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The Effects Of Modulating Accommodative-Vergence Stress Within The Context Of Operator Performance On Automated System Tasks

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THE EFFECTS OF MODULATING ACCOMMODATIVE-VERGENCE STRESS WITHIN THE CONTEXT OF OPERATOR PERFORMANCE ON AUTOMATED SYSTEM TASKS

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This dissertation, submitted by Kyle Anthony Bernhardt in partial fulfillment of the requirements for the Doctor of Philosophy from the University of North Dakota, has been read by the Faculty Advisory Committee under whom the work has been done and is hereby approved.

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ABSTRACT

Automated systems (e.g., self-driving cars, autopilot) can reduce an operator's (i.e., driver, pilot, baggage screener) task engagement, which can result in mind wandering, distraction, and loss of concentration. Consequently, unfavorable performance outcomes, such as missed critical signals and slow responses to emergency events, can occur. Because automation reverts the operator to a "visual monitoring" role, the oculomotor accommodative-vergence responses (the oculomotor responses that maintain a single focused image on the retina) may play a vital role in human-automation interactions. Prior research has shown that individuals with deficits in the accommodative-vergence responses can exhibit inattentive symptoms (e.g., poor concentration) characteristic of attention-deficit/hyperactivity disorder (ADHD) while performing prolonged close work (e.g., reading). Given the behavioral symptoms present in those experiencing accommodative-vergence stress, automated systems may exacerbate these negative effects. The current study examined the effects of accommodative-vergence stress in combination with automation on aspects of operator task engagement. Participants (N = 95) under accommodative-vergence stress wearing -2.0 diopter lenses or normal viewing conditions completed a 40 min flight simulation task either with or without automation. Physiological dependent measures included electroencephalographic (EEG) parietal-occipital alpha power spectral density (PSD), an EEG multivariate metric of engagement, and pupil diameter. Self-report measures of task engagement, cognitive fatigue, and

visual fatigue symptoms were also collected along with oculomotor measurements (accommodation and convergence) and flight simulation task performance. Multivariate analyses indicated that the application of -2.0 diopter lenses did not significantly alter oculomotor measurements or subjective reports of visual fatigue. Oculomotor stress modestly affected task performance and tended to result in increased EEG measures of engagement, while subsequently increasing feelings of fatigue, potentially indicating a compensatory effort response. Participants performing the simulation with automation exhibited significantly lower task engagement, as indicated by greater parietal-occipital alpha PSD, less multivariate EEG engagement, smaller pupil diameter, and lower self-reported engagement. Overall, oculomotor stress and automation did not interact synergistically to affect task engagement and associated performance outcomes. Automation and time on task were the main determinants of task engagement. These results underscore the negative effects automation can have on underlying operator cognitive states and the associated need to carefully design automation to combat reduced task engagement. Applications for system design and the use of EEG in augmented cognition systems involving automation are discussed.

CHAPTER I

INTRODUCTION

As computer technology continuously advances, automated systems are becoming more common in several domains. Today, automation can be found in areas including aviation (Mouloua, et al., 2000), automobiles (Merat & Lee, 2012), and maritime operations (Sauer et al., 2002). Automated systems complete tasks that would otherwise be performed by a human operator (i.e., pilot, driver; Parasuraman & Riley, 1997) and subsequently can reduce the amount of cognitive workload a human operator experiences (de Winter et al., 2014; Onnasch, et al., 2014; Saxby et al., 2013). By extension, the operator is then free to perform other tasks and increase his or her work efficiency. While the purpose of an automated system is to perform a function that would otherwise be completed by a human operator, automated systems typically do not completely supplant the human operator (Parasuraman & Riley, 1997). Rather, automation changes the human operator's role, from one of active system control to supervisory monitoring and vigilance (Parasuraman et al., 2000). For example, the Federal Aviation Administration is currently integrating a series of technologies called NexGen into the U.S. airspace system. Many of these technologies incorporate automated functions for air traffic controllers, such as automated aircraft sequencing, which relays separation vectors and speeds to aircraft automatically with only the supervision of the controller (Strybel et al., 2016). In daily life, several automobiles now include automated lane control and adaptive cruise control systems to aid with lateral and longitudinal control of the vehicle, respectively (Merat & Lee, 2012).

Despite the positive effects automation may have on human performance in terms of decreasing workload and increasing efficiency (de Winter et al., 2014), automated systems can impose a host of negative effects on operators (Parasuraman & Riley, 1997). For instance, operators may begin to rely heavily on automated systems and use them in inappropriate situations (e.g., emergencies). Additionally, operators may overestimate the reliability of automation and place too much trust in the system (Parasuraman et al., 1993). Therefore, a significant amount of research over the last three decades has been geared towards designing automated systems that avoid these negative outcomes (Endsley, 2017).

However, one issue that still faces human system engineers is the loss of task engagement that can accompany the use of automated systems for prolonged periods of time. Since automated systems shift human operators from active control to visually monitoring the system, the ability to remain actively engaged is an important feature when considering operator performance effectiveness with the implementation of automated systems (Saxby et al., 2013). Moreover, researchers in the human factors community are still searching for innovative ways to uphold task engagement in situations involving automated systems (Gouraud et al., 2018; May & Baldwin, 2009). Because a majority of the information an operator receives is in the visual modality, the operator’s oculomotor system may be an important physiological variable that modulates task engagement and subsequent performance outcomes when considering human-automation interactions. Specifically, individuals with oculomotor deficits may be more prone to losing task engagement while interacting with automated systems. Indeed, as will be discussed, research findings suggest that oculomotor pathologies may induce symptoms similar to attention-deficit/hyperactivity disorder (e.g., Borsting et al., 2005). Therefore, one way in which to improve human-automation interactions may be through augmentation of an operator's oculomotor system to buffer against task disengagement.

The overall purpose of this study was to determine the extent to which an operator's oculomotor system interacts with system automation to affect task engagement and performance outcomes. The literature to justify this study will be reviewed in the following manner. First, the literature on the effects of automation on task engagement is presented. Second, an overview of oculomotor functioning is given along with an examination of studies showing links between these deficits and sustained attention. Third, a review of the physiological correlates of visual processing and task engagement is given. Finally, the literature review will provide a theoretical framework for the effects of oculomotor functioning on task engagement.

Task Engagement – Overview

Operator Functional States

Measuring and classifying operator functional states (OFS) is integral for initial system design and system evaluation (Research and Technology Organization, 2004). An operator's functional state is a psychophysiological condition of the operator that modulates performance outcomes. That is, psychological and physiological processes work in tandem to allow the operator to meet task requirements (Gaillard & Kramer, 2000; Research and Technology Organization, 2004). Examples of OFS constructs are cognitive workload, cognitive fatigue, and task engagement. OFS constructs are usually inferred by using a triad of measurements including subjective measures, psychophysiological measures, and performance-based measures (Research and Technology Organization, 2004). Each measure has its own set of advantages and disadvantages. For example, subjective measures are easy to implement but do not allow researchers to monitor the operator in real time (Gaillard & Kramer, 2000). In contrast, psychophysiological measures are more cumbersome to implement but allow the operator to be monitored during task performance (Parasuraman, 2015). In an ideal situation, all three measures are used together to ascertain an operator's functional state.

OFS assessment plays a vital role in initial system design. Systems that human operators interact with should be designed in such a way as to minimize the probability of the system exceeding the physical, perceptual, and cognitive capabilities of the human operator. If systems can be designed in such a way as to optimize the functional state of the operator, then performance and safety outcomes can be maximized (Endsley, 2017). For example, OFS assessment can be used during the development and testing phases of flight systems that allow pilots to fly in degraded visual environments. In a series of studies, military researchers utilized subjective, physiological, and performance-based metrics to determine the optimum configuration of an integrated cueing package (haptic, visual, and auditory cueing) used for flight in degraded visual environments (Feltman et al., 2018; Feltman, et al., 2019; McAtee et al., 2017). The results of these studies helped make recommendations for improving the cueing package. Here, the focus is on the functional state of task engagement since it has salient implications for human-automation interactions.

Task Engagement

Task engagement is a multifaceted OFS construct involving aspects of energy, motivation, and concentration (Matthews et al., 2002). High task engagement implies that the operator is actively orientated towards a task (Hockey et al., 2009) and directing cognitive resources to process task-related stimuli efficiently (Berka et al., 2007; Kamzanova et al., 2011). A loss of task engagement puts the operator at risk for mind wandering, distractibility, and increased feelings of cognitive fatigue (Matthews et al., 2013). Moreover, operators in a disengaged state are likely to withdraw from the task and become reluctant to apply effort when needed to perform more difficult tasks (Matthews et al., 2002). Combined, these behaviors may result in sub-optimal performance (i.e., relying on heuristics, speed-accuracy tradeoffs, increased reaction times, and missed critical signals) when continuous monitoring of a system is required or when the operator needs to regain manual control of the system. Indeed, a meta-analysis by Onnasch et al. (2014) showed that as an automated system assists with higher cognitive processes carried out by the operator (i.e., decision making), performance deteriorates more so than when automation assists with lower cognitive processes (i.e., stimulus perception) when operators must regain manual control from an automated system.

Task engagement has been measured both subjectively and physiologically. Moreover, certain performance decrements, such as missed critical signals and increased reaction times, are typically used to indicate a loss of task engagement. Matthews et al.

(2002) developed the widely used Dundee Stress State Questionnaire (DSSQ), which measures three operator states, including task engagement. Examples of items relating to task engagement are, “I feel alert,” “I was committed to attaining my performance goals,” and “I felt active.” In the initial validation of the DSSQ, Matthews and colleagues found that the task engagement scale was sensitive to qualitatively different tasks that are associated with sustained attention, such as visual and auditory vigilance tasks. Later, Helton (2004) and Helton and Näswall (2015) shortened the DSSQ to form the Short Stress State Questionnaire (SSSQ) using a subset of items from the DSSQ.

At the physiological level, researchers have commonly used methods such as electroencephalography (EEG; Berka et al., 2007) and cerebral blood flow velocity (Matthews et al., 2010) to index task engagement. Several studies have shown that both physiological and subjective task engagement change during the performance of vigilance tasks (Berka et al., 2007; Matthews et al., 2002; Matthews et al., 2014).

The following section reviews pertinent literature on how these measures have been used to explore the effects system automation on operator task engagement.

The Effects of Automation on Task Engagement

Because system automation shifts the role of the operator from manual control to supervisory monitoring (Harris et al., 1995), the effects of automation on task engagement are important when considering human-automation interactions (Helton et al., 2009). Several studies have shown that operators using automated systems for prolonged periods of time exhibit significant reductions in task engagement. In a two-part study, Saxby et al. (2013) explored the effects of automobile automation on subjective task engagement and performance. In part one, participants performed a simulated drive under one of three automation conditions: standard manual control, manual control with high crosswinds, or fully automated. In the fully automated condition, both lateral and longitudinal control of the vehicle were automated, and the driver simply had to perform a basic system monitoring reaction time task consisting of a low number of targets. Participants were also randomly assigned to perform the drive for either 10, 30, or 50 min. Participants rated their level of task engagement using the DSSQ (Matthews et al., 2002) before and after the driving session. Results from part one indicated that participants in the fully automated condition driving for 50 min reported the greatest decline in task engagement. In part two of the study, Saxby and colleagues introduced an emergency event at the end of the drive to evaluate the effects of automation on driving performance. During the final 5 min of the drive, automation was disengaged, and an unexpected vehicle pulled out in front of the participant’s vehicle. Results from part two indicated that participants in the fully automated drive had slower breaking and steering reaction times as well as more collisions with the unexpected van compared to participants who performed the drive manually. Moreover, task engagement was significantly lower in the automation group compared to the manual control group. It should be noted that these results were obtained even after participants in the automated condition regained manual control for 30 s prior to the emergency event.

In a similar driving simulator study, Neubauer et al. (2012) assigned participants to one of two driving conditions to complete a 35 min drive. In one condition, participants had the option to engage vehicle automation for 5 min intervals. In the other condition, participants did not have access to automation. During the last 5 min of the drive, automation was disabled and the drivers were required to respond to an unexpected road hazard. The researchers found that drivers who were given the option to automate the vehicle reported significantly lower task engagement than participants who did not use automation. Moreover, drivers who used automation had slower steering reaction times in response to the unexpected road hazard. Another driving study by Greenlee and colleagues (2018) found that participant hazard detection rates decreased and reaction times slowed over the course of a 40 min automated simulated drive. Participants in this study also reported high ratings of task difficulty and increased feelings of distress.

Additionally, research in our laboratory has demonstrated parallel findings to those discussed above (Bernhardt, 2018; Bernhardt, Poltavski, Petros, & Ferraro, 2019). Participants were randomly assigned to perform a flight simulation task under one of three conditions for 50 min: manual control, automation with a high target rate paced task (one target every 10 s), or fully automated with low target rate (one target every 4-7 min). Subjective measures and electrophysiological (EEG) measures of task engagement were obtained. Overall, subjective task engagement decreased from pre to post simulation for all conditions. This decline in subjective task engagement was also accompanied by linear decreases in EEG markers of engagement across the 50 min simulation. However, the decline in both subjective and EEG engagement was the most severe for participants performing the simulation with automation and the low target rate monitoring task. In contrast to previous driving studies, we did not find any evidence of automation affecting performance.

Together, the above reviewed studies support the notion that automated systems can jeopardize task engagement and compromise subsequent performance. Because automation places operators in a supervisory monitoring role, vigilance is an important component of applied research on human-automation interactions (Warm et al., 2008).

Vigilance and Task Engagement

Vigilance can be found in a wide variety of professions such as industrial quality control, long distance driving, baggage inspection, and unmanned aerial vehicle operations (Warm et al., 2008). Maintaining vigilance requires operators sustain and focus their attention to respond to stimuli over an extended period of time, typically in situations involving more non-target stimuli than target stimuli (Davis & Parasuraman, 1982). Hence, operators are sustaining vigil while monitoring automated systems for potential critical failures or situations to intervene. This is a concept consistently echoed in human-automation interaction research (Greenlee et al., 2018; Parasuraman, 2015; Warm et al., 2008).

Studies using basic vigilance paradigms have reported declines in task engagement over time. For example, Matthews et al. (2010) had participants perform two different vigilance tasks, one relying on sensory processing and one relying on working memory. The sensory processing task required participants to monitor a simulated air traffic control display and determine when two aircraft (represented by grey lines) were on a collision course. The working memory vigilance task required participants to solve three simultaneously presented letter addition problems (e.g., R + 2, B + 3, K + 1 = T, E, L), hold the solution in working memory while reversing the solution, and determine if the solution was presented in a sequence of six letters following the initial string of letters. The researchers found that self-reported task engagement and cerebral blood flow velocity (an index of cognitive resources) significantly decreased across both tasks. These two measures also correlated with reduced vigilance performance, leading the researchers to conclude that task engagement is an important underlying construct that supports vigilance and that a loss of engagement reflects a reduction in cognitive-energetic resources. In another study, Helton and colleagues (2009) found similar results showing that self-ratings of task engagement were positively correlated with signal detection performance while participants completed an abbreviated vigilance task. Moreover, several studies employing structural equation modeling have shown that task engagement mediates the relationship between external stressors and overall vigilance performance (Helton et al., 2009; Matthews et al., 2014; Matthews et al., 2017), further supporting the importance of task engagement as a psychological construct vital for vigilance performance.

Another line of evidence relating task engagement to automation and vigilance comes from successful attempts to utilize brain measures to drive augmented cognition systems. Augmented cognition involves using physiological measures taken from an operator to dynamically alter the operator's control system (Prinzel et al., 2003). For example, adaptive automation relies on determining the operator's current state (i.e., overload or underload; disengaged or engaged) and dynamically alters the automation of a system to optimize operator performance. In the case of task engagement, if an operator becomes disengaged from a task, the adaptive automation system reduces the amount of automation to reengage the operator. In one study, Freeman et al. (2004) used an EEG metric of task engagement to automatically alter the size of a distractor grid while participants performed a visual search vigilance task. Results showed that when the EEG engagement metric was paired with a negative feedback loop (i.e., increased EEG engagement index caused the number of distractor letters to decrease), the vigilance decrement was not observed. In another study, Freeman et al. (1999) used the same EEG engagement index as Freeman et al. (2004) to drive adaptive automation while participants performed a manual compensatory tracking task. The tracking task could either be in automatic or manual mode and was adaptively controlled by the level of EEG engagement. Under negative feedback conditions (i.e., automation was disengaged when the engagement index was low), the adaptive automation system using the EEG engagement index resulted in superior performance compared to positive feedback or control conditions. Overall, the results of studies using adaptive automation systems articulate how assessing operator task engagement during task performance can be used to optimize performance. Moreover, these studies support the notion that automation and task engagement are intertwined.

In summary, past research has shown that automation can jeopardize task engagement and lead to suboptimal performance outcomes when operators must remain vigilant and monitor automated systems. Therefore, understanding potential operator characteristics that may further provoke the loss of task engagement over extended automated system use is vital for ensuring safety. Given that much of the information a human operator obtains while monitoring a system is in the visual modality, deficiencies in the oculomotor system may be an important physiological variable that modulates task engagement and thus affects ultimate performance outcomes. Currently, however, no studies have examined how the oculomotor system affects task engagement in work environments involving automated systems. The following section reviews the literature regarding the oculomotor accommodative and convergence responses (two responses vital for close work) as well as the effects of oculomotor deficits on overt cognitive performance outcomes. Then, the physiological relationship between task engagement and the oculomotor system is reviewed to illustrate how task engagement and visual processing may relate.

Oculomotor Near Reflex Triad, Task Engagement, and Behavior

Near Reflex Triad

The near reflex triad consists of three vital responses that allow an individual to properly form visual images for neural transduction: accommodation, binocular convergence, and pupil constriction/dilation (Edgar, 2007; Purves et al., 2012). The accommodative response is responsible for maintaining a focused image on the retina as individuals view targets at various distances (Purves et al., 2012). A crystalline lens in the eye changes in optical power to create a clear image on the retina. Small fibers called *zonule fibers* attach radially to the crystalline lens and connect to ciliary muscles surrounding the lens. When viewing a near object, the ciliary muscles contract, which reduces the tension in the zonule fibers and results in less tension on the lens. This reduced tension makes the lens more rounded in shape to focus the near image on the retina. The opposite process holds for far objects. Accommodation is primarily driven via a negative feedback loop with the perception of image blur (Bharadwaj & Candy, 2014). The convergence response is responsible for maintaining a single, fused image and is driven by image disparity cues (Bharadwaj & Candy, 2014). The eyes either converge or diverge to reduce image disparity as an object changes distance. These eye movements are controlled by a group of muscles surrounding the eye called the extraocular muscles, specifically the medial rectus and lateral rectus muscles control converging and diverging movements, respectively (Demer et al., 2003). Finally, pupillary constriction occurs to sharpen the image. Here, the focus is on the accommodative and vergence responses.

