Received: 10 June 2022 | Revised: 22 August 2022 | Accepted: 23 September 2022
DOI: 10.1002/hbm.26115

RESEARCH ARTICLE

WILEY

# Information-based multivariate decoding reveals imprecise neural encoding in children with attention deficit hyperactivity disorder during visual selective attention

Dongwei Li[1] | Xiangsheng Luo[2,3] | Jialiang Guo[1] | Yuanjun Kong[1] | Yiqing Hu[1] | Yanbo Chen[2,3] | Yu Zhu[2,3] | Yufeng Wang[2,3] | Li Sun[2,3] | Yan Song[1,4]

[1]State Key Laboratory of Cognitive Neuroscience and Learning and IDG/McGovern Institute for Brain Research, Beijing Normal University, Beijing, China

[2]Peking University Sixth Hospital and Peking University Institute of Mental Health, Beijing, China

[3]NHC Key Laboratory of Mental Health (Peking University) and National Clinical Research Center for Mental Disorders (Peking University Sixth Hospital), Beijing, China

[4]Center for Collaboration and Innovation in Brain and Learning Sciences, Beijing Normal University, Beijing, China

**Correspondence**
Yan Song, Center for Collaboration and Innovation in Brain and Learning Sciences, Beijing Normal University, Beijing, China.
Email: songyan@bnu.edu.cn

Li Sun, Peking University Sixth Hospital and Peking University Institute of Mental Health, Beijing, China.
Email: sunlioh@bjmu.edu.cn

**Funding information**
Beijing Brain Initiative of Beijing Municipal Science and Technology Commission, Grant/Award Number: Z181100001518003; Beijing Municipal Science and Technology Program, Grant/Award Number: Z171100001017089; Key scientific research projects of capital health development, Grant/Award Number: 2020-1-4111; National Defense Basic Scientific Research Program of China, Grant/Award Number: 2018110B011; National Natural Science Foundation of China, Grant/Award Numbers: 31871099, 81771479, 81971284; Sanming Project of Medicine in Shenzhen, Grant/Award Number: SZSM201612036

## Abstract

Attention deficit hyperactivity disorder (ADHD) is a common neurodevelopmental disorder in school-age children. Attentional orientation is a potential clinical diagnostic marker to aid in the early diagnosis of ADHD. However, the underlying pathophysiological substrates of impaired attentional orienting in childhood ADHD remain unclear. Electroencephalography (EEG) was measured in 135 school-age children (70 with childhood ADHD and 65 matched typically developing children) to directly investigate target localization during spatial selective attention through univariate ERP analysis and information-based multivariate pattern machine learning analysis. Compared with children with typical development, a smaller N2pc was found in the ADHD group through univariate ERP analysis. Children with ADHD showed a lower parieto-occipital multivariate decoding accuracy approximately 240–340 ms after visual search onset, which predicts a slower reaction time and larger standard deviation of reaction time. Furthermore, a significant correlation was found between N2pc and decoding accuracy in typically developing children but not in children with ADHD. These observations reveal that impaired attentional orienting in ADHD may be due to inefficient neural encoding responses. By using a personalized information-based multivariate machine learning approach, we have advanced the understanding of cognitive deficits in neurodevelopmental disorders. Our study provides potential research directions for the early diagnosis and optimization of personalized intervention in children with ADHD.

Dongwei Li and Xiangsheng Luo contributed equally to this study.

**KEYWORDS**
ADHD, attentional selection, children, decoding, ERP, machine learning, N2pc

## 1 | INTRODUCTION

Attention deficit hyperactivity disorder (ADHD) is a neurodevelopmental disorder characterized by inattentive, hyperactive, and impulsive symptoms. Approximately 5% of school-age children (Willcutt, 2012) suffer from attentional impairment, which profoundly affects many advanced cognitive functions and learning performance (Singer-Harris et al., 2001). However, the neuronal substrate of ADHD is unclear. We still lack clinical biomarkers to aid in the early diagnosis of ADHD and as potential targets for intervention.

Visual spatial abnormalities in children with ADHD, such as increased variability of reaction time, have been reported in many behavioral studies (Kofler et al., 2013). Existing fMRI studies have found that the blood oxygen level-dependent response of the parieto-occipital lobe in the attention selection process of children with ADHD is weaker than that of typically developing (TD) children (Schneider et al., 2010). Our previous study, using a visual search paradigm examined impaired attention in children with ADHD (Guo et al., 2022; Luo et al., 2021; Wang et al., 2016). With univariate event-related potential (ERP) analysis, we examined the processing time of spatial attention and identified deficits in the supporting mechanism of attentional selection in children with ADHD with a smaller posterior contralateral N2 (N2pc) component (Wang et al., 2016). However, conventional univariate ERP analysis loses abundant information from high-density EEG. We still lack a bridge to link inefficient neural responses with impaired visual discrimination.

Importantly, attentional orienting in multiple possible target locations is an important component in guiding selection in a visual search, a process which could not be solved by univariate ERP analysis. In the natural environment, the target location for a visual search is highly variable. Although N2pc is closely related to the lateralized attentional selection process, it is unclear whether it reflects the actual spatial location information of the target or is a byproduct of supporting attentional shift. Previous work has found impaired spatial encoding skills in children with ADHD (Ortega et al., 2013), which may be related to slower neural integration processes (Cross-Villasana et al., 2015) and increased neural noise (Pertermann et al., 2019; Saville et al., 2015). Therefore, we suggest that increased neural noise in children with ADHD may obscure normal physiological signals causing a chaotic and inefficient neural response, leading to impaired visual discrimination.

Information-based multivariate decoding analysis is a novel approach based on machine learning used to quantify the information represented in individual neural signals (Grootswagers et al., 2017). It has not been used to investigate cognitive processing in neurodevelopmental disorders with high neural noise (Pertermann et al., 2019). This approach not only preserves the high temporal resolution of univariate ERP analysis but also incorporates the spatial distribution of ERP signals into the measurement. Previous studies have demonstrated that the target location could be represented from a spatial distribution of scalp EEG rather than being represented in specific brain areas in healthy populations (Foster et al., 2017). Multivariate decoding analysis provides an overall measure based on a set of electrodes and can detect subtle aspects of neural representation of specific information stored in the brain that cannot be detected by conventional univariate ERP analysis (Grootswagers et al., 2017). Furthermore, previous studies have linked neural noise to decoding precision (Deneve & Chalk, 2016), and lower decoding accuracy may be related to increased neurological noise. There is good reason to expect that chaotic neural activities in the visual cortex of children with ADHD may lead to a decline in the precision of spatial localization during visual spatial attention. Therefore, applying multivariate machine learning to examine target localization during a visual search could help develop an understanding of the deficits in cognitive function in children with ADHD.

Both fMRI and ERP findings support that the visual cortex and ventral attention network (VAN) play vital roles in selective attention (Schneider et al., 2010; Wang et al., 2016). Here, we used information-based multivariate decoding analysis of parieto-occipital electrodes (a) to clarify whether and when representation of target location was precisely identified during a visual search in a noisy neural response environment; and (b) to examine the relationship between imprecise spatial position encoding and poor behavioral outcomes in school-age children with and without ADHD.

