Neuronal Correlates of Task Irrelevant Distractions Enhance the Detection of Attention Deficit/Hyperactivity Disorder

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***Abstract*— Early diagnosis and treatment can reduce the symptoms of Attention Deficit/Hyperactivity Disorder (ADHD) in children, but medical diagnosis is usually delayed. Hence, it is important to increase the efficiency of early diagnosis. Previous studies used behavioral and neuronal data during GO/NOGO task to help detect ADHD and the accuracy differed considerably from 53% to 92%, depending on the employed methods and the number of electroencephalogram (EEG) channels. It remains unclear whether data from a few EEG channels can still lead to a good accuracy of detecting ADHD. Here, we hypothesize that introducing distractions into a VR-based GO/NOGO task can augment the detection of ADHD using 6-channel EEG because children with ADHD are easily distracted. Forty-nine ADHD children and 32 typically developing children were recruited. We use a clinically applicable system with EEG to record data. Statistical analysis and machine learning methods were employed to analyze the data. The behavioral results revealed significant differences in task performance when there are distractions. The presence of distractions leads to EEG changes in both groups, indicating immaturity in inhibitory control. Importantly, the distractions additionally enhanced the between-group differences in NOGO α and γ power, reflecting insufficient inhibition in different neural networks for distraction suppression in the ADHD group. Machine learning methods further confirmed that distractions enhance the detection of ADHD with an accuracy of 85.45%. In conclusion, this system can assist in fast screenings for ADHD and the findings of neuronal correlates of distractions can help design therapeutic strategies.**

***Index Terms*— Attention deficit/hyperactivity disorder (ADHD), continuous performance test (CPT), electroencephalography (EEG), go/no-go task, machine learning, virtual reality (VR), distractions.**

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I. Introduction

ATTENTION Deficit/Hyperactivity Disorder (ADHD) is one of the most common neurodevelopmental disorders in childhood. Children with ADHD may exhibit difficulty paying attention, easily get distracted, perform impulsive or overly active behaviors, and be restless when compared with age-matched healthy subjects, resulting in academic, family and life difficulties [1]. These symptoms can affect an individual from early childhood into adulthood [2], so early diagnosis and treatment are important. Currently, the reference guide used by clinicians to diagnose ADHD is known as the Diagnostic and Statistical Manual of Mental Disorders – 5th Edition (DSM-5). This diagnosis is based on observing behavior through interviews and questionnaires; there is no standard objective laboratory tests (urine, blood, x-ray or psychological analysis) to further support the diagnosis of ADHD [3]. As a result, an increasing rate of ADHD disorder misdiagnosis with other types of brain disorder has been reported [4]. Furthermore, it has also been reported that medical diagnosis of ADHD is often delayed due to the heterogeneous nature of ADHD, combined comorbidities and a global shortage of diagnostic clinicians [5]. Hence, alternative ways to increase the efficiency of early diagnosis is important [5]. For instance, GO/NOGO task has been used in many studies to investigate the behavioral and neuronal aberrations in ADHD children [6], [7], [8]. In this study, we aim to use an intelligent VR system integrated with 6 channels of electroencephalogram (EEG) and machine learning methods to help diagnose children with ADHD. Specifically, given that children with ADHD are more easily distracted, we hypothesized that introducing distractions into a VR-based GO/NOGO task can augment the detection of ADHD.

This paper is organized as follows: Section II describes the updated findings regarding ADHD, EEG and GO/NOGO tasks in the literature. Section III describes the details of the stimulation materials and the VR system used, along with the experiment procedures, data analysis, and statistical tests. Section IV presents the experimental results. The discussion and conclusions are summarized in Section V.