Accommodation and convergence are coupled physiologically. As the eyes accommodate, they also converge and as the eyes converge, they also accommodate (American Optometric Association, 2011). It is this synchrony of responses that produces functional images for neural transduction. Deficits in this coupled response can result from several etiological factors including head trauma, neurodegenerative diseases (Arnoldi & Reynolds, 2007), or inadequate visual system development during infancy (Bharadwaj & Candy, 2009). Case studies using neurological patients have linked proper accommodative-vergence responses with the cerebellum. For example, Kawasaki et al. (1993) found that a patient with a lesion to the cerebellum had difficulty focusing on objects at near and far distances. Specifically, the patient had a large cyst on the cerebellum that resulted in a slowed accommodative response. After removal of the cyst, accommodative response times returned to normal. Moreover, lesions to the cerebellum have been shown to impair slow vergence movements and divergent eye movement velocities compared to healthy controls (Sander et al., 2009). Other than the cerebellum, neuroimaging studies indicate that other cortical areas including the right superior temporal sulcus, inferior temporal gyrus, and extrastriate cortex (Richer et al., 2004) are involved in the accommodative-vergence response in addition to several subcortical structures (i.e., nucleus reticularis tegementi pontis, superior colliculi).

When deficits occur in the accommodative/and or vergence responses, individuals can experience inattentive behavioral symptoms in addition to visual discomfort resulting from prolonged accommodative-vergence stress. Because the oculomotor system plays a vital role in operator performance while monitoring automated systems, deficits in oculomotor responses may result in suboptimal cognitive states (i.e., task engagement) that ultimately influence safety outcomes by impacting behavior.

Accommodative-vergence Deficits and Behavior

The most common disorders of the accommodative and vergence responses include accommodative insufficiency (AI) and convergence insufficiency (CI). AI is a sensory motor disorder characterized by an inability to focus or maintain focus on a near target, while CI is a sensory motor anomaly linked to deficits in the ability to attain and/or sustain accurate eye convergence at a near target (American Optometric Association, 2011; Marran et al., 2006). AI and CI often present with similar symptoms including image blur, headache, asthenopia, diplopia, and poor concentration while performing near work (American Optometric Association, 2011; Daum, 1983; Daum, 1984; Hinkley et al., 2016). According to the American Optometric Association (2011), individuals with these deficits must expend more effort to resolve image disparity and blur cues, which can result in increased feelings of fatigue or eye strain during sustained near work (e.g., reading), leading to increased accommodative-vergence stress over time.

Trends in the literature have shown associations between vergence and/or accommodative deficits and ADHD symptomology. Specifically, researchers have reported that AI and CI are associated with symptoms similar to attention-deficit/hyperactivity disorder (ADHD). Early research suggested a three-fold greater incidence of ADHD among children with CI (Granet et al., 2005). Borsting et al. (2005) found that children with accommodative dysfunction or CI had a significantly higher frequency of behaviors associated with ADHD and associated learning problems. Similar results were obtained by Rouse and colleagues (2009). The researchers had the parents of children with ADHD and CI, no ADHD and CI, and normal binocular vision (NBV) without ADHD complete a survey asking about their child's problems in school relating to academic work. Compared to children with CI and no ADHD diagnosis and NBV controls, children with CI and ADHD were rated by their parents has having greater difficulties in school during the past month. Moreover, Redondo et al. (2018) reported that children with ADHD generally exhibited a reduced accommodative response compared to controls across accommodative targets presented at 500, 40, and 20 cm during a 90 s fixation task.

Symptoms of AI have also been shown to be related to academic performance in college students. Chase et al. (2009) used the Conlon Visual Discomfort Survey (CVDS; Conlon et al., 1999), a measure of symptoms associated with AI, to predict self-reported academic problems and objective measures of the accommodative response. Results indicated that the CVDS accounted for 62% of the variability in academic problems associated with grades, homework, and reading. Moreover, the CVDS was associated (r = .47) with increased accommodative lag for stimuli at high accommodative demands (5+ diopters) and could classify students with AI with 75% sensitivity and 80% specificity when a cutoff total score of 27 was used. This study illustrates that symptoms of oculomotor deficits in populations other than children relate to academic problems that are potentially associated with compromised sustained attention.

Poltavski et al. (2012) provided experimental support for the link between accommodative-vergence stress and inattentive symptoms characteristic of ADHD by decoupling the accommodative and vergences responses with -2.0 diopter (D) lenses. Minus 2.0 D lenses induce a blur cue and impose a higher accommodative demand, thus inducing accommodative stress over time (Bharadwaj & Candy, 2009). Poltavski and colleagues had participants with normal binocular vision and no history of ADHD perform the Connors Continuous Performance Test (CPT; a sustained visual attention task used in part to diagnose ADHD) under accommodative stress with -2.0 D lenses and under no accommodative stress on two separate occasions. Compared to the non-stressed condition, the stress condition resulted in significantly reduced CPT performance (i.e., more commission errors and worse target detection). This reduced performance was accompanied by increased accommodative lag, indicating a worse accommodative response. Additionally, greater accommodative lag predicted an increased probability of clinical ADHD diagnosis according to CPT measures used to diagnose ADHD. However, in a later study, Poltavski et al. (2016) did not find evidence for -2.0 D lenses modulating sustained attention performance. Participants were assigned to either a high or low CI symptomology group based on total Convergence Insufficiency Symptom Survey Scores (CISS). Both groups performed the Connors CPT with -2.0 D lenses and under normal viewing conditions. While the high symptom group performed significantly worse on the CPT, -2.0 D lenses did not affect CPT performance in either group.

More recently, Daniel and Kapoula (2019) had healthy participants perform a Stroop test under normal viewing conditions, a 16Δ base-out prism condition, and a -2.5 D lens condition. The base-out prism condition stressed the accommodative-vergence response through increased image disparity cues. The Stroop test had three levels of difficulty requiring greater inhibition and cognitive processing at each successive level. The researchers also recorded participant eye movements. Results indicated that participants under the stress conditions exhibited a greater Stroop effect at the most difficult level of the Stroop task. Moreover, participants in the prism condition also exhibited greater saccadic drift compared to the lens and control conditions. Congruent with these results, Daniel and Kapoula (2017) found that college students with symptomatic CI exhibited a greater interference effect on the Stroop task than controls.

In a more applied setting, Vera et al. (2016) explored changes in the accommodative response during a simulated drive. The researchers measured accommodative lag (a measure of the accommodative response) with an autorefractor before and after participants performed a 2 hr monotonous drive under fully rested conditions. The researchers also collected subjective measures of cognitive fatigue before and after the drive. After the drive, accommodative lag increased from pre to post drive, with corresponding increases in fatigue ratings. These results indicate that reductions in the accommodative response likely accompany changes in operator cognitive states, specifically fatigue-related constructs.

In combination, these studies indicate that accommodative-vergence stress may play an important role in modulating performance outcomes during tasks requiring sustained task engagement. Because automated systems rely on visual monitoring and jeopardize operator task engagement from the outset, operators experiencing accommodative-vergence stress may be more likely to experience task disengagement and negative performance outcomes. Evidence from neuroimaging and eye-tracking studies further support this premise.

Physiological Correlates of Visual Processing and Task Engagement

Several cortical areas involved with visual processing are also involved with sustained attention and attentional control. Neuroimaging studies have shown that vigilance tasks activate diverse cortical networks, including mainly right-lateralized fronto-parietal regions (Coull et al., 1998; Paus et al., 1997), left prefrontal cortex (Kim et al., 2017), and the cerebellum (Buckner, 2013). Moreover, studies using transcranial direct current stimulation have shown that stimulating the left dorsolateral prefrontal cortex (McKinley et al., 2013; Nelson et al., 2014) or the right posterior parietal cortex (Li et al., 2015; Roe et al., 2016) can mitigate declines in vigilance performance. Coincidently, several of these areas, including the cerebellum, parietal cortex, and frontal cortex, also correspond to areas activated during the visual accommodative-vergence processes (Alkan et al., 2011; Daniel & Kapoula, 2019; Just & Varma, 2007; Richter et al., 2004). Therefore, when accommodative-vergence stress is present, these cortical areas may be competing for cognitive resources with those responsible for upholding vigilance (Daniel & Kapoula, 2019; Just & Varma, 2007; Poltavski et al., 2012).

Within the human factors and vision science literatures, there are parallel findings regarding visual perception, task engagement/vigilance, automation, and EEG oscillations. EEG has been used extensively to measure operator cognitive states (Berka et al., 2007; Bernhardt, 2018; Bernhardt, Poltavski, Petros, & Ferraro, 2019; Borghini et al., 2014; Caldwell et al., 2002; Gevins & Smith, 2007). Recently, our research team (Bernhardt, Poltavski, Petros, & Ferraro, 2019) demonstrated that a multivariate EEG marker of task engagement (Berka et al., 2007) was significantly lower for participants performing a flight simulation task under automation compared to manual control, indicating that changes in task engagement resulting from automation can be tracked at the level of cortical activation.

The EEG alpha oscillation (8-13 Hz) has been shown to strongly relate to task disengagement and cognitive fatigue onset. A review by Borghini et al. (2014) examined EEG studies from the driving and aviation domains to ascertain specific EEG patterns associated with task engagement and the development of cognitive fatigue. Across these studies, the authors concluded that increases in alpha power spectral density (PSD) at posterior-midline brain regions (i.e., parietal-occipital) indicates the development of task disengagement and cognitive fatigue. Using a basic vigilance task paradigm, Kamzanova et al. (2014) found that alpha power, specifically in the lower frequency (8–11 Hz), significantly increased during a simulated air traffic control vigilance task and corresponded with a decrease in vigilance performance (i.e., reduced number of signals detected and increased reaction times). However, these authors averaged alpha PSD across all scalp locations, not just posterior regions. Furthermore, the alpha oscillation has been also shown to relate to subjective task engagement. Fairclough and Venables (2006) had participants perform a generalized flight simulation task consisting of three subtasks (tracking, system monitoring, and resource management) for 80 min. Participant EEG and subjective task engagement ratings were recorded. Results indicated that during the last half of the task, alpha power negatively predicted task engagement. That is, the greater alpha power participants exhibited, the lower their self-reported task engagement. A line of studies in the applied sector have also demonstrated that changing the degree of system automation with a negative feedback loop based on operator alpha PSD can help uphold task performance and engagement (e.g., Freeman et al., 2004; Freeman et al., 1999; Prinzel et al., 2003).

Correspondingly, increases in posterior brain region alpha power also accompany reduced visual processing efficiency. For example, van Dijk et al. (2008) had participants determine if the level of gray contrast differed between two superimposed disks presented on a computer screen. The researchers recorded EEG alpha power prior to stimulus onset. Results indicated that increased alpha power in the parietal-occipital sulcus prior to the onset of stimuli corresponded to worse stimulus discrimination. A similar study conducted by Macdonald et al. (2011) found that pre-stimulus alpha power in the parieto-occipital region was negatively associated with performance on a rapid visual stimulus detection task and participant ratings of attention. The authors concluded that alpha power over this region may be a useful metric for monitoring operator task engagement. Other researchers (Hanslmayr et al., 2005; Romei et al., 2008; Willeford et al., 2013) have reported similar results using visual attention tasks. From these studies, researchers have suggested that increased alpha power in posterior brain regions (including the visual cortex) reflects “cortical idling” and reduced visual stimulus processing efficiency (Lange et al., 2013).

Overall, remaining actively engaged in a task and maintaining visual processing efficiency likely share similar cortical areas and EEG activation patterns in the alpha bandwidth. That is, reduction in task engagement and visual processing are both accompanied by increases in posterior brain region alpha power. With the above reviewed literature, it is predicted that individuals experiencing accommodative-vergence stress and automated conditions would exhibit more posterior brain region alpha power, indicating reductions in both task engagement and visual processing efficiency with corresponding declines in performance. Given this connection, it is likely that accommodative-vergence stress and system automation act in a synergistic manner to modulate operator functional states.

Eye-tracking and Task Engagement

In addition to EEG, eye-tracking has been used to infer task engagement in participants while performing extended vigilance tasks. One metric derived from eye-tracking devices that researchers have proposed to quantify task engagement is pupil diameter, due to the relationship between the locus coeruleus-norepinephrine system and task engagement (Gilzenrat et al., 2010; Murphy et al., 2014). Specifically, the release of norepinephrine from the locus coeruleus modulates task engagement via changes in output modes, mainly *phasic* and *tonic* modes, with the latter associated with increased task engagement (Aston-Jones & Cohen, 2005). Hopstaken, van der Linden, Kompier, and Bakker (2016) used pupil diameter in conjunction with self-report task engagement and the P3 event related potential (ERP) to measure task engagement while participants performed a 2 hr long vigilance task. Additionally, the researchers introduced a motivation manipulation at the end of the task as a means to reengage participants. Results indicated that pupil diameter linearly decreased during the vigilance task. Moreover, this decrease in pupil diameter was accompanied by reduced ratings of task engagement, decreased performance (increased reaction times, decreased signal detection), and reduced P3 ERP amplitude. After the motivation manipulation, these patterns of responses were reversed, indicating that manipulations tied to task engagement show predictable physiological patterns. An earlier study by the same research team (Hostaken et al., 2015) found that stimulus-evoked pupil diameter decreased while participants performed a memory task for 2 hr. Together, these studies support the use of pupil diameter as a potential marker of task engagement.

Other eye-tracking metrics have been shown to be sensitive to the vigilance decrement. For example, Bodala et al. (2016) found that saccade amplitude and velocity decreased while blink rate increased when participants exhibited the vigilance decrement during a target detection task. Increased mind wandering has also been shown to be associated with fewer, but longer fixations compared to when participants are actively engaged in viewing a scene (Krasich et al., 2018). Additionally, advanced modeling techniques using eye-tracking metrics have been shown to classify an operator's state of engagement. Marshall (2007) used machine learning algorithms to classify task engagement while participants performed a basic laboratory task or driving task. Specifically, linear discriminant function analysis and neural networks were used to classify the engagement state of participants with the use of seven continuously recorded eye-tracking metrics (e.g., blink rates, saccades, divergence). Marshall found that task conditions eliciting cognitive states could be classified using combinations of eye-tracking metrics with classification rates ranging from 69% to 92%.

Eye-tracking parameters have also been shown to be changed in scenarios involving automation. Driving simulator studies have demonstrated that when more automation is used, drivers tend to shift their gaze away from road areas needed to maintain an engaged driving state (i.e., lane boundaries, speedometer; Carsten et al., 2012; Merat et al., 2014; Navarro et al., 2016; Telpaz et al., 2015). In the aviation setting, researchers have found that pilots direct fewer gazes towards automated systems over time, leading to inadequate monitoring of the automated system and potential performance decrements (Sarter et al., 2007).

Overall, there is evidence to support that efficient visual processing and vigilance share similar cortical areas and neurophysiological responses. Specifically, reduced visual processing efficiency and reduced task engagement are both associated with increases in posterior brain region EEG alpha power. Furthermore, eye-tracking studies have also shown that changes in ocular parameters accompany alterations in task engagement over time. Not only do these studies support the link between visual processing and task engagement, but they also imply that the effects of visual system stress may compromise an operator's ability to remain actively engaged in a task. The theoretical justification for this claim relies on the distribution and utilization of information processing resources.

Theoretical Justification

The literature reviewed above points to a link between the oculomotor system, task engagement, and vigilance performance. Specifically, oculomotor stress may hamper the ability for individuals to remain engaged in a task, resulting in diminished performance on tasks requiring sustained engagement. Moreover, because automated systems reduce task engagement from the outset, individuals under oculomotor stress while using automated systems are more likely to exhibit greater declines in task engagement and thus vigilance performance.

One theory of the decline in vigilance performance is resource theory (Kahneman, 1973). Resource theory holds that individuals have a limited supply of cognitive-energetic resources to devote to performing a task at any given time (Wickens, 2002, 2008). Cognitive resources refer to information-processing units or assets that are used to carry out a cognitive task (Kramer & Weber, 2000) and stem from early capacity theories of attention (Broadbent, 197; Kahneman, 1973). Resource theory relies on a supply-demand relationship, that is, as a task demands more resources, the operator must supply those resources to meet demands. When the operator is unable to meet the resource demands, performance is predicted to decline. Advances in functional neuroimaging have made it possible to quantify cognitive resource deployment in real-time during the performance of a task (Parasuraman, 2015). For example, fMRI studies have shown cortical activation in predominantly prefrontal regions of the brain as a result of tasks demanding more resources (i.e., as task difficulty increases; Parasuraman & Caggiano, 2005; Vohn et al., 2007; Warm et al., 2008). In the case of vigilance, cognitive resources are depleted and not restored over time ultimately leading to a decline in vigilance performance (i.e., the vigilance decrement; Warm et al., 2008).

The argument proposed here linking oculomotor stress, task engagement, automation, and vigilance is the following sequence: (1) monitoring an automated system reduces task engagement from the outset, (2) task engagement plays an integral part of maintaining vigilance performance and affects performance when operators must regain manual control of the system, and (3) oculomotor stress acts as a stressor and diverts cognitive resources to continuously resolve image blur/disparity cues, resulting in fewer resources available for processing task stimuli (i.e., remaining engaged). More broadly, oculomotor stress “siphons-off” cognitive resources that individuals would otherwise use to be actively engaged in a task, resulting in worse performance outcomes and reduced task engagement.

The literature reviewed above indicates that automation does compromise task engagement (e.g., Freeman et al., 1999; Neubauer et al., 2012; Saxby et al., 2013). Moreover, the reviewed studies indicate that declines in task engagement are associated with subsequent declines in vigilance performance (e.g., Matthews et al., 2010). Point 3 regarding the divergence of cognitive resource hinges on the resource theory of vigilance and how stressors modulate cognitive resource availability. The following studies are used to illustrate this point.

