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Differentiating Active And Passive Fatigue States With The Use Of Electroencephalography

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DIFFERENTIATING ACTIVE AND PASSIVE FATIGUE STATES WITH THE USE OF ELECTROENCEPHALOGRAPHY

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ABSTRACT

With advances in automation technology, it is becoming essential to understand how automation affects human operators. A concern for the implementation of automation technology is the interactive effects it has with operator cognitive fatigue. Desmond and Hancock (2001) proposed that two types of fatigue can arise depending on the nature of the task: *active* and *passive*. Active fatigue results when operators must make constant perceptual-motor adjustments during high task demands, while passive fatigue results from operators executing little or no perceptual-motor adjustments during low task demands, similar to when automation is employed. The purpose of this study was to use electroencephalographic (EEG) indices of workload, engagement, and a candidate marker of strain under fatigue in conjunction with performance and subjective measures to differentiate active and passive fatigue states. Participants (N = 84) performed a generalized flight simulator for 62 min either under active, passive, or control conditions. Passive fatigue was characterized by reduced EEG engagement and initially elevated and stable ratios of Fz theta to POz alpha power compared to active fatigue. Subjective measure results indicated that passive fatigue was characterized by reduced ratings of alertness and workload compared to active fatigue. No performance differences were observed between fatigue conditions; however, an overall speed-accuracy trade-off was observed from pre to post fatigue induction. This study demonstrated that different fatigue states produce different effects on EEG indices. These results have potential

applications for developing augmented cognition technologies that deliver appropriate fatigue countermeasures in automated operational environments.

CHAPTER I

INTRODUCTION

Over the past three decades, a significant amount of research in the applied sector has focused on measuring and classifying operator functional states (OFS) during working conditions. OFS refers to a psychophysiological condition of the operator that modulates performance outcomes. Both psychological and physiological processes work in tandem to allow the operator to meet task requirements (Gaillard & Kramer, 2000; RTO, 2004). In other words, the functional state of the operator affects the efficiency and accuracy of task performance. Constructs such as workload, engagement, and fatigue compose important focal points of OFS assessment.

Perpetual technological advances in automated systems have increased the need to better understand how automated systems modulate human operator functional states and performance outcomes. The utility of this understanding lies in the application of system design and development. Indeed, it has been stressed that the design requirements of systems involving human operators should take into consideration the physical, perceptual, and cognitive capabilities of the human operator (Endsley, 2015). Moreover, the U.S. Department of Defense has adopted specific guidelines for designing systems involving human operators. In general, military systems design should prioritize personnel safety and work patterns, while operator constraints, such as workload and mental processing, are not surpassed (U.S. Department of Defense, 2012). Designing systems that exceed human operator capabilities can result in potentially dangerous consequences for not only the operator, but innocent lives as well (Lorist & Faber, 2011; RTO, 2004). Thus, knowledge of OFS is crucial for initial system design to produce systems that are compatible with human operator objectives.

Additionally, recent research has been geared toward using OFS data in conjunction with augmented cognition systems to improve operator performance (Parasuraman, 2015). More specifically, if an operator's functional state can be reliably detected and incorporated into a computer system that monitors and takes appropriate action when a detrimental state is detected, operator safety and efficiency could be enhanced. An example of such a system is adaptive automation. Adaptive automation systems incorporate operator state information and redirect system parameters via automation of systems to match that of the operator's current capabilities. Adaptive automation systems (and other adaptive aiding systems) driven by psychophysiological measures have had moderate amounts of success within laboratory settings (Freeman, Mikula, Scerbo, & Scott, 2004; Wilson & Russel, 2007), but have yet to be implemented in operational settings. Therefore, continued research regarding OFS is valuable for developing deployable augmented cognition systems.

Cognitive Fatigue – Overview

One of the more critical concerns for safety in all situations involving human operators is fatigue. With high paced work environments consuming 21st century daily life, fatigue is a recurrent concern in OFS assessment. Fatigue results in several job-related performance decrements including increased error rates, reduced productivity, and increased reaction times (Matthews & Desmond, 2002; Sievertsen, Gino, & Piovesan, 2016; Wang, Trongnetrpunya, Samual, Ding, & Kluger, 2016). Daily, individuals may experience fatigue resulting from long work shifts and sleep loss. A reported 37.9% of workers in the U.S. experience fatigue in their jobs, resulting in approximately $136.4 billion lost annually due to reduced productive work time (Ricci, Chee, Lorandeau, & Berger, 2007). More importantly, fatigue presents a serious threat to safety in several operational settings involving transportation. Between 2001 and 2012, 20% of major National Transportation Safety Board (NTSB) crash investigations implicated fatigue as a potential contributing or causal factor (NTSB, 2016). Congruently, per month, approximately 1.8 million drivers in the U.S. report driving in a drowsy cognitive state (Wheaton, Shults, Chapman, Ford, & Croft, 2014), contributing to approximately 7,500 fatal crashes per year (Tefft, 2012).