II. Related Work

ADHD is a neurodevelopmental disorder in which some brain areas mature several years later than normal, such as the amygdala, caudate, hippocampus, and putamen, as well as cortical regions (prefrontal, parietotemporal cortex) and cerebellum [9], [10], [11]. As a result, children with ADHD exhibit a variety of symptoms, including inattention, impulsiveness, and hyperactivity [1]. For clinical screening and/or treatment evaluation of attention-related diseases, behavioral and neuronal data have been used. For instance, the continuous performance test (CPT) objectively measures the behavioral performance of inattention and impulsivity, including the correct response, reaction time, omission error, and commission errors [12] and can be used as a supportive measure in the evaluation of ADHD [13]. Additionally, two electrophysiological components of event-related evoked potentials (ERPs) also provide an objective assessment of a subject's attention and response inhibition: (1) a negative peak around 200 ms after stimulus onset (N200); and (2) a positive peak around 300 ms (P300) from the EEG during a GO/NOGO task, a variation of CPT [14], [15]. Fisher et al. found that in the NOGO trial, ADHD subjects made more commission errors compared to controls and the P300 peak in ADHD group was smaller [16]. In healthy adults, N200 and P300 amplitudes were greater in NOGO trials than in GO trials [17]. These increases in NOGO trials were thought to reflect the inhibitory mechanism [18]. Specifically, the NOGO-N200 was related to central inhibition or response conflict, while the P300 is most probably related to inhibition of overt response [17]. In children with ADHD, significant differences were found in N200/P200 amplitude over the right centro-frontal regions [19] and in NOGO-P300 peak and latencies when compared with typically developing children [20], suggesting immature or impaired executive function associated with attention control and inhibition [21].

Additionally, oscillatory EEG activity also plays important functional roles in executive function, especially when concerning interference inhibition (see [21] for a review). For instance, theta power within the medial frontal cortex was greatest between successful response inhibition in NOGO events compared to GO responses, reflecting the recruitment of executive control in interference situations [22]. Alpha and beta power decreases were interpreted as greater cortical activation when motor preparation was needed in the GO condition while theta and gamma decreases could reflect inhibition of competing neural networks [23]. Regarding ADHD, Alexander et al. reported that low-frequency activity in the ADHD subjects was inversely related to clinical and behavioral measures of hyperactivity and impulsivity during CPT tasks and this reversed relation was normalized following treatment with stimulant medication [24]. Clarke et al. found that these oscillatory abnormalities during eyes-closed resting state in ADHD groups can help separate two subtypes of ADHD [25]. Barry et al. reviewed the articles that used resting EEG to assess ADHD and concluded that "*elevated relative theta power, and reduced relative alpha and beta, together with elevated theta/alpha and theta/beta ratios, are most reliably associated with AD/HD*" [26]. In summary, neuronal data of EEG during the GO/NOGO task or resting state can be used to evaluate attention and response inhibition of ADHD.

Recently, machine learning methods have been applied to EEG data to support the diagnosis of ADHD. Khoshnoud et al. extracted the nonlinear features from 19-channel EEG during eyes-closed resting state of 12 ADHD and 12 normal age-matched children and achieved an accuracy of 83.33% for separating the two groups using SVM [27]. Mueller et al. used ERPs and independent component analysis to extract features for 19 channel EEG for separating ADHD patients from normal subjects during a visual two-stimulus GO/NOGO task and reported an average classification accuracy of 92% [28]. Rodríguez et al. [29] and Areces et al. [30] used discriminant analysis and achieved 56.60% and 76.1% accuracy in distinguishing ADHD and non-ADHD, respectively. In 2019, Vahid. et al. used deep learning model and features extracted from 60 channel EEG during a time estimation task to distinguish ADHD from healthy subjects with an accuracy up to 86% [31]. In 2020, we used the task performance and neuro-behavioral data, such as head rotation (HR) and eye movements (EM), during a CPT in a virtual-classroom to separate children with ADHD from normally developing children with an accuracy of 83.6% [32]. In summary, the use of behavioral and neuronal data during GO/NOGO task to help detect ADHD can result in a range of accuracy from 53% to up 92%, depending on the employed methods and the number of EEG channels. It remains unclear whether data from a few EEG channels can still lead to a good accuracy of detecting ADHD.

Moreover, the GO/NOGO task was mostly given to subjects in a well-controlled laboratory setting and hardly considered the effect of unexpected distractions that occur regularly in daily life. From the therapeutic perspective, it is also important to study the impact of distractions as children with ADHD are more easily distracted and a better understanding of the mechanism underlying distraction suppression will help the design of behavior treatment for ADHD. Indeed, in our previous study, we demonstrated that introducing task-irrelevant distractions into a VR-based GO/NOGO task can better explore the functional roles of N200, theta, and beta oscillations in young adults [33].

In this study, we aim to use an intelligent VR system integrated with 6-channel EEG and machine learning methods to help diagnose children with ADHD. Importantly, we test whether introducing distractions into a VR-based GO/NOGO task can augment the detection of ADHD and investigate the neuronal correlates of distractions.