In a review of vigilance studies, Warm and colleagues (2008) articulated that maintaining vigilance is stressful and requires the utilization of cognitive resources. Not only does vigilance performance result in a loss of task engagement, but studies have also shown that individuals experience negative changes in mood, specifically, increases in distress over time (Matthews et al., 2002; Matthews et al., 2013). Moreover, gross motor activity tends to increase during vigilance performance, indicating an overt stress response (Galinsky et al., 1993). The resource account of vigilance holds that a decline in vigilance performance over time is the result of a depletion of cognitive resource that cannot be replenished during task performance (Warm et al., 2008). Several authors (e.g., Helton & Warm, 2008; Parasuraman, 2015; Smit et al., 2004; Warm et al., 2008) have argued this position and supported their reasoning using neuroimaging studies. Cerebral blood flow velocity has been suggested to be a measure of cognitive resource allocation (Parasuraman, 2015; Parasuraman & Caggiano, 2005). Thus, if reduced vigilance is due to a reduction in cognitive resources, a decline in a cerebral hemodynamic response is expected to occur.

Indeed, several studies have shown that over the course of vigilance performance, cerebral blood flow velocity, particularly in the right hemisphere, slows with corresponding reductions in vigilance performance (Matthews et al., 2010; Schnittger et al., 1997; Shaw et al., 2009). One specific prediction made by resource theory regarding vigilance performance is that when individuals are given reliable cues as to when a critical signal is to occur, the vigilance decrement should be erased and cerebral blood flow velocity should remain constant. Hitchcock et al. (2003) found support for this prediction. Participants performed a simulated air traffic control vigilance task with differing amounts of critical signal cue reliability (100%, 80%, 40%, and no cue). Participant cerebral blood flow velocity was monitored with transcranial Doppler sonography (TDC). Results indicated that performance remained high in the 100% cue reliability condition but declined with less reliable cues. Moreover, cerebral blood flow velocity mirrored the performance results, with blood flow velocities remaining stable for the 100% reliability condition and declining with less reliable cues. These results support the notion that actively performing vigilance tasks reduces cognitive resource availability. In a later study, Matthews et al. (2010) found that subjective task engagement was significantly correlated with cerebral blood flow velocity and vigilance performance, further supporting the link between task engagement and cognitive resource deployment.

Substantial support for the hypothesized sequence comes from Matthews et al. (2017). Matthews and colleagues used structural equation modeling to test the causal paths between a stressor, task engagement, and vigilance performance. In Matthews et al.'s study, the stressor was the common cold. Participants either with or without a cold performed a letter discrimination vigilance task and rated their level of task engagement before and after the task. Results indicated that task engagement directly impacted vigilance performance and mediated the effect of the common cold on vigilance performance. The authors concluded that stressors, like the common cold, reduce cognitive resource availability as evidenced by a reduction in task engagement. Thus, with the current line of thinking, task engagement would be predicted to be the lowest with the synergistic effects of automation and oculomotor stress.

Together, these finding indicate a potential link between task engagement and cognitive resource availability. Moreover, the findings of Matthews and colleagues (2017) further suggest that stressors reduce cognitive resource availability for individuals to remain actively engaged in a task. Thus, under conditions of oculomotor stress, the availability of cognitive resources for active task engagement is reduced, resulting in declines in engagement and subsequent performance due to the continuous utilization of cognitive resources to resolve image blur and/or disparity cues (Daniel & Kapoula, 2019; Poltavski et al., 2012). Because automation reduces task engagement from the outset, the introduction of oculomotor stress may further compromise task engagement and performance.

Preliminary Data

Recently, we have found evidence for the link between task engagement and oculomotor stress. In a preliminary study, Bernhardt and Poltavski (in press) examined the relationship between oculomotor discomfort, task engagement, cognitive fatigue, and task performance under different levels of task automation. Participants performed a 62 min flight simulation task under one of three conditions: highly automated, manual control, or partially automated with a paced vigilance task. Participants reported oculomotor discomfort symptoms prior to completing the task with the Convergence Insufficiency Symptom Survey (CISS). Self-report measures of task engagement and fatigue were collected pre and post simulation. EEG data were also recorded during the simulation. Three important results were found: (1) oculomotor discomfort symptoms were positively related to ratings of cognitive fatigue (i.e., participants with more symptoms tended to report more cognitive fatigue), (2) oculomotor discomfort was negatively related to self-reported task engagement, and (3) oculomotor discomfort was positively associated with fast-alpha power (10-13 Hz) in the parietal-occipital region during the final 10 min of the task for those completing simulations with automation, indicating less task engagement. Oculomotor symptoms were not related to task performance. This preliminary study provided initial evidence for the link between oculomotor stress and indicators of task engagement in automated environments. The current study seeks to build upon these initial results by including experimental controls, manipulations of oculomotor stress, and additional eye-tracking measures.

The Current Study

The overall objective of the current study was to determine the extent to which accommodative-vergence stress and system automation interact to affect sustained task engagement and cognitive performance. To accomplish this, accommodative-vergence stress was experimentally manipulated with -2.0 D lenses. Participants under no accommodative-vergence stress or accommodative-vergence stress with -2.0 D lenses were randomly assigned to complete a 40 min flight simulation task either with or without automation. Task engagement was measured with EEG, eye-tracking, and self-report measures. Additionally, oculomotor measurements were taken prior to and after the simulation to quantify changes in oculomotor responses over time. The current study tested four hypotheses:

Hypothesis 1: Participants under accommodative-vergence stress will report significantly more severe symptoms of visual fatigue and exhibit reductions in accommodative and vergence responses than non-stressed participants.

Hypothesis 2: Accommodative-vergence stress and automation will interact, such that participants under stress and using automation will be significantly less engaged in the task than the other conditions, as operationalized by increased parieto-occipital alpha power, reduced multivariate EEG engagement (see Dependent Variables section), smaller pupil diameter, higher ratings of cognitive fatigue, and lower ratings of task engagement.

Hypothesis 3: Accommodative-vergence stress and automation will interact, such that participants under accommodative-vergence stress and using automation will exhibit the greatest decrement in simulator performance compared to the other conditions when required to regain manual control of the system.

Hypothesis 4: The effects of accommodative-vergence stress on outcomes measures will be time dependent, such that over increased time on task, accommodative-vergence stress will accrue and lead to greater visual fatigue, reduced engagement, increased fatigue, and worse task performance (i.e., the above effects are time-dependent).

Innovation

There is a dearth in the literature regarding how human-automation interactions are modulated by physiological variables, specifically the visual system. Currently, the role of oculomotor health in affecting cognitive performance has only been investigated within the limited scope of ADHD etiology (e.g., Borsting et al., 2005; Hinkley et al., 2016). Investigations in the human factors literature have also been limited in scope by examining only characteristics like operator illness, trust in automation, and time on task in relation to the effects automation has on operator engagement and performance outcomes (Balfe et al., 2018; Matthews et al., 2017; Saxby et al., 2013). This study is innovative in that it suggests a potential bottom up approach for improving human-automation interactions. That is, by limiting accommodative-vergence stress, human operators may be able to maintain task engagement longer in working conditions involving automation and sustained attention. In understanding how oculomotor stress affects task engagement, potential interventions can be devised to improve safety outcomes.

CHAPTER II

METHOD

Participants

In total, 110 (41 women and 69 men) undergraduate students from the University of North Dakota participated in this study. After excluding participants for having ADHD (*n* = 1), not performing their assigned condition correctly (*n* = 12), and leaving before the study ended (*n* = 2), a final usable sample of 95 was obtained (37 men and 58 women). Participant ages ranged from 18 to 35 years (*M* = 19.31, *SD* = 2.07). A small proportion of individuals (*n* = 8) reported flight experience, with total flight hours ranging from 15-78 hours (*M* = 44.74, *SD* = 22.22). All participants had 20/20 or corrected to 20/20 vision with no self-reported visual abnormalities including convergence insufficiency, accommodative insufficiency, partial blindness, amblyopia, or strabismus. Seventeen participants reported a history of concussion, with no incidences occurring within the past 6 months. Moreover, no participants reported having a history of severe head trauma (excluding concussion), brain injury, cerebrovascular events, or seizures.

Exclusionary criteria

To reduce variability in outcome measures, individuals with the following conditions were excluded: current or past ADHD diagnosis (Tucha et al., 2017), current prescription stimulant use (Turner et al., 2014), tobacco users (Shoaib & Bizarro, 2005), lazy eye (amblyopia and/or strabismus), worse than 20/20 corrected vision, accommodative insufficiency, convergence insufficiency (Poltavski et al., 2012, 2016), partial blindness, a concussion within the past six months (Brett et al., 2018), history of severe head trauma, brain injury, or seizures. These conditions were evaluated via a self-report demographics questionnaire.

Design

This study followed a 2 (Stress: stress, non-stressed) x 2 (Automation: on, off) x 2 (Time: pre, post) mixed factorial design, with time serving as the within-subjects factor. Continuous EEG measurements of task engagement, including parietal-occipital midline (POz) alpha power and a multivariate index of task engagement, were recorded while participants performed a 40 min flight simulation task either with or without automated features under accommodative-vergence stress or under normal viewing conditions. Moreover, continuous pupil diameter measurements supplemented EEG measures of task engagement. Measures of the accommodative and vergence responses were taken before and after the flight simulation task. Pre and post self-report measures included task engagement, cognitive fatigue, and visual fatigue.

Materials

Simulation and Automation Conditions

The Multi-Attribute Task Battery-II (MATB; Santiago-Espada et al., 2011) was used as the experimental task for this study. MATB is a low-fidelity, computerized flight simulation task developed by the National Aeronautics and Space Administration (NASA) to mimic the types of cognitive tasks pilots typically perform during flight. The MATB interface is displayed in Figure 1. Three simultaneously occurring subtasks included within the MATB were used for this study: system monitoring, tracking, and communications. These subtasks can be automated to varying degrees. The MATB requires a joystick, keyboard, speakers, and a mouse to complete. The MATB was chosen because the subtask automation parameters are customizable and it has been used in several human factors studies involving task engagement, automation, cognitive fatigue, and/or workload (e.g., Caldwell et al., 2004; Caldwell & Ramspott, 1998; Fairclough & Venables, 2006; Freeman et al., 1999; Fournier et al., 1999; Wilson et al., 2007). Additionally, the MATB has been rated as a face-valid simulation for aviation tasks (Caldwell & Ramspott, 1998) and was designed for non-aviators as well (Santiago-Espada et al., 2011). The following describes the MATB subtasks.

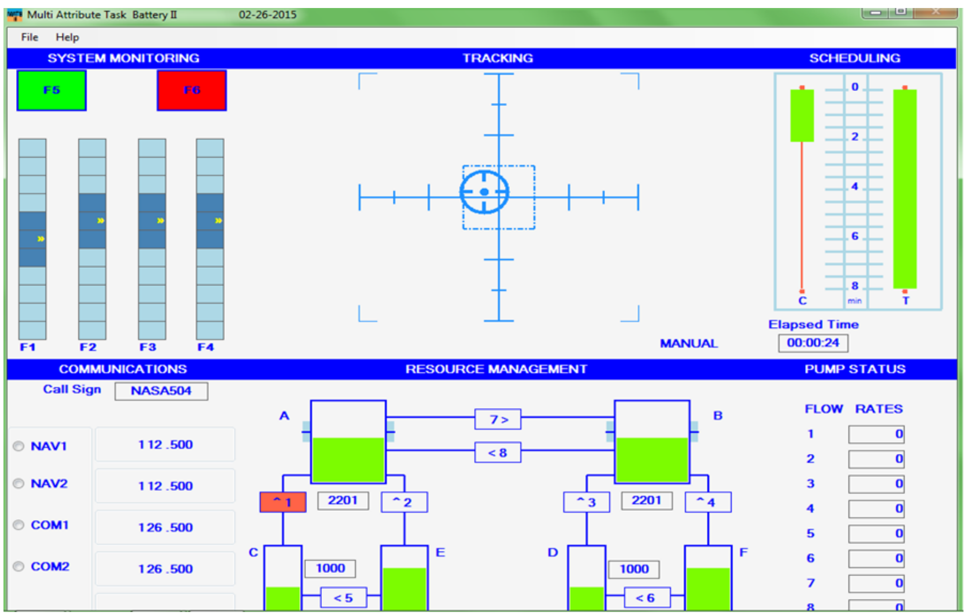

Figure 1. A screenshot of the Multi-Attribute Task Battery-II Display (Santiago-Espada et al., 2011). Subtasks are as follows: system monitoring (upper left), tracking (upper center), communications (lower left), resource management (lower center).

System Monitoring. The system monitoring subtask (Figure 1 upper left) requires participants to monitor two dials and four gauges for state changes. A normal system state consists of a green left dial, colorless right dial, and center oscillating gauges. Any deviations from this normal state requires the participant to respond with the appropriate key on the keyboard to return the system to stasis. The F1, F2, F3, and F4 keys on a standard keyboard spatially correspond to the four oscillating scales. The F5 and F6 keys correspond to the left and right dials, respectively. Changes in system monitoring parameters are independent of one another. That is, a gauge and a dial can be in a non-normal status at the same time, and a response to one does not affect the other. Performance for this task is measured by throughput (number of hits divided by mean hit response time). Higher throughput indicates better performance.

Tracking. The tracking subtask (Figure 1 upper center) is a compensatory tracking task that requires participants to maintain a circular reticle in the center of a square fixed between the intersection of two crosshairs using a joystick. The MATB program introduces random reticle movement with the use of a 4:3 horizontal-to-vertical sine wave function at either a low, medium, or high rate according to manufacturer. The tracking task has two modes: auto and manual. When in the auto mode, the crosshairs and circular reticle are grayed out and an “auto” indicator light is illuminated, indicating that no response is needed. This subtask simulates the flight controls of an aircraft. The outcome measure is root-mean-square deviations from the center pixel. Higher root-mean-square deviations indicate worse performance.

Communications. The communications subtask (Figure 1 lower left) simulates pilots responding to air traffic control commands. During this subtask, participants hear several simulated air traffic control radio calls. Radio calls begin with a call sign. Participants are assigned the call sign "NASA-504" and only respond to radio calls hailing this call sign. The radio calls then instruct participants to tune one of four simulated radios to a specific six-digit frequency. For example, a radio call hailing the participant may state, "NASA five zero four, NASA five zero four, tune your COMM one radio to frequency one one eight point one two five." The participant would then use the mouse, select the appropriate radio, and dial in the frequency by clicking on arrow tabs next to the radio frequency that control the radio frequency numbers. The purpose of this subtask is to emulate the working memory demands experienced by pilots. Performance for this task is measured by throughput (number of hits divided by mean response time to hits).

Simulation Parameters and Manipulations. The two levels of the automation independent variable were as follows. In the *automation on* condition, the tracking and communications tasks were fully automated. The system monitoring subtask was semi-automated. For the tracking task, the "auto mode" was turned on. For the communications task, participants were told that all radio calls would be handled by an automated system that automatically changes the radio frequencies (in reality the frequencies do not change). The system monitoring task required participants to make one response every 4-7 min to maintain some level of task engagement (Saxby et al., 2013). Participants were told that as long as the left green light is illuminated, they did not need to make a response to other events. However, if the green light is off, this corresponds to an automation failure and they had press the appropriate key on the keyboard to return the system back to normal.

In the *automation off* condition, participants were required to perform all three subtasks without automation. Subtask parameters for this condition were set to induce a moderate amount of cognitive load to simulate a normal working state. System monitoring events occurred 10 times per minute, the tracking task was set to a medium refresh rate, and the communications task required a response from the participant 5 times per minute. This condition has been validated in prior work (Smith et al., 2001). Both conditions were 30 min long.

Simulation Performance Evaluations. To standardize performance across the automation manipulation, participants completed a performance evaluation before and after their respective 30 min MATB simulations (i.e., with automation present or not present). Figure 2 depicts the stimulation sequence. These performance evaluations were 5 min long and required participants to respond to a high cognitive load scenario different from their respective experimental conditions (van der Linden, 2011). Performance evaluations were identical across the automation conditions. All three subtasks were set to their highest difficulty to simulate a high workload emergency situation (communications task = 10 events/min, system monitoring = 20 events/min, tracking refresh rate = high; Smith et al., 2001). Participants in the automation condition had a 30 s buffer to regain manual control of all the subtasks before performance was recorded. This procedure has been used by researchers to standardize performance across different degrees of automation (Bernhardt, 2018; Navarro et al., 2016; Saxby et al., 2013) and to simulate automation to manual control transitions.

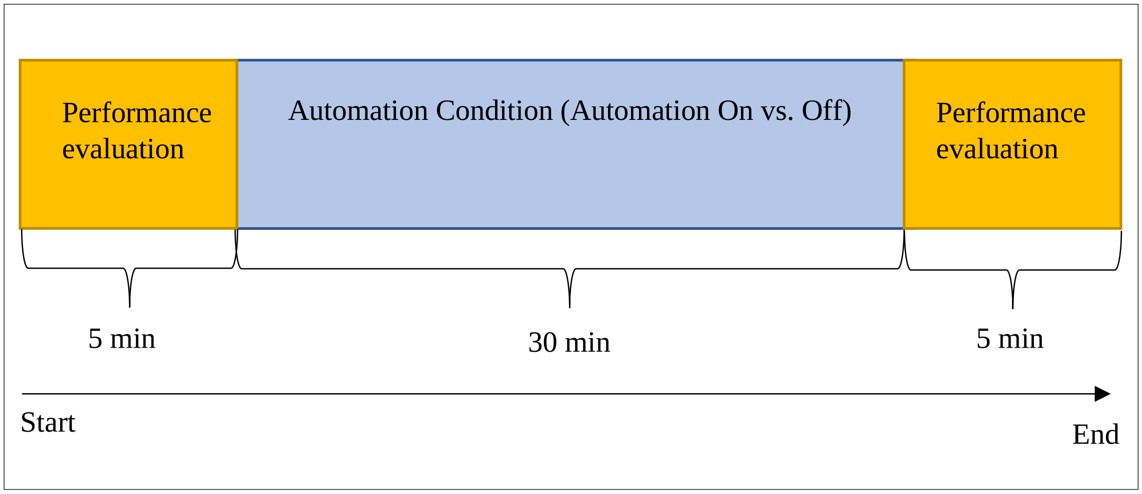

Figure 2. The MATB testing sequence.

MATB performance outcomes included metrics from the three subtasks during performance evaluations. For the systems monitoring and communications tasks, performance was quantified with throughput (correct hits divided by mean reaction time for correct hits). Tracking task performance was measured in root-mean-square deviations from the center pixel point of the crosshairs in pixels. These metrics have been used in previous studies using the MATB (e.g., Founier et al., 1999; Wilson et al., 2007).

