DISSERTATION

THE RELATIONSHIP BETWEEN COGNITIVE FUNCTIONS AND OCCUPATIONAL PERFORMANCE IN CHILDREN, ADULTS, AND ADULTS WITH ATTENTION DEFICIT HYPERACTIVITY DISORDERS (ADHD)

Submitted by

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ABSTRACT

THE RELATIONSHIP BETWEEN COGNITIVE FUNCTIONS AND OCCUPATIONAL PERFORMANCE IN CHILDREN, ADULTS, AND ADULTS WITH ATTENTION DEFICIT HYPERACTIVITY DISORDERS (ADHD)

The overarching goal of this dissertation is to explore the relationship between cognitive functions and occupational performance in neurotypical children, neurotypical adults, and adults with attention-deficit/hyperactivity disorder (ADHD). Electroencephalography (EEG)/event-related potential (ERP) techniques were used to measure the neural processes while participants performed a speeded computer-based task for the three studies conducted in this dissertation.

The first study examined the test-retest reliability on the amplitudes of two ERP components associated with performance monitoring, the error-related negativity (ERN) and error-positivity (Pe), in 53 neurotypical adults and 118 neurotypical children aged 8-12-year-old. The findings indicated that the test-retest reliability of these measures was moderate for children (r_{ERN} = 0.55, r_{Pe} = 0.62), and was moderate to strong for adults (r_{ERN} = 0.69, r_{Pe} = 0.75). Moreover, the adaptive Woody filter was implemented to adjust for the trial-to-trial variation in latency (i.e., latency jitter) when measuring the ERN and Pe amplitudes. The findings showed that adjusting for the latency jitter did not improve the reliability of ERN and Pe amplitudes for both groups, suggesting that the latency variability may be a trait-like variable which systematically occurred across sessions. Furthermore, the test-retest reliability of stimulus-locked ERP components on correct trials was higher compared to the reliability of response-locked

ERPs for children and adults, confirming that both children and adults generally attended to the task consistently across sessions.

The second study demonstrated the feasibility of utilizing the structural equation modeling (SEM) approach to model the complicated inter-relationship between neural processes and simple task behaviors (e.g., response times) in 143 children with typical development aged 8-12 years. The findings from the latent models indicated that the brain-and-behavior relationships were significant on correct trials but were not significant on incorrect trials after controlling for trait and state factors. Moreover, both models demonstrated different patterns of relationship among latent variables to response time, yet both models yielded excellent model fit indices. This finding suggested that our conceptual models were valid in terms of detecting the distinct patterns of neural processes leading to opposite behavioral outcomes (e.g., correct and incorrect). The final model demonstrated that the post-error adjustment in the stream of neural processes provided an adaptive effect on the early neural processing of the stimulus on correct trials. To our knowledge, this is the first study demonstrating how the post-error adjustment occurs at the level of neural processing.

The third study (1) compared the group differences (children, adults, and adults with ADHD) on neural and occupational performance measures, (2) examined the inter-relationship between these measures for each group, and (3) investigated which measures can best differentiate three groups. The findings suggested that adults with ADHD demonstrated significantly lower quality of occupational performance particularly on the motor aspect of the activities of daily living (ADL). Moreover, for neurotypical children, larger ERN amplitudes were associated with lower quality of social interaction. For adults with ADHD, larger N2 amplitude was associated with lower quality of social interaction. Lastly, discriminant analyses demonstrated that the combination of neural and occupational performance measures differentiated children, adults, and adults with ADHD with 93.2% classification accuracy.

Taken together, this dissertation demonstrated significant brain-and-behavior relationships especially for neurotypical children and adults with ADHD by relating the neural measures (e.g., ERP components) to behaviors obtained from the computer-based task (e.g., response times), and to the quality of occupational performance (e.g., social interaction and ADL). Moreover, this dissertation demonstrated that having both neural and occupational performance measures is beneficial to obtain a comprehensive understanding of dimensions of maturation and disability.

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CHAPTER 1: LITERATURE REVIEW

Introduction

Cognitive functions are critical for individuals to successfully interact with the environment, especially in today's fast-paced world that requires a vast amount of information exchange. In recent years, researchers have begun to develop psychophysiological measures associated with cognitive functions as potential biomarkers for clinical diagnosis. However, the psychometric properties of these measures have not been fully established. Moreover, in the past decades, researchers have applied these measures to investigate the underpinnings of cognitive functions, yet the underlying neural mechanisms have not been fully understood because of the complex nature. Understanding the neural mechanisms associated with cognitive functions could guide clinicians to develop effective and targeted intervention. Furthermore, even though cognitive functions are considered important in our everyday lives, how these functions relate to occupational performance has yet to be critically examined. Specifically, occupational performance refers to the completion of meaningful tasks within a major life area including activities of daily living (ADL), work, and leisure, and involves complex interactions between an individual and his or her environment (Baum, 2011; Schell et al., 2013). Therefore, the purposes of this dissertation are to (1) examine the psychometric properties of psychophysiological measures associated with cognitive functions, (2) investigate the underlying neural mechanisms of cognitive functions and how these mechanisms relate to behavioral outcome (Glisky, 2007), and (3) explore how these neural processes relate to occupational performance in different populations—neurotypical children, neurotypical adults, and adults with attention deficit hyperactivity disorder (ADHD).

The literature review focuses on four domains. I will review the neuroimaging techniques and the psychophysiological measures that have been utilized to understand the neural mechanisms underlying specific cognitive functions in humans. I will proceed to introduce occupational performance, focusing on activities of daily living (ADL) and social interactions in children and adults. I will then introduce the diagnosis of adults with ADHD. Lastly, I will review the theoretical frameworks that assist in explaining the relationships between cognitive functions and occupational performance in children, adults, and adults with ADHD.

Neuroimaging Techniques

With today's advances in technology, researchers are able to implement high-end neuroimaging techniques to study changes in neural activities while people perform tasks that require cognitive functions (Petersen & Posner, 2012). These techniques include positron emission tomography (PET), single-photon emission computed tomography (SPECT), functional near-infrared spectroscopy (fNIRS), functional magnetic resonance imaging (fMRI), diffusion tensor imaging (DTI), and electroencephalogram (EEG), each measuring brain activity or different aspects of physiological change in the brain.

fMRI is a noninvasive technique that utilizes differences in magnetic resonance between oxygenated and deoxygenated hemoglobin to detect areas of the brain that are active (Luck, 2014). fMRI provides excellent spatial localization and has been used for research and clinical diagnosis (Luck, 2014). However, despite the fact that fMRI can detect changes within one second, its relatively lower temporal resolution limits its application in the study of the whole course of neural processing that occurs within a second (van Veen & Carter, 2002). PET constructs functional brain images by injecting radioisotopes and calculates the distribution of the radiotracer over time to estimate brain physiology, such as cerebral blood flow or glucose metabolism (Loane & Politis, 2011). PET is a powerful diagnostic tool for brain disorders and neural degenerative diseases; however, because of its high cost and the time required to perform the procedure, PET has not been widely available to date for research and especially research involving children (Loane & Politis, 2011). SPECT is another type of nuclear imaging test that shows the way blood flows through arteries and veins in the brain (Wernick & Aarsvold, 2004). Similar to PET, SPECT constructs functional brain images by injecting radioisotopes. The difference between PET and SPECT is the type of radiotracers used (Wernick & Aarsvold, 2004). Moreover, SPECT is less expensive and more common compared to PET for research purposes. However, the radioisotopes only travel in the blood stream, hence the images are limited to areas where blood flows (Wernick & Aarsvold, 2004). Furthermore, due to the use of radioisotopes needed for PET and SPECT imaging, these two techniques are considered invasive and for most research involving children would not be appropriate methods.

fNIRS is hemodynamic-based and its applications have been growing over the past 20 years. fNIRS detects simultaneous changes in optical properties of the cortex as the concentration of oxygenated and deoxygenated hemoglobin fluctuates in the brain. fNIRS provides a non-invasive and portable method to monitor brain activity (Hoshi, 2003; Irani, Platek, Bunce, Ruocco, & Chute, 2007). However, the primary limitation of fNIRS is that fNIRS measurements are restricted to outer cortex (Quaresima, Bisconti, & Ferrari, 2012).

DTI is a technique that measures the diffusion of water molecules in the brain and examines the microstructure, such as axons or the volume of brain areas (Mori & Zhang, 2006; Whitford et al., 2011). DTI has been useful in providing the anatomical structure of the brain and has been used to study the development of white and gray matter (Mori & Zhang, 2006).

EEG is a technique that measures neural activities by recording electrical signals from the scalp (Luck, 2014). EEG has excellent temporal resolution up to 1 millisecond (ms), allowing researchers to understand the course of neural processes associated with specific cognitive functions. As a result, EEG is a powerful tool that helps researchers to understand the dynamic neural processes and how these neural processes relate to behaviors (Davies, Chang, & Gavin, 2010). In the following sections, the EEG technique will be described in more detail to provide background for the primary technology used in the studies included in this dissertation.

Electroencephalogram (EEG). EEG has been widely applied as a clinical diagnostic tool for seizures and sleep disorders, as a brain–computer interface, or as a research tool for measuring neurophysiological changes. The EEG technique records electrical signals produced by the brain (Davies et al., 2010; Luck, 2014). These electrical signals are collected, amplified, filtered, and displayed as voltage in real time (Luck, 2014). Specifically, these electrical signals are a summation of postsynaptic potentials generated from billons of neurons across the brain (Luck, 2014). Because the combination of neurons producing postsynaptic potentials is constantly changing, the ongoing EEG signal can contain different voltages within a very short period of time. Importantly, researchers have found that these EEG recordings can reveal certain rhythmic or repetitive neural oscillations associated with different cognitive processes via a time-frequency analysis (Luck, 2014). The time-frequency analysis is a signal-processing approach that converts EEG signals into a series of sine waves composed of different frequencies (Luck, 2014). These neural oscillations are described in hertz (i.e., number of cycles of oscillation within a second). Generally, the most common neural oscillations described in the literature include delta (2–4 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (13–30 Hz), and gamma (>30 Hz) oscillations. These neural oscillations provide information regarding sensory, motor, or cognitive processes based on their synchronization and the intensities (Luck, 2014).

Event-related potentials (ERPs) correlates of cognitive functions. ERPs are a set of positive and negative components extracted from EEG signals and are indicative of neural activities in response to sensory, motor, or cognitive processes (Luck, 2014). Generally, researchers obtain the ERPs by segmenting and averaging the EEG recordings that are time-locked to events of interest (e.g., visual or auditory stimuli or button presses). Mathematically, when averaged, the signals are time-locked to repeated events, background noise that occurs randomly on the EEG recording will be cancelled, and the neural activity specifically evoked by the event of interest will remain (Roach, 2008; see Figure 1.1).

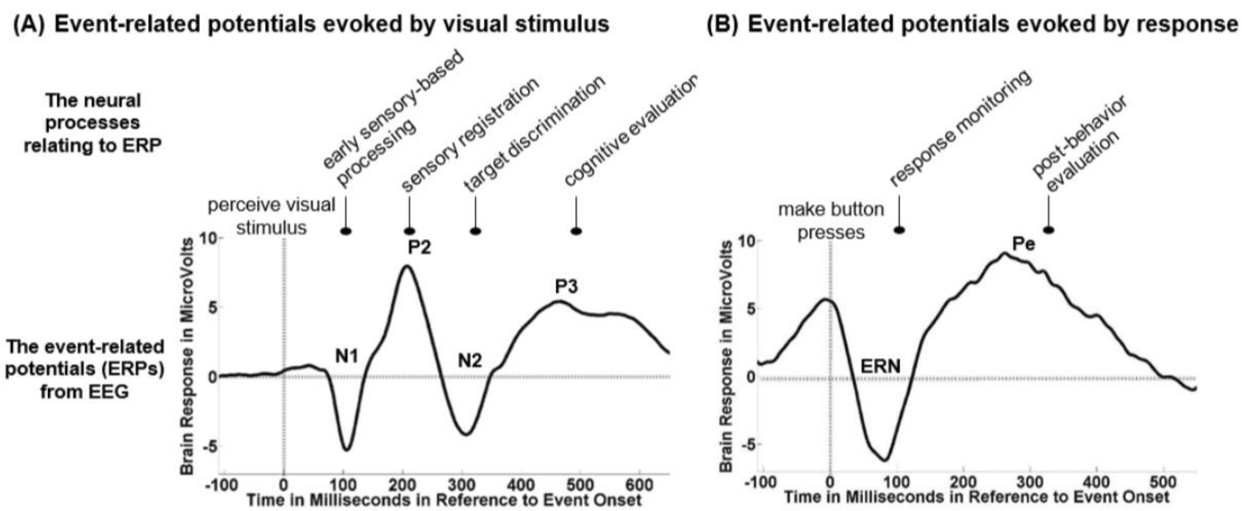


Figure 1.1. (A) Stimulus-locked ERPs elicited by and time-referenced to stimulus; (B) Response-locked ERPs elicited by and time-referenced to incorrect responses at button closure.

These ERPs are often described in terms of amplitude (voltages) and latency (time in milliseconds). Generally, each ERP component is named with a letter and a number; the letter represents either positive or negative deflection for the component, and the number indicates the ordinal position of the ERP component (see Figure 1.1; Luck, 2014). In the following section, I will introduce ERP components that represent different phases of neural processes that are associated with information processing of a visual stimulus.

N1. The N1 component, which is also called N100 component, is a negative voltage deflection that peaks at around 100–150ms at the frontal midline scalp site after stimulus onset (Luck 2014). N1 is associated with the early stimulus processing and selective attention, and its amplitude has been shown to be larger for attended stimuli than ignored stimuli (Lackner, Santesso, Dywan, Wade, & Segalowitz, 2013; Luck & Girelli, 1998; Polich, 1993; see Figure 1.1). N1 amplitude has been shown to be sensitive to the properties such as intensity or frequency of stimuli, such that it is larger for high intensity and high frequency tones but smaller for low intensity and low frequency tones (Adler and Adler, 1989, 1991; Picton et al., 1974). Furthermore, the N1 amplitude elicited by visual or auditory stimuli has been shown to be smaller in children with ADHD than in children with typical development, indicating that children with ADHD are less able to selectively attend to stimuli (Satterfield, Schell, & Nicholas, 1994). Moreover, Crasta et al. (2017) found that the N1 amplitudes in children with sensory processing disorder, a clinical group that demonstrate difficulties in integrating sensory (visual, tactile, and auditory) information, significantly predicted their behavioral performances on the selective attention tasks.

P2. The P2 component, which is also called P200, is an ERP component that follows the N1 component and it peaks at around 150-200 ms at the frontal-central scalp midline site after the onset of the stimulus presentation (Luck, 2014; see Figure 1.1). The P2 component has been associated with detection or sensory registration processes (Davies & Gavin, 2007). Other studies have shown that P2 amplitude is larger for stimuli containing target features, and this effect is enhanced when the targets are relatively infrequent (Luck, 2014).

N2. N2 is an ERP component that appears around 200-350 ms after stimulus representation, and it is also called N200 (Luck, 2014; see Figure 1.1). The functional association of N2 varies based on paradigms. Generally, N2 has been associated with three different cognitive processes: target detection, executive control, and the inhibitory process (Luck, 2014). First, an enhanced N2 amplitude was found when participants were instructed to press buttons to the target stimuli, suggesting that N2 reflects the process that discriminates the target from nontargets (Luck, 2014). Second, the association between N2 and the executive control process is evident by the Flanker task paradigm (Eriksen & Eriksen, 1974). In this paradigm, participants are presented with an array of five letters consisting of combinations of the letters "H" or "S." In this task, there are two congruent arrays, "HHHHH" and "SSSSS," and two incongruent arrays, "SSHSS" and "HHSHH." Participants are instructed to press either the right or left button corresponding to the central letter. Interestingly, studies have shown that N2 amplitude is larger for the incongruent arrays as compared to the congruent arrays, indicating that N2 reflects a process that detects a mismatch between the central letter and the peripheral letters in the incongruent stimuli.

Last, the N2 component also indicates an inhibitory process (Jodo & Kayama, 1992). Paradigms such as the Go-No/Go paradigm are often used to measure inhibitory processes. For this paradigm, participants are instructed to press the button for one type of stimuli (Go stimuli) and withhold pressing the button for another type of stimuli (NoGo stimuli). The inhibitory N2 component is significantly larger when participants perceive stimuli that require them to withhold their responses (e.g., button press), and when they do successfully inhibit their responses to the stimuli (Jodo & Kayama, 1992). Pliszka, Liotti, and Woldorff (2000) found that children with ADHD demonstrated reduced N2 amplitude as compared to the control group, indicating that children with ADHD have reduced response inhibition ability. Moreover, they found that the reduced N2 amplitude is negatively associated with the number of trials in which participants fail to inhibit their responses when performing the tasks, suggesting that the better inhibitory process indicates the greater N2 amplitude (Pliszka et al., 2000).

P3. P3 is a positive deflection occurring around 300-500 ms after stimulus presentation, which is also called P300 (Luck, 2014; see Figure 1.1). Generally, the P3 component indicates cognitive process or memory updating; thus it has been used to study cognitive functions such as attentional switching and working memory. For example, several dual-task paradigms are designed to assess the ability of attentional switching by the P3 component. Gherri and Eimer (2011) conducted an experiment that required participants to perform a dual task—to search for visual targets with unique features (e.g., different colors, such as red or green) while listening to stories at the same time. Researchers compared the P3 amplitude among those who performed the dual tasks of identifying visual targets while listening to stories and the P3 amplitude of participants who performed the single task of searching for visual targets. Results demonstrated that the P3 amplitude was smaller among participants who performed dual tasks than among subjects who performed single tasks, suggesting that when someone is performing dual tasks, the ability to attend to a task is compromised because of limited attentional resources (Gherri & Eimer, 2011). Kida, Kaneda, and Nishihira (2012) found that the correlation between P3 amplitude and reaction time on tasks was higher for the dual-task condition compared to the single-task condition, suggesting that stimulus- and response-related processing are coupled to serve as a compensatory mechanism while attentional resources are limited.

Moreover, the P3 component also indicates the memory updating process (Polich, 1993). Studies have shown that P3 amplitude is greater for stimuli that require participants' recall than for those that do not (Karis, Fabiani, & Donchin, 1984). Polich et al. (1983) found a significant correlation between P3 latency and the digit span memory task in people without neurological impairments, suggesting a relationship between the neural and behavioral measures of working memory ability. Likewise, Dolu, Başar-Eroğlu, Özesmi, and Süer (2005) also found a significant relationship between the working memory load and P3 amplitude. Specifically, with a greater working memory load, participants demonstrated larger P3 amplitudes.

Error-related negativity (ERN). ERN component is a negative voltage deflection that is frontally distributed on the scalp and peaks at 0–80ms every time an individual gives an incorrect response (Coles et al., 2001; Falkenstein, Hohnsbein, Hoormann, & Blanke, 1991). Thus, the ERN is a component in an ERP that is time-locked to a response, rather than in an ERP time-locked to a stimulus as in the previously discussed components - N1, P2, N2, P3 (see Figure 1.1). The ERN has been used to represent self-regulation, response monitoring, error detection, or conflict detection processes (Coles et al., 2001; Davies et al., 2004; Gehring & Fencsik, 2001; Swick & Turken, 2002). Both fMRI and EEG dipole modeling studies have confirmed that the ACC, a brain region beneath the medial surface of the frontal lobe, is the neural generator of the ERN (Carter et al., 1998; Coles et al., 2001; Holroyd, Dien, & Coles, 1998; Mathalon, Whitfield, & Ford, 2003; van Veen & Carter, 2002). Several studies have shown that individuals with ADHD, schizophrenia, autism, or brain injury demonstrate smaller ERN amplitude compared to control groups, suggesting that people in these populations have a reduced ability to monitor and regulate their behaviors (Bates, Kiehl, Laurens, & Liddle, 2002; Groen et al. 2008; Henderson et al., 2006; Wiersema, van der Meere, & Roeyers, 2005).

Ladouceur et al. (2007) found that ERN amplitude is significantly larger for the incorrect trials with longer reaction times than those with shorter reaction times, indicating a positive relationship between error detection and subsequent compensatory behavior. Specifically, studies have shown that, following errors, participants initiate compensatory behaviors by decreasing task speed to prevent future errors (Gehring, Goss, Coles, Meyer, & Donchin, 1993). Such a slowdown in reaction time after an error is called post-error slowing, a widely used indicator of post-error adjustment behaviors (Danielmeier & Ullsperger, 2011; Gupta, Kar, & Srinivasan, 2009).

Error positivity (Pe). Error positivity (Pe) is a slow positive deflection that follows the ERN component and peaks at 300–500ms centro-parietal scalp distribution after an individual makes an error (Falkenstein, Hohnsbein, Hoormann, & Blanke, 1991). Pe, like ERN, is a component in an ERP time-locked to a response, and immediately follows ERN (see Figure 1.1). Studies have shown that Pe component is associational with consciously processing of errors (Davies, Segalowitz, Dywan, & Pailing, 2001; Falkenstein et al., 2000; Ridderinkhof, Ramautar, & Wijnen, 2009) and initiating post-error adjustment (e.g., inhibit ongoing behaviors; Overbeek et al., 2005; van Veen & Carter, 2006). Researchers found a relationship between the Pe amplitude with the post error behaviors, and stated that the greater Pe amplitude is, the more significant that the participants activate their post error adjustment (Nieuwenhuis, Ridderinkhof, Blom, Band, & Kok, 2001). For example, participants will slow down their reaction time on the trial immediately following a trial on which they commit an error to ensure their overall performance (Nieuwenhuis, Ridderinkhof, Blom, Band, & Kok, 2001). While the functional significance of Pe has yet to be determined, several studies have shown that Pe is also influenced by behavioral performance, personality, and disorders (Burgio-Murphy et al., 2007; Schrijvers, De Bruijn, Destoop, Hulstijn, & Sabbe, 2010).

Test-retest reliability of the ERP components in children and adults. Several studies have demonstrated that the ERP components are associated with phenotype of neurological disorders (Bates et al., 2004; Kim et al., 2006; Larson, Kaufman, Kellison, Schmalfuss, & Perlstein, 2009; Marquardt, Eichele, Lundervold, Haavik, & Eichele, 2018; Morris et al., 2008; Vlamings et al., 2008). Moreover, the Research Domain Criteria (RDoC) framework launched by the National Institute of Mental Health (NIMH) provides guidelines for researchers and clinicians to consider various dimensions (e.g., physiology, behavior, self-report) other than solely relying on behavioral symptoms to understand mental disorders (https://www.nimh.nih.gov/research-priorities/rdoc/index.shtml). The RDoC implies that the combination of the neural and behavioral measures may provide a more comprehensive picture in understanding the dysfunction of the mental disorders than relying on behavioral measures alone. Specifically, if researchers or clinicians only focus on behavioral symptoms, a significant inadequacy in diagnoses and subsequent intervention occurs if different groups (e.g., children with ADHD or children with autism spectrum disorder) exhibit similar behavioral symptoms. However, distinct neural processing profiles may underlie different functional challenges regardless of diagnoses. Ignoring the neural underpinnings of impairment can lead to poorly-targeted interventions. Thus, for neural measures, such as ERP components, to be useful in supplementing other methods of diagnostics and intervention planning, they will need to demonstrate appropriate psychometrics. As a result, there is a growing body of literature investigating the psychometric properties of both stimulus-locked (e.g., N1, P2, N2, P3) and response-locked components (e.g., ERN and Pe; Foti, Kotov, & Hajcak, 2013; Meyer, 2017; Riesel, Weinberg, Endrass, Meyer, & Hajcak, 2013).

Taylor, Gavin, and Davies (2016) found that moderate to strong test-retest reliability of the stimulus-locked ERPs in neurotypical adults and moderate reliability in children. Similarly, the test-retest reliability of the amplitudes of stimulus-locked ERP components (e.g., N1, P2, N2, and P3) has been shown to be strong using the oddball task in neurotypical adults (Cassidy, Robertson, & O'Connell, 2012). In terms of the response-locked ERPs, studies investigating the test-retest reliability of the ERN and Pe components in neurotypical adults have reported strong test-retest reliability of ERN and Pe amplitudes across two sessions ranging from 20 minutes to 2 years in adults (Cassidy et al., 2012; Olvet & Hijcak, 2009; Segalowitz et al., 2010; Weinberg et al., 2011). We only found one study examined the test-retest reliability of the ERN amplitude in children, and the reported reliability was moderate (Meyer et al., 2014). To our knowledge, none of the studies examined the test-retest reliability of the Pe amplitude in children.

Summary. EEG and ERPs have been widely used in the literature to understand neural processes associated with cognitive functions. However, only a few studies have examined the test-retest reliability especially for the response-locked ERPs (e.g., ERN and Pe amplitudes) in children, thus test-retest reliability in children has not been fully established. Therefore, more studies are needed to further investigate the test-retest reliability of the response-locked ERPs for children.

Occupational Performance

Occupational performance refers to individuals' ability to perform daily activities that are meaningful to them appropriate to their social, cultural, environmental, and developmental stages (Schell, Gillen, Scaffa, & Cohn, 2013). Schell et al. (2013) have provided a definition of occupational performance: "Doing a task related to participation in a major life area; or the accomplishment of the selected occupation resulting from the dynamic transition among the client, the context and environment, and the activity" (p. 1238). Specifically, occupational performance reflects an individual's dynamic experience of engaging in daily activities within his or her environment (Schell et al., 2013). The American Occupational Therapy Association (AOTA) practice framework categorized occupation into eight different categories, include activities of daily living (ADL; e.g., feeding, dressing, and grooming), education, work (e.g., school, home, and family management), play and leisure (e.g., sports, hobbies), rest and sleep, and social participation. In this dissertation, the ADL and social participation are selected as primary measures to assess the quality of occupational performance, therefore, I will introduce these two domains in detail in the following sections.

Activities of daily living (ADL). ADL can be broadly described as activities that people perform routinely to take care of themselves and can be categorized into "basic ADL" (BADL) and "instrumental ADL" (IADL). The former refers to activities involved with taking care of one's body, such as feeding, grooming, and dressing; the latter involves a person interacting with their environment to live independently in a community and encompasses complex skills such as cooking, handling transportation, and shopping (Schell, 2013). ADL has been an emphasis for evaluation, intervention, and setting goals in occupational therapy, and has been a critical component for occupational performance evaluation.

Occupational performance assessments that emphasize ADLs. A handful of standardized assessments have been developed in the field of occupational therapy to evaluate an individual's occupational performance. The Canadian Occupational Performance Measure (COPM) is an assessment tool that has been widely used to clinically measure a client's self-perception of his or her own occupational performance. Specifically, it requires clients to identify their occupational performance issues in three different domains, including self-care, productivity, and leisure, as well as evaluate the importance of these activities (Hemphill-Pearson, 2008; Schell et al., 2013). The Occupational Performance History Interview (OPHI) is another subjective assessment tool that gathers history information of occupational performance from an individual (Apte, Kielhofner, Paul-Ward, & Braveman, 2005; Schell et al., 2013).

In contrast to subjective measurements of occupational performance, other standardized assessments have been designed to measure occupational performance objectively. For example, the Functional Independence Measures (FIM) and the Assessment of Motor and Process Skills (AMPS; Fisher & Jones, 2014) were developed to evaluate ADL; in both assessments, an occupational therapist observes an individual performing daily tasks. The FIM is used to evaluate the overall aspects of an individual's functional capacity, such as walking, transferring, bathing, and dressing (Stineman et al., 1996). The FIM has been widely used in clinical settings to assess individuals who have suffered from strokes, spinal cord injuries, or cognitive impairments (McKinley, Santos, Meade, & Brooke, 2007). The AMPS is a client-centered assessment method in which occupational therapists observe the ways in which clients perform two everyday occupational tasks that are familiar and meaningful to them (Fisher & Jones, 2014). These ADL and IADL tasks might include making a sandwich with peanut butter and jelly, vacuuming, or washing dishes. Although both the FIM and the AMPS measure a participant's occupational performance under a natural setting, studies have shown that the AMPS is more sensitive in detecting changes in performance than the FIM is (Fioravanti, Bordignon, Pettit, Woodhouse, & Ansley, 2012). Thus, the AMPS has been more widely used in clinical and research settings (Fioravanti et al., 2012).

Social participation. Social participation is defined as involvement with interpersonal interactions in social, leisure, community, and/or work activities (Goll, Charlesworth, Scior, &

Stott, 2015). Social participation is important for human beings; it allows us to function in a community on a daily basis. Goll et al. (2005) demonstrated that reduced social participation is often associated with a sense of loneliness and decreased health outcomes in older adults. Other studies have shown that social participation can predict an individual's well-being (Di Cagno et al., 2013; Gilmour, 2012), and that reduced quality of social participation might lead to lower self-esteem or even mental illness (Mikula et al., 2016). To engage in successful social participation, a person must have social interaction skills. Social interaction skills refer to "the individual actions or units of social behaviors that are observable within the ongoing stream of occupation that involves social interaction" (Fisher & Griswold, 2015, p. 201).

Social interaction assessments. Most available tools that therapists and researchers use to evaluate an individual's social interaction skills focus on subjective perceptions that are derived by means of checklists or questionnaires, or by observation (Schell et al., 2013). While using the checklists or questionnaires to assess social interaction has several advantages (e.g., easy to administer, and requires minimal training), it also has several disadvantages (e.g., the results may be difficult to be compared across individuals; Schell et al., 2013). A lack of objective measures on the social interactions skills might fail to reveal the true social skills from participants. Currently, the Evaluation of Social Interactions (ESI) is the only standardized assessment method that involves an occupational therapist directly observing an individual's social interactions under a natural context (Fisher & Griswold, 2015). Similar to the AMPS, the ESI is administered under natural, real-life contexts in which an occupational therapist observes a participant as he or she performs two meaningful and consensual social episodes with a familiar social partner (e.g., their mom, dad, or siblings). The ESI has the potential to provide a quantitative assessment of a client's social skills and may be useful for clinicians when they plan and measure the outcomes of the intervention.

Relationship between cognitive functions and occupational performance. Surprisingly, studies that investigate the relationship between cognitive function and occupational performance in individuals without neurological impairments are limited to older adults. Cahn-Weiner et al. (2002) have examined the relationship between frontal executive functioning and occupational performance in older adults. Specifically, the behavioral measures include perseverative behaviors, cognitive shifting, and response generation. The results found that these cognitive functions significantly predicted IADL as measured by Occupational Therapy Assessment of Performance & Support (OTAPS). Moreover, the researchers also administered a modified version of the IADL assessment and the Physical Self-Maintenance Scale to measure physical activities or BADL, including dressing, grooming, and toileting, as well as IADL, such as financial management and use of public transportation. Results demonstrated that, whereas perseverance did not significantly predict the scores on OTAPS or physical activities and BADL, cognitive shifts significantly predicted both scores on OTAPS and physical activities or BADL, suggesting that a relationship between cognitive function and IADL is established in older adults. Similarly, Bell-McGinty, Podell, Franzen, Baird, and Williams (2002) have found that cognitive shifting, perseverative behaviors, as well as other executive function tests, significantly predict functional status in older adults.

Summary. Previous studies have demonstrated relationships between cognitive functions and BADL performance in older adults. However, such a relationship has not been comprehensively studied in children, younger adults, and adults with attention deficit hyperactivity disorder (ADHD). Understanding the brain-and-behavior relationship especially in individuals with disorders such as ADHD will assist in guiding rehabilitative interventions and provide another means of studying the effectiveness of such interventions. Therefore, the overarching goal of this dissertation is to explore the relationship between cognitive function and occupational performance in children, adults, and adults with attention deficit hyperactivity disorder (ADHD).

Attention Deficit Hyperactivity Disorder (ADHD)

Studies have shown that the estimates of prevalence ranging from 5% to 10% in school-aged children (Scahill & Schwab-Stone, 2000) and 3% to 5% in adults (Almeida Montes, Hernandez Garcia, & Ricardo-Garcell, 2007; Biederman, 2005). The core symptoms of ADHD are inattention, hyperactivity, and impulsivity across multiple settings such as home or school (American Psychiatric Association, 2013). While ADHD is a most common diagnosis in childhood, studies have shown that about 60% of cases clinically diagnosed in childhood persist into their mid-20s, and 41% or more persist into adulthood (Barkley, 1997; Sibley et al., 2017). As a result, the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5; APA, 2013) has revised its criteria for diagnosis. Specifically, while the age of onset criteria was age 7 or earlier in the previous version, now the age of onset criteria has been raised to age 12 or earlier in DSM-5. Moreover, the revised DSM-5 provides examples such as disorganized work and failure to meet deadlines that apply more to adults with ADHD (APA, 2013). Therefore, while many studies have investigated the disorder in children, it is critical to understand the way it affects adults to understand its underpinnings.