III. Methods

A. System Equipment and Software

In this study, we used our previously validated VR- system integrated with 6-channel EEG to collect multi-modal data

Fig. 1. Brain electrodes and positions.

from participants. The details of this virtual classroom can be found in our previous papers [32], [33]. The VR device used is the HTC Vive™jointly developed by HTC International Electronics and Villefort. It provides users an immersive experience of a three-dimensional virtual space and achieves experimental purposes with a handheld remote controller. The EEG device is produced by Looxid®, which can receive 6-channel EEG data (Fig. 1). The virtual classroom environment was developed using the game engine Unity3D. The HTC Vive™and VR controllers are connected to the computer, enabling users to interact with the virtual environment. Furthermore, the VR system was also integrated with various sensors to measure the physiological signals of galvanic skin response (GSR), and eye movement.

This VR-based GO/NOGO paradigm was designed to be in a virtual classroom environment and has been used in our previous studies (see papers [32], [33] for details). During the VR-based GO/NOGO task, participants were seated in a fixed position within the precise range of the VR system and were instructed to continually look at numbers on a blackboard directly in front during the experiment. Throughout the 10-minute experiment, numbers from 0 to 9 randomly appeared on the blackboard with an interstimulus interval (ISI) of 2 seconds. There were two conditions: GO and NOGO. Subjects were asked to respond when they saw 0 after 1 as the GO condition and hold their response when 0 was not after 1 as the NOGO condition. The GO and NOGO stimulus appeared randomly. Additionally, 25 trials (12 GO stimuli, 13 NO-GO stimuli) were accompanied by different task-irrelevant auditory and visual distractions. Specifically, a total of ten different distractive events were used and the physical properties of those distractions, including type, loudness (in dB) and duration (in second) were listed in Table I. Depending the presence durations, the probabilities for visual, auditory and visual-auditory hybrid distractions are 19%, 24%, and 57%, respectively. Figure 2A illustrates the VR scenario in which the red dashed lines indicate the places of the introduced distractions and 2B shows the rundown of the distractions.

B. Participants and Data Acquisition

The study was approved by the Institutional Review Board (2) of Taipei Veterans General Hospital (TPEVGH IRB No.: 2020-11-001B) in accordance with the Declaration of Helsinki and Good Clinical Practice Guidelines. Forty nine ADHD children and 32 disease-free children with normal vision (or normal after correction) participated in this study. All subjects signed an informed consent after receiving an explanation of the study. Throughout the experiment, EEG data from six channels (AF3, AF4, Fp1, Fp2, AF7, and AF8; international 10-20 system) were integrated into the VR headset (see Fig. 1 right) and recorded with a sampling rate of 512 Hz. In addition, behavioral data were collected throughout the experiment for the calculation of task performance, including correct detection, reaction times, omission errors, and commission errors.

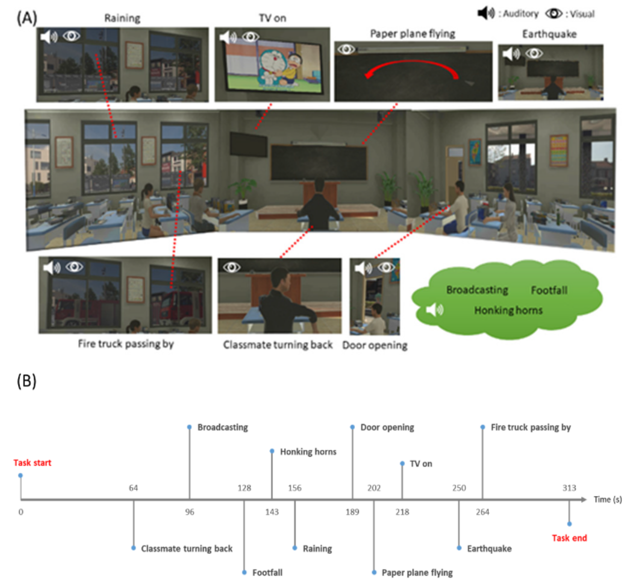

Fig. 2. VR scenario with distractions. (A) types and locations of the distractions; (B) the rundown of the distractions.