## 2 | METHODS AND MATERIALS

### 2.1 | Participants

A total of 135 children participated in this study (Table 1), including 70 children with ADHD (age = 10.61 ± 1.93, range = 7.08–13.83, female = 17) and 65 age- and sex-matched TD children (age = 10.73 ± 1.93, range = 7.17–13.83, female = 20). Children with ADHD were recruited from the clinics of Peking University Sixth Hospital/Institute of Mental Health, and controls were enrolled from local primary schools. The diagnosis of ADHD was based on the semistructured interview K-SADS with DSM-IV criteria by qualified psychiatrists, and the parent ADHD Rating Scale-IV (ADHD-RS) score was used to measure the severity of symptoms. There were 15 children with ADHD comorbid with oppositional defiant disorder, 1 comorbid with conduct disorder, 5 comorbid with tic disorder, and 1 with Tourette's syndrome.

All participants were right-handed with a full-scale intelligence quotient (IQ) above 80 measured by the Wechsler Intelligence Scale

**TABLE 1** Demographic information of children with ADHD and TD in the final sample

| | Mean ± SD | | | |
|---|---|---|---|---|
| | ADHD | TD | $\chi^2$ or $t$ | $p$ |
| Number | 70 | 65 | | |
| Age (years) | 10.6 ± 1.9 | 10.7 ± 1.9 | 0.840 | .403 |
| Gender (male: female) | 54:16 | 40:20 | 0.712 | .399 |
| FSIQ | 106.8 ± 13.7 | 122.8 ± 14.8 | 6.511*** | <.001 |
| Accuracy (%)[#] | 91.1 ± 9.0 | 94.0 ± 6.2 | 2.577* | .011 |
| RT (ms)[#] | 738.3 ± 193.2 | 634.6 ± 176.2 | 3.253** | .001 |
| RTSD (ms)[#] | 245.9 ± 93.3 | 187.3 ± 80.9 | 3.887*** | <.001 |
| ADHD-$RS_{total}$ | 48.9 ± 7.8 | 27.7 ± 5.8[a] | 17.065*** | <.001 |
| ADHD-$RS_{inattention}$ | 27.5 ± 3.5 | 14.8 ± 3.3[a] | 20.886*** | <.001 |
| ADHD-$RS_{hyperactivity}$ | 21.4 ± 5.8 | 12.9 ± 3.3[a] | 9.736*** | <.001 |
| Subtypes | ADHD-I (47)<br>ADHD-C (23) | – | | |

Abbreviations: ADHD, attention-deficit/hyperactivity disorder; ADHD-C, ADHD combined type; ADHD-I, ADHD inattention type; ADHD-$RS_{hyperactivity}$, hyperactivity/impulsivity subscale of ADHD Rating Scale; ADHD-$RS_{inattention}$, inattention subscale of ADHD Rating Scale; FSIQ, full-scale IQ; ADHD-$RS_{total}$, total scores of ADHD Rating Scale; RT, reaction times; RTSD, standard deviation of reaction times; TD, typically developing.

[a]ADHD Rating Scale of 8 TD children were missing;

[#]Behavioral measures shown in this table are averaged across all spatial locations.

*$p < .05$. **$p < .01$. ***$p < .001$.

for Children (WISC). Both the WISC-III and WISC-IV versions were used, and there was no significant group difference in the distribution of the WISC version. IQ was not matched and controlled in this study, as the decrease in IQ is one of the cognitive characteristics of ADHD (Deneve & Chalk, 2016), and IQ may not be suitable as a control factor (Dennis et al., 2009). The IQ of children with ADHD was significantly lower than that of controls (ADHD: 106.81, control: 122.79, $t_{133} = -6.511$, $p < .001$, $d = 1.121$). Written consent was obtained from all children and their parents according to the Declaration of Helsinki. The study was approved by the Ethics Committee of Peking University Sixth Hospital/Institute of Mental Health.

## 2.2 | Task paradigm

Some of the EEG data has been analyzed and published in previous studies (Guo et al., 2022) but was reanalyzed from the perspective of spatial information encoding. The experimental paradigm is a classical visual pop-out search paradigm with 11 diamonds (distractors) and a circle (target) distributed in a clockwise manner (Figure 1a). The circle was placed in the 2, 4, 8, and 10 o'clock positions (25% for each position) in a pseudorandom manner (Figure 1b). Following previous studies, participants were asked to determine the upper or lower direction of the circle with their eyes gazing at the central fixation (Sun et al., 2018). The target presentation time was 200 ms, the response time was up to 2800 ms, and the intertrial interval was 900–1100 ms. For a detailed description of the paradigm, please refer to the Appendix and our previous study (Luo et al., 2021).

## 2.3 | Electroencephalography recording and preprocessing

Task EEG was recorded by EGI (Electrical Geodesics, Inc.) with a 128-channel HydroCel Geodesic Sensor Net (HGSN-128). The online reference was Cz, the sample rate was 1000 Hz, the bandpass filter was 0.01–400 Hz, and the impedance was kept below 50 kΩ.

EEG preprocessing was performed using custom scripts and the EEGLAB toolbox in the MATLAB environment (Delorme & Makeig, 2004). Thirty-eight lateral electrodes that were susceptible to eye, face, and head movements were excluded, leaving 91 electrodes for analysis (Figure A.1). EEG data were then offline resampled to 250 Hz, bandpass filtered between 1 and 25 Hz and re-referenced by using the average reference of all 91 electrodes. Excessive artifacts were manually removed, and bad electrodes were manually checked and interpolated before independent component analysis (ICA). After manually identifying and removing the vertical and horizontal eye movement ICs, automatic artifact rejection was further applied to discard the EEG epochs when voltages exceeded ±100 μV at any electrode. From the epoch data (−200 to 800 ms relative to stimulus onset), 80 epochs were randomly selected for each participant in the following decoding process to eliminate the influence of different epoch numbers for the ADHD and TD groups.

## 2.4 | Univariate ERP analysis

For ERP analysis, the baseline of each segment was removed between −200 and 0 ms before the onset of the visual search. Then, baseline-