Cognitive functions in adults with ADHD. The central deficits of cognitive functions in people with ADHD have long been discussed yet remain inconclusive. Initially, Barkley (1997) stated that decreased behavioral inhibition is the core symptom of ADHD. People with ADHD failed to inhibit prepotent responses, stop ongoing responses, or maintain self-directed responses when facing interference. For example, adults with ADHD commit more errors on the continuous performance task, in which they need to inhibit prepotent responses (i.e., button presses) when they see the infrequent stimulus (Epstein, Johnson, Varia, & Conners, 2001). Moreover, adults with ADHD demonstrate longer stop signal reaction time, an indicator that reflects the time taken to inhibit a response once it has begun (Aron, Dowson, Sahakian, & Robbins, 2003). Adults with ADHD also made more errors on the Stroop tasks compared to control adults (Johnson et al., 2001). Barkley (1997) described such a reduction in inhibition is the central symptom of ADHD and that further affects other executive and cognitive functions such as working memory, self-regulation, speech internalization, and reconstitution.

In recent years, more and more researchers have stated that the deficits of ADHD consist of more than just the primary symptoms in the diagnosis. Reduced self-regulation and performance monitoring might be global deficits of the disorder (Barkley & Murphy, 2011; Van De Voorde, Roeyers, & Wiersema, 2010). Self-regulation refers to any response that alters the probability of a later consequence related to that event, which enables efficient interaction with one's environment (Van De Voorde et al., 2010). Chang, Davies, and Gavin (2009) showed that college students with ADHD demonstrated reduced performance monitoring by showing reduced brain processing and more difficulties in self-monitoring compared to healthy adults (Chang et al., 2009). The study suggested college students with ADHD failed to monitor and regulate their ongoing behaviors, thus made more errors and had fewer post-error behavioral adjustments compared to healthy adults. Other studies also demonstrated the reduced ability in people with ADHD in almost all the domains of cognitive functions such as attention, working memory, planning, and initiation compared to healthy adults (Barkley & Murphy, 2011).

Occupational performance in adults with ADHD. Barkley and Murphy (2010) evaluated the self-reported occupational problems in adults with ADHD and examined whether the subcomponents of executive function significantly predict the outcomes of self-rated occupational performance in each domain. Results showed that adults with ADHD have had more work difficulties, arrests, driving violations, and divorces than adults without ADHD. Moreover, adults with ADHD demonstrated worse productivity, outlook, and psychological health than adults without ADHD. Specifically, based on the self-report, adults with ADHD experienced difficulties in daily occupations, such as failure to ignore distractions when doing household chores such as cooking and cleaning. They had difficulty getting things started and tended to have trouble with financial tasks such as paying the bills or taxes. They also had symptoms of forgetfulness about where things were placed such as they could not remember where they parked (Stern & Maeir, 2014). Barkley & Murphy (2011) demonstrated several difficulties that beset adults with ADHD in daily life activities, including self-management of time, self-organization, self-discipline, self-motivation, and self-activation. Interestingly, studies that examine occupational performance in people with ADHD mostly focus on job satisfaction, but not activities of daily living. Moreover, Friedman et al. (2003) showed that adults with ADHD viewed themselves as less socially competent and more sensitive toward violations of social norms than controls. Wehmeier, Schacht, and Barkley (2010) also showed that adolescents with ADHD experience difficulties with social interactions which in turn, impair their overall quality of life. However, while there are several studies that demonstrate that adults with ADHD experience difficulties with occupational performance, little is known about the underpinnings of the reduced occupational performance in adults with ADHD.

The relationship between cognitive functions and occupational performance in adults with ADHD. Studies further investigating the impact of cognitive functions on occupational performance in adults with ADHD are limited. Barkley & Murphy (2011) predicted the deficits in daily life activities from the behavioral results on the executive functions tests using regression analysis. They found inhibition ability and the ability of self-management to time significantly predicted trouble with work behavior and work performance in adults with ADHD. Likewise, Stern and Maeir (2014) found the scores on the behavioral rating inventory of executive function-adult version correlated with Canadian Occupational Performance Measure (COPM) in adults with ADHD. Specifically, adults with ADHD who have more difficulties with executive functions demonstrated lower self-rating occupational performance (Stern & Maeir, 2014). Moreover, the study found that not only do executive functions significantly correlate with the occupational performance in adults with ADHD, but the COPM score, Behavior Rating Inventory of Executive Function (BREIF) score, and adults' self-report scale together significantly predicted quality of life in adults with ADHD (Stern & Maeir, 2014). This study suggested a relationship between cognitive function—especially executive function—and occupational performance in adults with ADHD. However, it is worth noting that self-rated measures like the COPM are subjective and might be influenced by self-esteem of participants. Future studies should use more objective measurements to study the relationship between executive function and occupational performance.

Summary. Studies have shown that adults with ADHD have decreased cognitive functions and difficulties with occupational performance. While several studies showed that the cognitive functions are associated with occupational performance in adults with ADHD, the underlying interactions between these factors is unclear and requires further investigation.

Theoretical Frameworks for Understanding Brain-and-Behavior Relationships

While there are no existing frameworks that explicitly explain the relationship between cognitive functions and occupational performance, several fundamental frameworks illustrate these brain and behaviors interactions. In this literature review, these frameworks serve as a basis to predict the relationship between cognitive functions and occupational performance. Here I will review the most prevalent of these frameworks: the dynamic systems theory; the International Classification of Functioning, Disability and Health (ICF) framework; the Person-Environment-Occupation model (PEO model); and the Connectionist Theory.

Dynamic systems theory. The central tenet of dynamic system theory is that behaviors emerge from interactions between multiple systems over time (Elman, 2003; Hayes & Strauss, 1998). These systems could be neurons, tissues, muscles, tasks, and environment (Samuelson, Jenkins, & Spencer, 2015). For example, the disappearance of the stepping reflex has long been considered a sign of maturation of the brain, as the higher order cortex matures and inhibits this primary reflex. However, researchers of dynamic systems theory have shown that the disappearance of stepping reflex is also associated with infant's weight (Levine & Munsch, 2010). That is, the reflex is shown to be more frequent when infants step in the water and less when researchers put more weight on infants' legs. Such a finding supports the belief that neural maturation is not the only factor for the disappearing stepping reflex. Rather, all systems that are involved in the dynamic interactions must be considered for the emergence of motor behaviors (Levine & Munsch, 2010). Specifically, the term *dynamic* suggests the flexibility among interactions between systems (e.g., neurons, tissues, muscles, tasks, and environment), meaning these interactions are not predetermined or pre-specified but are rather unique and self-organized (Thelen & Bates, 2003). Self-organization refers to the process that these systems interact with one another and move toward an attractor—that is, toward a more stable status—from a less stable state. Moreover, such a process occurs from the interactions among systems without explicit instructions (Samuelson et al., 2015; Thelen & Smith, 2007). Some developmental psychologists consider this process to be a developmental trajectory in which these systems integrally interact with one another with flexibility (Thelen & Smith, 2007). In other words, development involves ever-changing relationships among multiple systems over time.

Major principles of the dynamic systems theory include, first, the dynamic interactions among systems follow a nonlinear pattern (Thelen & Smith, 2007). That is, the process that systems interact with one another and move toward an attractor often changes in nonlinear ways. For example, Hayes et al (2007) adopted the dynamic systems theory to investigate changes of the symptoms for people with anxiety disorders during psychological therapy, specifically exposure therapy. They found that the symptoms changed with a nonlinear pattern over time and stated that anxiety must be increased before it can be decreased (Hayes et al., 2007). Second, each system involved with dynamic interactions has its own developmental timetable (Effgen, 2012). Changes in the developmental timetable create opportunities for the emergence of new behaviors. For example, various systems including postrual control, strength, and gait pattern generation are associated with acquisition of locomotion. These systems have their own developmental timetables. Changes in one system alters the trajectory of dynamic interactions and produces new loconotion behaviors (Effgen, 2012; Heriza, 1991; Thelen & Smith, 2007). Third, dynamic systems theory, with its emphasis on embodiment, claims that the process of dynamic interactions among systems is always connected with its environment (Thelen & Smith, 2007). Specifically, the term *embodiment* refers to the phenomenon that a human's body is continuously coupling to events in the world. For example, Gibbs (2005) stated that cognition develops when "the body engages in the physical, cultural world, and must be studied in terms of dynamic interactions between people and their environment" (p. 21-22). These critical principles have been widely applied to understand cognition and motor development of human beings (Thelen & Smith, 2007).

Perspectives on the brain and behavior relationships. Samuelson et al. (2015) applied the concept of dynamic systems theory to explain the relationship between neural structures and functions, cognition, and behaviors. Specifically, Samuelson et al. (2015) stated that behaviors are influenced by interactions among neurons and determined by the environment and task that is performed. This perspective posits an argument that neurons in the brain dynamically interact with one another to produce behaviors, which are influenced by the environment and tasks (Samuelson et al., 2015; Thelen & Smith, 2007). Moreover, based on the dynamic system theory, human behaviors could also influence the neural structure. For example, the constraint-induced movement therapy (CIMT) is a rehabilitation approach that is based on the theory. Specifically, the CIMT approach forces individuals with stroke to use their affected limbs to perform daily activities, which significantly enhances brain functional reorganization in patients with strokes (Cooper & Mosby, 2012). In other words, instead of viewing behaviors as predetermined by the brain, dynamic system theorists consider behaviors as emerging from the dynamic interactions among many subsystems over time, and behaviors can mutually influence other systems.

Perspectives on cognitive functions and occupational performance. Several researchers have applied dynamic system theory to understand the relationship between cognitive functions and occupational performance. Occupational performance is defined as *doing* a task related to participation in a major life area, it can be viewed as a type of behavior by its definition (Schell et al., 2013; Thelen & Smith, 2007). Darrah et al. (2011) proposed that the interaction among three factors, namely the child, task, and environment, is critical to achieve functional goals for children with cerebral palsy (CP). Specifically, child characteristics include both physical abilities (e.g., muscle tone, range of motion, balance) and cognitive abilities. Task characteristics include descriptive features of activities that a child is trying to perform. Environmental characteristics include physical accessibility and availability of assistance. Darrah et al. (2011) modified the task and environment to help children with CP to achieve their functional goals without remediation of a child's physical and cognitive abilities. Similarly, Yancosek and Howell (2010) applied the dynamic system theory to understand the way systems interact to influence motor behaviors, and emphasized the importance of environment in influencing human behaviors. Taken together, based on the dynamic system theory, these studies demonstrate the relationship between cognitive functions and occupational performance.

International Classification of Functioning, Disability and Health (ICF). ICF is a widely used framework in the fields of health professions. ICF provides standardized language to facilitate the communication among professions, and offers a new perspective on the way people understand disability (Vargus-Adams & Majnemer, 2014; World Health Organization, 2002). Further, ICF has been applied in clinical settings and research fields to monitor progress of patients and to depict the interactions between multiple factors (Vargus-Adams & Majnemer, 2014). Unlike the model that was previously proposed by World Health Organization (WHO)– International Classification of Impairments, Disabilities, and Handicaps (ICIDH)—which indicates that the disability terminates the health condition—the ICF model focuses on the overall health condition and functioning of an individual (World Health Organization, 2002). Specifically, the ICF framework describes the relationships in the changes across multiple factors including body function and body structure, activity, participation, environment, and personal factors, and how these factors bidirectionally influence each other and contribute to the overall health condition (see Figure 1.2). Specifically, the factor of body function and body structure is defined as the physiological and psychological functions of body systems. The factor of activity refers to the execution of tasks or actions by an individual (see Figure 1.2) and it has a bidirectional relationship with the factor of participation, which is defined as involvement in a life situation. Such a relationship is also influenced by larger contextual factors, including environment and personal factors. Specifically, environment factor refers to physical, social, and attitudinal environment (i.e., general attitudes of community and society) that either facilitate or hinder people to function in their lives. The personal factor refers to gender, age, coping styles, education, and experiences that influence the way an individual experiences disability. Both environment and personal factors influence body function and body structure, activity, and participation factors (WHO, 2002; Figure 1.2).

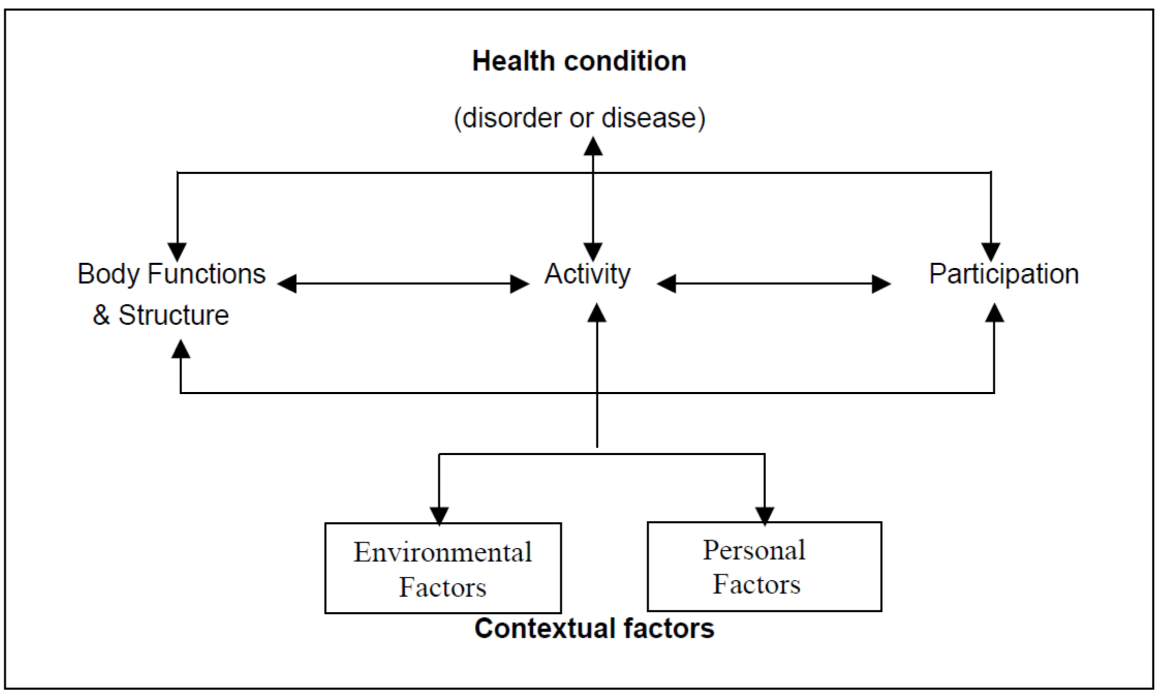


Figure 1.2. The ICF framework (WHO, 2002)

Perspectives on the brain and behavior relationship. The ICF model describes multiple factors that bidirectionally influence each other and contribute to one's overall health. In terms of the brain and behavior relationship, I highlight the interactions among factors—body function and body structure, activity, and participation—in this section. The factor of body function and body structure includes items such as mental functions (e.g., attention and memory). This factor has a bidirectional relationship with the factor of activity, which also has a bidirectional relationship with the factor of participation. Specifically, the detailed items listed under the factors of activity and participation include self-care, communication, and domestic lives, which are largely associated with day-to-day behaviors. Thus, these bidirectional arrows among these primary factors suggest that our brain functions influence our behaviors, and the behaviors can influence our brain (WHO, 2002).

A handful of studies in the field of rehabilitation have mapped the parameters of interest on each factor of the ICF model and examine the interactions among these factors. Here I highlight one study that especially addresses relationships between the factors of body function and body structure, activity, and participation in terms of the brain and behavior relationship. Üstüin (2007) implemented the ICF model to monitor the treatment progress in children with ADHD. The researchers found that factors such as smaller brain volumes, asymmetry of the caudate nucleurs, and corpus callosum size and shape influenced body functions (e.g., poor attention) and are linked with activity limitations and participation restrictions (e.g., reading, writing, communication, and work performances) in children with ADHD. This study indicated a relationship between factors of body function and body structure, activity, and participation in children with ADHD.

Perspectives on cognitive function and occupational performance. Based on ICF model, cognitive functions are regarded as mental functions (e.g., attention and memory), which are associated with brain functions that belong to the factor of body function and body structure.

Further, since occupational performance refers to *doing* a task related to *participation in* day to day tasks including self-care activities, work, and leisure (American Occupational Therapy Association, 2014; Schell et al., 2013), occupational performance is overlapped with factors of activity (i.e., the execution of tasks or actions) and participation (i.e., involvement in a life situation) based on the ICF model. Therefore, based on the ICF model, cognitive functions and occupational performance bidirectionally influence one another.

Person-Environment-Occupation (PEO) Model. The PEO model was proposed by Law et al. (1996) to describe the transactional relationships between three components: person, environment, and occupation. The interactions among these components result in occupational performance (Law et al., 1996). The term *transactional* indicates that the relationship between these three components are interdependent with one another, instead of a linear cause-effect relationship. Such an interdependent relationship assumes that these components are essential in relation to occupational performance and could not exist independently of one another (Law et al., 1996). Specifically, occupation refers to tasks or activities with cultural or personal meanings that individuals do to occupy their time, and keep their mind and body active within a context (Christiansen & Townsend, 2010; Schwartzman, Atler, Borg, & Schwartzman, 2006). Because the PEO model was developed by occupational therapists, the model focuses on occupational performance and has been applied in both clinical practice and basic research in the fields of rehabilitation, occupational therapy, and occupational science.

Perspectives on brain and behavior relationship. Since the PEO model does not directly address the brain and behavior relationship, such a relationship can be derived from the way the PEO model addresses the transactional relationships between person, environment, and occupation resulting in occupational performance. Specifically, the PEO model defines a person as a “dynamic, motivated, and ever-developing being” (Law et al., 1996, p. 17) who consistently interacts with the environment, resulting in occupational performance. Thus, the component of person encompasses the person’s cognitive abilities, problem-solving skills, sensory and motor abilities as well as personal values, and motivations (Strong et al., 1999). To this end, such features are believed to reside in brain function (Darrah et al., 2011). Further, the PEO model defines occupation as tasks or activities with cultural or personal meanings. Therefore, based on the PEO model, the person factor (which is partly associated with brain function) dynamically interacts with occupation (tasks and activity) and environment, which, in turn, produces occupational performance (behavior). Based on the transactional relationship among person, environment, and occupation resulting in occupational performance, we know that our brain interacts with the environment and tasks we perform, and thereby produces behaviors.

Perspectives on cognitive functions and occupational performance. In this model, occupational performance is considered as an outcome. On the other hand, cognitive functions, which reside within the component of person, engage in the transactional relationship, and partially contribute to the outcome along with components of the environment, and occupation. Thus, such a relationship suggests that cognitive functions partially determine the occupational performance.

Connectionist Theory. The connectionist theory, which is also called the parallel distributed processing models, utilizes computational models to construct the complex interrelationships of the units within the neural networks (Pastur-Romay, Cedrón, Pazos, & Porto-Pazos, 2015; Rogers, 2009). The primary tenets of the connectionist theory include (1) cognitive functions arise from the successive activation among a single neuron or a group of neurons that shared the same function (e.g., units); (2) this successive activation among neurons can be described by weighted connections (e.g., edge) among those units (Pastur-Romay et al., 2015). The connectionist theory has been applied in psychology, social science, neuroscience and computer science to stimulate the underlying mechanisms among multiple components within the system (Rogers, 2009).

Perspectives on brain and behavior relationship. Similar with the dynamic system theory, the connectionist theory assumes behaviors as the consequences or the outputs that emerged from the interconnections of the neural network (McClelland et al., 2010). Specifically, these behavioral outputs can be reinforced or shaded by strengthening or weakening the interconnections among the units in the system (McClelland et al., 2010). For example, the effect of learning can be explained by the changes in the weights of the interconnections among the units in the neural network (McClelland et al., 2010). However, the behavioral outputs are not merely considered as outcomes, but these outputs can provide feedback to modify the underlying neural networks (Davelaar, 2012).

Perspectives on cognitive functions and occupational performance. Based on the connectionist theory, the subcomponents of cognitive functions are considered as units within the neural network (McClelland et al., 2010). The relationships among these subcomponents, either linear or non-interrelationships, are considered as edges and can be described as weighted connections, to produce the behavioral output (e.g., occupational performance). As such, occupational performance can be considered as the consequences that are emerged from the interconnected network. According to the connectionist theory, behavioral output (e.g., occupational performance) could provide the feedback to modify the connections of these underlying neural networks (McClelland et al., 2010).

Summary. These models suggested dynamic interactions among multiple elements including cognitive functions, person, task, environment, and outcome behaviors. However, the cognitive functions and occupational performance have not been examined empirically and thus requires further investigation.

Overview of The Studies

Several research questions emerged based on gaps in the current literature. These research questions include: (1) what is the test-retest reliability of the response-locked ERPs in children with a short interval between sessions, (2) what are the interrelationships of the neural processes associated with information processing in children, and how these neural processes relate to the behavioral output (e.g., response time), (3) what are the relationships between cognitive functions and occupational performance in children, adults, and adults with ADHD. Three studies were conducted to answer these questions (Table 1.1). The findings of the first study could provide insights into the most reliable approach to measure the ERPs, which in turn, can be beneficial in determining the appropriate ERP measures that we should obtain for the second and the third study. The second study could help to delineate the stream of neural processes in children, which could inform the third study in terms of fundamental neural mechanism associated with information processing in children. The third study allows researchers to have a more comprehensive perspective on how trait factors, namely maturation and disability, influence neural processes and occupational performance by having three groups (children, adults, and adults with ADHD) in the study. The findings of the third study could inform future studies exploring the potential relationship between neural processes and behavioral measures of occupational performance in individuals with and without disabilities. The details of each study are addressed in the following chapters.

Table 1.1. Overview of three proposed studies

	Purpose(s)	Participants	Measures
Study 1	• To examine the test-retest reliability of the response-locked ERPs in children and adults	• 118 children • 53 adults	• ERP components
Study 2	• To establish a model that depicts the full stream of neural processes from stimulus to response (task behavior) measured by event-related potentials (ERPs) and response time in neurotypical children aged 8-12 years old. • To examine the role of performance monitoring on the full stream of neural processes from stimulus to response (task behavior)	• 143 children	• ERP components • Response times
Study 3	• To examine the differences in neurological measures of cognitive functions and occupational performance in children, adults, and adults with ADHD • To investigate the relationship between neural and occupational performance measures in the three groups • To explore which type of measures (e.g., neural measures, or occupational performance measures, or the combination of the two) could best differentiate these three groups	• 63 children • 17 adults • 8 adults with ADHD	• ERP components • Occupational performance

CHAPTER 2: TEST-RETEST RELIABILITY OF ELECTROENCEPHALOGRAPHIC MEASURES OF PERFORMANCE MONITORING IN CHILDREN AND ADULTS

Introduction

Performance monitoring is a set of mental processes including the evaluation of ongoing behavior, detection of performance errors, and initiation of post-error behavioral adjustment (Coles, Scheffers, & Holroyd, 2001). Collectively, these processes allow individuals to perform goal-directed behaviors. Electroencephalography (EEG) has been used to understand underlying neural mechanisms of performance monitoring, which is indicated by two event-related potential (ERP) components, namely error-related negativity (ERN), and error positivity (Pe). The ERN component is a frontally distributed negative voltage deflection and peaks at 0–80 ms following incorrect responses and has been associated with error detection and conflict monitoring (Coles et al., 2001; Falkenstein, Hohnsbein, Hoormann, & Blanke, 1991; Yeung, Botvinick, & Cohen, 2004). Studies from functional magnetic resonance imaging (*f*MRI) and EEG dipole modeling suggested that the primary neural generator of the ERN is located at anterior cingulate cortex (ACC; Carter et al., 1998; Coles et al., 2001; Holroyd, Dien, & Coles, 1998; Mathalon, Whitfield, & Ford, 2003; van Veen & Carter, 2002). The Pe component is a slow positive deflection that follows the ERN and peaks at 300–500ms following incorrect responses (Falkenstein, Hohnsbein, Hoormann, & Blanke, 1991). The Pe has been associated with conscious cognitive processing of errors, error awareness, and initiation of post-error adjustment (Davies, Segalowitz, Dywan, & Pailing, 2001; Falkenstein et al., 2000; Nieuwenhuis, Ridderinkhof, Blom, Band, & Kok, 2001; Overbeek et al., 2005; Ridderinkhof, Ramautar, & Wijnen, 2009; van Veen & Carter, 2006), and its primary neural generator is believed to be the rostral ACC (Herrmann, Rommler, Ehlis, Heidrich, & Fallgatter, 2004). Studies have shown a significant relationship between the Pe amplitude and the post-error slowing (i.e., a prolonged response time following errors to ensure the overall performance accuracy (Nieuwenhuis et al., 2001; Overbeek, Nieuwenhuis, & Ridderinkhof, 2005).

Several studies have demonstrated that individuals with neurological disorders show atypical ERN and Pe amplitudes compared to neurotypical peers. For instance, the ERN amplitude has been shown to be smaller in adults with schizophrenia (Bates, Liddle, Kiehl, & Ngan, 2004; Kim et al., 2006; Morris, Heerey, Gold, & Holroyd, 2008; Morris, Yee, & Nuechterlein, 2006), traumatic brain injury (Larson, Kaufman, Kellison, Schmalfuss, & Perlstein, 2009), and depression (Ruchsow et al., 2006). Likewise, Pe amplitude has been shown to be smaller in children with attention-deficit hyperactivity disorders (Van De Voorde, Roeyers, & Wiersema, 2010) and schizophrenia (Rabella et al., 2016). On the other hand, a larger ERN has been reported in individuals with obsessive compulsive disorders (Carrasco et al., 2013) and anxiety disorders (Ladouceur, Dahl, Birmaher, Axelson, & Ryan, 2006). These findings suggest that the ERN and Pe are trait-like measures, and imply the potential utility of the ERN and Pe as biomarkers for screening individuals with neurological disorder or psychiatric conditions. As a result, there is a growing body of literature investigating the psychometric properties of the ERN and Pe components (Foti, Kotov, & Hajcak, 2013; Meyer, 2017; Riesel, Weinberg, Endrass, Meyer, & Hajcak, 2013).

Several studies have investigated the test-retest reliability of the ERN and Pe components in neurotypical adults and reported strong test-retest reliability of ERN and Pe amplitudes across two sessions ranging from 20 minutes to 2 years. Segalowitz et al. (2010) showed moderate to strong ERN test-retest reliability ($r = 0.87$, $p < .01$; ICC = 0.66, $p < .01$) in neurotypical adults with 20 minutes interval between the sessions. Olvet and Hijcak (2009) examined the reliability on the ERN amplitude collected from two visits with two weeks apart using the flanker task on 45 undergraduate students. The ERN amplitude (peak measure) demonstrated strong test-retest reliability ($r = 0.74$, $p < .001$; ICC = 0.70, $p < .001$), similarly, strong test-retest reliability was observed in the Pe amplitude (area measure; $r = 0.75$, $p < .001$; ICC = 0.75, $p < .001$). Moreover, Cassidy et al. (2012) reported that ERN and Pe amplitudes (peak measure) collected from two separate visits with a month apart demonstrated strong test-retest reliability (ERN: $r = 0.75$, $p < .001$; ICC = 0.74, $p < .001$; Pe: $r = 0.74$, $p < .001$; ICC = 0.71, $p < .001$) on 25 neurotypical adults using the flanker task. Similarly, Weinberg et al. (2011) also demonstrated moderate to strong test-retest reliability of ERN on two sessions separated 1.5 to 2 years in 26 undergraduate students ($r = 0.65$, $p < .01$; ICC = 0.62, $p < .01$). Despite consistent findings in adult literature, little research exists examining the test-retest reliability of the ERN and Pe components in children. We only found one study conducted by Meyer et al. (2014), and their findings demonstrated that the ERN has moderate to strong test-retest reliability in 44 children aged 8-13 year-old with testing completed 2 years apart ($r = 0.63$, $p < .01$). However, the ERN amplitude has been shown as a developmental phenomenon such that the amplitude gradually increased across the age range from 7 up to 18 years old (Davies et al., 2004). As a result, the developmental changes of the ERN amplitude across two years might possibly confound the test-retest reliability reported in the Meyer et al. (2014).

Moreover, when investigating the psychometric properties of the ERPs in children and adults, researchers need to consider other sources of variance in order to obtain robust measure of underlying cognitive processes (Segalowitz & Dywan, 2009). Gavin and Davies (2008) proposed a model to conceptualize five potential sources of variance that contribute to any psychophysiological measures (PM) such as ERPs, the model is presented as:

$$\text{PM} = \text{Effect}_{\text{STIMULUS}} + \text{Effect}_{\text{STATE}} + \text{Effect}_{\text{TRAIT}} + \text{Effect}_{\text{PM\_PROCESSING}} + \text{Measurement error}$$

Specifically, these variables are: (1) $\text{Effect}_{\text{STIMULUS}}$, the influence of the stimuli being presented (e.g., paradigm researchers used for testing); (2) $\text{Effect}_{\text{STATE}}$, the state of individuals at the time of testing (e.g., fatigue); (3) $\text{Effect}_{\text{TRAIT}}$, the trait(s) of individuals (e.g., age, gender, or cognitive capacities being investigated); (4) $\text{Effect}_{\text{PM\_PROCESSING,}}$ the signal processing parameters implemented to obtain the ERPs; and (5) measurement error, any unaccounted variance. When examining the test-retest reliability of ERPs, such as the ERN and Pe amplitudes, researchers strive to control for or minimize the variance associated with stimuli, state, trait, and data processing parameters. For instance, researchers may utilize the same testing paradigm, make sure participants were emotionally stable and physically comfortable during the time of testing, set age, and gender as covariates, and standardize the signal processes procedure across two sessions.

However, even with best intentions, most researchers do not control for the trial-to-trial variation in latency (i.e., latency jitter), embedded in the traditional ERP data analyses when examining the test-retest reliability in adults and children (Lin, Gavin, & Davies, 2015; Luck, 2014). The latency jitter, could in turn, be regarded as a source of unaccounted variance (measurement error), and confound the results. Specifically, by using the traditional data analysis approach, researchers assume that the ERP evoked by certain events (e.g., incorrect button presses) are invariant and time-locked over multiple event presentations (Luck, 2014). Thus, averaging ERPs across multiple segments reduces irrelevant background noise and retains the brain responses evoked by the events. By making this assumption researchers overlook the impact of the trial-to-trial latency jitter on the averaged ERP amplitude (DuPuis et al., 2014; Luck, 2014). Particularly, the considerable amount of latency jitter across segments can attenuate the amplitude of averaged ERP for a single individual (Luck, 2014; Lukie, Montazer-Hojat, & Holroyd, 2014; Unsal & Segalowitz, 1995; van Boxtel, 1998). Additionally, latency jitter has been shown to be larger in children compared to adults (Lin, Gavin, & Davies, 2015; Lukie et al., 2014; Segalowitz & Dywan, 2009). For example, Lukie et al. (2014) explored the developmental changes of an ERP component related to decision-making, namely the reward positivity, in children (8-13 years), adolescents (14-17 years), and young adults (18-23 years). In this article, the researchers' visual inspection of the averaged ERP of children revealed greater latency variability compared to adolescents and adults. Correction of the latency variability was made by re-aligning the times of the reward positivity of the averaged ERPs across individuals of each age group to create new grand averages. While the new grand-averaged ERP figures illustrated the effect of latency jitter on attenuating the grand-average of the ERP especially in children, this approach to the latency jitter correction did not alter the underlying statistical results (Lukie et al., 2014). However, correcting the averaged ERP by accounting for the trial-to-trial variation in latency of the component did directly affect the amplitude of the ERP component by accounting for measurement error within an individual. This in turn, may improve on the reliability of the measure as well.

Therefore, the purpose of the present study was to examine the test-retest reliability of the ERN and Pe amplitude before and after correcting for the trial-to-trial latency variability in neurotypical children aged 8-12 years and neurotypical adults. Specifically, we utilized a speeded, force-choice visual flanker task to elicit errors for each participant who completed 2 sessions, 1-3 weeks apart. The reasons that this study included children aged 8 to 12 years were because (1) based on the developmental trajectory, the ERN amplitude is relatively stable between ages 8 to 12 years (Lin, Gavin, & Davies, 2015); (2) children aged 8-12 years are able to follow the task instruction and maintain seated throughout the EEG sessions; and (3) currently Meyers et al. (2014) was the only study that examined the test-retest reliability in neurotypical children, and the age range of the sample reported in Meyers et al. (2014) was ages 8 to13 years. Thus, by using children aged 8 to 12 years allows the researchers of this study to compare their findings with the previous research. Our specific research questions were the following: (1) What is the test-retest reliability of the ERN and Pe amplitude in children and adults? According to Williams, Hultsch, Strauss, Hunter, and Tannock (2005), the inconsistency in response time is higher during early and middle childhood compared to adults. Such inconsistency in response time may reflect the inconsistency in the latency of the ERP components. Thus, we hypothesize that the test-retest reliability of the ERN and Pe amplitude will be stronger in adults compared to children; and (2) Does the implementation of latency jitter correction via the implementation of Woody Filter technique improve the reliability of the ERN and Pe amplitudes? We hypothesize that the reliability will be stronger after the latency jitter correction, due to correcting for the variations in the ERN and Pe components at single trial level. Additionally, we investigated the test-retest reliability of the mid-to-late ERP components elicited by the stimulus to evaluate the consistency of overall attention and adherence to the task across sessions as well as a procedural control for evaluating the validity of the reliability of the ERN and Pe.

