Temporal Alpha Dissimilarity of ADHD Brain Network in Comparison With CPT and CATA

Jo-Wei Lin, Zuo-Cian Fan, Shey-Cherng Tzou, Liang-Jen Wang, and Li-Wei Ko, *Member, IEEE*

***Abstract*— Attention deficit hyperactivity disorder (ADHD) is a chronic neurological and psychiatric disorder that affects children during their development. To find neural patterns for ADHD and provide subjective features as decision references to assist specialists and physicians. Many studies have been devoted to investigating the neural dynamics of the brain through resting-state or continuous performance tests (CPT) with EEG or functional magnetic resonance imaging (fMRI). The present study used coherence, which is one of the functional connectivity (FC) methods, to analyze the neural patterns of children and adolescents (8-16 years old) under CPT and continuous auditory test of attention (CATA) task. In the meantime, electroencephalography (EEG) oscillations were recorded by a wireless brain-computer interface (BCI). 72 children were enrolled, of which 53 participants were diagnosed with ADHD and 19 presented to be typical developing (TD). The experimental results exhibited a higher difference in alpha and theta bands between the TD group and the ADHD group. While the differences between the TD group and the ADHD group in all four frequency domains were greater than under CPT conditions. Statistically significant differences ($p<0.05$) were observed between the ADHD and TD groups in the alpha rhythm during the CATA task in the short-range of coherence. For the temporal lobe FC during the CATA task, the TD group exhibited statistically significantly FC ($p<0.05$) in the alpha rhythm compared to the ADHD group. These findings offering new possibilities for more techniques and diagnostic methods in finding more ADHD features. The differences in alpha and beta frequencies were more pronounced in the ADHD group during the CPT task compared to the CATA task. Additionally, the disparities in brain activity were more evident across delta, theta, alpha and beta frequency domains when the task given was a CATA as opposed to a CPT. The findings presented the underlying mechanisms of the FC differences between children and adolescents with ADHD. Moreover, these findings should extend to use machine learning approaches to assist the ADHD classification and diagnosis.**

***Index Terms*— Attention deficit hyperactivity disorder, electroencephalography, Conners continuous performance test 3, Conners CATA, wireless wearable brain–computer interface, functional connectivity.**

Manuscript received 3 August 2023; revised 10 December 2023 and 11 January 2024; accepted 20 January 2024. Date of publication 30 January 2024; date of current version 28 March 2024. This work was supported in part by the National Yang Ming Chiao Tung University (NYCU) and Kaohsiung Chang Gung Memorial Hospital Annual Research Cooperation under Project CORPG8L0081, Project CORPG8M0061, and Project CORPG8N0061; in part by the National Science and Technology Council (NSTC) under Grant 112-2321-B-A49-020; and in part by the Center for Intelligent Drug Systems and Smart Bio-devices (IDS^{2}B) and NYCU Digital Medicine and Smart Healthcare Research Center from the Featured Areas Research Center Program within the Framework of the Higher Education Sprout Project by the Ministry of Education (MOE) in Taiwan. *(Corresponding authors: Liang-Jen Wang; Li-Wei Ko.)*

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Chang Gung Medical Foundation Institutional Review Board under Application No. 202101562A3.

Jo-Wei Lin is with the International Ph.D. Program in Interdisciplinary Neuroscience, the Center for Intelligent Drug Systems and Smart Bio-Devices (IDS^{2}B), the Department of Biological Science and Technology, and the College of Biological Science and Technology, National Yang Ming Chiao Tung University, Hsinchu 300, Taiwan.

Zuo-Cian Fan is with the Center for Intelligent Drug Systems and Smart Bio-Devices (IDS^{2}B), the Department of Biological Science and Technology, and the College of Biological Science and Technology, National Yang Ming Chiao Tung University, Hsinchu 300, Taiwan.

Shey-Cherng Tzou is with the Center for Intelligent Drug Systems and Smart Bio-Devices (IDS^{2}B), the Department of Biological Science and Technology, the College of Biological Science and Technology, and the Institute of Molecular Medicine and Bioengineering, National Yang Ming Chiao Tung University, Hsinchu 300, Taiwan.

Liang-Jen Wang is with the Department of Child and Adolescent Psychiatry, Kaohsiung Chang Gung Memorial Hospital and Chang Gung University College of Medicine, Kaohsiung 83301, Taiwan (e-mail: anus78@cgmh.org.tw).

Li-Wei Ko is with the Center for Intelligent Drug Systems and Smart Bio-Devices (IDS2B), the Department of Electronics and Electrical Engineering, the Institute of Electrical and Control Engineering, and the Department of Biological Science and Technology, National Yang Ming Chiao Tung University, Hsinchu 300, Taiwan, and also with the Department of Biomedical Science and Environment Biology, Drug Development and Value Creation Research Center, Kaohsiung Medical University, Kaohsiung 807, Taiwan (e-mail: lwko@nycu.edu.tw).

Digital Object Identifier 10.1109/TNSRE.2024.3360137

I. Introduction

ATTENTION deficit hyperactivity disorder (ADHD) is a chronic neurological and psychiatric disorder that was reported to affect children during their development. The global prevalence of ADHD ranges from 2% to 7% [1]. Children with ADHD exhibit symptoms of hyperactivity, impulsivity, inattention and combinations of these types. The ADHD symptoms can persist in adulthood. To reduce the impact of ADHD on families and academic performances, early diagnosis and intervention are crucial for improving lives of children with ADHD [2]. Clinicians typically use diagnostic criteria from the Diagnostic and Statistical Manual of Psychiatric Disorders, 5th edition (DSM-V) and questionnaires such as the Disruptive Behaviour Disorder Rating Scale (DBDRS) or the Swanson, Nolan, and Pelham version IV (SNAP-IV) to determine whether a child has ADHD [3], [4]. The treatment of ADHD may include medication (e.g. Ritalin) or behavioral therapies, depending on the condition of each child with ADHD. Regarding the clinical assessment tools for ADHD, such as the Conners Continuous Performance Test 3rd edition (CPT 3 or CPT), the Conners Continuous Auditory Test of Attention (CATA), the Kiddie Continuous Performance Test (k-CPT) and the Integrated Visual and Auditory Continuous Performance Test (IVA-2), were used in clinical trials to provide additional information for clinicians assessing ADHD symptoms [5], [6], [7].

Electroencephalography (EEG) is a neuroscientific tool that uses electrodes placed on the scalp to measure electrical activity in the brain [8], [9]. EEG has several advantages: (1) availability, (2) real-time monitoring, (3) non-invasive and harmless, (4) efficient, and (5) inexpensive [10]. The functional connectivity (FC) analysis using resting-state EEG has been used to identify the characteristics and EEG indicators of ADHD [11]. Other studies have applied EEG to various cognitive tasks, such as the emotional face recognition task, and used classification algorithms to identify ADHD in children [12], [13], [14], [15], [16], [17], [18], [19], [20], [21]. resting-state EEG FC analysis has been reported as a neuromarker in adults with ADHD [22], [23]. G. Michelini et al. used resting-state EEG to measure information transmission efficiency associated with symptom intensity [24]. The neurofeedback (NF) treatment of children with ADHD has also been evaluated the connectivity of resting-state EEG [2]. S. Wang et al. and S. Coeli et al. used the coherence connectivity measure and graph analysis approach on EEG to explore the FC changes during CPT in a group of ADHD and typically developing (TD) children to study the changes and suggested that there were less efficient network integrations within children with ADHD [25], [26].