EEG Measurement

EEG indices of task engagement were measured with the Advanced Brain Monitoring (ABM) B-Alert X-10 EEG system (ABM, 2009). This system incorporates a validated multivariate measure of task engagement (Berka et al., 2007) and has been rated as a highly ergonomic system (Hairston et al., 2014). The X-10 is a wireless, Bluetooth enabled EEG device consisting of nine electrodes placed according to the international 10-20 system (F3, Fz, F4, C3, Cz, C4, P3, POz, P4). The X-10 also incorporates algorithms to remove artifacts from the EEG signal, including eye blinks and electromyography (ABM 2009). For each 1 s epoch of data, power spectral density (PSD) is automatically computed by the software for four standard bandwidths using the Fast Fourier transformation after signal decontamination. Four bandwidths are outputted by the system: delta (1-2 Hz), theta (3-7 Hz), alpha, (8-13 Hz), and beta (13-29 Hz). Data are sampled at 256 Hz and filtered with 50, 60, 100, and 120 Hz notch filters as well as a Low Pass FIR filter during data collection prior to PSD computation.

For the proposed study, relative alpha PSD at site POz (parietal occipital midline) was used as the primary measure of task engagement (Macdonald et al., 2011). Relative alpha power was computed by dividing the summed alpha PSD from 8-13 Hz by summed PSD from 1-40 Hz. Additionally, the X-10 system incorporates a multivariate metric of task engagement, which was used as a second measure of task engagement. This metric uses an algorithm developed by Berka et al. (2007) that utilizes absolute and relative PSD values from multiple PSD bandwidth ranges from differential sites FzPOz and CzPOz in a four class quadradic discriminant function to classify individuals as being in a sleep onset, distracted, low engaged, or high engaged state. The classification model is individualized to each participant during the performance of three neurocognitive benchmark tasks performed prior to recordings (3-choice vigilance task, visual psychomotor vigilance task, and auditory psychomotor vigilance task). During data acquisition, the individualized models produce posterior probabilities (ranging from 0.0-1.0) of the participant being in either a sleep onset, distracted, low engaged, or high engaged state. For this study, the high engagement posterior probability was used for ease of interpretation (i.e., higher probabilities indicate more engagement). This metric has been shown to correspond to reductions in vigilance performance (Berka et al., 2007) as well as differentiate manual from automated control simulations (Bernhardt et al., 2019).

Eye-tracking

Eye-tracking was recorded with the Tobii X2-60 eye tracker (60 Hz sampling rate). The X2-60 is a display-mounted eye-tracker that uses infrared light to capture eye movements as well as pupil diameter. For this study, the X2-60 was mounted directly below the computer monitor. Before recordings, the system is calibrated with a nine-point calibration routine requiring the participant to follow a red circle along nine points on the screen. Participants sit at a normal working distance (approximately 40-60 cm) from the screen for proper recordings. The system provides data quality codes in the data stream to indicate epochs in which both eyes are reliably detected. Only epochs in which both eyes can be reliably determined were used. Pupil diameter was used as a measure of task engagement, which has been shown to correspond to declines in vigilance performance (Hopstaken et al., 2016). Two-dimensional density plots were also generated using the X-axis and Y-axis coordinates of the participants' eyes to determine which subtasks they focused overt attention during performance evaluations.

Accommodative and Convergence Measurements

To measure changes in the accommodative and vergence responses, participants completed three standard optometric tests before and after the MATB. To measure accommodative amplitude, Donders' pushup method was used. Donders' pushup method is commonly used to diagnose accommodative deficits (Burns et al., 2014). Participants binocularly viewed a target containing a row of letters that is brought closer to the eye using a Royal Air Force rule until sustained blur is reported by the participant. The target was then pulled away from the participant, and the participant reported when a clear image formed again. Blur and recovery distances were recorded. This procedure was repeated three times. The average break point was subtracted from the average recovery point to obtain a difference score.

Convergence was measured with near-point of convergence (NPC) and near-point of fixation disparity (NPFD). NPC is measured in a similar way to accommodative amplitude using a RAF rule. Instead of letters, the stimulus is a vertical line. Participants viewed this target binocularly as it is moved closer to their eyes. Participants reported when diplopia occurred and this distance is recorded as the NPC. The researcher then pulled the target away from the participants and the point at which a fused image (recovery) occurred is reported. The procedure is repeated three times and the recovery-break distance is taken. NPFD also measures convergence but has been shown to be more sensitive than NPC in identifying convergence deficits (Lederer et al., 2015). Participants wore polarized vectograph glasses while binocularly viewing a target placed on a card that was slid closer to the participant's eyes using a Bernell Rule. The participant was instructed to focus on the letter E centered on the card and report when the vertical lines begin to move out of alignment, at which point the distance from the participant's eyes was recorded. The target was then receded from the participant and the recovery point was reported and recorded. This procedure was repeated three times and the average recovery-break distance was recorded.

Self-report Dependent Measures

In addition to the physiological dependent measures, self-report measures of task engagement, cognitive fatigue, and visual fatigue were collected.

Short Stress State Questionnaire. The Short Stress State Questionnaire (SSSQ; Helton, 2004) is a shortened version of the commonly used Dundee Stress State Questionnaire (DSSQ; Matthews et al., 2002) and measures the constructs of task engagement, worry, and distress. For this study, only the task engagement scale was used as an outcome measure. The SSSQ includes 24-items, eight of which load onto the task engagement scale, that are administered pre and post task completion. The pre-task version has participants rate how they felt during the past 10 min. The post-task version has participants rate how they felt during the task. Both pre and post-task engagement scales have good internal reliability (α = .80 and .84, respectively; Helton & Näswall, 2015). Three experimental items were added to the scale: *happy, joyful,* and *bored*. The first two items were used to combat potential affective bias in the scale. The last item was added to attempt to augment the task engagement scale. The SSSQ was selected because it is a shorted version of the DSSQ, which has been shown to negatively correlate with EEG alpha power (Fairclough & Venables, 2006). The SSSQ task engagement subscale has also been shown to be sensitive to automation manipulations (Bernhardt, 2018; Navarro et al., 2016; Saxby et al., 2013).

Samn-Perelli Fatigue Scale. The Samn-Perelli Fatigue Scale (Samn & Perelli, 1982) was used to measure cognitive fatigue. A measure of cognitive fatigue was included because cognitive fatigue often accompanies a loss of task engagement (Matthews et al., 2002). This scale consists of a single item asking participants to rate their current level of fatigue from 1 (*fully alert, wide awake*) to 7 (*completely exhausted, unable to function effectively*). The Samn-Perelli Fatigue Scale correlates with flight hours for pilots performing long-haul flights (r = .52; Samn & Perelli, 1982) and corresponds with decreased vigilance performance (Petrilli et al., 2006). This scale was presented pre and post MATB.

Visual Fatigue Symptom Scales. Visual fatigue symptoms were evaluated with the visual fatigue symptom scales developed by Sheedy et al. (2003) to determine the strength of the -2.0 D lens manipulation. These scales were administered pre and post MATB. Nine, 100 mm visual analogue scales correspond to one of nine symptoms: burning, ache, strain, irritation, tearing, blurred vision, double vision, dryness, and headache. Scale anchors are 0 (*none*) and 100 (*severe*) with the descriptors *mild, modest,* and *bad* located at each quartile. Principal components analysis of the scales revealed two distinct components: external symptoms and internal symptoms (Sheedy et al., 2003). External symptoms consist of burning, irritation, dryness, and tearing (α = .87). Internal symptoms consist of strain, headache, ache, double vision, and blur (α = .82).

Potential Covariates

Trait daytime sleepiness, existing symptoms of accommodative and convergence insufficiency, and age may have impacted findings. Individuals with higher tendencies toward being sleepy during the day may be more prone to task disengagement (Johnson et al., 2001). Trait daytime sleepiness was measured with the Epworth Sleepiness Scale (ESS; Johns, 1992). The ESS consists of eight items asking participants to rate their chances of dozing off during everyday activities (e.g., riding in a car, reading a book) from 0 (*would never doze*) to 3 (*high chance of dozing*). The ESS has good internal (α = .88) and test-retest reliability (r = .82; Johns, 1992).

The Convergence Insufficiency Symptom Survey (CISS; Borsting, Rouse, & De Land, 1999) was used to measure existing symptoms of convergence insufficiency. The CISS is a 15-item questionnaire that asks participants to rate how often they experience symptoms of convergence insufficiency on a scale of 0 (*never*) to 4 (*always*). The CISS has been shown to be both a valid and reliable tool for identifying convergence insufficiency (α = .96), with scores greater than or equal to 21 reliably identifying individuals with convergence insufficiency (Rouse et al., 2004).

The Barkley Adult ADHD Rating Scale-IV (BAARS; Barkley, 2011) was used to evaluate existing symptoms of ADHD. The BAARS consists of 27 items that correspond to clinical symptoms of ADHD. These 27 items load on to four factors: inattention (9 items), hyperactivity (5 items), impulsivity (4 items), and sluggish cognitive tempo (9 items). Participants rate how often they experience symptoms on a scale from 1 (*never or rarely*) to 4 (*very often*). Items are summed to create a total score (α = .91, Barkley, 2011). Higher scores indicate greater ADHD symptom severity. Age was also explored as a covariate since the crystalline lens of the eye tends to thicken with age resulting in presbyopia (Purves et al., 2012).

Summary of Measures

Table 1 summarizes the dependent variables and covariates that were used this study along with their respective constructs and measurement times.

Table 1

Dependent Variables and Covariates

Type	Outcome Measure	Construct	Measurement Time
Performance	1. System monitoring throughput 2. Tracking root-mean-square deviations 3. Communications throughput	1-3. Cognitive performance	Pre/post 50 min MATB condition
EEG	1. POz alpha relative power spectral density 2. Multivariate task engagement metric	1-2. Task engagement	Continuous during MATB
Eye-tracking	1. Pupil diameter	1. Task engagement	Continuous during MATB
Self-report	1. Short Stress State Questionnaire 2. Samn-Perelli Fatigue Scale 3. Visual fatigue symptom scales	1. Task engagement 2. Cognitive fatigue 3. Visual fatigue symptoms	Pre/post MATB
Oculomotor	1. Accommodative recovery-break distance (Donders' method) 2. Convergence (NPC, NPFD) recovery-break distances	1. Accommodative functioning 2. Convergence functioning	Pre/post MATB
Covariates	1. CISS total scores 2.ESS Total Scores 3. BAARS total scores 4. Age	1. Existing symptoms of AI & CI 2. Trait daytime sleepiness 3. Symptoms of ADHD	Pre MATB

Procedure

Participants came to the laboratory for one visit and were instructed to not consume caffeine (Olson et al., 2010) 2 hr or alcohol (Jongen et al., 2016) 8 hr prior to their visits as these substances have been shown to affect vigilance. After providing informed consent, participants completed a demographics questionnaire to verify eligibility criteria. Next, baseline measures of accommodation (Donders' pushup method) and convergence (NPC and NPFD) were taken. After these measures, the research assistant administered the ESS, CISS, BAARS, and pre-task versions of the Samn-Perelli Fatigue Scale, SSSQ, and visual fatigue symptom scales.

The research assistant then applied the B-Alert X-10 EEG system to the participant's scalp and checked electrode impedances. Any electrode impedances exceeding 80 kΩ were adjusted as per the manufacture's recommendation (ABM, 2009). After EEG application, participants performed three neurocognitive benchmark tasks to individualize the discriminant function coefficients used in ABM's multivariate EEG engagement metric. These tasks include a three-choice vigilance task, visual psychomotor vigilance task, and auditory psychomotor vigilance task. The three tasks are included in the B-Alert Live EEG acquisition software.

Next, participants watched a brief instructional video (provided by NASA) on how to complete the MATB. After the video, the Tobii X2-60 was calibrated and participants completed a 15 min MATB practice session facilitated by a research assistant. During the practice session, participants practiced the subtasks individually for 3 min each. During the last 6 min of the practice session, participants performed all three subtasks to practice the performance evaluations. During both the MATB instructional video and the practice session, EEG and eye tracking data were collected to obtain a comprehensive baseline for EEG and pupil diameter values. This baseline was recommended by Fishel et al. (2007) in order to obtain a large enough sample of a physiological response to avoid bias in detecting changes in cognitive states. After the MATB practice session, the Tobii X2-60 eye-tracker was calibrated again prior to the testing session.

Before completing their MATB testing session, participants were randomly assigned to one of four conditions: Automation off without stress (n = 24), automation off with stress (n = 23), automation on without stress (n = 25), or automation on with stress (n = 23). In the stressed condition, participants wore -2.0 D lenses to induce accommodative-vergence stress. This manipulation has been used to induce accommodative-vergence stress in previous studies (e.g., Daniel & Kapoula, 2019; Poltavski et al., 2012; Poltavski et al., 2016). In the non-stressed condition, participants completed the MATB under normal viewing conditions. Participants with previous flight experience were approximately evenly distributed among the experimental conditions (Automation off without stress = 1, automation off with stress = 2, automation on without stress = 3, automation on with stress = 2).

Once participants were assigned to their experimental conditions, the research assistant briefed the participant on their assigned automation condition and informed the subject that auditory cues will direct them when to perform the MATB subtasks. After this briefing, the 40 min MATB testing session commenced following a performance evaluation (5 min), automation condition (30 min), performance evaluation (5 min) sequence (see Figure 2). EEG and eye-tracking data were recorded continuously during the MATB with markers inputted into the data streams to section off data for analysis (i.e., performance evaluations separate from the 30 min automation conditions). Once participants completed the testing session, post accommodative and vergence measurements were taken with the -2.0 D lenses removed if applicable. Finally, participants completed post-task versions of the SSSQ, Samn-Perelli Fatigue Scale, and visual fatigue symptom scales.

Data Reduction and Analysis

EEG and eye-tracking data were sectioned off during testing using markers inputted by a research assistant at the following times: at the commencement of the MATB testing session, after the first performance evaluation, every 5 min during the assigned automation condition yielding six intervals, before the last performance evaluation, and after the last MATB performance evaluation. EEG and eye-tracking were aggregated across segments using 5% trimmed means to reduce the effects of extreme values for the two performance evaluations and each 5 min interval between performance evaluations. Only epochs of EEG and eye-tracking data for which signal quality was deemed acceptable (absence of artifacts as indicated by B-Alert EEG software or indications of both eyes reliably detected by Tobii Studio eye-tracking software) were used in analyses. Each epoch of EEG and eye-tracking data during the testing session was baseline adjusted using Z-scores, with means and standard deviations for each participant derived from their baseline recordings. Specifically, for each participant, the mean value from the baseline recording was subtracted from each value in the testing session and divided by the baseline session standard deviation. Negative values indicate decreases relative to baseline and positive values indicate increases from baseline. Custom made batch processing scripts programmed using R (R Core Team, 2019) efficiently aggregated the data.

Bivariate correlations between covariate measures and dependent variables were computed. Covariates that significantly correlated with outcome measures were entered in the final model. Four, 2 (Stress: non-stressed, stressed) x 2 (Automation: on, off) between-subjects ANOVAs were used to ensure group equality on covariate measures (ESS, age, CISS, BAARS).

R (R Core Team, 2019) and SPSS (IBM Corp, 2015) were used to analyze data. Research hypotheses were addressed with three, 2 (Stress: non-stressed, stressed) x 2 (Automation: on, off) x 2 (Time: pre, post) doubly multivariate mixed analysis of covariances (MANCOVAs). Time served as the within-subjects factor. If covariates did not significantly correlate with outcome measures or contribute significantly to model fit, multivariate analysis of variance (MANOVA) was conducted. Potential covariates included trait daytime sleepiness (ESS total score), self-report symptoms of ADHD (total BAARS score), symptoms of convergence insufficiency (total CISS score), and age. The doubly multivariate nature of these tests determined differences in means on linear combinations of dependent variables representing underlying dimensions between the four groups, as well as any effect of time, while removing the variance associated with potential covariates for between-subjects factors.

Statistical assumptions for MANCOVA/MANOVA were assessed prior to computing main analyses according to the procedure advocated by Tabachnick and Fidell (2007). Univariate outliers were identified using a critical Z-score cutoff of 3.29 (α = .001). Multivariate outliers were identified using Mahalanobis distances with a cutoff equal to a χ^2 value with degrees of freedom equal to the number of dependent variables using the *mahalanobis_distance()* function from the *rstatix* package (Kassambra, 2020). Univariate and multivariate normality were assessed using Shapiro-Wilk and Henze-Zikkler tests, respectively, using the *mvn()* function in the *MVN* package (Korkmaz et al., 2014). Bartlett's test was used to assess if the correlations between dependent variables were sufficient to warrant multivariate grouping. Finally, Box's test was used to assess homogeneity of covariance matrices. Bartlett's and Box's tests were assessed within the SPSS *MANOVA* function.

Three MACOVA/MANOVAs were computed on the prior premise that certain groups of dependent variables would correlate more so than others and represent systems of variables (Huberty & Morris, 1989). Field et al. (2012) recommended entering dependent variables according to theoretical reasoning rather than simultaneously into one multivariate analysis. One MACOVA/MANOVA with accommodation, convergence measures (NPC, NPFD), and visual fatigue symptoms as dependent variables addressed hypothesis 1.

One MANCOVA/MAOVA with EEG POz alpha power, the multivariate EEG engagement index, pupil diameter, SSSQ engagement scores, and Samn-Perelli Fatigue Scale scores entered as dependent variables addressed hypothesis 2. EEG data from the first and the last 5 min of the assigned automation condition were used for this analysis as we have previously shown the effects of oculomotor discomfort on EEG measures to be present during the latter portions of a simulation (Bernhardt & Poltavski, in press).

One MANCOVA/MANOVA with MATB communications task throughput, system monitoring task throughput, and tracking task root-mean-square deviations addressed hypothesis 3. The general hypothesis regarding the effects of time (hypothesis 4) was addressed in all three multivariate analyses.

Significant multivariate analyses were followed by both univariate Roy-Bargmann stepdown tests for the individual dependent variables and descriptive discriminant analysis (DDA; Barton et al., 2016) as recommended by Field et al. (2012) and Tabachnick and Fidell (2007). Univariate tests provided information on which groups differ on single dependent variable for each effect, while DDA provided information on how groups differ based on a linear combination of related dependent variables that represent underlying dimensions. DDA accounts for the multivariate nature of the omnibus analysis and is considered more appropriate than univariate ANOVAs (Barton et al., 2016). Univariate step-down tests were calculated using the SPSS *STEPDOWN* command within the *MANOVA* function. DDAs were calculated using the *candisc*() function from the *candisc* package in R (Friendly & Fox, 2017). If a significant multivariate effect was a between-subjects factor, outcome measures were averaged across the time points and these averages were used as predictors in the DDA. DDAs for the main effect of time were not computed as the correlations between timepoints cannot be accounted for in current R and SPSS syntax (Lix & Sajobi, 2010). For any interactions involving time, DDA was computed at each level of time with the between-subjects factors as dependent variables (Barton et al., 2016; de Coster et al., 2005).