Methods

Participants. A total of 241 participants - 74 neurotypical adults, aged 18-30 year-old, and 167 typically-developing children, aged 8-12 year-old, - were recruited from the university and local community through campus emails, flyers, research subject pool of the Psychology department, and word of mouth. All participants were screened for neurological disorders and use of psychopharmaceutical drugs (e.g., antidepressants) by parent- or self- report. Application of exclusion criteria resulted in a few participants being excluded from data analysis; 3 adults and 12 children due to parent- or self-reported diagnoses of brain injury, learning disability, reading disability, depression, or attention-deficit hyperactivity disorders. Additionally, 1 adult and 9 children were excluded due to failure to complete one or both sessions. Furthermore, participants who had an error rate greater than 30% (144 trials out of 480 trials) or less than 2.5% (12 trials out of 480 trials) on either one of the sessions were excluded (Davies, Segalowitz, & Gavin, 2004). This resulted in the loss of an additional 17 adults and 8 children for not making enough errors on either or both sessions, and 20 children due to making too many errors on either or both sessions. After imposing all of the exclusion criteria, data from 53 adults (*M* = 22.13 years, *SD* = 2.66) and 118 children (*M* = 10.19 years, *SD* = 1.47), were included for statistical analysis; see Table 2.1 for participants' age and sex distribution. Participants were compensated after each session with a choice of a cocoa mug, T-shirt, or cash, except for participants recruited from the Psychology department research subject pool who received course credits for participation. The study protocol was approved by the university institutional review board. Prior to study onset, all adult participants signed written consent forms, parents of child participants signed parental consent forms, and child participants signed assent forms. Detailed information regarding participant distribution by age and gender is presented in Table 2.1.

Table 2.1. Participant distribution by age and gender after applying screening procedures and performance exclusion criteria.

Age Groups	Gender		Total
	Males	Females	
8	12	19	31
9	13	13	26
10	11	12	23
11	11	8	19
12	7	12	19
Adults	21	32	53
Total	75	96	171

Procedure. Participants were invited to the laboratory for two visits that occurred 1 to 3 weeks apart. To control for any potential confounding factors, both visits were always held on the same day of the week and at the same time of the day. Each visit included 1.5 hours of EEG tasks followed by 1 hour of behavioral testing with a 10-15 minute break between the EEG and behavioral testing. For the EEG portion, two trained research assistants prepped the participant for EEG recordings. After a 3-minute artifact training period, participants performed 3 separate ERP paradigms in a quiet recording room though only the results from the speeded visual flanker task are reported in this study. The behavioral testing included tasks of attention and executive function (these are reported elsewhere) and were administered by a research assistant in another quiet testing area.

The ERP Paradigm. The speeded visual flanker task (Eriksen & Eriksen, 1974) was presented using E-prime software version 2.0 (Psychology Software Tools, Pittsburgh) in two blocks of 240 trials (480 trials total). In this task, participants were randomly presented four types of character arrays on the screen. Each character array consisted of combinations of the letters "H" or "S" organized as congruent arrays ("HHHHH" and "SSSSS", 80 trials each) and two incongruent arrays ("SSHSS" and "HHSHH", 160 trials each). Participants were instructed to press either the left button on a 4 button keypad using their left index finger if the middle letter was an H and to press the right button using their right index finger if the middle letter was an S. Participants were told that the letters would be presented quickly, and they were instructed to perform as accurately as possible. The stimulus duration was 250 ms and the initial inter-stimulus interval (ISI) was set at 1400 ms. Following each set of 30 trials, the E-prime program was designed to evaluate the overall error rate and adjust the ISI by increasing or decreasing it by 100 ms if the error rate was greater than 25% or fewer than 10%, respectively. A minimal ISI was set at 800 ms to allow adequate time for brain processing of the stimulus and response to resolve prior to the onset of the stimulus on the subsequent trial. Behavioral measurements of error rate, response time (RT) on correct and incorrect trials were calculated for each of the two sessions.

Electrophysiological recording. EEG data were collected from the scalp using either a 33 channel or 64 channel, Active Two BioSemi system (BioSemi, Inc., Amsterdam, the Netherlands) based on a modified 10-20 electrode placement system (American Electroencephalographic Society, 1994). Two electrodes, namely the common mode sense (CMS) and the driven right leg (DRL), were used to generate a common reference voltage (https://www.biosemi.com/faq/cms&drl.htm). Additional signals collected from the left and right earlobes were averaged and used for offline referencing. Two electrodes were placed at the supra- and infraorbital regions of the left eye to measure vertical eye movements, and two electrodes were placed at the left and right outer canthi to measure the horizontal eye movements. The sampling rate was 1024 Hz.

Electrophysiological data reduction. The EEG data were analyzed offline using Brain Vision Analyzer 2.0 software (www.brainproducts.com). The data were referenced to the averaged signals of bilateral earlobes and then filtered with a bandpass filter of 0.1–30 Hz with 24 dB/oct. The data were then segmented into response-locked and stimulus-locked segments.

For response-locked segments, the data on incorrect trials were segmented into 1400 ms time periods, which spanned from 600 ms before the incorrect response to 800 ms after the incorrect response. Segments with premature button responses (e.g., response times that were faster than 100 ms) were excluded from the analysis. Then, the segments were baseline-corrected based on the average voltage of -600 to 400 ms preceding the incorrect response (Davies, Segalowitz, & Gavin, 2004). Eye movement artifacts were removed via a regression approach based on the VEOG channel (Segalowitz, 1996) then baseline-corrected again using the period of -600 to 400 ms preceding the incorrect response. Segments containing voltage greater than ± 100 μV in the midline (e.g., Fz, FCz, Cz, Pz) and VEOG channels were rejected. The segments were then averaged using traditional ERP data analysis and also processed with the Woody filter (defined below) then subsequently averaged after adjusting for latency jitter. The windows for selecting the peaks for ERN and Pe are reported below in the Adaptive Woody Filter section.

For stimulus-locked segments, the data were segmented into 1200 ms time periods, which spanned from 200 ms before stimulus onset to 1000 ms after stimulus onset. Then, the segments were baseline-corrected based on the average voltage of -200 to 0 ms of stimulus onset. Eye movement artifacts were removed via a regression approach based on the vertical EOG (VEOG) channel (Segalowitz, 1996) then baseline-corrected again using the period of -200 to 0 ms of stimulus onset. Segments containing voltage greater than ± 100 μV in the midline (e.g., Fz, FCz, Cz, Pz) and VEOG channels were rejected. The data were then averaged to obtain an averaged stimulus-locked ERP for each participant. The stimulus-locked averaged ERPs obtained for each participant were scored using a customized peak-picking procedure programmed in MATLAB (Mathworks, Natick, MA). We used different time windows for measuring stimulus-locked ERPs in adults and children (Table 2.2), because two groups demonstrated different morphology of the ERP waveforms. The peaks were calculated based on the peak-to-peak measure. All of component were measured at the site FCz except for the P3 component was measured at Pz in addition to FCz. The topographic map that was used to determine the channel sites is presented in Figure 2.1).

Table 2.2. *Time windows for scoring stimulus-locked ERPs for adults and children*

	P1 window (ms)	N1 window (ms)	P2 window (ms)	N2 window (ms)	P3 window (ms)
Adults	0-100	70-150	110-240	170-350	320-575
Children	0-100	70-170	130-270	200-375	320-600

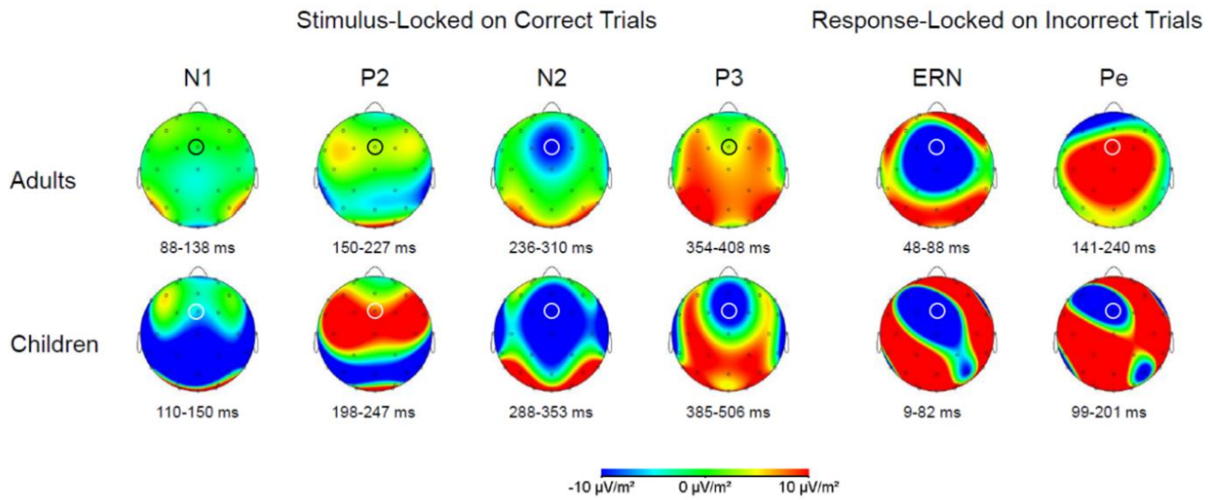


Figure 2.1. The topographic distribution on the stimulus-locked correct trials (N1, P2, N2, and P3 components) and response-locked incorrect trials (ERN and Pe components) for adults and children. The channel FCz is marked with a while/black circle. Note: the time windows used to determine the topographic distribution for each component were calculated based on the averaged mean latency across sessions +/- averaged mean standard deviation across sessions for each age group.

Adaptive Woody filter. After stimulus-locked ERP components were scored, the response-locked ERPs on the incorrect trials were processed using an adaptive Woody filter programmed in MATLAB (Woody, 1967). The individual MATLAB files containing all incorrect trial segments were passed to the Woody filter to adjust for the trial-to-trial variability in the latency of the ERN component. This template-matching process was performed for each individual and included the following steps. First, a template was obtained by averaging all incorrect trials segments using traditional ERP data analysis. Then, each segment was shifted one data point at a time (either to the left or right) to match the segment to the averaged ERN waveform template that was created in step one. After each data point shift, the program calculated a correlation coefficient between the shifted segment ERN waveform and the template ERN waveform for the template period defined as 0-300 data points after incorrect response (note: 1 data point = 0.98 ms). This expanded time frame allowed the program to match morphology of a complete ERN waveform and half of the Pe waveform to enhance the overall matching accuracy. The data point position for the maximum coefficient was obtained was taken as the amount of shift needed for each segment to maximally align with the template. To prevent the program from misidentifying the N2 component as the ERN component, we also set the N2 boundary for each segment (i.e., the amount of right shift allowed to be made; formula: [(response time on each single trial in ms) - (peak latency of the N2 on averaged ERP for each participant in ms - 30)] / Sampling Rate). We subtracted the value of 30 from the peak-latency of the averaged N2 amplitude because it allows us to take the half cycle of the N2 component into account, and gives us the most optimal estimation of the N2 boundary based on the visual inspection at the single trial level. Once the maximal coefficient was identified, the shifted segments were then averaged to obtain a "latency-adjusted" averaged ERP waveform for the ERN and Pe components. After the data were processed through the adaptive Woody filter, the data were subject to the customized peak-picking program for scoring ERN and Pe amplitudes at the FCz site. The window for measuring ERN component was 10 ms prior to 180ms after incorrect responses. The window for measuring Pe component was 120 – 450ms after incorrect responses. We used the same window for both children and adults. The peaks were calculated based on the peak-to-peak measure.

Statistical analyses. For overall behavioral outcomes, a three-way ANOVA was used to examine the effect of Group (Children and Adults), Session (Session 1 vs Session 2), and Trial

Type (Correct vs Incorrect) on response times. A two-way ANOVA was used to investigate the effect of the Group (Children and Adults) and Session (Session 1 vs Session 2) on error rate. Two three-way ANOVAs were used to examine the effect of Group (Children and Adults), Session (Session 1 vs Session 2), and Latency Jitter Correction (Before correction vs After correction) on ERN amplitude and Pe amplitude, respectively. Pairwise post hoc analyses were conducted using the pooled error term according to Kirk (1968). Pearson correlations and two types of Intraclass Correlations (ICCs), ICC consistency and absolute agreement, were used to assess the reliability of the ERN amplitude across two sessions for behavioral performances (e.g., response times and error rates), stimulus-locked ERPs (e.g., N1, P2, N2, P3), and response-locked ERPs (e.g., ERN, and Pe). Two online calculators were utilized to conduct the significance testing between correlation coefficients. Specifically, the correlation test for independent samples (http://www.quantpsy.org/corrtest/corrtest.htm) was used to compare the reliability of the ERPs obtaining across sessions between children and adults (Preacher, 2002); the correlation test for dependent correlations (http://www.quantpsy.org/corrtest/corrtest3.htm) was used to compare the reliability of the ERPs obtaining across sessions before and after latency jitter correlation for each group (Lee & Preacher, 2013).

Results

Descriptive results. The descriptive results are presented in Tables 2.3 and Figure 2.2.

Behavioral results on the Flanker task.

Response times (RTs). The three-way ANOVA demonstrated that the interaction between Group (Children vs Adults) x Session (Session 1 vs Session 2) x Trial Type (Correct vs Incorrect) on RTs was statistically significant, $F(1,169) = 9.223$, $p = .003$, $\eta_p^2 = 0.052$, as well as the main effect of the Group, $F(1,169) = 137.949$, $p < .001$, $\eta_p^2 = 0.449$. Post hoc analyses using the pooled error term according to Kirk (1968) demonstrated that the RTs in adults were significantly faster than the RTs in children under all conditions (Correct trials on Session 1: $q_{.05}$ = -17.75; Correct trials on Session 2: $q_{.05}$ = -18.06, Incorrect trials on Session 1: $q_{.05}$ = -9.87; Incorrect trials on Session 2: $q_{.05}$ = -12.38, critical $q_{.05}$ value = 2.8). For adults, the simple main effect of Trial Type was significant, $F(1, 52) = 136.431$, $p <.001$, $\eta_p^2 = 0.724$, post hoc analyses demonstrated that the RTs for correct trials were slower than the RTs for incorrect trials for both sessions for adults (Session 1: $q_{.05}$ = 3.44; Session 2: $q_{.05}$ = 3.12, critical $q_{.05}$ value = 2.8). For children, the two-way interaction between Session x Trial Type was statistically significant, $F(1, 117) = 31.223$, $p < .001$, $\eta_p^2 = 0.211$. Post hoc analyses showed that the RTs for incorrect trials were faster than the RTs for correct trials for both sessions in children (Session 1: $q_{.05}$ = 14.39; Session 2: $q_{.05}$ = 11.33, critical $q_{.05}$ value = 2.8). No differences in RTs were found for correct and incorrect trials across sessions, (Correct trials: $q_{.05}$ = 0.32; Incorrect trials: $q_{.05}$ = -2.74, critical $q_{.05}$ value = 2.8).

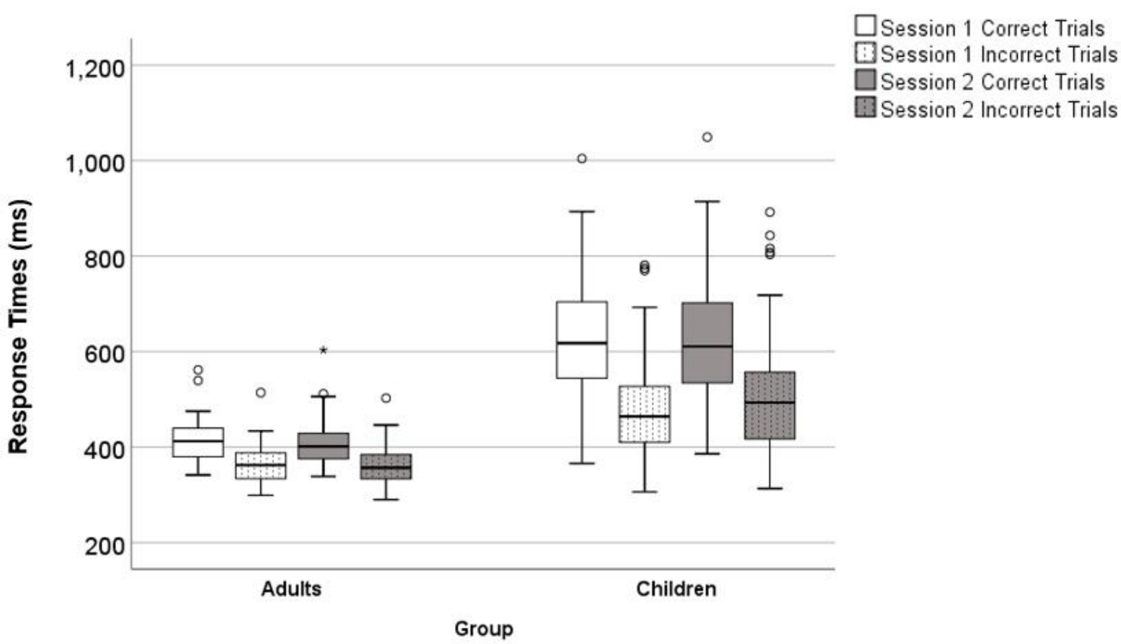


Figure 2.2. The boxplot of response times on correct and incorrect trials for Session 1 and Session 2 in children and adults

Table 2.3. Means, standard deviations of response times in correct and incorrect trials, and error rates for session 1 and session 2 in children and adults

	Sessions		**Reliability**		
	Session 1	Session 2	*r*	ICC (3,1) consistency	ICC (3,1) absolute agreement
Response times in correct trials (ms)					
Adults (n=53)	414.04 (45.98)	407.12 (47.94)	0.806***	0.806***	0.800***
Children					
All (n=118)	623.56 (115.51)	620.38 (117.19)	0.911***	0.910***	0.911***
8 yr (n=31)	720.39 (99.93)	699.24 (116.25)	0.919***	0.908***	0.894***
9 yr (n=26)	662.19 (89.51)	664.23 (105.25)	0.843**	0.833***	0.838***
10 yr (n=23)	586.72 (76.15)	589.64 (81.37)	0.789***	0.788***	0.794***
11 yr (n=19)	594.95 (71.21)	595.08 (73.97)	0.866***	0.865***	0.871***
12 yr (n=19)	485.90 (76.74)	494.23 (75.02)	0.802***	0.801***	0.805***
Response times in incorrect trials (ms)					
Adults (n=53)	362.43 (40.71)	360.28 (39.93)	0.771***	0.771***	0.773***
Children					
All (n=118)	478.93 (93.31)	506.47 (115.84)	0.829***	0.810***	0.784***
8 yr (n=31)	542.96 (95.70)	570.03 (137.17)	0.859***	0.806***	0.790***
9 yr (n=26)	504.95 (87.82)	530.41 (100.34)	0.894***	0.886***	0.859***
10 yr (n=23)	440.60 (77.01)	483.82 (87.87)	0.630***	0.624**	0.557**
11 yr (n=19)	474.10 (50.59)	491.56 (104.26)	0.617***	0.484*	0.487*
12 yr (n=19)	390.09 (50.45)	412.34 (59.51)	0.702***	0.693***	0.650***
Error rate (%)					
Adults (n=53)	9.07 (4.14)	7.70 (4.10)	0.736***	0.736***	0.701***
Children					
All (n=118)	14.79 (5.21)	10.73 (4.92)	0.624***	0.623***	0.473***
8 yr (n=31)	14.77 (5.77)	12.56 (6.16)	0.766***	0.765***	0.720***
9 yr (n=26)	17.12 (4.42)	11.89 (4.69)	0.630**	0.629***	0.382***
10 yr (n=23)	12.76 (4.85)	9.05 (3.90)	0.434*	0.423*	0.319*
11 yr (n=19)	14.74 (4.93)	9.77 (4.04)	0.564*	0.553**	0.349**
12 yr (n=19)	14.12 (5.20)	9.17 (3.70)	0.511*	0.483*	0.307*

Note: the data were presented as mean (standard deviation); yr = year-old; *** $p < .001$, ** $p < .01$, * $p < .05$

Error rates. The descriptive results are presented in Table 2.3 and Figure 2.3. The two way ANOVA showed that the interaction between Group x Session reached statistical significance, $F(1, 169) = 16.329$, $p < .001$, $\eta_p^2 = 0.088$. Post hoc analyses showed that children made significantly more errors than adults on both sessions (Session 1: $q_{.05} = 11.02$, Session 2:

$q_{.05}$ = 5.85, critical $q_{.05}$ value = 2.8). For children, their error rate on Session 1 was significantly greater than the error rate on Session 2 ($q_{.05}$ = 9.18, critical $q_{.05}$ value = 2.8). However, for adults, no significant differences were found on the error rate across sessions ($q_{.05}$ = 2.08, critical $q_{.05}$ value = 2.8).

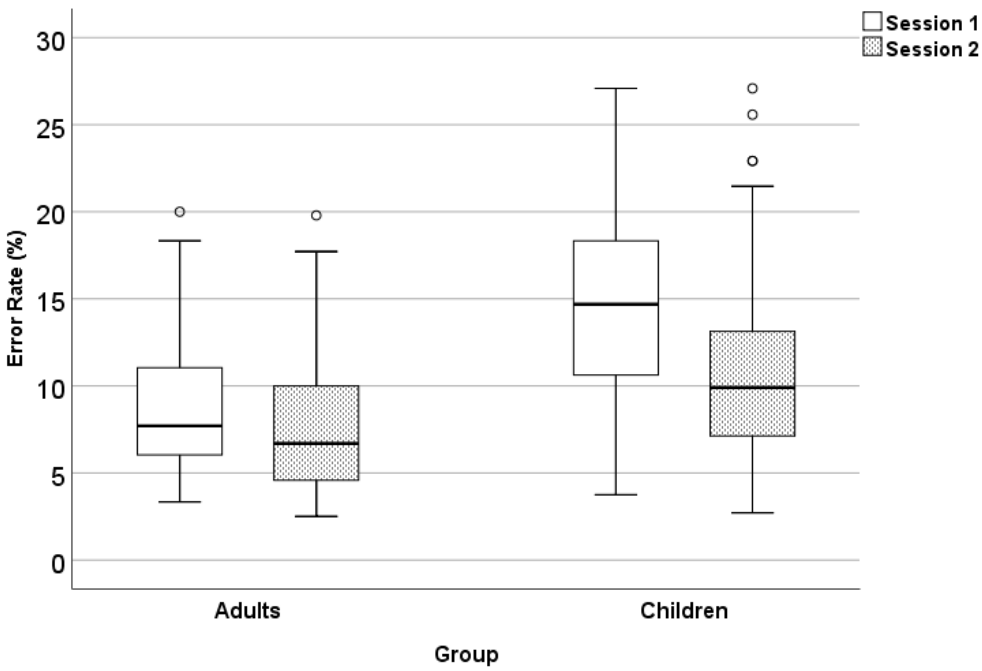


Figure 2.3. The boxplot of error rates for Session 1 and Session 2 in children and adults

Electrophysiological results.

Response-locked EPR components. The means and standard deviation of the ERN and Pe amplitudes and latencies before and after latency jitter correction for both sessions are reported in Tables 2.4 and 2.5. The ERPs are presented in Figure 2.4. Two three-way ANOVA examined the effect of Group (Children vs Adults) x Session (Session 1 vs Session 2) x the Latency Jitter Correction (Before vs After) on the ERN and Pe amplitudes, respectively. For the ERN amplitude, the three way interaction reached significant, $F(1,169) = 5.546$, $p = .02$, $\eta_p^2 = .032$, as well as the main effect of the Group, $F(1,169) = 23.395$, $p < .001$, $\eta_p^2 = .122$. The post hoc analyses demonstrated that for adults, the ERN amplitude was significantly larger after the latency jitter correction for both sessions (Session 1: $q_{.05}$ = 5.47, Session 2: $q_{.05}$ = 7.01, critical $q_{.05}$ value = 2.8). The ERN amplitude for the Session 2 was significantly larger than the Session 1 after the latency jitter correction but not before (Before latency jitter correction: $q_{.05}$ = 2.21, Session 2: $q_{.05}$ = 3.76, critical $q_{.05}$ value = 2.8). For children, the ERN amplitude was significantly larger after the latency jitter correction for both sessions (Session 1: $q_{.05}$ = 10.07, Session 2: $q_{.05}$ = 9.72, critical $q_{.05}$ value = 2.8). No difference was found between sessions either before or after latency jitter correction (Session 1: $q_{.05}$ = 0.74, Session 2: $q_{.05}$ = 0.39, critical $q_{.05}$ value = 2.8).

For the Pe amplitude, the interaction between Session x Group, $F(1,169) = 6.813$, $p = .01$, $\eta_p^2 = .039$, as well as the Latency Jitter Correction x Group reached significance, $F(1,169) = 56.472$, $p < .001$, $\eta_p^2 = .250$. The post-hoc analyses showed that for adults, the Pe amplitude was significantly larger after the latency jitter correction for both sessions (Session 1: $q_{.05}$ = -7.04, Session 2: $q_{.05}$ = -7.57, critical $q_{.05}$ value = 2.8). Similar to the findings on the ERN amplitude for adults, the Pe amplitude for the Session 2 was significantly larger than the Session 1 after the latency jitter correction but not before (Before latency jitter correction: $q_{.05}$ = -2.68, Session 2: $q_{.05}$ = -3.21, critical $q_{.05}$ value = 2.8). For children, the Pe amplitude was significantly larger after the latency jitter correction for both sessions (Session 1: $q_{.05}$ = -18.47, Session 2: $q_{.05}$ = -17.67, critical $q_{.05}$ value = 2.8). No difference was found between sessions either before or after latency jitter correction (Session 1: $q_{.05}$ = -1.70, Session 2: $q_{.05}$ = -0.90, critical $q_{.05}$ value = 2.8).

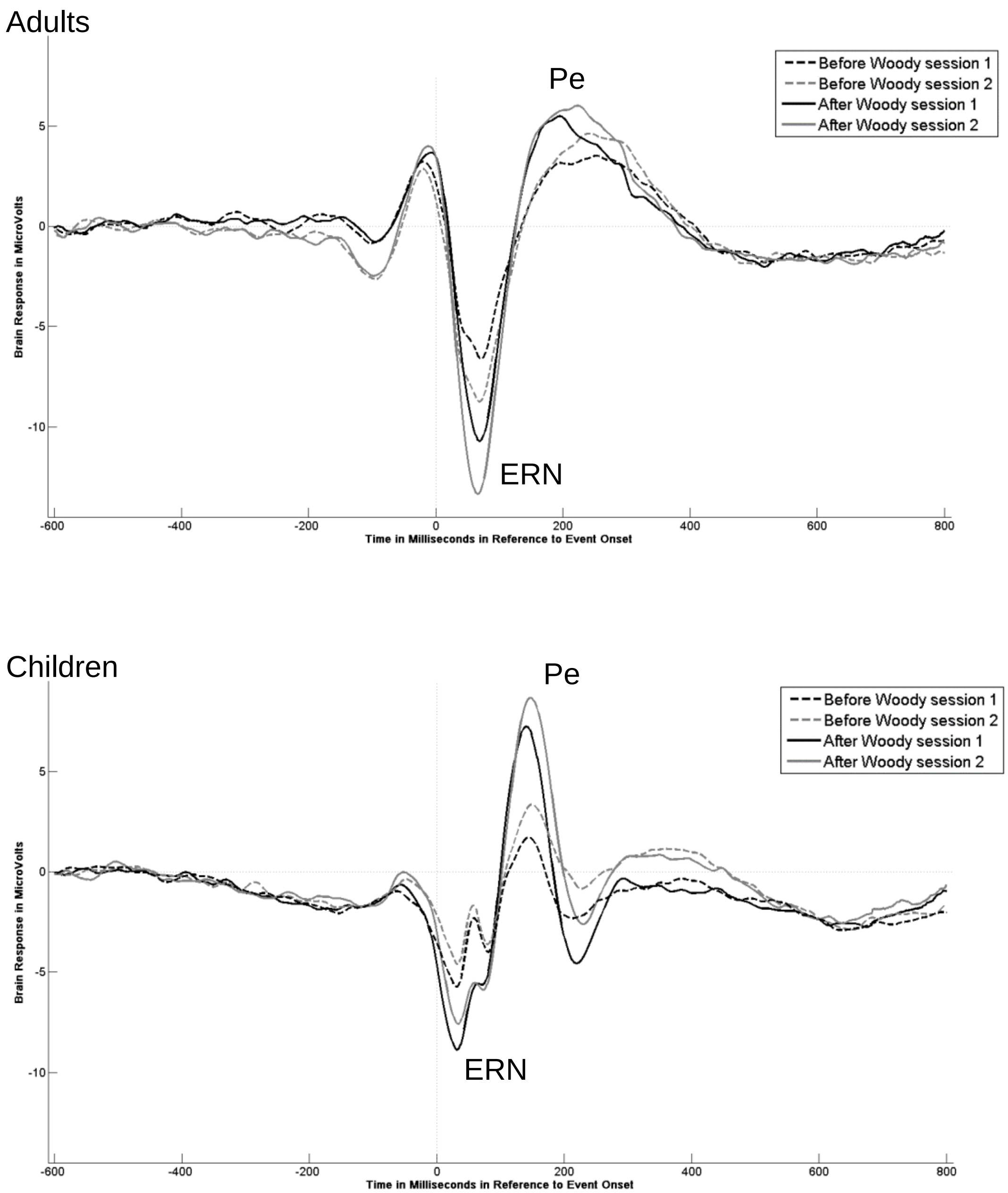


Figure 2.4. The ERN amplitude for Session 1 and Session 2 before and after latency jitter correction in adults and children

Table 2.4. Means, standard deviations, and reliability indices of response-locked ERP component (ERN and Pe) amplitudes and latencies (ms) in Session 1 and Session 2 for incorrect trials before Woody filter

	Before Jitter Correction				
	Sessions		Reliability		
	Session 1	Session 2	*r*	ICC (3,1) consistency	ICC (3,1) absolute agreement
ERN amplitude (μV)					
Adults (n=53)	-11.80 (5.77)	-14.00 (6.49)	.693***	.688***	.650***
Children (n=118)	-8.10 (4.63)	-8.60 (5.43)	.548***	.541***	.540***
8 yr (n=31)	-7.92 (4.61)	-7.68 (4.76)	.482**	.481*	.489**
9 yr (n=26)	-6.11 (3.33)	-5.37 (2.06)	.112	.101	.101
10 yr (n=23)	-8.38 (4.31)	-8.56 (4.71)	.489*	.487*	.498**
11 yr (n=19)	-8.23 (2.54)	-9.78 (4.98)	.561*	.454*	.433*
12 yr (n=19)	-10.67 (6.80)	-13.39 (7.31)	.578*	.576*	.548**
ERN latency (ms)					
Adults (n=53)	68.08 (19.14)	67.94 (21.07)	.330*	.328**	.332*
Children (n=118)	46.36 (39.78)	44.66 (33.12)	.159	.156*	.157*
8 yr (n=31)	46.12 (56.87)	30.68 (29.21)	.028	.023	.022
9 yr (n=26)	31.17 (29.95)	38.80 (32.58)	.129	.128	.129
10 yr (n=23)	38.13 (19.24)	43.82 (33.33)	.039	.034	.035
11 yr (n=19)	62.45 (39.56)	50.32 (27.53)	.222	.208	.204
12 yr (n=19)	61.42 (26.43)	70.83 (31.25)	.218	.215	.213
Pe amplitude (μV)					
Adults (n=53)	13.20 (6.15)	16.23 (7.04)	.749***	.743***	.675***
Children (n=118)	11.19 (4.90)	12.48 (6.18)	.619***	.603***	.589***
8 yr (n=31)	11.53 (4.23)	10.74 (4.91)	.589***	.582***	.581***
9 yr (n=26)	9.16 (2.67)	10.93 (3.87)	.294	.275	.247
10 yr (n=23)	10.61 (3.84)	12.13 (6.66)	.410	.355*	.351*
11 yr (n=19)	11.70 (5.48)	14.17 (7.40)	.787***	.752***	.710***
12 yr (n=19)	13.61 (7.45)	16.17 (7.20)	.716**	.716***	.684***
Pe latency (ms)					
Adults (n=53)	187.28 (49.39)	195.04 (50.62)	.521***	.521***	.519***
Children (n=118)	149.27 (61.31)	151.67 (42.42)	.187*	.175*	.176*
8 yr (n=31)	132.37 (64.44)	130.20 (41.65)	.109	.100	.103
9 yr (n=26)	123.99 (38.69)	153.02 (31.30)	.180	.176	.134
10 yr (n=23)	163.17 (75.44)	156.25 (49.86)	-.047	-.043	-.045
11 yr (n=19)	171.57 (60.19)	160.31 (46.38)	.579*	.560**	.561**
12 yr (n=19)	172.34 (45.86)	170.64 (31.21)	-.252	-.235	-.251

Note: the data were presented as mean (standard deviation); the amplitude was calculated based on the peak-to-peak approach; *** $p < .001$, ** $p < .01$, * $p < .05$

Table 2.5. Means, standard deviations, and reliability indices of response-locked ERP component amplitudes (ERN and Pe) and latencies (ms) in Session 1 and Session 2 for incorrect trials after Woody filter

	After Jitter Correction				
	Sessions		Reliability		
	Session 1	Session 2	*r*	ICC (3,1) consistency	ICC (3,1) absolute agreement
ERN amplitude (μV)					
Adults (n=53)	-17.25 (6.57)	-20.99 (8.62)	.747***	.720***	.646***
Children (n=118)	-14.83 (7.05)	-15.08 (7.01)	.567***	.567***	.568***
8 yr (n=31)	-15.07 (7.74)	-13.98 (7.36)	.725***	.724***	.723***
9 yr (n=26)	-12.17 (3.92)	-11.19 (4.02)	.080	.080	.080
10 yr (n=23)	-13.84 (5.13)	-15.52 (6.29)	.594**	.582**	.568**
11 yr (n=19)	-15.07 (5.61)	-15.33 (4.69)	.493*	.485*	.498*
12 yr (n=19)	-19.00 (10.40)	-21.43 (8.32)	.381	.372	.372
ERN latency (ms)					
Adults (n=53)	70.59 (20.40)	67.01 (20.58)	.289*	.289*	.288*
Children (n=118)	47.12 (41.34)	48.32 (34.07)	.201*	.197*	.198*
8 yr (n=31)	41.65 (60.12)	32.64 (34.19)	.121	.104	.105
9 yr (n=26)	30.16 (22.30)	40.72 (33.42)	-.139	-.129	-.125
10 yr (n=23)	43.44 (23.95)	52.10 (30.49)	.052	.05	.05
11 yr (n=19)	65.12 (44.57)	51.55 (25.19)	.470*	.403*	.387*
12 yr (n=19)	65.69 (22.73)	76.53 (29.99)	.093	.090	.087
Pe amplitude (μV)					
Adults (n=53)	21.15 (7.03)	24.78 (7.44)	.743***	.742***	.662***
Children (n=118)	25.18 (8.40)	25.86 (9.10)	.650***	.647***	.647***
8 yr (n=31)	26.96 (8.75)	25.25 (9.04)	.693***	.693***	.687***
9 yr (n=26)	22.75 (4.57)	24.44 (6.56)	.534**	.501**	.489**
10 yr (n=23)	23.19 (8.45)	24.79 (10.36)	.530**	.519**	.522**
11 yr (n=19)	26.36 (8.23)	26.57 (8.89)	.707**	.705***	.716***
12 yr (n=19)	26.82 (11.12)	29.39 (10.63)	.742***	.742***	.731***
Pe latency (ms)					
Adults (n=53)	179.36 (43.10)	186.93 (45.84)	.526***	.525***	.522***
Children (n=118)	147.40 (48.26)	148.87 (39.54)	.183*	.179*	.180*
8 yr (n=31)	135.81 (58.96)	131.55 (38.01)	-.004	-.004	-.004
9 yr (n=26)	128.49 (30.52)	151.22 (29.80)	.272	.272	.217
10 yr (n=23)	154.81 (48.76)	148.40 (43.39)	-.005	-.005	-.005
11 yr (n=19)	171.26 (56.06)	154.91 (47.04)	.518*	.510*	.498*
12 yr (n=19)	159.39 (20.81)	168.43 (32.27)	-.132	-.120	-.121

Note: the data were presented as mean (standard deviation); the amplitude was calculated based on the peak-to-peak approach; *** $p < .001$, ** $p < .01$, * $p < .05$

Test-retest reliability results.