TABLE I
THE PHYSICAL PROPERTIES OF THE DISTRACTIONS

Distractions		Duration (s)
Description	Type	
Classmate turning back	**V**	**32**
Broadcasting	**A (30 dB)**	**31**
Footfall	**A (20 dB)**	**16**
Honking horns	**A (30 dB)**	**13**
Raining	**V + A (30 dB)**	**33**
Door opening	**V + A (20 dB)**	**12**
Paper plane flying	**V**	**16**
TV on	**V + A (30 dB)**	**32**
Earthquake	**V + A (30 dB)**	**14**
Fire truck passing by	**V + A (30 dB)**	**50**

V: visual stimuli; A: auditory stimuli

C. EEG Data Processing and Feature Extraction

The steps for EEG data analysis have been described in our previous studies in detail [33], [34]. Basically, EEG data were bandpass filtered (2-56 Hz) offline using SPM12 (Wellcome Trust Centre for Neuroimaging, http://www.fil.ion.ucl.ac.uk/spm/) and then divided into GO and NOGO trials with distraction (D) and without distraction

(ND) conditions, resulting in four subsets for each group for analysis: GO-D, GO-ND, NOGO-D, and NOGO-ND. For ERPs analysis, the EEG were epoched into trials with peristimulus time of −1000 ms to +1000 ms with respect to the onset of visual cues. Then, the four subsets were averaged across trials to obtain the ERPs. The baseline was set at −200 ms to 0 ms and the time windows for N2 and P3 were from150 to 400 and from 300 to 700 ms after visual cue, respectively. We extracted four ERP features for comparison: the peak amplitudes and latencies of N2 and P3.

To obtain frequency-related features, the four subsets for each group were first transformed into the time-frequency domain from 4 to 48 Hz using a Morlet wavelet (wavelet number: 7). The spectral densities at each channel were epoched into trials with peristimulus time of −1000 ms to +2000 ms and then averaged across trials and frequencies with respect to the four frequency bands of interest (FOI), including the ⊖ (4-7 Hz), α (8-14 Hz), β (15-24 Hz), and γ (25-48 Hz) bands. After baseline correction (-500 to 0 ms), we extracted the frequency-specific peak power named event-related spectral power (ERSP) [35]. We first identified the peaks of ERSP and then the frequency-specific spectrum was further averaged over time points from 0 to 1000 ms to obtain the ERSP mean. Therefore, two frequency-related parameters (i.e., ERSP peak and ERSP mean) for each subset of data were identified for comparison.

D. Statistical Analysis and Machine Learning Methods

Task performance, ERPs and ERSP features were statistically tested for the within-group factor of distractions (i.e., the D vs. ND; paired t-test) and the between-group differences (i.e., healthy vs. normal groups; Welch's t-test). The significant level was set at p<0.05 after correction for multiple comparisons (Bonferroni correction). In addition to univariate analysis of data, we employed 8 different machine learning methods for multiple-variate analysis, including Support Vector Machine (SVM), K-nearest neighbor (KNN), Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), Adaptive Boosting (AB), Gradient Boosting (GB), and eXtreme Gradient Boosting (XGB) to separate the data of the two groups for two-class classification. Five-fold cross-validation was applied for cross-validation. Finally, classification accuracy, sensitivity, specificity, precision, F1-score and AUC were reported for evaluating the performance of classifiers and data.

IV. Results

A. Statistical Analysis on CPT Task Performance

Table II summarizes the statistical results of behavioral differences between 32 normal children and 49 ADHD children in different states (with or without interference) of CPT. It can be seen that behaviorally the two groups showed significant differences in reaction times and omission errors when there are distractions. Children with ADHD exhibited significantly shorter reaction times (p=0.004) and higher omission errors (p<0.001) with distractions when compared to the normal children (Table I, marked with grey). The between-group performance differences in ND trials were insignificant after correction for multiple comparisons. Furthermore, children with ADHD had significantly higher omission errors with the presence of distractions compared with no distractions (p=0.0024) (Table I, marked with grey).

