains less understood. Given the high comorbidity between ASD and ADHD [60], the observed TBR alterations may reflect shared disruptions in attentional circuitry. Importantly, the present findings should be interpreted as group-level differences rather than diagnostic markers, but they nonetheless offer valuable insights into the neural mechanisms underlying attentional impairments in ASD.

4.7 Limitations and Future Work

Strengths of the current study include the use of TBR as an EEG marker of attentional impairments in ASD and the investigation of emotion-cognition interactions, revealing atypical neural patterns in ASD. Nevertheless, minor deviations from normality should be acknowledged as a limitation. Future studies may benefit from larger sample sizes or the use of robust statistical frameworks that are less sensitive to distributional assumptions. Taken together, several limitations should be noted. First, the focus on school-aged pupils enhances developmental control but limits generalizability to younger and older age groups. Second, age, gender, and intelligence quotient (IQ) may jointly influence the observed effects; future work should examine their main and interaction effects, particularly regarding differences in emotional processing across cognitive ability levels. In addition, the imbalance in gender distribution between the ASD and TD groups, particularly the relatively small number of female participants in the ASD group, should be acknowledged. Although including gender as a covariate did not alter the significance of the findings, the limited female representation may have reduced the ability to detect potential gender-related effects. Therefore, the present findings may primarily reflect characteristics of male participants with ASD, limiting the generalizability of the results to females with ASD. Future studies with more balanced gender distributions are warranted. Third, participants were classified using ASRS scores, and while parental confirmation of prior clinical diagnosis was obtained for high-ASRS children, no formal diagnostic re-evaluation was conducted, which may limit diagnostic certainty. Fourth, different EEG recording systems were used for high- and low-ASRS groups, which may introduce systematic variability in the raw EEG signals. Fifth, the relatively small sample size limits statistical power and generalizability. Sixth, although the study combined MOT tasks with affective prosody, the emotional stimuli were limited to the auditory domain. Prior research indicates that emotion recognition from prosody alone may remain relatively intact in ASD [61,62], whereas difficulties may emerge with increased stimulus complexity, particularly during audiovisual integration [63]. As multimodal emotional processing was not examined, the generalizability of the findings to more naturalistic social contexts remains limited. Future studies should investigate emotion-attention interactions using multimodal stimuli. Finally, although multiple EEG feature types exist, this study focused solely on TBR; future research should incorporate additional linear and nonlinear features to better characterize ASD-related neural differences.

5. Conclusions

This study demonstrates that EEG-based TBR features are associated with attentional processing in children with ASD across varying cognitive demands (IAPS, MOT-4, and MOT-8) and emotional states (happiness and sadness). The results suggest differences in brain activity between children with ASD and TD, particularly in temporal regions (tTBR), which are implicated in emotional and cognitive processing. TBR-based EEG features also revealed group-level differences in neural responses to emotional stimuli under higher attentional load (e.g., MOT-8). These findings suggest that emotional dysregulation and attentional challenges in ASD may be reflected in distinct patterns of brain activity. Nevertheless, further studies with larger samples and longitudinal or experimental designs are needed to validate these findings and establish their practical and clinical applicability. Overall, these findings provide preliminary insights into attentional impairments and emotion-cognition interactions in ASD, which may inform future research in this area.

Availability of Data and Materials

This study adopted a publicly accessible database, which was hosted at the Mendeley Data (see the site http://doi:10.17632/spwnt8t25y.1).

Author Contributions

Conception and design: MZU, and DY. Data acquisition: MZU, and NT. Data analysis: MZU, HW, and DY. Data interpretation: MZU, and DY. Original draft: MZU and DY. All authors contributed to editorial changes in the manuscript. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

Before data collection, written informed consent was obtained from all children and one of their legal guardians or parents. Approval for all protocols was granted on November 30, 2021, by the Ethics Committee of the School of Medicine at Tecnológico de Monterrey (registered with the National Committee of Bioethics, CONBIOÉTICA 19 CEI 011-2016-10-17) under the following registration number: P000409-autismoEEG2020-CEIC-CR004. Data collection was conducted in accordance with the guidelines of the Declaration of Helsinki.

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Conflicts of Interest

The authors declare no conflicts of interest.

Supplementary Material

Supplementary material associated with this article can be found, in the online version, at https://doi.org/10.31083/JIN49624.

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