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Mental Fatigue: Examining Cognitive Performance and Driving Behavior in Young Adults

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A Dissertation Presented

by

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DEDICATION

To Patricia Hogan-Cerasuolo

For teaching me about psychology and the most important things in life.
Thank you for encouraging me to become the person I am now.

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ABSTRACT

MENTAL FATIGUE: EXAMINING COGNITIVE PERFORMANCE AND DRIVING BEHAVIOR IN YOUNG ADULTS

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Mental fatigue causes an increase in task-based EEG theta and alpha power and a decrease in performance (for a review, see Tran et al., 2020). However, little is known about the emergence of mental fatigue in resting state EEG recordings and whether the progression of mental fatigue over time is influenced by individual differences. The current dissertation examined the utility of resting state EEG as a measure of mental fatigue by testing whether EEG power changed in young adults over the course of a cognitively demanding battery of tasks. The current dissertation also tested how this measure of mental fatigue interacted with individual differences in ADHD symptomology to predict performance on one of the cognitive tasks as well as performance in a driving simulator. Resting state EEG was recorded at four intervals, before and after the three cognitively demanding tasks. Driving outcomes were collected at a separate visit to a driving simulator lab. Results indicated that resting state EEG theta and alpha power significantly decreased over time, but this association was not influenced by levels of ADHD symptomology. There was no evidence that resting state EEG power changes over time predicted cognitive or driving performance, even when

ADHD symptomology was included. The current findings present preliminary evidence that resting state EEG power can be used as a marker of mental fatigue and provide unique insight into how mental fatigue develops by including an initial measurement of neural readiness before individuals engage in a cognitively demanding task.

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1.1 Introduction

Mental fatigue is induced following prolonged cognitive engagement (Arnau, Möckel, Rinkenauer, & Wascher, 2017). A common explanation for the underlying cause of mental fatigue is that sustained attentional engagement and behavioral action demand substantial cognitive resources, leaving a person mentally fatigued and causing disruptions in performance (Muraven & Baumeister, 2000). In addition, some people exhibit impaired performance and mental fatigue after very little time spent completing a cognitively challenging task, while others take a significant amount of time to show impairments related to mental fatigue.

As such, examining individual differences in the development of mental fatigue can guide our understanding of the different ways in which cognitive and behavioral performance are compromised and can inform methods of reducing or coping with mental fatigue. Mental fatigue has been tested in lab settings using cognitive measures and in real world circumstances that require constant vigilance such as driving. However, very little work has examined the combined effects of individual differences and mental fatigue on cognitive and behavioral performance. Furthermore, it is important to consider how individual differences may influence distinct temporal dynamics of mental fatigue that are not readily observed in typical methodological practices, thus this study sought to enhance the body of mental fatigue research by investigating neural measures that are seldom studied in the literature.

The aims of the current study were three-fold. First, lab-based neural measures of mental fatigue were explored, and these measures were also evaluated based on individual differences in attention and impulsivity. Although prior research on neural markers of mental fatigue has mainly focused on individuals' psychophysiology during *tasks*, the current study took a novel approach by focusing on the measurement of mental fatigue during *rest intervals* that occur before, in between, and after a sequence of various cognitively challenging tasks in order to broaden the understanding of mental fatigue development. Second, this study assessed whether these neural measures of mental fatigue predicted performance on a cognitive task and examined the impact of attention and impulsivity difficulties on this association. Finally, this study investigated whether the neural measures of mental fatigue, individual differences in attention and impulsivity, and overall cognitive performance predicted young adults' driving behavior.

1.2 Mental Fatigue

Mental fatigue is characterized by decreasing alertness and impaired performance as compared to usual functioning levels (Ackerman & Kanfer, 2009). Research has assessed individuals' subjective reports of fatigue to measure mental fatigue before, during, and after difficult cognitive tasks (Ackerman, 2011). These types of assessments are useful when objective assessment may not be practical or if changes in task performance do not occur (Smith, Chai, Nguyen, Marcora, & Coutts, 2019). Although there is some evidence that subjective ratings reflect mental fatigue before an individual begins to show deficits in task performance (Kanfer, 2011), people can be inaccurate or even dishonest reporters of their own experiences of mental exhaustion. Thus, researchers have employed more objective means of investigating mental fatigue.

One objective method of examining mental fatigue is to assess how behavioral performance changes over time during a variety of cognitive tasks. Another avenue is to examine deficits in behavioral performance on a subsequent task, after the mentally exhausting task has been completed. Tasks used to induce mental fatigue include n-back, go/no-go, flanker, oddball paradigm, Stroop, continuous performance, psychomotor vigilance, and others. Changes in behavioral performance during such tasks can be best explained by a reduction in top-down processing, leading to an inability to focus and meet task demands (Tran, Craig, Craig, Chai, & Nguyen, 2020). As a result, the skills needed for these tasks decline in efficiency when a person is experiencing mental fatigue.

The literature is currently unclear as to what is an ideal task duration to induce mental fatigue in young adults, thus it is not known how long it takes for a change in task performance to become significant. Some experimental procedures that aim to induce mental fatigue use tasks that last for approximately 2 to 4 hours (Arnau et al., 2017; Boksem, Meijman, & Lorist, 2005; Tanaka, et al., 2012; Wang, Trongnetrpunya, Samuel, Ding, & Kluger, 2016; Wascher et al., 2014). However, evidence from these studies and others suggests that shorter task durations may suffice to induce mental fatigue as significant deficits in cognitive performance were evident after only 60 minutes (Washer et al., 2014) or 90 minutes (Wang et al., 2016).

There is also evidence from studies that have used other objective measures of mental fatigue, such as brain activity and eye-tracking, in addition to task performance. Barwick, Arnett, and Slobounov (2012) administered a 90-minute neuropsychological concussion test battery composed of visuospatial memory, working memory, verbal memory, reaction time, and processing speed tests. Changes in brain activity and increased subjective ratings of fatigue during the tests as well as worse performance on a Stroop task from pretest to posttest were indicative of mental fatigue. Additionally, Hopstaken and colleagues (2016) used a combination of eye-tracking, brain activity, subjective, and task performance measures to examine mental fatigue during a 90-minute n-back task. In addition to increases in self-reported mental fatigue, participants also showed decreases in task performance and physiological engagement as measured by brain activity, gaze, and pupil diameter.

Other studies that include even shorter task sessions have produced evidence of mental fatigue as well. For example, mental fatigue was reflected in subjective ratings and brain activity measures during a 60-minute sustained attention task (Cao, Wan, Wong, Nuno da Cruz, & Hu, 2014). In comparison, Smith and colleagues (2019) examined brain activity, subjective ratings, reaction time, and heart rate variability in a pre/post design to look at mental fatigue and subsequent recovery. After 45 minutes of a psychomotor vigilance task, a continuous performance task, or a Stroop task, only the comparison of pre-test and post-test subjective ratings reflected significantly increased mental fatigue. Post-test subjective ratings of fatigue also remained higher than pre-test ratings for 20 minutes after the vigilance task, 50 minutes after the Stroop task, and 60 minutes after the continuous performance task. Furthermore, Tanaka, Ishii, and Watanabe (2014) administered a 10-minute continuous performance task and found that brain activity during the task as well as subjective ratings of sleepiness provided evidence of mental fatigue, even after such a brief duration.

Overall, evidence from a variety of biological, behavioral, and self-report measures suggests that mental fatigue can occur during different durations of cognitively demanding tasks. Prior studies have used tasks that last multiple hours, but additional research suggests 60 to 90 minutes is enough time to induce mental fatigue. Less is known about tasks that have durations shorter than an hour, thus future research should aim to fill this gap in the literature. Individual differences may also play an important role in the development of mental fatigue and the task durations necessary to induce it. However, few studies have examined individual differences in the emergence of mental fatigue.

Research has indicated that personality traits can predict subjective ratings of mental fatigue across various durations of a cognitively demanding task. Individuals higher in neuroticism and anxiety tend to report higher mental fatigue, whereas individuals motivated by achievement and learning typically report lower mental fatigue (Ackerman & Kanfer, 2009). Understanding individual differences and their influence on mental fatigue development is essential. If researchers learn more about the various impacts on cognitive and behavioral performance, they will be able to develop tailored approaches to help individuals reduce or manage their mental fatigue. Future research must consider that task durations necessary to induce mental fatigue may be different for people with attention difficulties, such as attention-deficit/hyperactivity disorder (ADHD).

1.2.1 ADHD

Individuals with ADHD present behaviors from one or both subtypes of symptoms: hyperactivity/impulsivity and inattention. Hyperactivity and impulsivity are typically combined into one subtype of ADHD because research has indicated that they are highly correlated and commonly load onto one factor in factor analyses (Roberts, Milich, & Barkley, 2015). Hyperactivity is characterized by feelings of restlessness as well as excessive speech and motor activity, and impulsivity is characterized by difficulties inhibiting, waiting, or sharing. Individuals who display symptoms of inattention spend less time on-task and tend not to finish their work on time because they can be easily distracted and have a hard time concentrating (American Psychiatric Association [APA], 2013).

ADHD affects approximately 2.5% of adults and 5% of children, but the number of adults who are being diagnosed with ADHD has been increasing dramatically over the last decade (APA, 2013). This increase can be attributed to improved recognition of the disorder, or possibly overdiagnosis (Paris, Bhat, & Thombs, 2015). With respect to symptomology, adults with ADHD experience similar attention problems as children with ADHD, such as difficulty concentrating and completing tasks. In contrast, adult symptoms of hyperactivity are exemplified by excessive speech rather than gross motor activity (Roberts et al., 2015). In addition, factor analyses of ADHD symptoms in adults reveal that hyperactivity may split from impulsivity to form its own symptom dimension, resulting in three distinct categories for adult ADHD as compared to the dual symptom structure (hyperactivity/impulsivity and inattention) for children with ADHD (Roberts et al., 2015).

Given these symptom categories, hyperactivity, impulsivity, and inattention may each be responsible for additional deficits in performance under mentally fatiguing conditions for people with ADHD. However, the literature on mental fatigue among individuals with ADHD is very limited. In a study of adults with ADHD, their performance was more susceptible to mental fatigue, even if they were taking medication for their symptoms, as they performed worse than healthy controls on a cognitive task following 2.5 hours of neurocognitive testing (Maruta, Spielman, Tseretopoulos, Hezghia, & Ghajar, 2014). Research with children also supports this theory, as 7- to 10-year-old children with ADHD were unable to sustain performance on a challenging 14-minute continuous performance task as compared to their typically developing peers (Bioulac et al., 2012).

Mental fatigue may have a greater impact on cognitive and behavioral performance in individuals with ADHD. A possible explanation is that individuals with ADHD may need to use more cognitive resources to perform at levels equal to those of individuals without ADHD (Fassbender & Schweitzer, 2006). As a result, mental fatigue may have an earlier onset in individuals with ADHD as more cognitive resources are being utilized and top-down processes are impaired sooner. It is critical to know how behavioral measures of mental fatigue worsen in individuals with and without ADHD, as mental fatigue may compound differences in task performance, especially by the end of the testing session.

Maruta and colleagues (2014) suggest that 20 minutes of a cognitively demanding task could result in substantial differences in task performance between individuals with and without ADHD. Such differences would reflect more rapid development of mental fatigue in those individuals with ADHD. Moreover, the limited number of previous studies have only used behavioral performance on cognitive tasks as a marker of mental fatigue to compare people with and without ADHD, thus other measures should also be examined in order to broaden our understanding of the influence of individual differences on the development of mental fatigue.

For example, in addition to task performance, electroencephalography (EEG) is an objective measure that can provide insight into neurophysiological changes during the development of mental fatigue. Neural measures are helpful beyond behavioral measures because they can provide evidence of mental fatigue developing before cognitive performance begins to decline. Additionally, observing neural measures before and after task performance will illuminate how temporal dynamics of mental fatigue may differ across individuals with and without ADHD.

1.2.2 EEG

EEG is one of the most widely used methods for measuring brain electrical activity (Buzsáki, Anastassiou, & Koch, 2012). EEG is a recording of synchronized firing of cortical neurons, which leads to negative charges near the dendrites of neurons and positive charges around the cell body of the neuron (Jackson & Bolger, 2014). Electrodes placed on the scalp detect this activity from nearby neurons and the signal is derived from the sums of these positive and negative charges. EEG recordings provide a continuous measure of electrocortical rhythms or frequency bands (Anderson & Perone, 2018). There are five separate EEG bands characterized by different oscillation speeds: delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz), and gamma (30-50 Hz).

Research on mental fatigue typically examines the alpha and theta EEG frequency bands, as both are commonly observed during cognitive task performance and have been linked with top-down processing (Min & Park, 2010; van Driel, Ridderinkhof, & Cohen, 2012). The alpha frequency band is also pronounced during relaxed wakefulness and is blocked by intense concentration, whereas the theta frequency band is additionally linked with drowsiness (Nayak & Anilkumar, 2020). Changes in EEG spectral power, the inverse of neural activation, are commonly referenced as evidence for mental fatigue during cognitively demanding tasks. Increases in alpha and theta EEG power are strongly associated with mental fatigue (Tran et al., 2020), and these EEG power changes that reflect mental fatigue can be evident during a cognitively demanding task after only 15 to 30 minutes (Trejo, Kubitz, Rosipal, Kochavi, & Montgomery, 2015). As such, higher alpha and theta EEG power during task performance are considered reliable indicators of mental fatigue.

There is mixed evidence for where in the brain these changes in EEG power might occur when reflecting mental fatigue. For both alpha and theta frequency bands, research has commonly pointed to the frontal (Arnau et al., 2017; Trejo et al., 2015) and central regions (Barwick et al., 2012; Wascher et al., 2014) as primary regions that reflect EEG power changes associated with mental fatigue. There are also a few studies that show evidence of power changes in parietal and occipital regions (Boksem et al., 2005; Fan, Zhou, Liu, & Xie, 2015; Tanaka et al., 2012). Across these studies, power changes in alpha and theta have been measured while people are engaged with cognitively demanding tasks that test abilities such as visual attention, visuospatial memory, working memory, verbal memory, reaction time, and processing speed. Results from these studies indicate increases in EEG power for both frequency bands regardless of task type (Tran et al., 2020).

In addition to measuring EEG power during task performance, it can also be recorded while an individual is not performing any tasks by using a technique called resting state EEG. Resting state EEG is useful due to its simplicity, as subjects are simply asked to sit quietly with their eyes open and/or closed. This simple procedure enables researchers to examine people at all developmental levels in both typical and atypical populations (Anderson & Perone, 2018). Furthermore, investigations of changes in alpha and theta EEG power during resting state EEG before and after cognitively demanding tasks also provide evidence of mental fatigue (Li et al., 2020). However, resting state EEG patterns may be different than patterns recorded during a cognitive task. For example, Tanaka and colleagues (2012) measured resting state EEG in healthy adult males before and after mental fatigue induction. Following a cognitively demanding 2-hour lab task, participants' resting state EEG showed increased theta power in central regions but decreased alpha power in parietal and occipital regions as compared to their resting state EEG before the task.