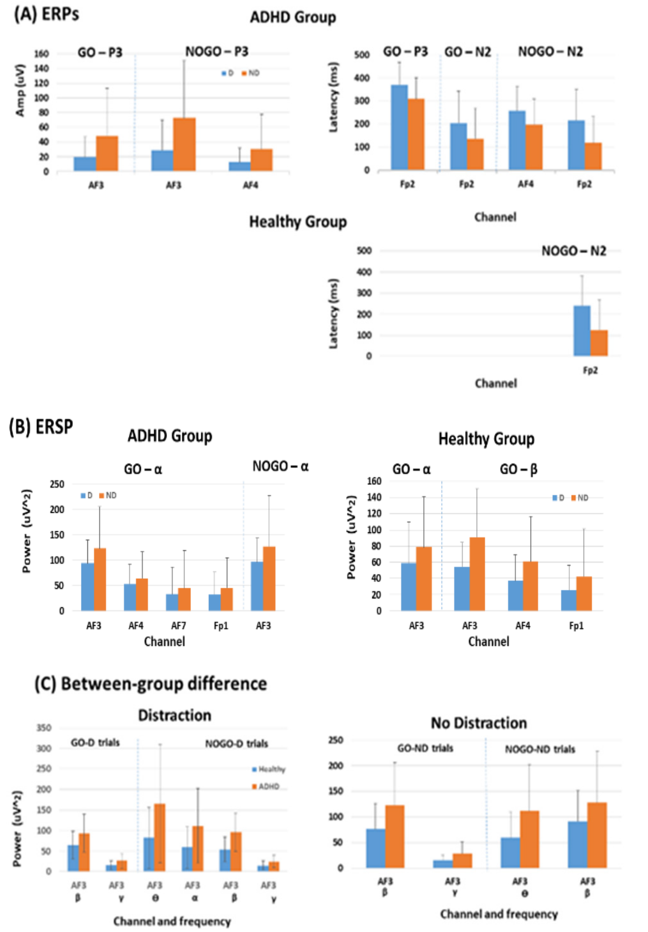

Fig. 3. Significant differences in brain responses with and without distraction trials.(A) Group-specific differences in ERPs; (B) Group-specific differences in ERSP; (C) Between-group differences with and without distractions.

B. ERP and ERSP Results on Distractions

Paired t-test was used to identify group-specific significant differences in brain responses with and without distraction trials. Fig. 3 A shows the significant group-specific differences in ERP peak and latency with and without distractions. The ADHD group exhibited significantly smaller P300 peaks at AF3 and AF4 in D trials in both GO an NOGO conditions when compared to that in the ND trials (Fig. 3 A, upper left). The latencies of GO-P3 and GO-N2 at Fp2, as well as the NOGO-N2 latencies at AF4 and Fp2 were significantly longer in D trials (Fig. 3 A, upper right). By contrast, the healthy group only shows a significantly prolonged latency in NOGO-N2 at Fp2 (Fig. 3 A, lower panel). There is no significance in P3 peak or latency in the healthy group after correction for multiple comparisons.

For ERSP, the ADHD group have significantly decreased α power at AF3, AF4, AF7 and Fp1 in GO conditions and at AF3 in NOGO conditions with distractions when compared

TABLE II
BEHAVIOR RESULTS OF CPT TASK PERFORMANCE (*: P<0.05 AFTER CORRECTION FOR MULTIPLE COMPARISONS)

							Between Group	
	D	ND	Within-group Significance	D	ND	Within-group Significance	D (p-value)	ND (p-value)
Correct Detection (%)	94.23%	94.04%	0.4609	90.03%	87.52%	0.1807	0.05	0.05
Reaction times (ms)	409.4±130.0	416.1±128.0	0.4148	337.0±172.5	362.5±163.2	0.1374	0.0040*	0.05
Omission errors	0.1458781	0.0752688	0.05	0.300542	0.1544715	0.0024*	0.0003*	0.05
Commission errors	0.2419291	0.2306068	0.4329	0.3987426	0.3899937	0.4449	0.05	0.05

to without distractions (Fig. 3B, left). For the healthy group, the α power at AF3 and β power at AF3, AF4 and Fp1 decreased only in GO conditions with distractions (Fig. 3 B, right). No significant differences in $\ominus$ and γ ERSP were found in this study.

C. ERP and ERSP Results on Normal and ADHD Groups

Regarding the differences between the two groups, we used Welch's t test to examine the ERP and ERSP between normal and ADHD groups with and without distractions. Fig. 3 C shows the significant differences between the two groups. We observed that the ADHD group has higher ERPS power at different channels and frequencies when compared with the healthy group, including θ, α, β and γ power at AF3 in NOGO-D trials and greater β and γ power at AF3 in GO-D trials when there are distractions (Fig. 3C, left). Fewer increases of ERSP in the ADHD group were identified under ND conditions, including β and γ power at AF3 in GO-ND trials and θ and β power at AF3 in NOGO-ND trials (Fig. 3C, right).