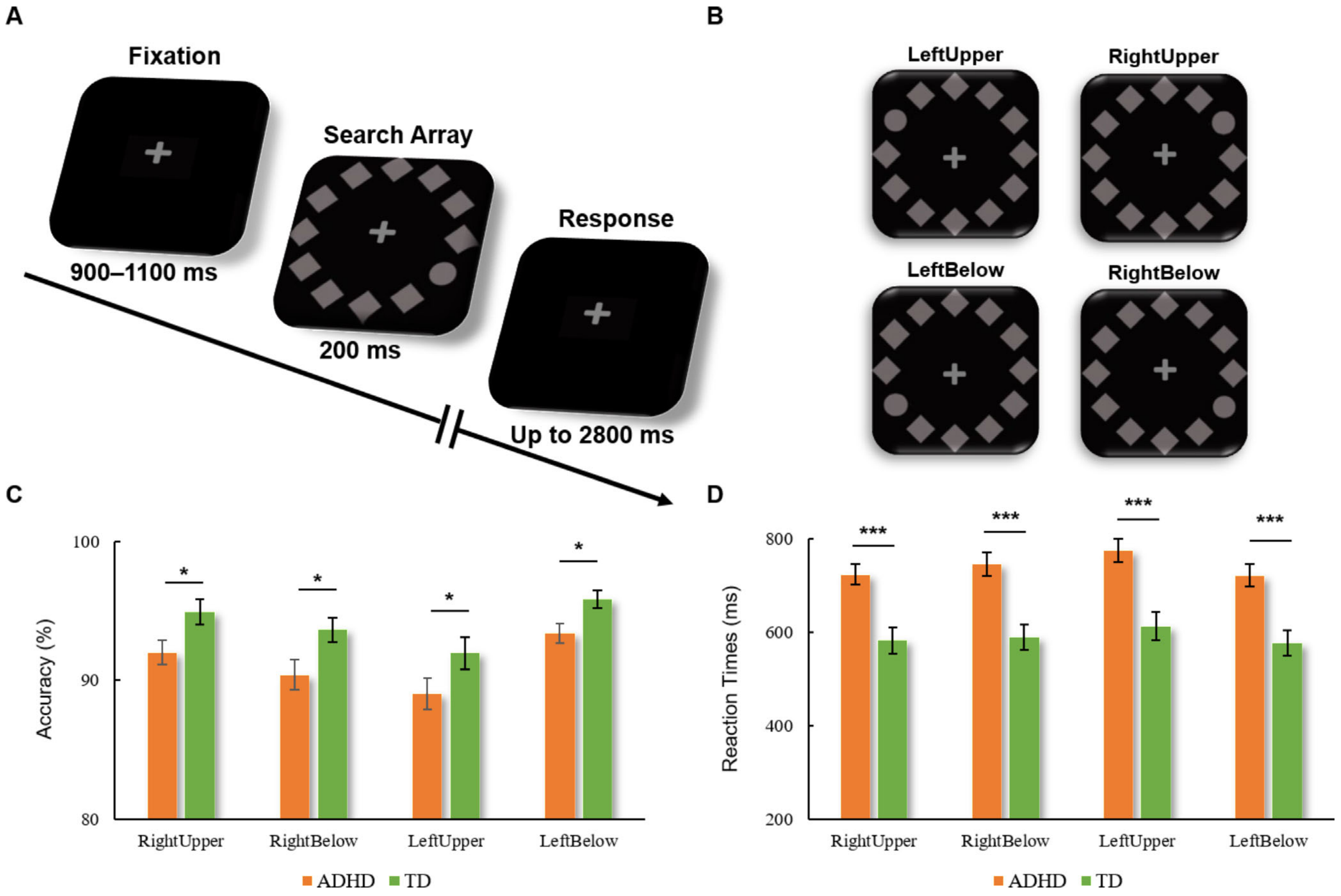


FIGURE 1 Trial sequences and behavioral outcomes. (a) 900–1100 ms trial interval with a "+" in the center of the screen, 200 ms search array and up to 2800 ms response interval. (b) Four possible target (circle) locations in the task. (c and d) children with ADHD showed lower accuracy and longer reaction times than TD children for all four target locations. ADHD, attention-deficit/hyperactivity disorder; TD, typically developing; *represents $p < .05$; ***represents $p < .001$

removed segments were averaged separately for contralateral and ipsilateral electrodes (PO7, PO8). To isolate the lateralized attentional effect, the N2pc component was extracted by subtracting the averaged ERP measured at contralateral electrodes from the averaged ERP measured at ipsilateral electrodes. N2pc amplitudes were calculated by averaging voltages of 220–260 ms in different waves (Sun et al., 2018; Wang et al., 2016).

## 2.5 | Multivariate pattern decoding

We applied a recently proposed multivariate pattern decoding approach (Bae & Luck, 2019; Hong et al., 2020; Li et al., 2022) to classify the target locations (Figure 2). Decoding was considered correct only if the classifier correctly determined the target location, and chance performance was therefore 25%. Although most EOG signals could be corrected by ICA, some residual EOGs could also influence the decoding results (20; Figure A.5). Therefore, only parieto-occipital electrodes were involved in the decoding analysis (Figure A.1). Decoding results based on all 91 electrodes can be found in the Appendices (Figure A.4). Several EEG epochs from the same target location in both the ADHD and TD groups were first averaged at each channel, and decoding was then performed on multichannel patterns of ERPs. Each epoch for decoding analysis was defined as −200 to 800 ms at the visual search display onset. Then, the data were resampled to 50 Hz (1 data point per 20 ms) to reduce the noise of the ERP signals and to increase the efficiency of the analyses. This resampling gave us a three-dimensional (3D) data matrix for each participant, with dimensions for channels (52 electrodes), time (50 time points), and trials (20 trials × 4 target locations). For each participant, the classifier was based on a linear support vector machine (SVM) and trained through the MATLAB fitcecoc() function at each data point. The decoding procedure at a given data point included a training phase and a testing phase. The training and testing phases were based on different trials. Specifically, a fivefold cross-validation procedure was applied at each data point. Epochs in each target location were divided into five bins (randomly selected), and each bin was averaged. The procedure described above was iterated 10 times, each time with a new random assignment of trials into five bins. Specifically, 20 trials from the same target location were randomly arranged into five bins. This iteration procedure could help to minimize idiosyncrasies associated with trial assignments and thus yield a more robust and stable estimate of

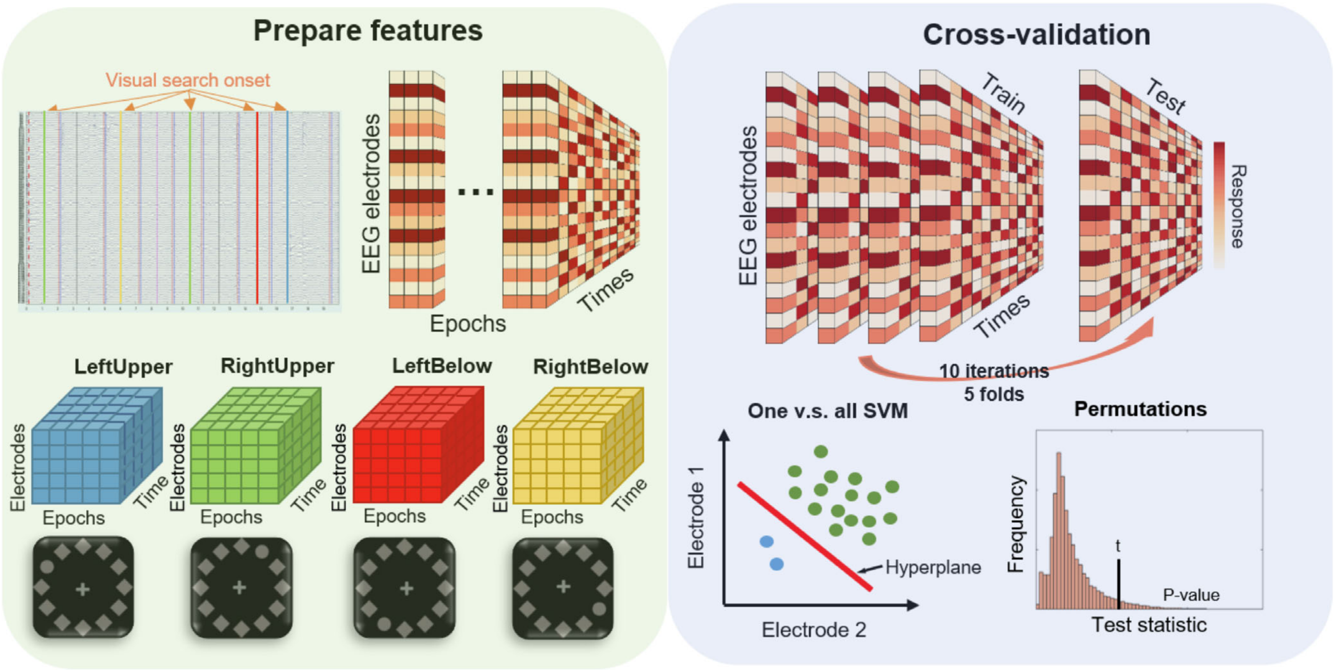


FIGURE 2 A pipeline for information-based multivariate pattern decoding. Epochs were arranged with four different labels according to target locations. The training and testing of the classifier was based on a linear one-vs.-all SVM at each data point. A permutation test was used to assess the significance of decoding accuracy. SVM, support vector machine