The ERN and Pe amplitudes before the latency jitter correction. To answer our first research question, the results on the Pearson correlation analyses and the ICC analyses showed that for adults, the reliability of the ERN and Pe amplitudes were .693 to .749, respectively. For children, the reliability of the ERN and Pe amplitudes were .548 and .619, respectively (Tables 2.4 and 2.5, Figure 2.5). In terms of the group differences on the reliability measures, the findings showed that before the latency jitter correction, the reliability of the ERN amplitude in adults was not significantly higher than children (ERN: z = -1.41, p = .08 one tail).

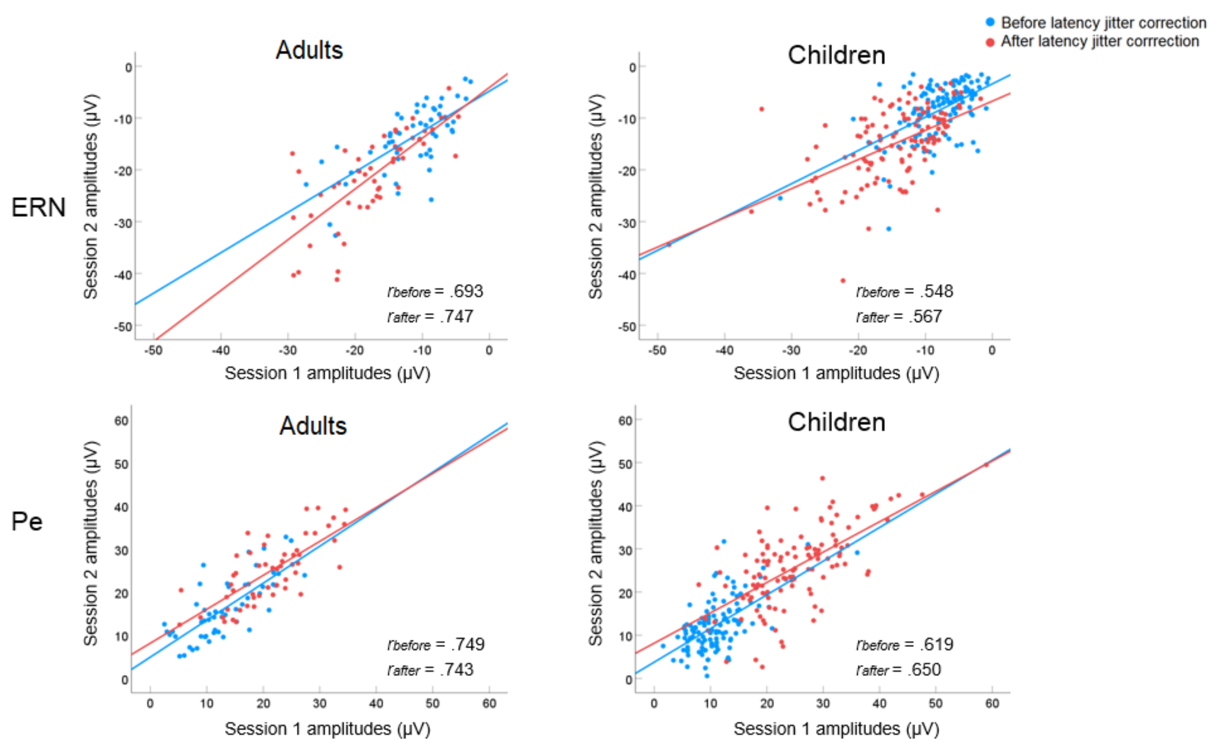


Figure 2.5. The scatter plots depicting reliability of the ERN and Pe amplitudes between Session 1 and Session 2 before and after latency jitter correction in adults and children (Note: r_{before} represents the correlation coefficient between Session 1 and Session 2 before the latency jitter correction; r_{after} represents the correlation coefficient between Session 1 and Session 2 after the latency jitter correction)

The ERN and Pe amplitudes after the latency jitter correction. To answer our second research question, we conducted the Pearson correlation analyses and the ICC analyses to examine the test-retest reliability on the ERN and Pe amplitudes after the latency jitter correction. The results showed that for adults, the reliability of the ERN and Pe amplitudes were .747 and .743, respectively. For children, the reliability of the ERN and Pe amplitudes were .567 and .650, respectively (Tables 2.4 and 2.5, Figure 2.5).

Contrary to what we hypothesized, the latency jitter correction did not significantly improve the reliability of the ERN and Pe amplitude in either adults and children (differences on the reliability of the ERN amplitude before and after Woody filter adjustment: adults: z = -1.065, p = .14, one tail, children: z = -0.307, p = .38, one tail; differences on the reliability of the Pe amplitude before and after Woody filter adjustment: adults: z = 0.129, p = .44, one tail, children: z = -0.6, p = .27, one tail). To examine the reliability in more detail, we broke down the child group by age and investigate the reliability of the ERN and Pe amplitude before and after latency jitter correction for each age group (Tables 2.4 and 2.5). The findings showed that for 8 year-old, and 10 year-old groups, the reliability of the ERN amplitude increased after the Woody filter adjustment, and these increments were statistically significant for 8 year-old (z = -1.981, p = .02, one tail) but not for 10 year-old (10 year-old: z = -0.61, p = .27, one tail). However, for groups of 9 year-old, 11 year-old, and 12 year-old, the ERN reliability decreased after the Woody filter, and the decrements were statistically significant for 12 year-old (12 year-old: z = 1.91, p = 0.03, one tail) but not for 9 and 11 year-old (9 year-old: z = 0.12, p = .45, one tail; 11 year-old: z = 0.29, p = .38, one tail).

In terms of the Pe, the reliability of the Pe amplitude increased after the Woody filter adjustment for 8 year-old, 9 year-old, 10 year-old, 12 year-old, yet none of these increments were statistically significant (8 year-old: z = -0.852, p = .20, one tail; 9 year-old: z = -1.23, p = .11, one tail; 10 year-old: z = -0.90, p = .19, one tail; 12 year-old: z = -0.35, p = .36, one tail). The reliability of the Pe amplitude decreased after the Woody filter adjustment for adults and 11 year-old, and the decrements were not statistically significant (11 year-old: z = 0.64, p = .26, one tail).

In terms of the group differences on the reliability measures, after the latency jitter correction, adults demonstrated significantly higher reliability of ERN amplitudes than children (z = -1.91, p = .028, one tail), but there were no significant differences before latency jitter. The reliability of Pe amplitude for adults was not significantly higher than children either before or after latency jitter correction (before: Pe: z = -1.46, p = .07, one tail; after: z = 1.07, p = .14, one tail; see Figures 2.6).

Test-retest reliability on stimulus-locked ERP components. We analyzed the reliability on the stimulus-locked ERPs (N1, P2, N2, P3) on correct and incorrect trials for contrastive purposes. The descriptive results and reliability indices of stimulus-locked ERPs of correct trials in Session 1 and Session 2 are reported in Tables 2.6 and 2.7. The ERPs are presented in Figure 2.6. Generally, the amplitude of stimulus-locked ERP components (N1, P2, N2, P3) were strongly correlated among sessions for correct trials for adults and children, (adults: r_{min} = .780, r_{max} = .868; children: r_{min} =.707, r_{max} = .929), but weaker for incorrect trials, (adults: r_{min} = .318, r_{max} = .739; children: r_{min} = .368, r_{max} = .749), especially for N1 amplitude.

Table 2.6. Means, standard deviations, and reliability indices of stimulus-locked ERP component amplitudes (N2, P2, N2, P3) and latencies (ms) in Session 1 and Session 2 for correct trials

	Correct Trials				
	Sessions		Reliability		
	Session 1	Session 2	*r*	ICC (3,1) consistency	ICC (3,1) absolute agreement
Adults					
N1 amplitude (μV)	-3.40 (1.74)	-3.30 (1.57)	.780***	.777***	.780***
N1 latency (ms)	111.90 (24.69)	114.15 (25.09)	.756***	.755***	.756***
P2 amplitude (μV)	7.03 (3.20)	6.58 (3.15)	.868***	.868***	.862***
P2 latency (ms)	190.52 (35.58)	186.27 (39.68)	.479***	.476***	.478***
N2 amplitude (μV)	-7.53 (2.94)	-7.69 (2.99)	.785***	.785***	.787***
N2 latency (ms)	276.02 (37.16)	269.24 (35.73)	.877***	.876***	.863***
P3 amplitude (μV)	11.40 (3.84)	12.69 (3.60)	.824***	.822***	.778***
P3 latency (ms)	381.73 (27.15)	380.69 (27.17)	.677***	.677***	.681***
P3 amplitude (μV) @Pz	11.71 (4.68)	12.52 (5.23)	.849***	.844***	.835***
P3 latency (ms) @Pz	382.43 (35.44)	371.65 (29.18)	.658***	.645***	.616***
Children					
N1 amplitude (μV)	-8.14 (2.85)	-8.67 (2.92)	.829***	.829***	.817***
N1 latency (ms)	127.97 (20.23)	132.18 (19.75)	.857***	.857***	.839***
P2 amplitude (μV)	16.51 (5.78)	15.02 (5.66)	.929***	.928***	.899***
P2 latency (ms)	223.15 (26.39)	221.89 (23.13)	.730***	.723***	.724***
N2 amplitude (μV)	-16.29 (6.89)	-14.82 (6.11)	.891***	.884***	.863***
N2 latency (ms)	321.98 (32.01)	317.94 (32.07)	.753***	.753***	.749***
P3 amplitude (μV)	11.84 (4.56)	12.50 (4.46)	.720***	.720***	.714***
P3 latency (ms)	447.30 (61.63)	442.99 (59.45)	.629***	.628***	.629***
P3 amplitude (μV) @Pz	16.50 (7.69)	15.71 (7.20)	.707***	.705***	.704***
P3 latency (ms) @Pz	421.79 (73.62)	407.62 (64.43)	.551***	.546***	.537***

Note: the data were presented as mean (standard deviation); the amplitude was calculated based on the peak-to-peak approach; *** $p < .001$, ** $p < .01$, * $p < .05$

Table 2.7. Means, standard deviations, and reliability indices of stimulus-locked ERP component amplitudes (N2, P2, N2, P3) and latencies (ms) in Session 1 and Session 2 for incorrect trials

	Incorrect Trials				
	Sessions		Reliability		
	Session 1	Session 2	*r*	ICC (3,1) consistency	ICC (3,1) absolute agreement
Adults					
N1 amplitude (μV)	-4.99 (2.69)	-5.06 (3.00)	.318*	.317*	.321*
N1 latency (ms)	114.39 (26.24)	114.29 (27.68)	.251	.250*	.254*
P2 amplitude (μV)	7.98 (3.13)	7.44 (3.71)	.630***	.621***	.618***
P2 latency (ms)	190.85 (36.48)	183.59 (38.20)	.400**	.399**	.396**
N2 amplitude (μV)	-9.31 (3.64)	-9.43 (4.13)	.739***	.733***	.737***
N2 latency (ms)	281.14 (34.57)	272.15 (37.22)	.745***	.743***	.723***
P3 amplitude (μV)	10.77 (3.91)	11.75 (4.83)	.508***	.496***	.489***
P3 latency (ms)	375.48 (58.57)	378.08 (56.24)	.575***	.574***	.578***
P3 amplitude (μV) @Pz	10.34 (4.71)	11.35 (5.22)	.587***	.584***	.577***
P3 latency (ms) @Pz	373.08 (56.72)	368.00 (55.42)	.690***	.690***	.691***
Children					
N1 amplitude (μV)	-9.87 (4.10)	-10.93 (4.67)	.368***	.365***	.357***
N1 latency (ms)	127.76 (21.46)	129.43 (23.53)	.586***	.583***	.584***
P2 amplitude (μV)	17.15 (6.57)	16.11 (6.20)	.640***	.639***	.632***
P2 latency (ms)	220.80 (28.01)	219.32 (25.99)	.575***	.574***	.575***
N2 amplitude (μV)	-17.29 (7.67)	-16.46 (6.65)	.749***	.741***	.738***
N2 latency (ms)	319.93 (32.04)	315.31 (42.21)	.396***	.381***	.380***
P3 amplitude (μV)	11.85 (5.20)	13.83 (5.51)	.580***	.579***	.544***
P3 latency (ms)	439.01 (65.28)	428.60 (58.62)	.414***	.411***	.408***
P3 amplitude (μV) @Pz	15.97 (7.12)	16.76 (8.46)	.623***	.614***	.612***
P3 latency (ms) @Pz	426.84 (72.90)	404.01 (76.52)	.347***	.347***	.333***

Note: the data were presented as mean (standard deviation); the amplitude was calculated based on the peak-to-peak approach; *** $p < .001$, ** $p < .01$, * $p < .05$

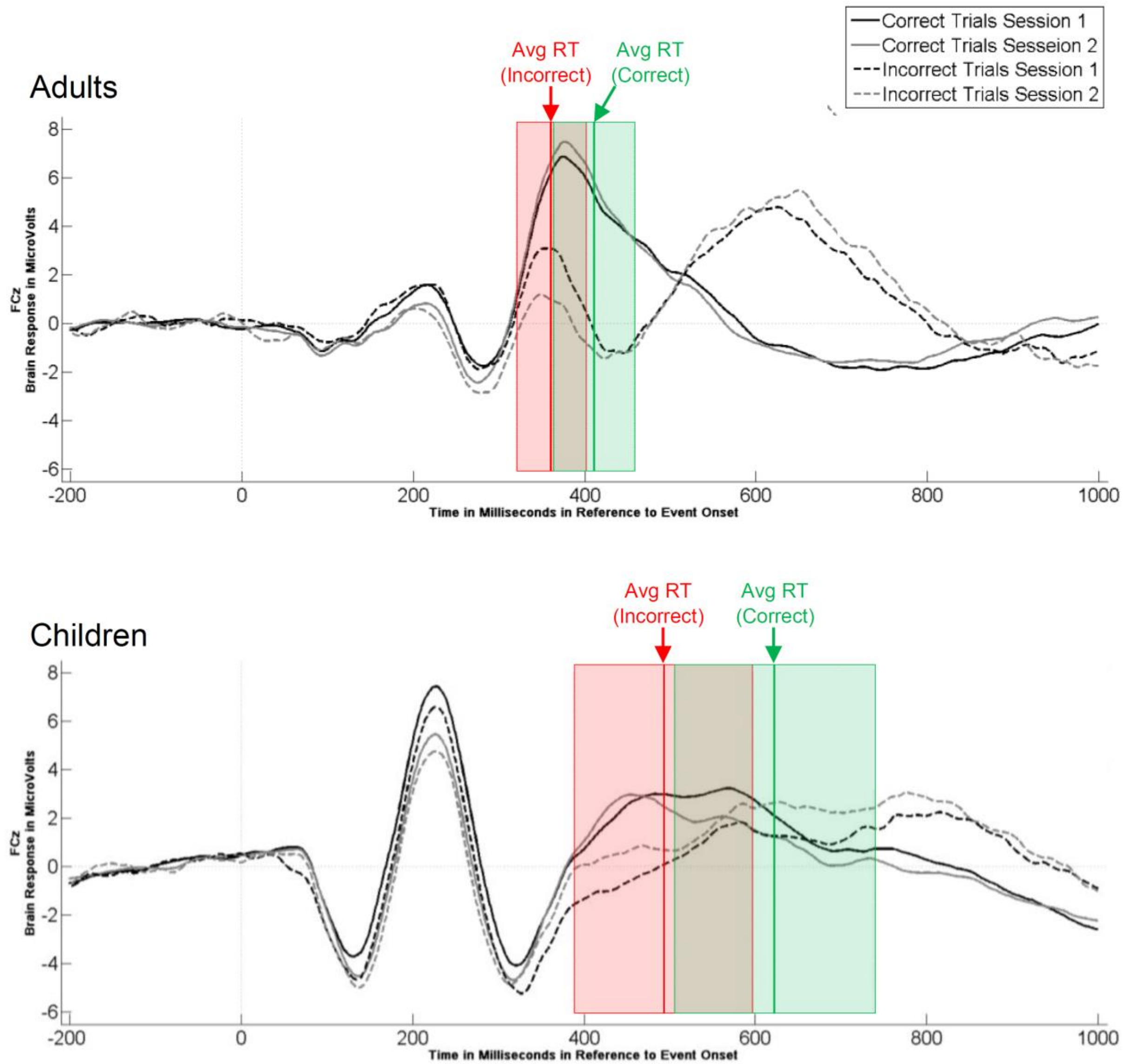


Figure 2.6. Stimulus-locked ERPs for Session 1 and Session 2 for correct and incorrect trials in adults and children; note: dotted vertical red line represents the average reaction time on incorrect trials with the red colored box indicating +/- one standard deviation from this mean; dotted vertical green line represents the average reaction time on correct trials with the green colored box indicating +/- one standard deviation.

Discussion

The present study examined the test-retest reliability of the ERN and Pe amplitudes before and after adjusting for the latency jitter in 53 neurotypical adults and 118 typically-developing children. For contrastive information, we also investigated the test-retest reliability of the mid-to-late ERP components elicited by the stimulus onset (i.e., stimulus locked). We will discuss the results in terms of three aspects: the test-retest reliability of response-locked ERPs (ERN and Pe), the reliability of the stimulus-locked ERPs (N1, P2, N2, P3) on correct and incorrect trials, and the role of the latency jitter in the grand-averaged ERN and Pe amplitudes in adults and children.

The test-retest reliability of the ERN and Pe in children and adults. To our knowledge, this is the first study to examine the test-retest reliability of the ERN and Pe amplitudes over a short period (1- to 3-week) in typically-developing children. We found moderate to strong reliability of the ERN and Pe amplitudes across sessions in typically-developing children aged 8-12 year-old (reliability of the ERN amplitude before latency jitter correction: $r = 0.548$, after latency jitter correction: $r = 0.567$; reliability of the Pe amplitude before latency jitter correction: $r = 0.619$, after latency jitter correction: $r = 0.650$). Previous studies on the test-retest reliability of the ERN amplitude have shown a general decreasing trend in the reliability of ERN amplitude with increasing interval between sessions. However, the reliability of the ERN amplitude found in our study is slightly lower even with a shorter interval compared to the reliability of the ERN amplitude ($r = 0.63$) measured with a 2-year interval in children and adolescents aged 8-13 year-old (Meyer et al., 2014). There are several possible explanations for the discrepancy between the r value in the current study and the previous literature. First, our study required two visits with 1-3 weeks interval, participants might have felt nervous at the first visit as the laboratory setting, equipment, procedures, and research assistants were novel to them. However, participants might have felt less nervous at the second visit. Whereas, in the Meyer et al. (2014) study that had a 2-year interval between sessions, both sessions would more likely be a novel experience for the young children and the state effects may be more similar between the 2-year interval sessions compared to a 1 to 3 week interval as in this present study (Gavin & Davies, 2008). The differences in the state across sessions may contribute to the unaccounted variance in the ERN and Pe measures which could lead to a lower test-retest reliability than previous studies. Specifically, we considered that the state effect is associated with anxiety, fatigue, attention, motivation, learning effect, practice effect or other transient factors that may influence the ERP components across sessions (Gavin & Davies, 2008; Hagemann & Naumann, 2009; Tsai, Young, Hsieh, & Lee, 2005). Also in the shorter 1 to 3 week period in this current study, practice and learning strategies could also contribute to variable neural responses in the two sessions among children. Second, this study utilized a different study design compared to Meyer et al. 2014. For example, the sample sizes (118 vs 44), paradigm (letter version vs arrowhead version), ISIs (1400ms +/- adjusted for error rate vs variable rate of 2300 – 2800 ms) and even task instructions in this study were different compared to Meyer et al., 2014, and these differences increase the difficulties for comparing the results.

Consistent with previous literature, our findings with neurotypical adults demonstrated moderate to strong test-retest reliability of the ERN and Pe amplitudes (r_{min} = .693 to r_{max} =.749; Cassidy et al., 2012; Olvet & Hijcak, 2009; Segalowitz et al., 2010; Weinberg et al., 2011). Taken together, the findings suggest that the ERN and Pe amplitudes are reliable measures across time for both adults and children. However, for clinical diagnostic purposes the reliability measures exceeding .80 are more desirable (Nunnally, 1978, p. 245). Given that studies are not yet demonstrating this level, there are still other sources of uncontrolled variance (e.g., state effect) that need to be considered if researchers are to establish ERN and Pe amplitudes as biomarkers for neurological disorders. For example, studies have shown that the ERN component is influenced by state effects such as fatigue (Lorist, Boksem, & Ridderinkhof, 2005), or sleep deprivation (Scheffers et al., 1999), such that people with sleep deprivation have a smaller ERN and Pe amplitudes (Tsai, Young, Hsieh, & Lee, 2005). The majority of the adult participants in our sample are graduate or undergraduate students who were evaluated during the school year. Although we scheduled their visits on the same time of the day during the same day of the week, we did not take the level of the sleep deprivation into the consideration (e.g., if the session was scheduled on the same day when the participant had mid-term or final tests, he/she might have stayed up late the previous night). Moreover, the potential session effect (e.g., practice effect) should also need to be taken into consideration when measuring the test-retest reliability in adults and children.

Lastly, despite that we have obtained strong test-retest reliability of the stimulus-locked ERPs on the correct trials, we acknowledge that the measurement error produced during the procedure of cap preparation could impact the test-retest reliability of the ERP components especially for the ERN and Pe amplitudes. In this study, while the research assistants who ran the EEG experiments were well-trained and that the sessions were conducted under supervision of senior researchers, there could be several potential sources for the measurement error. For example, according to the protocol, researcher assistants always used the measuring tape to make sure the EEG cap was centered for each participant, however, even with the best intention, the cap may not be placed at the exactly same location on the scalp across sessions for the same participant. Similarly, the placement of the external sensors on the faces and the earlobes may not be exactly on the same location across sessions. While the impact of the random measurement error on measuring the ERP components were unclear, such a random measurement error needs to be taken into account when measuring the ERN and Pe amplitudes in children and adults and interpretation of the reliability results of this study.

Reliability of the stimulus-locked ERPs. We analyzed the reliability on the stimulus-locked ERPs (N1, P2, N2, P3) on correct and incorrect trials for contrastive purposes. As expected, the test-retest reliability is moderate to strong on the stimulus-locked ERPs for correct trials (adults: r_{min} = .780, r_{max} = .868; children: r_{min} = .707, r_{max} = .929), but relatively weak for the incorrect trials (adults: r_{min} = .318, r_{max} = .739; children: r_{min} = .368, r_{max} = .749). We will discuss the findings in terms of two aspects. First, the moderate to high test-retest reliability on the stimulus-locked ERPs especially for N1 on correct trials for both adults (r_{N1} = 0.78) and children (r_{N1} = 0.82) speaks to our task validity such that participants generally attended to the stimuli in the task across sessions. Specifically, the N1 component has been associated with selective attention and the early stimulus discrimination process and is larger for attended stimuli compared to ignored stimuli (Girelli, 1998; Lackner, Santesso, Dywan, Wade, & Segalowitz, 2013; Luck & Polich, 1993). Had participants not attended to the task stimuli consistently across the sessions, we would not have obtained the high reliability on the N1 amplitude. The high test-retest reliability on the stimulus-locked ERPs implies that the relatively less strong test-retest reliability on the response-locked ERPs (i.e., ERN and Pe) is not due to a lack of attention to the task in general. It could be that the response-locked ERPs involved with more endogenous cognitive processes, such as error detection and could have been influenced by motor responses such as button presses (Ullsperger & Von Cramon, 2001). Second, the reliability on the stimulus-locked ERPs on the incorrect trials is lower compared to that of the correct trials. These results indicate a lapse in the attention to the stimulus—which, in turn, led to a failure to inhibit the prepotent motor response (i.e., button press) and an insufficient processing of the stimuli, and subsequently, resulting in an incorrect button presses (van Veen and Carter et al., 2006).

Latency jitter as a trait-like measure. Contrary to our hypothesis, our findings demonstrated that the test-retest reliability of the ERN and Pe amplitudes were not significantly improved after adjusting for the latency jitter in adults and all ages of children. One possible explanation could be that the latency jitter may be a trait-like variable and consistently occurred across the two sessions. As a result, removing the latency jitter across two sessions did not improve the test-retest reliability of the ERN and Pe amplitudes. Several studies support the notion that the latency jitter is a trait-like measure whereby individuals with certain traits have greater amount of latency jitter. For instance, the latency jitter has been shown to be greater in people with schizophrenia compared to their neurotypical peers (Young et al., 2001) and in older adults compared to young adults (McDowell, Kerick, Santa Maria, & Hatfield, 2003). Moreover, in a study that employed a three-stimuli visual oddball task on young to elderly adults aged 20-89 year-old, latency jitter of the P3a component was shown to be correlated with age (r = 0.28, p < .002; Fjell, Rosquist, & Walhovd, 2009). Additionally, latency jitter may be an indicator of processing efficiency (i.e., the efficiency of the neural transduction) and has been associated with other trait measures such as working memory (Shucard, Covey, & Shucard, 2016) and shifting/inhibition (Fjell et al., 2009). It is unlikely that the neural systems or cognitive functions underwent drastic changes during our experimental period (i.e., 1-3 weeks), as a result, it is understandable that adjusting for the latency jitter did not improve the reliability of the ERN and Pe amplitude. Furthermore, previous studies have suggested that the intra-individual variability in response time on behavioral tasks as a trait-like measure (Hultsch, Hunter, MacDonald, &

Strauss, 2005). While the latency jitter correction did not improve the reliability of ERN and Pe amplitudes in children and adults as a group, it is worth noting that when we examined the reliability of these ERP components for each age group in children, the reliability of the ERN amplitude significantly improved for age group 8 and significantly decreased for age group 12 after adjusting the latency jitter. Since the groups of 8 year-olds and 12 year-olds are the lower and upper bound of participant's age range in this study, the findings suggest that the latency jitter could reflect different neural processing characteristics for younger or older children. Future studies needed to investigate the differential effect of correcting for latency jitter across development including younger and older age groups.

Conclusion

We found moderate to strong test-retest reliability of the ERN and Pe amplitudes in neurotypical adults and moderate test-retest reliability of the ERN and Pe amplitudes in typically-developing children aged 8-13 year-old with a 1 to 3 week interval between the sessions. However, contrary to our hypothesis, the test-retest reliability did not improve after the latency jitter correction, suggesting that latency jitter may not markedly contribute to variance across sessions. Additionally, the stimulus-locked ERPs on correct trials demonstrated strong reliability in children and adults, ruling out the possibilities that variant attention levels on the task stimuli across sessions caused a lower reliability of the ERN and Pe amplitudes compared to previous studies. Future studies could explore other factors such as controlling for state effects that may enhance the psychometric properties of the ERN and Pe amplitudes in children and adults.

CHAPTER 3: MODELING NEURAL PROCESSES OF EVENT-RELATED POTENTIALS (ERPS) FROM STIMULUS TO RESPONSE IN TYPICALLY-DEVELOPING CHILDREN

Introduction

This study incorporates the connectionist model framework and structural equation modeling (SEM) statistical analyses to understand brain-and-behavior relationships in typically-developing children. The connectionist model framework utilizes a series of computational modeling approaches to construct the connection among multiple units, which can vary from individual neurons to a set of abstract subdomains of cognitive processes (Houghton, 2005). The framework provides a wide range of applications to understand the neural networks underlying behavioral performances, and has influenced areas such as psychology, behavioral, cognitive, and language sciences (Houghton, 2005). In this study, we consider information processing as a system encompassing multiple stages (i.e., units) that are activated in sequential order to process stimulus and produce behavioral output (Houghton, 2005). For example, to successfully perform a simple two-choice computer-based task such as the Flanker task (Eriksen & Eriksen, 1974), the brain goes through several processing stages which includes attending to the stimuli, registering the sensory information, discriminating sensory-based characteristics, selecting the most optimal behavioral output, and evaluating the outcome (Brion, Pitel, & D'Hondt, 2016) .

Neurologically, these processing stages can be indicated by scalp-recorded event-related potentials (ERPs), a series of voltage deflections obtained from electroencephalography (EEG) that are evoked by sensory, cognitive, or motor events (Luck, 2014). Specifically, the N1 component is a negative voltage deflection which peaks at around 100–150 ms at the frontal scalp site after presentation of stimuli, and it has been associated with selective attention and sensory-based processes (Lackner, Santesso, Dywan, Wade, & Segalowitz, 2013; Luck & Girelli, 1998; Polich, 1993). The N1 component is followed by the P2 component, a positive voltage deflection peaking at around 150-250 ms at the frontal-central scalp site after presentation of stimuli. The P2 component has been associated with early processes of sensory stimuli or sensory registration processes (Davies & Gavin, 2007; Polich, 1993). The P2 component is followed by the N2 component, a negative voltage deflection peaking around 200-350 ms after presentation of stimuli, and it has been related to target discrimination, executive control, or impulse inhibition (Luck, 2014; Polich, 1993). The N2 component is followed by the P3 component, a positive deflection peaking around 300-500 ms after stimulus presentation and has been associated with cognitive evaluation processes such as attention allocation, or memory updating (Luck, 2014; Polich, 1993).

When incorrect responses are made (e.g., pressing the left button instead of the appropriate right hand button in a two-choice speeded task), two ERP components, namely error-related negativity (ERN) and error positivity (Pe), are evoked. These two components have been associated with error detection and performance monitoring (Coles et al., 2001; Falkenstein, Hohnsbein, Hoormann, & Blanke, 1991; Gehring & Fencsik, 2001; Swick & Turken, 2002). Specifically, the ERN component is a negative voltage deflection that is frontally distributed on the scalp and peaks at 0–80 ms after incorrect responses, and has been associated with response monitoring, error detection, or conflict detection processes (Coles et al., 2001; Falkenstein et al., 1991; Gehring & Fencsik, 2001; Swick & Turken, 2002). The ERN is followed by the Pe, a slow positive deflection peaking at 300–500 ms centro-parietal scalp distribution (Falkenstein, Hohnsbein, Hoormann, & Blanke, 1991). The Pe has been associated with conscious processing of errors, error awareness, and initiation of post-error adjustment (Davies, Segalowitz, Dywan, &

Pailing, 2001; Falkenstein et al., 2000; Nieuwenhuis, Ridderinkhof, Blom, Band, & Kok, 2001; Overbeek et al., 2005; Ridderinkhof, Ramautar, & Wijnen, 2009; van Veen & Carter, 2006).

