



Linking Connectivity Dynamics to Symptom Severity and Cognitive Abilities in Children with Autism Spectrum Disorder: An fNIRS Study

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Functional near-infrared spectroscopy (fNIRS) has emerged as a valuable tool for investigating neurobiological markers in children with autism spectrum disorder (ASD). While previous studies have identified abnormal functional connectivity in ASD children compared with typically developing (TD) peers, brain connectivity dynamics and their associations with autism symptoms and cognitive abilities remain underexplored. We analyzed fNIRS data from 44 children (30 boys, 21 ASD/23 TD) aged 2.08–6.67 years while they viewed a silent cartoon. Using sliding window correlation and *k*-means clustering, we assessed group differences in dynamic connectivity and the correlations with symptom severity and cognitive performance. Our results revealed that children with ASD showed reduced dwell time in a specific brain state and fewer state transitions compared with TD children. These atypical brain state patterns were negatively correlated with autism symptom severity and positively correlated with adaptive behavior and cognitive performance across participants. Mediation analysis revealed that adaptive behavior fully mediated the relationship between brain dynamics and cognitive performance. Furthermore, dynamic connectivity features achieved 74.4% accuracy in distinguishing ASD from TD children. Importantly, the link between brain dynamics and cognitive performance was replicated in an independent TD sample, underscoring the robustness of this finding. Together, these findings highlight altered brain dynamics in young children with ASD and underscore the critical role of adaptive behavior in bridging neural activity and cognitive performance. These insights advance our understanding of neural mechanisms underlying ASD and point to potential pathways for early interventions and clinical applications.

Key words: adaptive behavior; autism spectrum disorder; cognitive performance; dynamic functional connectivity; functional near-infrared spectroscopy

Significance Statement

The brain dynamics and their relationships with symptom severity and cognitive abilities in children with autism spectrum disorder (ASD) remain poorly understood. Using dynamic functional connectivity analysis, our study identified distinct brain state patterns in children with ASD. These patterns were associated with both autism symptom severity and cognitive performance. Importantly, adaptive behavior emerged as a crucial mediator between brain dynamics and cognitive function. Our findings provide novel insights into the neural mechanisms of ASD and highlight the critical role of adaptive behavior in formulating future intervention strategies. By linking specific neural dynamics to adaptive behaviors and cognitive abilities, our study enhances our understanding of ASD neurobiology and has the potential to improve outcomes for affected children.

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Introduction

Autism spectrum disorder (ASD) is a prevalent neurodevelopmental condition characterized by challenges in social communication and restricted, repetitive behaviors, with considerable individual variability (Lord et al., 2020; Zeidan et al., 2022). The preschool age represents a critical window for ASD diagnosis and early intervention (Daniels and Mandell, 2014), yet current diagnostic practices rely predominantly on behavioral assessments that are susceptible to the disorder's phenotypic heterogeneity (Masi et al., 2017). Advancing our understanding of the neurobiological underpinnings underlying ASD in early childhood is therefore essential for improving diagnostic precision and informing the design of effective, individualized interventions.

As a noninvasive, motion-tolerant technique with adequate temporal and spatial resolution for measuring cortical hemodynamic responses, functional near-infrared spectroscopy (fNIRS) is well suited for studying young children in naturalistic settings (Moriguchi and Hiraki, 2013; Quaresima and Ferrari, 2019; Mauri et al., 2020). Previous research has used fNIRS to examine neural markers of ASD, primarily focusing on local activation and static functional connectivity (Liu et al., 2019). While regional activation highlights specific brain areas involved, functional connectivity captures coordination between brain regions and better reflects individual variability (Plitt et al., 2015; Finn and Bandettini, 2021).

Findings from static functional connectivity using fNIRS in ASD, however, have been inconsistent. Some studies reported hyperconnectivity (Kikuchi et al., 2013), while others observed hypoconnectivity (Zhu et al., 2014; Li and Yu, 2016; Sun et al., 2021). These discrepancies may arise from the limitations of static analyses, which average connectivity over the entire recording and assume temporal stability. Such assumption may be inappropriate for ASD populations, whose brain activity shows high variability (Takahashi et al., 2016; Yin et al., 2025), potentially obscuring transient and spatiotemporal network properties (Mash et al., 2019). Dynamic functional connectivity (DFC) addresses this limitation by capturing time-varying patterns of brain network reconfiguration (Hutchison et al., 2013; Preti et al., 2017). Despite their dynamic nature, these patterns exhibit functional stability across time (Madhyastha et al., 2015). Growing evidence suggests that DFC can reveal abnormal connectivity states in psychiatric and neurodevelopmental disorders, including ASD (Calhoun et al., 2014; Damaraju et al., 2014; Gu et al., 2020). DFC metrics not only differentiate ASD from TD populations (Chen et al., 2017; Mash et al., 2019; Zhuang et al., 2023) but also show strong associations with cognitive abilities, adaptive function, and symptom severity (Plitt et al., 2015; Cohen, 2018).

Previous research has demonstrated the viability of applying DFC analyses to fNIRS (Li et al., 2015; Sutoko et al., 2020; Tang et al., 2021; Lu et al., 2023) and reported altered connectivity dynamics in children with ASD compared with TD peers (Li et al., 2018; Fan et al., 2024). However, few have linked these dynamic features to clinical manifestations or functional outcomes (Wan et al., 2024). Of particular relevance is adaptive behavior—the set of conceptual, social, and practical skills needed for everyday functioning (Yang et al., 2016). Deficits in adaptive behavior are a hallmark of ASD (Tillmann et al., 2019), and measures of adaptive skills reliably distinguish TD children from those with developmental disorders (Deng et al., 2025).

To address this gap, the present study used fNIRS-based DFC analysis in a cohort of Chinese children with ASD and TD

controls aged 2–6 years. Our objectives were as follows: (1) to identify group differences in DFC features; (2) to examine relationships between DFC metrics and ASD symptom severity, adaptive behavior, and cognitive performance; and (3) to evaluate the potential of DFC features to differentiate ASD from TD children. Given the novel applying DFC in this population, the study was exploratory. We hypothesized that children with ASD would exhibit distinct DFC profiles relative to TD peers and that these features would correlate with clinical measures, though we made no directional predictions.

Materials and Methods

Participants

Main sample. We recruited 58 children (40 M/18 F) aged 2.08–6.67 years (mean age, 4.5 ± 1.17 years) from the Third Affiliated Hospital of Guangzhou Medical University and Shenzhen Institute of Neuroscience, China, between September 2023 and May 2024. After fNIRS data quality inspection at the individual level, 14 participants were excluded: seven due to multiple bad channels and seven due to incomplete signal acquisition (see below, fNIRS data acquisition, for details). The final sample comprised 44 participants: 21 children with ASD (mean age, 4.06 ± 1.13 years; range, 2.08–6.25 years) and 23 TD children (mean age, 5.07 ± 0.98 years; range, 3–6.67 years). All participants completed the Gesell Developmental Schedule (GDS), assessing developmental domains including fine motor, gross motor, personal-social, language, and adaptive behavior. Parents or caregivers of all participants completed the Autism Behavior Checklist (ABC), a widely used questionnaire for assessing autistic behaviors and symptom severity in individuals with ASD (Krug et al., 1980). Although the ABC was not utilized for diagnosing ASD, it is notable that all TD children had an ABC score <25 , indicating the absence of ASD. Conversely, the majority of children with ASD scored above 53, indicating a high likelihood of autism. All participants diagnosed with ASD met the DSM-V criteria for ASD through clinical interview and underwent the Childhood Autism Rating Scale (CARS) (Schopler et al., 1980), administered by the same clinician. TD children had GDS total scores >85 , indicating normal development. All participants were native Mandarin or Cantonese speakers with normal hearing and no reported family history of mental or psychiatric disorders. This study was approved by the Ethics Committee of Shenzhen Institute of Neuroscience (IRB number: SION202304). Informed consent was obtained from parents or caregivers of all participants.

Regarding socioeconomic status, 34.1% (15/44) of families reported annual incomes of 200,000–500,000 RMB, 38.6% reported 50,000–200,000 RMB, 9.1% reported over 500,000 RMB, and 2.3% reported below 50,000 RMB. Most parents held a bachelor's or associate degree (mothers, 61.4%; fathers, 52.3%), while 6.8% of mothers and 11.4% of fathers had junior high school education or below. A total of 15.9% (7/44) of participants did not report income and parental education data. Additionally, 16 of the 22 children with ASD reported that they were receiving interventions and their parents provided information regarding intervention types and weekly treatment duration.