Three supplementary multilevel linear models were computed on the outcome measures of EEG POz alpha power, the multivariate EEG index, and pupil diameter. Time served as a continuous predictor. These models allowed for a more finite analysis of continuous physiological measures over time and clarified hypothesis 4. Multilevel linear models are preferred over the standard mixed ANOVA approach because a covariance structure between repeated (3+ times) measurement times can be specified (Field et al., 2012). An autoregressive 1 (AR1) covariance structure was predicted to fit the EEG and eye-tracking measures over time. Moreover, random slopes and intercepts can be included in the model as well to better account for individual trajectories. Models were specified in a step-up fashion and used maximum likelihood parameter estimation to facilitate model comparisons (West et al., 2015). Models were computed using the *lme()* function from the *nlme* package (Pinheiro et al., 2019) in R.

Statistical significance for all analyses was set at $\alpha < .05$ unless corrected to protect from Type I errors during follow-up analyses. In cases with multiple follow-up tests, the Bonferroni correction was used.

CHAPTER III

RESULTS

Preliminary Analyses

Covariates: ESS, CISS, BAARS, Age

Descriptive statistics for the ESS, CISS, BAARS, and age are displayed in Table 2. Four 2 (Automation: on, off) x 2 (Stress: non-stressed, stressed) factorial ANOVAs were used to evaluate group equivalence on the five covariate measures. No main effects of Automation or Stress were significant, nor was the interaction between automation and stress (all *p*-values > .05), indicating that the four groups were roughly equivalent on potential covariate measures. Significant correlations were found between three covariate measures. ESS and CISS scores were positively correlated, $r(93) = 0.39$, $p < .001$. Furthermore, ESS and BARRS scores, $r(93) = 0.20$, $p = .048$, and CISS and BAARS scores, $r(93) = 0.37$, $p < .001$, significantly correlated. That is, participants reporting higher symptoms of CI generally reported greater daytime sleepiness and more severe symptoms of ADHD. Similarly, higher ADHD symptom scores corresponded to generally greater daytime sleepiness. Age did not significantly correlate with any of the other covariates.

Table 2

Descriptive Statistics for Covariate Measures by Automation and Oculomotor Stress

	Automation							
	Off				On			
	Stressed (n = 23)		Non-stressed (n = 24)		Stressed (n = 23)		Non-stressed (n = 25)	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
ESS	5.96	3.39	6.33	2.26	7.33	3.09	7.80	3.63
CISS	14.35	8.78	15.51	10.27	11.03	6.22	15.85	8.24
BAARS	25.22	4.22	24.30	3.64	24.02	3.04	25.52	3.62
Age	18.91	0.85	19.63	2.04	19.22	1.28	19.92	3.45

Main Analyses

MATB Performance

Three participants were excluded from MATB performance analyses for not performing the two performance evaluations correctly. Dependent variables included communications task throughput, system monitoring task throughput, and tracking task root-mean-square deviations from the center. Descriptive statistics for these variables are displayed in Table A1 in Appendix A. No univariate outliers using a Z-score cutoff of ± 3.26 (α = .001) were detected. Likewise, no multivariate outliers were detected using a Mahalanobis distance cutoff of 16.27 (α = .001). Within each cell of the design, the univariate and multivariate distributions were approximately normal (all p-values > .05) after all variables were natural log transformed to correct for positive skewness. Finally, Box's test was not significant at the α = .001 level, indicating that the assumption of homogeneity of covariances was tenable (p = .005), and Bartlett's test was significant (p < .001), indicating sufficient correlation between the variables for a multivariate analysis.

Table 3 displays correlations between the covariates and MATB dependent variables as well as and the intercorrelations between the MATB dependent variables. None of the covariate measures were significantly related to the MATB measures; therefore, these covariates were omitted from the multivariate analysis. Additionally, moderate correlations were found between the different MATB subtask performance measures, indicating the absence of collinearity.

Table 3

Correlations between Covariate Measures and MATB Performance

	ESS	CISS	BAARS	Age	1.	2.	3.	4.	5.	6.
1. COMM E1	-.03	-.01	.08	-.11	-					
2. COMM E2	-.06	-.03	.14	-.02	.74**	-				
3. Tracking E1	-.03	.13	.03	-.05	-.15	-.16	-			
4. Tracking E2	.01	.10	.10	-.01	-.15	-.17	.82**	-		
5. SYSM E1	-.13	-.15	-.07	-.03	.26*	.22*	-.50**	-.57**	-	
6. SYSM E2	-.11	-.03	.08	-.06	.16	.19	-.34**	-.47**	.74**	-

Note. E1 = first performance evaluation, E2 = second performance evaluation.

**$p < .001$, *$p < .05$.

Results of the 2 x 2 x 2 doubly multivariate MANOVA are displayed in Table 4. The main effect of Time and the Stress by Time interaction were significant. These effects were qualified by a significant three-way interaction between Automation, Stress, and Time. Roy-Bargman stepdown F-tests for the three-way interaction revealed a significant effect for communications task throughput, $F(1, 86) = 7.43$, $p = .008$, $\eta_p^2 = .09$. Initial analysis of the main effect of Time revealed that throughput generally increased from pre to post test, indicating a slight learning effect with the MATB. Within each level of time and stress, post-hoc comparisons revealed that in the automation on condition, participants in the non-stressed condition exhibited an increase in throughput, while those in the stressed condition did not. However, in the automation off condition, this pattern was reversed. Thus, in the automated condition, the learning effect for participants under oculomotor stress was diminished compared to participants not under stress.

DDA was then carried out for the three-way interaction at each level of Time using the three MATB metrics as predictors. Coefficients and centroids for the two discriminant functions are displayed in Table B1 in Appendix B. Figure 3 summarizes the results of the DDA. During the first performance evaluation, reduced communications task throughput, increased tracking RMSD, and increased system monitoring throughput characterized the stressed group in the automation on condition. This pattern was reversed in the automation off condition. However, during the second performance evaluation, participants in the stressed condition were characterized by reduced communications and system task throughput but better tracking task performance (note that lower RMSD values indicate better performance). This effect during the second performance evaluation appears to not depend on whether participants performed the MATB with or without automation. Overall, the large, negative contribution of tracking task RMSD to the discriminant variate during the second performance evaluation potentially indicates the propensity for participants under oculomotor stress to improve tracking task performance at the expense of speed and accuracy on the communications and system monitoring task after the accumulation of oculomotor stress.

Table 4

Multivariate Effects for MATB Performance

	V	*F*	*p*	η_p^2
Time	.57	37.61	< **.001**	.57
Automation	.003	0.11	.954	.003
Stress	.07	2.01	.118	.07
Automation x Stress	.03	0.84	.474	.03
Stress x Time	.09	2.89	**.040**	.09
Automation x Time	.05	1.40	.250	.05
Automation x Stress x Time	.09	2.77	**.046**	.09

Note. Degrees of freedom = 3, 86.

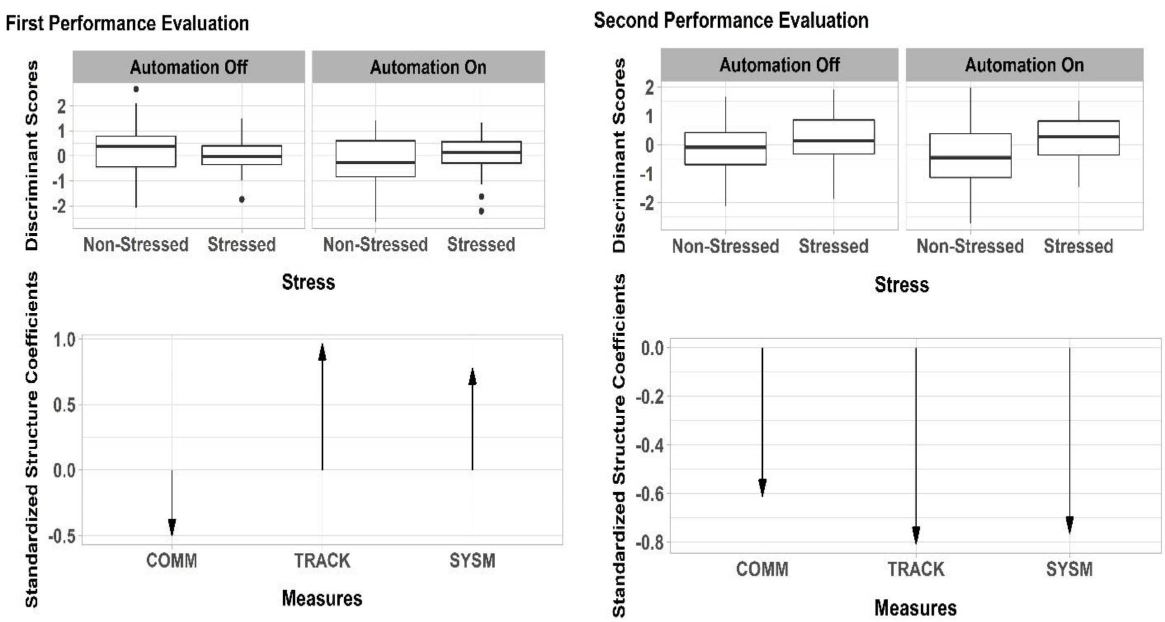

Figure 3. Descriptive Discriminant Analysis Discriminant Scores and Standardized Structure Coefficients for the Stress x Automation x Time Interactive Effect on MATB Performance. The first performance evaluation is on the left and the second on the right. Boxplots indicate group centroid distributions and the arrow diagrams display the standardized structure coefficients. COMM = Communications task throughput, TRACK = Tracking task root-mean-square deviations, SYSM = System monitoring throughput.

Visual Measures

Visual measures included accommodation, NPC, NPFD, and self-report visual fatigue symptoms. Initial univariate analysis of these variables revealed significant deviations from normality. Square root transformations for these variables were used to achieve approximately normal distributions within each cell of the design. Descriptive statistics for these variables are displayed in Table A2 in Appendix A. NPC and NPFD were highly correlated (r = .71) and measure the same construct. Therefore, only NPFD was used in the analysis to avoid redundancy. One multivariate outlier was identified using a Mahalanobis distance cutoff of 16.27 (α = .001). Inspection of this case revealed that the participant did not understand the directions for the NPFD test. This observation was removed from analyses. Finally, Box's test was not significant (p = .001) and Bartlett's test was significant (p < .001).

Correlations between the covariates and visual dependent variables as well as the intercorrelations between the MATB dependent variables are displayed in Table 5. CISS scores positively correlated with visual fatigue scores both before and after the MATB. BAARS scores also correlated with visual fatigue symptoms but only before the MATB. Intercorrelations between the ocular measures were moderate.

Table 5

Correlations between Covariate Measures and Visual Measures

	ESS	CISS	BAARS	Age	1.	2.	3.	4.	5.	6.
1. AA T1	.04	-.15	-.06	.03	-					
2. AA T2	.04	-.07	.02	.09	.55***	-				
3. NPFD T1	.01	-.03	-.05	-.09	.46***	.50***	-			
4. NPFD T2	-.08	-.05	.12	.03	.25*	.34***	.62***	-		
5. VFS T1	-.10	.40***	.32**	.06	-.03	.11	.07	.06	-	
6. VFS T2	-.01	.29**	.13	-.04	-.21*	-.07	-.07	-.14	.51***	-

Note. T1 = Time 1 (pre MATB), T2 = Time 2 (post MATB)

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

Initially, CISS scores and BAARS scores were entered into the MANCOVA model as covariates. However, the addition of these covariates did not affect the statistical significance of any of the tests. Therefore, the covariates were omitted. Table 6 displays the doubly multivariate MANOVA results for the visual measures. Time and Automation separately affected the linear composite of the visual measures. For the main effect of Time, Roy-Bargman stepdown F-tests showed that subjective visual fatigue symptoms significantly increased from pre (M = 4.60, SD = 3.75) to post MATB (M = 9.75, SD = 5.23), $F(1, 90) = 114.01$, $p < .001$, $\eta_p^2 = .56$. No significant stepdown F-tests were found for the main effect of Automation. Thus, this effect was not explored further at the univariate level.

Table 6

Multivariate Effects for Visual Measures

	V	F	p	η_p^2
Time	.56	37.53	**< .001**	.56
Automation	.10	3.43	**.020**	.10
Stress	.04	1.34	.265	.04
Automation x Stress	.02	0.70	.555	.02
Stress x Time	.02	0.73	.539	.02
Automation x Time	.03	0.80	.499	.03
Automation x Stress x Time	.08	2.70	.050	.08

Note. Degrees of freedom = 3, 88.

DDA for the main effect of Automation revealed that NPFD recovery-break distance was the most important variable for discriminating the automation on and automaton off conditions. Group centroids for the automation off and automation on groups derived from the discriminant variate were -0.33 and .33, respectively. Table B2 in Appendix B numerically displays the discriminant coefficients. Figure 4 below pictorially displays the group centroids and associated standardized structure coefficients. Overall, accommodation made little contribution to the multivariate composite. Greater NPFD recovery-break and less severe visual fatigue scores characterized the automation condition.

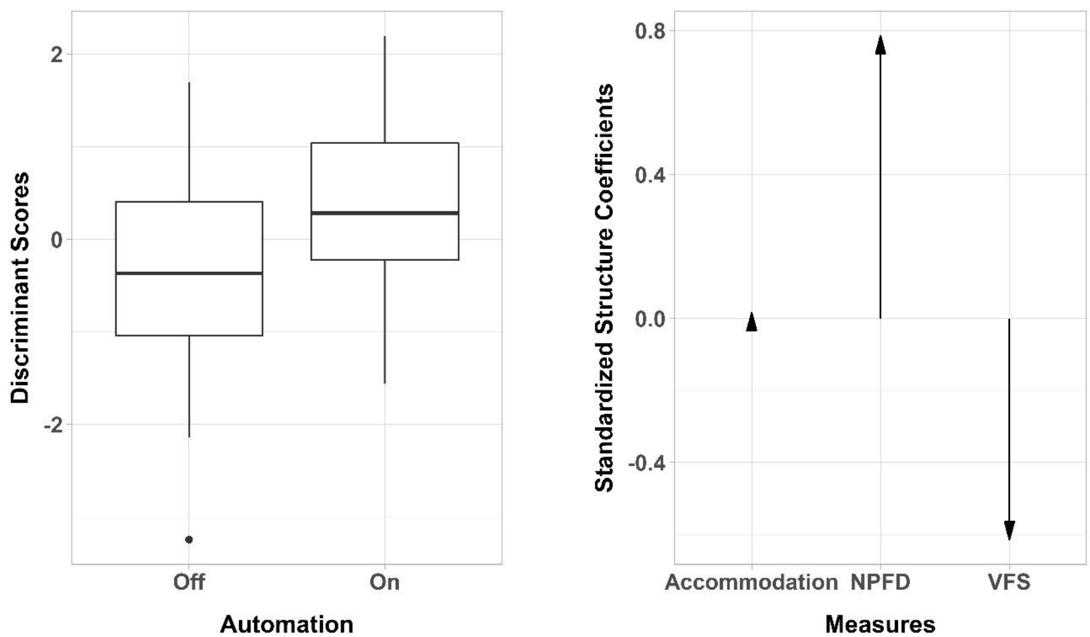

Figure 4. Descriptive discriminant analysis for the main effect of automation on visual measures. NPFD = Near-Point Fixation Disparity. VFS = Visual Fatigue Symptoms.

Task Engagement

The task engagement system of variables consisted of Sman-Perelli Fatigue Scale ratings, SSSQ Engagement scores, pupil diameter, composite EEG engagement metric, and POz alpha PSD. The experimental item (*bored*) added to the SSSQ was first analyzed to determine its effect on scale reliability. With the new item included, reliability of the pre (Chronbach's α = .79) and post scales (Chronbach's α = .81) were similar to if the item was not included (α = .79 and .83, respectively). This item also had the lowest correlation with the composite score at .44 (pre) and .36 (post). Moreover, inclusion of the item did not affect any of the following analyses. Therefore, the scale was computed an analyzed as originally published by Helton (2004).

Initial analysis for univariate outliers revealed one participant had a Z-score exceeding ± 3.29 for POz alpha PSD. Analysis of the participant's EEG data quality revealed excessive artifacts in the POz channel that were not removed by the artifact detection algorithm. Therefore, this participant was removed the analysis. No multivariate outliers were identified using Mahalanobis distances with a cutoff value of 20.51 ($\alpha = .001$). Multivariate normality for all cells of the design was met except for one (automation off and non-stressed at 25-30 minute interval). Because only one of these distributions was not multivariate normal, the analysis proceeded without transformation of variables. Box's test was also not significant ($p = .001$) and Bartlett's test was significant ($p < .001$).

Bivariate correlations between the possible covariate measures and engagement outcomes at each time point are displayed in Table 7. Notably, the CISS negatively correlated with SSSQ engagement at both time points and positively correlated with Samn-Perelli fatigue scale scores at both time points. That is, participants reporting more severe CI symptoms tended to report being less engaged and more fatigued overall. Moreover, CISS scores positively correlated with pupil diameter during the last 5 min of the MATB. Only one significant correlation between EEG and pupil diameter was found, with the EEG engagement metric positively correlating with pupil diameter during the last 5 min of the MATB condition. In general, correlations between outcome measures were low.