The FC analysis approaches regarding coherence, phase-locking value (PLV) and phase lab index (PLI), each represent methods for analyzing synchronization and connectivity in EEG or other neural signals. They have distinct advantages and are applicable in different contexts. Coherence is suitable for overall connectivity analysis in whole-brain networks, for it provides information about relative phase consistency at different frequencies. It is commonly used to describe coordinated oscillations between two signals in the frequency domain [62]. PLV offers a measure of phase synchronization between two signals, particularly accurate for describing instantaneous phase synchrony. PLV is sensitivity to phase synchrony of non-periodic or non-sinusoidal signals. It is Useful for studying transient phase synchrony, especially in event-related analyses [12]. PLI offers a measure of phase synchronization between two signals, particularly accurate for describing instantaneous phase synchrony. PLI is sensitivity to phase synchrony of non-periodic or non-sinusoidal signals. PLI is useful for studying transient phase synchrony, especially in event-related analysis [63]. Bearden et al. [27] in resting state EEG using the functional magnetic resonance imaging (fMRI) data of children with ADHD [28], [29], [30], and FC of default mode network (DMN) and dorsal attention network (DAN) in children with ADHD [31], another example was that [32] combined resting state functional magnetic resonance imaging (rsfMRI) and FC to study the default mode network (DMN). In [32], the event-related potential (ERP) was investigated from childhood to adulthood during cognitive tasks; in another paper, a deep learning model was applied to classify ADHD [24] by using a publicly available fMRI database of adolescents with ADHD. The study also used the FC approach to increase model accuracy. FC analysis has also been used to evaluate neurofeedback treatment in adolescents with ADHD [13]. Studies have investigated the FC of rsfMRI and individual severity of ADHD symptoms in adults [33]. Their results showed that a more severe form of hyperactivity was associated with higher FC in certain brain regions, including the left putamen, right caudate nucleus, right central operculum and a portion of the right postcentral gyrus, which is located within the auditory/sensorimotor network. Their findings broadened the understanding of the role of the striatum in the development of ADHD, particularly in relation to hyperactivity. The authors used resting-state fMRI neuroimaging in a deep learning (DL) algorithm to classify ADHD or healthy controls. They showed the importance of increasing model accuracy by applying FC [34]. Riaz et al. used rsfMRI and FC to investigate resting-state networks (RSNs) within the DMN and frontal control in children diagnosed with ADHD and found that FC increased in the right inferior frontal gyrus (IFG) and bilateral medial prefrontal cortex (mPFC) under the DMN [35]. In addition, studies have investigated changes in FC in ADHD patients with comorbid social phobia [36] and used rsfMRI to evaluate the effectiveness of neurofeedback treatment in adults with ADHD [37].

The EEG is gradually took into considerations of tools for studying the functioning of the nervous system. The aforementioned studies have focused on analyzing functional correlations with resting state or other cognitive tasks of fMRI neuroimaging technique from children, adolescence and adult with ADHD. However, there is still a need to further investigate the specific FC patterns and their relationships with ADHD symptoms using these techniques. The present study aims to contribute to the current understanding of ADHD by investigating FC patterns using EEG in children and adolescents with ADHD.

II. Related Works

Literatures on the application of EEG measures with CPT discussed an ADHD assessment protocol using brain activation measures (nir-HEG/Q-EEG) and executive measures (CPTs) [38]. Another explores the use of EEG-based long short-term memory (LSTM) networks to identify neurological state changes indicative of ADHD in children [39]; [40] examines the relationship between alpha oscillations, attention and inhibitory control in adult ADHD using EEG neurofeedback. [41] investigates between-group differences and associations with sluggish cognitive tempo symptoms in children with and without ADHD symptoms using EEG; [42] uses a multimodal fNIRS and EEG study to investigate executive dysfunction in medication-naïve children with ADHD. Reference [43] proposes an EEG-based decision support system for the diagnosis of adults with ADHD. Reference [44] presents a phase-space reconstruction of EEG signals for the classification of ADHD and control adults. Reference [45] conducts a systematic review on whether electroencephalography (EEG) can identify ADHD subtypes. References [9], [46], and [47] provides a systematic review and meta-analysis of the sustained effects of neurofeedback in ADHD. An example of using multiple method combinations of children with ADHD (<7 years old), such as: DBDRS, k-CPT and EEG [51], one of the combinations furnished the best probability scores, indicating that the assessment with EEG and behavioral data ought to bring attention to the clinical diagnosis. The analysis of CPT, CATA, and combination of CPT and CATA were compared. The results showed that the combination performed higher sensitivity, specificity and more values than using single test [52].

Regarding auditory tasks, [48] aimed to investigate the effects of mindfulness training on attention-related EEG measures in adolescents with ADHD, and the results showed that mindfulness training was associated with increased theta power and enhanced event-related potential amplitudes related to attention processes, suggesting that mindfulness may enhance attentional processes in adolescents with ADHD. However, the authors also highlighted some methodological considerations, such as the need for larger sample sizes and control groups to further support the findings.

To the best of our knowledge, most of the previous studies on ADHD have used fMRI neuroimaging to analyze the FCs in individuals of different ages. While some studies have used EEG measures to classify ADHD primarily in resting conditions with eyes closed or open, others have focused on applying EEG to CPT. However, to our knowledge, no studies have investigated FC using both EEG and CATA as measures. The study can contribute as follows:

1. The study used a combination of CPT, CATA and EEG to investigate FC in ADHD, which is a novel approach compared to previous studies that used resting-state EEG or fMRI data.
2. The paper demonstrated that the addition of CATA to the FC analysis can provide important insights into temporal lobe differences.
3. The study showed that short-range FC in the alpha band was statistically significant during CPT, which can be used as a reference for critical decision making in clinical settings.
4. The use of EEG as a measurement tool in combination with clinical assessment tools such as CPT and CATA was found to be fast, convenient and safe.

III. Materials and Analysis Procedure

The clinical assessment tools and recorded EEG oscillations were used to study the FCs of brain dynamic activities. The strength of using EEG during clinical assessment tests was that the participants were able to coordinate in the process of clinical diagnosis, and children, parents or guardians were more acceptable of the non-invasive EEG recording tools. To investigate the brain activity changes of FC with a non-invasive neuroimaging measurement, EEG during clinical assessment tools, we enrolled children and adolescents with ADHD and TD peers to perform CPT and CATA. During their task, their EEG oscillations would be recorded by a brain-computer interface (BCI) for the FC analysis in this study.

TABLE I
Demography of Participants

Characteristic	Study group			
	ADHD n=53		TD control n=19	
	Male	Female	Male	Female
Number	11	42	14	5
Age (Mean ±SD)	9.595±6.62	9.09±6.62	11.857±2.62	8.4±2.62

A. Experiment Procedure

In this study, children with ADHD were recruited as the experimental group and children with TD were recruited as the control group to investigate the difference in FC between the two groups. Recruited participants were instructed to sit at a desk and press the button when targets appeared. While the recruited participants performed the test, participants were put on a wireless wearable BCI, which included the EEG cap with sponge electrodes to receive and record the EEG signals, as shown in Fig. 1. The differences in FC between the control and experimental groups during different tasks were observed using Conners CPT 3 and Conners CATA.

Throughout the experimental procedure, shown in Fig. 2. The time spent in the procedure was modified according to the level of understanding of the participants, until the participants were able to recognize and follow the task instructions. The tasks given in the experiment were CPT 3 and CATA. The order effects could produce biases, where the presentation order of stimuli or tasks affects responses of participants. By reducing order effects, counterbalancing could minimize potential confounds associated with the sequence [53], [54]. In order to eschew the order effect due to the fixed order of the tasks and optimize the experimental procedure, the order of these two tasks was randomly counterbalanced. A one-minute rest period was added between tasks to allow participants to avoid overexerting themselves during the two fourteen-minute tasks. Participants were given one minute to rest after the second task of the experiment.

B. Participants

The experiment was conducted by enrolling school-aged, 8 to 16 years old, including boys and girls, participants with TD and ADHD. Diagnosis of ADHD was confirmed based on DSM-V criteria and questionnaires from parents and educators. The age range followed the age suggestions of CPT and CATA [5]. Table I presented a total of 72 children were enrolled in this study, 53 (42 boys, mean±SD age: 9.595±6.626, 11 girls, mean±SD age: 9.09±6.626) of whom were enrolled in the experimental group of school-aged participants with ADHD. The ADHD participants were taking Ritalin or participating in behavioral therapies.