Fatigue is also pervasive in civil and military aviation domains. A search of the NTSB Aviation Accident Database revealed that in the past 10 years, fatigue has been implicated in 659 aviation incidents – both fatal and non-fatal. Empirical studies also support a high prevalence of fatigue in commercial aviation. In a study of 162 commercial pilots from the United Kingdom, 75% of pilots were classified as having severe fatigue and 78% were concerned with the level of fatigue they experienced (Jackson & Earl, 2006). Moreover, in a sample of 456 Portuguese airline pilots, Reis, Mestre, and Canhãom (2013) found that 51.3% percent of pilots reported that they should not have been at the controls on a few occasions due to being tired. On the same measure, 16.4% of pilots reported feeling this way frequently. Even more alarming, Reis and colleagues also uncovered 91.4% of their sample reported making mistakes in the cockpit as a result of fatigue.

Furthermore, fatigue in military aviation presents a serious threat to mission success and combat precision (Caldwell, 2005). Military aviators often have higher duty demands placed on them due to night mission readiness requirements. Advances in night vision optics and precision navigation instruments make missions during many environmental conditions possible. Thus, even in darkness or low visibility, military aviators are often called upon to meet mission requirements. Reversed shifts (i.e., working at night and sleeping during the day) are common among military aviators and can produce disruptions in adequate sleep/wake cycles contributing to increased fatigue (Caldwell & Gilreath, 2001). Overall, research regarding fatigue continues to be of importance in daily work, transportation, and military safety domains. Finding effective ways to identify and counteract the effects of fatigue is essential to transportation safety and work productivity.

Defining Fatigue

Although studied empirically for over 100 years (Ackerman, 2011), fatigue continues to be a critical concern in several applied areas in which humans are an integral part of system operation (e.g., aircraft cockpits, motor vehicles). Interestingly, for as self-evident as the laymen's understanding of fatigue is, there remains great difficulty within the fatigue research community to reach a consensus on the definition of fatigue (Ackerman, 2011; Soames & Dalziel, 2001).

Fatigue to the general population is commonly associated with physical exertion, which leads individuals to typically quantify their level of fatigue by estimating how tired their body feels (Ackerman, 2011; National Aeronautics and Space Administration, 1996). Generally, individuals will say they are fatigued if they are unable to mobilize effort to do a task, using the term synonymously with exhaustion (van der Linden, 2011). Fatigue resulting from physical activity and muscular tiredness is generally referred to as *central fatigue* and is often the main concern of athletes and other professions involving strenuous physical activity (Budgett, 1998). *Cognitive fatigue*, on the other hand, is a lack of energy not associated with physical activity (van der Linden, 2011). In general terms, cognitive fatigue can be defined as, "a mental state associated with tiredness and loss of motivation experienced during cognitively demanding tasks" (Matthews, 2011, p. 209). Cognitive fatigue can be characterized as either *chronic* or *acute*, with the former being a symptom of serval medical diseases with lasting effects over an extended period of time (Persson, Welsh, Jonides, & Reuter-Lorenz, 2007), and the latter being short-lived and associated with performing cognitive tasks (van der Linden, 2011). Acute cognitive fatigue can often be reversed with short rest breaks or switching tasks (e.g., Hartzler, 2014). The focus of the current study was acute cognitive fatigue because of its relevance to operational settings and task performance (van der Linden, 2011).

The hallmark of cognitive fatigue is the associated decrements in task performance observed when individuals perform tasks for extended periods of time. Cognitively fatigued individuals generally demonstrate increased reaction times (e.g., Gander et al., 2014; Lim et al., 2010) and error rates (e.g., Barwick, Arnett, & Slobounov, 2012; Wascher et al., 2014). Moreover, these deficits in basic task performance translate to complex, operational task performance. For example, increased automobile breaking times and worse steering control are associated with cognitive fatigue (e.g., Lal & Craig, 2001; Liu & Wu, 2009; Saxby, Matthews, Warm, Hitchcock, & Neubauer, 2013). Aviator flight performance also suffers from cognitive fatigue effects with potential decrements in heading, altitude, airspeed, vertical velocity, and bank angle flight performance parameters (Caldwell, Caldwell, Brown, & Smith, 2004).