decoding accuracy. The 3D data matrix for each participant was transformed into a new matrix with channel dimensions (52 electrodes), time (50 time points), and ERPs (5 ERPs $\times$ 4 target locations). For each data point for each participant, the features were defined as ERPs at the given data point from 52 electrodes, and the data from four-fifths of the ERPs (16 ERPs) were used to train a classifier (training). Then, the classifier performance was assessed with the data from the remaining one-fifth of ERPs (4 ERPs for testing) through the MATLAB function predict (). This decoding procedure was repeated five times, once with each of the five ERPs serving as the testing dataset. Decoding accuracy was then computed by comparing the true labels of target locations with the predicted labels. Similar to previous studies (Bae & Luck, 2018), we performed a 10,000 times cluster-based permutation test to examine the significance of decoding accuracy over time (please refer to Bae & Luck, 2018 for more details).

## 2.6 | Statistical analysis

ANOVA was performed for behavioral data with Group (ADHD, TD) as the between-subject factor and target location (left upper, right upper, left below, and right below) as the within-subject factor. Independent sample t tests were used to identify whether electrophysiological measurements and decoding accuracy showed significant differences between the ADHD and TD groups. Pearson correlation analysis was conducted to establish links among N2pc components, decoding accuracy, and behavioral outcomes in both groups. The significance level was set at $p < .05$.

# 3 | RESULTS

## 3.1 | Behavioral outcomes

Regardless of where the target appeared, compared with the TD group, the ADHD group showed lower accuracy ($F_{1,133} = 6.503$, $p = .012$, $\eta_p^2 = 0.047$; Figure 1c) and longer reaction times ($F_{1,133} = 17.447$, $p < .001$, $\eta_p^2 = 0.116$; Figure 1d), suggesting that visual selective attention is impaired in children with ADHD. However, no significant interaction between target positions and groups was found in accuracy ($F_{3,131} = 0.176$, $p = .912$, $\eta_p^2 = 0.001$) or response time ($F_{3,131} = 1.652$, $p = .177$, $\eta_p^2 = 0.012$). Other behavioral outcomes that did not distinguish among the four target locations are presented in Table 1.

## 3.2 | Univariate ERP results

The ERP waveforms after visual search onset from electrodes (PO7/8) contralateral and ipsilateral to the target and grand-average ERP difference waveforms (contralateral minus ipsilateral) in both ADHD and TD groups are shown in Figure 3. A reliable N2pc component was induced within 200–300 ms after the onset of visual search in both the ADHD and TD groups. Our previous work showed that children with ADHD showed a smaller N2pc component than TD children (Wang et al., 2016). Here, we replicated the smaller N2pc component in the ADHD group with a larger sample size ($t_{1,133} = 2.075$, $p = .040$; Figure 3d), supporting the impaired attentional selection in children with ADHD.

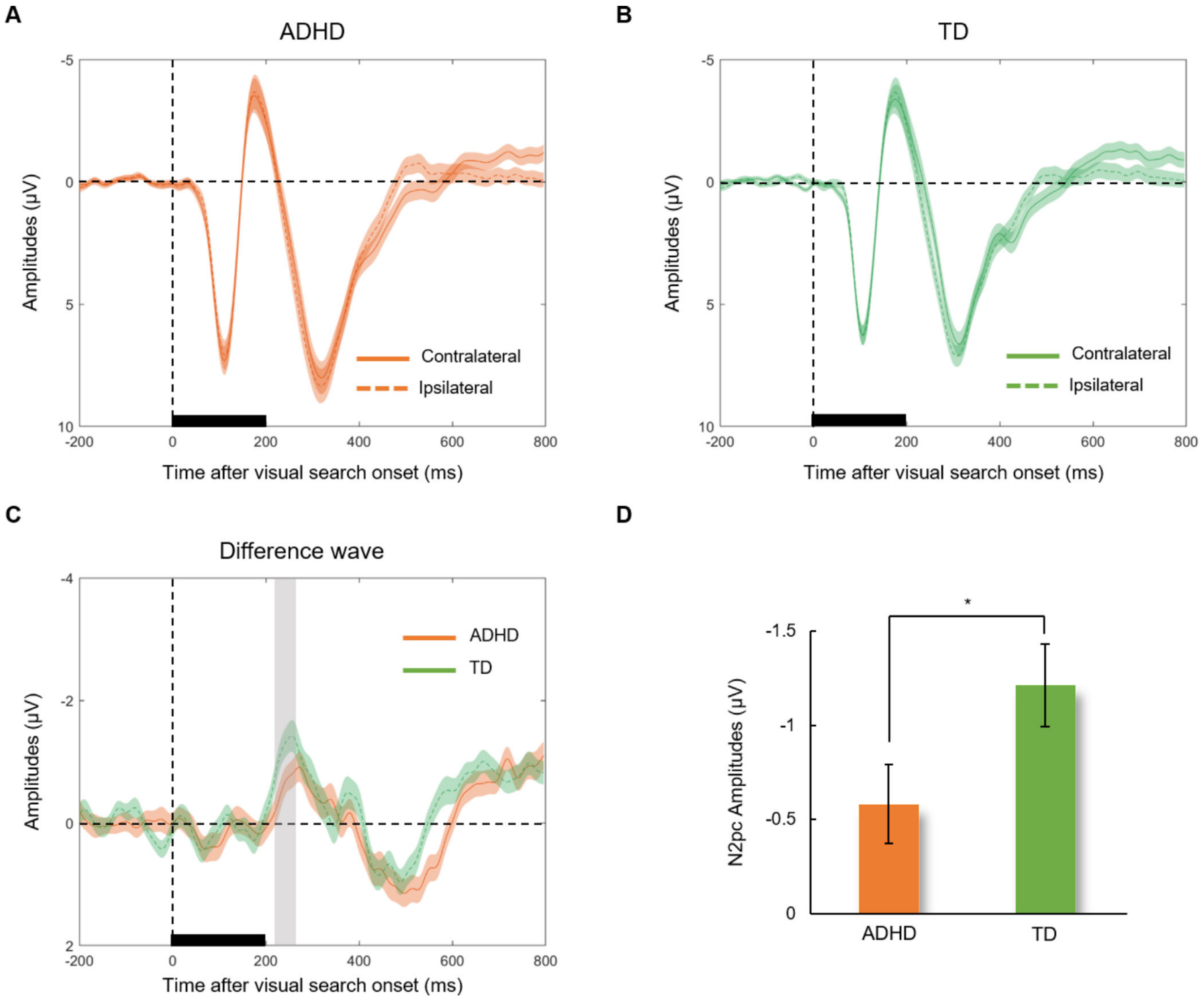


**FIGURE 3** ERP and correlation results. Grand averaged ERPs at electrodes contralateral and ipsilateral to the target in the ADHD (a) and TD (b) groups. (c) Grand average difference waveforms of ERPs were obtained by subtracting the ipsilateral waveforms from the contralateral waveforms for ADHD and TD groups. (d) Averaged N2pc amplitudes in the ADHD and TD groups. The black solid line represents the duration of stimuli presentation. ADHD, attention-deficit/hyperactivity disorder; N2pc, N2-posterior-contralateral; TD, typically developing; *represents $p < .05$