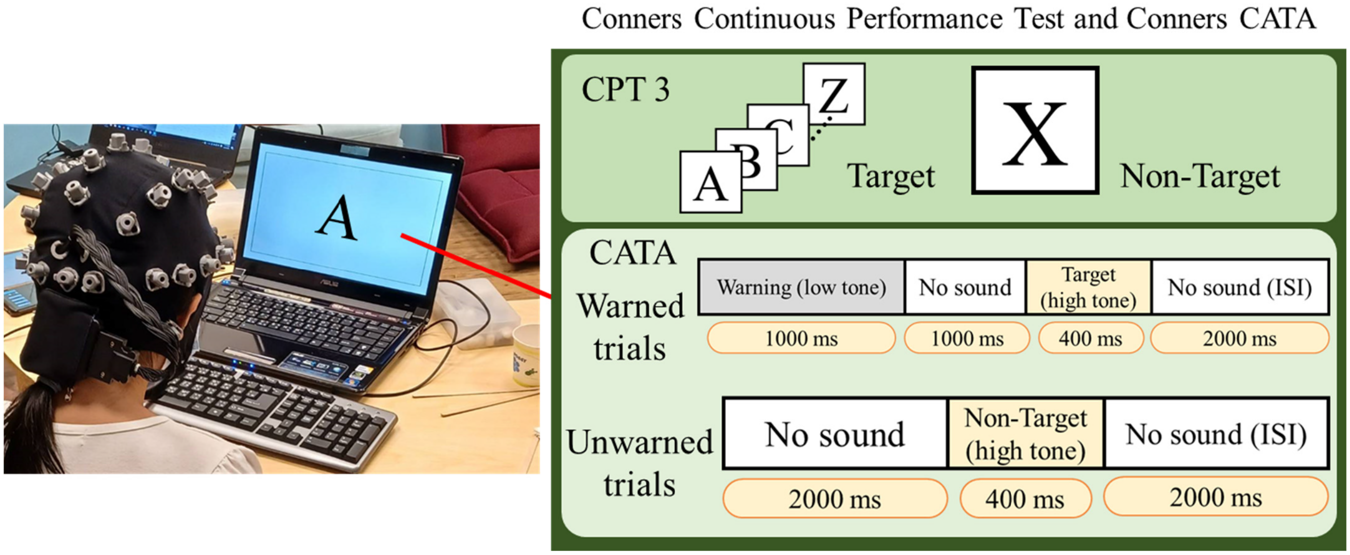

Fig. 1. Experimental setting in this study. The participants take Conners CPT 3 and CATA task, the procedure was recorded using the wireless wearable brain-computer interface (BCI) for the further analysis. While taking the CPT 3 task, participants were instructed to focus on the screen, and pressed the space button when the target showed. When the non-target shows, participant need to not press the space button. The CATA task would play a low tone or a high tone, participants were asked to press the button when hearing a low tone and a high tone.

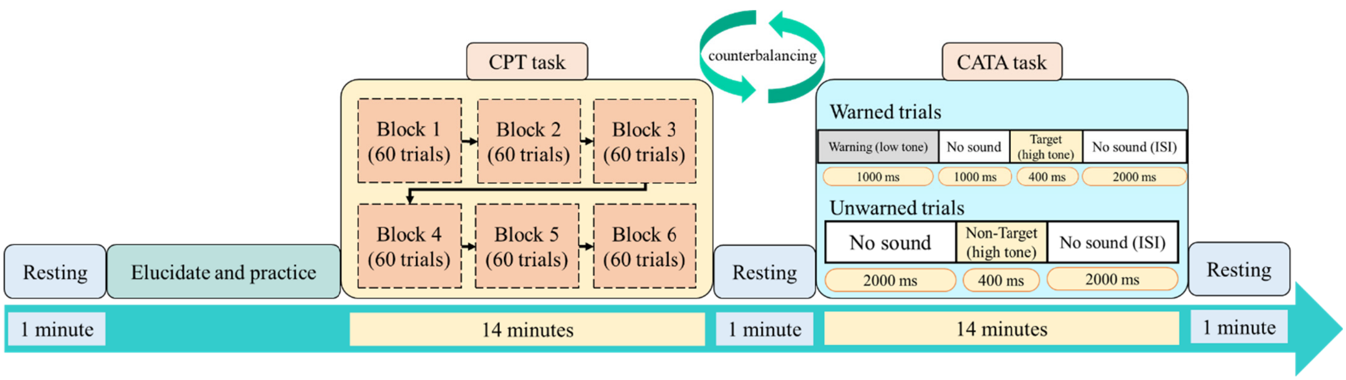

Fig. 2. The experiment procedure includes resting, CPT 3, and CATA task. The resting state took one minute, and both CPT 3 and CATA task takes fourteen minutes. The CPT and CATA task orders were randomly switched for counterbalancing. ADHD participants were diagnosed by the physicians based on DSM-V criteria. ADHD and TD participants would rest for one minute. Before performing the CPT and CATA task, physicians would elucidate the method of operating tasks. CPT 3: Conners Performance Task 3, CATA: Conners continuous auditory test of attention.

Additionally, 19 children with TD and no history of psychiatric disorders were enrolled in the control group (14 boys, mean±SD age: 11.857±2.626; 5 girls mean±SD age: 8.4±2.626). Physician from child psychiatry department confirmed all the clinical diagnosis according to the DSM-V criteria and SNAP-IV questionnaires in clinical setting. All parents or guardians consented participants to engage tests. Our participant enrollment was approved by the institutional review boards (IRB) of Kaohsiung Chang Gung Memorial Hospital and Chang Gung University College of Medicine.

C. Equipment

In this study, the EEG recordings of the participants were obtained using the BCI system (fig. 1 and fig. 3) during their CPT 3 and CATA tasks. Collaborated with the medical device developer: Artise Biomedical Co., Ltd. The BCI utilized in this study is a wearable wireless 32-channel EEG cap with semi-dry sponge electrodes for data collection. The BCI system conformed the international 10-20 system, the locations of the electrodes were distributed as follows: Fp1, Fp2, AF3, AF4, F7, F3, Fz, F4, F8, FT7, FC3, FCz, FC4, FT8, T7, C3, Cz, C4, T8, TP7, CP3, CPz, CP4, TP8, P7, P3, Pz, P4, P8, O1, Oz, O2. The reference electrode of 32-channel wireless EEG cap was located on the mastoid (A1 and A2) as reference for the remaining electrodes. Before started recording, the electrodes adjusted until the electoral impedances were below 100 kΩ. The sampling rate of the BCI is 1000 Hertz. The Bluetooth transmission device is placed on the neck area (fig. 1), and the collected EEG signals are transmitted to the BCI for data recording and the storage was completed via the Bluetooth module.

D. Continuous Performance Test 3

The Conners Continuous Performance Test 3 (CPT 3) is a task-oriented computerized assessment of attention-related problems in individuals aged 8 years and older [4], it is standardized and can be used in clinical setting. Participants need to respond (press space button) once the target shows on the

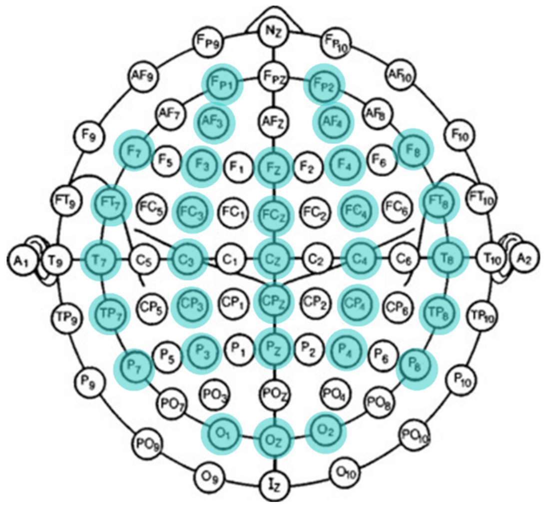

Fig. 3. The electrode distributions of the BCI. BCI: brain-computer interface.

screen, while they were asked to hold their impulse when the non-target appears. The CPT 3 task lasts for fourteen minutes. Participants would go through six blocks of target/non-target tasks, shown as Fig. 1 and 2. Three sub-blocks were in each main block. Each main block has one, two and four seconds of inter-stimulus intervals (ISIs) randomly assigned to the three sub-blocks, allowing the child to focus on the entire CPT 3 task completely and thoroughly. The CPT 3 task would measure scores: (1) Inattentiveness; (2) Impulsivity; (3) Sustained Attention, and (4) Vigilance.

E. Conners Continuous Auditory Test of Attention

The Conners Continuous Auditory Test of Attention (CATA) is a test for individuals aged from eight to sixteen or older ages. Enrolled participants were instructed to being heedful to a pair of a low tone and a high tone. CATA procedure demonstrated on the right side of Fig. 1 and Fig. 2. Upon hearing the pairs, participants taught to respond (press the space button) in less than no time. In Fig. 1 and 2, the warned trials and unwarned trials randomly appeared during the task. In the warned trials, the warning tone (low tone) would appear first for 1000 milliseconds, then the target tone (high tone) would appear after warning tone and 1000 milliseconds of pause (no sound), then the trial continued the inter-stimulus interval for 2000 milliseconds. Participants were instructed to respond and press the space button in the warned trials. In the unwarned trials, there was only a high tone, which is the non-target in CATA task. Participants need to pay attention whether there were low tone appears in trials during the CATA task.

F. Preprocessing

In order to mitigate the affecting factors resulting from environmental artifacts, eye movements, muscle movements, and other physiological artifacts during EEG signal recordings from the scalp of participants while performing tasks [46]. Removing these artifacts were essential preprocessing steps for further observing the EEG oscillations.