Validation sample. For validation analyses, we collected an independent TD sample between December 2024 and May 2025 in Shenzhen, China. This dataset included 40 children (19 M/21 F) aged 3–6.92 years (4.93 ± 1.14 years), each of whom completed a 5 min fNIRS recording while watching the cartoon *Partly Cloudy* (<https://www.pixar.com/partly-cloudy>). According to parental reports, none of these children had a history of genetic or neurodevelopmental disorders. A developmental screening further confirmed that all were healthy and typically developing. All participants completed the same visual search task as the main sample. Following identical fNIRS preprocessing and quality control criteria, 24 children (10 M/14 F) aged 3–6.83 years ($4.96 \pm$

Table 1. Demographic information, clinical, and behavioral characteristics in main and validation samples

Characteristics	Main sample		t/χ^2	p	Validation sample
	ASD ($n = 21$)	TD ($n = 23$)			TD ($n = 24$)
Age (years)	4.06 ± 1.13	5.07 ± 0.98	−3.18	0.003	4.96 ± 1.15
Gender (M/F)	18/3	12/11	5.69	0.017	10/14
Annual family income					
<50,000	1 (5.88%)	0 (0.00%)	10.29	0.036	0 (0.00%)
50,000–100,000	5 (29.41%)	1 (5.00%)			1 (4.17%)
100,000–200,000	5 (29.41%)	6 (30.00%)			5 (20.83%)
200,000–500,000	6 (35.29%)	9 (45.00%)			11 (45.83%)
>500	0 (0.00%)	4 (20.00%)			7 (29.17%)
Maternal education level					
Junior high school or below	3 (17.65%)	0 (0.00%)	5.19	0.159	0 (0.00%)
Senior high school or technical secondary school	2 (11.76%)	2 (10.00%)			0 (0.00%)
Associate degree or Bachelor's degree	11 (64.71%)	16 (80.00%)			20 (83.33%)
Master's degree or above	1 (5.88%)	2 (10.00%)			4 (16.67%)
Paternal education level					
Junior high school or below	4 (23.53%)	1 (5.00%)	6.55	0.088	0 (0.00%)
Senior high school or technical secondary school	3 (17.65%)	1 (5.00%)			1 (4.17%)
Associate degree or Bachelor's degree	7 (41.18%)	16 (80.00%)			19 (79.17%)
Master's degree or above	3 (17.65%)	2 (10.00%)			4 (16.67%)
Weekly intervention (h)	8.48 ± 10.08	/	/	/	/
ABC ^a	65.80 ± 17.49	8.83 ± 7.78	13.46	<0.001	6.75 ± 8.90
CARS ^b	31.98 ± 4.47	/	/	/	/
GDS ^c					
Language	61.96 ± 20.19	93.51 ± 12.01	−6.22	<0.001	/
Adaptive behavior	66.83 ± 15.04	93.38 ± 10.45	−6.69	<0.001	/
Fine motor	72.09 ± 17.67	91.99 ± 9.77	−4.46	<0.001	/
Gross motor	69.47 ± 15.45	90.31 ± 11.24	−5.03	<0.001	/
Personal–social	57.44 ± 20.66	95.81 ± 17.51	−6.51	<0.001	/
Total	65.75 ± 14.67	93.45 ± 10.43	−7.10	<0.001	/
Visual search task ^d					
ACC (%)	80.59 ± 16.47	96.52 ± 7.75	−3.70	0.001	92.36 ± 10.14
RT (ms)	2,171.05 ± 836.37	1,214.21 ± 263.41	4.55	<0.001	1,892.75 ± 410.0

Annual family income and parental education levels (both maternal and paternal) were reported as number (percentage of participants), and group comparisons were conducted using chi-square tests. The valid sample sizes were 17 (with 4 missing data) for the ASD group and 20 for the TD group (with 3 missing data). ASD, autism spectrum disorder; TD, typical development; ABC, Autism Behavior Checklist; CARS, Childhood Autism Rating Scale; GDS, Gesell Developmental Schedule; ACC, accuracy; RT, response time.

^aABC scores were available for 20 ASD and 23 TD participants in the main sample.

^bCARS were conducted exclusively among children with ASD.

^cGDS data were obtained for 19 ASD and 22 TD children in the main sample.

^dThe visual search task was completed by 17 ASD and 23 TD children in the main sample. Demographic and behavioral data were complete for all 24 participants in the validation sample.

1.15 years) with high-quality signals across all 24 channels were retained for analysis. The detailed information was presented in Table 1.

Visual search task

We evaluated participants' attention using a reach-tracking adaptation of the visual search task described by Erb et al. (2022). In this task, participants were required to touch a circle that appeared alongside three diamonds on a digital display. There were two types of trials: distractor-absent trials, where all shapes shared the same color, and distractor-present trials, where one diamond varied in color from the other shapes. Each trial type accounted for 50% of the total. Before the test, participants completed five training trials to familiarize themselves with the rules. To proceed to the test session, participants had to achieve an accuracy rate of at least 80% during training. The test session consisted of 30 trials, during which we recorded the accuracy rate (ACC) and the response time (RT) for correctly performed trials for each participant.

fNIRS data acquisition

The fNIRS data were collected using a 24-channel continuous wave system (Brite MkIII, Artinis Medical Systems) at a sampling rate of 25 Hz. The optode template consisted of two 3*3 source-detector arrays covering large areas of the frontal, temporal, and parietal regions. Each array included 12 channels, made up of five transmitters emitting two wavelengths (845 and 761 nm) of light and four receivers. The positioning of the optodes was based on the international 10–20 coordinate system.

During fNIRS signal recording, all children were accompanied by their caregivers in a quiet room and seated in a comfortable chair in front of a computer screen playing silent cartoons of their own choice. This approach was chosen to accommodate the challenge of keeping young children, especially those with ASD, calm and engaged for an extended period (Li and Yu, 2016; Jia et al., 2018; Li et al., 2018). Once the headcap, with a pre-set optode template, was placed on the participant, we ensured that the optodes had good skin contact to prevent environmental light leakage. During the session, children were instructed to watch cartoons and to remain as still as possible. The whole session lasted 8 min.

Preprocessing

Prior to data analysis, we visually inspected all raw fNIRS data ($n = 58$) and excluded seven participants due to incomplete data acquisition. The preprocessing of fNIRS data was performed using MNE-Python v1.7.1 (Gramfort, 2013). First, raw intensity signals were converted to optical density, and data were extracted from the marker onset for a duration of 8 min. Second, channel quality was assessed using the scalp coupling index (SCI), which quantifies the coupling between optodes and scalp (Pollonini et al., 2014). Channels with an SCI value below 0.6 were rejected following previous research (Klein et al., 2022; Steinmetzger et al., 2022). Due to methodological considerations, we applied a strict inclusion criterion requiring all participants to have 24 valid fNIRS channels. Based on this criterion, seven participants (five TD, two ASD) were excluded from further analysis because one or more bad channels had poor signal quality (SCI value <0.6). Motion artifacts were then using

temporal derivative distribution repair (TDDR), which mitigates baseline shift and spike artifacts (Fishburn et al., 2019). The optical density data were subsequently converted to hemoglobin concentration changes using the modified Beer–Lambert law with a partial pathlength factor (PPF) of 6. The units were converted from molar to micromolar (μM). A bandpass filter (0.01–0.08) was applied to remove biological noise including heart rate, Mayer waves, and respiration (Li et al., 2018).

The same preprocessing and data quality control procedures were applied to both the main and validation samples. After exclusion, the main sample consisted of 44 participants (21 ASD/23 TD) who retained all 24 channels and had complete 8 min recordings. The validation sample included 24 children (10 M/14 F) who also met these criteria.

Dynamic functional connectivity

The preprocessed fNIRS data were used to construct DFC matrices. Given that HbO and HbR exhibited qualitatively similar yet opposite trends, with HbR showing a lower signal-to-noise ratio, only HbO signals were selected for this analysis (Ferrari and Quaresima, 2012). The DFC analysis was conducted using MATLAB with the DynamicBC toolbox (Liao et al., 2014). The overall analysis workflow is illustrated in Figure 1.

All 24 channels were used to calculate the between-channel functional connectivity. To better depict the connectivity pattern, as shown in Figure 1a, 22 of the 24 channels were grouped into six regions of interest (ROIs) according to the Montreal Neurological Institute (MNI) coordinates (Supplementary Table S1): right frontal (channels 1, 2, 3, 4), right temporal (channels 6, 10, 11, 12), right parietal (channels 7, 8, 9), left frontal (channels 13, 14, 15, 16), left temporal (channels 18, 22, 23, 24), and left parietal (channels 19, 20, 21). Channels 5 and 17, which were located between the frontal and temporal gyri, were excluded from all ROIs.

A sliding window correlation analysis was applied to examine the dynamics over time. In line with previous fNIRS studies (Li et al., 2015; Niu et al., 2019; Urquhart et al., 2020), we used a 60 s window with 1 s step size, resulting in 421 windows for each participant (Fig. 1b). To address the lack of consensus on the optimal window size, we also evaluated the results using 45 and 90 s windows. The main text presented results for the 60 s window size, while the corresponding results for other window sizes were provided in the supplementary materials. Pearson's correlation was computed between each pair of channels, generating a ($24 \times 24 \times 421$) data matrix for each participant.

To identify recurring connectivity states, we applied the k -means clustering algorithm to classify the matrices into k clusters representing distinct connectivity states. The optimal number of clusters was determined using the Elbow method with k varying from 2 to 10. The "elbow" of the curve, where the rate of decrease in intra-cluster variation (measured by the within-cluster sum of squared Euclidean distances) slowed significantly, occurred at $k=4$ in our data. As a result, each windowed functional connectivity map (all 421×44 maps) was assigned to one of four clusters, each representing a unique brain state (Fig. 1c).

To compare the DFC states between groups, we used three main indicators: (1) proportion of occurrence (PO)—the proportion of windows assigned to each state, calculated as the number of windows in a specific state divided by the total number of windows (421×44). (2) Mean dwell time (MDT): The average duration (in consecutive windows) a participant remained in a particular state before transitioning to another state. This was computed by averaging the number of continuous windows that belonged to one state. (3) Transition matrix: The probability of transitioning from one state to another, defined as the number of transitions from one state i to state j divided by the total number of windows in state i .