## 3.3 | Multivariate pattern decoding

Based on previous work using the univariate ERP approach, the ADHD group showed an increased P1 amplitude and a decreased N2pc amplitude compared with the TD group (Luo et al., 2021; Wang et al., 2016). Therefore, we applied the ERP-based multivariate pattern decoding approach (see Section 2) to further investigate whether and when the information of target locations was maintained in the scalp ERP pattern. Figure 4a shows the time course of decoding accuracy for the ADHD and TD groups when decoding the target locations based on the parieto-occipital topographic pattern of ERP. The corresponding weight maps of the channels are shown in Figure 4c. The cluster-based permutation test revealed that decoding accuracy was significantly greater than chance level (25%) in both the ADHD and TD groups, and starts at approximately 200 ms after visual search onset ($p < .001$ for both groups; see Figure 4a, solid green and orange lines).

More importantly, decoding accuracy showed a significant difference during 240–340 ms after visual search onset between the ADHD and TD groups ($p_{corrected} < .05$, Figure 4a). The averaged decoding accuracy within this time window for both groups suggested that children with ADHD showed a more imprecise target localization than TD children ($t_{1,133} = 2.255$, $p = .026$; Figure 4b left panel). We also decoded the target location with EOG electrodes and with eye movement-related IC components to avoid the contribution from eye movements (please see Appendices for more details; Figure A.5). Furthermore, we analyzed the peak latency of decoding accuracy during 200–500 ms after visual onset (ADHD:

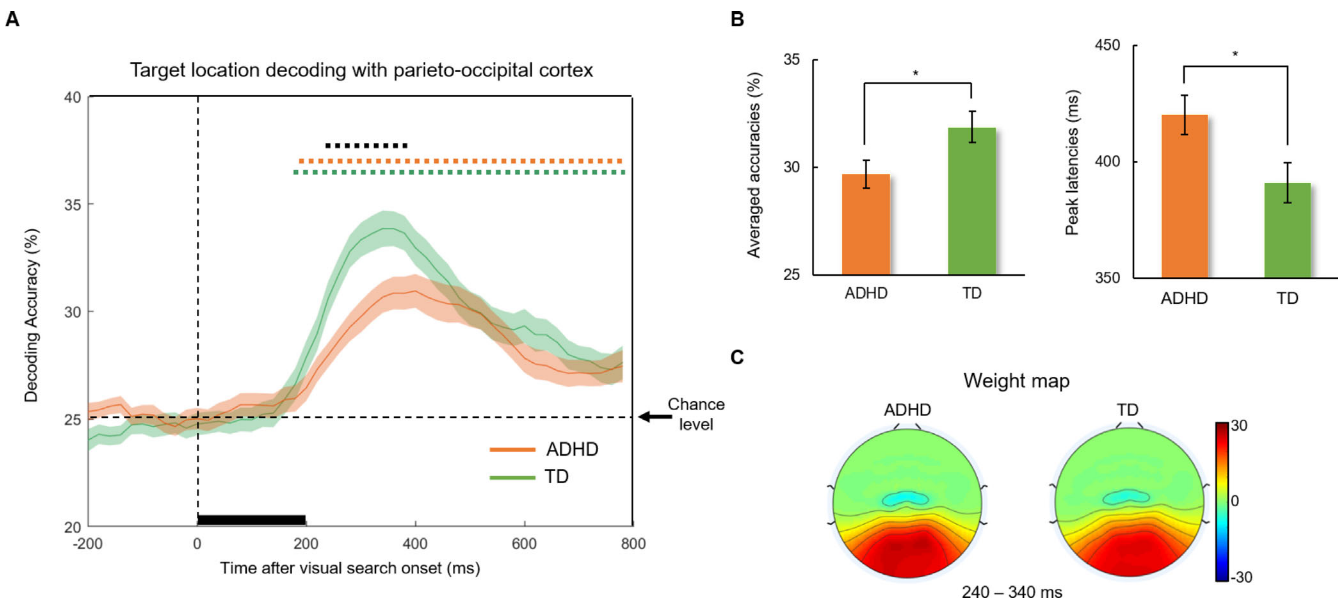


**FIGURE 4** Impaired target localization in children with ADHD. (a) ERP-based decoding accuracy for both the ADHD and TD groups. The green and orange lines at the top represent the period that was significantly larger than the chance level (25%), and the black line represents the period in which the ADHD group showed lower decoding accuracy than the TD group. (b) The averaged decoding accuracy during 240–340 ms (left panel) and the peak latency of decoding accuracy (right panel) for the ADHD and TD groups. (c) The averaged weight map of electrode contributions during y for the ADHD and TD groups. The black solid line represents the duration of stimuli presentation. ADHD, attention-deficit/hyperactivity disorder; TD, typically developing; *represents $p < .05$

420 ± 70 ms; TD: 391 ± 70 ms). The results showed a significant delay in the peak latency in the ADHD group ($t_{1,133} = 2.426$, $p = .017$; Figure 4b right panel), suggesting delayed target localization in children with ADHD. To evaluate the decoding model more generally, the sensitivity and specificity of the decoder are reported in the Appendices (Figure A.2).

### 3.4 | Correlation analysis

A significant correlation was found between N2pc amplitudes and decoding accuracy ($r = -0.403$, $p < .001$; Figure 5b) in TD children but not in children with ADHD ($r = -0.058$, $p = .636$; Figure 5a). This result suggested that children with ADHD encoded the target location with a unique representation, which is not contributed to by N2pc components. Additionally, to investigate whether imprecise target localization impaired behavioral performance, we calculated correlations between decoding accuracy and behavioral outcomes. The results showed that decoding accuracy was significantly negatively correlated with RT ($r = -0.328$, $p = .006$; Figure 5c) and RTSD ($r = -0.318$, $p = .007$; Figure 5d) but not significantly correlated with accuracy ($r = -0.026$, $p = .830$) in children with ADHD. These correlations were absent in TD children ($ps > .119$) and were absent between N2pc and RT/RTSD ($p > .092$) in the ADHD group (Figure A.3). We also found a significant correlation between decoding accuracy and age in the ADHD group ($r = 0.238$; $p = .046$), suggesting developmental delay in spatial localization. No other significant correlation was found between decoding accuracy and symptoms in the ADHD group ($ps > .318$).