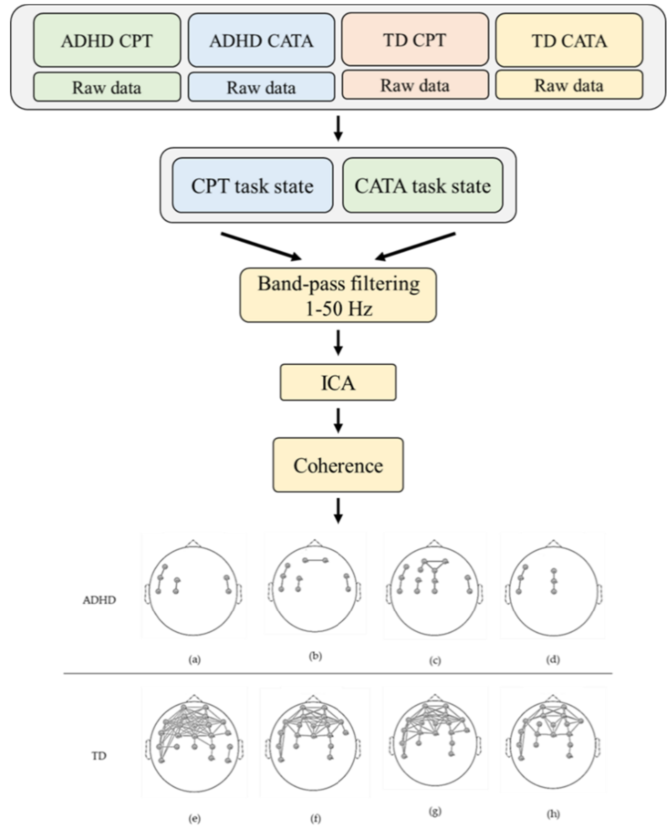

Fig. 4. The processing pipeline in this study involved several steps. First, the EEG data were divided into three states: resting state, CPT task state, and CATA task state. Next, the signal was filtered with a bandpass filter ranging from 1 to 50 Hz, and independent component analysis (ICA) was applied to remove artifacts. Finally, coherence analysis was conducted. CPT for continuous performance test, CATA for continuous auditory test of attention, and ICA for independent component analysis.

The EEG signal preprocessing pipeline displayed as Fig. 4. The preprocessing steps including band-pass filtering (range from 0 to 50 Hertz) for preliminary remove artifacts, and the independent component analysis (ICA), which is provided by the EEGLAB toolkit, to further eliminate these abovementioned artifacts and for facilitating further analysis of EEG oscillations.

G. Task Segments Extraction

To extract task segments from the original signals, event markers were initially placed at the beginning of tasks with the assistance of physicians. However, since the tasks used in this study did not have event markers to record specific times of stimuli or responses for investigating event-related potentials (ERPs) and extracting epochs [48], this study followed the pipeline presented in Fig. 4 to separate the task segments from the original signals.

H. Band-Pass Filtering and Frequency Band Separations

The band-pass filtering step involved applying a high-pass finite impulse response (FIR) filter with a cutoff frequency of 1 Hz to allow signals higher than 1 Hz to pass, followed by a low-pass FIR filter with a cutoff frequency of 50 Hz to

TABLE II
FC DIFFERENCES BETWEEN ADHD AND TD GROUPS DURING CPT AND CATA TASK CONDITIONS

		delta		theta		alpha		beta	
		CPT	CATA	CPT	CATA	CPT	CATA	CPT	CATA
Short range	ADHD	0.695	0.624	0.679	0.612	0.660	**0.590** *	0.659	0.602
	TD	0.648	0.701	0.633	0.691	0.622	**0.681**	0.630	0.691
Long range	ADHD	0.278	0.250	0.221	0.193	0.243	0.172	0.233	0.209
	TD	0.273	0.311	0.270	0.289	0.253	0.273	0.248	0.305
Frontal	ADHD	0.636	0.564	0.618	0.542	0.627	0.535	0.561	0.521
	TD	0.601	0.644	0.586	0.623	0.604	0.636	0.580	0.622
Temporal	ADHD	0.498	0.407	0.428	0.342	0.406	**0.313** *	0.433	0.352
	TD	0.532	0.576	0.467	0.520	0.464	**0.517**	0.490	0.526
Occipital	ADHD	0.627	0.558	0.592	0.532	0.570	0.518	0.573	0.546
	TD	0.536	0.504	0.564	0.507	0.584	0.507	0.577	0.526

allow signals lower than 50 Hz to pass. The signals primarily retained to the EEG oscillations the desired frequency range. After band-pass the signal of each participants, The EEG signals were extracted into delta rhythms (1-3 Hz), theta rhythms (4-7Hz), alpha rhythms (8-12Hz), and beta rhythms (13-30Hz). Subsequently, the extracted EEG signals were further divided into delta rhythms (1-3 Hz), theta rhythms (4-7 Hz), alpha rhythms (8-12 Hz), and beta rhythms (13-30 Hz). Delta rhythms are associated with deep sleep states and can be affected by artifacts such as muscle movements from the neck or jaw. Theta rhythms are generated during unconscious activities and deep meditation. Alpha rhythms are typically observed during resting or idling states and are associated with consciousness and moderate activity. Beta rhythms, on the other hand, are often found in frontal or central areas [49], [50] and are associated with spontaneous activity, such as problem-solving and attention [55].

I. Functional Connectivity During Task Conditions

FC is a methodology to investigate the cognitive functions and behavior emerge from brain network activations and interactions in human cortex [56]. In this study, FC approach was utilized to analyze alpha band oscillations in adolescents with ADHD during closed eyes resting condition [57] and more frequency bands. The calculated boundary for FC was set between 0 and 1, representing the cross-signal density and similarities in frequency domain.

$$coherence_{xy}(f) = \left| \frac{S_{xy}(f)}{\sqrt{S_{xx}(f)S_{yy}(f)}} \right|^2 \tag{1}$$

$S_{xx}(f)$ denotes the power density of x, $S_{yy}(f)$ is the power density of y, $S_{xy}(f)$ is the cross-spectral density between x and y. The $coherence_{xy}(f)$ boundary is between 0 and 1. This formula is to evaluate the linear relations of x and y in specific frequency band: delta, theta, alpha, beta frequency rhythm.

J. Statistical Analysis

The statistical analysis was performed using MATLAB R2020a (MathWorks, Natick, MA, USA). Demographic and EEG data were compared using independent t-tests between two independent conditions: CPT and CATA, for two groups (ADHD and TD). The t-test was used to evaluate whether the differences between the mean values of the two samples were caused by random variation or if there were statistically significant (p-value < 0.05). The effect size was calculated using Cohen's d.

For the analysis of the four regions (short-range, long-range, frontal, temporal, and occipital), separate t-tests were performed for each region between the two conditions (CPT and CATA) for both groups (ADHD and TD). The p-values were reported in Table II and the effect sizes were calculated using Cohen's d.

In summary, the statistical analysis included independent t-tests to compare demographic and EEG data between conditions and groups, and separate t-tests for each region between conditions and groups. All statistical tests were two-tailed, and the level of significance was set at $p < 0.05$.

IV. RESULT

In this study, the recorded EEG signals were segmented into CPT task segments and CATA task segments for both groups. Then applied band-pass filtering method, the ICA approach to remove artifacts, and the FC analysis for these task segments. The FC analysis was used to study region-of-interest (ROI) contrary to analyzing the entire brain area [58]. Specifically, short-range FC investigated the metabolic and time-cost, and prevail with FC strength. Compared to long-range FC, it investigated larger metabolic and time-cost [59]. The FC measures for EEG can utilized to explore associations in delta, theta, alpha and beta rhythms in this study. In Fig. 5 and 6, the coherences were illustrated as connectivity matrix, and the difference column was to show the differences between ADHD/TD groups under CPT/CATA task. In Fig. 5,

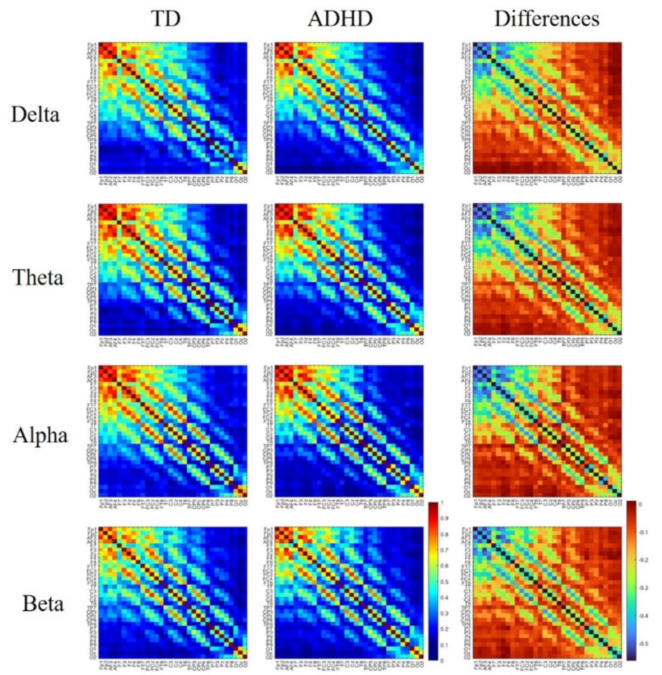

Fig. 5. The FC of TD and ADHD group under CPT task. There was a greater difference in alpha and theta frequencies between the TD group and the ADHD group. FC: functional connectivity; TD: typical development; ADHD: attention deficit hyperactivity disorder; CPT: continuous performance test.