D. Classification on Distraction

We first used machine learning classification to verify whether distractions have any impact on brain signals. Specifically, we tested different combinations of EEG features, including ERPs, ERPS and both to see which features best reflect the effects of distractions. TABLE III lists the classification results of the machine learning methods. To increase readability, we coded the best accuracies given data in grey. The ERP features can result in the best accuracy of 90.00% in ADHD group using XGB but failed in the healthy group (accuracy <70.00%). For ERSP features, the best classifications were 90.00% for the ADHD group using XGB and 84.62% for the healthy group using DT, RF, AB and XGB. The combination of ERP and ERSP features leads to the best accuracy of 100.00% in both the ADHD and healthy groups using RF, GB and XGB. It should be noted that the variances of accuracy across different classifiers were considerable in both groups.

E. Classification on ADHD

Finally, we tested whether the presence of distractions can enhance the separation of the ADHD group from the healthy group by comparing the classification results with and without distractions using both behavioral and EEG data because they displayed significant within- and between-group differences. Table IV lists the classification results with and without distractions. It can be seen that the presence of distractions during the task increases the classification accuracies of all classifiers tested. Specifically, the best separation accuracy of all when used ND and D trials was 85.45% obtained by XGB, followed by 83.64% of AB (Table IV). When used only ND trials, the best accuracy was 80.00% for both DT and XGB. When used only D trials, all classifiers failed to obtain a good classification result (<80%).

V. DISCUSSION

A. The Effects of Distractions on Behaviors

Previous studies of ADHD using a VR classroom with visual and auditory distractions has reported that children with ADHD committed significantly more omission errors and commission errors when compared with normal children [36]. Furthermore, it was suggested that virtual classrooms have good potential for the controlled attention performance assessment of children with ADHD compared to standard neuropsychological methods [37], [38]. In line with previous studies, we found significantly higher omission errors and shorter reaction times in the ADHD group compared with normal controls using the VR classroom, confirming that children with ADHD were more susceptible to distractions [36]. Furthermore, there were no significant performance differences in the normal group when comparing D and ND trials, but the ADHD group exhibited significantly greater omission errors (<1%) in tasks with distractions than without distractions. This behavioral difference suggests that normal children were less impacted by distractions.

It should be noted that a variety of distractions were used to interfere the subjects' attention. Because different forms of distractions (for instance, visual or auditory stimulus) engage different neuronal systems for processing the information of these distractions (i.e. functional specialization in neuroscience), it is possible that different distractions may have different effectiveness in modulating attention [39]. However, this effect is negligible in this study as the difference in the probabilities of visual (19%) and auditory (24%) distractions is only about 5%. The majority of the distractions (57%) have simultaneously visual and auditory stimulus. Further study that