Statistical analysis

Considering the non-normality of the DFC measures, we followed previous studies (Engels et al., 2018; Wu et al., 2019) and employed non-parametric tests, specifically Mann–Whitney U test, to compare the differences between the ASD and TD groups. Age and gender were not controlled for in the group comparisons, as neither was significantly correlated with any of the DFC measures ($ps > 0.05$; Table S2). Bonferroni's correction was applied to adjust for multiple comparisons.

Additionally, we calculated Spearman rank correlations between behavioral scores (ABC and Gesell adaptive behavior scores), cognitive performance (ACC and RT on the visual search task), and the dynamic measures that showed significant group differences across the entire sample, controlling for age and gender. In the main text, we performed correlation analyses using the combined sample of all participants, following previous studies (Zhao et al., 2022; Luo et al., 2023). This approach was adopted because clinical symptoms and cognitive abilities represent continuous variables with individual differences across both ASD and TD groups, allowing us to examine the brain–behavior relationships across diagnostic categories. Nevertheless, to address potential group-specific effects, we also conducted supplementary analyses with separated groups to examine correlations within each diagnostic category independently. False discovery rate (FDR) correction was applied to adjust for multiple comparisons.

Mediation analysis

To further investigate the relationships between the dynamic measures that showed significant group differences and cognitive performance, we conducted the mediation analyses using the PROCESS macro in SPSS (v22) (Hayes, 2017) on participants with available brain and cognitive performance data (14 ASD, 22 TD). Specifically, the dynamic measures with significant group differences were treated as the independent variable, response time on the visual search task as the outcome, and Gesell adaptive behavior scores as the mediator (Fig. 1d). All variables were standardized. The significance of the indirect effect was assessed via bootstrapped with 5,000 samples with replacement. If the 95% bias-corrected confidence interval did not include zero, the mediation effect was considered significant.

Classification analysis using support vector machine

In an exploratory analysis, we investigated whether DFC state characteristics could distinguish between the ASD and TD groups, and we employed a machine learning classification approach using the MVPANI toolbox (Peng et al., 2020). We used a linear support vector machine (SVM) with leave-one-out cross-validation (LOOCV) to accommodate our small sample size. Brain state features showing significant between-group differences were used as input features.

In the LOOCV procedure, one sample was iteratively held out as the test set, while the remaining $N-1$ samples formed the training set (Fig. 1e). Classification accuracy was calculated after all samples were tested. We calculated the area under the curve (AUC) of the receiver operating characteristic (ROC) curve, which plots the true positive rate against the false positive rate, to assess the classification performance. To test the statistical significance of the classification, we performed 5,000 permutations.

Results

Demographic and behavioral information

In the final sample (21 ASD, 23 TD), the valid sample sizes for each index were as follows: 20 ASD and 23 TD participants for the ABC; 19 ASD and 22 TD participants for the GDS; and 17 ASD and 23 TD participants for the visual search task. Demographic statistics and group differences between ASD and TD were summarized in Table 1. Significant group differences were observed in age, with the ASD group being younger than the TD group ($t_{(42)} = -3.181, p = 0.003$), and in gender, with a higher proportion of males in the ASD group ($\chi^2 = 5.692, p = 0.017$). To ensure that our findings regarding group differences in DFC metrics and their correlations with clinical and cognitive measures were not confounded by demographic factors, we conducted supplementary analyses to examine whether age and gender significantly influenced the brain state metrics. The correlation analyses revealed no statistically significant correlations between any of the brain state metrics and either age or gender (Table S2; all $ps > 0.05$). In addition, the two groups showed significant difference in annual family

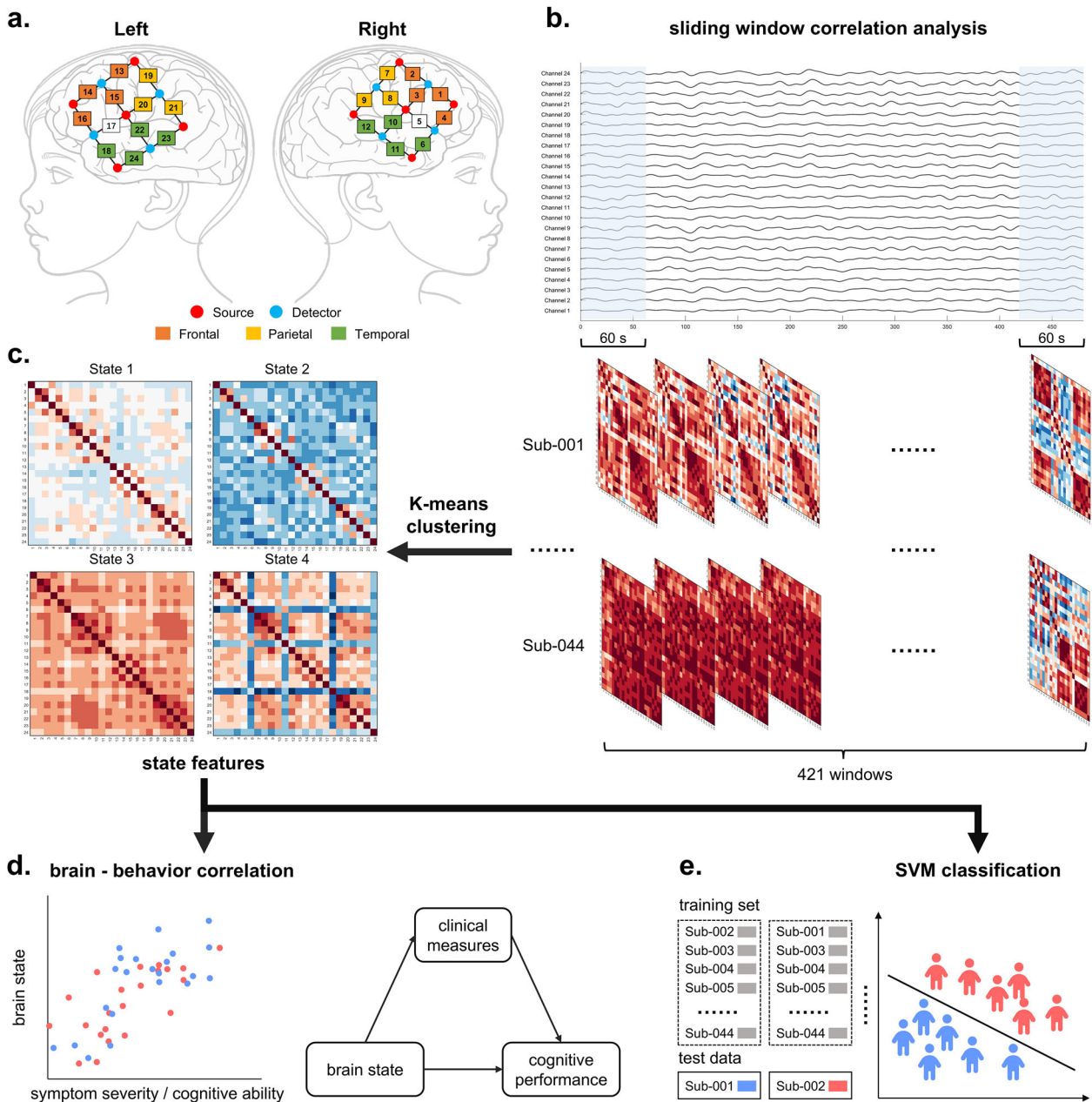


Figure 1. The flowchart of signal acquisition and analysis workflow. **a**, The example figure illustrated a child wearing a 24-channel fNIRS cap, with red dots indicating the sources, blue dots representing the detectors, and rectangles connecting the red and blue dots denoting the channels. **b**, Preprocessed data from 24 channels of one participant during an 8 min fNIRS session was presented, and a sliding window analysis was performed using a 60 s window size with a 1 s step, resulting in 421 dynamic functional connectivity maps for each participant. **c**, k-means clustering was applied to group all participants' dynamic functional connectivity maps (or matrices) into four states, with the centroid maps displayed. **d**, Brain state characteristics were extracted and analyzed to examine their correlations with clinical measures and cognitive performance. Subsequently, mediation models were constructed to investigate the interrelationships among these three variables. **e**, A support vector machine with leave-one-out cross-validation was employed to classify participants into ASD and TD groups based on these state features.

income ($\chi^2 = 10.294$, $p = 0.036$), but not in maternal or paternal education level ($ps > 0.05$). Children with ASD exhibited higher ABC scores than the TD group ($t_{(41)} = 13.458$, $p < 0.001$). There were significant differences in total scores and all domains measured by the GDS between TD and ASD groups ($ps < 0.001$). For the visual search task, significant differences were found in RT ($t_{(38)} = 4.553$, $p < 0.001$) and ACC ($t_{(38)} = -3.698$, $p = 0.001$).