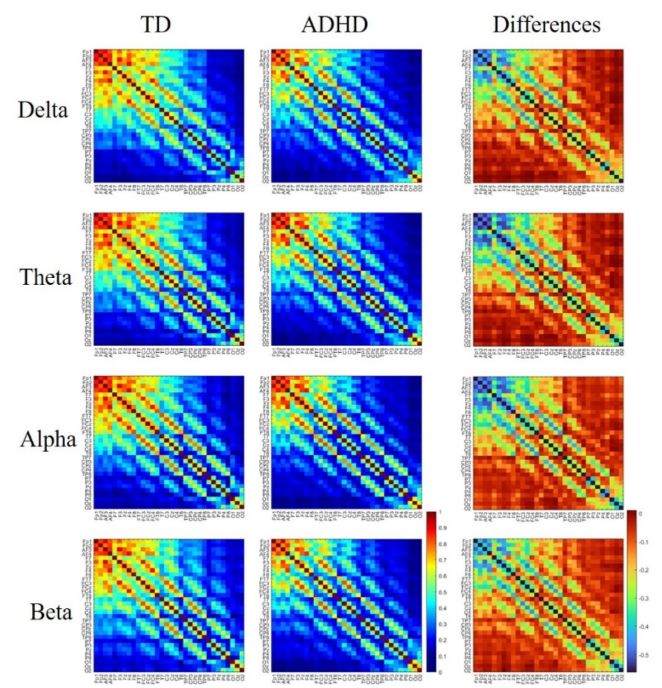

Fig. 6. The FC of TD and ADHD group under CATA task, the differences between the TD group and the ADHD group in all four frequency domains were greater than under CPT conditions. FC: functional connectivity; TD: typical development; ADHD: attention deficit hyperactivity disorder; CATA: continuous auditory test of attention.

coherence was applied to observe the FC of TD and ADHD group under CPT task condition. A greater difference was observed in alpha and theta frequencies between the TD group and the ADHD group. While the FC of TD and ADHD group under CATA task, there were greater disparities than CPT task observed in all four frequency domains between these two groups, shown in Fig. 6.

A. Frontal Lobe Functional Connectivity

The analysis of frontal lobe FC during the CPT task showed subtle differences in the four frequency bands, and the rhythm differences in FC during the CATA task were also indistinct. However, the TD group exhibited higher FC compared to the ADHD group during the CATA task, but not during the CPT task.

B. Temporal Lobe Functional Connectivity

The analysis of temporal lobe FCs, as presented in Table II, indicated higher disparities in FCs across all frequency bands between the two groups during the CATA condition. Furthermore, in addition to the temporal lobe FCs during the CATA task, the TD group exhibited statistically significantly higher FC ($p<0.05$) in the alpha rhythm compared to the ADHD group, which contrasts with the results of the CPT task.

C. Overall Functional Connectivity Presentations Between Two Groups

The FCs in the four frequency bands for the CPT task were higher in the TD group compared to the ADHD group, as displayed in Fig. 7. Fig. 7 and Fig. 8 the coherence range from 0.7 to 1 were illustrated as head diagrams. Fig. 7 (a) to (d) are the 4 frequency bands of the ADHD group. While Fig. 7 (e) to (h) are for the TD group. Fig. 8 illustrated in the same manner. Similarly, the CATA task showed more abundant FCs in the TD group compared to the other group. Using FCs is sufficient for distinguishing ADHD in both tasks. However, there were fewer FCs observed in the CPT task compared to the CATA task in both groups, displayed in Fig. 7 and 8. Table II showed that in the CPT condition, the alpha band of both groups in the short range had the most statistically significant FC, indicating that CPT could be used as a tool to differentiate between the two groups. The results also suggested that the temporal region could be considered as a potential neurological indicator for EEG analysis with CPT. In the CATA condition, statistically significant differences were observed in the alpha band of the temporal region between the two groups, which was effective in both CPT and CATA tasks. The above findings indicate that both CPT and CATA tasks can distinguish between the two groups using FC analysis. Notably, the alpha rhythm of short-range FC during the CPT task and the alpha frequency band during the CATA task exhibited noteworthy differences between the ADHD and TD groups, as shown in table II.

D. The FC of TD and ADHD Group Between CPT and CATA Task Condition

As illustrated in Fig. 5, our analysis revealed notable differences between the two groups in delta, theta, alpha, and beta frequencies during the CPT task. In the "difference" column on the right side, it was observed that the differences

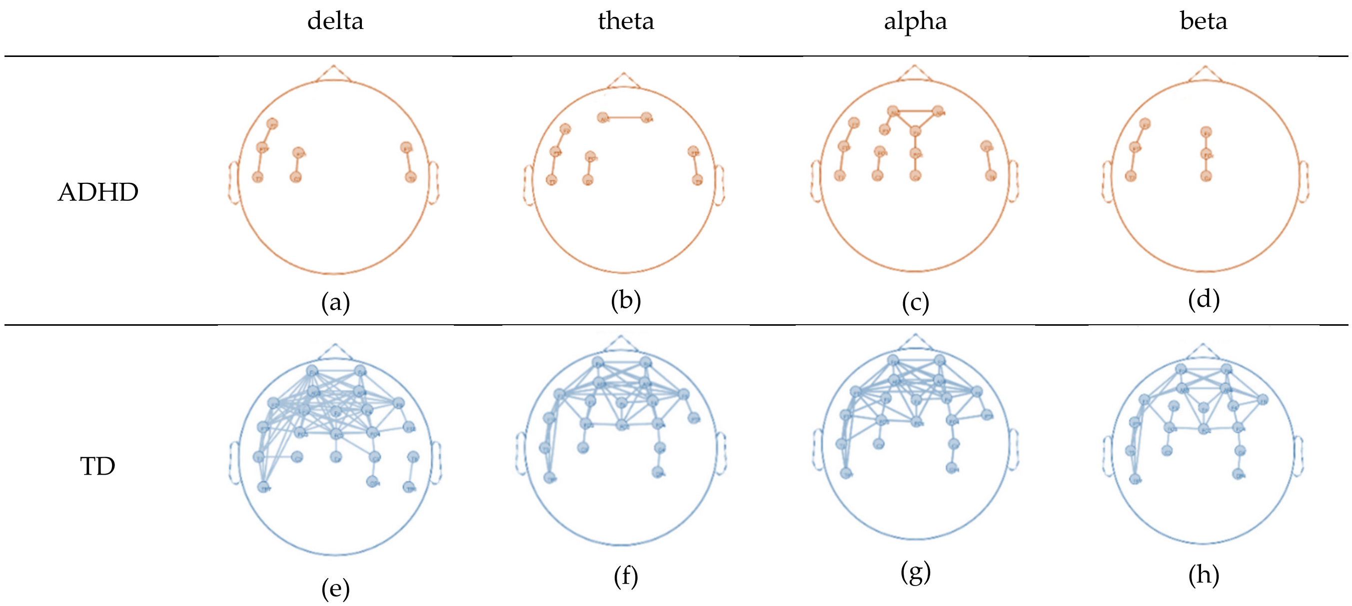

Fig. 7. FC in four frequency band for ADHD and TD during CPT task. FC: functional connectivity. ADHD: attention deficit hyperactivity disorder. TD: typical development. CPT: Conners continuous performance test.