The purposes of this study are to understand the relationship between underlying neural processes of information processing as indicated by ERPs components, and to examine how these neural processes predict the behavioral output as indicated by response time. Taylor, Gavin, Grimm, Passantino, & Davies (2018) applied the SEM approach to understand the interrelationship among the ERPs and the response time using a cued Go/No-Go task. Their findings suggested that applying a sophisiticated statisical analyses approach like SEM to understand the nature of complicated brain-and-behavior relationships are viable and beneficial. In this study, we propose three conceptual models (Figure 3.1) and test these models empirically step-by-step using the EEG data collected from typically-developing children aged 8-12 year-old. Our first proposed conceptual model is presented in Figure 3.1A. In this manifested path model, each stage of neural processes is represented by a designated ERP component, and is hypothesized to predict the next phase of neural process in a sequential order, which in turn, significantly predicts the response time. We test the model in two conditions that result in opposite behavioral output (i.e., correct and incorrect responses) for contrastive purpose. The trait measures of age and sex are included in the model as both measures are demonstrated as significant predictors of ERPs and response times based on previous literature (Clayson, Clawson, & Larson, 2011; Davies, Segalowitz, & Gavin, 2004; Lahat et al., 2014; Taylor et al., 2018).

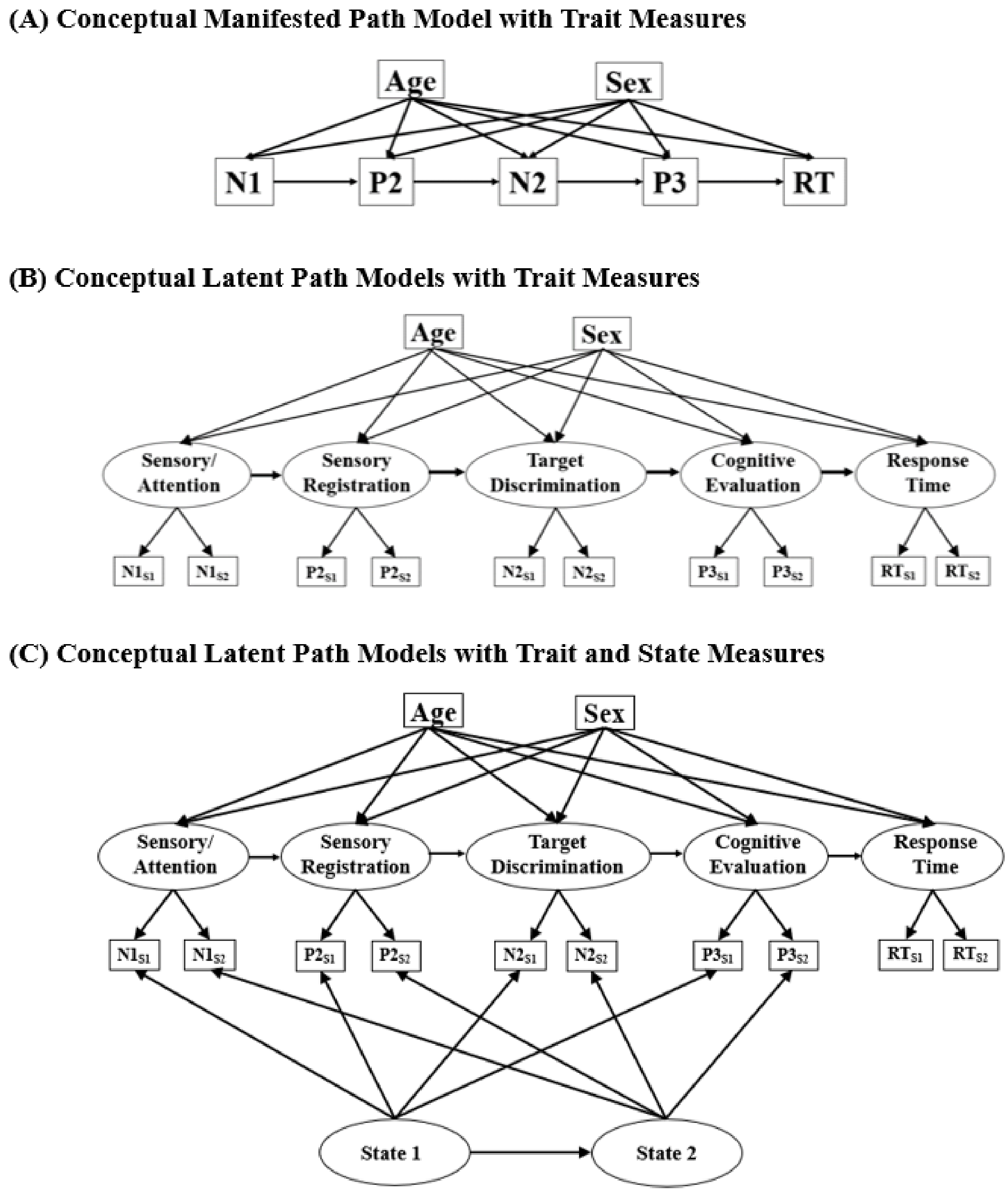


Figure 3.1 (A). Conceptual manifested path model with trait measures to be tested on correct and incorrect trials via path analyses; (B) Conceptual latent path model with trait measures to be tested on correct and incorrect trials via a structural equation modeling approach (state effect is assumed to be random); (C) Conceptual latent path model with trait and state measures to be tested on correct and incorrect trials. Note: S1 = Session 1; S2 = Session 2; State 1 = Effect of the state effect on Session 1; State 2 = Effect of the state effect on Session 2.

While the path analyses estimate the relationships among variables in the model simultaneously, this approach fails to account for the measurement error in each of the variables in the model. Gavin and Davies (2008) proposed a conceptual formula to demonstrate the potential sources of variance contributing to any psychophysiological measures (PM). The formula is presented as follows:

PM = Effect $_{STIMULUS}$ + Effect $_{STATE}$ + Effect $_{TRAIT}$ + Effect $_{PM\_PROCESSING}$ + Measurement Error

These variables indicate:

(1) Effect $_{STIMULUS}$: the influence of the stimuli presented (e.g., task paradigm),

(2) Effect $_{STATE}$: the state of individuals at the time of testing (e.g., fatigue),

(3) Effect $_{TRAIT}$: the trait of individuals (e.g., age, gender, or cognitive processes of interest),

(4) Effect $_{PM\_PROCESSING:}$ the signal processing procedures for analyzing the data,

(5) Measurement Error: unaccounted variance.

In this formula, Gavin and Davies (2008) suggested that any given PM such as an ERP component (e.g., N1) incorporates some degree of measurement error. Failing to minimize or account for the measurement error in these variables may undermine the robustness of a study's statistical analyses and prevent researchers from obtaining reliable results (Gavin and Davies, 2008; Maruyama, 1997). In our first proposed model, the manifest path model (Figure 3.1A), while we model the paths among the ERPs leading to RTs, we assume that all variables in this model are measured with minimal measurement error, which is not likely according to Gavin and Davies (2008). Therefore, to effectively account for measurement error, we propose our second conceptual model as presented in Figure 3.1B. The model is examined using the SEM, an advanced statistical analyses approach that utilizes common variance of a set of manifested variables (e.g., N1 components) to define a single latent construct (e.g., sensory-based processing). This approach allows researchers to account for and remove the measurement error from the latent construct; thus providing for a set of more refined latent constructs to be modeled. Similarly, we test this model in correct and incorrect conditions for contrastive purpose.

The model shown in Figure 3.1B assumes that any state effect in an individual's PM is random and if not accounted for, would contribute to inflating the measurement error of the individual's PM. In addition, the model assumes that, across participants, state effects will sum to a zero. However, given that the two manifested ERP variables that are used to define each latent construct are collected on two separate sessions, one could assume that the ERP variables collected on the same sessions might share some common variance with one another within the sessions. In other words, while the second proposed model has accounted for the measurement error, yet it fails to distill a potential systematic source of error variance (i.e., not random) that is shared across the variables within each session. This systematic source of error variance could be a state effect (such as anxiety, fatigue, attention, learning effect, practice effect…etc) that may systematically influence the amplitudes of ERPs from session to session (Gavin and Davies, 2008). Specifying this source of systematic measurement error may lead to more integrated and better fitting models. Therefore, we propose the third model to be tested as shown in Figure 3.1C. This conceptual model includes measures of both trait and state effect.

In addition to examining the neural processes associated with information processing (e.g., N1, P2, N2, P3), we also investigated the role of the performance monitoring in view of the stream of neural processes leading to behaviors. Previously studies have shown that performance monitoring is beneficial and can improve our performance (Danielmeier & Ullsperger, 2011; King et al., 2010). For example, subjects tended to slow down their response times on the correct trials that immediately follow error trials (Danielmeier & Ullsperger, 2011). Such a phenomenon is called post-error slowing, and has been shown to be related with the Pe amplitude (Hajcak, McDonald, & Simons, 2003). Moreover, researchers also found that the performance accuracy on the trial immediately after an error is improved (Danielmeier, Eichele, Forstmann, Tittgemeyer, & Ullsperger, 2011). However, while studies pointed out the role of performance monitoring on improving the performance outcomes, the underlying mechanism of how performance monitoring involves a process for adapting behavior based on performance remains unclear. Therefore, the purposes of this study are (1) to examine whether the stream of neural processes associated with information processing (e.g., N1, P2, N2, P3) could successfully predict the response time, (2) to understand how the neural processes of performance monitoring (e.g., ERN, and Pe) lead to behavioral adaptation to improve performance, (3) to investigate how the trait measures (e.g., age, and gender) are related to the stream of neural processes and response times, and (4) to investigate whether the state effect was random or systematic across sessions.

Methods

Participants. A total of 167 children aged 8-12 year-old were recruited from the university and local community through convenience sampling (campus emails, flyers, and word of mouth). All participants were screened for neurological and developmental disorders as well as use of psychopharmaceutical drugs (e.g., antidepressants). Twelve participants were excluded due to having an attention-deficit hyperactivity disorders (n = 9), a speech disorder (n = 1), or a reading disability (n = 2). Additionally, 12 participants were excluded due to an error rate over than 30% (n = 9), or less than 2.5% (n = 1) in both sessions of the Flanker task (Davies, Segalowitz, & Gavin, 2004), or failed to complete the first session (n = 2). As a result, data from 143 participants (M = 10.24 years, SD = 1.48) were included for statistical analysis. Of 143 participants, 118 participants had usable data from both sessions, 15 participants had usable data from Session 1, 10 participants had usable data from Session 2. See Table 3.1 for participants' age and sex distribution.

Table 3.1. Participant distribution by age and gender

Age Groups	Gender		Total
	Males	Females	
8	16	19	35
9	14	17	31
10	15	14	29
11	12	12	24
12	8	16	24
Total	65	78	143

Procedure. Participants were invited to the laboratory for two visits, with 1 to 3 weeks apart. In order to control for potential confounding variables, both visits were scheduled on the same day of the week, and at the same time of the day. Parents of participants signed consent forms prior to their visits; all participants signed the assent form on the first visit. Both visits were consisted of 1.5 hours of EEG tasks and an hour of behavioral testing.

The ERP paradigm. The speeded visual flanker task (Eriksen & Eriksen, 1974) was presented by the E-prime software version 2.0 to each participant on both sessions. The task contains 480 trials that were presented in two blocks of 240 trials. In this task, participants were presented four different stimuli (two congruent stimuli with 80 trials for each stimulus: "HHHHH" and "SSSSS"; two incongruent stimuli with 160 trials for each stimulus: "HHSHH" and "SSHSS). Participants were instructed to press the left button on a 4 button keypad using their left index finger if the middle letter is an H; and to press the right button using their right index finger if the middle letter is an S. Participants were told that the letters would be presented quickly, and they were instructed to perform as accurately as possible. The stimulus duration was 250ms and the initial intertrial stimulus (ISI) was set at 1400 ms. Following each set of 30 trials, the E-prime program was designed to evaluate the overall error rate and adjust the ISI by increasing or decreasing it by 100 ms if the error rate was greater than 25% or fewer than 10%, respectively. A minimal ISI was set at 800 ms to allow adequate time for brain processing of the stimulus and response to resolve prior to the onset of the stimulus on the subsequent trial.

Electrophysiological recording. EEG data were collected using the Active Two BioSemi system, either 32 or 64 channels (BioSemi, Inc., Amsterdam, the Netherlands) based on a modified 10-20 electrode placement system (American Electroencephalographic Society, 1994). Two electrodes, namely the common mode sense (CMS) and the driven right leg (DRL), were used to generate a reference voltage (https://www.biosemi.com/faq/cms&drl.htm). Averaged signals from the left and right earlobes were used for offline referencing. Two electrodes were placed at the supra- and infraorbital regions of the left eye to measure eye blinks or vertical eye movement, and two electrodes were placed at the left and right outer canthi to measure the horizontal eye movements. The sampling rate was set to 1024 Hz.

Electrophysiological data reduction. The Brain Vision Analyzer 2.0 software (www.brainproducts.com) was used to conduct the offline EEG data analyses. The data were referenced to the averaged signals of bilateral earlobes and then filtered with a bandpass filter of 0.1–30 Hz with 24 dB/oct. The data were then segmented into stimulus-locked and response-locked segments. For stimulus-locked segments, the data were segmented into 1200 ms time periods, which spanned from 200 ms before stimulus onset to 1000 ms after stimulus onset. Then, the segments were baseline-corrected based on the average voltage of -200 to 0 ms of stimulus onset. Eye movement artifacts were removed via a regression approach based on the vertical EOG (VEOG) channel (Segalowitz, 1996) then baseline-corrected again using the period of -200 to 0 ms of stimulus onset. Segments containing voltage greater than ± 100 µV in the midline (e.g., Fz, FCz, Cz, Pz) and VEOG channels were rejected. For each participant, the data were then averaged to obtain an averaged stimulus-locked ERPs for correct and incorrect trials separately.

For response-locked segments, the data on incorrect trials were segmented into 1400 ms time periods, which spanned from 600 ms before the incorrect response to 800 ms after the incorrect response. Segments with premature button responses (e.g., response times that were faster than 100 ms) were excluded from the analysis. Then, the segments were baseline-corrected based on the average voltage of the period between 600 to 400 ms preceding the incorrect response (Davies, Segalowitz, & Gavin, 2004). Eye movement artifacts were removed via a regression approach based on the VEOG channel (Segalowitz, 1996) then baseline-corrected again using the period of -600 to -400 ms preceding the incorrect response. Segments containing voltage greater than ± 100 µV in the midline (e.g., Fz, FCz, Cz, Pz) and VEOG channels were rejected.

The averaged ERPs obtained for each participant were scored using a customized peak-picking computer program in MATLAB that also allows for visual inspection to adjust for any values that were scored on a slope instead of a peak. Both the stimulus-locked and response-locked components were measured using baseline-to-peak approach. The windows for scoring the peaks are reported in Table 3.2 for stimulus-locked and response-locked ERPs. All of the ERP components were measured at the site FCz. The reasons we used a single channel site FCz for all of the ERP components were: (1) upon visual inspection, the topographic distribution map showed that the FCz channel site covered the largest brain activity for majority of ERP components; (2) previous modeling work on a cued Go/No Go paradigm showed that the brain-and-behavior model only converged when a single channel site was used (Taylor, Gavin, Grimm, Prince, & Davies, 2018).

Table 3.2. Time windows (ms) for scoring stimulus-locked and response-locked ERPs

	Stimulus-locked ERPs					Response-locked ERPs	
	P1 (ms)	N1 (ms)	P2 (ms)	N2 (ms)	P3 (ms)	ERN (ms)	Pe (ms)
Windows	0–100	70–150	110–240	170–350	320–575	-10-180	120 – 450

Statistical analyses. To test our hypotheses, we conducted four path analyses to examine the sequential effect of the ERPs components on response time with age and sex as covariates for both correct and incorrect trials on Session 1 and Session 2 (Figure 3.1A). Then, we conducted two structural equation models to test the same hypothesis using the ERP components to define the latent constructs of neural processes on correct and incorrect trials (Figure 3.1B). As illustrated in Figure 3.1B, each latent construct was defined by the amplitudes of the components collected in both sessions, and the direct effect between latent variables was defined based on the current stage of neural processes regressed on the preceding stage of neural processes. To examine the role of the state effect in the model, we then used the ERP components collected from session 1 to define the latent construct of state 1; and we used the ERP components collected from session 2 to define the latent construct of state 2 (Figure 3.1C). Finally, a structural equation model was conducted to examine the role of the ERN and Pe amplitudes obtained from incorrect trials on the established stream of neural processing obtained from the correct trials. The data analyses were conducted using Mplus 7.4 (Muthén & Muthén, 1998–2012). Prior to data analyses, we conducted assumption testing using SPSS version 25 (IBM). The assumptions for conducting such statistical analyses were tested. All variables were on the continuous scale except for sex, which is dummy coded (0 = boys, 1 = girls). Among 16 variables that were used, 5 variables violated the assumption of normality, these variables included: age (Shapiro-Wilk value = 0.943, $p < .001$), P2 amplitude on Session 1 (Shapiro-Wilk value = 0.971, $p = .013$), ERN amplitude on Session 1 (Shapiro-Wilk value = 0.951, $p < .001$) and Session 2 (Shapiro-Wilk value = 0.949, $p < .001$), and response time on Session 2 (Shapiro-Wilk value = 0.9781, $p = .045$). However, the default estimation approach of the Mplus software is the Maximum Likelihood (ML) estimation, which has been found to be relatively robust to the violation of the normality assumption (Hoyle, 1995). Therefore, no data transformation technique was used. The missing data were handled by default in Mplus using full information maximum likelihood (FIML) technique.

Effect size and model fit indices and criteria. The following model fit indices and criteria suggested by Hu and Bentler (1999) were used to determine the overall model fit: (1) the comparative fit index (CFI) > .95, (2) Tucker–Lewis Index (TLI) > .95, (3) root mean square error of approximation (RMSEA) < .06, and (4) standardized root mean square residual (SRMR) < .08. Additionally, we evaluated the Chi-Square test of model fit, where a non-significant test outcome indicates good fit of the model to the data. The best fitting model was selected using the model fit indices described above, and only the best fitting model was reported in this dissertation study. The standardized regression coefficients (i.e., β) were used as an index of effect size, with values of .1, .3, and .5 being considered as small, medium, and large, respectively (Kline, 2011).

Results

Descriptive statistics. The means and standard deviation of the amplitude of each ERP component and the RTs are reported in Table 3.3. The findings showed that the N1 and Pe amplitudes were significantly larger on Session 2 compared to Session 1, however, the P2 amplitude was significantly larger on Session 1 than Session 2. The correlations among age, stimulus-locked and response-locked ERP components, and response time are presented in Table 3.4. The findings demonstrated that the effect of correlation among ERPs were small to moderate.

Table 3.3. The means and standard deviations of averaged baseline-to-peak ERP amplitudes (μV), and averaged reaction times (RT; ms) for each session and the paired sample *t*-test results comparing Session 1 and Session 2 on each variable

	All available samples		Samples included in the paired-sample *t* test*			
	Session 1 *N=133* *M (SD)*	**Session 2** *N=128* *M (SD)*	**Session 1** *N=118* *M (SD)*	**Session 2** *N=118* *M (SD)*	***t* value *df* = 117**	***p* value**
N1	-6.48 (3.14)	-7.33 (3.23)	-6.61 (3.06)	-7.13 (3.14)	2.77	.007
P2	9.72 (5.48)	7.86 (5.43)	9.90 (5.61)	7.90 (5.35)	8.55	<.001
N2	-6.27 (5.16)	-7.23 (4.81)	-6.39 (4.95)	-6.92 (4.76)	1.82	.07
P3	5.63 (5.19)	5.49 (5.10)	5.45 (5.19)	5.58 (4.94)	-0.39	.70
RT	620.14 (113.10)	614.38 (119.66)	623.56 (115.51)	620.38 (117.19)	0.7	0.49
ERN	-7.38 (6.00)	-6.85 (5.51)	-7.30 (5.89)	-6.89 (5.57)	-0.96	0.34
Pe	4.18 (5.69)	5.42 (5.92)	3.89 (5.59)	5.59 (6.01)	-3.73	<.001

Note: * The sample used in the *t*-test is different from the full sample is because of 143 participants, only 118 participants have usable data from both sessions that allow us to conduct the paired sample *t* test

Age and sex represent maturation of brain and behavior measures. Consistent with previous literature, age significantly correlated with several ERP components and response time (see Table 3.3). We plotted the stimulus-locked and response locked ERP waveforms and response time distribution by each age group in Figure 3.2. The ERP morphology demonstrated that the stimulus-locked ERPs especially the N1 amplitude gradually decreased with age. Contrarily, the ERN amplitude gradually increased with age. In terms of the RTs, older children have a narrower distribution (i.e., less variation), and the distribution is clustered closer to the onset of the stimulus (i.e., faster RTs, especially for correct trials) compared to younger children. Moreover, independent sample *t* tests (Table 3.5) also demonstrated three variables (the P3 amplitude on Session 1 and Session 2, and the ERN amplitude on Session 2) differed between sex, such that boys had significantly larger P3 amplitude compared to girls on both sessions, and that girls had significantly larger ERN amplitude than boys on Session 2. Taken together, these findings confirmed the legitimacy of having the trait measures of age and sex in the model, therefore, in the following data analyses, age and sex were included.

Table 3.4. Correlations of baseline-to-peak ERP component amplitudes (μV), average reaction times (RT; ms), and age for session 1 and session 2.

		Session 1							
		Age	**N1**	**P2**	**N2**	**P3**	**RT**	**ERN**	**Pe**
Session 1	**Age**	–							
	N1	.31**	–						
	P2	-.14	.24**	–					
	N2	.23**	.46**	.20*	–				
	P3	.22*	.26**	.35**	.61**	–			
	RT	-.68**	-.11	.14	-.24**	-.36**	–		
	ERN	-.19*	.17*	.32	.48**	.38**	.18*	–	
	Pe	-.08	.008	.04	.34**	.57**	-.06	.44***	–
		Session 2							
		Age	**N1**	**P2**	**N2**	**P3**	**RT**	**ERN**	**Pe**
Session 2	**Age**	–							
	N1	.39**	–						
	P2	-.13	.15	–					
	N2	.25**	.46**	.25**	–				
	P3	.16	.27**	.37**	.59**	–			
	RT	-.58**	-.09	.07	-.16	-.16	–		
	ERN	-.33***	.05	.12	.30**	.32***	.32***	–	
	Pe	.012	.029	.30**	.41***	.59***	-.07	.61***	–

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

Table 3.5. The means and standard deviations of averaged baseline-to-peak ERP amplitudes (μV), and averaged reaction times (RT; ms) for each session and the independent sample *t*-test results comparing girls and boys on each variable

		Session 1		
	Boys (n=59) *M (SD)*	**Girls** (n=74) *M (SD)*	***t* value**	***p value***
N1	-6.77 (3.26)	-6.25 (3.04)	-0.950	.344
P2	9.62 (5.07)	9.79 (5.82)	-0.180	.858
N2	-5.47 (5.10)	-6.90 (5.15)	1.596	.113
P3	6.92 (5.03)	4.61 (5.11)	2.609	.010
RT	612.03 (120.46)	626.60 (107.26)	-0.736	.463
ERN	-6.66 (5.89)	-7.95 (6.06)	1.231	.221
Pe	4.61 (5.70)	3.85 (5.69)	0.764	.446
		Session 2		
	Boys (n=60) *M (SD)*	**Girls** (n=68) *M (SD)*	***t* value**	***p value***
N1	-7.82 (3.49)	-6.89 (2.94)	-1.642	.103
P2	7.75 (5.53)	7.95 (5.38)	-0.206	.837
N2	-6.95 (4.45)	-7.48 (5.13)	0.628	.531
P3	6.45 (4.93)	4.64 (5.13)	2.034	.044
RT	613.86 (122.60)	614.84 (117.91)	-0.046	.963
ERN	-5.74 (5.49)	-7.83 (5.39)	2.168	.032
Pe	5.66 (5.29)	5.21 (6.45)	0.431	.667

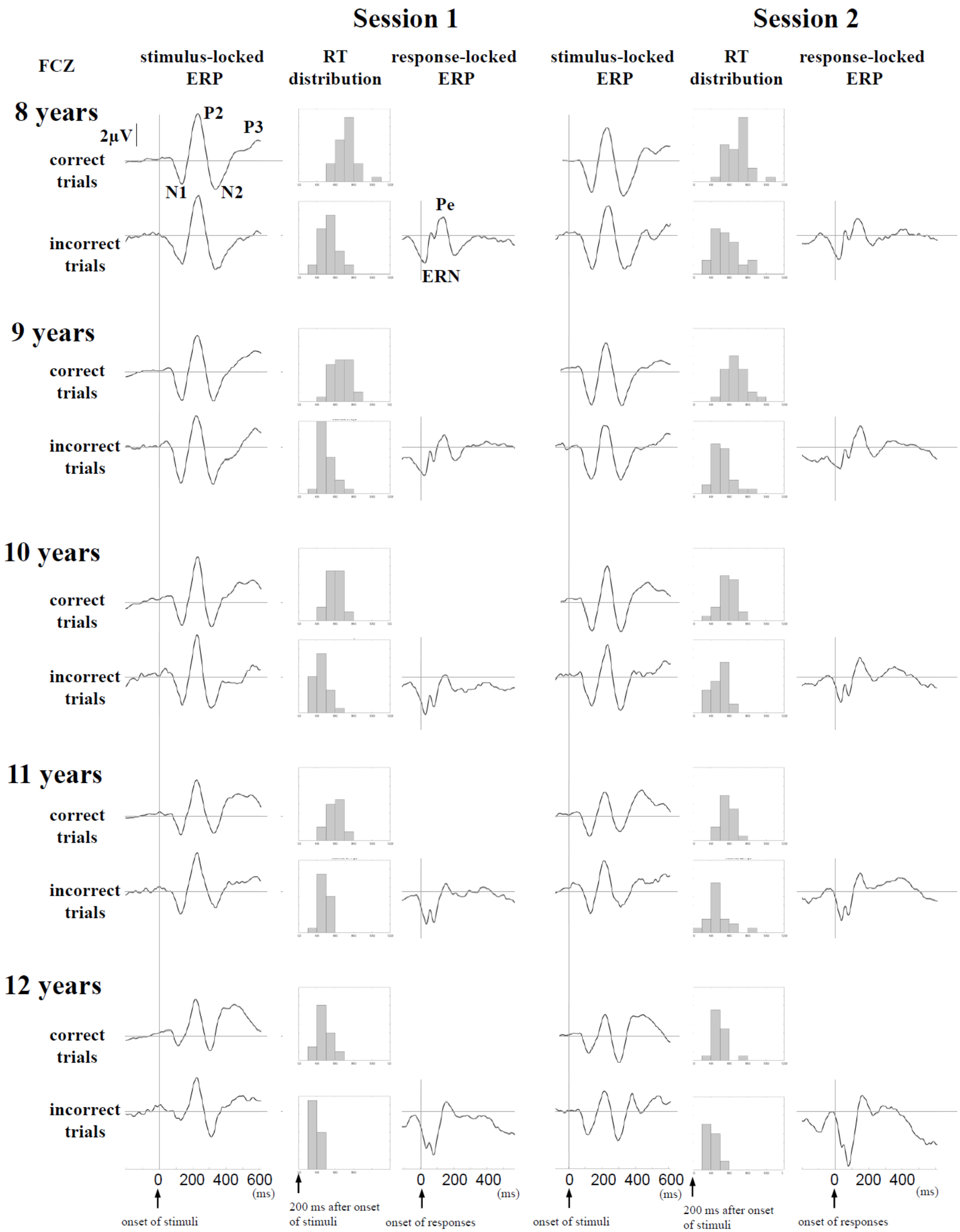


Figure 3.2. The stimulus-locked and response-locked ERP components and the frequency distribution of response times on both sessions for all age groups

Manifest variable models of brain processing predicting response times. The results on the model fit indices for four manifest models via path analyses are reported in Table 3.6 and the models are presented Figure 3.3. Overall, the model fit indices yielded acceptable to excellent model fit for these four models. It is worth noting that in addition to the hypothesized model depicted in Figure 3.1A, we added two correlated paths between N1 and N2 amplitudes, and between P2 and P3 amplitudes, because based on the findings on the correlation coefficients reported on the Table 3.4, the N1 amplitude significantly correlated with the N2 amplitude, and the P2 amplitude significantly correlated with the P3 amplitude on both sessions.

Four path analyses revealed the effect of Session (session 1 vs session 2) and Trial Type (correct vs incorrect) on the stream of neural processing. Specifically, the relationship between the P2 and N2 was not significant for Session 1 but was significant for Session 2, suggesting the relationship between the P2 and N2 might reflect the shifting of cognitive strategies across sessions (e.g., learning or practice effect). Further, for the Session 1, the relationship between the P3 and response time was significant on correct trials but was not significant on incorrect trials, such that the larger the P3 amplitude was associated with faster response time on correct trials but not incorrect trials. In contrast, for the Session 2, this relationship was only significant on incorrect trials but not correct trials. These four models yielded diverse results in terms of the brain-and-behavior relationship, and such a discrepancy may be due to the uncontrolled measurement error in the models. Therefore, in the next section, we conducted the structural equation modeling to examine the relationship between latent constructs for correct and incorrect trials.

Table 3.6. Model fit indices results for each of the established manifest variable path models

	Chi Square	RMSEA	CFI	TLI	SRMR
Session 1 Correct Trials	$\chi^2(4) = 9.78$ $p = .044$	RMSEA = .104 90% CI = [.015, .189] $p = .115$	0.975	0.906	0.039
Session 1 Incorrect Trials	$\chi^2(4) = 1.273$ $p = .87$	RMSEA = 0 90% CI = [0, .068] $p = .921$	1	1.088	0.011
Session 2 Correct Trials	$\chi^2(4) = 6.15$ $p = .19$	RMSEA = 0.065 90% CI [0, 0.16] $p = .327$	0.988	0.955	0.03
Session 2 Incorrect Trials	$\chi^2(4) = 7.405$ $p = .12$	RMSEA = .082 90% CI [0, 0.172] $p = .23$	0.973	0.867	0.039

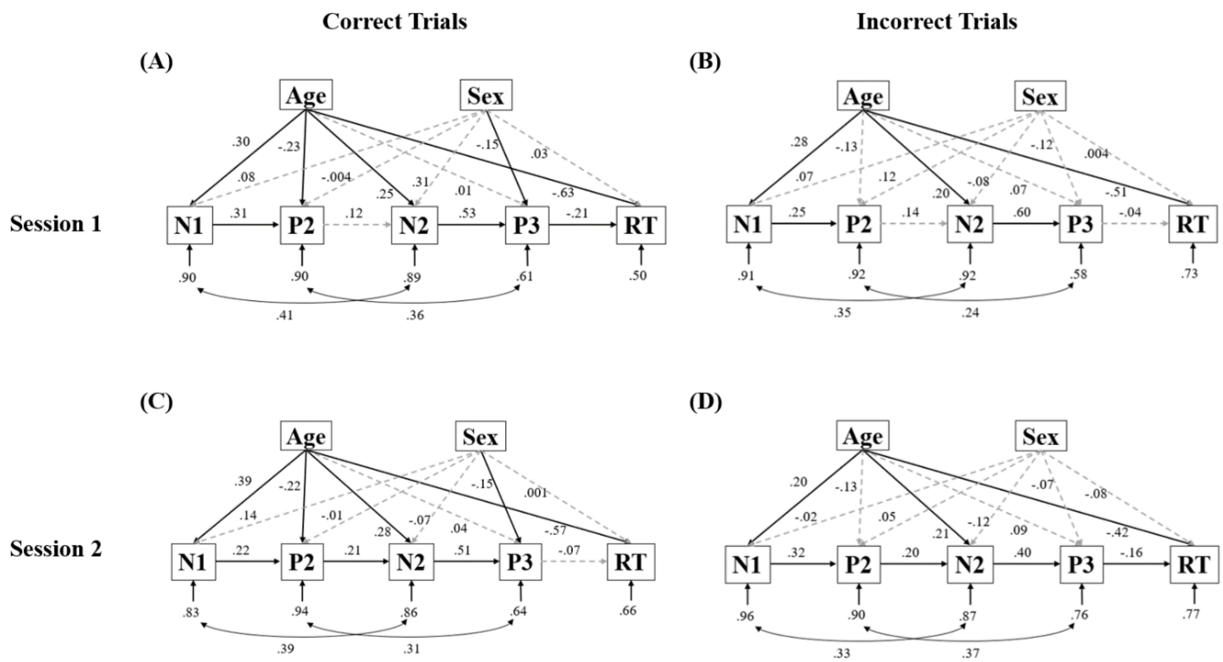


Figure 3.3. The four manifest models of ERPs predicting task behaviors (averaged response times). Each figure indicates the stream of neural processing on (A) Session 1 correct trials; (B) Session 1 incorrect trials; (C) Session 2 correct trials; and (D) Session 2 incorrect trials. Gray dotted arrows indicate non-statistically significant relationships. Residual variance is reported below for each variable. The standardized coefficients β are reported for each model.