Table 7

Correlations between Covariate Measures and Engagement Measures

	ESS	CISS	BAARS	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. POz Alpha Time 1	.23*	-.01	-.03	-									
2. POz Alpha Time 2	.21	.01	-.05	.44***	-								
3. EEG Eng. Time 1	-.07	.20	-.03	-.16	-.04	-							
4. EEG Eng. Time 2	.01	.06	-.07	-.10	-.27*	.53***	-						
5. SSSQ Eng. Time 1	-.28*	-.36**	-.03	-.03	.06	-.12	-.07	-					
6. SSSQ Eng. Time 2	-.11	-.32**	-.07	-.09	-.03	-.09	-.09	.35***	-				
7. SP Time 1	.20	.38***	.23*	-.03	.03	.09	-.12	-.56***	-.28**	-			
8. SP Time 2	.18	.29***	-.01	.05	.16	.03	-.06	-.26*	-.38***	.43***	-		
9. Pupil Time 1	-.23*	.15	.02	.16	.01	.24	.15	-.07	-.08	.12	.01	-	
10. Pupil Time 2	-.09	.23*	.13	-.08	-.13	.17	.25*	.05	-.17	.24*	.01	.60***	-

Note. SSSQ Eng. = Short Stress State Questionnaire Engagement; SP = Samn-Perelli Fatigue Scale; Pupil = Pupil Diameter

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

As with the visual measures, the inclusion of CISS and BAARS scores did not change the results of significance tests. Therefore, the covariates were omitted from the final model. MANOVA results for the engagement system of variables are displayed in Table 8. Significant main effects for Time, Automation, and Stress were found. Follow-up Roy-Bargman stepdown univariate ANOVAs for the main effect of Time revealed that POz alpha PSD [$F(1, 81) = 15.11$, $p < .001$, $\eta_p^2 = .16$] and Samn-Perelli Fatigue Scale scores [$F(1, 77) = 11.63$, $p = .001$, $\eta_p^2 = .33$] significantly increased from Time 1 to Time 2 (note that higher Samn-Perelli Fatigue Scale scores indicate greater fatigue). Additionally, pupil diameter significantly decreased from Time 1 to Time 2, $F(1, 78) = 28.24$, $p < .001$, $\eta_p^2 = .33$.

For the main effect of Automation, POz alpha PSD was significantly higher when automation was on compared to off, $F(1, 81) = 8.95$, $p = .004$, $\eta_p^2 = .10$. Finally, for the main effect of Stress, pupil diameter was significantly smaller for the stressed group compared to the non-stressed group, $F(1, 78) = 7.55$, $p = .007$, $\eta_p^2 = .07$.

Table 8

Multivariate Effects for Engagement Measures

	V	F	p	η_p^2
Time	.48	14.44	**< .001**	.48
Automation	.16	2.84	**.021**	.16
Stress	.14	2.59	**.032**	.14
Automation x Stress	.04	0.59	.711	.04
Stress x Time	.03	0.42	.836	.03
Automation x Time	.03	0.51	.768	.03
Automation x Stress x Time	.01	0.17	.974	.01

Note. Degrees of freedom = 5, 77.

DDA was used to clarify the multivariate main effects of Automation and Stress. Figure 5 displays the distribution of discriminant scores and associated standardized structure coefficients (see Table A3 in Appendix A for a table of values). For the main effect of Stress, centroids for the non-stressed and stressed groups were -0.37 and 0.43, respectively. Pupil diameter and the EEG engagement metric were the most important for differentiating the groups. Less alpha PSD, smaller pupil diameter, greater EEG engagement, greater subjective engagement, and greater fatigue tended to characterize the stressed group. For the main effect of Automation, the standardized coefficients showed that POz alpha PSD contributed the most to discriminating the automation on group from the automation off group. Centroids for the automation on and automation off groups were -0.42 and 0.41, respectively. Overall, more alpha PSD, less EEG engagement, smaller pupil diameter, less subjective engagement, and less fatigue characterized the automation on group.

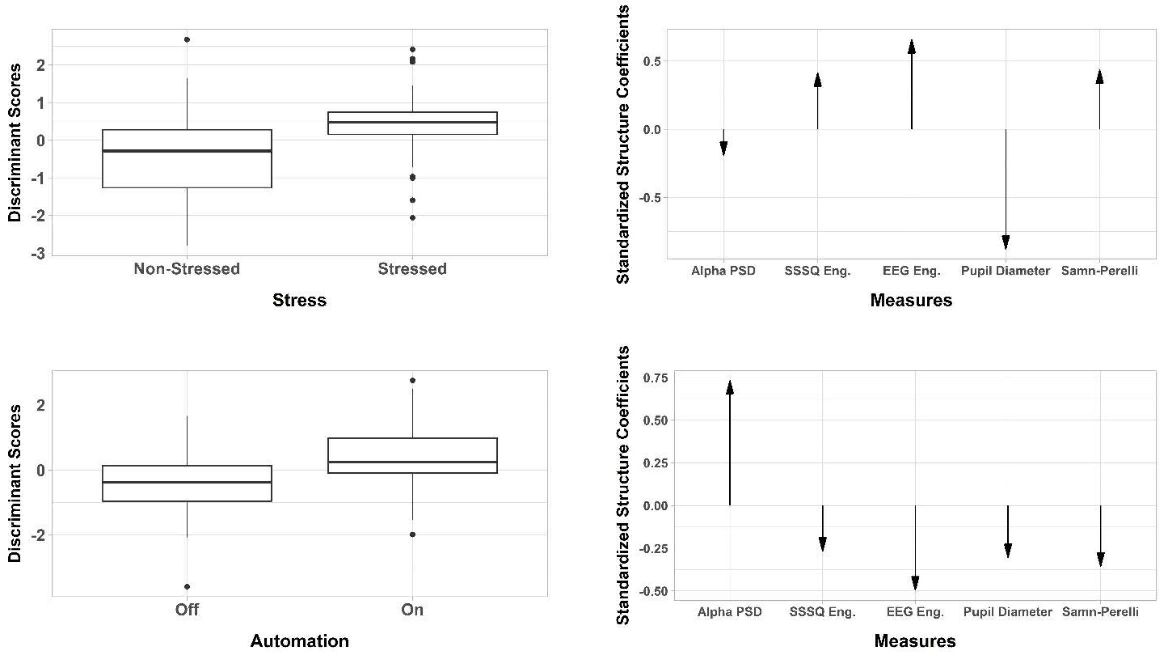

Figure 5. Descriptive discriminant analysis for the main effects of Stress (top) and Automation (bottom) on task engagement measures. Boxplots of discriminant scores are displayed on the left. Standardized structure coefficients for the discriminant variate are opposite right of the boxplots.

Multilevel Linear Modeling

Three multilevel linear models were computed for alpha PSD, the EEG multivariate engagement metric, and pupil diameter. Models were specified in a step-up fashion in the following way adding to each successive step: null model, random intercept for subjects, effect of Time, random slope for Time, effect of Automation, Time by Automation interaction, effect of Stress, Stress by Time interaction, Stress by Automation interaction, Time by Automation by Stress interaction. Log likelihood tests were used to determine whether each successive step significantly improved model fit. In all models, the use of an AR1 covariance matrix and covariates did not significantly improve model fit.

POz Alpha PSD

Initial modeling showed that the addition of a random intercept for each subject significantly improved model fit, $\chi^2(3) = 275.52$, $p < .001$. Moreover, the addition of Time, $\chi^2(4) = 24.05$, $p < .001$, and the random slope for Time, $\chi^2(6) = 66.82$, $p < .001$, significantly improved model fit. The main effect of Automation, $\chi^2(7) = 8.94$, $p = .003$, and the Automation by Time interaction, $\chi^2(8) = 4.00$, $p = .047$, also improved model fit. No effects for Stress were found. Figure 6 compares the slopes of the automation on and automation off conditions over the course of the MATB. Participants in the automation on condition ($b = .06$, $SE = .02$, 95% CI = [0.02, 0.10]) exhibited a steeper increase in POz alpha PSD over time compared to participants in the automation off condition ($b = 0.01$, $SE = .01$, 95% CI = [-0.001, 0.04]).

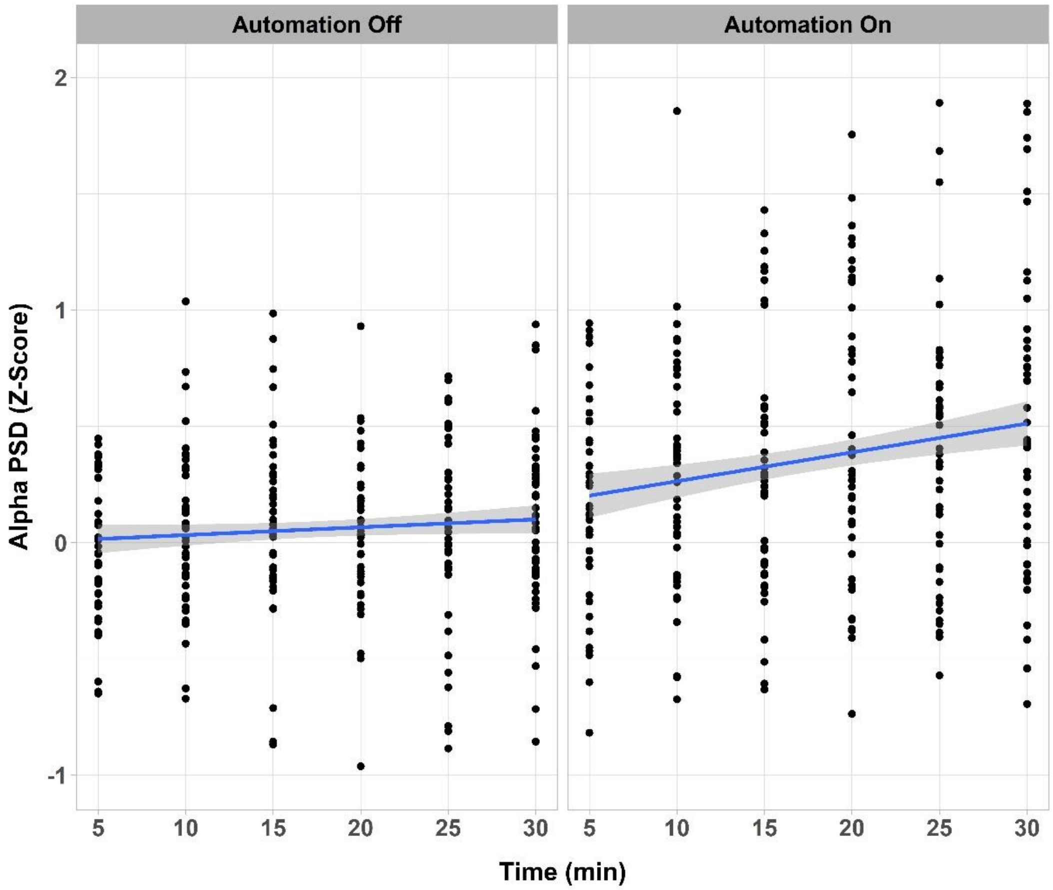

Figure 6. The interactive effect of Automation condition and Time on POz alpha PSD. Shaded regions indicate 95% confidence intervals and points indicate raw observations.

EEG Engagement Metric

The inclusion of random intercepts for each subject significantly improved model fit for the EEG engagement metric, $\chi^2(3) = 344.96$, $p < .001$. The addition of Time as a predictor, $\chi^2(4) = 16.50$, $p < .001$, and the random slope for Time, $\chi^2(6) = 31.95$, $p < .001$, also significantly improved model fit. Finally, the main effect of Automation was significant, $\chi^2(7) = 15.42$, $p < .001$. The slope for the effect of Time was negative (b = -0.01, SE = .004, p = .002, 95% CI = [-0.02, -0.01]), indicating that engagement tended to decrease during the MATB simulation. Furthermore, examination of the group means for the main effect of automation showed that the automation on group (*M* = -0.18, *SD* = 0.24) exhibited significantly less engagement than the automation off group (*M* = -0.03, *SD* = 0.20), mirroring the results of the multivariate analysis. No effects of Stress nor any interactions were significant.

Pupil Diameter

The model for pupil diameter was significantly improved with the addition of a random intercept for each participant, $\chi^2(3) = 436.88$, $p < .001$. The effect of Time, $\chi^2(4) = 84.68$, $p < .001$, and the random slope for Time, $\chi^2(6) = 81.58$, $p < .001$ also improved model fit. Finally, the main effect Automation, $\chi^2(7) = 4.73$, $p = .030$, and the main effect of Stress, $\chi^2(8) = 6.94$, $p = .008$, significantly improved model fit. The overall negative slope for the effect of Time indicated that pupil diameter tended to decrease during the MATB simulation, $b = -0.08$, $SE = .01$, $p < .001$, 95% CI = [-0.11, -0.06]. Pupil diameter was smaller in the automation on group (*M* = -1.01, *SD* = 0.79) compared to the automation off group (*M* = -0.69, *SD* = 0.55). Additionally, pupil diameter tended to be smaller in the stressed (*M* = -1.03, *SD* = 0.69) compared to the non-stressed (*M* = -0.69, *SD* = 0.67) group. These findings support the multivariate analyses.

Supplementary Fixation Plots

To augment the MATB performance findings, the X and Y coordinates from each participant's eyes were extracted from the eye-tracking data stream and plotted using a two-dimensional density plot (see Figure 7). The coordinates were split by the Automation and Stress conditions as well as Time (first performance evaluation vs.

second performance evaluation). The three subtasks are outlined in red rectangles and spatially map to the MATB display. The percentage of fixation points located within the subtask's area located next to the rectangle. Because of the 60 Hz sampling rate of the eye-tracker and the large sample size, changes in density are difficult to observe. However, from these plots, it is evident that participants prioritized the tracking task across all conditions, with 38-48% of fixations occurring within the task area. From the first performance evaluation to the second performance evaluation, participants in all conditions tended to shift fixations to the tracking task and reduce fixations on the system monitoring and communications tasks. There were small differences between the groups in terms of tracking task fixations. Participants in both stressed groups tended to have about 5-8% more fixations on the tracking task compared to the automation off non-stressed group. Participants in the automation on non-stressed group tended to be more similar to the stressed groups in terms of shifting fixations. It is interesting to note the small cluster of fixations in the lower right corner of the screen. These fixations indicate the checking of the computer clock. The stressed automation on group tended to check the time substantially less than the other conditions during the second performance evaluation. This may indicate the propensity for participants in the stressed automation group to direct more visual attention to the task instead of exploring their environment (Hopstaken et al., 2015).

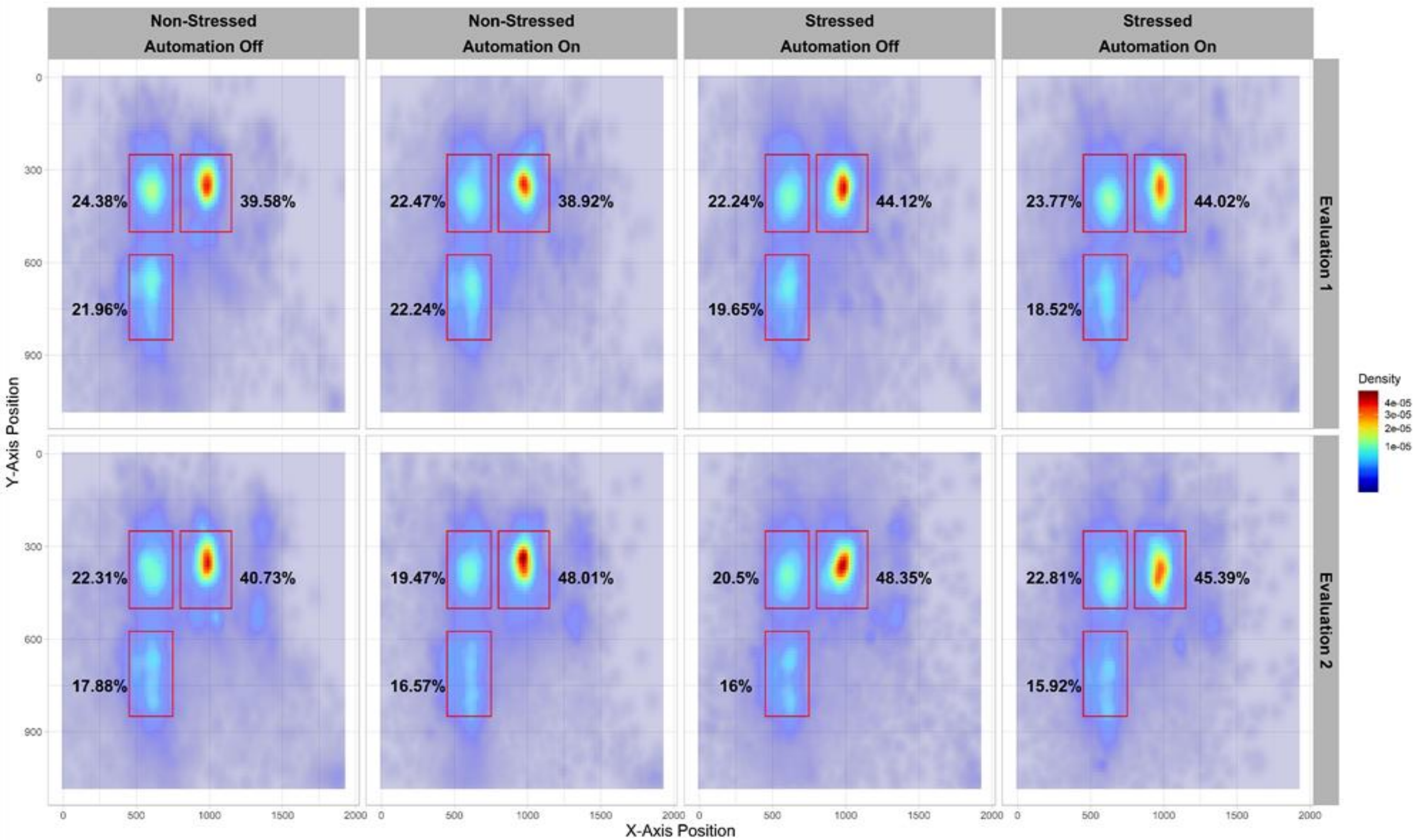

Figure 7. Two-dimensional density plots for participant fixation point data. MATB subtasks are outlined in red. Percentages indicate the percentage of fixations within the bounds of the subtask relative to the total number of fixations. Top center = Tracking; top left = system monitoring; bottom left = communications.

CHAPTER IV

DISCUSSION

As automation continues to be implemented into a variety of user systems, uncovering variables that may compromise the operator's performance and cognitive state is essential to improving safety. Although automated systems may reduce cognitive workload, human operators are also prone to several negative effects, such as overreliance on the system (Parasuraman & Manzey, 2010), loss of situation awareness (Onnasch et al., 2014), and a reduction in task engagement leading to a loss of vigilant monitoring (Saxby et al., 2013). Human factors case studies examining accidents caused in part due to human error with an automated system (BEA, 2012; Wakabayashi, 2018) highlight the continued need to determine the extent to which certain operator characteristics compromise performance while automation systems are in use. Therefore, finding innovative ways to enhancing human performance by leveraging knowledge of these characteristics could improve safety outcomes with automated systems (May & Baldwin, 2009).