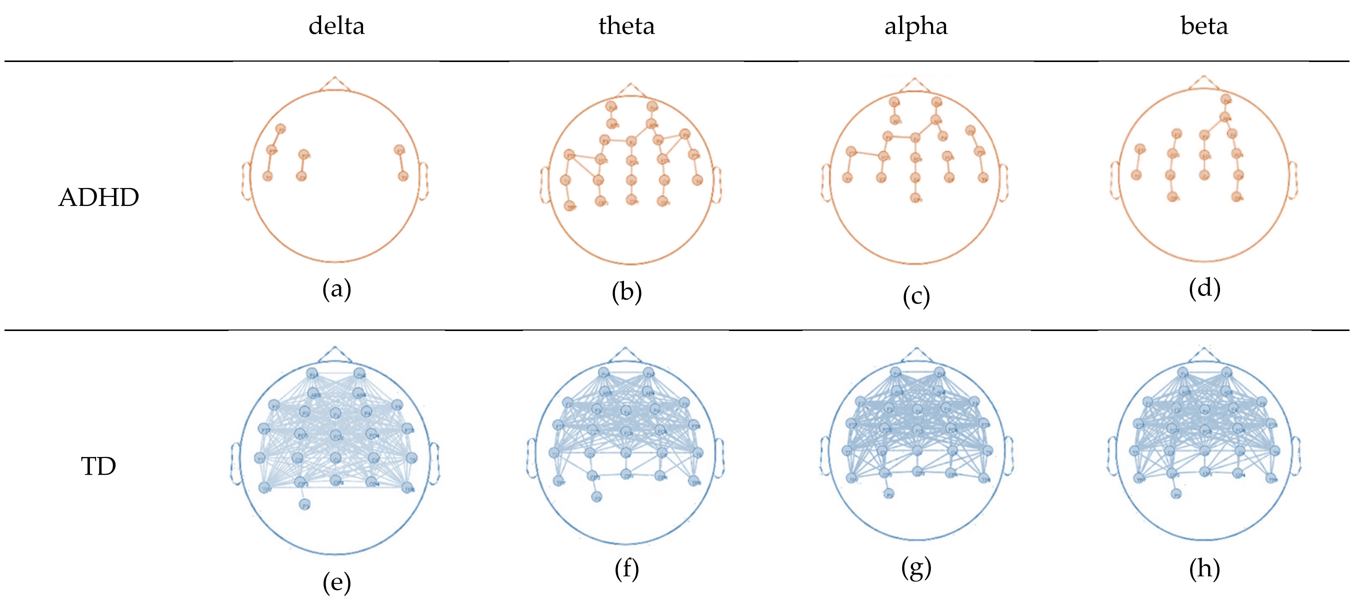

Fig. 8. FC in four frequency band for ADHD and TD during CATA task. FC: functional connectivity. ADHD: attention deficit hyperactivity disorder. TD: typical development. CATA: Conners continuous auditory test of attention.

between the two groups were more prominent in alpha and theta frequencies compared to delta and beta frequencies. Furthermore, in Fig. 6, the disparities in brain activity between the two groups were more evident across all four frequency domains when the task given was a CATA, as opposed to a CPT.

In simpler terms, when comparing the brain activity of individuals with ADHD to TD, we found that the differences in alpha and beta frequencies were more pronounced in the ADHD group during the CPT task compared to the CATA task. Additionally, the disparities in brain activity were more evident across delta, theta, alpha and beta frequency domains when the task given was a CATA as opposed to a CPT.

V. Discussion

According to our best knowledge, this is the first study to observe the FC dynamics and differences between ADHD and TD children and adolescents during the CPT and CATA tasks. To ensure reliable results, we applied rigorous preprocessing techniques, including band-pass filtering from 1 to 50 Hertz and ICA to remove artifacts such as eye movements, muscle motions, and physiological artifacts from the EEG signals acquired during the tasks. The primary signals were filtered within reached to the EEG oscillations. In this study, we used the FC to investigate the cognitive functions and behavior emerge from brain network interactions during tasks. FC analysis was used to investigate the cognitive functions and behavioral outcomes arising from brain network interactions during the tasks, specifically focusing on delta, theta, alpha, and beta band rhythms in adolescents with ADHD. Our results showed the statistically significant differences between the two groups in the temporal lobe and short-range during the CATA task. By analyzing the differences in various frequency bands between the two groups in the FC matrix during different tasks, we found that during the CPT task, the TD group showed statistically greater differences in the alpha and theta bands compared to the ADHD group. Alpha and theta changes have applied to the alpha/theta ratio (ATR) as an evaluation index for neurofeedback [60], [61]. During the CATA task, the FC of the TD group was statistically greater than the ADHD group in all frequency bands, Debnath et al. [58] indicates that the interindividual differences of ADHD in the predominant frequency of alpha-band oscillations. The beta rhythm is associated with thinking, attention and problem-solving [17]. Smit et al. found that the theta oscillations can be considered as the neural "working language". They observed that the groups differ in dynamical theta power during conflict monitoring. The theta power in conflict monitoring relates to behavior and complaints in daily life [64]. A. Bestmann et al. investigated the sigma (link to cognitive abilities) relationship of children with ADHD during their sleep [65]. K. Machida et al. found that the sigma were not able to classify participants. In selecting the frequency bands for our study, we drew upon existing research findings that demonstrated the relevance of specific frequency bands to cognitive functions and ADHD. The study by Bestmann et al. [66] provided insights into the associations between cognitive performance and sigma power during sleep in children with ADHD. These results indicate that the differences between the two groups can be more clearly observed during the CATA task. Given the clinical use of CPT and CATA as assessment tools, our study, using EEG data acquired through the convenience and non-invasive approach, combined with FC evaluation through CPT and CATA, provides valuable information on the differences between the two groups during these tasks compared to most studies that use resting fMRI evaluation.

Results demonstrated that the short-range and temporal lobe FC throughout the CATA task presented statistically significant differences ($p<0.05$) between ADHD and TD groups in alpha rhythm. There were no statistically significant differences within the short-range FC during CPT condition delta, beta, alpha and beta bands between two groups. Four bands of long-range for TD group performed more connectivities than ADHD group in CATA condition. During CPT task, no statistically significant long-range FC dissimilarities between ADHD and TD groups. Though both tasks showed no statistically significant dissimilarities among all frequency bands, the dissimilarities between two groups in CATA still performed higher than the CPT task. The frontal lobe FC in CPT task presented that the dissimilarities of four bands were tenuous, and the FC differences throughout the CATA task were also indistinct. TD group presented more FC than the ADHD group in CATA task, other than in CPT task. The temporal lobe FCs showed that there were more CATA FCs disparities in all frequency bands between two groups during CATA condition. Additionally, the TD group performed statistically significantly more FC ($p<0.05$) in the alpha rhythm to the ADHD group within the temporal lobe FC through CATA condition, opposite to the CPT task. Previous research has shown that there were distinct variations in alpha and beta frequency between the TD group and the ADHD group when observed through EEG under CPT conditions. However, when the same groups were studied through EEG under CATA conditions, it was found that the differences between the two groups were even more pronounced across all four frequency domains. This suggests that the CATA conditions may have a greater impact on the EEG of individuals with ADHD, and that this difference is even more statistically significant than under CPT conditions. The results suggest that CATA combined with CPT can be used as an auxiliary feature for the evaluation of ADHD. The findings of this study could serve as a valuable auxiliary diagnostic reference in clinical settings for ADHD. Additionally, it provides a foundation for future research to investigate the underlying mechanisms of FC differences between participants with ADHD and TD participants. This study recommend using the CATA, which is mainly based on auditory stimuli, as a reference in addition to the more commonly used CPT visual test, to help detect ADHD in more children at an early stage and take actions.

VI. Conclusion

This study focused on investigating the FC of EEG during the combination of Conners CPT and Conners CATA task in ADHD and TD group. Most of the literature on ADHD utilized resting-state EEG or fMRI data for analysis and research, there are limited studies that use a combination of CPT, CATA and EEG to investigate the advantages of adding CATA with FC. The results showed that the alpha band of short-range FC was most statistically significant in CPT, while CATA had statistically significant difference ($p<0.05$) in the temporal lobe. Therefore, the combination of CPT and CATA can be used as a reference for critical decision making and can be used for multi-measure evaluation with the clinical process. This paper (1) applied a fast and convenient measurement instrument and method: EEG of FC with CPT and CATA, (2) compared to previous studies that mostly used resting-state as the basis for FC analysis, this study uses recording and analysis while the participants participated in clinical assessment tools: CPT and CATA, which was a measurement that physicians adapted into the clinical assessment process, and (3) the study also identified CATA testing as a potential neuromarker for ADHD, providing new research directions and reference for diagnosis and auxiliary diagnosis of ADHD, and contributing to a deeper understanding of the neurobiological mechanisms of ADHD. Therefore, this study offering new possibilities for techniques and diagnostic methods in finding more ADHD features. Future research should also be conducted to replicate these findings and investigate the underlying mechanisms of the FC differences between participants with ADHD and TD participants. Moreover, machine learning methods, deep learning methods or other artificial intelligence approaches should extend to assist the ADHD classification, heterogeneity types detection, prediction and diagnosis.

References

[1] K. Sayal, V. Prasad, D. Daley, T. Ford, and D. Coghill, “ADHD in children and young people: Prevalence, care pathways, and service provision,” *Lancet Psychiatry*, vol. 5, no. 2, pp. 175–186, Feb. 2018, doi: 10.1016/s2215-0366(17)30167-0.