## 4 | DISCUSSION

The present study adopted a classical visual search paradigm (Guo et al., 2022; Luo et al., 2021; Wang et al., 2016) to explore whether and how target spatial location could be encoded in school-age children with and without ADHD through a newly established multivariate neural decoding approach. Behaviorally, regardless of which visual field the target presents, children with ADHD show a decline in accuracy and a delayed response time, suggesting slow and imprecise target localization in children with ADHD. Importantly, target locations could be identified by the topographic map of ERP during the visual search task for both children with and without ADHD, indicating that the spatial information of the target could be decoded from scalp EEG in individuals with high neural noise. Additionally, children with ADHD showed poor neural decoding ability for the target location, suggesting imprecise neural activity and impaired spatial localization ability. A further negative correlation between neural activity and RT as well as RTSD revealed that deteriorating neural imprecision would have an adverse influence on attentional performance for children with ADHD. Therefore, the decoding of neural signals can better help us understand the dense information contained in neurophysiological signals and provide novel insights into the fundamental neural pattern abnormality of selective attention in neurodevelopmental disorders.

### 4.1 | Deteriorating neural decoding in children with attention-deficit/hyperactivity disorder

Attention serves as a spotlight to form different neural patterns for different target locations (Bruce & Tsotsos, 2009; Eimer, 2014). We

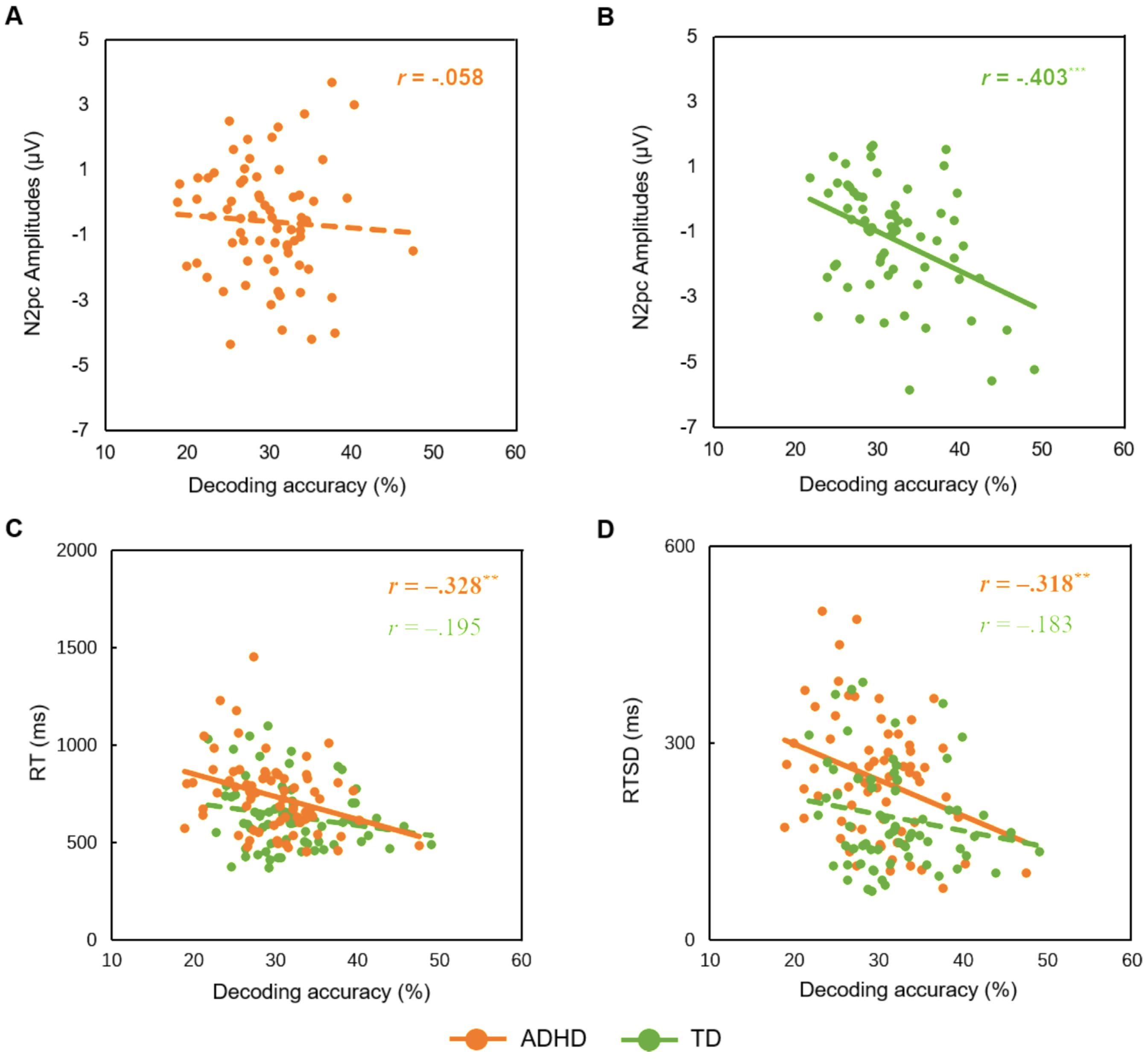


**FIGURE 5** Correlation analysis. (a) No significant correlation was found between decoding accuracy and N2pc amplitudes in children with ADHD. (b) A significant correlation between decoding accuracy and N2pc amplitudes in TD children. (c) Significant correlations between decoding accuracy and RT in children with ADHD. (d) Significant correlations between decoding accuracy and RTSD in children with ADHD. ADHD, attention-deficit/hyperactivity disorder; N2pc, N2-posterior-contralateral; TD, typically developing; **represents $p < .01$

investigated the decline in neural spatial decoding ability for children with ADHD. Visual spatial abnormalities of ADHD have been reported in many studies. Our study also found that the ERP component N2pc produced from the posterior region in children with ADHD is significantly smaller than that in TD children (Wang et al., 2016). However, the univariate analysis could not fully explain variability in behavior and deficits in complex and subtle neural processing of selective attention. Consistent with previous studies (Bae & Luck, 2018; Bae & Luck, 2019; Hong et al., 2020; Li et al., 2022), through machine learning of multichannel ERP signals, the ability of children with ADHD to represent the target spatial location was significantly worse than the target localization ability of TD children. In addition, a delayed peak latency of decoding accuracy in children with ADHD revealed slower target detection during a visual search. Our results demonstrate the deteriorating and delayed visual spatial localization ability of children with ADHD. A significant correlation between decoding accuracy but not N2pc and RT provided evidence for a unique contribution of target representation from decoding analysis. We also found that decoding accuracy increased with age in children with ADHD, suggesting a developmental delay in spatial localization. In short, our results confirm that there is an overall deterioration in the spatial coding ability of neural activity in children with ADHD, and the decrease in overall function may involve a more general neurological abnormality.

According to existing studies (Bae et al., 2020), information decoding ability is closely related to the efficiency and robustness of neural signals, which reflects the clarity of neural activities. For neural activity with high noise interference, the transmission efficiency of neural information is significantly affected (Li et al., 2001) and leads to poorer cognitive performance. The neural noise theory may be closely related to neurodevelopmental disorders. Previous studies have reported increased neural noise in children with ADHD, which has a detrimental influence on their inhibitory function (Grootswagers et al., 2017). Decoding accuracy is considered to be highly related to neural noise (Bae et al., 2020). Therefore, we hypothesize that higher neural noise might reduce the decoding precision of the spatial position in children with ADHD. In our study, the decrease in neural decoding in children with ADHD confirmed deteriorating neural function, which might result from increased neural noise. More importantly, the negative correlation between decoding accuracy and RTSD further confirmed the potential effects of neural noise. As increased levels of intraindividual variability indicate noisier neural processes, ADHD is characterized by high intraindividual variability, which can be reflected by higher RTSD during cognitive tasks. Our findings provide evidence for this hypothesis, as the decoding accuracy during the visual search task decreased, the RTSD in children with ADHD increased.