Latent models of brain processing predicting task behavior while controlling for trait measures. The results on the model fit indices for two latent models are reported in Table 3.7, the models are presented in Figure 3.4. Overall, tests for model fit revealed indices with values that were informative but suggested further refinement of the models are needed. The latent model on the correct trials showed that all manifested variables significantly loaded on the corresponding latent constructs. In this model, each latent construct of neural processes significantly predicted the following latent construct as hypothesized, which in turn, significantly and negatively predicted the response time, such that the larger the P3 amplitude, the shorter the response time. Similarly, the latent model on the incorrect trials showed that all manifested variables significantly loaded on the corresponding latent constructs. However, while each phase of neural processes significantly predicted the next phase, the latent construct of cognitive evaluation (as indicated by the P3 amplitude) did not significantly predict the response time, suggesting that on the incorrect trials, the stream of neural processing failed to predict the behavioral outcome. It is worth noting that the correlations at the bottom of each model in the Figure 3.4 are the continuation of the depicting relationships included in the manifest path models in Figure 3.3.

Table 3.7. Model fit indices results for the latent models for correct and incorrect trials predicting task behavior while controlling for trait measures.

	Chi Square	**RMSEA**	**CFI**	**TLI**	**SRMR**
Correct Trials	$\chi^2(38) =$ 136.96 *p* <.001	RMSEA = .135 90% CI = [.11, .16] *p* < .001	0.91	0.84	0.08
Incorrect Trials	$\chi^2(37) =$ 94.251 *p* <.001	RMSEA = .104 90% CI = [.078, .130] *p* = .001	0.90	0.83	0.06

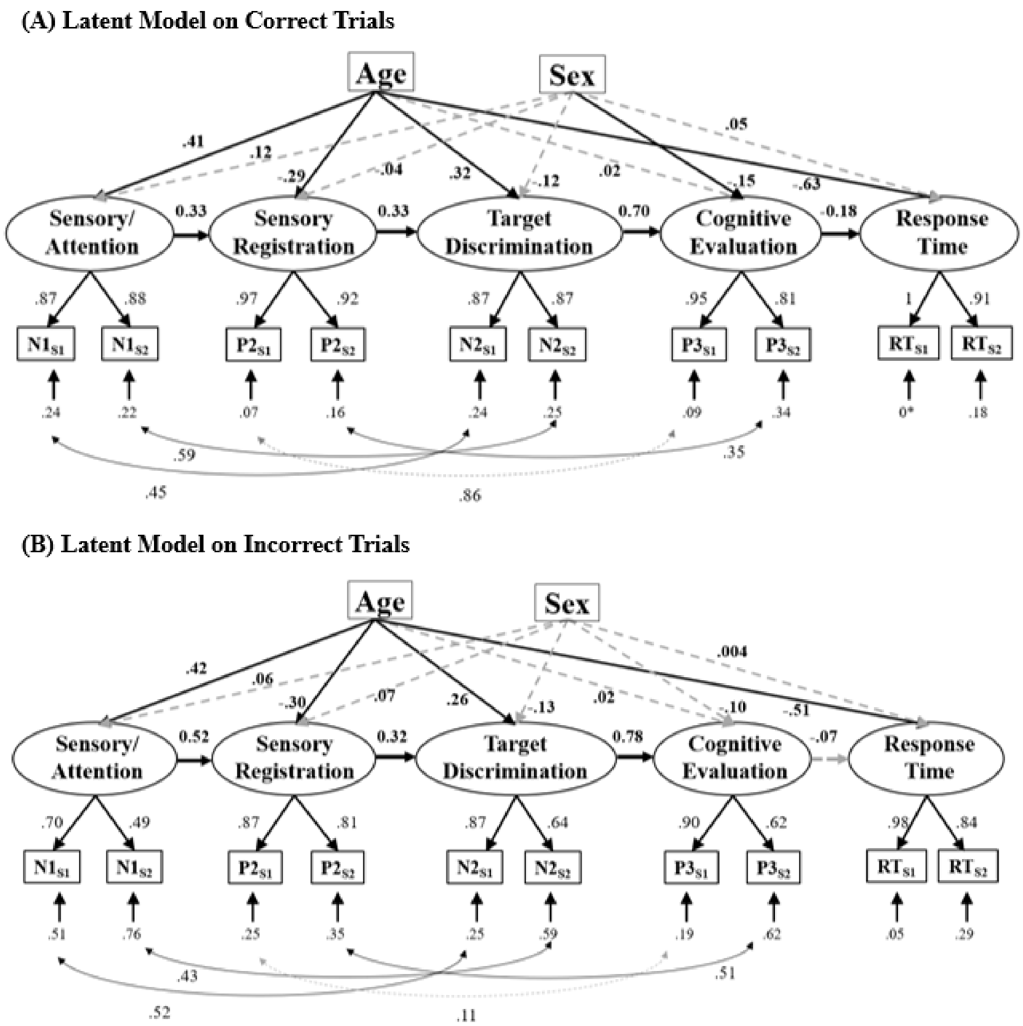


Figure 3.4. Results on the structure equation model with standardized coefficients on (A) correct Trials, and (B) incorrect trials. Dotted lines indicate non-significant relationship; solid lines represent significant relationships. Note: * the residual variance for the RT_{S1} has been constrained to 0 to fix negative residual variance of this variable; S1 = Session 1; S2 = Session 2. The correlations at the bottom of each model are the continuation of the depicting relationships included in the manifest path models in Figure 3.3.

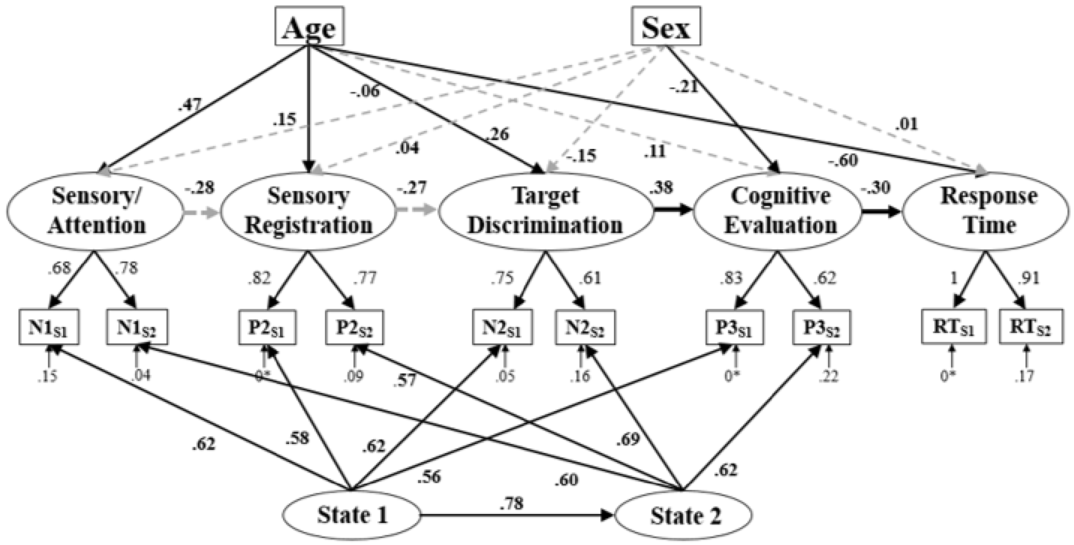
Latent models of brain processing predicting task behavior while controlling for trait and state measures. The results on the model fit indices for two latent models that control for both trait and state effects are reported in Table 3.8 and the models are presented in Figure 3.5. The model fit indices yielded excellent model fit for these for models. It is worth noting that the models that controlled both trait and state effects had better model fit indices than the models that only controlled for trait measures (Table 3.7, Figure 3.4), indicating that the state effect is a critical factor in investigating the brain-and-behavior relationships in children. Previous studies have shown that fatigue and anxiety levels could impact EEG/ERP measures (Hagemann & Naumann, 2009; Tsai, Young, Hsieh, & Lee, 2005). Although in this current study we have not empirically examined the underlying mechanisms of the state effect, however, we considered that the state effect is associated with anxiety, fatigue, attention, motivation, learning effect, practice effect or other transient factors that may systematically influence the ERP components across sessions (Gavin & Davies, 2008; Hagemann & Naumann, 2009; Tsai, Young et al., 2005). Figure 3.5 illustrates that all manifested variables significantly loaded on the corresponding latent constructs, and that the state on Session 1 significantly predicted the state on Session 2 for both correct and incorrect trials. In other words, the participants' state on Session 1 (e.g., attention, emotion, fatigue, anxiety…etc) is associated with their state on Session 2.

Compared to the models without state factors shown in Figure 3.4A, this model with state factors (Figure 3.5A) demonstrates that the predictive relationships no longer existed for the first three latent variables on correct trials. This could suggest that the significant relationships between the latent construct of sensory/attention (indicated by the N1 amplitudes), sensory registration (indicated by the P2 amplitudes), and target discrimination (indicated by the N2 amplitudes) shown in 4A were driven by the relationship between the latent state variables between sessions rather than being an effect among the latent variables themselves. Note however, that for correct trials, the latent construct of target discrimination (indicated by the N2 amplitudes) still significantly predicts the latent construct of cognitive evaluation (indicated by the P3 amplitudes), such that larger N2 amplitude is associated with smaller P3 amplitude. This finding suggests that greater brain activation while detecting the targets stimuli may result in less effort in cognitively evaluate the decision. Subsequently, the latent construct of cognitive evaluation (indicated by the P3 amplitudes) significantly predicts the response times, such that the larger the P3 amplitude, the shorter the response time. In contrast, for the incorrect trials with state factors (Figure 3.5B), none of the relationships among the latent brain variables were significant.

Table 3.8. Model fit indices results for the latent models

	Chi Square	**RMSEA**	**CFI**	**TLI**	**SRMR**
Correct Trials	$\chi^2(34)$ = 32.873 *p* = .523	RMSEA = 0 90% CI = [0, .058] *p* = .901	1	1.002	0.05
Incorrect Trials	$\chi^2(34)$ = 37.723 *p* = .303	RMSEA = .028 90% CI = [0, .069] *p* = 775	0.994	0.988	0.044

(A) Latent model on Correct Trials with State Factors



(B) Latent model on Incorrect Trials with State Factors

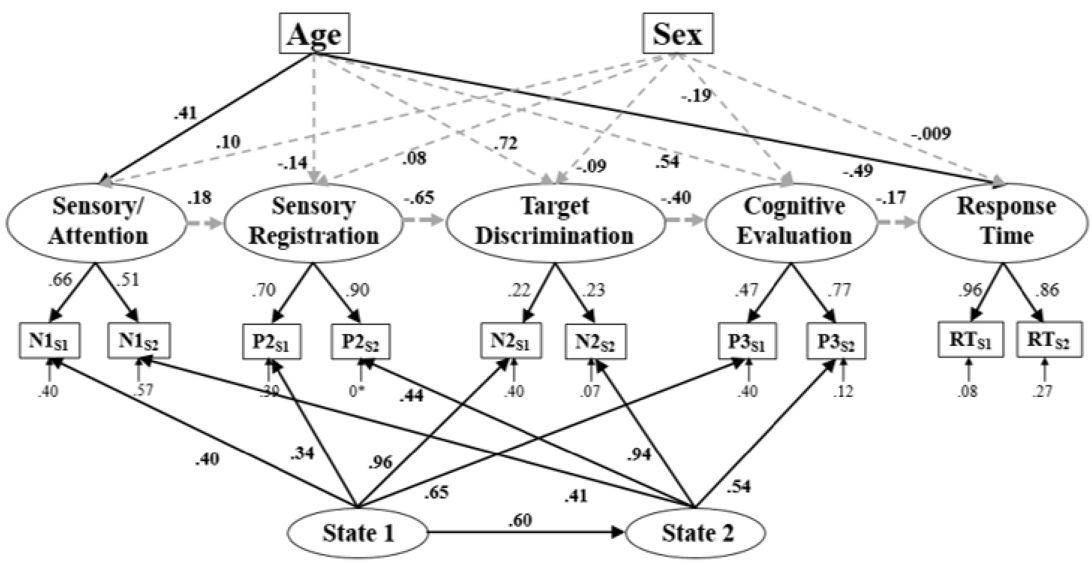


Figure 3.5. Results on the structure equation model with standardized coefficients on (A) correct trials, and (B) incorrect trials. Dotted lines indicate non-significant relationship; solid lines represent significant relationships. Note: * the residual variance for the RT_{S1} has been constrained to 0 to fix negative residual variance of this variable; S1 = Session 1; S2 = Session 2.

Including performance monitoring measures in latent models predicting task behavior. Building upon the model presented in Figure 3.5A, we added two latent constructs of error detection and post-error adjustments as defined by the ERN amplitudes and Pe amplitudes, respectively, to examine the role of the performance monitoring on the stream of neural processing for correct trials. The results on the model fit indices for this model are reported in Table 3.9 and the model is presented Figure 3.6. The majority of the model fit indices yielded acceptable model fit, except that the Chi square test of model fit was significant *(p* $<.001$) and that the RMSEA is greater than 0.06. In this model, the latent construct of post-error adjustments (indicated by the Pe amplitudes) significantly predicted the latent construct of sensory-based processing (indicated by the N1 amplitudes) and target discrimination (indicated by the N2 amplitude), such that larger Pe amplitude was associated with larger N1 amplitude but smaller P2 amplitude. This finding suggests that greater brain activation while initiating behavioral adjustments (e.g., post error slowing) may enhance the brain processing of the sensory-based aspects of the stimuli, which may result in less effort in registering the sensory information in the brain. Moreover, the model also demonstrates that the latent construct of error detection significantly predicts the latent construct of post-error adjustment, such that the larger (more negative) the ERN amplitude, the smaller (less positive) the Pe amplitude, indicating that greater brain activation while detecting performance errors was associated with less brain activation while initiating post-error behavioral adjustments. Lastly, in this model, the latent construct of sensory registration (indicated by the P2 amplitudes) significantly predicts the latent construct of the target discrimination (indicated by the N2 amplitude), such that larger P2 amplitude was associated with larger N2 amplitude. The finding suggests that greater brain activation while registering and processing the sensory stimuli may enhance the brain activities while discriminating the targets. This finding was also reported in the model 4A.

Table 3.9. Model fit indices results on the latent model

	Chi Square	RMSEA	CFI	TLI	SRMR
Correct Trials with Performance Monitoring Measures	$\chi^2(74)$ = 122.63 *p* <.001	RMSEA = .068 90% CI = [.046, .089] *p* = .088	0.967	.946	0.059

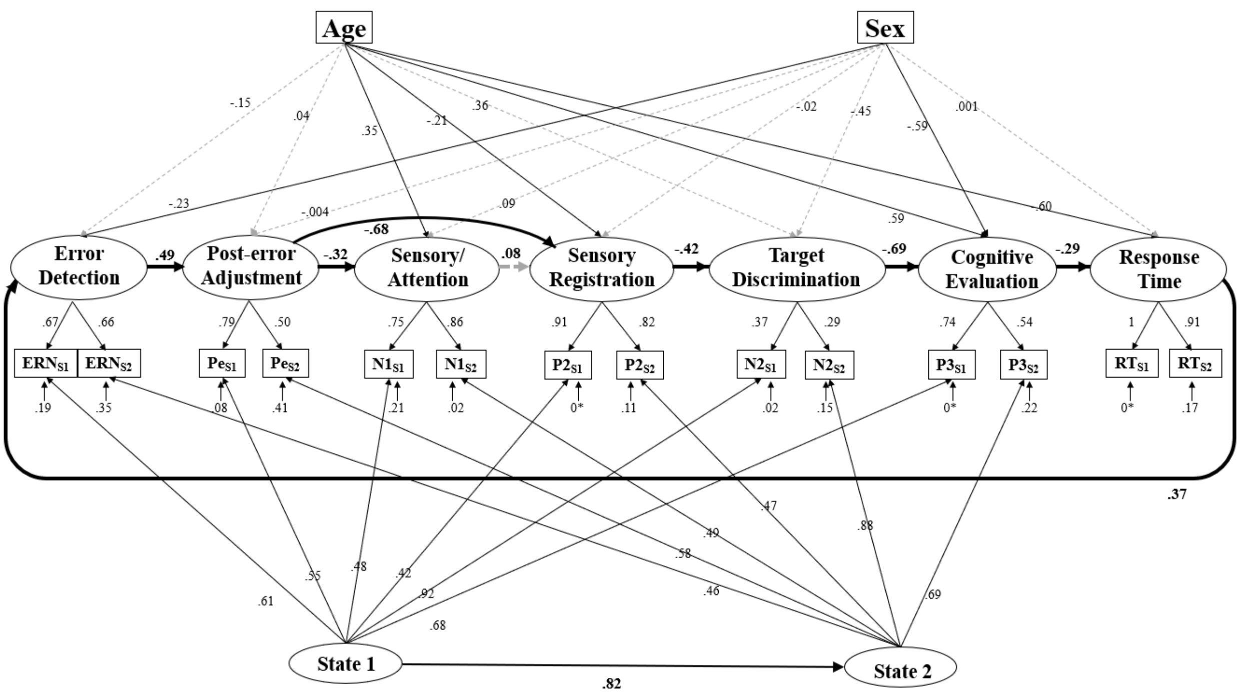


Figure 3.6. Results on the structure equation model with standardized coefficients on the relationship between successive stimulus-locked ERPs on correct Trials with response-locked ERPs on incorrect trials. Dotted lines indicate non-significant relationship; solid lines represent significant relationships. * the residual variance of the variable has been constrained to 0 to fix negative residual variance of this variable; S1 = Session 1; S2 = Session 2.

Discussion

This study explored the interrelationships between stages of neural processes measured in stimulus and response-locked ERPs to predict the response time in a speeded Flanker task obtained from two sessions in children aged 8-12 year-old by implementing the path analyses and SEM. We examined three conceptual models: (1) manifested path model with trait measures, (2) latent model with trait measures, and (3) latent model with trait and state measures. For contrastive purpose, we applied the model on stimulus-locked ERPs collected from correct trials and incorrect trials, to validate whether the model could differentiate the distinct neural processes leading to opposite behavioral outcomes. Lastly, we incorporated the response-locked ERPs (i.e., ERN and Pe amplitudes) into the model to explore the role of performance monitoring on neural processes associated with successful behavioral outcome.

The manifested models on understanding brain-and-behavior relationships. Four manifested path models showed mixed findings in terms of the effect of Session and Trial Type on the stream of neural processing. These discrepancies included (1) the stream of neural processing broke down between P2 and N2 amplitudes for Session 1, yet remained connected for Session 2, and (2) the relationship between the P3 and RT was significant on correct trials but was not significant on incorrect trials for Session 1, yet this pattern was reversed for Session 2. While it is possible that these differences reflect the underlying neural processes across sessions, the discrepancies could also be partly due to the uncontrolled measurement error in these models which makes the results difficult to interpret (Gavin and Davies, 2008; Maruyama, 1997).

The latent models on understanding brain-and-behavior relationships. Generally, the findings from the latent models indicated that the brain-and-behavior relationships were not significant on incorrect trials but were significant on correct trials. Specifically, on the correct trials, the greater brain activation that reflects cognitive evaluation of the stimulus, the shorter the response time that participants needed to correctly respond (i.e., press the buttons). Interestingly, the models on the correct and incorrect trials (Figure 3.5) demonstrate different patterns of relationship among latent variables to response time, yet both models yield excellent model fit indices. Collectively these findings suggested that our conceptual models are valid in terms of detecting the distinct patterns of neural processes leading to opposite behavioral outcomes. Importantly, the latent models with both state and trait factors yielded better model fit compared to the latent models without the state factors. This confirmed our hypothesis that there was an underlying systematic state effect in our latent models (Gavin and Davies, 2008), which could potentially confound the relationships between neural processes if not accounted during statistical analyses. After accounting for the state effect in the models, we found that on correct trials, the predictive relationships among the first three latent brain variables were no longer significant. The finding implies that on the correct trials, participants may not substantially rely on the sensory-based aspects of processing to discriminate the target and make decisions. However, despite the fact that the p value for these relationships did not reach statistical significance, the standardized regression coefficients (βs = .27 - .28) suggested a small to moderate effect size for these relationships. A larger sample size might be required for future studies to further investigate whether a lack of significant relationships between first three latent brain variables was because of the small sample size.

Contrarily, on incorrect trials, none of the predictive relationships between each stage of neural processes were significant. This finding suggests that on incorrect trials, a disconnected or disrupted stream of neural processes may cause the incorrect behavioral outcome (e.g., incorrect button presses). Specifically, the speeded Flanker task that we used in this study may have built a strong pre-potent motor response (e.g., press the button either with the right or the left hand) that needs to be cognitively controlled. That is, if two consecutive stimuli required the participant to press different buttons, when responding to the second stimuli, he/she needs to inhibit the prepotent motor response, and flexibly switch his/her hands to ensure a correct motor response to the second stimuli (Burle, van den Wildenberg, Spieser, & Ridderinkhof, 2016). Moreover, our findings also showed response times on the incorrect trials were significantly faster compared to the response times on the correct trials, supporting the notion that failing to inhibit pre-portent responses leads to impulsive errors, which in turn, disrupts the stream of neural processes (Burle et al., 2016).

The role of performance monitoring on mediating stages of brain processing. The final model demonstrated the adaptive effect of the post-error adjustment in the stream of the neural processes. Specifically, the latent construct of post-error adjustment, as indicated by the Pe amplitudes, significantly predicted the latent construct of sensory-based processing (as indicated by the N1 amplitudes), such that the stronger the brain response associated with post-error behavioral adjustments or error awareness, the stronger the brain response associated with the sensory-based processing and the selective attention on the task. Moreover, the latent construct of post-error adjustment, also mediated the relationship between error detection and target discrimination, such that the greater the brain response associated with activating behavioral adjustments, the smaller brain response associated with registering the sensory stimuli. The model also demonstrated a significant relationship between latent constructs of error detection and post-error adjustments, such that the larger the ERN amplitude, the smaller the Pe amplitude. While several studies claimed that the ERN and Pe components are independent from one another (Herrmann et al., 2004; Nieuwenhuis et al., 2001), our findings suggested the predictive relationship among error detection and post-error behavioral adjustments, yet their roles on the stream of neural processing remain different (Danielmeier & Ullsperger, 2011; King et al., 2010).

The utility of modeling in the understanding of brain-behavior relationships. This study not only successfully demonstrated the feasibility of utilizing the modeling approach to understand the interrelationships among the ERP components, but also demonstrated the differential neural processes on the correct and incorrect trials. Over the past decades, researchers have begun to apply advanced statistical techniques such as the SEM to understand the brain-and-behavior relationships. Brydges, Fox, Reid, and Anderson (2014) applied SEM to examine whether the amplitudes and latencies of the N2 and P3 amplitude could predict the executive function skills in neurotypical children. They found that the N2 difference waveform and P3 amplitude and latency collected from the Flanker task significantly predicted the latent variable of executive function, which is defined by a battery of behavioral measures of executive function (Brydges et al., 2014). Their work has laid a critical foundation for researchers to apply advanced statistical analyses to understand the interrelationship between neural (e.g., ERP components) and behavioral aspects of cognitive function. However, in their model, the researchers did not take the interrelationship between the ERP components (e.g., N2, and P3) into consideration (i.e., no predictive relationship was drawn between the N2 and P3 amplitudes). Our study was developed based on the connectionist theory (Houghton, 2005), that is, rather than viewing each phase in the stream of neural processing as independent from one another, we consider each phase in the stream of neural processing as interdependent. In other words, the influence from the current phase of neural processes could be carried out into the next phase of neural processes, and ultimately, lead to behavioral outcome. Moreover, most of the studies examining the brain-and-behavior relationships often examined the relationship between a single ERP component and a behavior measure. Failing to take the interrelationship among the ERP components into consideration may be one of the reasons for the inconclusive findings in the current literature. Taken together, the modeling approach may be a promising technique for better understand the brain-and-behavior relationships.

To our knowledge, the latent model that includes performance monitoring measures in our study is the first model that demonstrated the neural mechanisms of performance monitoring on information processes leading to response times. Although previous studies have demonstrated a significant relationship between Pe amplitude and post-error slowing, a phenomenon which subjects slowed down their response times after committing errors (Danielmeier & Ullsperger, 2011; Hajcak, McDonald, & Simons, 2003), none of the studies have empirically demonstrated the mechanism underlying such a behavioral phenomenon. The model in this study clearly explains the mechanism of the post-error adjustment (indicated by the Pe amplitudes) and by what means performance monitoring can adjust our behaviors for successful performance in subsequent trials. Moreover, the significant relationship between the response times and the latent construct of the error detection (as indicated by the ERN amplitudes) suggested a dynamic bi-directional brain-and-behavior relationship instead of viewing one (either brain or behavioral measures) predicts another. We do recognize that the models that we attempted to establish in this study did not encompass all possible underlying neural processes and that the behavioral measures (e.g., response times) that we used in this study may not explain real-life behaviors. Hence, future studies could expand the models by adding (1) other variables indicating the underlying neural processes of other cognitive functions such as attention and executive functions, and (2) functional behavioral assessments.

Lastly, the ultimate goal of the modeling approach is to provide a framework of brain-and-behavior relationship that could assist in clinical diagnosis and guide the intervention. While researchers began to investigate the utility of single ERP component as a biomarker for screening individuals with neurological or developmental disorders (Foti, Kotov, & Hajcak, 2013; Meyer, 2017; Riesel, Weinberg, Endrass, Meyer, & Hajcak, 2013), our findings suggested that the modeling appraoch may provide more enriched information into the neural mechanisms and brain-and-behavioral relationships. The Research Domain Criteria (RDoC; https://www.nimh.nih.gov/research-priorities/rdoc/index.shtml), a framework provided the National Institute of Mental Health (NIMH), also provided guidelines for researchers and clinians to consider various dimensions (e.g., physiology, behavior, self-report) other than relying on traditional symptoms when investigating human behaviors and mental disorders. Consistent with RDoC framework, the modeling approach that we implemented in this study allows us to more comprehensively explore the dynamic interactions between dimensions.

Conclusion

This study demonstrated the feasibility of utilizing the SEM to model the inter-relationship between neural processes and simple task behaviors in 143 children with typical development aged 8 to 12 years. Three models with trait and state as controlled variables were tested to examine the neural mechanism of information processing that leads to different outcomes. The findings demonstrated that differential neural processes lead to correct and incorrect trials. The findings also provided empirical evidence of the adaptive roles of performance monitoring.

CHAPTER 4: THE RELATIONSHIP BETWEEN COGNITIVE FUNCTIONS AND OCCUPATIONAL PERFORMANCE IN CHILDREN, ADULTS, AND ADULTS WITH ADHD

Introduction

In the United States, about 8 million adults have been diagnosed with attention deficit hyperactivity disorder (ADHD), a clinical diagnosis with symptoms of inattention, disinhibition, and hyperactivity (American Psychiatric Association, 2013). While ADHD is a most common diagnosis in childhood, studies have shown that 60% of cases clinically diagnosed in childhood persist into their mid-20’s, and 41% or more persist into adulthood (Barkley, 1997; Sibley et al., 2017). Moreover, the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) has revised its criteria for diagnosis of ADHD, raising the age criteria to symptoms present by age 12 or earlier (revised from age 7 or earlier in previous editions of the DSM; American Psychiatric Association, 2013). Furthermore, the revised DSM-5 provides examples of how the symptoms may present in adults with ADHD, including disorganized work conditions and failure to meet deadlines.

Recent electroencephalography (EEG) studies have shown that adults with ADHD demonstrate different characteristics in terms of cognitive functions such as performance monitoring and information processing abilities compared to their neural typical peers (Chang, Davies, & Gavin, 2009; McLoughlin et al., 2009; Wiersema, van der Meere, & Roeyers, 2009). Performance monitoring is defined as the ability to detect performance errors and activate post-error behavioral adjustments (Holroyd & Coles, 2002). The neural activity associated with performance monitoring can be measured using event-related potentials (ERPs), a series of voltage deflections recorded from the scalp EEG. Specifically, in the Flanker Task paradigm, performance monitoring is indicated by two ERP components, the error-related negativity (ERN), and error positivity (Pe). The ERN is a negative voltage deflection that peaks around 80 milliseconds (ms) after incorrect responses, is associated with early stage of error detection (Coles et al., 2001; Falkenstein et al., 1991; Gehring & Fencsik, 2001; Swick & Turken, 2002). The error positivity (Pe) component is a positive voltage deflection that immediately follows the ERN, and has been associated with error awareness and activation of behavioral adjustments after incorrect responses (Davies, Segalowitz, Dywan, & Pailing, 2001; Falkenstein et al., 2000; Nieuwenhuis, Ridderinkhof, Blom, Band, & Kok, 2001; Overbeek et al., 2005; Ridderinkhof, Ramautar, & Wijnen, 2009; van Veen & Carter, 2006). The findings on the ERN and Pe amplitudes in adults with ADHD are inconclusive. Chang et al. (2009) found that adults with ADHD demonstrated smaller ERN amplitude compared to their control peers, while no significant difference was found in the Pe amplitude, suggesting that adults with ADHD may be less efficient in detecting their performance errors. However, Wiersema, van der Meere, & Roeyers (2009) showed opposite results in which no group difference was found in the ERN amplitude, yet adults with ADHD had smaller Pe amplitude compared to neurotypical adults. These inconclusive findings on the underlying neural processes associated with performance monitoring in adults with ADHD warrants further investigation.

Adults with ADHD not only demonstrated different amplitudes in the ERN and Pe components (i.e., components that are time-locked to button presses) compared to neurotypical adults (Chang et al., 2009; Wiersema, van der Meere, & Roeyers, 2009), but they also had different amplitudes in the ERP components that are time-locked to the stimuli (Bekker et al., 2005; McLoughlin et al. 2009). Specifically, the ERP components that are evoked by visual stimili (e. g. pictures presented on the screen), or auditory stimuli (e.g., tones), and are associated with information processing to the presented stimuli. Information processing is defined as the ability to process information in multiple stages whereby each mental process influences a subsequent stage across time (e.g., orienting to sensory information, or evaluating performance outcomes) thereby allowing individuals to interact with the environment efficiently (Brion, Pitel, & D'Hondt, 2016). The various stages of information processing can be indicated by ERP components that include N1, P2, N2, and P3. Specifically, the N1 component is a negative voltage deflection which peaks at around 100–150ms at the frontal scalp site after presentation of stimuli, and it has been associated with selective attention and sensory-based processes (Lackner, Santesso, Dywan, Wade, & Segalowitz, 2013; Luck & Girelli, 1998; Polich, 1993). The N1 component is followed by the P2 component, a positive voltage deflection peaking at around 200ms at the frontal-central scalp site after presentation of stimuli. The P2 component has been associated with early processes of sensory stimuli or sensory registration processes (Davies & Gavin, 2007; Polich, 1993). The P2 component is followed by the N2 component, a negative voltage deflection peaking around 200ms after presentation of stimuli, and it has been related to target discrimination, executive control, or impulse inhibition (Luck, 2014; Polich, 1993). The N2 component is followed by the P3 component, a positive deflection peaking around 300ms after stimulus presentation and has been associated with cognitive evaluation process such as attention allocation, or memory updating (Luck, 2014; Polich, 1993). Several studies have reported that the ERPs associated with the information processing in adults with ADHD tend to have attenuated ERP components (e.g., N2 and P3) compared to neurotypical adults (e.g., Bekker et al., 2005; McLoughlin et al. 2009).

Studies have shown that adults with ADHD also demonstrate reduced quality of occupational performance across multiple domains (Barkley & Murphy, 2011). For example, Barkley and Murphy (2010) showed that adults with ADHD experienced difficulties at work such as having trouble with others, quitting a job out of boredom, or demonstrating some behavior problems at work compared to adults without ADHD. Further, Barkley & Murphy (2011) demonstrated several difficulties that beset adults with ADHD in daily life activities, including self-management of time, self-organization, self-discipline, self-motivation, and self-activation. Moreover, Friedman et al. (2003) showed that adults with ADHD viewed themselves as less socially competent and more sensitive toward violations of social norms than controls. Wehmeier et al. (2010) also showed that adolescents with ADHD experience difficulties with social interactions which in turn, impair their overall quality of life. However, while there are several studies that demonstrated adults with ADHD experience difficulties with occupational performance, little is known about the underpinnings of the reduced occupational performance in adults with ADHD.

Most available tools that therapists and researchers utilize to evaluate an individual's occupational performance focus on subjective perceptions that are derived by means of questionnaire or by observation (Schell et al., 2013). While using the checklists or questionnaires to assess social interaction has several advantages (e.g., easy to administer, and requires minimal training), it also has several disadvantages (e.g., the results may be difficult to be compared across individuals; Schell et al., 2013). Therefore, in this study, we implemented two standardized assessments, the Assessment or Motor and Process Skills (AMPS; Fisher & Jones, 2014), and the Evaluation of Social Interaction (ESI; Fisher & Griswold, 2015) to measure occupational performance. Both assessments are observation-based assessments, and are administered in the real-life contexts to assess the quality of the occupational performance.