DFC state characteristics and group differences

The DFC maps of all participants were classified into four distinct states, as shown in Figure 2a. State 1 was the most frequent (33.29%), followed by State 2 (28.61%), State 3 (25.45%), and

State 4 (12.66%). Regarding overall connectivity, States 1 and 2 exhibited relatively weak connectivity across channels (blue to white), while States 3 and 4 displayed stronger connectivity (pink to red). To further highlight the differences between these states, we extracted the top 5% strongest connections (absolute values) from each state's connectivity matrix (Fig. 2b). This analysis revealed that State 1 and State 3 were characterized by intense within-region connectivity, while State 2 and State 4 showed more across-region connections. Notably, State 4 showed more left-right interhemispheric connections and sparser within-region connections. One participant was excluded from following analyses due to abnormal DFC patterns (exceeding 3 SDs

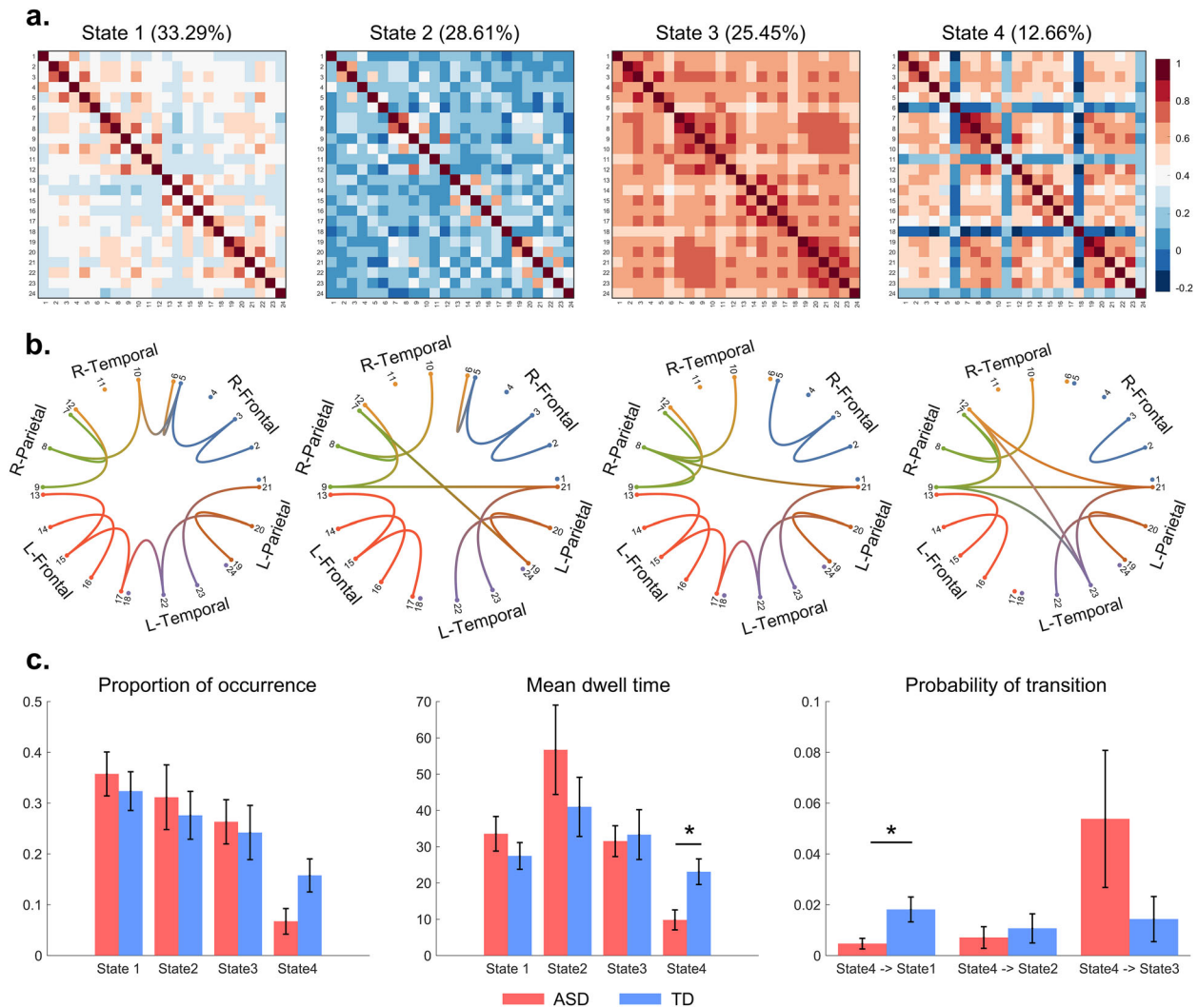


Figure 2. Patterns of dynamic functional connectivity (DFC) states and group comparisons. **a**, The centroids of the DFC states were displayed, with the percentage of occurrences for each state indicated above each centroid. **b**, The strongest 5% of connectivity within each state was visualized using circos plots, with the 24 channels grouped into six brain regions. R, right, L, left. **c**, The group differences between ASD and TD in three characteristics of each state were presented in bar charts, showing the mean and standard error (SE). * $p < 0.0125$ (0.05/4, Bonferroni's correction).

from the mean), leaving final samples of 20 ASD and 23 TD participants.

To examine the differences between the ASD and TD groups across the four states, we compared the PO and MDT for each state. No significant differences were observed between the groups for State 1 (PO: $z = -0.463$, $p = 0.644$; MDT: $z = -0.925$, $p = 0.355$), State 2 (PO: $z = -0.292$, $p = 0.77$; MDT: $z = -1.059$, $p = 0.289$), or State 3 (PO: $z = -0.744$, $p = 0.457$; MDT: $z = -0.573$, $p = 0.567$). However, significant group differences were found in State 4, with the ASD group showing a lower PO ($z = 2.296$, $p = 0.022$, not statistically significant after Bonferroni's correction) and a shorter MDT ($z = 2.704$, $p = 0.007$, significant after correction) than the TD group.

To validate the robustness of these findings, we conducted supplementary analyses by adjusting the window length to 45 and 90 s while maintaining the step size at 1 s. The pattern of these results remained consistent with our main findings (see Fig. S1 for temporal dynamics and Table S3 for detailed statistics). This convergence across different time windows suggests that our results are not dependent on the specific choice of temporal parameters.

Since the difference was only evident in State 4, we further explored group differences by analyzing the transition probabilities from State 4 to the other three states (Fig. 2c). To control for multiple comparisons (three tests), a Bonferroni's correction was applied, with a significance threshold of $p < 0.05/3 = 0.017$. The results showed that the transition probability from State 4 to State 1 was significantly different between groups ($z = 2.478$, $p = 0.013$). However, no significant differences were observed in transition probabilities from State 4 to State 2 ($z = 0.4$, $p = 0.689$) or from State 4 to State 3 ($z = -1.28$, $p = 0.202$).

Associations between DFC state characteristics and behavior

Next, we examined the associations between state characteristics that showed significant group differences (i.e., MDT of State 4 and the probability of transitioning from State 4 to State 1) and both symptom severity (ABC scores) and cognitive abilities (Gesell adaptive behavior scores) using the Spearman rank correlation, controlling for age and gender. The results showed that the MDT of State 4 was significantly negatively correlated with ABC scores ($\rho_{(39)} = -0.48$, $p = 0.002$; Fig. 3a). Conversely, the MDT of State 4 was positively correlated with adaptive behavior