[2] S. Furlong, J. R. Cohen, J. Hopfinger, J. Snyder, M. M. Robertson, and M. A. Sheridan, “Resting-state EEG connectivity in young children with ADHD,” *J. Clin. Child Adolescent Psychol.*, vol. 50, no. 6, pp. 746–762, Nov. 2021.

[3] *Diagnostic and Statistical Manual of Mental Disorders*, APA, Washington, DC, USA, The American Psychiatric Association, 2013.

[4] D. S. Costa, J. J. de Paula, L. F. Malloy-Diniz, M. A. Romano-Silva, and D. M. Miranda, “Parent SNAP-IV rating of attention-deficit/hyperactivity disorder: Accuracy in a clinical sample of ADHD, validity, and reliability in a Brazilian sample,” *J. de Pediatria*, vol. 95, no. 6, pp. 736–743, Nov. 2019, doi: 10.1016/j.jped.2018.06.014.

[5] C. K. Conners, “Conners’ continuous performance test,” Multi-Health Syst., North Tonawanda, NY, USA, 2000.

[6] I.-C. Chen, C.-H. Chang, Y. Chang, D.-S. Lin, C.-H. Lin, and L.-W. Ko, “Neural dynamics for facilitating ADHD diagnosis in preschoolers: Central and parietal delta synchronization in the kiddie continuous performance test,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 29, pp. 1524–1533, 2021.

[7] T. S. Bearden, J. E. Cassisi, and J. N. White, “Electrophysiological correlates of vigilance during a continuous performance test in healthy adults,” *Appl. Psychophysiol. Biofeedback*, vol. 29, no. 3, pp. 175–188, Sep. 2004.

[8] J. Van Doren, M. Arns, H. Heinrich, M. A. Vollebregt, U. Strehl, and S. K. Loo, “Sustained effects of neurofeedback in ADHD: A systematic review and meta-analysis,” *Eur. Child Adolescent Psychiatry*, vol. 28, no. 3, pp. 293–305, Mar. 2019.

[9] A. Craik, Y. He, and J. L. Contreras-Vidal, “Deep learning for electroencephalogram (EEG) classification tasks: A review,” *J. Neural Eng.*, vol. 16, no. 3, Jun. 2019, Art. no. 031001.

[10] M. Soufineyestani, D. Dowling, and A. Khan, “Electroencephalography (EEG) technology applications and available devices,” *Appl. Sci.*, vol. 10, no. 21, p. 7453, Oct. 2020.

[11] M. A. Bell and K. Cuevas, “Using EEG to study cognitive development: Issues and practices,” *J. Cognition Develop.*, vol. 13, no. 3, pp. 281–294, Jul. 2012.

[12] A. M. Bastos and J.-M. Schoffelen, “A tutorial review of functional connectivity analysis methods and their interpretational pitfalls,” *Frontiers Syst. Neurosci.*, vol. 9, p. 175, Jan. 2016.

[13] M.-L. Tsai, C.-C. Wang, F.-C. Lee, S.-J. Peng, H. Chang, and S.-H. Tseng, “Resting-state EEG functional connectivity in children with rolandic spikes with or without clinical seizures,” *Biomedicines*, vol. 10, no. 7, p. 1553, Jun. 2022.

[14] K. Rubia et al., “Functional connectivity changes associated with fMRI neurofeedback of right inferior frontal cortex in adolescents with ADHD,” *NeuroImage*, vol. 188, pp. 43–58, Mar. 2019, doi: 10.1016/j.neuroimage.2018.11.055.

[15] H. Chen, Y. Song, and X. Li, “A deep learning framework for identifying children with ADHD using an EEG-based brain network,” *Neurocomputing*, vol. 356, pp. 83–96, Sep. 2019.

[16] Y. Chen, Y. Tang, C. Wang, X. Liu, L. Zhao, and Z. Wang, “ADHD classification by dual subspace learning using resting-state functional connectivity,” *Artif. Intell. Med.*, vol. 103, Mar. 2020, Art. no. 101786, doi: 10.1016/j.artmed.2019.101786.

[17] M. Moghaddari, M. Z. Lighvan, and S. Danishvar, “Diagnose ADHD disorder in children using convolutional neural network based on continuous mental task EEG,” *Comput. Methods Programs Biomed.*, vol. 197, Dec. 2020, Art. no. 105738, doi: 10.1016/j.cmpb.2020.105738.

[18] M. Mafi and S. Radfar, “High dimensional convolutional neural network for EEG connectivity-based diagnosis of ADHD,” *J. Biomed. Phys. Eng.*, vol. 12, no. 6, p. 645, 2022.

[19] R. Moqadam, N. Loghmani, A. K. Moghaddam, and A. Allahverdy, “Differentiating brain connectivity networks in ADHD and normal children using EEG,” in *Proc. 30th Int. Conf. Electr. Eng. (ICEE)*, May 2022, pp. 231–235.

[20] M. Shen, P. Wen, B. Song, and Y. Li, “ADHD children identification based on EEG using effective connectivity techniques,” in *Proc. Int. Conf. Health Inf. Sci.* Cham, Switzerland: Springer, 2021, pp. 71–81.

[21] M. Bakhtyari and S. Mirzaei, “ADHD detection using dynamic connectivity patterns of EEG data and ConvLSTM with attention framework,” *Biomed. Signal Process. Control*, vol. 76, Jul. 2022, Art. no. 103708.

[22] H. Dini, F. Ghassemi, and M. S. E. Sendi, “Investigation of brain functional networks in children suffering from attention deficit hyperactivity disorder,” *Brain Topography*, vol. 33, no. 6, pp. 733–750, Nov. 2020.

[23] H. Kiiski et al., “Functional EEG connectivity is a neuromarker for adult attention deficit hyperactivity disorder symptoms,” *Clin. Neurophysiol.*, vol. 131, no. 1, pp. 330–342, Jan. 2020.

[24] G. Michelini et al., “Atypical functional connectivity in adolescents and adults with persistent and remitted ADHD during a cognitive control task,” *Translational Psychiatry*, vol. 9, no. 1, p. 137, Apr. 2019.

[25] S. Wang et al., “A study on resting EEG effective connectivity difference before and after neurofeedback for children with ADHD,” *Neuroscience*, vol. 457, pp. 103–113, Mar. 2021.

[26] S. Coelli, A. Calcagno, E. Iascone, L. Gaspari, M. P. Canevini, and A. M. Bianchi, “Sustained attention task-related changes of functional connectivity in children with ADHD,” in *Proc. IEEE 21st Medit. Electrotechnical Conf. (MELECON)*, Jun. 2022, pp. 585–589.

[27] A. Ekhlasi, A. M. Nasrabadi, and M. Mohammadi, “Analysis of EEG brain connectivity of children with ADHD using graph theory and directional information transfer,” *Biomed. Eng./Biomedizinische Technik*, vol. 68, no. 2, pp. 133–146, Apr. 2023.

[28] G. Fraga González et al., “EEG resting state functional connectivity in adult dyslexics using phase lag index and graph analysis,” *Frontiers Hum. Neurosci.*, vol. 12, p. 341, Aug. 2018.

[29] B. Sutcubasi, B. Metin, M. K. Kurban, Z. E. Metin, B. Beser, and E. Sonuga-Barke, “Resting-state network dysconnectivity in ADHD: A system-neuroscience-based meta-analysis,” *World J. Biol. Psychiatry*, vol. 21, no. 9, pp. 662–672, Oct. 2020, doi: 10.1080/15622975.2020.1775889.

[30] U. Kumar, A. Arya, and V. Agarwal, “Neural network connectivity in ADHD children: An independent component and functional connectivity analysis of resting state fMRI data,” *Brain Imag. Behav.*, vol. 15, no. 1, pp. 157–165, Feb. 2021, doi: 10.1007/s11682-019-00242-0.

[31] M. Nentwich et al., “Functional connectivity of EEG is subject-specific, associated with phenotype, and different from fMRI,” *NeuroImage*, vol. 218, Sep. 2020, Art. no. 117001.

[32] H. Lin et al., “Functional connectivity of attention-related networks in drug-naive children with ADHD,” *J. Attention Disorders*, vol. 25, no. 3, pp. 377–388, Sep. 2018, doi: 10.1177/1087054718802017.

[33] H. Ke, F. Wang, H. Ma, and Z. He, “ADHD identification and its interpretation of functional connectivity using deep self-attention factorization,” *Knowl.-Based Syst.*, vol. 250, Aug. 2022, Art. no. 109082.

[34] P. Sörös et al., “Hyperactivity/restlessness is associated with increased functional connectivity in adults with ADHD: A dimensional analysis of resting state fMRI,” *BMC Psychiatry*, vol. 19, no. 1, pp. 1–11, Dec. 2019.