As the literature on resting state EEG and mental fatigue is very limited, more work must be done to examine whether changes in alpha and theta power related to mental fatigue are different when measured using resting state EEG. It would be valuable to measure an individual's resting state EEG before they engage in fatiguing tasks because this measurement will provide a baseline measure of neural readiness to perform cognitive tasks. From this starting point, researchers can examine changes in resting state EEG as markers of mental fatigue and examine associations between these neural patterns and subsequent behavioral task performance. Multiple resting state EEG recordings over the duration of a lab visit would also provide an opportunity to examine the development of mental fatigue more closely.

Additionally, it is important to expand the field's knowledge of how individual differences such as ADHD might impact the development of mental fatigue as measured by resting state EEG. When simply comparing individuals with and without ADHD, higher alpha power during eyes-closed resting state EEG is observed in those with

ADHD (Poil et al., 2014; van Dongen-Boomsma et al., 2010). Research has also indicated that individuals with ADHD show increased alpha and theta power across frontal, central, and parietal regions as compared to normal controls (Loo et al., 2009; Snyder & Hall, 2006). Further research is also needed to provide clarity on whether EEG markers of mental fatigue in individuals with and without ADHD can be applied across other contexts that could be negatively and dramatically impacted by mental fatigue, such as driving.

1.3 Mental Fatigue and Driving Behavior

Drivers experiencing mental fatigue tend to make more mistakes behind the wheel and thus endanger not only themselves but others on the road as well. Research shows that driver fatigue tends to account for approximately 15 to 20% of traffic accidents (Horne & Reyner, 1999; Phillip, 2005). Some reports even suggest that mental fatigue may be responsible up to 40% of all motor vehicle accidents (Fletcher, McCulloch, Baulk, & Dawson, 2005). In addition to damage to cars involved in such accidents, serious if not fatal injuries can result from these accidents as well. To make our roads safer, research can provide insight into how mental fatigue impacts driving and how drivers might be able to cope with it. For instance, if drivers learn to recognize signs of mental fatigue, they may be more apt to take precautions on the road. Additionally, helping drivers understand how their individual differences may impact their own driving behavior will also aid in increasing safety for all.

Getting in the car and driving while mentally fatigued is dangerous, but driving itself can also cause mental fatigue. Participants who complete on-road and lab-based simulated driving assessments designed to induce mental fatigue spend more time speeding and weaving in their lanes over the duration of the tasks (Morales et al., 2017; Perrier et al., 2016). Research has also sought to examine neurophysiological changes related to mental fatigue that occur during driving. The driving tests and simulations in these studies range from 1 to 2 hours in duration, timing durations that are much shorter than many mental fatigue studies that use cognitive tasks. As with other cognitively demanding tasks, driving can trigger similar patterns of increasing alpha and theta EEG power across a variety of regions (Borghini, Astolfi, Vecchiato, Mattia, & Balboni, 2014).

For instance, mental fatigue caused by driving has been linked with increased alpha power in frontal and posterior regions over various durations of driving sessions. After a 54-minute session of mentally fatiguing simulated driving, individuals have shown increased alpha power in frontal and posterior regions (Getzmann, Arnau, Karthaus, Reiser, & Wascher, 2018; Wascher, Arnau, Gutberlet, Karthaus, & Getzmann, 2018). Gharagozlou and colleagues (2015) used EEG to assess mental fatigue in the first 10 minutes and final 10 minutes of a 70-minute driving task, and they found increases in alpha power in parietal regions. Additionally, EEG assessments of mental fatigue recorded in the first 5 minutes and last 5 minutes during a 90-minute driving task revealed that alpha power increased significantly at central, parietal, occipital, and temporal regions (Zhao, Zhao, Liu, & Zheng, 2012). In comparison, the patterns of theta power as a measure of mental fatigue while driving are not clear. Although EEG studies of mental fatigue and driving do find that theta power increases at frontal, central, and occipital regions (Zhao et al., 2012), mental fatigue caused by driving has been linked with decreases in theta power at frontal and posterior regions (Getzmann et al., 2018; Wascher et al., 2018).

A main limitation of these prior studies is that they tend to focus on healthy adults around 25 years of age (Tran et al., 2020). There is very little research about how younger drivers and individuals with attention difficulties, such as ADHD, might be particularly vulnerable to mental fatigue and thus must endure an increased influence of mental fatigue while driving. The latter population is critical to focus on as individuals with ADHD are already more likely to speed, get into more crashes, and make more driving errors than those without ADHD (Fuermaier et al., 2015). Thus far, the limited evidence suggests that mental fatigue imposes a stronger negative effect on attention and driving performance among adults with ADHD as compared to healthy controls. For instance, drivers with ADHD were more likely to get into a collision during a mentally fatiguing driving simulation than drivers without ADHD (Reimer, D'Ambrosio, Coughlin, Fried, & Biederman, 2007). A possible explanation for why the drivers in this study had more collisions were the driving conditions: a long, monotonous drive on an open road. The combination of mental fatigue and boredom is a recipe for mind-wandering in anyone, but it can become a big problem for drivers with ADHD, as their difficulties with attention may result in more frequent mind-wandering under mentally fatiguing conditions.

Research across different driving settings has helped to shed light on the difficulties that individuals with ADHD experience behind the wheel. During simulated driving, drivers with ADHD tend to display poorer steering control and more lane swerving, while also showing higher rates of hard braking and sudden decelerating during actual driving in on-road assessments (Fuermaier et al., 2015). Common issues for individuals with ADHD who show higher rates of inattention are difficulties regulating speed, maintaining lane position, scanning for hazards, and using signals (Classen et al., 2013). In comparison, individuals with greater hyperactivity and impulsivity symptoms tend to have higher rates of motor vehicle accidents and receive more tickets for speeding (Thompson, Molina, Pelham, & Gnagy, 2007). Future research on the effects of mental fatigue on driving outcomes should aim to expand the scope of the literature by investigating the impacts of ADHD, especially in young drivers.

1.3.1 Driving Patterns Among Young Adult Drivers

Research on the effects of mental fatigue on driving does not often include young adult drivers, as most studies have mean ages of 25 years old or older. Yet, it is important to assess mental fatigue and its potential impact on driving behavior among younger populations because of the high rates of automobile accidents and mortality within this age group. For example, motor vehicle accidents were the cause of 23% of total deaths among 15- to 24-year-olds in 2015 (Murphy, Xu, Kochanek, Curtin, & Arias, 2017). Compared to all other ages, this age group had the highest number of fatal motor vehicle accidents as well.

Before a person has had an adequate amount of time to learn and get comfortable behind the wheel of a car, driving demands more cognitive resources (Gregersen & Bjijrulf, 1996). For more experienced drivers, many actions become automatic, thus minimizing the drain on their cognitive resources. If driving conditions are increasingly stressful (e.g., bad weather, heavy traffic, unfamiliar location), making safe decisions becomes more important but also more difficult for inexperienced drivers (Deery, 1999).

Age predicts the likelihood of drivers being involved in an accident, even when controlling for driving experience. Among adults under 25 years of age with at least one year of driving experience, Constantinou and colleagues (2011) found that younger drivers reported more dangerous driving behaviors and got into more accidents.

Young adult drivers also tend to overestimate their driving skills. When young drivers rate their driving ability and complete driving simulations, there are discrepancies between perceived skill and actual performance (Brown, 1982; Finn & Bragg, 1986). Once again, these self-report ratings and driving performance could both be linked to lack of driving experience. In addition, Lajunen and Summala (1995) reported that more experienced drivers tend to rate themselves as being more capable behind the wheel, but they do not always rate themselves as being safer than drivers with less experience.

In comparison to older drivers, drivers under the age of 25 are also experiencing ongoing neurophysiological development (Paus, 2005). With underdeveloped cognitive abilities, young adult drivers can struggle to be as safe as older and more experienced drivers. They might simply be unprepared to face the risks of the complex task of driving, especially in unfavorable conditions exacerbated by distractions, mental fatigue, or even substance use (Constantinou et al., 2011). Although lack of knowledge about and experience with road hazards may be the underlying causes of incidents on the road, it is also plausible that negative driving outcomes among young drivers could be associated with immaturity of cognitive abilities (Romer, Yi-Ching, McDonald, & Winston, 2014; Walshe, McIntosh, Romer, & Winston, 2017).

1.3.2 Cognitive Abilities Implicated in Driving

Driving requires the utilization of multiple cognitive abilities to operate a vehicle safely and effectively. To gauge actual driving performance, researchers test drivers using cognitive and motor tasks which have been shown to correlate with performance in driving simulators as well as during on-road assessments. Results from experimental assessments performed during lab tasks and on-road tests indicate that cognitive abilities such as attention, inhibitory control, and working memory show the most consistent connections with several aspects of driving behavior.

In self-reports of driving behavior, drivers with greater inattentiveness admit to making many errors while behind the wheel (Garner et al., 2004) as well as receiving more traffic tickets and getting into more vehicle collisions (Ledesma, Montes, Poó, & López-Ramón, 2015). Both simulated driving and on-road driving outcomes are significantly predicted by drivers' performance during assessments of attention (Baldock, Mathias, McLean, & Berndt, 2007; Hoffman, McDowd, Atchley, & Dubinsky, 2005). Data from various types of attention tasks are strongly correlated with many critical aspects of driving, including turning, merging, evaluating distances, and scanning surroundings (Richardson & Marottoli, 2003). When a driver has poor selective attention and attention shifting skills, they are more likely to make errors related to checking blind spots, using indicators, braking, accelerating, and maintaining lane position (Anstey & Wood, 2011). Sustained attention is typically examined in continuous performance tasks, and worse performance during these types of tasks is correlated with more driving errors, such as failing to notice pedestrians and getting into the wrong lane, as well as worse driving habits overall (Tabibi, Borzabadi, Stayrinos, & Mashhadi, 2015).

Another cognitive ability that is important for driving outcomes is inhibitory control. This skill refers to controlling behavior by withholding a strong prepotent response (Diamond, 2013). Strong inhibitory control is associated with more skill in specific aspects of safe driving such as recognizing and responding to hazards in the road as well as maintaining lane position (Ross et al., 2015). In addition, better inhibitory control has been linked with increased skill under both normal and difficult driving conditions, such that individuals with strong inhibitory control abilities are able to maintain high levels of performance under distracting conditions as compared to peers with weaker inhibitory control (Guinosso, Johnson, Schulteis, Graefe, & Bishai, 2016). Inhibitory control difficulties have also been linked with increased risk taking while driving such as speeding, unsafe acceleration, and more errors related to blind spots around the vehicle (Anstey & Wood, 2011; Brown et al., 2016). Drivers who display poor performance on inhibitory control tasks also are more likely to get into accidents and commit violations such as speeding and going through an intersection when the stoplight is yellow (Daigneault, Joly, & Frigon, 2002; Tabibi et al., 2015). Worse inhibitory control performance on a go/no-go task has also been associated with more frequent speeding and slower response times to salient stimuli in the driving environment such as lane merges, oncoming traffic, and stoplights (Hatfield, Williamson, Kehoe, & Prabhakharan, 2017; O'Brien & Gormley, 2013).

Driving also relies on a person's working memory, or their skill at remembering and using information to solve a problem (Diamond, 2013). Drivers with poor working memory have difficulty recognizing hazards in the road and taking their feet off the accelerator (Engström, Aust, & Viström, 2010; Wood, Hartley, Furley, & Wilson, 2016).

Both verbal and visuospatial (non-verbal) working memory have been linked with specific negative driving outcomes. Poor verbal working memory has been associated with increased lane weaving in a simulated driving environment, whereas strong visuospatial working memory has been linked with a tendency to drive through yellow lights and follow other cars too closely (Ross et al., 2015). In a study by Johannsdottir and Herdman (2010), when drivers completed a verbal working memory task while driving, they had more difficulty remembering the position and proximity of vehicles behind them. Then, when drivers completed a visuospatial working memory task while driving, they had more difficulty remembering the cars in front of them.

Cognitive performance is a strong predictor of driving behavior, and this association is particularly relevant for young adults who are new drivers and whose cognitive abilities are still developing. When driving scenarios are complex and demanding, unsafe behavior of inexperienced drivers is easily distinguishable from driving behavior of more experienced drivers, and it can be linked with ongoing development of cognitive abilities (Guinosso et al., 2016). Young adults' poor performance on a visual attention task helps to predict their crash risk and driving speed (Michaels et al., 2017). In addition, young drivers with strong inhibitory control typically perform better during challenging driving scenarios, whereas those with weaker inhibitory control tend to show more swerving behavior (Jongen, Brijs, Komlos, Brijs, & Wets, 2011), slower reactions to road hazards (Ross et al., 2015), and increased rates of speeding (Hatfield et al., 2017). Additionally, young drivers with weak inhibitory control are more likely to run red lights when accompanied by a risky peer (Cascio et al., 2015). Interestingly, the likelihood of running yellow lights and disregarding the maintenance of a safe following distance increases among young drivers with strong working memory (Ross et al., 2015).

In summary, safe driving behavior is influenced dramatically by cognitive abilities, especially for young adults whose cognitive abilities are still developing. Poor attention and weak inhibitory control in young adult drivers are both linked with adverse driving outcomes. Additionally, individuals with ADHD have difficulty modulating their attention and engaging inhibitory control, thus young adults with ADHD display even more unsafe driving behaviors than typically developing young adults (Classen et al., 2013; Thompson et al., 2007). In addition, little is known about the combined effects of mental fatigue and cognitive abilities on safe driving behavior, especially in young adults with and without attention difficulties. Understanding how these factors influence safe driving will aid in identifying at-risk drivers and informing these drivers about the dangers of mental fatigue.

1.4 The Current Study

The current study had three primary aims. The first aim of the current study was to examine resting state EEG before, in between, and after three cognitive tasks to explore its utility as a measure of mental fatigue in young adults. In most prior research, EEG recorded during cognitively demanding tasks has been typically examined as a measure of mental fatigue (Tran et al., 2020). However, the demands of the tasks may influence the patterns of EEG and impact how clearly these measures can reflect mental fatigue. Measuring resting state EEG at the beginning of the session provided a baseline measurement of mental fatigue for individuals before they engaged in any tasks. Resting state EEG measurements after each of the three tasks provided clear comparisons to the first measurement as they occurred in the same resting recording context that eliminated the possibility of task engagement interfering with the EEG patterns of mental fatigue. Previous studies on mental fatigue have generally focused on typically developing adults, thus there is a large gap in the literature surrounding individuals with attention difficulties who may be more susceptible to mental fatigue and its subsequent negative effects (Fassbender & Schweitzer, 2006). Consequently, this study compared this measure of mental fatigue across individuals with high versus low levels of ADHD symptomology.