TABLE III
FEATURE-SPECIFIC CLASSIFICATION ACCURACY

Features	ERPs															
Data	Healthy								ADHD							
Classes	D vs. ND								D vs. ND							
Classifier	SVM	KNN	LR	DT	RF	AB	GB	XGB	SVM	KNN	LR	DT	RF	AB	GB	XGB
Accuracy (%)	46.15	56.92	52.31	52.31	55.38	63.08	64.62	56.92	67.00	70.00	63.00	83.00	87.00	84.00	84.00	84.00
Sensitivity	0.47	0.50	0.57	0.57	0.73	0.70	0.73	0.63	0.82	0.70	0.62	0.78	0.90	0.84	0.84	0.84
Specificity	0.46	0.63	0.49	0.49	0.40	0.57	0.57	0.51	0.52	0.70	0.64	0.88	0.84	0.84	0.84	0.84
Precision	0.42	0.54	0.49	0.48	0.52	0.59	0.60	0.53	0.63	0.70	0.64	0.86	0.85	0.84	0.84	0.84
F1_score	0.44	0.52	0.52	0.52	0.61	0.64	0.66	0.57	0.71	0.70	0.63	0.82	0.87	0.84	0.84	0.84
AUC	0.46	0.56	0.53	0.53	0.57	0.64	0.65	0.57	0.67	0.70	0.63	0.83	0.87	0.84	0.84	0.84
Features	ERSP															
Data	Healthy								ADHD							
Classes	D vs. ND								D vs. ND							
Classifier	SVM	KNN	LR	DT	RF	AB	GB	XGB	SVM	KNN	LR	DT	RF	AB	GB	XGB
Accuracy (%)	83.08	69.23	84.62	81.54	78.46	81.54	80.00	81.54	84.00	85.00	85.00	73.00	83.00	82.00	86.00	87.00
Sensitivity	0.90	0.93	0.93	0.90	1.00	0.97	0.87	0.93	84.00	85.00	85.00	73.00	83.00	82.00	86.00	87.00
Specificity	0.77	0.49	0.77	0.74	0.60	0.69	0.74	0.71	0.94	0.94	0.96	0.84	0.86	0.82	0.92	0.94
Precision	0.78	0.61	0.79	0.75	0.68	0.73	0.74	0.74	0.74	0.76	0.74	0.62	0.80	0.82	0.80	0.80
F1_score	0.83	0.74	0.85	0.81	0.81	0.83	0.80	0.82	0.78	0.8	0.79	0.69	0.82	0.82	0.82	0.82
AUC	0.84	0.71	0.85	0.82	0.80	0.83	0.80	0.82	0.85	0.86	0.86	0.75	0.83	0.82	0.87	0.88
Features	ERPs +ERSP															
Data	Healthy								ADHD							
Classes	D vs. ND								D vs. ND							
Classifier	SVM	KNN	LR	DT	RF	AB	GB	XGB	SVM	KNN	LR	DT	RF	AB	GB	XGB
Accuracy (%)	69.23	72.31	73.85	72.31	80.00	80.00	78.46	81.54	88.00	75.00	86.00	72.00	81.00	84.00	84.00	86.00
Sensitivity	0.73	0.90	0.80	0.70	1.00	0.97	0.77	0.90	1.00	0.82	1.00	0.78	0.88	0.86	0.96	0.92
Specificity	0.66	0.57	0.69	0.74	0.63	0.66	0.80	0.74	0.76	0.68	0.72	0.66	0.74	0.82	0.72	0.80
Precision	0.64	0.64	0.69	0.70	0.70	0.71	0.80	0.75	0.81	0.72	0.78	0.71	0.77	0.83	0.78	0.82
F1_score	0.68	0.75	0.74	0.70	0.82	0.82	0.76	0.82	0.89	0.77	0.88	0.73	0.82	0.84	0.86	0.87
AUC	0.70	0.74	0.74	0.72	0.81	0.81	0.78	0.82	0.88	0.75	0.86	0.72	0.81	0.84	0.84	0.86

uses adequate uni-modal distractions can allow the comparison of distraction-specific effects on attention.

B. The Effects of Distractions on ERPs

The functional roles of N2 peak were thought to be related to inhibitory control, inference suppression [40] and monitoring of conflict (see [41] for a review) in CPT tasks. In our previous study, the NOGO-D N2 was greater than the GO-D N2 in healthy adults and this suggests the inhibitory control of N2 [33]. In a study of children with ADHD, it was reported that the differences of N2 peak between NOGO and GO trials diminished after correction for the confounding factors of oppositional defiant/conduct disorder [42]. In this study, we found that neither between ADHD and control groups nor

TABLE IV
CLASSIFICATION RESULTS OF ADHD AND HEALTHY

Data	ND trials							D+ND trials						
Features	TP+ERPs + ERSP							TP+ERPs+ERSP						
Classes	ADHD v.s. Healthy							ADHD v.s. Healthy						
Classifier	KNN	LR	DT	RF	AB	GB	XGB	KNN	LR	DT	RF	AB	GB	XGB
Accuracy (%)	60.00	75.29	80.00	75.29	76.47	74.12	80.00	65.45	70.91	64.85	80.00	83.64	78.79	85.45
Sensitivity	0.66	0.98	0.90	0.96	0.92	0.94	1.00	0.67	0.96	0.71	0.97	0.97	0.86	0.93
Specificity	0.51	0.43	0.66	0.46	0.54	0.46	0.51	0.63	0.32	0.55	0.54	0.63	0.68	0.74
Precision	0.66	0.71	0.80	0.72	0.74	0.71	0.75	0.74	0.69	0.71	0.76	0.80	0.81	0.85
F1_score	0.66	0.82	0.84	0.82	0.82	0.81	0.86	0.70	0.80	0.71	0.85	0.88	0.83	0.89
AUC	0.59	0.70	0.78	0.71	0.73	0.70	0.76	0.65	0.64	0.63	0.75	0.80	0.77	0.83