[35] A. Riaz, M. Asad, E. Alonso, and G. Slabaugh, “DeepFMRI: End-to-end deep learning for functional connectivity and classification of ADHD using fMRI,” *J. Neurosci. Methods*, vol. 335, Apr. 2020, Art. no. 108506, doi: 10.1016/j.jneumeth.2019.108506.

[36] Y. Gao et al., “Impairments of large-scale functional networks in attention-deficit/hyperactivity disorder: A meta-analysis of resting-state functional connectivity,” *Psychol. Med.*, vol. 49, no. 15, pp. 2475–2485, Nov. 2019.

[37] B. Kim, X. Niu, and F. Zhang, “Functional connectivity strength and topology differences in social phobia adolescents with and without ADHD comorbidity,” *Neuropsychologia*, vol. 178, Jan. 2023, Art. no. 108418.

[38] D. Areces, M. Cueli, T. García, P. González-Castro, and C. Rodríguez, “Using brain activation (nir-HEG/Q-EEG) and execution measures (CPTs) in a ADHD assessment protocol,” *J. Visualized Exp.*, no. 134, Apr. 2018, Art. no. e56796.

[39] Y. Chang, C. Stevenson, I.-C. Chen, D.-S. Lin, and L.-W. Ko, “Neurological state changes indicative of ADHD in children learned via EEG-based LSTM networks,” *J. Neural Eng.*, vol. 19, no. 1, Feb. 2022, Art. no. 016021.

[40] M.-P. Deiber et al., “Linking alpha oscillations, attention and inhibitory control in adult ADHD with EEG neurofeedback,” *NeuroImage, Clin.*, vol. 25, 2020, Art. no. 102145.

[41] M. A. Jarrett, P. A. Gable, A. T. Rondon, L. B. Neal, H. F. Price, and D. C. Hilton, “An EEG study of children with and without ADHD symptoms: Between-group differences and associations with sluggish cognitive tempo symptoms,” *J. Attention Disorders*, vol. 24, no. 7, pp. 1002–1010, May 2020.

[42] Y. Kaga et al., “Executive dysfunction in medication-naïve children with ADHD: A multi-modal fNIRS and EEG study,” *Brain Develop.*, vol. 42, no. 8, pp. 555–563, Sep. 2020.

[43] S. Kaur, P. Arun, S. Singh, and D. Kaur, "EEG based decision support system to diagnose adults with ADHD," in *Proc. IEEE Appl. Signal Process. Conf. (ASPCON)*, Dec. 2018, pp. 87–91.

[44] S. Kaur, S. Singh, P. Arun, D. Kaur, and M. Bajaj, "Phase space reconstruction of EEG signals for classification of ADHD and control adults," *Clin. EEG Neurosci.*, vol. 51, no. 2, pp. 102–113, Mar. 2020.

[45] J. Slater, R. Joober, B. L. Koborsy, S. Mitchell, E. Sahlas, and C. Palmer, "Can electroencephalography (EEG) identify ADHD subtypes? A systematic review," *Neurosci. Biobehavioral Rev.*, vol. 139, Aug. 2022, Art. no. 104752.

[46] A. Sibalis, K. Milligan, C. Pun, T. McKeough, L. A. Schmidt, and S. J. Segalowitz, "An EEG investigation of the attention-related impact of mindfulness training in youth with ADHD: Outcomes and methodological considerations," *J. Attention Disorders*, vol. 23, no. 7, pp. 733–743, May 2019.

[47] M. Esmaeilzadeh, H. Soltanian-Zadeh, and Y. M. Tabrizi, "Effect of neurofeedback on brain functional connectivity in adult ADHD patients: A resting-state fMRI study," in *Proc. 28th Nat. 6th Int. Iranian Conf. Biomed. Eng. (ICBME)*, Nov. 2021, pp. 260–264.

[48] R. Debnath, G. A. Buzzell, S. Morales, M. E. Bowers, S. C. Leach, and N. A. Fox, "The Maryland analysis of developmental EEG (MADE) pipeline," *Psychophysiology*, vol. 57, no. 6, Apr. 2020, Art. no. e13580, doi: 10.1111/psyp.13580.

[49] C. Chen et al., "Altered functional connectivity in children with ADHD revealed by scalp EEG: An ERP study," *Neural Plasticity*, vol. 2021, pp. 1–9, May 2021.

[50] J. D. Kropotov, *Quantitative EEG, Event-Related Potentials and Neurotherapy*. Cambridge, MA, USA: Academic Press, 2010.

[51] I.-C. Chen, P.-W. Lee, L.-J. Wang, C.-H. Chang, C.-H. Lin, and L.-W. Ko, "Incremental validity of multi-method and multi-informant evaluations in the clinical diagnosis of preschool ADHD," *J. Attention Disorders*, vol. 26, no. 10, pp. 1293–1303, Aug. 2022.

[52] L.-J. Wang et al., "Validity of visual and auditory attention tests for detecting ADHD," *J. Attention Disorders*, vol. 25, no. 8, pp. 1160–1169, Jun. 2021.

[53] J. K. Marsh and W.-K. Ahn, "Order effects in contingency learning: The role of task complexity," *Memory Cognition*, vol. 34, no. 3, pp. 568–576, Apr. 2006.

[54] F. J. López, D. R. Shanks, J. Almaraz, and P. Fernández, "Effects of trial order on contingency judgments: A comparison of associative and probabilistic contrast accounts," *J. Experim. Psychol., Learn., Memory, Cognition*, vol. 24, no. 3, pp. 672–694, 1998.

[55] A. Delorme and S. Makeig, "EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis," *J. Neurosci. Methods*, vol. 134, no. 1, pp. 9–21, Mar. 2004, doi: 10.1016/j.jneumeth.2003.10.009.

[56] A. K. Maddirala and R. A. Shaik, "Separation of sources from single-channel EEG signals using independent component analysis," *IEEE Trans. Instrum. Meas.*, vol. 67, no. 2, pp. 382–393, Feb. 2018.

[57] A. T. Reid et al., "Advancing functional connectivity research from association to causation," *Nature Neurosci.*, vol. 22, no. 11, pp. 1751–1760, Oct. 2019, doi: 10.1038/s41593-019-0510-4.

[58] R. Debnath, N. V. Miller, S. Morales, K. R. Seddio, and N. A. Fox, "Investigating brain electrical activity and functional connectivity in adolescents with clinically elevated levels of ADHD symptoms in alpha frequency band," *Brain Res.*, vol. 1750, Jan. 2021, Art. no. 147142.

[59] N. Liu et al., "Different functional alteration in attention-deficit/hyperactivity disorder across developmental age groups: A meta-analysis and an independent validation of resting-state functional connectivity studies," *CNS Neurosci. Therapeutics*, vol. 29, no. 1, pp. 60–69, Jan. 2023.

[60] R. Salvador, J. Suckling, M. R. Coleman, J. D. Pickard, D. Menon, and E. Bullmore, "Neurophysiological architecture of functional magnetic resonance images of human brain," *Cerebral Cortex*, vol. 15, no. 9, pp. 1332–1342, Sep. 2005, doi: 10.1093/cercor/bhi016.

[61] W. Nan, M. Wan, Y. Jiang, X. Shi, F. Wan, and D. Cai, "Alpha/theta ratio neurofeedback training for attention enhancement in normal developing children: A brief report," *Appl. Psychophysiol. Biofeedback*, vol. 47, no. 3, pp. 223–229, Sep. 2022.

[62] S. Çağdaş, "A comparative analysis of coherence measures for electroencephalography," İzmir Inst. Technol., Turkey, 2018.

[63] Y. Yan et al., "Functional connectivity alterations based on the weighted phase lag index: An exploratory electroencephalography study on Alzheimer's disease," *Current Alzheimer Res.*, vol. 18, no. 6, pp. 513–522, May 2021.

[64] D. Smit, L. Trevino, S. M. H. Mohamed, and S. Enriquez-Geppert, "Theta power and functional connectivity as neurophysiological markers of executive functions in individuals with cognitive complaints in daily life," *Biol. Psychol.*, vol. 178, Mar. 2023, Art. no. 108503.

[65] A. Bestmann, A. Conzelmann, L. Baving, and A. Prehn-Kristensen, "Associations between cognitive performance and sigma power during sleep in children with attention-deficit/hyperactivity disorder, healthy children, and healthy adults," *PLoS ONE*, vol. 14, no. 10, Oct. 2019, Art. no. e0224166.

[66] K. Machida et al., "Which measures from a sustained attention task best predict ADHD group membership?" *J. Attention Disorders*, vol. 26, no. 11, pp. 1471–1482, Sep. 2022.