The purpose of this study was to determine if artificially induced accommodative-vergence stress and system automation interact to compromise task engagement and performance. Participants performed a 40 min flight simulation task either with or without automated features and either under accommodative-vergence stress or normal vision. EEG, eye-tracking, subjective ratings, oculomotor measures, and task performance metrics were collected from participants. Overall, the interactive hypothesis between automation and accommodative-vergence stress was not supported. Specifically, it was predicted that participants under accommodative-vergence stress who performed the simulation with automated features would exhibit the largest decrement in task engagement over the course of the simulation. However, the effects reported here were mostly isolated to main effects of automation and time on task, rather than oculomotor stress modulating the effects of automation. The results regarding each hypothesis are discussed in turn followed by a general discussion, practical implications, limitations, and future research.

Hypothesis 1: Participants under accommodative-vergence stress will report more severe symptoms of visual fatigue and exhibit reductions in accommodative and vergence responses than non-stressed participants.

Participants under accommodative-vergence stress did not experience an increase in visual fatigue symptoms or reduced oculomotor functioning. However, time on task and automation did affect visual measures. Specifically, from pre to post MATB, visual fatigue symptoms increased regardless of stress condition. This finding is consistent within the human factors literature reporting that visual fatigue tends to increase over time as operators use computer systems (Proctor & Van Zandt, 2018; Saito et al., 2000; Tribley et al., 2011). Moreover, DDA analysis of automation multivariate main effect revealed that those in the automation condition tended to experience less visual fatigue symptoms but greater reductions in the convergence response.

Prior research has shown that extended driving (2 hrs) decreases intraocular pressure and increases accommodative lag (Vera et al., 2016). No studies, however, have examined how automation affects oculomotor responses over time. Literature using basic laboratory tasks involving sustained attention has shown that accommodative lag increases under conditions of accommodative stress (Poltavski et al., 2012). In the current study, accommodation was relatively unaffected by the three independent variables. One explanation for this is the technique used to measure accommodation. In other studies that reported changes in accommodation, either due to stress or to time on task, an autorefractor was used to measure accommodative lag (e.g., Daniel & Kapoula, 2017). Autorefractors are high precision instruments that can measure small changes in accommodation continuously over time. In contrast, the current study utilized a manual rule technique at pre and post time periods after the accommodative stressor was removed from the participant. Importantly, the manual rule technique is a subjective method in that participants report break and recovery distances, while the autorefractor is an objective measure of accommodation. Therefore, the method used in this study was likely not sensitive enough to detect subtle changes in accommodation. Moreover, accommodation could not be tracked in real-time, further limiting the precision of this measurement technique.

Automation also had a significant multivariate effect on the visual parameters. Using DDA, accommodation contributed very little to the differentiation between the automation on group and the automation off group, while NPFD and visual fatigue symptoms contributed the most to the multivariate composite. Increased recovery-break distance and reduced visual fatigue symptoms tended to characterize the automation on group. Because automation and extended time on task tend to reduce visual scanning behavior (Navarro et al., 2016) and increase accommodative lag (Vera et al., 2016), participants may have experienced greater convergence demand from continuously shifting focus back to the appropriate accommodative demand. With greater accommodative lag, greater divergence requirements could have been placed on the participants causing the rotation of the eyes inward to correct for the mismatched accommodative and convergence demand, fatiguing the muscles responsible for convergence (i.e., medial rectus and lateral rectus) in the process. In turn, NPFD recovery-break distances would have been longer. However, although convergence might be mildly strained when operators utilize automated systems, the global effect on visual symptoms, such as blurred vision and headache may not have been severe enough to manifest as overt symptoms, which would have increased Visual Fatigue Symptom scale scores. Furthermore, the relatively short duration of the MATB simulation likely did not produce severe enough visual fatigue symptoms for the effect of stress to be significant. The robust visual system of young, healthy participants also could have contributed to this lack of effect.

Overall, the application of -2.0 D lenses did not significantly affect oculomotor measurements or increase visual fatigue symptoms. Time and automation affected these measures, with visual fatigue generally increasing from pre to post MATB and automation generally resulting in less visual fatigue but greater NPFD recovery-break distances. The increased NPFD recovery-break distances in the automation group indicates greater visual fatigue. Because the NPFD recovery-break distances indicate the resilience of the convergence response, greater recovery-break distances indicate a longer duration for returning the target to center within Panum's fusional area (Lederer et al., 2015). Therefore, the task characteristics that modulate cognitive activity may subsequently affect the convergence response.

Hypothesis 2: Accommodative-vergence stress and automation will interact, such that participants under stress and using automation will be significantly less engaged in the task than the other conditions, as operationalized by increased parieto-occipital alpha power, reduced multivariate EEG engagement, smaller pupil diameter, higher ratings of cognitive fatigue, and lower ratings of task engagement.

The main hypothesis of this study surrounded the synergistic effect of automation and accommodative-vergence stress on measures of task engagement. Automation, with the addition of accommodative-vergence stress, was predicted to produce the largest decrease in task engagement metrics. The multivariate model revealed significant main effects of stress and automation but no interaction. Therefore, the central hypothesis that oculomotor stress and system automation interact to decrease task engagement was not supported. However, the main effects of stress and automation present interesting results worthy of further examination.

First, univariate follow-up tests for the main effect of stress showed that pupil diameter was significantly smaller in the stressed group compared to the non-stressed group. Pupil diameter has been shown to decrease under extended vigilance and correspond to the vigilance decrement, likely via changes in norepinephrine (Hopstaken et al., 2016). Additionally, the two muscles that control pupil diameter, the sphincter pupillae and the dilator pupillae, are controlled by the parasympathetic and sympathetic nervous system, respectively (McDougal & Gamlin, 2015). Studies in the human factors literature have shown that pupil diameter increases with increased mental demands and corresponding sympathetic activation (Borghini et al., 2014; Bernhardt, Poltavski, Petros, Ferraro, Jorgenson, et al., 2019; Marinescu et al., 2018; Orlandi & Brooks, 2018). Moreover, studies have shown greater parasympathetic activation during vigilance tasks using cardiac and skin conductance responses (e.g., Oken et al., 2006; Pattyn et al., 2008). Therefore, participants in the stressed condition could have experienced greater parasympathetic activation consistent with reductions in arousal. This univariate effect suggests reduced task engagement for those under oculomotor stress. The effects -2.0 D lenses could have also been influenced by the near-triad of responses for binocular vision. When transitioning from far to near stimuli, the eyes converge inwards, the lens thickens, and the pupils constrict. With the addition of -2.0 D lenses, the added blur cue may have induced pupil constriction in stressed participants. Likely, the loss of engagement and the effects of the near-triad response share variance. However, if -2.0 D lenses affected the construct of engagement, an interaction between stress and automation would have likely occurred, with smaller pupil diameter in the automation and stressed condition. Therefore, the effects of -2.0 D lenses were likely driven in large part by pupil constriction from the near-triad response to an increased accommodative demand.

Within the multivariate context, however, a different picture emerged. Similar to the univariate analyses, pupil diameter was the most useful in separating the stressed group from the non-stressed group. In contrast to the prediction that engagement would be less in the stressed group, follow-up DDA for the multivariate main effect of stress showed that subjective ratings of task engagement and fatigue were positively related to the multivariate composite (note that the group centroid for the stressed group was positive). Moreover, the EEG engagement metric was also positively associated with the composite variable. Thus, from the multivariate findings, oculomotor stress affected task engagement in the direction opposite to what was hypothesized. Moreover, POz alpha PSD contributed very little to the discriminant variate. Previous literature has shown that reductions in task engagement and visual processing efficiency correspond to increases in posterior alpha power (e.g., Borghini et al., 2014; Macdonald et al., 2011; van Dijk et al., 2008). Here, the application of -2.0 D lenses was predicted to increase alpha PSD relative to the non-stressed group. However, POz alpha PSD made little contribution to the discrimination between stressed and non-stressed participants. One explanation for this lack of effect could be that the sample consisted of young, healthy participants and a relatively mild application of stress was applied. As with the null findings regarding visual measures and the application of stress, participants may have been able to successfully adapt to the stress. It should be noted that only one participant complained of adverse effects (headache) due to the -2.0 D lenses. All other participants reported being able to adapt to the lenses without difficulty. The use of clinical populations, such as those with diagnosed CI or AI, may have produced different results. These individuals would likely experience compounded oculomotor stress due to a reduced capacity to adapt to the added accommodative demand (Lederer et al., 2015). Moreover, actual operational conditions involve several other stressors like sleep deprivation, environmental stress, and high-pressure situations. For example, airline pilots have been found to report being routinely fatigued during flights (Caldwell, 2005; Jackson & Earl, 2006) and military pilots often perform missions during reverse shift hours (Caldwell & Gilreath, 2001). In real world operational scenarios, accommodative-vergence stress may play a greater role in affecting cognitive states and performance outcomes because of stressors already present (Hockey, 1998).

Another explanation concerns the type of task participants performed. In this study, a multifaceted flight simulation task was used. Other researchers reporting decrements in cognitive performance using -2.0 D lenses had participants perform computer tasks requiring fixed locations on a screen. For example, Poltavski et al. (2012) had participants perform the Connor's Continuous Performance Test (CPT). During the CPT, letters are sequentially presented in the center of the screen requiring participants to fixate on a single point for the duration of the task. This fixation on a single point could have led to more accommodative and convergence strain. In contrast, the MATB is a more dynamic environment requiring participants to continually make saccadic eye movements to accomplish tasks. Continually shifting the eyes may have reduced the strenuous effects on accommodation and convergence. Moreover, participants could have also shifted their distance from the screen to offset the effects of the -2.0 D lenses, despite being instructed to remain static.

Finally, the increased EEG engagement metric coupled with increased ratings of fatigue and engagement may point to a compensatory response for stressed participants.

A recent study showed that novice air traffic controllers exhibited higher levels of the EEG engagement metric (the same used in the current study) compared to experienced controllers while maintaining similar performance (Bernhardt, Poltavski, Petros, Ferraro, Jorgenson, et al., 2019). Johnson et al. (2001) reported similar results with novice versus expert shooters. Furthermore, studies using cerebral hemodynamic measures have shown that cortical activation tends to attenuate in experts compared to novices (Ayaz et al., 2012). These findings point to a compensatory mechanism for less experienced individuals to maintain performance via the implementation of additional cognitive resources (Hockey et al., 1997). In the current study, rather than exhibiting reduced engagement, participants may have had to increase cognitive resource implementation to sustain performance, which likely manifested as increases in cortical activity (see General Discussion below).

The effects of automation on task engagement metrics were less equivocal and conformed with previous research. DDA for the main effect of automation suggested that POz alpha PSD was the most important variable for discriminating the automation on group from the automation off group, followed by the multivariate EEG engagement metric. Furthermore, subjective engagement ratings tended to be lower and pupil diameter was generally smaller for the automation on group compared to the automation off group. These findings are consistent with previous human factors studies examining the effects of automation on metrics of task engagement (Freeman et al., 2004; Neubauer et al., 2012; Saxby et al., 2013). Therefore, the pattern of physiological responses observed in the composite discriminant scores affirm that automation does indeed compromise the underlying cognitive states of operators, which are essential for upholding concentration and motivation to actively engage in a task (Matthews et al., 2002). Several authors have suggested that automation creates a state of downward-regulated effort leading to withdrawal from the task (Desmond & Hancock, 2001; Hobstaken et al., 2015; Saxby et al., 2013). In driving (Desmond & Matthews, 1997; Saxby et al., 2013) and air traffic control (Desmond & Hoyes, 1996) studies, researchers have shown that participants often exhibit worse performance during easy situations compared to more difficult situations, indicating a mismatch between the task demands and effort employed for underload situations. This led Desmond and Hancock (2001) to propose that declines in performance due to automation are the result of a condition called *passive fatigue*. Passive fatigue results when operators make little to no overt psychomotor adjustments. In this study, participants in the automation condition made few responses to the system monitoring tasks. Therefore, the low task engagement found in this study could have been the result of the development of passive fatigue. Indeed, the EEG results found here mirror those found in a previous study investigating the effects of passive fatigue on physiological indicators of task engagement (Bernhardt, 2018).

Furthermore, multilevel linear models showed that over the course of the simulation, those in the automation on condition exhibited a steeper increase in POz alpha power than those in the automation off condition (see Figure 6). Therefore, the multilevel linear modeling approach assisted in clarifying the effects of automation and time on task. It is also important to note that no effects of stress were found, indicating that the increase in POz alpha power over time varied as a function of automation and not stress. This further refutes the initial hypothesis that stress and automation would accentuate the increase in POz alpha power.

The multilevel liner models for the EEG engagement metric showed no significant interactive effects. However, the main effects for automation and time supported the multivariate analysis. The differences between the patterns observed with POz alpha power and the EEG engagement metric likely stem from the computation of the EEG engagement metric. This metric incorporates absolute and relative PSD values from several channels on the scalp and is individualized using participant performance on a set of cognitive benchmark tasks. A four-class quadratic discriminant function is then used to classify each epoch of data as either high engagement, low engagement, distraction, or sleep onset. Thus, this metric is a posterior probability of group assignment based on the linear combination of several different EEG frequencies and channels thought to be related to task engagement (Berka et al., 2007). For this study, alpha power was computed at only the POz electrode. Therefore, the engagement metric computed by the EEG system likely contained signal shared with other cognitive processes (e.g., working memory demands) and may not be a "pure measure" of task engagement since several scalp locations and frequencies are used. Moreover, the generalization from the simple cognitive tasks used to individualize the discriminant coefficients also may also account for the slight differences between raw POz alpha power and the system's EEG engagement metric. Thus, using only a single posterior EEG channel may be sufficient to determine changes in engagement states over the course of systems incorporating automation.

Overall, automation compromised participant engagement; however, the application of oculomotor stress did not accentuate the effects of automation. Instead, oculomotor stress acted independently of automation and time in the direction opposite hypothesized.

Hypothesis 3: Accommodative-vergence stress and automation will interact, such that participants under accommodative-vergence stress and using automation will exhibit the greatest decrement in simulator performance compared to the other conditions, as evidenced by increased reaction times and reduced simulation accuracy when required to regain manual control of the system.

In association with changes in measure of engagement and vision-related parameters, it was predicted that participants under accommodative-vergence stress and using automation would exhibit the greatest decline in task performance. Past research has shown that returning from manual control after using automation can lead to a reduction in performance. For example, Saxby et al. (2013) found that drivers who utilized full longitudinal and lateral control automation in a driving simulator exhibited worse driving performance (e.g., lane control, avoiding hazards) when regaining control back from automation. Moreover, studies using basic cognitive tasks reported declines in performance when individuals perform the task with artificial oculomotor stress (Daniel & Kapoula, 2017, 2019; Poltavski et al., 2012). The performance results found in this study partially support the synergistic hypothesis and previous research.

Multivariate tests showed that the interaction between time, automation, and stress significantly impacted the synthetic composite MATB performance variable.

Interpretation of the three-way interaction at the univariate level showed that communications task performance improved overall; however, this improvement was less pronounced for participants in the automation condition under accommodative stress. However, the multivariate DDA for this interaction revealed a more finite pattern. During the first performance evaluation, participants in the automation on and stressed condition were characterized by worse communications and tracking task performance but better system monitoring performance. However, during the second performance evaluation, participants under oculomotor stress, regardless of automation condition, were characterized by worse communications and system monitoring task performance and better tracking task performance. This shift potentially indicates a change in cognitive strategy under oculomotor stress. Specifically, participants in the stressed condition may have opted to uphold tracking task performance at the expense of system monitoring and communications task performance. The MATB tracking task requires consistent monitoring and oculomotor tracking in order to maintain adequate performance. Under oculomotor stress, participants may have sacrificed the other tasks in order to conserve limited cognitive resources by narrowing attention to the tracking task, which is centered on the screen. Researchers have shown that under conditions of stress, operators may uphold overall task performance but may adopt subtle suboptimal performance strategies, such as speed accuracy tradeoffs (Hockey, 1997, 2011; Hockey et al., 1998). Over time, these suboptimal strategies may result in more systemic decline in performance and compromise safety (Hockey, 1997).

The pattern of performance results described above fits with predictions made by the compensatory control model (CCM; Hockey, 1997). The CCM holds that human operators, while operating under stress (e.g., high workload, fatigue, etc.), allocate effort in one of two ways: (1) task goals and performance can be upheld but at the expense of increased effort and physiological activation, or (2) effort is conserved and performance goals are lowered. Hockey (1997) asserted that changes in performance are likely to appear in the form of "latent decrements" or subtle changes in task efficiency when operators choose to implement more effort. Indeed, the multivariate analysis conducted here revealed latent performance changes instead of gross changes in MATB performance at the univariate level. In this study, all three subtasks negatively correlated with the composite (note lower tracking task RMSD values indicate better performance) and the stressed group had a positive group centroid. According to Hockey (1997), this change may represent a "subsidiary task failure" characterized by "selective impairment of lower priority task components" (p. 84). Since the tracking task is located centrally, stressed participants may have assigned more priority to this task and off-loaded the communications and systems monitoring tasks. However, the fixation plots in Figure 7 show that both stressed and non-stressed participants tended to increase their fixation points on the tracking task. However, both stressed groups had 5-8% more fixations on the tracking task compared to the automation off + non-stressed group. Although slight, the resulting changes in performance strategy may have been due to changes in covert attention rather than overt attention (Wickens & McCarley, 2008).

The physiological results also support the prediction made by the CCM. Using DDA, participants in the stressed group generally showed elevated levels of EEG engagement, less alpha PSD, greater subjective engagement, and higher levels of fatigue. Hockey (1997, 1998) proposed that when operators counteract stress, the implementation of more effort results in a physiological cost. Here, the cost was seen in terms of greater cortical activation with corresponding increases in subjective feelings of fatigue.

Overall, the MATB performance results point to a slight tradeoff in performance strategy for participants under oculomotor stress. Rather than exhibiting large declines in performance, latent decrements were observed at the multivariate level.

Hypothesis 4: The effects of accommodative-vergence stress on outcome measures will be time dependent, such that over increased time on task, accommodative-vergence stress will accrue and lead to greater visual fatigue, reduced engagement, increased fatigue, and worse task performance (i.e., the above effects are time-dependent).

Hypothesis 4 concerns the accumulation of oculomotor stress over time, leading to time-dependent effects on measures of task engagement, performance, and oculomotor parameters. The results of this study provide limited support for the accumulation of oculomotor stress over time affecting outcome measures. It was expected that the application of -2.0 D lenses would significantly modulate the effects of time on task. That is, declines in task performance, engagement, and visual parameters would be more drastic for those under stress than those not under stress.

Time was a significant main effect in all analyses but only interacted with stress for MATB performance, partially supporting hypothesis 4. Furthermore, the change in performance appeared to be mostly due to a tradeoff in cognitive strategy. Therefore, it seems that the accumulation of oculomotor stress over time only modestly affected performance outcomes and did not affect visual parameters or task engagement.