Cognitive Fatigue Risk Factors

Several state variables (transient factors affecting the operator) have been identified that exacerbate the effects of cognitive fatigue (Ackerman, 2011). Sleep deprivation has been studied extensively as a strong catalyst of cognitive fatigue effects. Extended periods of wakefulness impair decision making skills, an effect that is more pronounced in emergency-type situations where time pressure is an added factor (Harrison & Horne, 2000). Decrements in overt piloting performance have also been observed in aviators experiencing sleep deprivation upwards of 24 hr (Caldwell et al., 2004; Caldwell, Hall, & Erickson, 2002). Moreover, certain drugs have been shown to affect cognitive fatigue states. In a study of U.S. Army UH-60 Blackhawk pilots, Caldwell, Caldwell, Smythe, and Hall (2000) subjected aviators to two, 40 hr periods of continuous wakefulness. In one period, the aviators were given 200 mg of modafinil (a psychostimulant) and a placebo in the other. Aviators then performed flight maneuvers in a simulator after their experimental manipulations. Results indicated that when aviators received modafinil, flight performance was significantly better on a majority of maneuvers compared to the placebo condition. Moreover, subjective symptoms and electrophysiological markers of fatigue were reduced. Other state variables such as meal composition (e.g., Kennedy et al., 2008) and time of day (e.g., Bougard, Moussay, Espié, & Davenne, 2016; Caldwell, 2005) have been shown to contribute to cognitive fatigue onset.

Additionally, task-related factors also contribute to the experience of cognitive fatigue. Time on task (TOT) and task workload are often cited as leading factors when individuals report increased levels of cognitive fatigue during task performance (Ackerman, 2011; Hopstaken, van der Linden, Bakker, Kompier, & Leung, 2016). Specifically, highly demanding tasks performed over a longer period of time will contribute more to the development of cognitive fatigue than low demand tasks performed over a short period of time (Ackerman, 2011). However, as is the focus of this study, this view of cognitive fatigue is not entirely accurate as cognitive fatigue effects can occur in situations of underload as well (Desmond & Hancock, 2001). The amount of control a participant has over the task interacts with task workload to produce varying cognitive fatigue effects. Under conditions of high workload and low task controllability, cognitive fatigue effects on performance are stronger compared to high workload, high controllability tasks (Hockey & Earle, 2006). Tasks that are highly redundant or not interesting are also more likely to produce cognitive fatigue and performance decrements. For instance, the psychomotor vigilance test (PVT; Dinges & Powell, 1985) requires participants to simply press a button when a visual stimulus (usually a dot or increasing millisecond numerals) appears on a computer screen. The presentation of the stimulus is varied to occur at 2 to 10 s inter-stimulus intervals. The PVT is not an inherently interesting task and thus displays performance decrements typically after 10-15 min of continuous performance (e.g., Basner & Dinges, 2011; Lim et al., 2010). Overall, an amalgam of different variables, both state and task-related, may influence cognitive fatigue etiology, making cognitive fatigue a multidimensional construct difficult to model with aspects of human performance.

Cognitive Fatigue and Human Performance Theory

Active and Passive Fatigue

Currently, no fully formulated scientific theory of the relationship between cognitive fatigue and human performance resonates within the cognitive fatigue research community (Hockey, 2011). With advances in automation technology, the ways in which human operators interact with systems possessing automation capabilities is becoming a growing area of concern for several branches of applied research, including how automation affects cognitive fatigue (Mustapha, Deaton, & Hitt, 2001; Parasuraman, 2015; Parasuraman & Manzey, 2010; Saxby et al., 2013; Sheridan, 2002; Wickens & Tsang, 2015). Automation has been incorporated into several systems involving human operators such as nuclear power plants (Itoh, Sakuma, & Monta, 1995), automobiles (Kashiwazaki et al., 2012; Murray, 2007), ships (Evdokimov & Sorokin, 2009; Jackson, 1989), and manufacturing (Bond, 2016). Arguably, the most well-known area where automation has been applied is aviation. Automation in aviation has been adopted in order obtain several benefits including decreasing pilot workload and increasing flight efficiency (Mustapha et al., 2001).