This study is a feasibility study with three primary purposes: (1) to examine the differences in neurological measures of cognitive functions and occupational performance in neurotypical children, neurotypical adults, and adults with ADHD, (2) to understand the relationship between neural and occupational performance measures in these three groups; and (3) to explore which type of measures (e.g., neural measures, or occupational performance measures, or the combination of the two) best differentiate these three groups. Our research questions ask: (1) what are the differences between ERPs, and scores on the occupational performance assessments among neurotypical children, neurotypical adults, and adults with ADHD? We hypothesized that adults with ADHD will demonstrate different characteristics in the ERP components and occupational performance compared to neurotypical adults, (2) what are the relationships between ERP measures and occupational performance scores? We hypothesized that there will be significant relationships on neural and occupational performance for the three groups, and (3) What measures that we use (e.g., neural measures such as ERPs, or occupational performance measures, or the combination of the two) best differentiates the three groups? We hypothesized that combing both neural and occupational performance measures will provide us higher accuracy for classifying members of the three groups than using neural measures alone or occupational performance measures alone.

The reason neurotypical children, neurotypical adults, and adults with ADHD were included in this study was because by having these three groups researchers are able to understand two dimensions in one study, the impact of both maturation and disability on performance monitoring. Specifically, by comparing the group differences between neurotypical children and neurotypical adults, researchers could understand the typical maturation effect of cognitive functions and occupational performance. Moreover, comparing the group differences between adults with ADHD and neurotypical adults could inform researchers about the manifestations of atypical neural processes or difficulties in occupational performance in adults with ADHD compared to neurotypical adults. Lastly, by comparing the group differences between neurotypical children and adults with ADHD, researchers are able to understand whether or not there is a difference between the maturation level of the neural processes and occupational performance between neurotypical children and adults with ADHD.

Methods

Participants. A total of 102 neurotypical children, 28 neurotypical adults, and 12 adults with ADHD were recruited from the university and local community through convenient sampling (campus emails, flyers, psychology 100 research participant pool, and word of mouth). All participants in the neurotypical adult and child groups were screened for neurological and developmental disorders as well as use of psychopharmaceutical drugs (e.g., antidepressants) using self- or parent-report. Participants that reported neurological or developmental disorders or the use of psychopharmaceutical drugs were excluded. Participants with error rates either greater than 30% or fewer than 2.5 % on the computer-based task on the first of three sessions were excluded. Table 4.1 details the complete list of exclusion criteria and the number of participants lost to each. After exclusion, data from 63 neurotypical children (M = 10.10 years, SD = 0.18), 17 neurotypical adults (M = 21.31 years, SD = 0.54), and 8 adults with ADHD (M = 22.11 years, SD = 1.70) were entered for the final data analyses. Table 4.2 shows the final distribution participants by age and sex.

For the ADHD group, a formal diagnosis by a clinical psychiatrist was required to participate in the study based on self-report. The symptoms for ADHD were confirmed by the Conners' Adult ADHD Rating Scale (CAARS). The T-scores above 65 on subscales suggests symptoms are clinically significant. All participants with ADHD had at least one subscale above the T-score of 65, except one participant with ADHD who did not have any subscales above the T-score of 65. The participants in the ADHD group were asked to discontinue methylphenidate or other related medications 24 hours prior to their visits if applicable. Among 8 adults with ADHD who entered the final data analyses, five of them have other comorbidities: two participants had comorbidity of learning disability, one participant had comorbidity of depression, one participant had comorbidity of sensory processing disorder, one participant had comorbidity of both reading and learning disabilities.

Table 4.1. Detailed number of participants excluded from the study

		Groups		
		Children	Adults	Adults with ADHD
	Initially recruited	102 (100%)	28 (100%)	12 (100%)
Exclusion criteria	having neurological disorders	8 (7.84%) (4 had ADHD, 4 had reading disorders)	1 (3.57%) (brain injury)	0 (0%)
	did not complete the first session	2 (1.96%)	0 (0%)	0 (0%)
	did not complete the third session	16 (15.69%)	8 (28.57%)	4 (33.33%)
	error rate on the computer-based task was higher than 30%	12 (11.76%)	0 (0%)	0 (0%)
	error rate lower than 2.5%	1 (0.98%)	2 (7.14%)	0 (0%)
	final analyses	**63 (61.76%)**	**17 (60.71%)**	**8 (66.67%)**

Note: the percentage following the number of participants in each cell was calculated based on the number of subjects for that cell divided by the number of subjects initially recruited for each group.

Table 4.2. Participant distribution by group and gender

Groups	Children (n = 63)		Adults (n = 17)		Adults with ADHD (n = 8)	
Gender	Males	Females	Males	Females	Males	Females
n	23	40	8	9	3	5

Procedure. This study was part of a larger study. Participants were invited to the laboratory for three visits. The first and the second visits were separated with 1 to 3 weeks apart. In order to control for potential confounding variables, both visits were scheduled on the same day of the week, and at the same time of the day. Parents of child participants signed consent forms prior to their visits; all child participants signed the assent form and adult participants signed the consent forms on their first visit. Both first and second visits were consisted of 1.5 hours of EEG tasks and an hour of behavioral testing. The third visit lasted for an hour and focused on occupational performance (e.g., activities of daily living and social interaction tasks). The third visit was conducted in a room with a well-equipped kitchen environment.

The ERP paradigm. The speeded visual flanker task (Eriksen & Eriksen, 1974) was presented by the E-prime software version 2.0 to each participant on both sessions. The task contains 480 trials that were presented in two blocks of 240 trials. In this task, participants were presented four different stimuli (two congruent stimuli with 80 trials for each stimuli: “HHHHH” and “SSSSS”; two incongruent stimuli with 160 trials for each stimuli: “HHSHH” and “SSHSS). Participants were instructed to press the left button on a 4 button keypad using their left index finger if the middle letter is an H; and to press the right button using their right index finger if the middle letter is an S. Participants were told that the letters would be presented quickly, and they were instructed to perform as accurately as possible. The stimulus duration was 250ms and the initial inter-trial stimulus (ISI) was set at 1400ms. Following each set of 30 trials, the E-prime program was designed to evaluate the overall error rate and adjust the ISI by increasing or decreasing it by 100ms if the error rate was greater than 25% or fewer than 10%, respectively. A minimal ISI was set at 800ms to allow adequate time for brain processing of the stimulus and response to resolve prior to the onset of the stimulus on the subsequent trial.

Electrophysiological recording. EEG data were collected using the Active Two BioSemi system, either 32 or 64 channels (BioSemi, Inc., Amsterdam, the Netherlands) based on a modified 10-20 electrode placement system (American Electroencephalographic Society, 1994). Two electrodes, namely the common mode sense (CMS) and the driven right leg (DRL), were used to generate a common reference voltage (https://www.biosemi.com/faq/cms&drl.htm). Averaged signals from the left and right earlobes were used for offline referencing. Two electrodes were placed at the supra- and infraorbital regions of the left eye to measure the vertical eye movements (VEOG), and two electrodes were placed at the outer canthi of the left and the right eyes to measure the horizontal eye movement (HEOG). The sampling rate was set to 1024 Hz.

Electrophysiological data reduction. The Brain Vision Analyzer 2.0 software (www.brainproducts.com) was used to conduct the offline EEG data analyses. The data were referenced to the averaged signals of bilateral earlobes and then filtered with a bandpass filter of 0.1–30 Hz with 24 dB/oct. The data were then segmented into stimulus-locked segments on the correct trials, and response-locked segments on the incorrect trials. For stimulus-locked segments on the correct trials, the data were segmented into 1200 ms time periods, which spanned from 200 ms before stimulus onset to 1000 ms after stimulus onset. Then, the segments were baseline-corrected based on the average voltage of -200 to 0 ms of stimulus onset. Eye movement artifacts were removed via a regression approach based on the bipolar VEOG channel (Segalowitz, 1996) then baseline-corrected again using the period of -200 to 0 ms of stimulus onset. Segments containing voltage greater than ± 100 μV in the midline (e.g., Fz, FCz, Cz, Pz) and VEOG channels were rejected. For each participant, the data were then averaged to obtain an averaged stimulus-locked ERPs for correct trials separately.

For response-locked segments, the data on incorrect trials were segmented into 1400 ms time periods, which spanned from 600 ms before the incorrect response to 800 ms after the incorrect response. Segments with premature button responses (e.g., response times that were faster than 100 ms) were excluded from the analysis. Then, the segments were baseline-corrected based on the average voltage of the period between 600 to 400 ms preceding the incorrect response (Davies, Segalowitz, & Gavin, 2004). Eye movement artifacts were removed via a regression approach based on the bipolar VEOG channel (Segalowitz, 1996) then baseline-corrected again using the period of -600 to -400 ms preceding the incorrect response. Segments containing voltage greater than ± 100 µV in the midline (e.g., Fz, FCz, Cz, Pz) and VEOG channels were rejected.

The averaged ERPs obtained for each participant were scored using a customized peak-picking computer program in MATLAB that also allows for visual inspection to adjust for any peaks that were scored on a slope. Both the stimulus-locked components on the correct trials and response-locked components on the incorrect trials were measured using peak-to-peak approach. Additionally, the response-locked ERP components were processed through the adaptive Woody filter, and the peak-to-peak latency jitter corrected ERN and Pe amplitudes were used (Gavin, Lin, Davies, under review). The windows for scoring the peaks are reported in Table 4.3 for stimulus-locked and response-locked ERPs. All of the ERP components were measured at the site FCz.

Table 4.3. Time windows for scoring stimulus-locked ERPs on the correct trials and response-locked ERPs on the incorrect trials for adults and children

	Windows (ms) for stimulus-locked ERP components					Windows (ms) for response-locked ERP components	
	P1	N1	P2	N2	P3	ERN	Pe
Neurotypical adults and adults with ADHD	0-100	70-150	110-240	170-350	320-575	-10-180	120-450
Children	0-100	70-170	130-270	200-375	320-600	-10-180	120-450

Occupational performance measures. We administered the Evaluation of Social Interaction (ESI; Fisher & Griswold, 2015) and the Assessment of Motor and Process Skills (AMPS; Fisher & Jones, 2014) to measure the quality of occupational performance in participants of the three groups.

The Evaluation of Social Interactions (ESI). The ESI was conducted in a classroom in the Occupational Therapy department at Colorado State University (CSU). The ESI is an assessment that evaluates the quality of social exchange of the participant. A certified ESI assessor observed the participant as he or she interacted with their social partners (e.g., mom, siblings, or friend) in two meaningful and desired social episodes under naturalistic, real-life contexts. The types of social interactions varied from gathering information, sharing information, problem solving/decision making, collaborating/producing, acquiring goods and services, providing/delivering goods and services, or conversing socially/small talk. According to standardized procedures, the role of the assessor is to take notes on the observations, to record the purpose of the social interactions, and to score the quality of social interactions of participants' social partners while the participant and his or her social partner are performing social interactions. The ESI logit score from Rasch analysis was used to indicate participant's quality of social interaction after adjusting for the challenge of the social episodes, and the severity of the rater who scored the performance. This procedure results in logit scores that are comparable across different social episodes, raters, and participants regardless of age (ESI; Fisher & Griswold, 2015).

The ESI has 27 items that examine the quality of social interactions and can be categorized into seven domains: (1) initiating and terminating social interaction, (2) producing social interaction, (3) physically supporting social interaction, (4) shaping content of social interaction, (5) maintaining flow of social interaction, (6) verbally supporting social interaction, and (7) adapting social interaction. The occupational therapist scored each social interaction item using a 4-point rating scale for each social episode. Specifically, each skill has specific criteria that define competent, questionable, ineffective, or severely limited skill performance. A score of 4, indicating competent performance, is given when the certified assessor observes the client to consistently demonstrate behavior that is “polite, respectful, timely, and socially appropriate.” The ESI has been shown to be an effective tool that detects the changes in social skills resulting from interventions for patients with traumatic brain injuries (Simmon & Griswold, 2010) and is sensitive to differentiating children with disabilities from typical developing children (Griswold & Townsend, 2012). The ESI demonstrates high inter- and intra-rater reliability and high parallel-forms reliability in which, the scores obtained from two social episodes are highly correlated (r = 0.86; Fisher & Griswold, 2015). The internal validity is also well-supported in the literature (Fisher & Griswold, 2014).

The Assessment of Motor and Process Skills (AMPS). The AMPS was administered in a kitchen area designed to approximate a home environment located in the occupational therapy building at CSU. The AMPS was developed by occupational therapists to measure clients’ occupational performance (Fisher & Jones, 2014). The assessment focuses on the client-centered, occupation-based, and top-down manner in which professionals, such as occupational therapists, observe the way clients actually perform two everyday occupational tasks that are familiar and meaningful to clients. Examples of these ADL tasks include making a sandwich with peanut butter and jelly, vacuuming, or washing dishes. Overall, the AMPS contains 36 scoring items and these items are categorized into two categories: motor skills and process skills. For motor skills, there are four domains that include: body position, obtaining and holding objects, moving self and objects, and sustaining performance. For process skills, there are five domains that include: sustaining performance, applying knowledge, temporal organization, organizing space and objects, and adapting performance. Similar to the ESI logit score, the logit scores of AMPS motor and AMPS process skills were used to indicate the quality of participant's performance of ADL after adjusting for the difficulty of the tasks, and the severity of the rater who scored the performance. This procedure allows the resulting logit scores comparable across different daily tasks, raters, and participants regardless of age (AMPS; Fisher & Jones, 2014).

The AMPS has been used as an outcome measure that is able to detect changes in scores reflecting real changes in occupational performance in people with disabilities (Ayres & John, 2015; James, Ziviani, Ware, & Boyd, 2016). Moreover, the AMPS has been researched extensively with various population groups and has been found to be sensitive in detecting problems with efficiency, safety, and quality of performance in ADLs (Bray, Fisher, & Duran, 2001; Fisher & Jones, 2014). The AMPS has 83 standardized personal and instrumental ADL tasks and is appropriate for clients aged 3 to 99 (Fisher & Jones, 2014). Studies have demonstrated that the AMPS has high validity (Gantschnig et al., 2012; Kottorp et al., 2003).

The test-retest reliability was 0.90-0.91 for motor scale, and 0.87-0.90 for process scale (Fisher & Jones, 2014).

Statistical analyses.

Group differences. A series of one-way ANCOVAs with Group (children, adults, and adults with ADHD) as a between-subject variable and Sex (Males versus Females) as a controlled variable were performed to examine the group differences on the Flanker task behaviors (e.g., error rate, response times), each ERP measure (e.g., ERN amplitude) and occupational performance scores (e.g., ESI, AMPS motor and AMPS process scores). We also conducted the pairwise post-hoc tests on the variables to determine if observed scores differed between two groups were significant. Since the sample sizes are unequal among each group, in order to avoid making type I error, we conducted our ANCOVA analyses on two datasets. The first dataset included the complete sample (children: n = 63, adults: n = 17, adults with ADHD: n = 8). Then we down sampled the participants via random selection in neurotypical child and adult groups, so that each group has the same number of participants (children: n = 8, adults: n = 8, adults with ADHD: n = 8). We recognized that by implementing the down-sampling approach we decreased our statistical power to detect the differences across groups. However, this is a conservative approach that allows us to further confirm whether the significant differences obtained from the complete sample were confounded by the unequal sample sizes across groups.

The relationship between the ERN components and occupational performance. A series of regression analyses were conducted to examine the relationship between six ERP components and occupational performance with age and gender as controlled variables for neurotypical children and neurotypical adults. However, since we only had 8 participants for the adults with ADHD group, rather than using the regression analyses to investigate the relationship between ERP components and occupational performance, we used the Pearson correlation analyses to explore the relationship between these variables.

Determining the contributions of ERP components and occupational performance for classifying group membership of individuals. Three discriminant analyses were used to understand the relative importance of (1) neural measures (i.e., amplitudes of ERP components), (2) occupational performance measures (i.e., AMPS or ESI scores), and the (3) combination of the neural and occupational performance measures in classifying participants according to their group memberships. Specifically, for the first discriminant analysis, the independent variables were the ERP amplitudes (i.e., amplitudes of the N1, P2, N2, P3, ERN and Pe). For the second discriminant analysis, the independent variables were the ESI score, AMPS motor and AMPS process scores. For the third discriminant analysis, the independent variables were the combination of the neural and occupational performance measures that are listed above. The accuracy of classification functions was evaluated based on the percent agreement between the predicted group membership and the sampled group membership. All statistical analyses were conducted using the Statistical Package for Social Sciences (SPSS) version 25.0.

Results

Group differences on the behavioral and ERP results. The descriptive results and the results from the ANCOVA analyses on the complete dataset are reported in the Table 4.4. The results on the down-sampled dataset are reported in the Table 4.5. The grand-averaged stimulus-locked and response-locked ERPs are presented in Figure 4.1.

Table 4.4. The means, standard deviations, and results from the ANCOVA tests with post-hoc pairwise comparisons between groups on the Flanker-task behaviors, the ERP components, and the occupational performance tasks obtained from the complete sample

	Children (n = 63)	Adults (n = 17)	Adults with ADHD (n = 8)	$F_{(2,82)}$	p value	η_p^2
Performance on the Flanker task						
error rate (%)	0.14±0.01[a]	0.08±0.01[b]	0.15±0.03[a]	9.65	<.001	0.19
RTs on correct trials (ms)	642.72±15.20[a]	435.58±13.07[b]	414.45±12.60[b]	34.90	<.001	0.46
RTs on incorrect trials (ms)	489.79±12.43[a]	384.38±11.62[b]	351.57±10.36[b]	16.78	<.001	0.29
Occupational performance						
AMPS motor logit score	2.02±0.31[a]	2.56±0.29[b]	2.21±0.28[a]	20.20	<.001	0.33
AMPS process logit score	1.18±0.27[a]	1.46±0.17[b]	1.34±0.18[a,b]	9.13	<.001	0.18
ESI logit score	0.88±0.23[a]	1.12±0.23[b]	0.94±0.18[a,b]	7.83	.001	0.16
Peak-to-peak ERP amplitude						
N1	-8.58±0.36[a]	-3.27±0.40[b]	-3.30±0.63[b]	35.45	<.001	0.46
P2	16.39±6.58[a]	7.45±3.62[b]	6.70±4.20[b]	19.64	<.001	0.32
N2	-16.52±7.24[a]	-7.42±2.83[b]	-9.80±5.51[b]	13.72	<.001	0.25
P3	11.16±3.87	9.51±3.23	13.86±7.18	2.70	0.07	0.06
ERN	-16.69±7.59	-16.23±6.59	-14.92±5.15	0.37	0.69	0.01
Pe	27.63±8.87[a]	19.14±7.67[b]	21.26±4.73[a,b]	7.87	.001	0.16

Note: The results from the post-hoc pairwise comparisons are denoted by subscripted letters, the means that share the same subscripted letter are not statistically different from each other, the means that share different subscripted letters are statistically different from each other

Table 4.5. The means, standard deviations, and results from the ANCOVA tests with post-hoc pairwise comparisons between groups on the Flanker-task behaviors, the ERP components, and the occupational performance tasks obtained from the subset of the sample

	Children (n = 8)	Adults (n = 8)	Adults with ADHD (n = 8)	$F_{(2,18)}$	p value	η_p^2
Performance on the Flanker task						
*error rate (%)	0.14±0.09	0.11±0.05	0.15±0.09	0.83	0.45	0.09
RTs on correct trials (ms)	689.92±174.90^{a}	433.97±36.48^{b}	414.45±35.64^{b}	11.72	.001	0.57
RTs on incorrect trials (ms)	543.10±130.41^{a}	385.28±30.03^{b}	351.57±29.31^{b}	8.96	0.002	0.50
Occupational performance						
AMPS motor logit score	1.96±0.28^{a}	2.58±0.24^{b}	2.21±0.28^{a}	6.45	0.01	0.42
*AMPS process logit score	1.18±0.32	1.45±0.19	1.34±0.18	2.54	0.11	0.22
*ESI logit score	0.96±0.25	1.03±0.16	0.94±0.18	0.26	0.78	0.03
Peak-to-peak ERP amplitude						
N1	-8.04±3.07^{a}	-3.18±1.71^{b}	-3.30±1.79^{b}	22.34	<.001	0.71
P2	15.99±7.35^{a}	6.88±4.48^{b}	6.70±4.20^{b}	9.11	0.002	0.50
N2	-16.40±6.41^{a}	-8.06±3.59^{b}	-9.80±5.51^{a,b}	3.89	0.04	0.30
P3	11.03±6.16	10.13±4.21	13.86±7.18	0.77	0.48	0.08
ERN	-19.91±15.33	-17.28±8.40	-14.92±5.15	0.51	0.61	0.05
*Pe	30.88±14.81	21.55±9.61	21.26±4.73	1.35	0.28	0.13

Note: The results from the post-hoc pairwise comparisons are denoted by subscripted letters, the means that share the same subscripted letter are not statistically different from each other; the means that share different subscripted letters are statistically different from each other . An asterisks(*) before the variable denotes that the findings on the subset of the sample are different from those obtained from the complete sample.

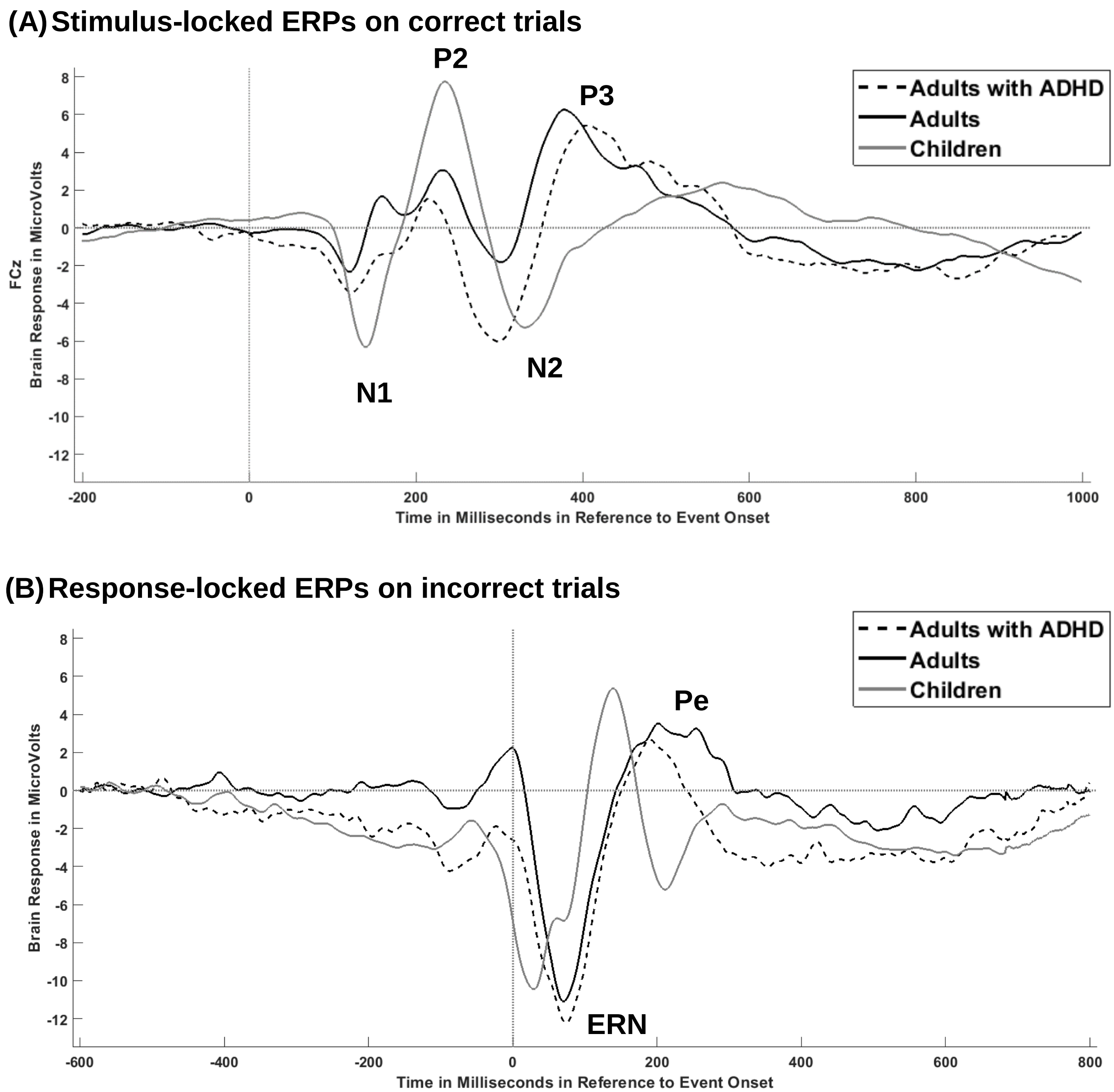


Figure 4.1. The grand-averaged of the (A) stimulus-locked ERPs on the correct trials (the time zero indicates the onset of the stimuli) and (B) response-locked ERPs on incorrect trials (the time zero indicates the closure of button presses) for the children, adults, and adults with ADHD

The relationship between the ERN and Pe components and occupational performance. For neurotypical children and adults, a series of regression analyses with ESI score, AMPS motor score, and AMPS process score were conducted to examine the relationship between the ERP components and the occupational performance score. For adults with ADHD, Pearson correlations were used to examine these relationships.

ESI score. For neurotypical adults, none of the independent variables significantly predicted the ESI score. For neurotypical children, only the ERN amplitude significantly predicted the ESI score (b = 0.012, β = 0.391, t = 2.12, p = 0.04), such that the larger the ERN amplitude, the lower the ESI score after controlling for other ERP components, age, and sex (overall model: $F(8,54) = 2.32$, $p = 0.032$, $R^2 = 0.26$, adjusted $R^2 = 0.15$). For adults with ADHD, Pearson correlation coefficients showed that only the N2 component was significantly correlated with the ESI score, such that the larger the N2 amplitude, the lower the ESI score (r = 0.72, p = 0.046).

AMPS motor score. For neurotypical adults, none of the independent variables significantly predicted the AMPS motor score. For neurotypical children, only the Pe amplitude significantly predicted the AMPS motor score (b = -0.012, β = -0.344, t = 2.14, p = 0.037), such that the larger the Pe amplitude, the lower the AMPS motor score after controlling for other ERP components, age, and sex (overall model: $F(8,54)$ =4.703, p = < .001, $R^2 = 0.411$, adjusted R^2 = 0.323). For adults with ADHD, Pearson correlation coefficients showed that none of the ERP components are associated with the AMPS motor score.

AMPS process score. For neurotypical adults, none of the independent variables significantly predicted the AMPS process score. Similarly, for neurotypical children, none of the independent variables significantly predicted the AMPS process score. For adults with ADHD, Pearson correlation coefficients showed that none of the ERP components are associated with the AMPS process score.

Discriminant analyses results.

ERP components (N1, P2, N2, P3, ERN, and Pe amplitudes) as independent variables. The results from the first discriminant analysis with the ERP components as independent variables showed that 90.9% of the participants were accurately classified according to their group membership by the ERP measures alone. The neurotypical child participants were 96.8% correctly classified, 88.2% neurotypical adults were correctly classified, while only 50% adults with ADHD were correctly classified (see Figure 4.2). Four neurotypical adults were misclassified: two were misclassified as children and 2 were misclassified as adults with ADHD; two children were misclassified as neurotypical adults, four adults with ADHD were misclassified: three were misclassified as neurotypical adults and 1 was misclassified as a neurotypical child. Function 1 was significant ($\lambda = 0.36$, $p < .001$), and Function 2 was not significant ($\lambda = 0.89$, $p = 0.094$). The standardized canonical coefficients and structure matrix coefficients for the first discriminant analysis is reported in Table 4.6 and the scatter plot is presented in Figure 4.2.

Table 4.6. The discriminant analysis results of the ERPs components

Standardized Canonical Coefficients			Structure Matrix		
Variables	Function 1	Function 2	Variables	Function 1	Function 2
N1	0.66	-0.04	N1	0.77*	0.01
P2	0.03	-0.85	P2	-0.58*	-0.10
N2	0.64	-0.72	N2	0.48*	-0.26
P3	0.43	0.74	Pe	-0.35*	0.18
ERN	-0.35	0.69	P3	-0.02	0.77*
Pe	-0.67	0.36	ERN	0.05	0.13*

Note: *indicates largest absolute correlation between each variable and any discriminant function

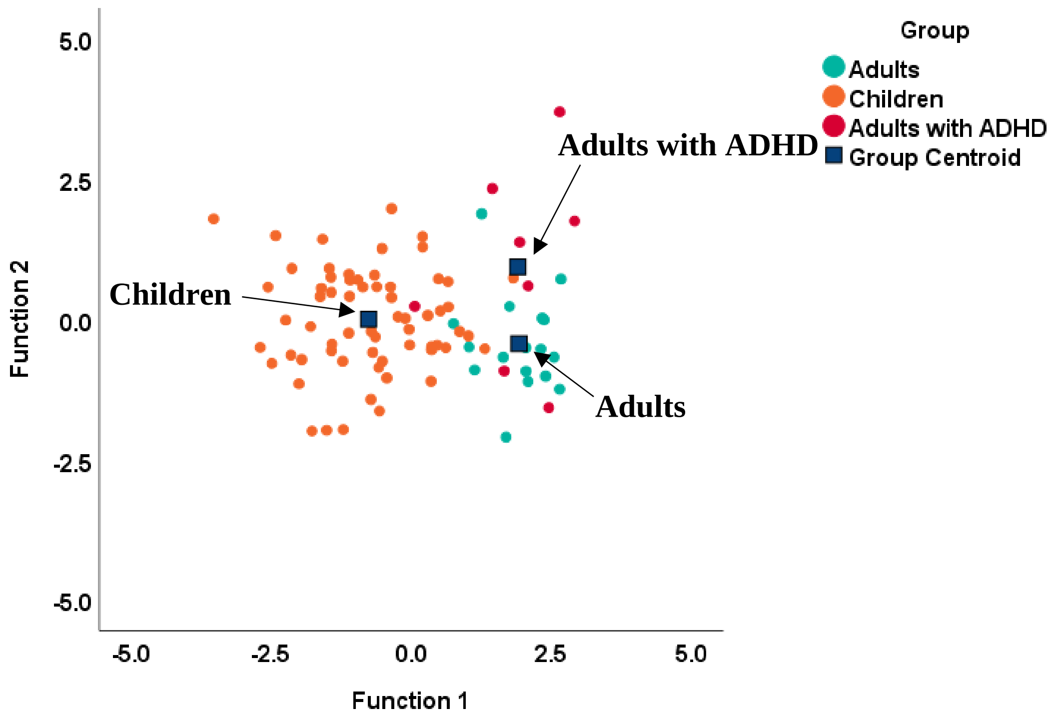


Figure 4.2. Scatter plot for the discriminant analysis model with ERPs (N1, P2, N2, P3, ERN, and Pe) as independent variables

Occupational performance measures as independent variables. The results from the second discriminant analysis with the occupational performance scores as independent variables showed that 80.7% of the participants were accurately classified according to their group membership. Ninety-five point two percent (95.2%) of the neurotypical children were correctly classified, 64.7% neurotypical adults were correctly classified, yet 0% adults with ADHD were correctly classified (see Figure 4.3). Six neurotypical adults were misclassified as children. Three neurotypical children were misclassified as neurotypical adults. Eight adults with ADHD were misclassified; one was classified as neurotypical adult and seven were classified as children. Function 1 was significant ($\lambda = 0.63$, $p < .001$), and Function 2 was not significant ($\lambda = 0.99$, $p = 0.71$). The standardized canonical coefficients and structure matrix coefficients for the first discriminant analysis is reported in Table 4.7 and the scatter plot is presented in Figure 4.3.

Table 4.7. The discriminant analysis results of the occupational performance measures.