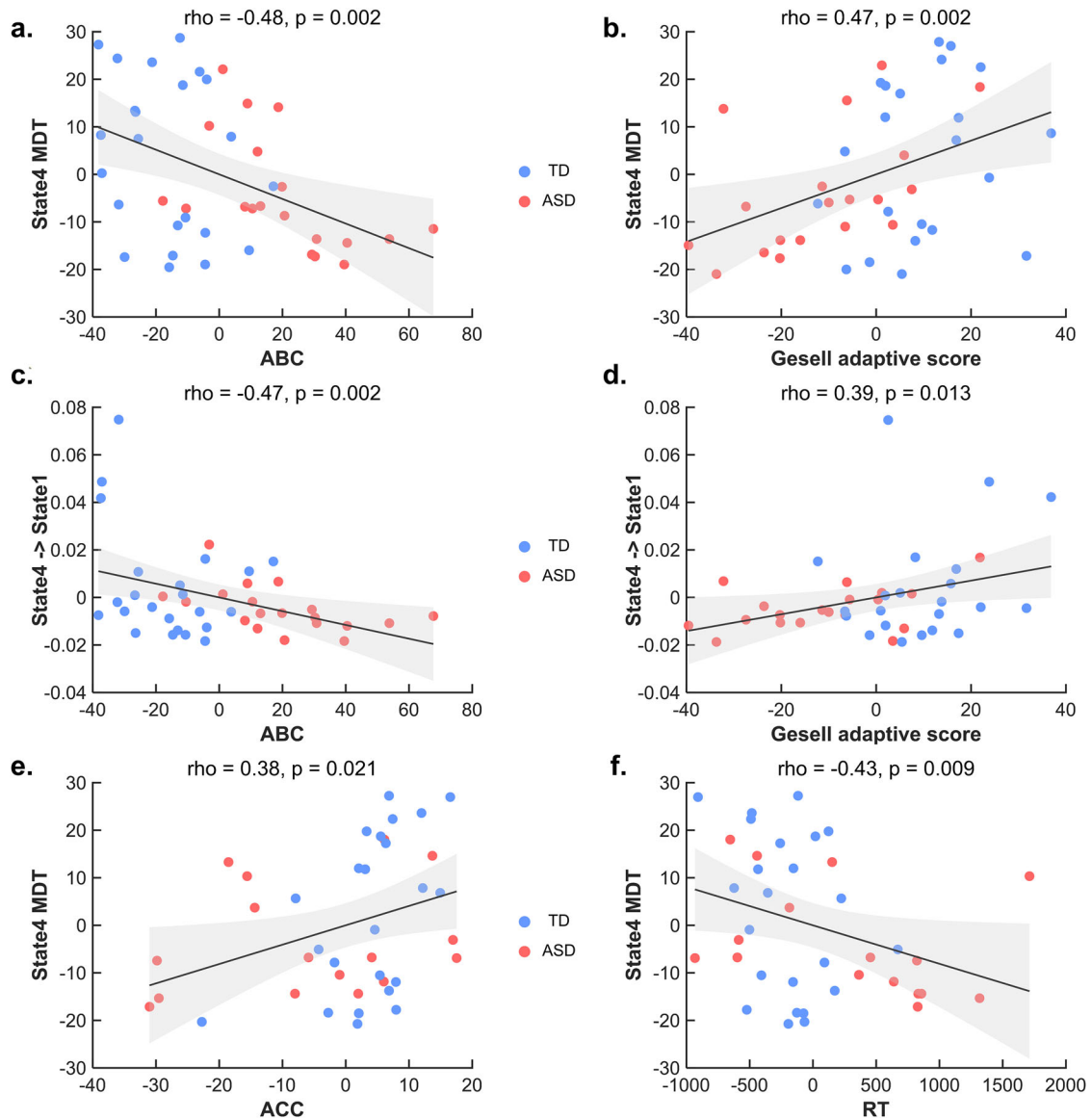


Figure 3. Scatterplot showing the relationship between brain state characteristics, clinical measures, and cognitive task performance. The mean dwell time (MDT) of State 4 showed significantly negative correlation with autism symptom severity (ABC scores; **a**) and positive correlation with adaptive behavior (**b**). Similarly, the transition probability from State 4 to State 1 was also negatively correlated with ABC scores (**c**) and positively correlated with adaptive behavior (**d**). The MDT of State 4 also demonstrated significant correlations with accuracy rate (ACC, **e**) and response time (RT, **f**) on a visual search task. Red dots represent individuals with ASD, and blue dots represent TD individuals. Residuals, adjusted for age and gender, were used for plotting. The shaded region around the trend line represents the 95% confidence interval.

scores ($\rho_{(37)} = 0.47, p = 0.002$; Fig. 3*b*). Similar patterns were observed for the transition probability from State 4 to State 1, where higher transition frequencies were linked to less severe autism symptoms ($\rho_{(39)} = -0.47, p = 0.002$; Fig. 3*c*) and better adaptive behavior ($\rho_{(37)} = 0.39, p = 0.013$; Fig. 3*d*).

We further examined the relationship between DFC state characteristics and cognitive performance (ACC and RT on the visual search task) using the Spearman's rank correlation analysis, controlling for age and gender. We observed significant correlations between the MDT of State 4 and both ACC ($\rho_{(35)} = 0.38, p = 0.021$; Fig. 3*e*) and RT ($\rho_{(35)} = -0.43, p = 0.009$; Fig. 3*f*). All aforementioned correlations survived after FDR correction. However, no significant correlation was observed for the transition probability from State 4 to State 1 in relation to either ACC ($\rho_{(35)} = 0.11, p = 0.515$) or RT ($\rho_{(35)} = -0.08, p = 0.622$).

Additionally, we explored potential group-specific effects by conducting correlation analyses separately for each group, and

results were presented in Supplementary Figure S2. Overall, the general trends between brain dynamics and behavioral measures remained consistent with our combined analysis. In the ASD group, the MDT of State 4 maintained significantly correlated with ABC and Gesell adaptive behavior ($ps < 0.05$, uncorrected), although its relationship with cognitive task performance (ACC, RT) did not reach significance. In the TD group, while the MDT of State 4 did not significantly correlate with either ABC or Gesell adaptive behavior, it showed a marginally significant relationship with RT ($p = 0.059$). Notably, the transition probability from State 4 to State 1 showed a significant negative correlation with ABC scores in the TD group ($p = 0.004$, uncorrected).

Results of mediation analysis

Further, we conducted a mediation analysis to investigate whether the relationship between brain dynamic states (with significant group differences) and cognitive performance was

mediated by adaptive behavior. In the analysis, the MDT of State 4 was treated as the independent variable (X), task RT as the outcome (Y), and Gesell adaptive behavior score was examined as mediator (M). As shown in Figure 4a, the results revealed a significant mediation effect of adaptive behavior. Specifically, MDT of State 4 influenced adaptive behavior (path a , $\beta = 0.34$, $p = 0.07$, 95% CI: $[-0.02, 0.69]$) and adaptive behavior, in turn, significantly predicted task performance (path b , $\beta = -0.57$, $p < 0.001$, 95% CI: $[-0.805, -0.339]$). The direct effect of MDT of State 4 on RT, controlling for adaptive behavior, was not significant (path c' , $\beta = -0.24$, $p = 0.058$, 95% CI: $[-0.479, 0.009]$). However, the bootstrap analysis revealed a significant indirect effect of MDT of State 4 on RT via adaptive behavior ($a*b$, $\beta = -0.19$, 95% CI: $[-0.449, -0.001]$; Fig. 4b).

The classification results based on DFC state characteristics

To classify ASD and TD individuals, we used DFC state characteristics (i.e., PO, MDT of State 4, and the transition probability from State 4 to State 1) that exhibited significant group differences as features in a linear SVM classifier. The classification accuracy was 74.4%, with an AUC of 0.77. We performed 5,000 permutations, resulting in a p -value of 0.03 (158/5,000), indicating that the classification results were statistically significant.

To better validate the promising role of DFC characteristics in distinguishing between ASD and TD individuals, we conducted additional comparative validation analyses to compare the performance of connectivity measures against local activation patterns. For local activation patterns, we included mean values from six ROIs (right frontal, right temporal, right parietal, left frontal, left temporal, and left parietal) as features in SVM analysis ($n = 43$).

Following the same LOOCV procedure, the SVM analysis demonstrated classification accuracies of 52.3% for local activation patterns (AUC = 0.48) when distinguishing between ASD and TD participants. These results provide empirical justification for our focus on connectivity metrics which outperformed local regional activation measures.

Validation of brain dynamics in an independent TD sample

We conducted a validation analysis to test whether brain dynamics could serve as a reliable neural marker of cognitive ability in

TD children and to verify that variations in fNIRS recording duration did not impact our main findings. First, DFC analysis identified similar four brain states in this independent sample (Fig. 5a), supporting the reproducibility of our results. Second, Spearman correlation analysis revealed a significant negative relationship between the MDT of State 4 and RT ($\rho = -0.47$, $p = 0.028$; Fig. 5b). Finally, using a data-driven approach, support vector regression (SVR) analysis with State 4 dynamics characteristics (PO, MDT, and transition probability) significantly predicted RT ($r = 0.455$, $p = 0.025$; Fig. 5c), further supporting the role of brain state dynamics as a potential neural marker of cognitive performance in TD children.

Discussion

In this study, we used fNIRS to examine DFC patterns in a cohort of young Chinese children with ASD and their TD peers, exploring the group differences in DFC characteristic and their associations with autism severity, adaptive behavior, and cognitive performance. Across participants, we identified four distinct states. Compared with TD children, those with ASD exhibited altered brain state dynamics, characterized by reduced MDT and transition probability in a specific state (i.e., State 4). These alterations were significantly associated with autism symptom severity, cognitive ability, and visual search performance. Mediation analysis revealed that adaptive behavior mediated the relationship between brain state dynamics and cognitive ability. Overall, DFC patterns effectively discriminated ASD from TD, suggesting their potential as neurobiological markers for ASD.

Our primary findings revealed distinct brain state dynamics in children with ASD compared with TD children during watching cartoons, specifically characterized by reduced dwell time in State 4. This state exhibited weaker connectivity between temporal channels and other brain regions, coupled with stronger inter-hemispheric connections, particularly in the temporal and parietal regions. These observations are in line with previous fNIRS resting-state studies, which reported reduced inter-hemispheric functional connectivity in bilateral temporal regions in children with ASD compared with TD controls (Zhu et al., 2014; Wu et al., 2021). According to the underconnectivity hypothesis in ASD research, reduced long-range functional

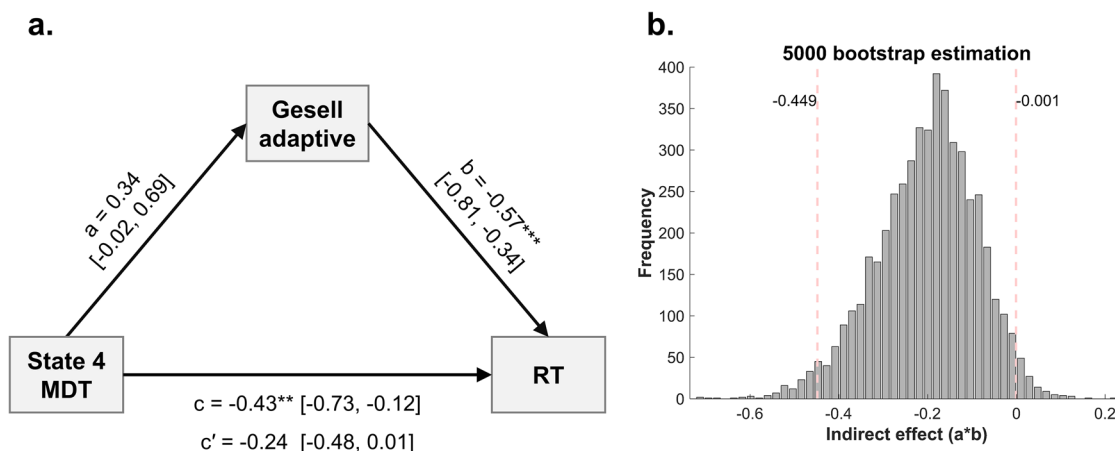


Figure 4. The mediation results. **a**, The mediation model illustrated the mediating role of Gesell adaptive behavior in the relationship between the brain state characteristics (mean dwell time, MDT) and cognitive task performance (response time, RT). Each path in the model was annotated with its standardized regression coefficient and corresponding 95% confidence interval. Significant paths were indicated with $**p < 0.01$, $***p < 0.001$. **b**, The histogram displayed the distribution of 5,000 bootstrapped indirect effects, with the 95% confidence intervals (marked by pink dashed lines) not containing zero.