The second aim of the current study was to assess whether mental fatigue as measured by resting state EEG predicted performance on cognitive tasks. Research suggests that mental fatigue dramatically impairs cognitive performance (Tran et al., 2020), and individuals with ADHD typically experience difficulties with their cognitive abilities (Roberts et al., 2015). Thus, this study also examined whether mental fatigue as measured by resting state EEG and ADHD symptomology predicted cognitive performance.

The third aim of the current study was to investigate whether mental fatigue (as measured by resting state EEG), ADHD symptomology, and overall cognitive task performance predicted young adults' driving behavior since mental fatigue is responsible for unsafe driving behaviors as well as a substantial number of injuries and fatalities due to motor vehicle accidents (Fletcher et al., 2005; Horne & Reyner, 1999; Phillip, 2005). The current study examined the combined effects of mental fatigue, ADHD symptomology, and cognitive performance on driving behavior because individuals with ADHD and drivers with weaker cognitive abilities are more likely to display unsafe driving behaviors (Anstey & Wood, 2011; Classen et al., 2013; Johannsdottir & Herdman, 2010; Ross et al., 2015; Thompson et al., 2007).

The hypotheses for the three aims of this study were:

Aim 1: (a) Explore the utility of resting state EEG as a measure of mental fatigue in young adults and (b) compare this measure across individuals with high versus low levels of ADHD symptomology

Based on prior literature examining task-based EEG power in the central region (Barwick et al., 2012; Wascher et al., 2014; Zhao et al., 2012), both alpha and theta resting state EEG power were predicted to increase from the first to the fourth recording, thus reflecting a similar pattern of mental fatigue development between both task-based and resting state EEG methods. Individuals high in self-reported ADHD symptoms were expected to show significant increases in resting state EEG power by the third resting state EEG recording because they experienced mental fatigue sooner than individuals with low levels of ADHD symptoms.

Aim 2: (a) Assess whether mental fatigue as measured by resting state EEG predicts cognitive performance and (b) examine whether ADHD symptomology moderates this association

Larger increases in resting state EEG alpha and theta power from the first to the third recording were predicted to be associated with worse performance on the third cognitive task, as this association has been commonly observed for task-based EEG power in the central region (Tran et al., 2020). Furthermore, the combined effects of larger increases in resting state EEG power from the first to the third recording and higher levels of ADHD symptoms were expected to be associated with worse performance on the third cognitive task.

Aim 3: Investigate whether mental fatigue (as measured by resting state EEG), ADHD symptomology, and overall cognitive performance predict young adults' driving behavior

Young adults with larger increases in resting state alpha and theta EEG power from the first to the fourth resting state EEG recording, higher levels of ADHD symptoms, and worse overall task performance were predicted to display riskier driving behavior due to more inattention, more impulsivity, and weaker cognitive abilities.

2 Methods

2.1 Participants

Individuals were recruited at the University of Massachusetts Amherst campus using flyers, table tents, website postings, and email advertisements. Participants had to be between the ages of 18 and 24 years old and were also required to have a valid US driver's license and at least two years of driving experience. Individuals were not eligible if they had a history of motion sickness or wore glasses. Contact lens wearers were eligible.

Participants also completed an online survey via Qualtrics to report their ADHD diagnosis history and whether they take medication for ADHD (if applicable). If participants indicated an ADHD diagnosis and took medication, they were asked to refrain from taking the medication at least 24 hours prior to their participation in each lab visit.[1] Participants were asked to complete two different lab visits, in no particular order. An attempt was made to randomize which visit participants completed first. However, the majority of participants completed the EEG visit first (see Figure 1) and a campus-wide shutdown of research activities due to the COVID-19 pandemic did not allow for more participants to complete the driving simulator visit.

For the EEG lab visit, 97 participants completed the full protocol. One additional participant's visit was stopped before data collection due to technical problems. For the driving simulator lab visit, 76 participants completed the full protocol. One additional participant succumbed to motion sickness during the driving simulation practice, thus the visit was stopped before data collection. The total number of participants who completed driving simulator lab visit with useable data was 74 because driving data for two participants was irretrievable due to technical failure. Coincidentally, these two participants did not complete the EEG lab visit. A total of 70 participants completed both visits fully.

2.2 EEG Lab Visit

2.2.1 Procedure

Individuals went to the Learning Lab at the University of Massachusetts Amherst for a 90-minute lab visit. Individuals were given a full description of the study and were asked to provide signed consent to participate. Participants' head circumferences were then measured to determine sizing for the EEG cap. Participants completed questionnaires on an iPad while research assistants completed the capping process. Once

[1] Of the six participants who reported an ADHD diagnosis, two participants reported that they take medication and reported taking it within 24 hours of their lab visits. When these participants were excluded, the patterns and significance of the analyses did not change.

the capping process and the questionnaires were complete, participants completed the first resting state EEG recording (RS-EEG 1). During the recording, participants first sat still and stared at a white '+' presented on a black computer screen for 60 seconds. Participants were then asked to sit still with their eyes closed for 60 seconds. Participants then completed both steps once more (see Figure 2). There were three more recordings of resting state EEG throughout the testing session, once after each computer task (see Figure 3).

After RS-EEG 1, participants completed one of three computer tasks: digit span (forward and backward), flanker, or go/no-go. The order of the tasks was counterbalanced across participants (see Table 1). All tasks were coded and run using Psychtoolbox-3 in Matlab (Mathworks, Natick, USA). After the first task, a second resting state EEG recording (RS-EEG 2) was completed, followed by the second task. After the second task, a third resting state EEG recording (RS-EEG 3) was completed, followed by the final task. After the final task, a final resting state EEG recording (RS-EEG 4) was completed. Research assistants then removed the cap, and the participant was compensated $20, or $30 if they had completed the driving simulator lab visit previously.

2.2.2 Measures

Electroencephalography. Electroencephalographic (EEG) activity was recorded using a 32-electrode Neuroscan Quick-cap EEG cap (Compumedics Neuroscan, Charlotte, NC) during the EEG lab visit. EEG activity was referenced to an external electrode located at the nasion and a midline electrode anterior to Fz served as the ground electrode. Impedances were kept below 50 kΩ. Electro-oculographic (EOG) activity was recorded by placing one external electrode above and one external electrode below the left eye. Continuous raw EEG data were collected using Curry 8 software (Compumedics Neuroscan, Charlotte, NC) and was amplified through a Grael 4K amplifier. Data were digitized at 1000 Hz and amplified with 0.1-100hz band-pass filter. EEG data were re-referenced off-line to the average mastoids. Eye blinks were regressed using principal components analysis projections, and data were filtered using a 30 Hz zero phase and Butterworth low-pass filter. Data were tapered with a Hamming window with 10% of the total segment length. Fast Fourier transformation (FFT) spectral analyses were calculated for each 60-second interval (two eyes open, two eyes closed) of the four resting state EEG recordings for all participants. Frequency power was averaged across 1-second epochs in each interval. Averaged spectra power values were extracted from all electrodes. Based on prior literature, the current study focused on alpha and theta frequency power at central region electrodes C3, Cz, and C4 (Boksem et al., 2005; Fan et al., 2015; Tran et al., 2020) during the first 60-second interval when participants had their eyes open.

Digit Span Task. Participants completed a forward and backward version of a digit span task. For both the forward and backward versions of the task, all participants were presented with different number sequences from two digits in length to nine digits in length. Both versions had a total of 16 trials. Digits were presented in 1 second intervals by a computer-generated voice played from the computer speakers at the same volume level for each participant. Participants were asked to listen to the sequence and wait until they saw a green square cue appear on the computer screen before repeating the sequence out loud for the research assistant. This cue appeared 2 seconds after the final digit in the sequence had been presented (see Figure 4). In the forward version of the task, participants were asked to repeat the digits in the same order they were presented. In the backward version of the task, participants were asked to repeat the digits in the reverse of the presentation order. After the research assistant determined whether the participant's response was correct, they continued to the next trial. After a participant completed two trials of the same length, a digit would be added to the length of the next sequence until two trials of nine digits were completed.

Flanker Task. In the flanker task, participants were asked to identify the middle or third letter presented in a line of five white letters on a black computer screen. There were four different stimuli, and trials were either congruent (SSSSS or HHHHH) or incongruent (SSHSS or HHSHH). The task was presented in two blocks, with 160 trials in each block for a total of 320 trials. In each block, there were 80 congruent trials (40 HHHHH, 40 SSSSS) and 80 incongruent trials (40 HHSHH, 40 SSHSS). In a trial, participants were first presented with a '+' for 50 milliseconds, followed by a blank screen for 100 milliseconds. Stimuli were then presented for 100 milliseconds, followed by a blank screen for up to 900 milliseconds to allow for participants' responses (see Figure 5). Participants pressed buttons on the keyboard to indicate that the middle or third letter was S (red button) or H (blue button). As soon as participants responded, the trial would continue with the presentation of a blank screen for 800 milliseconds before the following trial. If participants did not respond before the end of the 900-millisecond response window, a blank screen was still presented for 800 milliseconds before the next trial.

Go/No-Go Task. In the go/no-go task, participants were asked to respond to a white letter presented on a black computer screen if it was any letter in the alphabet other than X. If the letter was X, participants were asked to avoid responding. The task was presented in two blocks, with 200 trials per block for a total of 400 trials. In each block, there were 140 go trials (any letter except X) and 60 no-go trials (X). For each trial, participants were first presented with a '+' for 50 milliseconds, followed by a blank screen for 100 milliseconds. A letter was then presented for 80 milliseconds, followed by a blank screen for up to 900 milliseconds to allow for participants' responses (see Figure 6). Participants responded by pressing a white button on the keyboard. As soon as participants responded, the trial would continue with the presentation of a blank screen for 750 milliseconds before the following trial. If participants did not respond before the end of the 900- millisecond response window, a blank screen was still presented for 750 milliseconds before the next trial.

Questionnaires. Participants completed questionnaires on an iPad at the beginning of the study during the EEG capping process. Participants answered questions about their demographic information, ADHD diagnosis history, and ADHD medication status as well as the Adult Temperament Questionnaire Short Form (ATQ-Short; Evans & Rothbart, 2007), the Current Symptoms Self-Report Form (Barkley & Murphy, 1998), the Adult Self-Report (ASR; Achenbach & Rescorla, 2003), and the Behavior Rating Inventory of Executive Function – Adult (BRIEF-A; Roth, Isquith, & Gioia, 2005). The current study utilized participants' ratings from the Current Symptoms Self-Report Form (see Appendix A), an 18-item questionnaire for which participants select the rate of behavior problems related to ADHD, using choices from 0 (“never/rarely”) to 3 (“very often”).

2.3 Driving Simulator Lab Visit

2.3.1 Procedure

Individuals went to the Arbella Insurance Human Performance Laboratory at the University of Massachusetts Amherst for a 60-minute lab visit. Individuals were given a full description of the study and were asked to provide signed consent to participate. After filling out a brief questionnaire, participants were seated in the driving simulator and asked to adjust their seat until it was in a comfortable driving position. Researchers then instructed the participants to fasten their seatbelts, observe the posted speed limit, use indicators when necessary, and carry out on-screen prompts (e.g., Turn right at the intersection). The researcher then put an eye-tracker on the participant, but these data were not used in the current study. Participants were shown how to engage and disengage the automated technology system in the driving simulator. The automated features of the simulator consisted of adaptive cruise control and a lane centering control system. After being introduced to the features of the driving simulator, participants completed a 3-minute practice drive.

Participants were randomly assigned to one of two groups. Participants either drove normally in the driving simulator, or they were asked to drive while also completing a task aimed to distract them from the road. Regardless of group assignment, participants completed three different 3-minute driving scenarios twice. For the two attempts of each scenario, participants drove one attempt with the automated technology system engaged and drove the other attempt with the automated technology system disengaged. The automated technology system was either engaged for the first three scenarios or for the second three scenarios, as determined by counterbalancing. After completing the six driving scenarios, participants completed questionnaires about their driving history and driving tendencies. Participants were then compensated $20, or $30 if they had completed the EEG lab visit previously.

2.3.2 Measures

Driving Simulator. Driving data were collected using a fixed-based Realtime Technologies Inc. (RTI) driving simulator during the driving simulator lab visit. The simulator included a 2013 Ford Fusion and six screens that provided a 330° field of view. The simulator's rear-view mirror and side mirrors also provided simulated views of the surroundings. Speakers simulated environmental noise and engine sounds. Three different scenarios were designed for this study. In the intersection scenario, participants drove toward a four-way intersection with a stoplight and the light was green. A pedestrian approached the crosswalk of the intersection, but the pedestrian was obscured by a building close to the road until the car reached the crosswalk. During the curve scenario, participants drove along a two-lane road (one lane in each direction) that curves to the right. A truck was also parked on the right side of the curved section of road, protruding into the road and obscuring a pedestrian at a crosswalk. Participants had to drive over the dotted yellow dividing line to avoid hitting the truck. In the merge scenario, participants drove to the end of a four-lane road (two lanes in each direction) and reached the beginning of a section where the road merged from four lanes to two lanes. A bicyclist in a hidden driveway was waiting to cross the road at the beginning of this section, and a sign warning about the hidden driveway was placed a good distance before the actual driveway.

Questionnaires. Participants completed the pre-exposure section of the Simulator Sickness Questionnaire (SSQ; Kennedy, Lane, Berbaum, & Lilienthal, 1993) before getting into the driving simulator. After the drive in the simulator, participants completed the post-exposure section of the SSQ and three other questionnaires: a demographics and driving history questionnaire, the US version of the Driver Behavior Questionnaire (DBQ; Reason, Manstead, Stradling, Baxter, & Campbell, 1990), and an automated technology trust questionnaire. Responses from these questionnaires were not examined in the current analyses.

3 Analyses

The first set of analyses investigated the hypothesis that the development of mental fatigue can be reflected by changes in resting state EEG power over time. Changes in alpha and theta EEG power from all four resting state recordings were each compared in repeated measures ANOVAs to examine the development of mental fatigue. Task order was used as a between-subjects variable in these analyses to check for order effects of the cognitive tasks.[2]

Next, the influence of self-reported ADHD symptomology on the development of mental fatigue as measured by resting state EEG power was examined in additional repeated measures ANOVAs. Averages of total ADHD symptoms, inattention symptoms, and impulsivity/hyperactivity symptoms reported on the Current Symptoms Self-Report

[2] Gender and age were not included in these analyses. When they were included in preliminary analyses, the patterns did not change.

Form were used to assign individuals to groups. Individuals were grouped as either high (above the sample mean) or low (below the sample mean) separately for overall ADHD symptoms, inattention symptoms, and hyperactivity/impulsivity symptoms.