Multilevel linear models showed significant effects for time on task consistent with the literature on alpha power (Zhao et al., 2012), pupil diameter (Hopstaken et al., 2015, 2016), and the EEG engagement metric (Berka et al., 2007) during vigilance performance. In the current study, POz alpha power linearly increased and pupil diameter decreased over the course of the MATB simulation. Additionally, the EEG engagement metric decreased during the scenario. As previously mentioned, the increase in alpha PSD more so for the automation group potentially indicates a compromised cognitive state for handling emergency situations for operators utilizing excessive automation.

General Discussion

Overall, oculomotor stress and automation moderately changed task performance strategies, separately affected task engagement, and had little effect on visual fatigue symptoms and measurements. As discussed in the introduction, the theoretical justification for automation and oculomotor stress synergistically affecting task engagement stems from the "siphoning away" of cognitive resources that would otherwise be used to remain actively engaged in a task, resulting in reduced task engagement overall. Matthews et al. (2017) demonstrated this effect in participants infected with the common cold. The researchers used structural equation modeling to understand the relationships between the common cold, self-reported task engagement, and vigilance performance. Results showed that the effect of the common cold on vigilance performance was fully mediated by a loss of task engagement, leading the researchers to conclude that de-arousing stressors, like infections, result in a loss of cognitive resources. The authors also postulated several physiological mechanisms that may be responsible for this effect, including immunological changes, changes in neurotransmitter function, or the indirect effect of sleep loss. In the current study, the application of oculomotor stress was expected to have a similar effect, with the added prediction that automation would exacerbate the loss of cognitive resources and reduce task engagement and performance. However, contrary to this prediction, participants under oculomotor stress demonstrated a stress response pattern that aligns more with the Compensatory Control Model (CCM; Hockey, 1997). Specifically, cortical and subjective indications of task engagement tended to be greater for stressed participants compared to non-stressed participants.

When operators perform tasks under stress, either environmental, cognitive, or physiological, upholding task performance goals despite this stress comes at a physiological cost from the implementation of compensatory effort (Hockey 1997, Hockey, 2011). According to Hockey (1997), operators can either uphold performance with the implementation of increased effort at the cost of increased physiological activation and latent performance decrements or reduce performance goals and conserve effort. Hockey (1998) found that sleep deprived participants rated their effort implementation on a complex space environment monitoring task as higher than nonsleep deprived participants. Sleep deprived participants also exhibited latent performance decrements in the form of worse performance on subsidiary tasks. Moreover, studies comparing novice operators to experienced operators have found increased cortical activation in novice operators (Bernhardt, Poltavski, Petros, Ferraro, Jorgenson, et al., 2019; Johnson et al., 2001), indicating the physiological cost for performing at a level similar to their more experienced counterparts. Therefore, within the context of the current study, the CCM predicts that participants would exhibit greater physiological costs, latent performance decrements, and increased fatigue under oculomotor stress if task goals are upheld. The multivariate pattern observed in the analysis of engagement measures suggest that oculomotor stress resulted in a compensatory effort response. That is, those in the stressed condition had more cortical activation, higher ratings of task engagement, and higher ratings of fatigue. Rather than showing the result of declines in resource depletion, the multivariate analysis of EEG POz alpha power and the task engagement metric may have actually revealed the real-time process of resource depletion resulting from the implementation of effort. However, it should be noted that multilevel linear models did not reveal any effects for stress, indicating the multivariate nature of task engagement and potential resource depletion effects.

One way to determine if the compensatory response interpretation has merit is to use functional imaging techniques, such as functional near-infrared spectroscopy (fNIRS). fNIRS measures cerebral hemodynamics by detecting changes in oxygenated and deoxygenated hemoglobin using near-infrared light (Irani et al., 2007). Increased cognitive resource allocation is associated with increases in deoxygenated hemoglobin

(Ayaz et al., 2012). Therefore, if oculomotor stress elicits a compensatory effort response as predicted by the CCM, the application of -2.0 D lenses would increase the concentration of oxygenated hemoglobin, particularly in the visual cortex (Just & Varma, 2007). The current EEG results point to a depletion of cognitive resources, but fNRIS measurement would provide a more direct measurement of resource utilization due to the strong relationship between cerebral hemodynamics and cognitive resource utilization (Warm et al., 2008).

The argument could also be made that measures of cognitive workload, not measures of task engagement, would index resource depletion with the implementation of stress. However, studies using EEG in experienced and non-experienced operators have shown that EEG multivariate measures of task engagement, not workload, differentiate operators with differing levels of experience (Bernhardt, Poltavski, Petros, Ferraro, Jorgenson, et al., 2019; Johnson et al., 2001). Berka et al. (2007) asserted that EEG metrics of task engagement reflect the pool of the demands for sensory processing and attentional resources, while EEG metrics of workload generally reflect working memory demands. Indeed, in a study of air traffic controllers, our laboratory showed that the EEG engagement metric used in this study varied as a function of air traffic controller experience, not as a function of task difficulty (Bernhardt, Poltavski, Petros, Ferraro, Jorgenson, et al., 2019). Correspondingly, an EEG metric of workload varied as a function of task difficulty but not as a function of air traffic controller experience. Similarly, Stevens et al. (2007) found that an EEG measure of workload increased as the difficulty of a problem-solving task increased but did not decrease in skilled participants.

Therefore, it appears that EEG measures of task engagement and workload measure distinct aspects. Specifically, EEG engagement seems to measure the availability of resources at the level of the operator, while EEG workload measures reflect global demands imposed by the task. The multivariate analysis results of EEG metrics in this study support these past studies.

Practical Implications

Although the effects of oculomotor stress were limited, the negative effects of automation on measures of task engagement present a potential safety hazard for operators. System designs should be aware of the detrimental effects automation has on the underlying cognitive states of operators. While overall task performance may be preserved, the subtle changes in cognitive states may compromise the operator's ability to perform in high workload situations where automation cannot be utilized. In operational settings with added stressors, non-optimal cognitive states can lead to unsafe actions (May & Baldwin, 2009). Therefore, the results presented in the current study highlight the importance of including psychophysiological indices during system evaluation. The field of neuroergonomics utilizes brain-based measurements in order to better understand neurocognitive mechanisms surrounding operator work (Parasuraman, 2015). One problem with neuroergonomic techniques is that they typically involve many electrodes or sensors placed on the scalp. This limits the fieldability of such technologies in operational conditions (A. Kelley, personal communication, December 11, 2019). For example, the EEG engagement metric used in this study requires several EEG channels to compute the posterior probabilities of the individual being in a highly engaged state, making using this EEG system not practical for operators in the field. However, this study revealed that POz alpha power may be a suitable single channel candidate for providing the most non-invasive information regarding the engagement state of an operator over time, especially when automation is in use. A single electrode system provides more flexibility for integration into wearable headgear that can be used outside of laboratory settings (Oie et al., 2012). When paired with advanced machine learning algorithms, single EEG electrode recordings may be able to adequately classify operator states online during data collection to a degree similar to algorithms that incorporate multiple electrodes.

Furthermore, automated systems should be designed to include suitable counter measures to combat declines in task engagement. Certain interventions may include task switching, environmental lighting changes, or adaptive automation (May & Baldwin, 2009). Additionally, if oculomotor stress does increase cognitive resource consumption, optimization of the operator's cognitive state could be achieved through biomedical performance enhancement techniques, such as non-invasive brain stimulation. It is thought that brain stimulation techniques increase the availability of cognitive resources (McIntire et al., 2014). Therefore, increasing the availability of cognitive resources may alleviate a narrow resource bandwidth associated with increased resource allocation. This technique may then be used to enhance resource allocation in conditions of stress for operators in high-risk situations like special forces operators. However, safety considerations and the long-term effects of brain stimulation are still a concern for applying the technique in operational conditions (Feltman et al., 2019).

In addition to applications in operational environments, the results of the current study may also have applications in education. For example, the current study showed that participants under oculomotor stress may exhibit increased cortical activation consistent with the implementation of more cognitive resources. Therefore, students with oculomotor deficits may be implementing more effort to sustain classroom performance relative to their peers, potentially resulting in changes in performance strategy (e.g., fixating on portions of assignments or tests) or eventual burnout. Screening for accommodative and convergence insufficiency at all student age groups may be useful to for improving academic outcomes (Chase et al., 2009).

Limitations and Future Research

One limitation to this study is that oculomotor measures were taken using non-precision instrumentation. As previously mentioned, an autorefractor would have been ideal for measuring changes in accommodation. Therefore, there was likely considerable measurement error despite three measurements being taken each time. This likely contributed to the null findings regarding changes in oculomotor measurements.

Another limitation to the current study was the relatively short MATB duration. In operational environments, such as unmanned aerial vehicle missions, operators could be expected to perform tasks for more than eight hours. With only a 40 min session, oculomotor stress may not have been able to accrue significantly over time. Since no other studies have applied -2.0 D lenses to individuals for longer than about 15 min, the shorter duration was necessary to protect participants from significant discomfort. However, the results of this study indicate that participants with healthy oculomotor responses may be resilient to oculomotor stress when performing multifaceted cognitive tasks. Specifically, participants experienced increased visual fatigue symptoms regardless of whether they were in the stressed condition or not. Moreover, only one participant complained of significant symptoms of visual fatigue. The MATB simulation also lacks the fidelity of a true operational environment. For example, scenery changes while driving or flying may also change a participant's level of task engagement. Thus, changes in engagement may not have reflected what would be experienced in an operational environment. Despite this low fidelity, the results found in the current study support and extend previous research on automated systems (e.g., Saxby et al., 2013).

The amount of oculomotor stress applied to participants also may have not been severe enough to elicit significant changes in cognitive states due to stress over time. Although Poltavski et al. (2012) found meaningful performance decrements with -2.0 D lenses, the performance changes found in this study were modest. Daniel and Kapoula (2019) used -2.5 D lenses, which may have contributed to reliable declines in performance. Relatedly, the current study did not incorporate different methods of oculomotor stress, such as base-out prisms, which decouple accommodation and convergence through manipulation of the convergence response. Indeed, Daniel and Kapoula (2019) found the greatest declines in cognitive performance on a Stroop test using base-out prisms, particularly in more difficult conditions.

The timing for when participants responded to the self-report measures may have also influenced outcomes. Rather than responding to the self-report measures right after their assigned experimental MATB condition, participants responded after completing the last performance evaluation. Because this performance evaluation was consistent across all groups, this performance evaluation may have reduced the between groups variability by slightly increasing task engagement for the automation on groups.

Finally, the participants used in this study limit the generalizability of the findings to operators such as pilots, baggage screeners, and other operators. Operators in the field experience additional stressors that are difficult to replicate in a laboratory environment (e.g., high-stakes performance pressure, complex decision making). Future research should examine how oculomotor stress affects operators in their working environments.

Future research should also begin to explore specific mechanisms for upholding task engagement while automated systems are in use. For example, brain stimulation methods may be explored as a method for optimizing cognitive states for operators using automation for extended periods of time. McIntire et al. (2014) showed that anodal transcranial direct current stimulation (tDCS) applied to frontal cortical regions attenuated the vigilance decrement. However, no studies have examined how tDCS modulates underlying cognitive states that support vigilance with automated systems. In the current study, the use of automation was associated with lower task engagement as measured at the level of cortical activity, pupillometry, and subjective ratings. Using tDCS in conjunction with these measurement methods may give better insight into how tDCS may be a viable method for enhancing performance with automated systems. In conjunction, incorporating cerebral hemodynamic measurement techniques, such as fNIRS, could determine how the cerebral hemodynamic response changes with the application oculomotor stress. Future research should explore the fit between predictions made by the CCM regarding oculomotor stress using fNRIS recordings taken from the visual cortex.

Additionally, future research should explore how task characteristics and oculomotor stress interact. As previously mentioned, previous studies exploring the effects of oculomotor stress on cognitive performance used tasks that required a sustained gaze at a single foveal point (e.g., Poltavski et al., 2012; 2016). In contrast, the MATB required participants to continually scan the interface in order to maintain performance. An experimental design incorporating stimuli presented at both foveal and peripheral locations would help clarify the relationship between task characteristics and oculomotor stress.

Conclusion

This study provided initial data on the effects of oculomotor stress on the construct of task engagement. Oculomotor stress generally increased cortical indicators of task engagement, while also increasing subjective ratings of fatigue. Furthermore, oculomotor stress combined with system automation did not significantly reduce task engagement. Although the effects of oculomotor stress were slightly equivocal, automation reliably compromised task engagement at both a subjective and physiological level. This study reinforces the notion that automation compromises optimal task engagement; however, the addition of oculomotor stress does not appear to exacerbate these effects.

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APPENDIX A

DESCRIPTIVE STATISTICS

Table A1

Descriptive Statistics for MATB Performance Measures by Automation, Stress, and Time

	Automation							
	Off				On			
	Non-Stressed (n = 24)		Stressed (n = 23)		Non-Stressed (n = 23)		Stressed (n = 22)	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
COMM Throughput								
Time 1	0.59	0.51	0.37	0.60	0.60	0.67	0.49	0.62
Time 2	0.61	0.59	0.71	0.57	0.85	0.62	0.57	0.46
Tracking RMSD								
Time 1	3.91	0.28	3.75	0.22	3.80	0.24	3.79	0.19
Time 2	3.77	0.25	3.61	0.23	3.71	0.19	3.69	0.22
SYSM Throughput								
Time 1	2.21	0.27	2.31	0.32	2.22	0.27	2.28	0.33
Time 2	2.40	0.25	2.42	0.32	2.48	0.32	2.39	0.31

Note. Values displayed are natural log transformed. COMM = Communications task, SYSM = System monitoring task, Time 1 = first performance evaluation, Time 2 = second performance evaluation.

Table A2

Descriptive Statistics for Visual Measures by Automation, Stress, and Time

	Automation							
	Off				On			
	Non-Stressed (*n* = 24)		Stressed (*n* = 23)		Non-Stressed (*n* = 24)		Stressed (*n* = 23)	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
VFS								
Time 1	5.39	4.12	5.49	3.66	4.03	3.60	3.48	3.52
Time 2	10.07	5.42	10.88	5.48	8.31	4.73	9.73	5.36
NPFD								
Time 1	1.68	0.35	1.62	0.40	1.90	0.36	1.76	0.45
Time 2	1.70	0.41	1.45	0.31	1.76	0.31	1.78	0.49
Accommodation								
Time 1	1.41	0.32	1.36	0.27	1.59	0.26	1.46	0.29
Time 2	1.47	0.32	1.38	0.24	1.55	0.36	1.40	0.35

Note. Value displayed are square root transformed. VFS = Visual fatigue symptoms, NPFD = Near-point fixation disparity, Time 1 = pre MATB, Time 2 = post MATB.

Table A3

Descriptive Statistics for Engagement Measures by Automation, Stress, and Time

	Automation							
	Off				On			
	Non-Stressed (n = 24)		Stressed (n = 19)		Non-Stressed (n = 22)		Stressed (n = 20)	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
POz Alpha PSD[a]								
Time 1	0.00	0.25	-0.17	0.59	0.13	0.48	0.17	0.34
Time 2	0.26	0.60	-0.04	0.49	0.42	0.66	0.51	0.67
EEG Engagement[a]								
Time 1	-0.04	0.29	0.02	0.15	-0.15	0.15	-0.06	0.20
Time 2	-0.08	0.23	-0.03	0.18	-0.21	0.26	-0.13	0.37
Pupil Diameter[a]								
Time 1	-0.35	0.46	-0.65	0.57	-0.43	0.51	-0.74	0.62
Time 2	-0.66	0.53	-1.00	0.56	-0.96	0.97	-1.22	0.70
SSSQ Engagement[b]								
Time 1	3.69	0.47	3.62	0.64	3.67	0.53	3.68	0.54
Time 2	3.49	0.55	3.64	0.54	3.49	0.64	3.64	0.70
Samn-Perelli[b]								
Time 1	2.50	0.88	2.58	1.22	2.45	0.91	2.45	0.94
Time 2	3.38	1.64	3.37	1.21	3.23	0.97	3.35	1.04

Note. SSSQ = Short State Stress Questionnaire, Samn-Perelli = Samn-Perelli Fatigue Scale.

[a]Time 1 = measurement taken during the first 5 min of simulation condition; Time 2 = measurement taken during the last 5 min of simulation condition.

[b]Time 1 = measurement taken pre-MATB; Time 2 = measurement taken post-MATB

APPENDIX B

COEFFICIENTS FOR DESCRIPTIVE DESCRIMINANT ANALYSES

Table B1.

Descriptive Discriminant Analysis Coefficients for the Automation x Stress x Time Interaction Effect on MATB Performance Measures

	First Performance Eval.			Second Performance Eval.		
	b	*β*	Structure	*b*	*β*	Structure
COMM	-0.83	-0.50	-0.45	-1.08	-0.61	-0.61
TRACK	4.07	0.96	0.67	-3.64	-0.81	-0.35
SYSM	260	0.78	0.15	-2.54	-0.76	-0.47
	Centroids			Centroids		
Auto off + Non-Stressed	0.22			-0.13		
Auto on + Non-Stressed	-0.23			-0.37		
Auto off + Stressed	0.02			0.28		
Auto on + Stressed	-0.01			0.23		

Note. COMM = Communications task throughput, TRACK = tracking task root-mean-square deviation, SYSM = system monitoring throughput.

Table B2.

Descriptive Discriminant Analysis Coefficients for the Effect of Automation on Visual Measures

	b	*β*	Structure
Accommodative recovery-break	0.06	0.02	0.54
Visual Fatigue Symptoms	-0.16	-0.61	-0.63
NPFD recovery-break	2.19	0.79	0.80

Note. NPFD = near-point fixation disparity.

Table B3.

Descriptive Discriminant Analysis Coefficients for the Main Effects of Automation and Stress on Engagement Measures

	Automation			Stress		
	b	*β*	Structure	*b*	*β*	Structure
POz Alpha PSD	1.68	0.73	0.79	-0.42	-0.19	-0.22
EEG Engagement Metric	-2.37	-0.49	-0.62	3.08	0.66	0.42
Pupil Diameter	-0.53	-0.30	-0.41	-1.59	-0.88	-0.72
SSSQ Engagement	-0.57	-0.27	-0.03	0.88	0.41	0.17
Samn-Perelli Fatigue Scale	0.38	0.35	0.12	0.46	0.43	0.06

Note. SSSQ = Short Stress State Questionnaire.