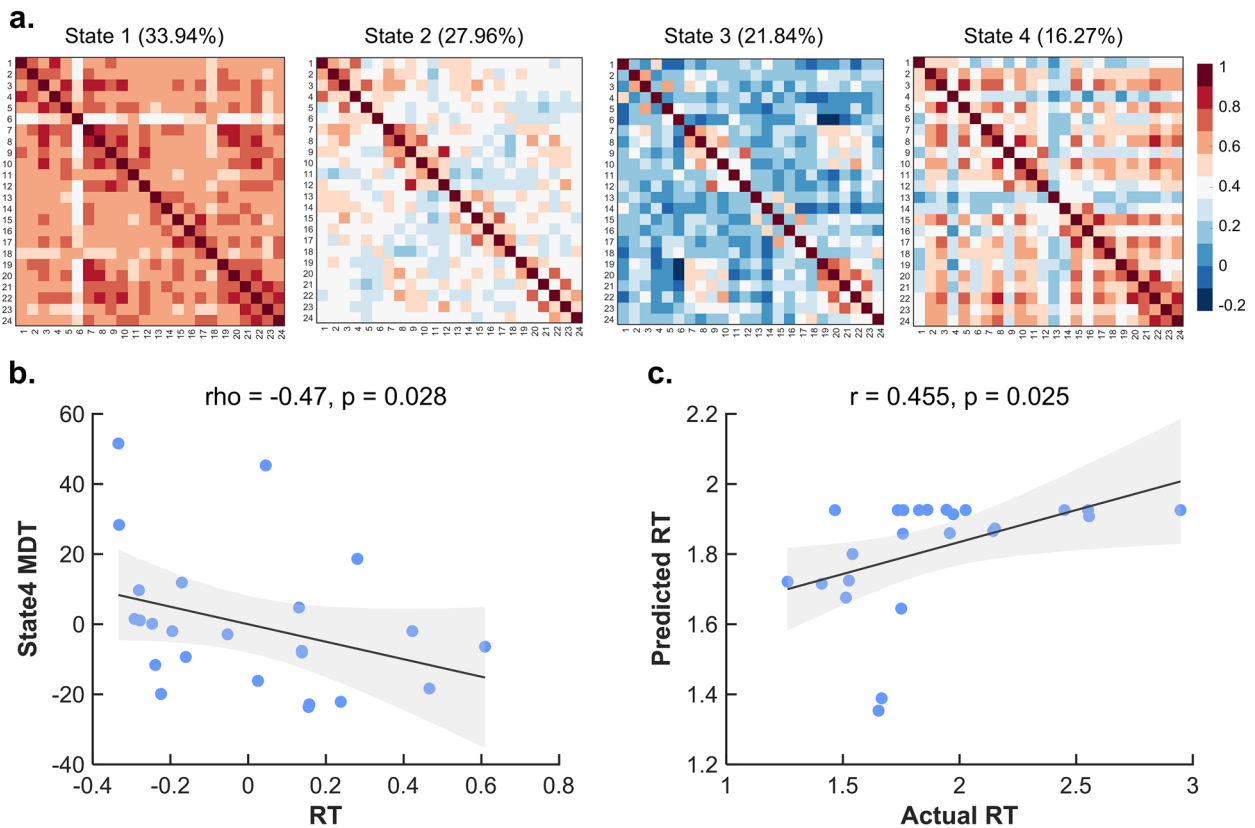


Figure 5. Brain state dynamics validation in an independent TD sample ($n = 24$). **a**, The four brain states identified through dynamic functional connectivity analysis with their corresponding occurrence rates (%). **b**, Partial correlation between mean dwell time (MDT) of State 4 and response time (RT) after controlling for age and sex. Gray shading represents the 95% confidence interval. **c**, Scatterplot showing the relationship between actual RT and predicted RT using support vector regression (SVR) based on State 4 dynamics parameters (PO, MDT, and transition probability), with 95% confidence interval (gray shading).

connectivity represents a core neurobiological mechanism underlying ASD (Anderson et al., 2011). Evidence from fMRI-based DFC studies further highlights state-specific alterations in ASD, marked by hypoconnectivity and increased variability in long-range connections (Chen et al., 2017). Long-distance neural connections, particularly interhemispheric connections, are crucial for efficient information exchange across the brain (Martínez et al., 2018). Studies have showed that children with ASD demonstrated weaker network efficiency compared with healthy controls (Lewis et al., 2014; Li and Yu, 2016), supporting the challenges they face in coordinating information across the brain. Our findings revealed that children with ASD spent significantly less time in brain states characterized by robust interhemispheric connectivity, especially in temporal regions. This atypical temporal pattern likely contributes to language and social impairments commonly observed in ASD, given the critical role of temporal regions in these functions (Redcay, 2008; Eyler et al., 2012; Xu et al., 2020; Xiao et al., 2022).

In contrast to previous DFC studies in ASD that reported increased state dwell time in individuals with ASD (Li et al., 2020; Wan et al., 2024), we did not observe significant increases in any brain state during rest in children with ASD compared with their TD peers. This discrepancy may be attributed to the limited channel coverage in our study, which focused primarily on frontal and temporal regions. Notably, we observed decreased transition frequency between two key connectivity states in children with ASD: cross-hemispheric hyperconnectivity (State 4) and intense local connectivity (State 1). This reduced dynamic reconfiguration flexibility likely reflects challenges in integrating

and processing information across spatial scales, potentially contributing to cognitive difficulties commonly observed in ASD (Wang et al., 2022). Dynamic state transitions have been linked to cognitive flexibility (Nomi et al., 2017) and creativity (Li et al., 2017). Thus, the reduced transitions we observed may represent a neural mechanism underlying cognitive inflexibility in children with ASD. In addition, it is worth noting that previous studies have also observed that PO significantly differed between ASD and TD groups (Rabany et al., 2019; Yue et al., 2022); however, in our study, this result did not survive multiple-comparison correction. Whether this brain state characteristic represents a stable group difference index warrants further validation in larger sample sizes.

The associations we identified between brain state characteristics and clinical measures provide crucial insights into the brain–behavior relationships in ASD. Previous studies have linked atypical brain dynamics to clinical features in ASD. For example, autism symptom severity has been associated with atypical hypervariable in DFC patterns (Li et al., 2020), and increased brain modular flexibility has been correlated with greater autism severity (Harlalka et al., 2019). Additionally, the neurovascular patterns derived from electroencephalography (EEG)- and fNIRS-based DFC features have shown predictive value for adaptive functioning development in ASD (Wan et al., 2024). In this study, we found that a longer duration in a state characterized by strong temporal-parietal connectivity and weak intratemporal regional connectivity was associated with less severe autistic symptoms and greater adaptive behaviors. Similarly, previous fNIRS research revealed weakened

long-range temporal correlations (LRTCs) in children with ASD, particularly in the left temporal and temporo-occipital regions, with LRTCs in left temporal region negatively correlated with autism severity (Jia et al., 2018). In contrast, a resting-state fMRI study found that higher levels of autistic traits were associated with longer dwell time in a globally disconnected state with weak intra- and internetwork connectivity (Rashid et al., 2018). The differences between our findings and prior studies may be due to differences in participant ages, as our study focused on younger children (2–6 years old) whose brain networks are in earlier, more dynamic developmental stages, while prior research primarily examined older children (6–10 years old) with relatively stable neural connectivity patterns. Differences in clinical measures, such as symptom severity versus autistic traits, may also contribute to these discrepancies.

Our findings also demonstrated that state-specific duration times were correlated not only with clinical measures but also with cognitive performance. This state-dependent relationship complements prior evidence linking brain dynamics with cognitive task performance. For example, increased variability in DFC has been associated with impaired task performance in resting-state fMRI studies (Douw et al., 2016; Lin et al., 2016). Additionally, accumulating evidence indicated that resting-state DFC predicts individual differences in attention (Madhyastha et al., 2015; Spadone et al., 2015; Fong et al., 2019). Our findings extend this body of work by demonstrating that hemodynamic signals measured with fNIRS are also associated with cognitive performance.

Furthermore, mediation analyses in our study elucidated the mechanisms linking brain dynamics to cognitive performance. Previous research has highlighted significant impairments in adaptive functioning among individuals with ASD and a negative relationship between adaptive behavior and executive functioning problems in this population (Gilotty et al., 2002; Pugliese et al., 2015). However, the relationship between brain dynamics, adaptive behavior, and cognitive performance remained unexplored. Our study clarified this pathway, demonstrating that brain states influence cognitive performance through adaptive behavior as a mediating factor.