The second set of analyses assessed whether the development of mental fatigue as measured by resting state EEG power was associated with young adults' cognitive task performance using multiple linear regression analyses. Difference scores for alpha and theta EEG power were calculated by subtracting RS-EEG 1 power from RS-EEG 3 power. Resting state EEG power difference scores were used to predict performance on Task 3. Due to counterbalancing of the three cognitive tasks between participants, participants completed different tasks for Task 3 depending on their assigned task order (Table 1). Z-scores of performance from participants' Task 3 were used as outcome variables (i.e., total digits correct from the backward version of the digit span task, percent correct on incongruent trials during the flanker task, or percent correct on no-go trials during the go/no-go task).

The influence of different self-reported ADHD symptomology on this association was then examined in separate multiple linear regression analyses. Along with standardized values of alpha or theta resting state EEG power difference scores between RS-EEG 1 and RS-EEG 3, the standardized averages of total ADHD symptoms, inattention symptoms, and impulsivity/hyperactivity symptoms reported on the Current Symptoms Self-Report Form were used to predict performance on Task 3 separately. An interaction term was calculated using the standardized EEG power difference scores and the standardized symptom averages.

To examine the third aim, the final set of analyses tested whether mental fatigue (as measured by resting state EEG power), ADHD symptomology, and cognitive performance predict driving behavior in young adults using several additive multiple linear regression analyses. Difference scores for alpha and theta EEG power were calculated by subtracting RS-EEG 1 power from RS-EEG 4 power. The standardized averages of total ADHD symptoms, inattention symptoms, and impulsivity/hyperactivity symptoms reported on the Current Symptoms Self-Report Form were used for these analyses. A composite score of cognitive performance was created by standardizing the averaged z-scores of performance on the digit span task (total digits correct from backward version), flanker task (percent correct on incongruent trials), and go/no-go task (percent correct on no-go trials). Driving outcomes included mean acceleration, mean velocity, and lane offset deviation from the scenarios when the automation systems were not activated during the driving lab visit.

4 Results

Demographic information can be found in Table 2 and Table 3. Variables were examined for outliers and nine participants were excluded from all analyses because their EEG measures were unusable (n = 5) or greater than 3.29 standard deviations above the mean (n = 4; Tabachnick & Fidell, 2013). To maximize individual differences in behavior, outliers on the cognitive tasks and driving measures were not excluded.[3] Descriptive data for the variables are included in Tables 4 to 7. Correlations between variables are presented in Table 8.

[3] When outliers on cognitive tasks and driving measures were included in preliminary analyses, the patterns did not change.

4.1 Aim 1: Changes in Resting State EEG Over Time

4.1.1 Theta

There was a main effect for Time ($F(3,240) = 9.94$, $p < .001$, $\eta_p^2 = .11$; see Figure 7). Follow-up tests showed that RS-EEG 1 power was significantly higher than RS-EEG 3 power ($F(1,82) = 15.31$, $p < .001$, $\eta_p^2 = .16$) and RS-EEG 4 power ($F(1,81) = 22.31$, $p < .001$, $\eta_p^2 = .22$), but not significantly higher than RS-EEG 2 power ($F(1,81) = 2.08$, $p = .153$, $\eta_p^2 = .03$). RS-EEG 2 power was significantly higher than RS-EEG 3 power ($F(1,83) = 5.94$, $p = .017$, $\eta_p^2 = .07$) and RS-EEG 4 power ($F(1,82) = 13.78$, $p < .001$, $\eta_p^2 = .14$), however, RS-EEG 3 power did not differ from RS-EEG 4 power ($F(1,83) = 2.15$, $p = .146$, $\eta_p^2 = .03$). There was not a main effect for task order ($p = .915$), nor an interaction between the variables ($p = .642$).

Overall ADHD Symptomology. There was a main effect for Time ($F(3,231) = 7.51$, $p < .001$, $\eta_p^2 = .09$).[4] There were no main effects for task order ($p = .952$) or ADHD group ($p = .924$), nor were there any significant interactions between the variables (ps > .064).

Hyperactive/Impulsive Symptomology. There was a main effect for Time ($F(3,231) = 8.59$, $p < .001$, $\eta_p^2 = .10$).[4] There was also a significant three-way interaction between Time, Task Order, and Hyperactivity/Impulsivity group ($F(6,231) = 2.67$, $p = .016$, $\eta_p^2 = .07$). Follow-up tests revealed that individuals in the high Hyperactivity/Impulsivity group who completed Task Order 2 had higher power at RS-

[4] Follow-up tests indicated that the patterns were the same as when overall ADHD symptomology group was not included.

EEG 1 as compared to others in the high Hyperactivity/Impulsivity group who completed Order 1 ($t(20) = -2.32$, $p = .031$) and Order 3 ($t(19) = 2.11$, $p = .048$; see Figure 8). Additionally, among individuals who completed Task Order 3, those in the high Hyperactivity/Impulsivity group had significantly higher power at RS-EEG 3 power as compared to those in the low Hyperactivity/Impulsivity group ($F(1,24) = 6.19$, $p = .020$, $\eta_p^2 = .21$; see Figure 9). There were no main effects for task order ($p = .864$) or Hyperactivity/Impulsivity group ($p = .309$), nor were there any other significant interactions between the variables (ps > .114).

Inattentive Symptomology. There was a main effect for Time ($F(3,231) = 8.59$, $p < .001$, $\eta_p^2 = .10$).[4] There were no main effects for task order ($p = .949$) or Inattention group ($p = .595$), nor were there any significant interactions between the variables (ps > .267).

4.1.2 Alpha

There was a main effect for Time ($F(3,240) = 10.74$, $p < .001$, $\eta_p^2 = .12$; see Figure 10). Follow-up tests showed that RS-EEG 1 power was significantly higher than RS-EEG 3 power ($F(1,82) = 16.76$, $p < .001$, $\eta_p^2 = .17$) and RS-EEG 4 power ($F(1,81) = 24.76$, $p < .001$, $\eta_p^2 = .23$), but not significantly higher than RS-EEG 2 power ($F(1,81) = 2.11$, $p = .151$, $\eta_p^2 = .03$). RS-EEG 2 power was significantly higher than RS-EEG 3 power ($F(1,83) = 6.56$, $p = .012$, $\eta_p^2 = .07$) and RS-EEG 4 power ($F(1,82) = 13.71$, $p < .001$, $\eta_p^2 = .14$). RS-EEG 3 power was not significantly higher than RS-EEG 4 power ($F(1,83) = 2.37$, $p = .127$, $\eta_p^2 = .03$). There was no main effect for task order ($p = .931$), nor was there a significant interaction between the variables ($p = .673$).

Overall ADHD Symptomology. There was a main effect for Time ($F(3,231) = 8.06$, $p < .001$, $\eta_p^2 = .10$).[4] There were no main effects for task order ($p = .964$) or ADHD group ($p = .961$), nor were there any significant interactions between the variables (*p*s > .073).

Hyperactive/Impulsive Symptomology. There was a main effect for Time ($F(3,231) = 9.21$, $p < .001$, $\eta_p^2 = .11$).[4] There was also a significant three-way interaction between Time, Task Order, and Hyperactivity/Impulsivity group ($F(6,231) = 2.77$, $p = .013$, $\eta_p^2 = .07$). Follow-up tests revealed that individuals in the high Hyperactivity/Impulsivity group who completed Task Order 2 had significantly higher power at RS-EEG 1 as compared to others in the high Hyperactivity/Impulsivity group who completed Order 1 ($t(20) = -2.23$, $p = .038$) and Order 3 ($t(19) = 2.20$, $p = .040$; see Figure 11). Additionally, among individuals who completed Task Order 3, those in the high Hyperactivity/Impulsivity group had significantly higher power at RS-EEG 3 as compared to those in the low Hyperactivity/Impulsivity group ($F(1,24) = 6.24$, $p = .020$, $\eta_p^2 = .21$; see Figure 12). There were no main effects for task order ($p = .902$) or Hyperactivity/Impulsivity group ($p = .293$), nor were there any other significant interactions between the variables (*p*s > .121).

Inattentive Symptomology. There was a main effect for Time ($F(3,231) = 10.14$, $p < .001$, $\eta_p^2 = .12$).[4] There were no main effects for task order ($p = .954$) or Inattention group ($p = .723$), nor were there any significant interactions between the variables (*p*s > .196).

4.2 Aim 2: Resting State EEG Change and Task Performance

4.2.1 Theta

There was not a significant relation between the change in power from RS-EEG 1 to RS-EEG 3 and performance on Task 3 (B = -.09, SE = .10, p = .357, $ß$ = -.10).

Overall ADHD Symptomology. Standardized average ADHD symptomology was included as a moderator. The main effect of EEG power change (B = -.10, SE = .11, p = .350, $ß$ = -.11) and the main effect of ADHD symptomology (B = -.03, SE = .11, p = .760, $ß$ = -.04) were not significant. The interaction between the variables was not significant (B = .07, SE = .15, p = .636, $ß$ = -.06).

Hyperactive/Impulsive Symptomology. Standardized hyperactive/impulsive symptomology was separately included as a moderator. The main effect of EEG power change (B = -.08, SE = .11, p = .430, $ß$ = -.09) and the main effect of hyperactive/impulsive symptomology (B = -.05, SE = .11, p = .658, $ß$ = -.05) were not significant. The interaction between the variables was not significant (B = .003, SE = .14, p = .981, $ß$ = .003).

Inattentive Symptomology. Standardized inattentive symptomology was separately included as a moderator. The main effect of EEG power change (B = -12, SE = .11, p = .267, $ß$ = -.13) and the main effect of inattentive symptomology (B = -.02, SE = .11, p = .855, $ß$ = -.02) were not significant. The interaction between the variables was not significant (B = -.13, SE = .14, p = .363, $ß$ = -.11).

4.2.2 Alpha

There was not a significant relation between the change in power from RS-EEG 1 to RS-EEG 3 and performance on Task 3 (B = -.09, SE = .10, p = .369, $ß$ = -.10).

Overall ADHD Symptomology. Standardized average ADHD symptomology was included as a moderator. The main effect of EEG power change (B = -.12, SE = .11, p = .308, ß = -.13) and the main effect of ADHD symptomology (B = -.03, SE = .11, p = .798, ß = -.03) were not significant. The interaction between the variables was not significant (B = -.11, SE = .16, p = .499, ß = -.08).

Hyperactive/Impulsive Symptomology. Standardized hyperactive/impulsive symptomology was separately included as a moderator. The main effect of EEG power change (B = -.09, SE = .11, p = .435, ß = -.09) and the main effect of hyperactive/impulsive symptomology (B = -.05, SE = .11, p = .670, ß = -.05) were not significant. The interaction between the variables was not significant (B = -.01, SE = .15, p = .924, ß = -.01).

Inattentive Symptomology. Standardized inattentive symptomology was separately included as a moderator. The main effect of EEG power change (B = -.14, SE = .11, p = .213, ß = -.15) and the main effect of inattentive symptomology (B = -.01, SE = .11, p = .894, ß = -.02) were not significant. The interaction between the variables was not significant (B = -.17, SE = .15, p = .257, ß = -.14).

4.3 Aim 3: Resting State EEG Change, Task Performance, and Driving

Preliminary t-tests were run to determine if any of the variables were significantly different between driving groups (distraction, no distraction). The mean difference score between RS-EEG 1 and RS-EEG 4 was significantly greater in the distraction group than in the no distraction group for both theta power ($t(59)$ = 2.59, p = .012) and alpha power

($t(59) = 2.52$, $p = .015$).[5] All other variables were not different between groups (*p*s > .264).

4.3.1 Theta

Overall ADHD Symptomology. The main effects of EEG power change, task performance, and standardized ADHD symptomology were not significant for acceleration (see Table 9), lane offset deviation (see Table 10), and velocity (see Table 11).

Hyperactive/Impulsive Symptomology. The main effects of EEG power change, task performance, and standardized hyperactive/impulsive symptomology were not significant for (see Table 9), lane offset deviation (see Table 10), and velocity (see Table 11).

Inattentive Symptomology. The main effects of EEG power change, task performance, and standardized inattentive symptomology were not significant for acceleration (see Table 9), lane offset deviation (see Table 10), and velocity (see Table 11).

4.3.2 Alpha

Overall ADHD Symptomology. The main effects of EEG power change, task performance, and standardized ADHD symptomology were not significant for acceleration (see Table 12), lane offset deviation (see Table 13), and velocity (see Table 14).

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[5] Driving group was not included as a predictor in the following analyses. When it was included as a predictor in preliminary analyses, the patterns did not change.

Hyperactive/Impulsive Symptomology. The main effects of EEG power change, task performance, and standardized hyperactive/impulsive symptomology were not significant for acceleration (see Table 12), lane offset deviation (see Table 13), and velocity (see Table 14).

Inattentive Symptomology. The main effects of EEG power change, task performance, and standardized inattentive symptomology were not significant for acceleration (see Table 12), lane offset deviation (see Table 13), and velocity (see Table 14).

5 Discussion

Mental fatigue undermines the cognitive skills required to be successful and safe in our daily lives, yet we know very little about how mental fatigue progresses over time, especially among individuals with heightened attention difficulties. The primary objective for the current study was to examine changes in EEG power from multiple resting state recordings in young adults over the course of a lab visit consisting of various cognitively demanding tasks. The secondary objective was to determine whether individual differences in attention difficulties as assessed via self-reports of ADHD symptomology influence the progression of mental fatigue as assessed by resting state EEG.

Since mental fatigue severely impacts cognitive functioning (Tran et al., 2020) and individuals with ADHD also demonstrate difficulties engaging cognitive abilities (Roberts et al., 2015), this study also examined whether EEG power derived from resting state recordings and ADHD symptomology predicted cognitive performance. Mental fatigue is also a major concern when individuals get behind the wheel of a car, especially when drivers are young and brain regions needed for efficient driving are still developing and/or when individuals may already be predisposed to have difficulty with certain cognitive skills essential to driving (Anstey & Wood, 2011; Classen et al., 2013; Johannsdottir & Herdman, 2010; Ross et al., 2015; Thompson et al., 2007). Thus, the current study also examined whether resting state EEG power, ADHD symptomology, and performance on cognitive tasks predicted driving outcomes measured in a driving simulator. These analyses aimed to broaden and enhance mental fatigue research by examining how individual differences in the progression of mental fatigue and in attention vulnerabilities might interact to influence cognitive performance over time as well as patterns of driving behavior in young adults.

The major finding in this study was that young adults' resting state theta and alpha EEG power significantly *decreased* in a linear pattern over time across the four recordings. Interestingly, resting state EEG changes over time did not predict cognitive performance nor driving behavior. Although ADHD symptoms have previously been linked to general driving behavior, the current study did not find that driving patterns vary depending upon ADHD symptomology. Each of these findings will be discussed in detail below.