### 4.2 | The value of information-based decoding for studying cognitive processing in neurodevelopmental disorders

In previous studies, machine learning was mainly used to distinguish children with ADHD from TD children (Chen et al., 2019; Öztekin et al., 2021; Yasumura et al., 2020), and the training of this decoder was based on group-level supervised learning. However, our information-based machine learning is aimed at assessing the specific cognitive processes represented by the neural activities of each individual. This approach can learn the differences in neural patterns within each individual and generate individualized decoders, which can help us better understand the uniqueness of cognitive impairment in each child with ADHD. Furthermore, conventional univariate ERP and group-level machine learning analysis can only perform statistical analysis based on the group level. Multivariate decoding analysis can perform statistical analysis within subjects, which provides a potential direction for future personalized precision medicine.

Recent studies have used neural decoding to investigate stimulus signals in different directions from the scalp EEG distribution maps of healthy adults. The present study, adopting a new information-based decoding analysis, reveals that the target locations can be effectively identified and represented in both children with and without ADHD. These findings provide the first evidence that rich and identifiable location information is involved in children's scalp EEG signals with high neural noise, which offers a new approach for understanding neurodevelopmental processes.

With the high temporal resolution of EEG signals, information-based multivariate decoding analysis further considers the characteristics of spatial distribution. Therefore, we can clearly examine the precise time processing and spatial distribution of spatial information encoding. Our findings confirmed that information of the target spatial location could be decoded after a 200 ms delay, indicating that an individual's spatial orientation occurs approximately 200 ms after the visual search onset and that the duration before 200 ms may mainly reflect the simple perception and coding process of stimuli signals. In addition, the saliency map theory of visual attention has pointed out that the visual cortex could separate pop-out novel stimuli through bottom-up processing (Li, 2002). Based on our neural decoding weight analysis of the parieto-occipital lobe, we found that the visual cortex has a greater contribution to the classification, which means that the coding of spatial position could occur primarily in the visual cortex.

However, machine learning results are blind-sourced and thus always lack neurophysiological evidence. Here, our information-based multivariate decoding analysis clarified the time course of the spatial attention process in children, which is consistent with the previously discovered N2pc component in the parieto-occipital lobe (Eimer, 1996; Li et al., 2021; Luck & Hillyard, 1994a; Luck & Hillyard, 1994b). More importantly, since the N2pc component is a good neural index of attentional selection, the correlation between N2pc and decoding accuracy provided direct physiological relevance of the machine learning approach in spatial attention ability (Wang et al., 2016).

## 5 | LIMITATIONS

In the present study, to prevent residual eye movement signals from potentially interfering with the results, only parieto-occipital electrodes were used in the decoding analysis, and prefrontal electrodes were not used. However, the prefrontal cortex, such as the frontal eye field, is also involved in attentional selection processing (Panichello & Buschman, 2021; Thompson et al., 2005; Veniero et al., 2021). Although we performed the decoding analysis with eye movement-related ICs (Figure A.5), it is difficult to rule out the possibility of secondary consequences from very small eye movements. Further methodological development is needed to explore the role of the prefrontal cortex in selective attention through neural decoding. In addition, although the difference in IQ between ADHD and TD children has been demonstrated in previous studies (Frazier et al., 2004), it may still cause potential confusion. The reason for the lack of balanced IQ is that the present research is an exploratory study, and a relatively large sample size can be used to obtain relatively stable decoding results. Follow-up research needs to use IQ-matched subjects and untrained data to further test the accuracy of the decoding model.

## 6 | CONCLUSIONS

This study explored the target localization ability in school-age children with ADHD during visual search processes through a new information-based decoding approach. The imprecise encoding characteristics of the attentional spotlight during visual search in school-age children with ADHD indicated that increased neural noise and chaotic neural responses are fundamental deficits of the neurodevelopmental disorder. Our results provide new neurophysiological evidence for understanding cognitive dysfunction in children with ADHD and offer potential directions for the early diagnosis and personalized intervention of neurodevelopmental impairments in children with ADHD.

## ACKNOWLEDGMENTS

This work was supported by the National Natural Science Foundation of China (Li Sun, 81971284, 81771479; Yan Song, 31871099); the Beijing Municipal Science and Technology Program (Li Sun, Z171100001017089), the Key Scientific Research Projects of Capital Health Development (2020-1-4111), the Beijing Brain Initiative of Beijing Municipal Science and Technology Commission (Yan Song, Z181100001518003), the National Defense Basic Scientific Research Program of China (Yan Song, 2018110B011) and Sanming Project of Medicine in Shenzhen "The AD/HD Research Group from Peking University Sixth Hospital" (SZSM201612036).

## CONFLICTS OF INTEREST

All authors reported no biomedical financial interests or potential conflicts of interest.

## DATA AVAILABILITY STATEMENT

Data supporting the findings of this study will be available upon reasonable request to corresponding authors.

## ORCID

*Dongwei Li* https://orcid.org/0000-0002-2432-8882
*Yan Song* https://orcid.org/0000-0002-5923-7673

## REFERENCES

Bae, G. Y., Leonard, C. J., Hahn, B., Gold, J. M., & Luck, S. J. (2020). Assessing the information content of ERP signals in schizophrenia using multivariate decoding methods. *Neuroimage: Clinical*, *25*, 102179.

Bae, G. Y., & Luck, S. J. (2018). Dissociable decoding of spatial attention and working memory from EEG oscillations and sustained potentials. *The Journal of Neuroscience*, *38*(2), 409–422.

Bae, G. Y., & Luck, S. J. (2019). Reactivation of previous experiences in a working memory task. *Psychological Science*, *30*(4), 587–595.

Bruce, N. D., & Tsotsos, J. K. (2009). Saliency, attention, and visual search: An information theoretic approach. *Journal of Vision*, *9*, 5.1–5.24.

Chen, H., Chen, W., Song, Y., Sun, L., & Li, X. (2019). EEG characteristics of children with attention-deficit/hyperactivity disorder. *Neuroscience*, *406*, 444–456.

Cross-Villasana, F., Finke, K., Hennig-Fast, K., Kilian, B., Wiegand, I., Müller, H. J., Möller, H. J., & Töllner, T. (2015). The speed of visual attention and motor-response decisions in adult attention-deficit/hyperactivity disorder. *Biological Psychiatry*, *78*, 107–115.

Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, *134*(1), 9–21.

Deneve, S., & Chalk, M. (2016). Efficiency turns the table on neural encoding, decoding and noise. *Current Opinion in Neurobiology*, *37*, 141–148.

Dennis, M., Francis, D. J., Cirino, P. T., Schachar, R., Barnes, M. A., & Fletcher, J. M. (2009). Why IQ is not a covariate in cognitive studies of neurodevelopmental disorders. *Journal of the International Neuropsychological Society*, *15*(3), 331–343.

Eimer, M. (1996). The N2pc component as an indicator of attentional selectivity. *Electroencephalography and Clinical Neurophysiology*, *99*, 225–234.