Although automated systems have reduced operator workload, automation has fundamentally changed the ways in which task-induced cognitive fatigue manifests. A common misconception is to equate workload with fatigue. That is, cognitive fatigue only arises during high workload situations (Brown, 2001; May & Baldwin, 2009). However, research has shown that cognitive fatigue effects can be observed in low workload situations, analogous to when automation is employed (Desmond & Hoyes, 1996; Desmond & Matthews, 1997). Desmond and Hancock (2001) proposed a model in which two different types of cognitive fatigue can develop depending on task characteristics: *active fatigue* and *passive fatigue*. Active fatigue results from "continuous and prolonged, task-related perceptual-motor adjustments" (Desmond & Handcock, 2001, p. 455). In contrast, passive fatigue results from "system monitoring with either rare or even no overt perceptual-motor response requirements" (Desmond & Handcock, 2001, p.455). In other words, active fatigue is linked with sustained high cognitive workload situations requiring substantial operator input, whereas passive fatigue is linked with relatively low, sustained cognitive workload situations where the operator's role is more supervisory. Thus, active and passive fatigue are potentially byproducts of maladaptive workload regulation associated with overload and underload task demands.

The distinction between active and passive fatigue can be visualized in an example involving aviators. If an aviator must fly a long stretch of a flight manually in high winds and severe turbulence, the constant control adjustments to remain on course results in persistent perceptual-motor adjustments and higher workload (Hart & Bortolussi, 1984). Presumably, this situation would culminate in the aviator experiencing active fatigue. In contrast, if the aviator were to engage an autopilot system in smooth air, he/she would be placed in a supervisory role and simply monitors aircraft systems for changes. In this situation, workload is relatively low and the pilot may be prone to passive fatigue.

Desmond and Hancock (2001) theorized that active and passive fatigue originate from adaptive processes where operators distribute attention toward the environment and the self. These processes are “contingent on the level of attention available” (p. 461). In active fatigue, the level of attention decreases due to constant high task-workload and the amount of attention distributed to the environment decreases, resulting in greater performance decrements. In passive fatigue, the constant under stimulation from a non-changing display results in less attention distributed to the environment, resulting in increased probability of missed signals or reduced capacity to cope with emergency situations.

Support for active and passive fatigue. Support for Desmond and Hancock’s (2001) model of active and passive fatigue comes from studies reporting performance decrements in low compared to high task demand conditions. Desmond and Matthews (1997) demonstrated this effect within the context of automobile driving. Participants performed control and fatigue inducing drives on separate days. The control drive consisted of driving under normal conditions. The fatigue inducing condition required participants to dual-task while driving. Both control and fatigue drives consisted of straight and curved road sections. Results showed that while dual tasking, driver performance was better on curved road sections compared to straight road sections.

Desmond and Matthews interpreted these results as fatigued drivers being unable to mobilize effort appropriately on sections of road that were straight compared to curved, making low-demand situations more hazardous than high-demand situations. In other words, the participants demonstrated a maladaptive workload regulation strategy that compromised performance during lower workload sections of driving.

A comparable effect was found in a simulated air traffic control study where controllers performed either a low, medium, or high workload air traffic control simulation (Desmond & Hoyes, 1996). Workload conditions consisted of two, four, and six aircraft, respectively, that were constantly present during the conditions. Participants in the low and medium workload conditions successfully landed proportionally fewer aircraft than participants in the high workload condition. Moreover, those in the low workload condition successfully allowed fewer aircraft to take off than those in the medium and high workload conditions. As with the previously mentioned driving study, the authors concluded that controllers were unable to mobilize appropriate effort when task demands were consistently low.

Active and passive fatigue states have only recently been explicitly tested and manipulated. In a two-part simulated driving study, Saxby et al. (2013) manipulated simulated driving demands to induce either active or passive fatigue. In Study 1, participants were randomly assigned to one of three fatigue manipulations (active, passive, or control) and one of three drive durations (10, 30, or 50 min). Those assigned to the active fatigue condition drove in continuous wind gusts requiring constant steering and accelerator adjustments. In the passive fatigue condition, the driving controls were automated and participants simply performed a low target density system monitoring task during the drive to maintain task engagement. Those in the control group manually performed the drive under normal driving load conditions. Participants were administered the Dunde State Stress Questionnaire (DSSQ; Matthews et al., 2002), to measure task engagement, distress, and worry. Additionally, the NASA-Task Load Index (NASA-TLX; Hart & Staveland, 1988) was utilized to measure subjective workload. Results indicated that workload was the highest in the active fatigue condition compared to the control and passive fatigue conditions. Over the longer driving durations, participants reported the highest reduction in task engagement during the passive fatigue condition. Moreover, drivers assigned to the active fatigue condition experienced elevated levels of distress from pre to post-drive.