5.1 Resting State EEG as a Measure of Mental Fatigue

Mental fatigue is typically examined during multiple hour sessions of cognitively demanding tasks (Arnau et al., 2017; Boksem, Meijman, & Lorist, 2005; Tanaka, et al., 2012; Wang, et al., 2016; Wascher et al., 2014), although evidence suggests that much shorter durations are sufficient to induce mental fatigue (Cao et al., 2014; Smith et al., 2019; Tanaka et al., 2014). For EEG measures of mental fatigue, prior research typically focuses on how EEG measured during task performance changes over time, however the rest period between tasks has yet to be explored in depth as an important assessment of how cognitive resources may be modulated to impact outcomes over time. The current study was therefore designed to explore this novel approach to measuring mental fatigue via resting state EEG change over time and investigate whether this type of assessment would interact with individual differences in attention difficulties when predicting performance across different contexts.

Results of the current study indicate that both alpha and theta measures of resting state EEG decrease in a linear fashion over time. This pattern for resting state EEG is distinct from task-based EEG power and reflects how quickly can mental fatigue develop. Thus far, the only other studies that have examined a pre-task and post-task recording resting state EEG power as a measure of mental fatigue do not reflect the same patterns. Tanaka and colleagues (2012) demonstrated that alpha power decreased and theta power increased, whereas Li and colleagues (2020) showed that both alpha and theta power increased. The patterns for alpha resting state EEG in the current study are in line with those demonstrated by Tanaka and colleagues, but the patterns for theta differ. These differing patterns could be due to the fact that these studies used only one cognitively demanding task and tested individuals on that task for two hours. Additionally, the first recording of resting state EEG in the current study provided a valuable baseline measure of neural activity in individuals before they began the cognitively demanding tasks. In studies that only focus on task-based EEG, they lack this critical component of measuring initial neural readiness in individuals, especially in populations which may exhaust their cognitive resources faster and show mental fatigue sooner.

Interestingly, this pattern of resting state EEG power did not correspond with the pattern presented in previous research on task-based EEG power where both theta and alpha EEG power tend to increase over time (Tran et al., 2020). Although, in many prior studies, individuals were required to complete the same cognitive or driving task during an extended period of time. Moreover, there is evidence that task-based theta power decreased over time after approximately an hour of simulated driving (Getzmann et al., 2018; Wascher et al., 2018). There is also evidence that resting state alpha power decreased as compared to resting state alpha recorded prior to a two-hour challenging cognitive task (Tanaka et al., 2012).

These findings also highlight that testing sessions do not need to be multiple hours in duration to measure mental fatigue with resting state EEG. Prior work on task-based EEG has demonstrated that 10 minutes to 30 minutes of a cognitively demanding task is enough to induce significant increases in alpha and theta EEG power (Tanaka et al., 2014; Trejo et al., 2015). In this study, individuals demonstrated significant decreases in resting state alpha and theta EEG power in a similarly brief time, from the first recording to the third recording. In between those recordings, individuals completed two different cognitively demanding tasks and the second resting state recording. This interval was a total duration of approximately 25 minutes, including approximately 20 minutes engaged with the cognitively demanding tasks. Thus, significant changes in resting state EEG power can be detected after much shorter durations than those traditionally used in mental fatigue research. These methodological differences could allow researchers to examine mental fatigue in a broader population (e.g., atypical samples, children) for which long testing sessions would not be ideal. Additionally, being able to examine changes in resting state EEG earlier than in task-based EEG would help to shed light on mental fatigue across more diverse contexts during a brief amount of time (i.e., short drives while fatigued).

Resting state EEG also provides an interesting contrast to task-based EEG recordings because there are few demands during the resting state recording. As such, engagement with the cognitively demanding tasks influences EEG power very differently than the disengagement that occurs during resting state recordings. Thus, these measurements may provide a glimpse of how an individual's base levels of cognitive resources fluctuate over the course of the experimental session. For the current study, individuals were instructed to stare at a fixation cue or sit with their eyes closed while resting state EEG was being recorded. This "task" is dramatically different than the flanker, go/no-go, or other cognitive tasks commonly used in mental fatigue research. There is minimal cognitive stress and participants are not required or encouraged to make motor or verbal responses during these resting state intervals. With fewer demands during this measurement of mental fatigue, researchers can use resting state EEG in mental fatigue research with a variety of typical and atypical populations.

The pattern of decreasing resting state EEG power over time in the current study also corresponds to a small body of mental fatigue research that has shown theta and alpha EEG power may decrease over time (Getzmann et al., 2018; Tanaka et al., 2012; Wascher et al., 2018). According to these studies and others, increased alpha EEG power is typically observed during relaxation and repetitive and dull tasks, indicating boredom and attentional withdrawal. In contrast, decreased or suppressed alpha EEG power is observed in situations of cognitive engagement and following demanding tasks which drain cognitive resources, causing mental fatigue (Borghini, et al., 2014; Wascher et al., 2014). Additionally, increased theta power has been observed during and after tasks with greater task difficulty (Tran et al., 2020).

The tasks in this study required constant alertness and flexibility to complete and meet the changing demands of each task. The resting state EEG data suggest this challenge compelled individuals to employ increasing amounts of cognitive resources over the course of the experimental session, resulting in heightened levels of mental fatigue during non-challenging periods of resting state EEG. Thus, these results uniquely demonstrate that mental fatigue of resting state cognitive resources can be induced by the sustained attentional engagement required by cognitively demanding tasks. Additional studies will be needed to determine how resting state EEG may interact with or drive emergence of task-based measures of mental fatigue.

5.2 ADHD Symptomology

There are very few studies that have examined the impact of individual differences in the emergence of mental fatigue, and the studies that have been run explore the influence of personality traits, such as neuroticism and conscientiousness, on mental fatigue development (Ackerman & Kanfer, 2009). The current study was designed to expand the field's knowledge of the influence of individual differences on mental fatigue by focusing on individual differences in attention skills. Specifically, this study examined whether high or low levels of ADHD symptoms could shed light on how mental fatigue may develop differently in the population as a whole. It was expected that individuals with attention and hyperactivity difficulties would be more susceptible to the pressures of the cognitively demanding tasks and mental fatigue would develop sooner (Fassbender & Schweitzer, 2006).

Interestingly, there were no main or interactive effects with attention symptomology. There could be several reasons for this unanticipated lack of findings. First, the overall ratings on inattention, hyperactivity, and hyperactivity in this sample were relatively low. In order to create the two groups used for analyses, the sample was divided at the mean to form a low symptomology group and a high symptomology group. Thus, many individuals who did not often experience many issues with inattention, hyperactivity, or impulsivity were included in the group with “higher” levels of symptomology. Follow-up exploratory analyses splitting into high, medium, and low symptomology groups still indicated similar patterns, suggesting that ADHD symptomology may not be a distinguishing factor in the progression of resting state measures of mental fatigue in this sample of high functioning college students.

Second, the variation of tasks used in this study may have provided interesting challenges that strongly engaged the attentional focus of the individuals with elevated levels of symptomology. More repetitive tasks that were not as engaging may have been more conducive to eliciting more rapid or intense changes in resting state EEG reflecting mental fatigue and task disengagement. Third, although, task-based mental fatigue research suggests that individuals with ADHD can experience mental fatigue more rapidly than their typically developing peers (Bioulac et al., 2012; Maruta et al., 2014), resting state EEG may reflect preparatory states such that variation among individuals with ADHD would be less likely to arise until they are cognitively challenged as in the task-based EEG. Additional studies should explore the change between resting state EEG and task-based EEG (Karamacoska, Barry, Steiner, Coleman & Wilson, 2018) as a potentially important distinguisher of ability to modulate cognitive resources across a task (and thus resist mental fatigue) among individuals high and low in ADHD symptomology.

5.3 Cognitive Performance

Another goal of the current study was to assess whether mental fatigue as measured by resting state EEG could predict performance on cognitive tasks. Mental fatigue research typically uses worsening task performance as an indicator of mental fatigue (Tran et al., 2020), thus this current study reflected a similar process by examining performance on the third task of three different tasks completed by participants. Due to counterbalancing, the third task was not the same for all participants, so performance variables from participants' third task were standardized, removing some of the existing variability in the data. As participants showed significant changes in resting state EEG from the first recording to the third recording, this third task was poised to provide useful information about how cognitive performance is impacted following the onset of mental fatigue.

However, the current study did not find any connections between the development of mental fatigue as measured by resting state EEG and subsequent task performance. As associations have been observed between EEG collected during a task and task performance, it is possible that EEG recorded during rest in this study does not directly map onto task performance. There is some evidence in the literature that mental fatigue can be observed using other objective and subjective measures while not impacting task performance (Cao et al., 2014; Smith et al., 2019). With different orders and tasks throughout the experimental session, performance comparisons across tasks over time were not used to assess the development of mental fatigue due to very small sample sizes. To include the important element of resting state EEG in the task performance tracking aspect of prior mental fatigue research, future studies should combine the use of resting state EEG and repeated measures of the same cognitive task over the duration of experimental sessions.

ADHD symptomology as a continuous measure was also examined in conjunction with resting state EEG power to predict task performance on the third cognitive task. Including ADHD symptomology as a predictor and in interaction with resting state EEG power did not reveal an association between these variables and task performance. The absence of findings for these analyses was interesting, given that individuals with ADHD commonly have problems engaging cognitive skills effectively (Roberts et al., 2015). However, there is currently no other research that expressly discusses and measures the development of mental fatigue using EEG among individuals with ADHD. Additionally, there is very little evidence that individuals with ADHD perform worse than their typically developing peers on tasks during sessions meant to induce mental fatigue (Bioulac et al., 2012; Maruta et al., 2014). As mentioned previously, there was also not a broad distribution in reported inattention, hyperactivity, and impulsivity symptoms, thus limiting the ability to draw clear conclusions about the connections between mental fatigue, individual differences, and cognitive performance in this study. With so few prior publications surrounding this topic, future research must continue to investigate whether resting state EEG can be used to predict cognitive performance, especially among individuals with ADHD.

5.4 Driving Behavior

The third objective for this research was to investigate whether young adults' driving behavior could be predicted by mental fatigue (as measured by changes in resting state EEG power over time), ADHD symptomology, and overall cognitive task performance. Although mental fatigue has long been noted as a leading cause for risky driving and traffic accidents (Fletcher et al., 2005; Horne & Reyner, 1999; Phillip, 2005), the current study also examined the additive effects of ADHD symptomology and cognitive performance specifically in young adults. Measures of working memory, attention, and inhibitory control have also been shown to predict driving behaviors (Baldock et al., 2007; Daigneault, Joly, & Frigon, 2002; Ross et al., 2015; Tabibi et al., 2015). For these analyses, overall cognitive performance was a composite of individuals' performance on all three cognitive tasks. Since drivers with ADHD and drivers with weaker cognitive skills are more likely to demonstrate risky driving behavior (Anstey & Wood, 2011; Classen et al., 2013; Johannsdottir & Herdman, 2010; Ross et al., 2015; Thompson et al., 2007), it was expected that these variables would play a role in predicting driving behavior.

Prior work suggests that driving can be linked with mental fatigue related changes in alpha and theta EEG power (Borghini et al., 2014; Getzmann et al., 2018; Wascher et al., 2018; Zhao et al., 2012), and drivers dealing with mental fatigue demonstrate more speeding and lane weaving (Morales et al., 2017; Perrier et al., 2016). However, resting state EEG power, ADHD symptomology, and overall cognitive performance did not predict young adults' driving behavior in this study. Exploratory analyses did show some connections between ADHD symptomology, task performance, and driving measures which align with prior research (Jongen et al., 2011; Ross et al., 2015). These analyses revealed that individuals with high levels of ADHD symptomology and weaker working memory skills, as measured in the backward digit span task, demonstrated more lane weaving, as measured by lane offset deviation in the driving simulations.

The absence of significant results in the prediction of driving measures from resting state EEG may be due to a low sample size, but it may suggest that this measure of mental fatigue in the EEG lab did not closely relate to the measures of driving in the very different atmosphere of the driving lab. Future studies on the associations between resting state EEG and driving behavior should combine the two visits, with individuals driving while wearing an EEG cap. These methods would allow for the investigation of how these patterns of mental fatigue develop among different populations, such as brand-new drivers. It would be critical to examine mental fatigue in drivers who are learning and devoting significant cognitive resources to the process of driving. Mental fatigue may emerge sooner under these cognitively demanding conditions and thus play a bigger role in determining the safety of these younger drivers.

5.5 Limitations

There were a few limitations to the current study. Although numerous recruitment efforts were made to oversample for individuals with ADHD, these efforts were not successful in ensuring a large sample size with clinically significant levels of ADHD symptomology. Many individuals scored very low on the measures of ADHD symptomology, reporting very few symptoms of inattention, hyperactivity, and impulsivity. As such, the measure of ADHD symptomology was heavily skewed and was standardized to provide clarity in the analyses. These findings also are limited in generalizability as our sample was predominantly white college students. Additionally, due to the onset of the COVID-19 pandemic, more data could not be collected, and many participants were unable to complete the driving simulator lab visit. This anomaly enforced a strict limit on the sample size available for any analyses using the driving variables.

Furthermore, there was an unanticipated drawback to the design of this study. During the EEG lab visit, the three different cognitive tasks were all cognitively demanding. However, the digit span tasks were inherently different from the go/no-go and flanker tasks due to the auditory presentation and the necessity of a verbal response during the tasks. Comparatively, the go/no-go and flanker tasks both were presented visually and required motor responses. The switches in presentation and response modality may have had unforeseen effects on task performance, especially across the different task orders. The three different tasks were counterbalanced among participants, however, interpreting any interactions involving ADHD groups and task order was problematic with the very limited group sizes.

5.6 Future Directions

The robust patterns in decreasing alpha and theta resting state EEG power over the course of the experimental session in this study provide support for using this measure as a marker of mental fatigue in future studies. For next steps, resting state EEG should be measured at various intervals while participants complete the same cognitively demanding task during the alternating intervals. This approach would address the potential issues surrounding task order effects on performance such as response modality and task presentation. Additionally, when using the same task, it would be possible to assess and compare changes in various variables related to task performance over time such as reaction time, accuracy, and error monitoring. Increasing the total duration of the cognitively demanding task to 60 or 90 minutes may also reveal changes in task performance (Barwick et al., 2012; Wang et al., 2016; Wascher et al., 2014) that could be linked with changes in resting state EEG.

To further explore whether resting state EEG reflects mental fatigue, individuals could be divided into separate groups. The main group could complete a classic task used to induce mental fatigue as in this study, and comparison groups could do a simple, relaxing activity or even nothing at all. Including one or more comparison group would allow researchers to extrapolate whether these decreases in resting state EEG power are in fact related to mental fatigue, rather than passage of time, sustained attention, motivation, or another variable (Hopstaken et al., 2016).