Eimer, M. (2014). The neural basis of attentional control in visual search. *Trends in Cognitive Sciences*, *18*, 526–535.

Foster, J. J., Sutterer, D. W., Serences, J. T., Vogel, E. K., & Awh, E. (2017). Alpha-band oscillations enable spatially and temporally resolved tracking of covert spatial attention. *Psychological Science*, *28*, 929–941.

Frazier, T. W., Demaree, H. A., & Youngstrom, E. A. (2004). Meta-analysis of intellectual and neuropsychological test performance in attention-deficit/hyperactivity disorder. *Neuropsychology*, *18*(3), 543–555.

Grootswagers, T., Wardle, S. G., & Carlson, T. A. (2017). Decoding dynamic brain patterns from evoked responses: A tutorial on multivariate pattern analysis applied to time series neuroimaging data. *Journal of Cognitive Neuroscience*, *29*(4), 677–697.

Guo, J., Luo, X., Kong, Y., Li, B., Si, B., Sun, L., & Song, Y. (2022). Abnormal reactivity of brain oscillations to visual search target in children with attention-deficit/hyperactivity disorder. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*. Published online 12 March 2022. https://doi.org/10.1016/j.bpsc.2022.03.002

Hong, X., Bo, K., Meyyappan, S., Tong, S., & Ding, M. (2020). Decoding attention control and selection in visual spatial attention. *Human Brain Mapping*, *41*(14), 3900–3921.

Kofler, M. J., Rapport, M. D., Sarver, D. E., Raiker, J. S., Orban, S. A., Friedman, L. M., & Kolomeyer, E. G. (2013). Reaction time variability in ADHD: A meta-analytic review of 319 studies. *Clinical Psychology Review*, *33*(6), 795–811.

Li, D., Zhang, X., Kong, Y., Yin, W., Jiang, K., Guo, X., Dong, X., Fu, L., Zhao, G., Gao, H., Li, J., Zhai, J., Su, Z., Song, Y., & Chen, M. (2022). Lack of neural load modulation explains attention and working memory deficits in first-episode schizophrenia. *Clinical Neurophysiology*, *136*, 206–218.

Li, D., Zhao, C., Guo, J., Kong, Y., Li, H., Du, B., Ding, Y., & Song, Y. (2021). Visual working memory guides spatial attention: Evidence from alpha oscillations and sustained potentials. *Neuropsychologia*, *151*, 107719.

Li, S. C., Lindenberger, U., & Sikström, S. (2001). Aging cognition: From neuromodulation to representation. *Trends in Cognitive Sciences*, *5*, 479–486.

Li, Z. (2002). A saliency map in primary visual cortex. *Trends in Cognitive Sciences*, *6*, 9–16.

Luck, S. J., & Hillyard, S. A. (1994a). Electrophysiological correlates of feature analysis during visual search. *Psychophysiology*, *31*, 291–308.

Luck, S. J., & Hillyard, S. A. (1994b). Spatial filtering during visual search: Evidence from human electrophysiology. *Journal of Experimental Psychology. Human Perception and Performance*, *20*, 1000–1014.

Luo, X., Guo, J., Li, D., Liu, L., Chen, Y., Zhu, Y., Johnstone, S. J., Wang, Y., Song, Y., & Sun, L. (2021). Atypical developmental trajectories of early perception among school-age children with ADHD during a visual search task. *Child Development*, *92*, e1186–e1197.

Ortega, R., López, V., Carrasco, X., Anllo-Vento, L., & Aboitiz, F. (2013). Exogenous orienting of visual-spatial attention in ADHD children. *Brain Research*, *1493*, 68–79.

Öztekin, I., Finlayson, M. A., Graziano, P. A., & Dick, A. S. (2021). Is there any incremental benefit to conducting neuroimaging and neurocognitive assessments in the diagnosis of ADHD in young children? A machine learning investigation. *Developmental Cognitive Neuroscience*, *49*, 100966.

Panichello, M. F., & Buschman, T. J. (2021). Shared mechanisms underlie the control of working memory and attention. *Nature*, *592*, 601–605.

Pertermann, M., Bluschke, A., Roessner, V., & Beste, C. (2019). The modulation of neural noise underlies the effectiveness of methylphenidate treatment in attention-deficit/hyperactivity disorder. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, *4*, 743–750.

Saville, C. W. N., Feige, B., Kluckert, C., Bender, S., Biscaldi, M., Berger, A., Fleischhaker, C., Henighausen, K., & Klein, C. (2015). Increased reaction time variability in attention-deficit hyperactivity disorder as a response-related phenomenon: Evidence from single-trial event-related potentials. *Journal of Child Psychology and Psychiatry*, *56*, 801–813.

Schneider, M. F., Krick, C. M., Retz, W., Hengesch, G., Retz-Junginger, P., Reith, W., & Rösler, M. (2010). Impairment of fronto-striatal and parietal cerebral networks correlates with attention deficit hyperactivity disorder (ADHD) psychopathology in adults—A functional magnetic resonance imaging (fMRI) study. *Psychiatry Research: Neuroimaging*, *183*, 75–84.

Singer-Harris, N., Forbes, P., Weiler, M. D., Bellinger, D., & Waber, D. P. (2001). Children with adequate academic achievement scores referred for evaluation of school difficulties: Information processing deficiencies. *Developmental Neuropsychology*, *20*, 593–603.

Sun, M., Wang, E., Huang, J., Zhao, C., Guo, J., Li, D., Sun, L., Du, B., Ding, Y., & Song, Y. (2018). Attentional selection and suppression in children and adults. *Developmental Science*, *21*, e12684.

Thompson, K. G., Biscoe, K. L., & Sato, T. R. (2005). Neuronal basis of covert spatial attention in the frontal eye field. *The Journal of Neuroscience*, *25*, 9479–9487.

Veniero, D., Gross, J., Morand, S., Duecker, F., Sack, A. T., & Thut, G. (2021). Top-down control of visual cortex by the frontal eye fields through oscillatory realignment. *Nature Communications*, *12*, 1–13.

Wang, E., Sun, L., Sun, M., Huang, J., Tao, Y., Zhao, X., Wu, Z., Ding, Y., Newman, D. P., Bellgrove, M. A., Wang, Y., & Song, Y. (2016). Attentional selection and suppression in children with attention-deficit/hyperactivity disorder. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, *1*, 372–380.

Willcutt, E. G. (2012). The prevalence of DSM-IV attention-deficit/hyperactivity disorder: A meta-analytic review. *Neurotherapeutics*, *9*, 490–499.

Yasumura, A., Omori, M., Fukuda, A., Takahashi, J., Yasumura, Y., Nakagawa, E., Koike, T., Yamashita, Y., Miyajima, T., Koeda, T., Aihara, M., Tachimori, H., & Inagaki, M. (2020). Applied machine learning method to predict children with ADHD using prefrontal cortex activity: A multicenter study in Japan. *Journal of Attention Disorders*, *24*(14), 2012–2020.

## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

**How to cite this article:** Li, D., Luo, X., Guo, J., Kong, Y., Hu, Y., Chen, Y., Zhu, Y., Wang, Y., Sun, L., & Song, Y. (2023). Information-based multivariate decoding reveals imprecise neural encoding in children with attention deficit hyperactivity disorder during visual selective attention. *Human Brain Mapping*, *44*(3), 937–947. https://doi.org/10.1002/hbm.26115