Standardized Canonical Coefficients			Structure matrix		
Variables	Function 1	Function 2	Variables	Function 1	Function 2
ESI	0.32	-0.71	AMPS-motor	0.92*	-0.01
AMPS-motor	0.77	-0.24	ESI	0.57*	-0.39
AMPS-process	0.19	1.04	AMPS-process	0.60	0.69*

Note: *indicates largest absolute correlation between each variable and any discriminant function

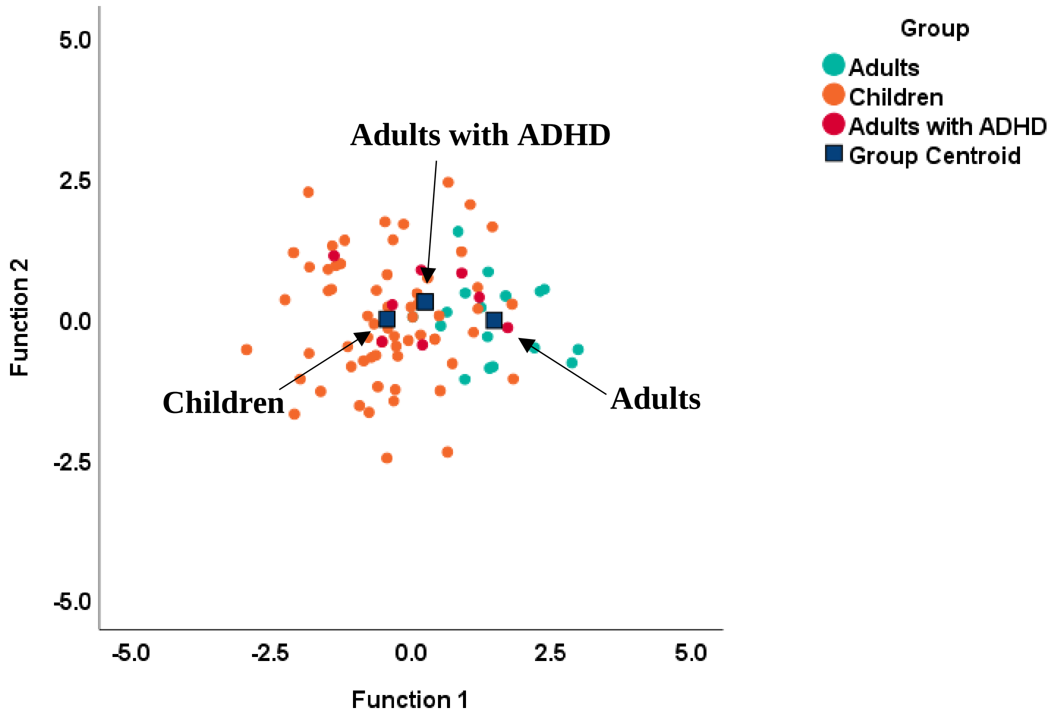


Figure 4.3. Scatter plot for the discriminant analysis model with occupational performance measures (ESI, AMPS motor and AMPS process scores) as independent variables

Combination of the ERP components (N1, P2, N2, P3, ERN, and Pe amplitudes) and occupational performance measures as independent variables. The results from the third discriminant analysis with the ERP components and occupational performance scores as independent variables showed that 93.2% of the participants were accurately classified according to their group membership. The neurotypical child participants were 98.4% correctly classified, 88.2% neurotypical adults were correctly classified, while only 62.5% adults with ADHD were correctly classified (see Figure 4.4). One neurotypical child was misclassified as a neurotypical adult. Two neurotypical adults were misclassified as adults with ADHD. Three adults with ADHD were misclassified; two was classified as neurotypical adults and one was classified as a child. Function 1 ($\lambda = 0.29$, $p < .001$) and Function 2 ($\lambda = 0.80$, $p = .023$) were both significant. The standardized canonical coefficients and structure matrix coefficients for the first discriminant analysis is reported in Table 4.8 and the scatter plot is presented in Figure 4.4.

Table 4.8. The discriminant analysis results using the combination of the ERP components (N1, P2, N2, P3, ERN, and Pe amplitudes) and occupational performance measures as independent variables

standardized canonical coefficients			Structure matrix		
variables	Function 1	Function 2	variables	Function 1	Function 2
N1	0.05	0.41	N1	0.71*	-0.20
P2	0.39	0.49	P2	-0.53*	0.22
N2	-0.03	-0.03	AMPS-motor	0.51*	0.43
P3	0.58	-0.23	N2	0.45*	0.06
ERN	0.02	0.56	AMPS-process	0.35*	0.16
Pe	0.56	0.24	Pe	-0.33*	-0.03
ESI	0.27	-0.84	P3	-0.04	-0.53*
AMPS-motor	-0.25	-0.29	ESI	0.31	0.34*
AMPS-process	-0.48	0.12	ERN	0.04	-0.10*

Note: *indicates largest absolute correlation between each variable and any discriminant function

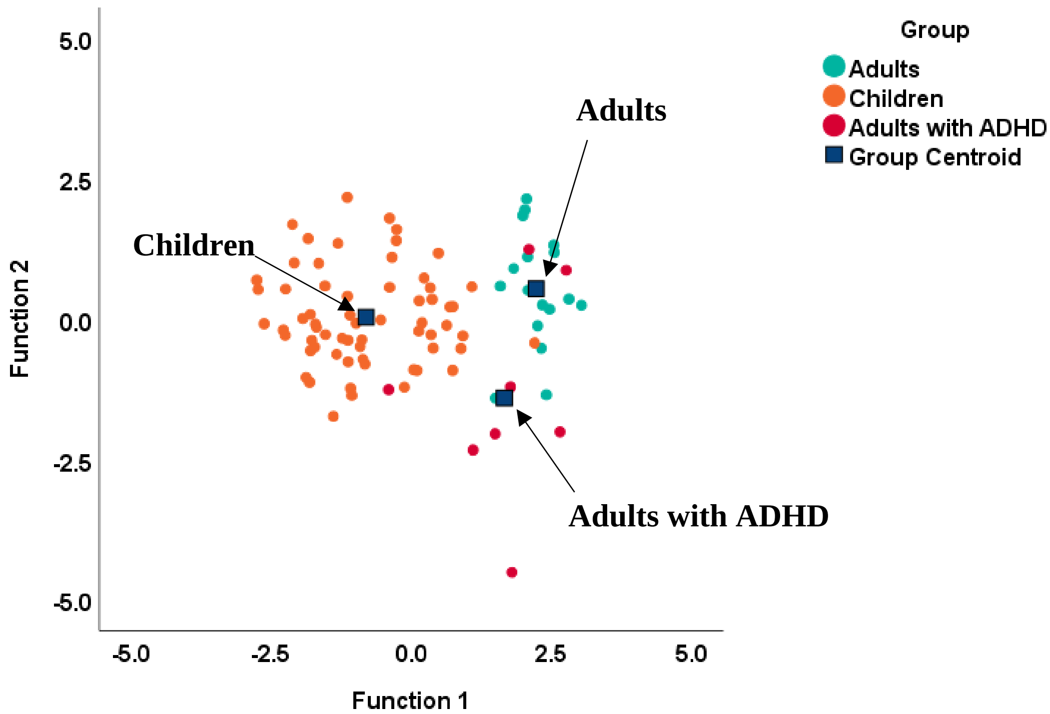


Figure 4.4. Scatter plot for the discriminant analysis model with ERP components (N1, P2, N2, P3, ERN, and Pe) and occupational performance measures (ESI, AMPS motor, and AMPS process scores) as independent variables

Discussion

This study is an exploratory study that investigates the differences between ERP component amplitudes and occupational performance scores among neurotypical children, neurotypical adults, and adults with ADHD. Moreover, we examined the relationship between neural processing measured by ERP component amplitudes and occupational performance scores for each group. We implemented three discriminant analyses to understand the relative importance of neural processes measured by ERP component amplitudes and occupational performance scores in classifying participants according to their group membership. The findings will be discussed in terms of these three investigative goals; 1) group differences in ERP measures and occupational performance, 2) relationship between ERP components and

Occupational Performance, and 3) determining if neural measures, occupational performance scores or a combination of both best distinguish the three groups.

Group differences on the ERN components and occupational performance scores. The findings from the complete sample suggested that the error rate was significantly higher in adults with ADHD compared to neurotypical adults, which were consistent with several studies (Balogh et al., 2017; Marquardt, Eichele, Lundervold, Haavik, & Eichele, 2018). However, the findings obtained from the smaller subset of the sample suggested that there were no group differences on the error rate. This outcome is similar to findings reported in several other studies (Chang, Davies, & Gavin, 2009; Wiersema, van der Meere, & Roeyers, 2009). The inconclusive findings may be due the heterogeneity especially in cognitive functions in individuals with ADHD (Mostert et al., 2015). Moreover, the contradicted findings may result from the inadequate sample size of the three groups after we down-sampled. Therefore, a larger sample size is needed to further examine the group differences on the error rate.

In terms of the ERP components, consistent with previous studies, the amplitudes of the N1, P2, N2, and Pe amplitudes were significantly larger in neurotypical children compared to adults (Ridderinkhof & Van der Stelt, 2000). However, contrary to the previous studies, we did not find differences between adults with ADHD and neurotypical adults on the amplitudes of all ERP components (N1, P2, N2, P3, Pe, and ERN; Chang, Davies, & Gavin, 2009; McLoughlin et al., 2009; Wiersema, van der Meere, & Roeyers, 2009). In addition to the small sample size, one possible explanation for the non-significant group differences may be associated with our sampling strategy. Since the participants in the study were mostly college students and were considered as high functioning, the sample we recruited in this study may not be representative of the general population of adults with ADHD.

Among three occupational performance measures (i.e., ESI score, AMPS motor, and AMPS process scores), adults with ADHD only showed significantly lower AMPS motor score compared to neurotypical adults. Similar findings were also shown in the results from the subset of sample. The findings suggested that adults with ADHD require increased effort in successfully performing the daily tasks. Some of the areas on this assessment that they demonstrated difficulties were in obtaining, moving, or holding objects with flexibility. Our findings demonstrated that there were no statistical differences between adults with ADHD and neurotypical adults on AMPS process scores and ESI scores. Interestingly, while neurotypical adults had significantly higher scores compared to children on the three occupational performance measures, there were no significant differences between children and adults with ADHD on the three occupational performance measures (e.g., the AMPS motor and process scores, and ESI score).

The relationship between the ERN and Pe components and occupational performance. For neurotypical adults, we did not find significant relationships between any of the ERP components and the occupational performance measures. It is possible that there might be other cognitive functions that underlie ADL and the social interaction tasks that we failed to take into consideration in this study. Again, since we only have 17 participants in this group, the small sample size might be another reason that we failed to obtain the significant relationships among neural and occupational performance measures.

For neurotypical children, the relationship between the ERN and the ESI score was significant such that the larger the ERN amplitude, the lower the ESI score. Previous studies have shown that a larger ERN amplitude in individuals with anxiety disorder, and obsessive-compulsive disorder, compared to a neurotypical sample, indicating that these individuals may have hyperactive performance monitoring ability and may be overly concerned about their errors (Carrasco et al., 2013; Ladouceur, Dahl, Birmaher, Axelson, & Ryan, 2006). This could inform our findings that hyperactive performance monitoring ability may be a challenge in social interaction. Additionally, the relationship between Pe amplitude and the AMPS motor score was also significant such that the larger the Pe amplitude, the lower the AMPS motor score. The Pe amplitude is associated with post-error behavioral adjustments, and is associated with post-error slowing, a phenomenon that individuals slow down their reaction times after committing errors (Hajcak, McDonald, & Simons, 2003). Several items on AMPS motor scores were scored based on whether the action was performed in a timely manner, therefore, an enhanced Pe amplitude may be associated with slower performance, which in turn could lead to lower motor scores.

For adults with ADHD, the findings showed that the larger the N2 amplitude, the lower the ESI score. Espinet, Anderson, & Zelazo (2012) found that children who had better executive functions skills that allowed them to flexibly switch between two tasks had smaller N2 amplitude, suggesting a positive relationship between small N2 amplitude and better executive function skills. The findings may suggest that adults with ADHD who had a larger N2 amplitude may be less flexible in engaging and switching the conversation which may cause delayed response time during the social interaction, leading to lower quality in the social interaction. However, we need to interpret the findings with caution since we only have 8 participants in this group. Contrary to what we hypothesized, the relationship between the ERN and the social interaction scores was not significant for adults with ADHD, however, a larger sample size would be needed to further examine the relationship.

Determining the contributions of ERP components and occupational performance for classifying group membership of individuals. The discriminant analyses differentiated three groups of participants, neurotypical children, neurotypical adults, and adults with ADHD with highest classification accuracy when both neural and occupational performance measures were used (total classification of 93.2%) compared to using neural measures alone (total classification of 90.9%) or occupational performance measures alone (total classification of 80.7%). To our knowledge, this is the first study utilizing the neural and occupational performance measures to classify children, adults, and adults with ADHD. The findings demonstrated the feasibility of combining the neural and occupational performance measures in classifying participants according to their group memberships. Specifically, these measures yielded two significant discriminant functions. The first function may be related to maturation or development, since it separated the neurotypical children from two adult groups. The second function may be related to the level of disability/functioning, since it separates three groups in terms of their disability and functioning, with neurotypical adults at the upper end and adults with ADHD at the lower end. The findings may inform researchers and clinicians that both neural and occupational performance measures are essential to provide a comprehensive picture to better describe the unique characteristics of groups in terms of maturation and disability.

Limitation

The major limitation of this study is the small sample size of the ADHD group. The small sample size may lead to low statistical power that prevents us from obtaining robust findings. Although we attempted to use a more conservative approach by down-sampling the participants in another two groups, we recognized that this approach might not be ideal. A future study could collect data in more participants with ADHD and match the size of the groups. Then Monte

Carlo simulation could be used to estimate missing data points. Another limitation of this study is that the research assistant who administered the ESI and AMPS was not blind to whether the adult had an ADHD diagnosis or not. Future studies could conduct blind studies in which the research assistants are blind to the diagnosis of ADHD in order to eliminate potential research biases and to obtain more robust findings.

Conclusion

This study demonstrated that adults with ADHD demonstrated significantly lower quality of occupational performance particularly on the motor aspect of the ADL. Moreover, we found a significant relationship between neural measures and occupational performance in neurotypical children and adults with ADHD. Moreover, for neurotypical children, larger ERN amplitude was associated with lower quality of social interaction. For adults with ADHD, larger N2 amplitude was associated with lower quality of social interaction. Lastly, the discriminant analyses demonstrated that the combination of the neural and occupational performance measures best differentiated children, adults, and adults with ADHD with 93.2% classification accuracy. Future studies could investigate what are other measures (e.g., attention or executive function measures) that can be used to increase the classification accuracy.

CHAPTER 5: DISCUSSION

The overarching goal of this dissertation is to explore the brain-and-behavioral relationships in neurotypical children, neurotypical adults, and adults with attention-deficit/hyperactivity disorder (ADHD). Three studies were conducted in this dissertation. For each study, electroencephalography (EEG)/event-related potential (ERP) techniques were used to measure the neural processes associated with cognitive functions. The first study demonstrated the psychometric properties, particularly the test-retest reliability, of the error-related negativity (ERN) and error positivity (Pe) components in children and adults. The second study showed the feasibility of utilizing the structure equation modeling (SEM) approach to examine the stream of neural processing predicting simple task behaviors (i.e., response time). The third study examined the differences among neurotypical children, neurotypical adults, and adults with ADHD on neural and occupational performance measures, and investigated the efficacy of using the combination of these measures in classifying the three groups according to their group membership. In the following sections, I will address the theoretical and methodological application, as well as the clinical implications of the dissertation. I will then relate the findings with occupation and rehabilitation sciences.

Theoretical Applications

The findings on the brain-and-behavior relationships in this dissertation are supported by several theoretical frameworks. Specifically, the second study successfully demonstrated the interrelationships among neural measures and that the stream of neural processes predicts simple task behaviors (e.g., response times). Such a predictive and interdependent relationship among neural measures predicting the response times portrayed in our models is consistent with the principles of the dynamic system theory and the connectionist theory (Elman, 2003; Hayes & Strauss, 1998; Pastur-Romay, Cedrón, Pazos, & Porto-Pazos, 2015; Rogers, 2009; Samuelson, Jenkins, & Spencer, 2015). Specifically, according to the dynamic system theory and the connectionist theory, behavioral outputs are produced by interactions among neurons, and are determined by the environment and tasks that are performed (Samuelson et al. 2015). Moreover, the interrelationships among neural measures (units), and the strengths of these relationships are in line with the way connectionist theorists described the neural networks underlying cognitive functions (McClelland et al., 2010; Rogers, 2009). Furthermore, our last model showed that the error detection brain signal (i.e., ERN) predicted the brain activity associated with initiation of post-error adjustment (i.e., Pe). Moreover, the last model also demonstrated the circular nature of the brain-and-behavior relationships, such that the neural processing leads to behaviors, and in turn the behaviors and cognitive strategies influence brain processing. Thus, the brain activity associated with error detection and post-error adjustment fed forward to predict early brain activity on the trials in which correct responses/behaviors were performed. Such a dynamic interaction between neural and behavioral measures is also supported by the International Classification of Functioning, Disability, and Health (ICF) framework with a bi-directional arrow between the domain of body function and body structure and the domain of activity (WHO, 2002).

The third study in this dissertation took the initial steps in expanding the brain-and-behavior relationships to a more functional level. The behavioral measures used in the first and the second study were the behavioral outcomes from the simple task behaviors (i.e., response times in the Flanker task). However, for the third study, we utilized the occupational performance assessments and examined how neural measures associated with the quality of the activities of daily living (ADL) and social interaction performed in natural contexts. Conducting the occupation-based assessment like the Assessment of Motor and Process Skills (AMPS) and the Evaluation of Social Interaction (ESI) is closely aligned with the Person-Environment-Occupation (PEO) and the ICF model (Law et al., 1996). Specifically, the PEO model describes the relationship among the person, environment, and occupation as translational and interdependent (Law et al., 1996). Observing the way participants performed meaningful daily occupations or engaging in the social conversation with their social partners under the real-life contexts allows researchers to obtain a holistic perspective on the dynamic transactions among participants, tasks, and the environment (Law et al., 1996; WHO, 2002). Moreover, currently in the third study we were not able to establish models combining the occupational performance measures due to small sample size, however, future studies with increased number of participants would be able to examine the relationship between neural responses and other constructs of cognitive functions such as attention and executive functions and then even to occupational performance such as ADL/IDAL and social interactions (See Figure 5.1).

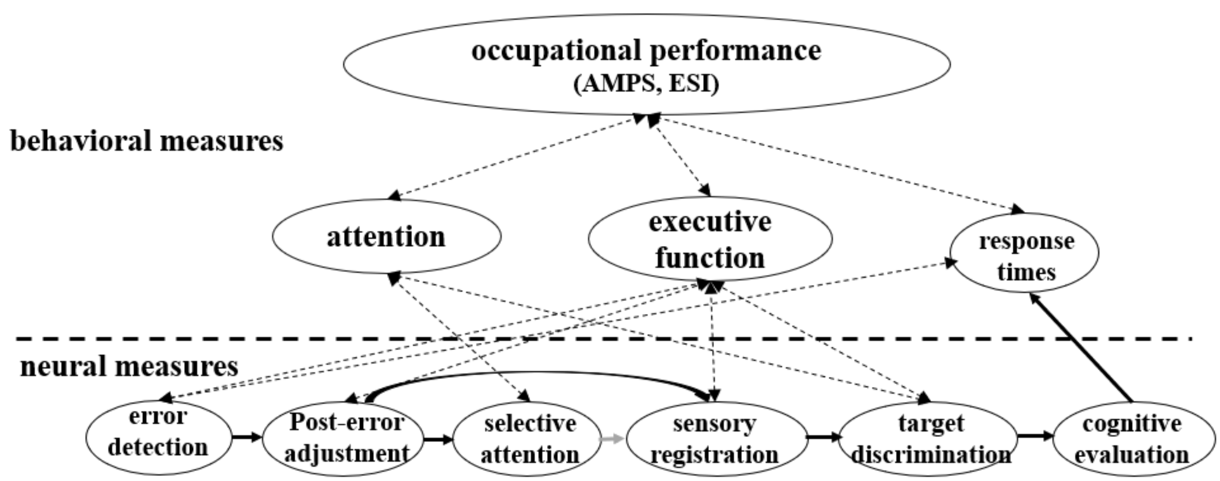


Figure 5.1. Conceptual latent path model with neural measures, attention, executive functions and occupational performance

Methodological Applications

Utilizing the SEM approach to model the brain-and-behavior relationship. This dissertation successfully demonstrated the feasibility of using the SEM in investigating the interrelationship of the neural processes and the simple task behavior (i.e., response times). The primary advantage of the SEM is that it uses the common variance of the manifested variables (e.g., N1 amplitude on session 1 and session 2) to define the latent variable (e.g., the construct of the sensory-based processing; Byrne, 2013). This approach minimizes error measurement in the latent variables so that researchers have cleaner variables that are free from the measurement error with which to model the relationships (Byrne, 2013). To our knowledge, this is the first study that utilizes the modeling approach to demonstrate the adaptive mechanisms of performance monitoring on the stream of neural processes leading to correct behaviors. Most of the studies that have examined brain-and-behavior relationships use a single ERP component and a behavioral measure as two variables in a bivariate correlation analyses. However, by conducting the simple correlation analysis to investigate the complicated brain-and-behavior relationship, the researchers overlook the interdependent nature of the complex underlying neural processes. Failing to account for these interdependent relationships among the neural processes may yield less robust and inconclusive findings. Therefore, we argue that when investigating the brain-and-behavior relationships, researchers should view the stream of neural processing as a whole discourse rather than a set of separate components (Brydges et al., 2014).

Importance of the state and trait effect. The findings suggested that the trait and the state effect need to be taken into consideration when collecting the psychophysiological measures. Specifically, the trait is considered as a feature or a characteristic that is stable over time and is associated with an individual’s temperament or personality (Gavin & Davies, 2008).

For example, the age, sex, or diagnosis of neurological or developmental disorders may be considered as traits. On the other hand, the state effect is defined as the factor that may vary between one situation to another (Hagemann & Naumann, 2009). It is considered as the psychological or physiological factor that are independent of the manipulations in the experimental paradigm, but may influence the psychophysiological measures (Gavin & Davies, 2008). For example, fatigue and anxiety levels are regarded as the state effect, since they are not related with the experimental design, yet studies have shown that these state effect could impact the EEG/ERP measures (Hagemann & Naumann, 2009; Tsai, Young, Hsieh, & Lee, 2005). Although in this dissertation we have not empirically examined the underlying mechanisms of the state effect, however, we hypothesized that the state effect is associated with the anxiety, fatigue, attention, motivation, learning effect, practice effect or other transient factors that systematically influenced the ERP components across sessions (Gavin & Davies, 2008). The findings also highlighted the importance of minimizing the measurement error associated with the state effect both during the data collection (e.g., building rapport with the subjects so that they are less nervous) or data analyses (e.g., controlling for the state and trait measures) in order to obtain reliable results (Gavin & Davies, 2008).

Utilizing the discriminant analyses to better understand the group characteristics. The discriminant analysis is a statistical analysis approach that is less commonly applied on the EEG/ERP data. The discriminant analysis allows researchers to include multiple variables (e.g., ERP components and occupational performance measures) to understand the group characteristics. It also has the potential to being more effective in understanding the nature of the disorder group (e.g., adults with ADHD) compared to other statistical approach that only use single variables (e.g., correlation between an ERP component with symptom severity in adults with ADHD). The findings from the discriminant analyses in the third study showed that combining ERP components and occupational performance gave us the highest classification accuracy (93.2%). This suggested that both neural and behavioral measures are necessary to best distinguish between the groups. Moreover, the discriminant analysis with the neural and occupational performance measures revealed two functions. One described the groups in terms of the maturation continuum such that it separated the child group from the two adult groups. One described the groups in terms of the disability continuum such that it separated three groups with the neurotypical adults and adults with ADHD at the upper and the lower end, and the children in between. Taken together, this study not only provided a crucial perspective that both neural and behavioral measures are critical in differentiating the three groups, but also showed how each measure contributes to group separation.

Clinical Applications

Biomarkers development. The first study examined the test-retest reliability of two ERP components, namely the error-related negativity (ERN) and error positivity (Pe), in children and adults. These two neural measures are shown to be associated with the phenotype of neurological or developmental disorders such as schizophrenia, depression, autism spectrum disorders, or attention-deficit/hyperactivity disorders (Bates et al., 2004; Kim et al., 2006; Larson, Kaufman, Kellison, Schmalfuss, & Perlstein, 2009; Marquardt, Eichele, Lundervold, Haavik, & Eichele, 2018; Morris et al., 2008; Vlamings et al., 2008). Thus, establishing the psychometric properties of these two ERP components are a critical step for developing the ERN and Pe components as biomarkers to assist in clinical diagnoses of developmental or neurological disorders and monitor the treatment effectiveness for clinical interventions.

The brain-and-behavioral models. The second study utilized the SEM to model the underlying neural processes predicting simple task behaviors (e.g., response times) in children. The model established in this study could set a critical foundation for understanding the neural processes in neurotypical children and can be compared to other models established in children with neurological and developmental disorders. For example, certain predictive relationships in the models established on children with ADHD or children with autism spectrum disorders (ASD) may not be significant compared to the relationships in the models established on neurotypical children. Such differences could further guide therapists or clinicians to target the strengths and the weakness and development strength-based treatment.

Relationship between neural measures and occupational performance. The third study demonstrated a significant relationship between the ERN amplitude and the quality of the social interaction in children, such that the larger the ERN amplitude, the lower the evaluation of the social interaction scores. The findings suggested that hyperactive performance monitoring may be associated with the challenge in the social interaction which is consistent with other studies (Barker, Troller-Renfree, Pine, & Fox, 2015; Wauthia & Rossignol, 2016). Hence, for clinical populations such as individuals with anxiety or obsessive-compulsive disorders who have been shown to have hyperactive performance monitoring, therapists and clinicians may develop treatment that helps to deemphasize their self-monitoring when making mistakes while interacting with others.

Relation to the Occupation and Rehabilitation Science

Occupation and rehabilitation science are two professions that share a lot of common ground, yet each science has its unique perspective to understand the human nature. In this section, I will utilize the ICF framework as a foundation to address the similarities and the differences between occupation and rehabilitation science and the relationship of these disciplines to my dissertation studies. Specifically, ICF is a model that focuses on the overall health condition and functioning of an individual (WHO, 2002; Figure 5.2). The ICF framework describes the relationships across multiple factors including body function and body structure, activity, participation, environment, and personal factors, and how these factors bidirectionally influence each other and contribute to the overall health condition (see Figure 5.2).

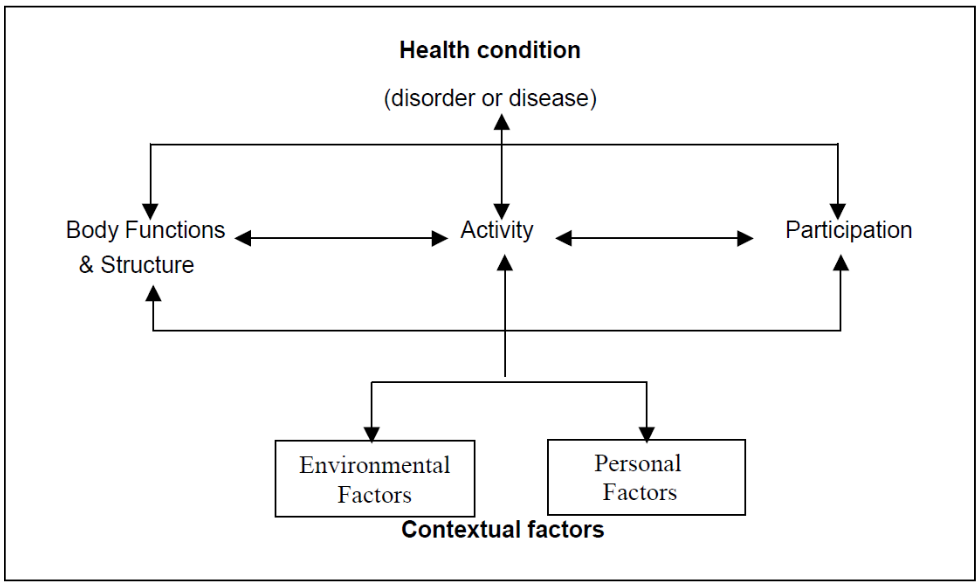


Figure 5.2. The ICF framework (WHO, 2002)

Both occupation and rehabilitation scientists value all the aspects depicted in the ICF model. However, since the central tenants and the core beliefs are different between these two sciences, scientists from these two disciplines may prioritize these factors differently. Specifically, the central tenant of occupational science is the engagement in meaningful occupation. Specifically, Wilcock (2002) stated that "occupation is a synthesis of doing, being, and becoming. (Wilcock, 2002)". Occupation encompasses what an individual does to occupy his/her time and keep his/her mind and body active within a place or a time frame and assign culturally and personally meaningful experience to the individual (Christiansen & Townsend, 2010; Schwartzman, Atler, Borg, & Schwartzman, 2006). Occupational scientists focused on understanding the meaningful occupations of an individual, and how an individual participates in these meaningful occupations (Christiansen & Townsend, 2010). That is, based on the ICF model, occupational scientists may consider the construct of participation, and how the contextual factors that may facilitate or hinder an individual from participating the daily tasks as a high priority for an individual (Christiansen & Townsend, 2010). However, focusing on the meaningful occupation does not mean that occupational scientists overlook the importance of the domain of body function and structure. Specifically, the domain of body function and structure is critical for occupational scientists since it allows scientists to comprehensively understand the dynamic interaction between the individual, occupation, and the environment to optimize their occupational performance (Law et al., 1996).

Similarly, rehabilitation scientists also consider that each domain in the ICF plays an important role in contributing to an individual's overall health. Yet, as mentioned earlier, the priorities and emphases from rehabilitation scientists may be different from the occupational scientists. Since rehabilitation science emerged from providing the medical care for the veterans returned from the war; rehabilitation science adopts the disability perspective based on the medical model (Brandt & Pope, 1997). In this respect, examining factors and pathologies that cause disabilities, developing effective interventions to reverse the disability process, or utilizing adaptive devise to compensate for the body functions and body structures are considered as priorities in rehabilitation science (Brandt & Pope, 1997). As such, rehabilitation scientists may highlight more on the factor of the body function and body structure, and how this factor impacts the way an individual participate in everyday activities (Brandt & Pope, 1997). In the following sections, I will relate the major aspects of this dissertation to occupation and rehabilitation science.

Cognitive functions. In this dissertation, cognitive functions (e.g., information processing and performance monitoring) are defined as the mental processes that allow individuals to interact with the environment efficiently. The cognitive functions were examined via the EEG/ERP technique in children, adults, and adults with ADHD. Investigating the underlying neural processes associated with cognitive functions via EEG/ERP is in line with the focus of the rehabilitation science, since rehabilitation science emphasizes the importance of the underlying function and structures in determining one's overall functioning (Brandt & Pope, 1997). Occupational scientists also consider the cognitive functions as one of the contributor to the personal health condition and well-being, and further explore whether having an individual to actively engage in occupation could help restore one's cognitive functions (i.e., occupation as means; Curtin, Molineux, & Webb, 2009). Such a perspective is also illustrated in the ICF model with the bi-directional arrows among the relationships among participation, activity, and body function and body structure (WHO, 2002).

Occupational performance. We administered two observation-based occupational performance assessments to measure the quality of the activities of daily living (ADL) and social interaction in children. Specifically, unlike other behavioral assessments that are required to be administered under certain contexts with standardized procedure, these occupational performance assessments were conducted under the natural contexts while individuals engaged in the tasks that are meaningful to them. For example, for the Assessment of Motor and Process Skills (AMPS; Fisher & Jones, 2014), almost all participants finished the meals they made for the assessment (e.g., scrambled eggs, cereal, or peanut butter and jelly sandwich). This assessment along with the Evaluation of Social Interaction (ESI; Fisher & Griswold, 2015) are considered as occupation-based evaluations, which assess an individual's strengths and weaknesses by observing how he/she performs daily life tasks under the nature context, and its rationale is closely aligned with the fundamental philosophies of occupational science (Fisher, 2013). From the rehabilitation science perspective, participation in the meaningful occupation under the everyday context is also critical, however, these often considered as remote goals but not the primary ones from the rehabilitation science perspective.

Disability. The third study of this dissertation focused on comparing the differences on the neural and occupational performance measures among neurotypical children, neurotypical adults, and adults with ADHD. Understanding the differences at the neural and behavioral levels in individuals with ADHD is important for diagnostic purposes and may assist in developing effective clinical intervention. Such a focus fits within the rehabilitation science perspective, since developing intervention by either restoring or compensating the dysfunction are critical to rehabilitation science (Brandt & Pope, 1997). On the other hand, occupational scientists focus on the idea of occupational balance in the everyday contexts. That is, instead of considering individuals with ADHD as dysfunction that requires medical intervention, they emphasize more on whether these individuals are able to engage the occupation that are meaningful to them, and whether these individuals have reached a balanced occupational performance in every domain (Christiansen & Townsend, 2010).

Conclusion

This dissertation demonstrated that utilizing the SEM approach to understand the underlying neural mechanisms associated with simple-task behaviors is feasible, and could inform the researchers and clinicians in terms of the dynamic interaction between brain and behaviors in children. Moreover, this dissertation revealed the association between the neural measures and the quality of the occupational performance in children. Lastly, the investigation on the neural and behavioral measures on adults with ADHD identified unique characteristics in this clinical population compared to neurotypical children and neurotypical adults. Based on the ICF model, this dissertation covered constructs of body function and body structure (i.e., cognitive functions), activity (i.e., response times on the computer-based task), participation (i.e., occupational performance assessments). Our model showing the dynamic interaction between the neural and behavioral measures also captures the bi-directional relationships between the constructs of body function and body structure (i.e., cognitive functions) and activity (i.e., response times on the computer-based task). The results reported in this dissertation advance the knowledge related to brain-and-behavior relationships and demonstrate the effectiveness of statistical methods such as SEM and discriminant analysis in examining brain-and-behavior relationships.

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