Moreover, future research on resting state EEG should examine how mental fatigue develops across different EEG bands and across levels of those bands. For instance, there is some work suggesting that the beta frequency is altered among children with ADHD (Barry, Clarke, Johnstone, McCarthy, & Selikowitz, 2009), and other literature has drawn a distinction between lower alpha from 8 to 10 Hz (linked to alertness) and upper alpha from 10 to 13 Hz (linked to target processing), which may correspond more closely to beta (Klimesch, Doppelmayr, Russegger, Pachinger, & Schwaiger, 1998; Li et al., 2020). Thus, future work should examine whether either upper alpha and/or beta frequency bands have differential patterns associated with task performance in individuals with varying levels of ADHD symptomology. In addition, future research should examine changes in resting state EEG power by creating a theta/beta ratio to determine if the patterns of resting state EEG in adults with high ADHD symptomology are similar to or distinct from the patterns in children (Lubar, 1991).

To further develop a comprehensive picture of how mental fatigue emerges over time, it would be important for future studies of resting state EEG to include additional measures such as participants' subjective ratings of fatigue. Collecting these ratings at multiple points during the session could provide interesting insights into people's perceptions of their own mental fatigue and perhaps illuminate whether they can accurately pinpoint when their performance is going to start to be impaired. Such insight would be critical for those who find themselves in potentially dangerous situations when driving, and this knowledge could prevent potential risks for that driver and others on the road with them.

Related objective measures that could be combined with resting state measures of mental fatigue are pupillometry and eye-tracking (Hopstaken et al., 2016). These measurements would also be valuable additional measures for future mental fatigue research examining resting state EEG, especially during driving behavior. Pupillometry could help point to both arousal and mental engagement. Additionally, it would be important to examine how effectively individuals track visual stimuli in their environment when they begin to get mentally fatigued, as measured objectively via EEG, as this type of assessment may link to the anticipation and detection of hazards while driving. In addition, many cars now are equipped with technology that alerts drivers when their eyes are diverted from the road or even appear to be closed. This type of eye-tacking technology and alert system could be life-changing for many people who struggle to recognize that they are mentally fatigued while they are behind the wheel. Future research on mental fatigue that investigates both resting state EEG and eye-tracking measures could help inform the development of these alert systems and potentially improve the technology by detecting signs of mental fatigue sooner.

Furthermore, as with some prior mental fatigue and driving studies, it would also be useful to examine these changes in resting state EEG while a person is driving. These recordings could be implemented in a manner similar to that of the current study, such that individuals would drive in a driving simulator for 10-15 minutes intervals with resting state EEG recordings occurring in between and throughout the course of the session. Additional studies should also examine how extending the duration of the driving task intervals would influence the induction of mental fatigue and how these changes in resting state EEG progress throughout the drive. Variability in this measure of mental fatigue should also be further explored by examining it in drivers with ADHD.

Finally, future studies should also continue to test different age groups. This study was the first of its kind to focus on mental fatigue and individual differences in attention and hyperactivity difficulties, particularly in young adults. In 2015, 23% of the total deaths among 15- to 24-year-olds were due to motor vehicle accidents and this age group also had the highest number of fatal motor vehicle accidents (Murphy et al., 2017). This high rate among young drivers is likely to be strongly linked with their amount of experience behind the wheel, thus subsequent research must consider how years of driving experience could moderate possible associations. Future work should also aim to extend the age range of this research into younger and older populations. With pioneering developments in this kind of research, newly licensed drivers as well as experienced older adult drivers can be taught specific signs of mental fatigue and encouraged to take breaks or develop habits to stay alert while driving.

5.7 Conclusions

The current study investigated the use of resting state EEG as compared to task-based EEG for the measurement of mental fatigue as well as its utility in predicting task performance and driving behavior. The study's findings provide preliminary evidence that changes in power derived from resting state EEG recordings may reflect a variant of mental fatigue in young adults. However, it is unclear how this measure of mental fatigue might correspond to changes in cognitive performance on challenging tasks. These findings may indicate that the cognitively demanding tasks induced mental fatigue, yet the duration of the experimental session was not long enough to generate variation in task performance in a high-performing sample. This study adds to the growing body of literature which suggests that experimental sessions aimed at inducing mental fatigue can be shorter in duration (e.g., 30-40 minutes), rather than lasting for hours as in prior work. These findings also call for examination of these measures in other age groups, as this phenomenon is likely not unique to young adults. Furthermore, individual differences and other measures must be examined closely to determine whether the development of mental fatigue looks different across the wider population.

Interestingly, the study did not show evidence that this measure of mental fatigue was able to predict performance in the driving simulator, suggesting that the associations described in prior literature may be dependent on measuring EEG and driving in the same context. The driving variables were of particular interest in this study because driving research that focuses on mental fatigue has not examined young adults. Future research should continue to investigate whether there are associations between resting state EEG as a measure of mental fatigue and behavioral measures. It would also be useful to identify whether task-based EEG and resting state EEG measures differ in their predictions of other outcomes, such as the amount of time an individual can maintain high performance before demonstrating fatigue or the amount of recovery time required for an individual to attain prior levels of performance after fatigue.

Previous mental fatigue research almost exclusively focuses on task-based EEG measures. The current study indicates that resting state EEG may also serve as a valuable measure of mental fatigue. Additional work should delve into which aspects of mental fatigue resting state EEG most closely relates to, in terms of performance outcomes and variability by age and/or individual differences (e.g., ADHD symptomology). Future work can build off this study to help identify how individual differences in attention and hyperactivity may impact mental fatigue development, with the ultimate goal of improving and designing driving technologies that can assist and alleviate mental fatigue vulnerabilities.

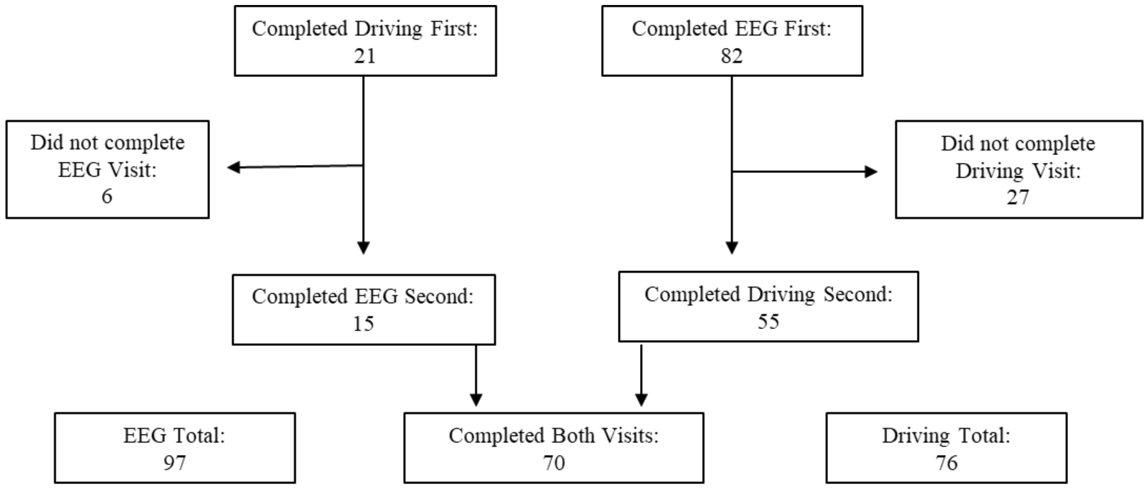

Figure 1. Study participation and attrition information

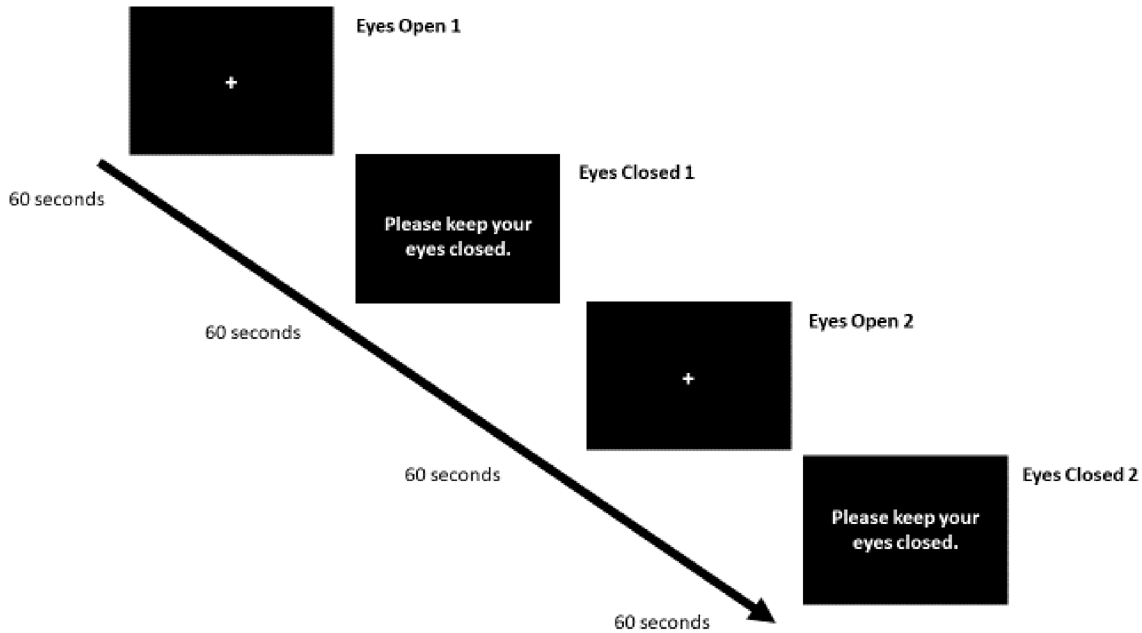

*Figure 2.*Resting state EEG recording sequence

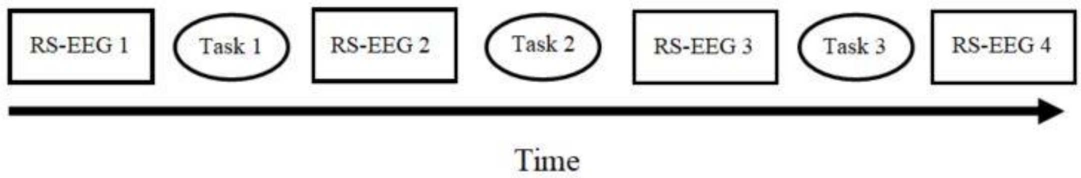

Figure 3. Procedure at EEG lab visit
Note. Resting state EEG recording = RS-EEG.

Table 1.
Task sequences during the EEG lab visit for different order groups

	Task 1	Task 2	Task 3
Order 1	Digit Span	Flanker	Go/No-Go
Order 2	Go/No-Go	Digit Span	Flanker
Order 3	Flanker	Go/No-Go	Digit Span