These findings may carry profound theoretical and practical implications. From a theoretical perspective, the results provide a nuanced understanding of how brain states influence cognitive abilities in ASD, highlighting the pivotal role of adaptive behavior in modulating this relationship. Practically, they underscore the need for tailored interventions that address the specific needs of children with varying symptom severities. However, given the small sample size included in the mediation analyses, these findings should be considered preliminary. Future research with larger samples is essential to validate these results and explore additional mechanisms that could guide the development of symptom-specific intervention strategies. Moreover, longitudinal studies are needed to examine how these mechanisms evolve across different developmental stages and their long-term impact on cognitive and adaptive outcomes.

This study has several limitations that are worth noting. First, the relatively small sample size may limit the generalizability of our findings. To assess the robustness of our findings, we replicated the main analyses in an independent sample of 24 TD children aged 3–6 years using 5 min fNIRS data collected during cartoon viewing. While this validation supports the reliability of our findings, differences in group characteristics and data acquisition durations (8 min in the original sample vs 5 min in the TD sample) led us to present these analyses as supplementary

rather than integrating them into a combined dataset. Future studies with larger samples are needed to validate our results. Second, while age and gender were controlled as covariates in our analyses, demographic differences between groups in the sample remain a consideration. Future studies could address this by employing more rigorous matching designs or larger samples to enhance the robustness of the findings. Third, the restricted channel coverage in this study, which focuses on specific brain regions, precludes whole-brain analysis. This limitation may have affected the stability of the clustered states, highlighting the need for future research examining this point. Fourth, although intervention information was collected for the ASD group, we did not gather specific information about medication use during data collection. Future studies should consider the potential effects of medications on neurobiological outcomes. Finally, as our study focused on early-stage ASD in children aged 2–6 years, caution is warranted when extrapolating these findings to other age groups or developmental stages. Comparative studies involving older children or longitudinal designs tracking changes over time would be valuable in broadening the applicability of these results.

Conclusion

In sum, this study advances our understanding of DFC patterns in children with ASD compared with TD controls. By identifying significant group differences in DFC characteristics and their associations with clinical symptoms, adaptive behavior, and cognitive performance, our findings offer valuable insights into the neuropsychological mechanisms underlying ASD. Notably, the results highlight the potential of DFC features as neuroimaging biomarkers for distinguishing children with ASD from their TD peers. Furthermore, the elucidation of pathways linking brain dynamics, adaptive behavior, and cognitive performance underscores the importance of tailored interventions that address the unique needs of individuals with ASD. Future clinical applications could leverage these findings to design interventions that not only improve adaptive functioning but also enhance cognitive outcomes by targeting specific neural mechanisms. By fostering a deeper understanding of the interplay between brain dynamics and behavior, this study lays the groundwork for more effective, individualized approaches to support children with ASD.

Data Availability

The tidy data used for the analyses reported in this article are available at <https://github.com/YaqiongXiao/asdfNIRS.DFC>.

References

- Anderson JS, et al. (2011) Decreased interhemispheric functional connectivity in autism. *Cereb Cortex* 21:1134–1146.
- Calhoun VD, Miller R, Pearlson G, Adali T (2014) The chronnectome: time-varying connectivity networks as the next frontier in fMRI data discovery. *Neuron* 84:262–274.
- Chen H, Nomi JS, Uddin LQ, Duan X, Chen H (2017) Intrinsic functional connectivity variance and state-specific under-connectivity in autism. *Hum Brain Mapp* 38:5740–5755.
- Cohen JR (2018) The behavioral and cognitive relevance of time-varying, dynamic changes in functional connectivity. *Neuroimage* 180:515–525.
- Damaraju E, et al. (2014) Dynamic functional connectivity analysis reveals transient states of dysconnectivity in schizophrenia. *Neuroimage* 5:298–308.
- Daniels AM, Mandell DS (2014) Explaining differences in age at autism spectrum disorder diagnosis: a critical review. *Autism* 18:583–597.

- Deng L, Xu M, Hu Y, Liu Y, Chen Z, Tan H, Du W, Xiao Y, Li F (2025) Assessing the validity and reliability of the Chinese vineland adaptive behavior scales for children with autism spectrum disorder aged 1–6. *Autism Res* 18:1412–1430.
- Douw L, Wakeman DG, Tanaka N, Liu H, Stufflebeam SM (2016) State-dependent variability of dynamic functional connectivity between frontoparietal and default networks relates to cognitive flexibility. *Neuroscience* 339:12–21.
- Engels G, Vlaar A, McCoy B, Scherder E, Douw L (2018) Dynamic functional connectivity and symptoms of Parkinson's disease: a resting-state fMRI study. *Front Aging Neurosci* 10:388.
- Erb CD, Moher J, Marcovitch S (2022) Attentional capture in goal-directed action during childhood, adolescence, and early adulthood. *J Exp Child Psychol* 214:105273.
- Eyler LT, Pierce K, Courchesne E (2012) A failure of left temporal cortex to specialize for language is an early emerging and fundamental property of autism. *Brain* 135:949–960.
- Fan Z, Gao Z, Xu L, Yu J, Li J (2024) Identification of autism spectrum disorder based on functional near-infrared spectroscopy using dynamic multi-attribute spatio-temporal graph neural network. *Biomed Sig Process Contr* 94:106364.
- Ferrari M, Quaresima V (2012) A brief review on the history of human functional near-infrared spectroscopy (fNIRS) development and fields of application. *Neuroimage* 63:921–935.
- Finn ES, Bandettini PA (2021) Movie-watching outperforms rest for functional connectivity-based prediction of behavior. *Neuroimage* 235:117963.
- Fishburn FA, Ludlum RS, Vaidya CJ, Medvedev AV (2019) Temporal derivative distribution repair (TDDR): a motion correction method for fNIRS. *Neuroimage* 184:171–179.
- Fong AHC, Yoo K, Rosenberg MD, Zhang S, Li C-SR, Scheinost D, Constable RT, Chun MM (2019) Dynamic functional connectivity during task performance and rest predicts individual differences in attention across studies. *Neuroimage* 188:14–25.
- Gilotty L, Kenworthy L, Sirian L, Black DO, Wagner AE (2002) Adaptive skills and executive function in autism spectrum disorders. *Child Neuropsychol* 8:241–248.
- Gramfort A, et al. (2013) MEG and EEG data analysis with MNE-Python. *Front Neurosci* 7:267.
- Gu Y, et al. (2020) Abnormal dynamic functional connectivity in Alzheimer's disease. *CNS Neurosci Therapeut* 26:962–971.
- Harlalka V, Bapi RS, Vinod PK, Roy D (2019) Atypical flexibility in dynamic functional connectivity quantifies the severity in autism spectrum disorder. *Front Human Neurosci* 13:6.
- Hayes AF (2017) *Introduction to mediation, moderation, and conditional process analysis: a regression-based approach*. New York: The Guilford Press.
- Hutchison RM, et al. (2013) Dynamic functional connectivity: promise, issues, and interpretations. *Neuroimage* 80:360–378.
- Jia H, Li Y, Yu D (2018) Attenuation of long-range temporal correlations of neuronal oscillations in young children with autism spectrum disorder. *Neuroimage* 20:424–432.
- Kikuchi M, et al. (2013) Anterior prefrontal hemodynamic connectivity in conscious 3- to 7-year-old children with typical development and autism spectrum disorder. *PLoS One* 8:e56087.
- Klein F, Lühns M, Benitez-Andonegui A, Roehn P, Kranczioch C (2022) Performance comparison of systemic activity correction in functional near-infrared spectroscopy for methods with and without short distance channels. *Neurophotonics* 10:013503.
- Krug DA, Arick J, Almond P (1980) Behavior checklist for identifying severely handicapped individuals with high levels of autistic behavior. *J Child Psychol Psychiatr* 21:221–229.
- Lewis JD, et al. (2014) Network inefficiencies in autism spectrum disorder at 24 months. *Transl Psychiatr* 4:e388.
- Li J, et al. (2017) High transition frequencies of dynamic functional connectivity states in the creative brain. *Sci Rep* 7:46072.
- Li Y, Jia H, Yu D (2018) Novel analysis of fNIRS acquired dynamic hemoglobin concentrations: application in young children with autism spectrum disorder. *Biomed Optic Exp* 9:3694.
- Li Y, Zhu Y, Nguchu BA, Wang Y, Wang H, Qiu B, Wang X (2020) Dynamic functional connectivity reveals abnormal variability and hyper-connected pattern in autism spectrum disorder. *Autism Res* 13:230–243.
- Li Y, Yu D (2016) Weak network efficiency in young children with autism spectrum disorder: evidence from a functional near-infrared spectroscopy study. *Brain Cogn* 108:47–55.
- Li Z, Liu H, Liao X, Xu J, Liu W, Tian F, He Y, Niu H (2015) Dynamic functional connectivity revealed by resting-state functional near-infrared spectroscopy. *Biomed Optic Exp* 6:2337.
- Liao W, Wu G-R, Xu Q, Ji G-J, Zhang Z, Zang Y-F, Lu G (2014) DynamicBC: a MATLAB toolbox for dynamic brain connectome analysis. *Brain Connect* 4:780–790.
- Lin P, Yang Y, Jovicich J, De Pisapia N, Wang X, Zuo CS, Levitt JJ (2016) Static and dynamic posterior cingulate cortex nodal topology of default mode network predicts attention task performance. *Brain Imag Behav* 10:212–225.
- Liu T, Liu X, Yi L, Zhu C, Markey PS, Pelowski M (2019) Assessing autism at its social and developmental roots: a review of autism spectrum disorder studies using functional near-infrared spectroscopy. *Neuroimage* 185:955–967.
- Lord C, et al. (2020) Autism spectrum disorder. *Nat Rev Dis Primers* 6:5.
- Lu J, et al. (2023) An fNIRS-based dynamic functional connectivity analysis method to signify functional neurodegeneration of Parkinson's disease. *IEEE Trans Neural Syst Rehabil Eng* 31:1199–1207.
- Luo L, et al. (2023) Patterns of brain dynamic functional connectivity are linked with attention-deficit/hyperactivity disorder-related behavioral and cognitive dimensions. *Psychol Med* 53:6666–6677.
- Madhyastha TM, Askren MK, Boord P, Grabowski TJ (2015) Dynamic connectivity at rest predicts attention task performance. *Brain Connect* 5:45–59.
- Martínez JH, Buldú JM, Papo D, Fallani FDV, Chavez M (2018) Role of inter-hemispheric connections in functional brain networks. *Sci Rep* 8:10246.
- Mash LE, Linke AC, Olson LA, Fishman I, Liu TT, Müller R (2019) Transient states of network connectivity are atypical in autism: a dynamic functional connectivity study. *Hum Brain Mapp* 40:2377–2389.
- Masi A, DeMayo MM, Glozier N, Guastella AJ (2017) An overview of autism spectrum disorder, heterogeneity and treatment options. *Neurosci Bull* 33:183–193.
- Mauri M, Crippa A, Bacchetta A, Grazioli S, Rosi E, Gazzola E, Gallace A, Nobile M (2020) The utility of NIRS technology for exploring emotional processing in children. *J Affect Dis* 274:819–824.
- Moriguchi Y, Hiraki K (2013) Prefrontal cortex and executive function in young children: a review of NIRS studies. *Front Hum Neurosci* 7:867.
- Niu H, Zhu Z, Wang M, Li X, Yuan Z, Sun Y, Han Y (2019) Abnormal dynamic functional connectivity and brain states in Alzheimer's disease: functional near-infrared spectroscopy study. *Neurophotonics* 6:1.
- Nomi JS, Vij SG, Dajani DR, Steimke R, Damaraju E, Rachakonda S, Calhoun VD, Uddin LQ (2017) Chronnectomic patterns and neural flexibility underlie executive function. *Neuroimage* 147:861–871.
- Peng Y, Zhang X, Li Y, Su Q, Wang S, Liu F, Yu C, Liang M (2020) MVPANI: a toolkit with friendly graphical user interface for multivariate pattern analysis of neuroimaging data. *Front Neurosci* 14:545.
- Plitt M, Barnes KA, Wallace GL, Kenworthy L, Martin A (2015) Resting-state functional connectivity predicts longitudinal change in autistic traits and adaptive functioning in autism. *Proc Natl Acad Sci U S A* 112:E6699–E6706.
- Pollonini L, Olds C, Abaya H, Bortfeld H, Beauchamp MS, Oghalai JS (2014) Auditory cortex activation to natural speech and simulated cochlear implant speech measured with functional near-infrared spectroscopy. *Hear Res* 309:84–93.
- Preti MG, Bolton TA, Van De Ville D (2017) The dynamic functional connectome: state-of-the-art and perspectives. *Neuroimage* 160:41–54.
- Pugliese CE, Anthony L, Strang JF, Dudley K, Wallace GL, Kenworthy L (2015) Increasing adaptive behavior skill deficits from childhood to adolescence in autism spectrum disorder: role of executive function. *J Autism Develop Disorder* 45:1579–1587.
- Quaresima V, Ferrari M (2019) Functional near-infrared spectroscopy (fNIRS) for assessing cerebral cortex function during human behavior in natural/social situations: a concise review. *Organ Res Meth* 22:46–68.
- Rabany L, Brocke S, Calhoun VD, Pittman B, Corbera S, Wexler BE, Bell MD, Pelphrey K, Pearlson GD, Assaf M (2019) Dynamic functional connectivity in schizophrenia and autism spectrum disorder: convergence, divergence and classification. *Neuroimage* 24:101966.
- Rashid B, et al. (2018) Connectivity dynamics in typical development and its relationship to autistic traits and autism spectrum disorder. *Human Brain Mapp* 39:3127–3142.
- Redcay E (2008) The superior temporal sulcus performs a common function for social and speech perception: implications for the emergence of autism. *Neurosci Biobehav Rev* 32:123–142.