Data	D trials						
Features	TP+ERPs + ERSP						
Classes	ADHD v.s. Healthy						
Classifier	KNN	LR	DT	RF	AB	GB	XGB
Accuracy (%)	77.65	76.47	75.29	70.59	68.24	76.47	76.47
Sensitivity	0.82	0.90	0.84	0.82	0.78	0.88	0.86
Specificity	0.71	0.57	0.63	0.54	0.54	0.60	0.63
Precision	0.81	0.75	0.78	0.72	0.71	0.76	0.77
F1_score	0.81	0.82	0.80	0.76	0.74	0.81	0.81
AUC	0.77	0.74	0.73	0.68	0.66	0.74	0.74

between D and ND trials have any significant differences in N2 peak. Instead, NOGO-N2 latencies were prolonged with distractions in both groups. Taken together, our findings of insignificant peaks and prolonged latencies of N2 may reflect the fact that both groups of children are still immature in inhibitory control.

The P3 amplitude is positively related with the attention amount toward target [41]. In this study, we observed that GO-P3 and NOGO-P3 amplitude in the ADHD group was significantly smaller with distractions than without distractions. Additionally, the presence of distractions prolonged the GO-P3 latency in the ADHD group. These P3 differences between D and ND trials, however, were absent in healthy controls. The P3 ERP findings signify that the ADHD group was distracted by inferences and diverted attentional resources toward the distractions, rather than properly suppressing irrelevant information.

C. The Effects of Distractions on ERSP

Local α oscillations are associated with cognitive performance, memory, attention, and inhibitory control of motor programs (see [43] for a review). Alpha power decrease was often seen during visual stimulation of visual attention [44] or during sensorimotor tasks for motor preparation [45], [46]. In our previous study, we found that the α power was decreased by the perturbations of distractions in GO but not NOGO trials in adult subjects, indicating α-related attention toward the task. Beta ERSPs also play an important role in attention regulation [47], [48], [49]. For instance, intentionally attending to sensory stimulus results in the decrease of beta power [50], [51]. In this study, we observed that both groups showed decreased α and β ERSPs in D trials compared to ND trials, suggesting attention shifting toward distractions (Fig. 3 B). Interestingly, only the ADHD group exhibited a decreased NOGO-D α ERSP. Because NOGO trials were used to study the response inhibition, the finding of decreased α ERSP in NOGO-D trials in the ADHD group reflects that response inhibition was affected by distractions only in children with ADHD, but not in healthy children or young adults [33]. This is further supported by the findings of between-group differences. We found that the presence of distractions additionally enhanced the between-group differences in NOGO α and γ power at AF3 (Fig. 3 C), which were absent in ND trials. It was reported that γ decreases were associated with the inhibition of competing neural networks [23]. Therefore, the higher γ ERSPs in NOGO-D trials in the ADHD group indicated insufficient inhibition in different neural networks for response inhibition and distraction suppression.

D. Classification on Distraction and ADHD

In addition to univariate statistic testing, we employed machine learning methods for multiple variate analysis. Regarding the impacts of distractions, we found that all types of EEG features, including ERPs, ERSP and their combination, provides useful information for the separation of trials with and without distractions, irrelevant to groups, with accuracy greater than 80%. This result verified that the distractions in this study were sufficient to alter the neuronal activities in children. Notably, the accuracy of separating trials with and without distractions in children was lower than in young adults [33]. This lower accuracy in children may be due to immature inhibition of distractions. Furthermore, the accuracy of separating ADHD data from normal children increased with the presence of features extracted from distraction trials when compared with the ND features. This reflects the fact that distractions enhanced the neuronal differences between ADHD and normal children.

VI. Conclusion

In this study, we used an intelligent VR system integrated with EEG and machine learning methods to help diagnose children with ADHD. We first examined the differences in ERP and ERSP with and without distractions and found that the presence of distractions leads to 1) decreased P300 peak in the ADHD group, 2) reduced α and β ERSPs, and 3) prolonged N2 and P3 latencies. Furthermore, the distractions additionally enhanced the between-group differences in NOGO α and γ ERSPs. By using machine learning methods, we validated that the presence of distractions can efficiently alter neuronal activities in children and improve detection of ADHD. The findings of neuronal correlates of distractions and neuronal abnormalities in ADHD children increases understanding of the underlying mechanism and can be used to design therapeutic strategies for attention-related diseases.

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