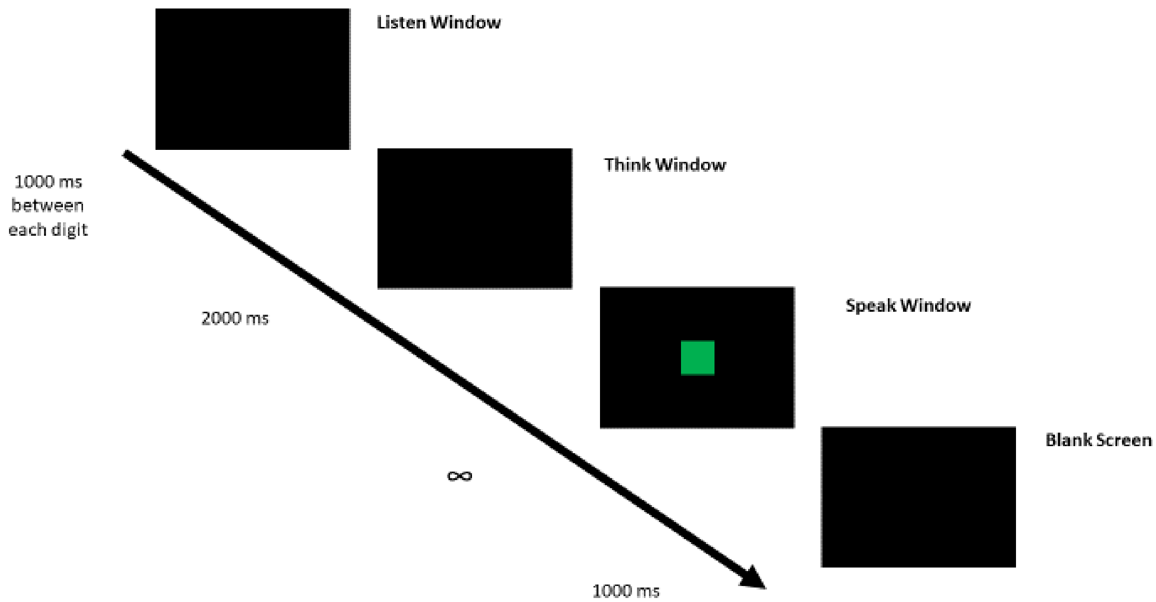

Figure 4. Digit span task sequence

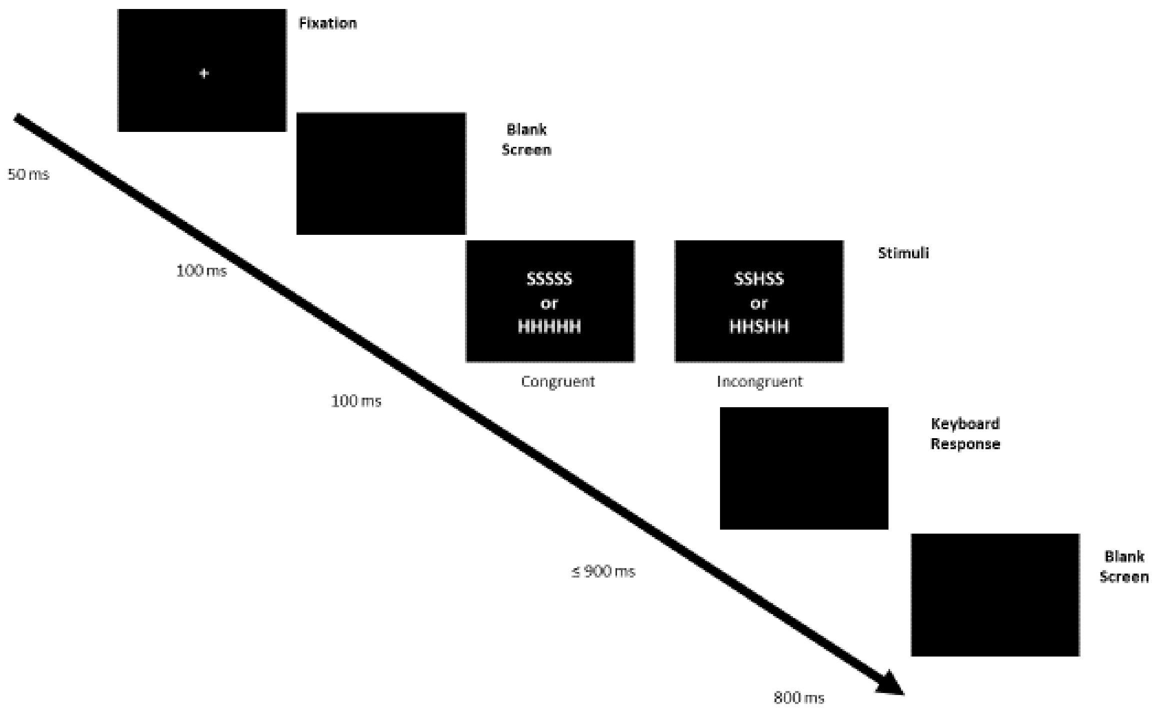

Figure 5. Flanker task sequence

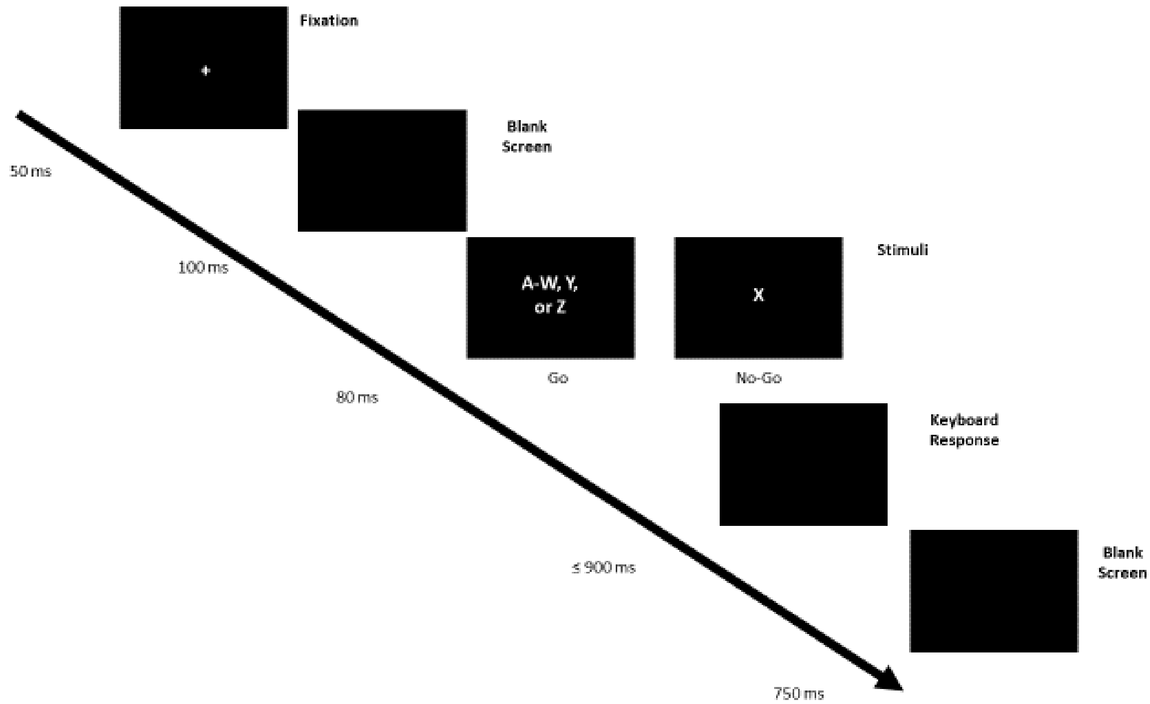

Figure 6. Go/No-Go task sequence

Table 2.
Demographic information for the full sample and the samples included and excluded

	Full sample	Included	Excluded
N	97	88	9
Sex (M/F)	40/57	38/50	2/7
Mean Age	19.84	19.81	20.11
Mean Age SD	1.75	1.75	1.83
White	70.10%	71.60%	55.60%
Asian	20.60%	20.50%	22.20%
Black	3.10%	2.30%	11.10%
Latino/Hispanic	3.10%	2.30%	11.10%
Multiracial	3.00%	3.30%	0%

Table 3.
Demographic information for the different ADHD groups

	Overall ADHD		Hyperactivity/impulsivity		Inattention	
	Low	High	Low	High	Low	High
N	55	33	52	36	48	40
Sex (M/F)	20/35	18/15	19/33	19/17	15/33	23/17
Mean Age	19.67	20.03	19.62	20.08	19.67	19.97
Mean Age SD	1.89	1.51	1.87	1.56	1.88	1.59
White	70.90%	72.70%	69.20%	75.00%	72.90%	70.00%
Asian	20.00%	21.20%	19.20%	22.20%	20.80%	20.00%
Black	1.80%	3.00%	3.80%	0%	0%	5.00%
Latino/Hispanic	3.60%	0%	3.80%	0%	4.20%	0%
Multiracial	3.60%	3.00%	3.80%	2.80%	2.10%	5.00%

Table 4.
Descriptive statistics of the study outcome variables

	Minimum	Maximum	Mean	Standard deviation
Backward Digit Span	4	9	5.68	1.17
Flanker	29.20%	98.80%	87.79%	11.48%
Go/No-Go	41.70%	99.20%	83.24%	11.02%
Mean Acceleration (m/s^2)	-.17	.19	.01	.07
Lane Offset Deviation	.21	1.71	.42	.23
Mean Velocity (m/s)	9.27	24.49	13.83	2.75

Notes: Backward Digit Span- longest length sequence correct; Flanker- accuracy on incongruent trials; Go/No-Go- accuracy on no-go trials

Table 5.
Descriptive statistics of the study outcome variables across overall ADHD symptomology group

	Low		High	
	Mean	SD	Mean	SD
Backward Digit Span	5.67	1.10	5.70	1.29
Flanker	88.28%	10.82%	86.95%	12.68%
Go/No-Go	83.76%	10.71%	82.39%	11.63%
Acceleration (m/s^2)	.01	.07	-.01	.07
Lane Offset Deviation	.44	.29	.38	.06
Velocity (m/s)	13.38	2.28	14.64	3.36

Notes: Backward Digit Span- longest length sequence correct; Flanker- accuracy on incongruent trials; Go/No-Go- accuracy on no-go trials

Table 6.
Descriptive statistics of the study outcome variables across hyperactivity/impulsivity symptomology group

	Low		High	
	Mean	SD	Mean	SD
Backward Digit Span	5.69	1.12	5.67	1.24
Flanker	88.60%	8.30%	86.58%	15.09%
Go/No-Go	84.29%	9.86%	81.68%	12.54%
Acceleration (m/s^2)	.01	.06	.00	.08
Lane Offset Deviation	.45	.30	.38	.06
Velocity (m/s)	13.37	2.31	14.48	3.21

Notes: Backward Digit Span- longest length sequence correct; Flanker- accuracy on incongruent trials; Go/No-Go- accuracy on no-go trials

Table 7.
Descriptive statistics of the study outcome variables across inattention symptomology group

	Low		High	
	Mean	SD	Mean	SD
Backward Digit Span	5.60	1.11	5.77	1.25
Flanker	87.96%	11.47%	87.59%	11.65%
Go/No-Go	83.54%	11.00%	82.90%	11.18%
Acceleration (m/s^2)	.02	.07	-.01	.07
Lane Offset Deviation	.45	.30	.38	.06
Velocity (m/s)	13.67	2.88	14.03	2.60

Notes: Backward Digit Span- longest length sequence correct; Flanker- accuracy on incongruent trials; Go/No-Go- accuracy on no-go trials

Table 8.
Bivariate correlations for the main study variables

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.
1. RS 1 T	1													
2. RS 2 T	-.11	1												
3. RS 3 T	-.03	.31**	1											
4. RS 4 T	-.15	.49**	.34**	1										
5. RS 1 A	.99**	-.09	-.04	-.15	1									
6. RS 2 A	-.11	.99**	.29**	.42**	-.09	1								
7. RS 3 A	-.01	.33**	.98**	.32**	-.01	.31**	1							
8. RS 4 A	-.16	.50**	.38**	.98**	-.16	.45**	.37**	1						
9. BDS	.09	-.18	.03	-.13	.09	-.19	.03	-.15	1					
10. Flanker	.08	-.11	.06	-.02	.08	-.10	.04	-.02	.26*	1				
11. GNG	.06	.01	.12	.06	.06	.01	.12	.05	.10	.53**	1			
12. Accel	.03	-.19	-.30*	-.34**	.01	-.16	-.38**	-.36**	.09	-.14	-.08	1		
13. LO	-.03	.21	.01	.05	-.02	.23	.03	.08	-.16	-.02	.10	-.03	1	
14. Vel	-.14	-.13	-.02	.03	-.15	-.14	-.05	.02	-.08	.04	-.05	-.09	-.04	1

Notes: RS - Resting state EEG recording; T – Theta EEG power; A – Alpha EEG power; BDS- longest length sequence correct in Backward Digit Span; Flanker- accuracy on incongruent trials in Flanker; GNG- accuracy on no-go trials in Go/No-Go; Accel- mean acceleration; LO – Lane Offset; Vel = Velocity; * p < .05, ** p < .01

Table 9.
Regression analyses for the main effects of resting state theta power change, Task 3 performance, and ADHD symptoms on mean acceleration

	Overall ADHD				Hyperactivity/Impulsivity				Inattention			
	B	SE	β	*p*	*B*	SE	β	*p*	*B*	SE	β	*p*
RS4 – RS1	.00	.00	-.08	.562	.00	.00	-.08	.555	.00	.00	-.08	.538
Task 3 Performance (z)	-.01	.01	-.10	.431	-.01	.01	-.11	.397	-.01	.01	-.10	.458
Symptoms (z)	-.01	.01	-.12	.369	-.01	.01	-.09	.491	-.01	.01	-.13	.327

Table 10.
Regression analyses for the main effects of resting state theta power change, Task 3 performance, and ADHD symptoms on lane offset

	Overall ADHD				Hyperactivity/Impulsivity				Inattention			
	B	SE	β	*p*	*B*	SE	β	*p*	*B*	SE	β	*p*
RS4 – RS1	.00	.00	.07	.619	.00	.00	.06	.648	.00	.00	.06	.637
Task 3 Performance (z)	-.01	.03	-.02	.874	-.01	.03	-.03	.811	-.03	.03	-.01	.930
Symptoms (z)	-.04	.03	-.16	.240	-.03	.03	-.11	.415	-.04	.03	-.19	.167

Table 11.
Regression analyses for the main effects of resting state theta power change, Task 3 performance, and ADHD symptoms on mean velocity

	Overall ADHD				Hyperactivity/Impulsivity				Inattention			
	B	SE	β	*p*	*B*	SE	β	*p*	*B*	SE	β	*p*
RS4 – RS1	.00	.00	.10	.455	.00	.00	.08	.524	.00	.00	.11	.390
Task 3 Performance (z)	-.20	.36	-.07	.581	-.19	.36	-.07	.605	-.19	.367	-.07	.607
Symptoms (z)	.44	.37	.15	.248	.61	.38	.21	.115	.23	.36	.09	.527

Table 12.
Regression analyses for the main effects of resting state alpha power change, Task 3 performance, and ADHD symptoms on mean acceleration

	Overall ADHD				Hyperactivity/Impulsivity				Inattention			
	B	SE	β	*p*	*B*	SE	β	*p*	*B*	SE	β	*p*
RS4 – RS1	.00	.00	-.07	.614	.00	.00	-.07	.608	.00	.00	-.07	.586
Task 3 Performance (z)	-.01	.01	-.10	.432	-.01	.01	-.11	.398	-.01	.01	-.10	.459
Symptoms (z)	-.01	.01	-.12	.365	-.01	.01	-.09	.487	-.01	.01	-.13	.324

Table 13.
Regression analyses for the main effects of resting state alpha power change, Task 3 performance, and ADHD symptoms on lane offset

	Overall ADHD				Hyperactivity/Impulsivity				Inattention			
	B	SE	β	*p*	*B*	SE	β	*p*	*B*	SE	β	*p*
RS4 – RS1	.00	.00	.07	.586	.00	.00	.07	.615	.00	.00	.07	.607
Task 3 Performance (z)	-.01	.03	-.02	.880	-.01	.03	-.03	.816	.00	.03	-.01	.935
Symptoms (z)	-.04	.03	-16	.236	-.03	.03	-.11	.408	-.04	.03	-.19	.165

Table 14.
Regression analyses for the main effects of resting state alpha power change, Task 3 performance, and ADHD symptoms on mean velocity

	Overall ADHD				Hyperactivity/Impulsivity				Inattention			
	B	SE	β	*p*	*B*	SE	β	*p*	*B*	SE	β	*p*
RS4 – RS1	.00	.00	.10	.444	.00	.00	.09	.518	.00	.00	.12	.377
Task 3 Performance (z)	-.20	.36	-.07	.586	-.18	.36	-.07	.609	-.19	.37	-.07	.613
Symptoms (z)	.43	.37	.15	.252	.61	.38	.21	.118	.23	.36	.08	.531