- Schopler E, Reichler RJ, DeVellis RF, Daly K (1980) Toward objective classification of childhood autism: Childhood Autism Rating Scale (CARS). *J Autism Develop Disorders* 10:91–103.
- Spadone S, Della Penna S, Sestieri C, Betti V, Tosoni A, Perrucci MG, Romani GL, Corbetta M (2015) Dynamic reorganization of human resting-state networks during visuospatial attention. *Proc Natl Acad Sci U S A* 112:8112–8117.
- Steinmetzger K, Meinhardt B, Praetorius M, Andermann M, Rupp A (2022) A direct comparison of voice pitch processing in acoustic and electric hearing. *Neuroimage* 36:103188.
- Sun W, Wu X, Zhang T, Lin F, Sun H, Li J (2021) Narrowband resting-state fNIRS functional connectivity in autism spectrum disorder. *Front Hum Neurosci* 15:643410.
- Sutoko S, et al. (2020) Atypical dynamic-connectivity recruitment in attention-deficit/hyperactivity disorder children: an insight into task-based dynamic connectivity through an fNIRS study. *Front Hum Neurosci* 14:3.
- Takahashi T, Yoshimura Y, Hiraishi H, Hasegawa C, Munesue T, Higashida H, Minabe Y, Kikuchi M (2016) Enhanced brain signal variability in children with autism spectrum disorder during early childhood. *Human Brain Mapp* 37:1038–1050.
- Tang TB, Chong JS, Kiguchi M, Funane T, Lu C-K (2021) Detection of emotional sensitivity using fNIRS based dynamic functional connectivity. *IEEE Trans Neural Syst Rehabil Eng* 29:894–904.
- Tillmann J, et al. (2019) Investigating the factors underlying adaptive functioning in autism in the EU-AIMS longitudinal European autism project. *Autism Res* 12:645–657.
- Urquhart EL, Wang X, Liu H, Fadel PJ, Alexandrakis G (2020) Differences in net information flow and dynamic connectivity metrics between physically active and inactive subjects measured by functional near-infrared spectroscopy (fNIRS) during a fatiguing handgrip task. *Front Neurosci* 14:167.
- Wan L, Li Y, Zhu G, Yang D, Li F, Wang W, Chen J, Yang G, Li R (2024) Multimodal investigation of dynamic brain network alterations in autism spectrum disorder: linking connectivity dynamics to symptoms and developmental trajectories. *Neuroimage* 302:120895.
- Wang M, Wang L, Yang B, Yuan L, Wang X, Potenza MN, Dong GH (2022) Disrupted dynamic network reconfiguration of the brain functional networks of individuals with autism spectrum disorder. *Brain Commun* 4:fcac177.
- Wu X, He H, Shi L, Xia Y, Zuang K, Feng Q, Zhang Y, Ren Z, Wei D, Qiu J (2019) Personality traits are related with dynamic functional connectivity in major depression disorder: a resting-state analysis. *J Affect Disorders* 245:1032–1042.
- Wu X, Lin F, Sun W, Zhang T, Sun H, Li J (2021) Relationship between short-range and homotopic long-range resting state functional connectivity in temporal lobes in autism spectrum disorder. *Brain Sci* 11:1467.
- Xiao Y, Wen TH, Kupis L, Eyler LT, Goel D, Vaux K, Lombardo MV, Lewis NE, Pierce K, Courchesne E (2022) Neural responses to affective speech, including motherese, map onto clinical and social eye tracking profiles in toddlers with ASD. *Nat Human Behav* 6:443–454.
- Xu J, Wang C, Xu Z, Li T, Chen F, Chen K, Gao J, Wang J, Hu Q (2020) Specific functional connectivity patterns of middle temporal gyrus subregions in children and adults with autism spectrum disorder. *Autism Res* 13:410–422.
- Yang S, Paynter JM, Gilmore L (2016) Vineland adaptive behavior scales: II profile of young children with autism spectrum disorder. *J Autism Develop Disorders* 46:64–73.
- Yin S, et al. (2025) Temporal and spatial variability of large-scale dynamic brain networks in ASD. *Eur Child Adolesc Psychiatry* 34:2555–2569.
- Yue X, et al. (2022) Abnormal dynamic functional network connectivity in adults with autism spectrum disorder. *Clin Neuroradiol* 32:1087–1096.
- Zeidan J, Fombonne E, Scora J, Ibrahim A, Durkin MS, Saxena S, Yusuf A, Shih A, Elsabbagh M (2022) Global prevalence of autism: a systematic review update. *Autism Res* 15:778–790.
- Zhao S, Liu Y, Wei K (2022) Pupil-linked arousal response reveals aberrant attention regulation among children with autism spectrum disorder. *J Neurosci* 42:5427–5437.
- Zhu H, Fan Y, Guo H, Huang D, He S (2014) Reduced interhemispheric functional connectivity of children with autism spectrum disorder: evidence from functional near infrared spectroscopy studies. *Biomed Optic Exp* 5:1262–1274.
- Zhuang W, Jia H, Liu Y, Cong J, Chen K, Yao D, Kang X, Xu P, Zhang T (2023) Identification and analysis of autism spectrum disorder via large-scale dynamic functional network connectivity. *Autism Res* 16:1512–1526.