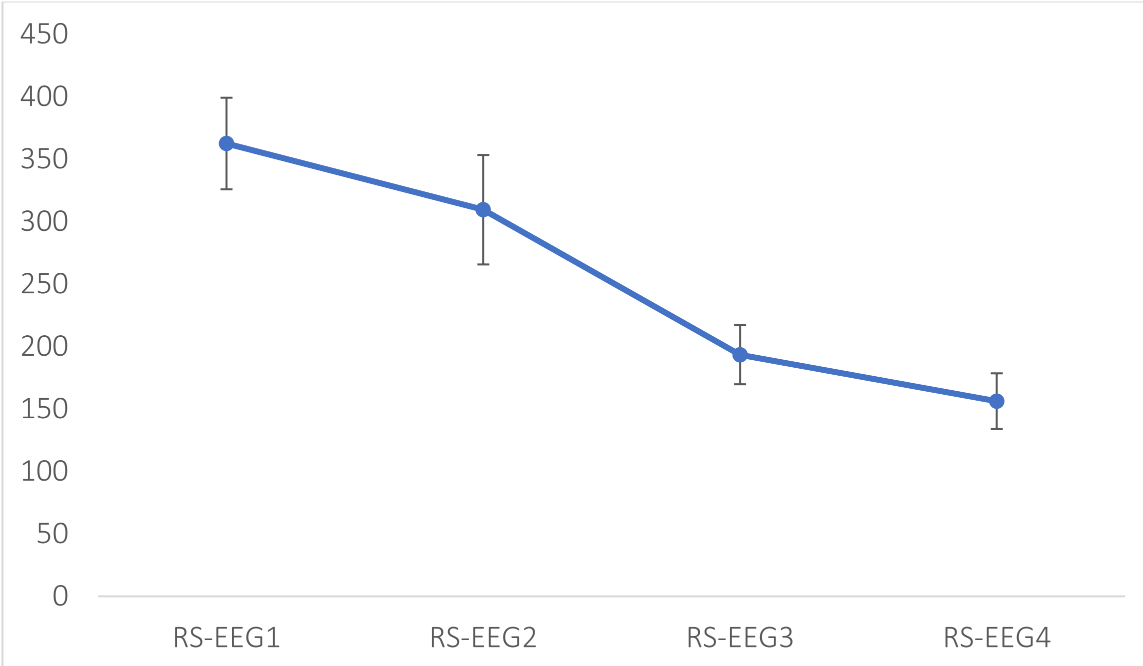

Figure 7. Changes in theta EEG power over time

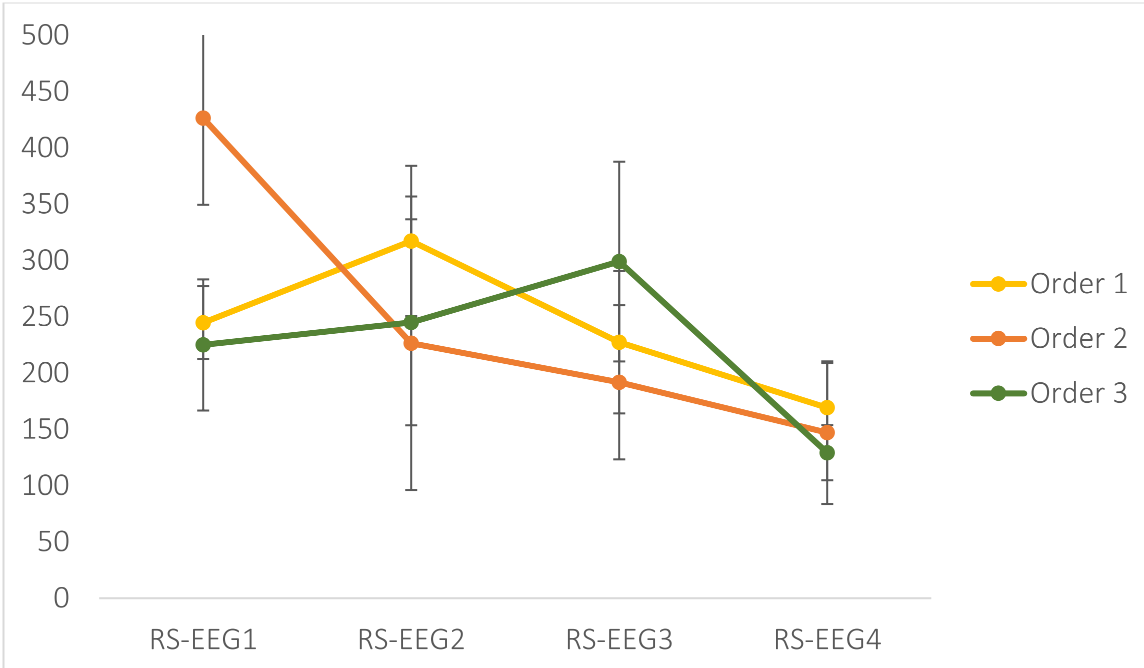

Figure 8. Changes in theta EEG power over time by task order in the high hyperactivity/impulsivity group

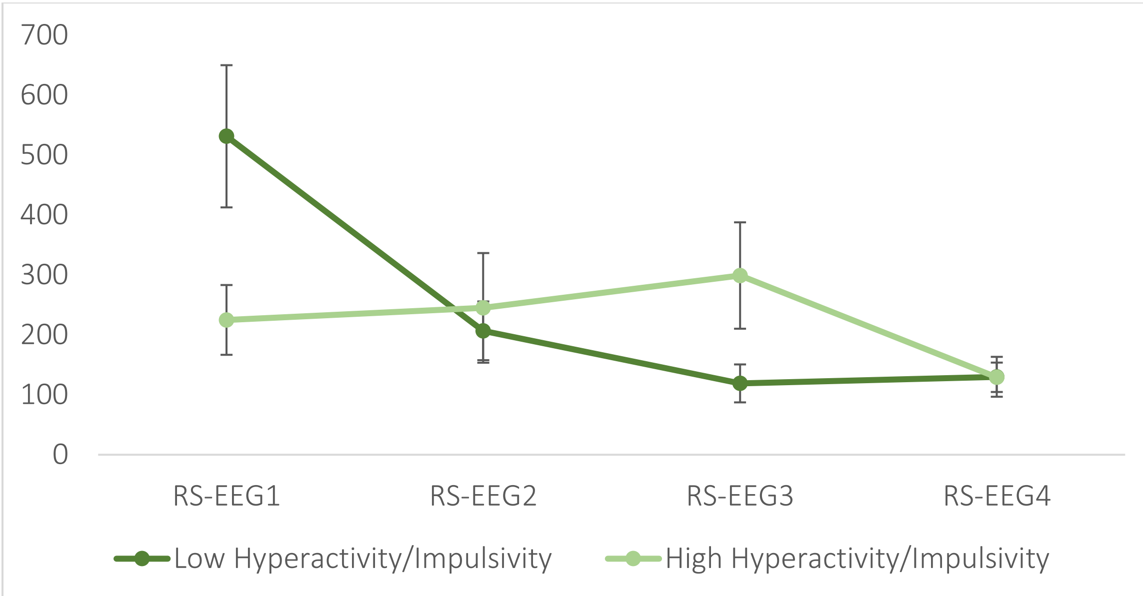

Figure 9. Changes in theta EEG power over time by hyperactivity/impulsivity group for individuals who completed Task Order 3

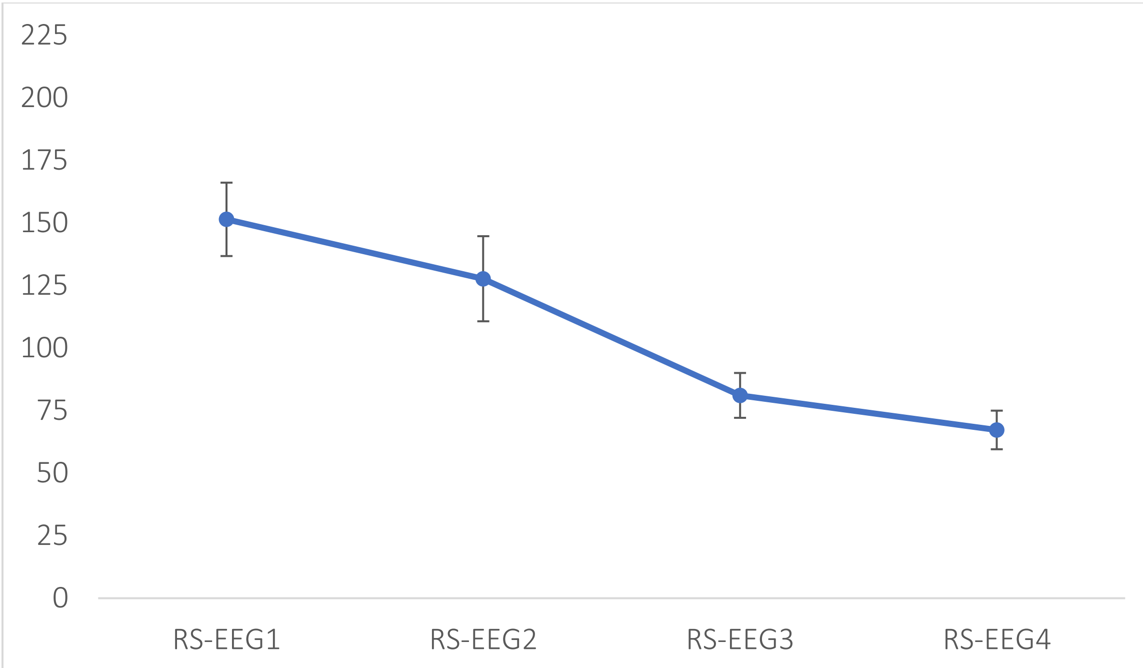

Figure 10. Changes in alpha EEG power over time

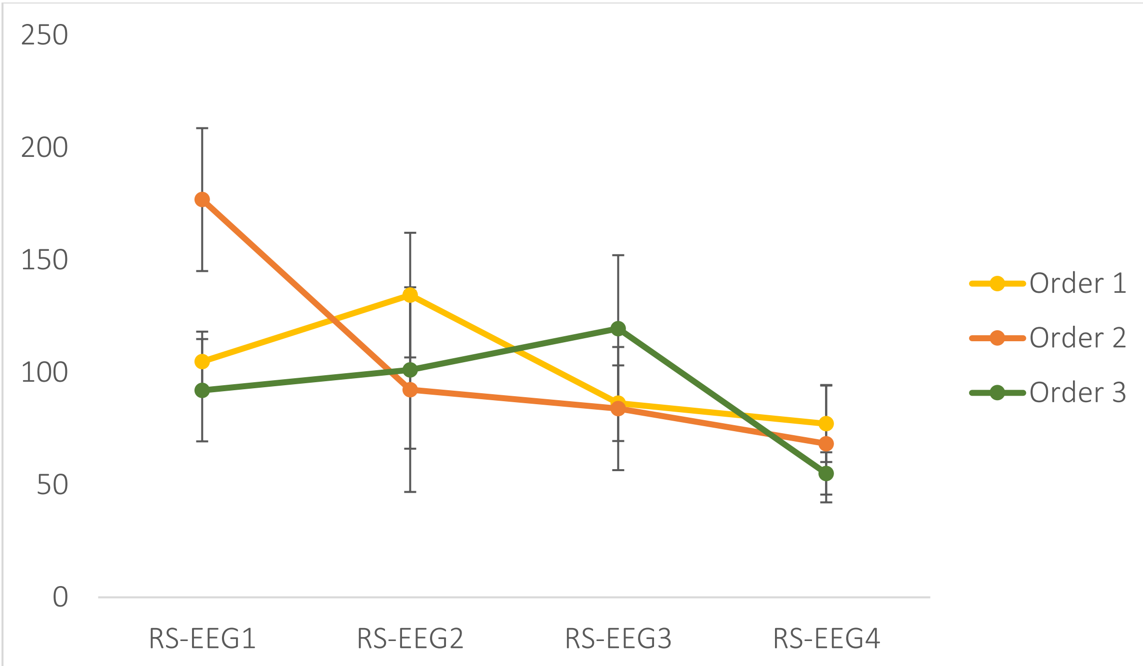

Figure 11. Changes in alpha EEG power over time by task order in the high hyperactivity/impulsivity group

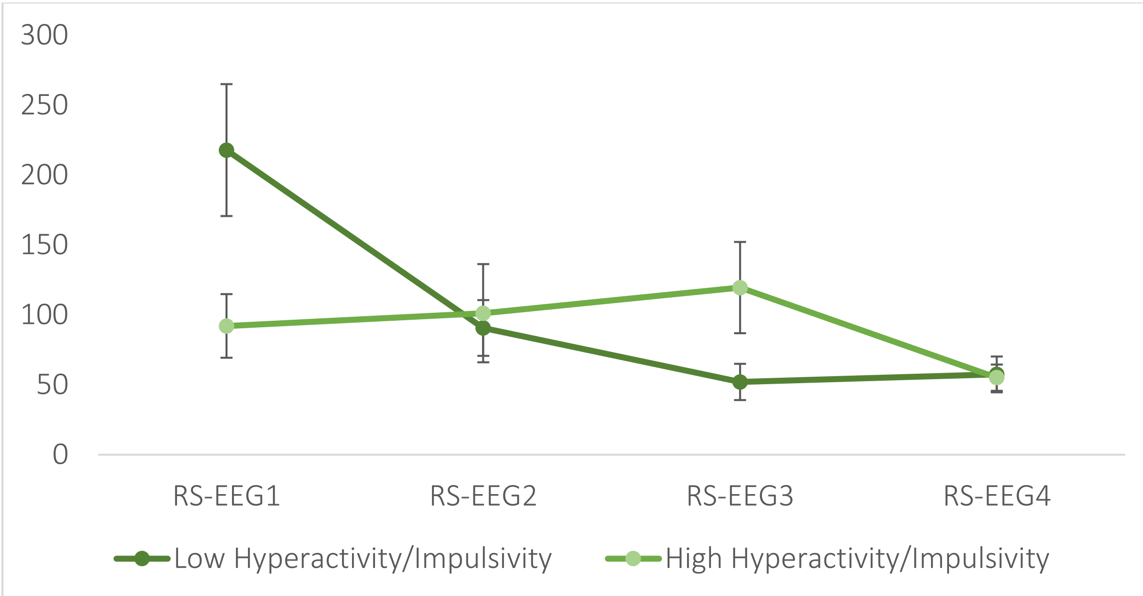

Figure 12. Changes in alpha EEG power over time by hyperactivity/impulsivity group for individuals who completed Task Order 3

APPENDIX A
CURRENT SYMPTOMS SELF-REPORT FORM
(BARKLEY & MURPHY, 1998)

Instructions: Please circle the number next to each item that best describes your behavior during the past 6 months.

Items:	Never/ rarely	Sometimes	Often	Very often
1. Fail to give close attention to details or make careless mistakes in my work	0	1	2	3
2. Fidget with hands or feet or squirm in seat	0	1	2	3
3. Have difficulty sustaining my attention in tasks or fun activities	0	1	2	3
4. Leave my seat in situations in which seating is expected	0	1	2	3
5. Don’t listen when spoken to directly	0	1	2	3
6. Feel restless	0	1	2	3
7. Don’t follow through on instructions and fail to finish work	0	1	2	3
8. Have difficulty engaging in leisure activities or doing fun things quietly	0	1	2	3
9. Have difficulty organizing tasks and activities	0	1	2	3
10. Feel “on the go” or “driven by a motor”	0	1	2	3
11. Avoid, dislike, or am reluctant to engage in work that requires sustained mental effort	0	1	2	3
12. Talk excessively	0	1	2	3
13. Lose things necessary for tasks and activities	0	1	2	3
14. Blurt out answers before questions have been completed	0	1	2	3
15. Am easily distracted	0	1	2	3

16. Have difficulty awaiting turn	0	1	2	3
17. Am forgetful in daily activities	0	1	2	3
18. Interrupt or intrude on others	0	1	2	3

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