In Study 2, Saxby and colleagues (2013) added an emergency event to the driving simulation to evaluate potential driver performance impairments. Driving conditions were similar to those of Study 1. At the end of each participant's drive, a 5-min supplementary drive was initiated where participants responded to an unexpected parked van pulling out in front of them. Participants also completed the same subjective measures as Study 1. Subjective questionnaire results replicated the results found in Study 1. In response to the emergency event, participants in the passive fatigue condition had significantly slower steering reaction times compared to those in the active fatigue condition. Moreover, those in the passive fatigue condition also had slower breaking times and more collisions compared to the active and control groups. To summarize Saxby and colleagues' two-part study, high workload, high task engagement, and elevated distress characterized active fatigue. In contrast, low workload, low task engagement, and low challenge characterized passive fatigue. More importantly, participants that were exposed to a passive fatigue drive demonstrated worse performance in response to an emergency event than participants exposed to the active fatigue drive. Overall, Saxby and colleagues demonstrated that active and passive fatigue can be experimentally induced (by manipulating task demand) and that each type of fatigue has its own distinct pattern of subjective and performance results. Therefore, cognitive fatigue can be conceptualized as a bipolar continuum, where cognitive fatigue onset can occur at both high and low task demands. This conceptualization of active and passive fatigue has theoretical underpinnings from stress adaptation theories of human performance and effort regulation.

Underlying theoretical mechanisms of active and passive fatigue. The emergence of Desmond and Hancock's (2001) conceptualization of active and passive fatigue draws from broad theories regarding stress adaptation and effort regulation. Generally, the underlying theories of active and passive fatigue rely on an operator's capacity to adapt to stress and how operators regulate effort in response to stress to maintain performance. Two theories, one proposed by Hancock and Warm (1989) and one proposed by Hockey (1997) will be described as they offer important theoretical understanding of active and passive fatigue and human performance in fatigued states.

Adaptation theory of stress and performance. Hancock and Warm (1989) proposed an adaptation theory of stress and performance in which task induced cognitive fatigue results from an interaction between time on task (TOT) and workload and is assumed to represent a type of stress resulting from environmental inputs (Desmond & Hancock, 2001; Desmond & Matthews, 1996). Handcock and Warm posited that operators strive to obtain stasis or comfort in response to stress. To accomplish this, operators must successfully adapt to inputs of stress in both psychological and physiological domains. The model acknowledges that changes in the psychological domain are closely linked with changes in the physiological domain, an assertion backed by research using physiological markers to infer operator states (e.g., Borghini, Astolfi, Vecchiato, Mattia, & Babiloni, 2014).

There are three levels that stress can act upon in Handcock and Warm's model: input, adaptation, and output. Stress inputs are the result of environmental factors acting upon the individual. These inputs can be either psychological (e.g., TOT, task demands) or physiological (e.g., temperature, noise, chemical agents). Specifically, the stress of cognitive fatigue results mainly from an interaction between TOT and task demands. Once stress is imposed upon the individual, adaptive mechanisms (both psychological and physiological) are employed to return the individual back to his/her comfort zone. As the stressor increases in intensity, the capacity of psychological and physiological adaptation mechanisms to cope with the input of stress begin to decline, placing stress on adaptive mechanisms. Psychological adaptivity is equated with the allocation of attention and physiological adaptivity is equated with homeostatic regulation (e.g., thermoregulation response). Hancock and Warm proposed an underload and overload continuum in which the stress can vary between the extremes and the operator's comfort zone is located between the two extremes. An increase in stress to either of the extremes can produce declines in adaptive capacity, resulting in changes in operator performance decrements and/or increased physiological indicators of stress (output stress).

Human adaptation to temperature illustrates the basic components of this theory. Centrally controlled by the hypothalamus, the thermoregulatory response in humans relies on vasoconstriction and vasodilation to regulate blood flow to conserve or disperse heat throughout the body (Charkoudian, 2003). When an individual experiences slight environmental temperature deviations, the capacity of the thermoregulatory system is effectively able to cope with these minor deviations via minor vasoconstriction or vasodilation responses. However, when environmental temperature conditions are extreme (extreme hot or cold), the capacity of the thermoregulatory system to adapt and maintain adequate body temperature decreases. Eventually, the thermoregulatory system is unable to return the individual back to stasis and the individual experiences life-threatening conditions (hypothermia or hyperthermia).

It is important to highlight the roles task demands and associated operator workload play in this model when applying it to cognitive fatigue. TOT is a necessary component to produce task-related cognitive fatigue and can be conceptualized as a constant, unidirectional contributor to task-related cognitive fatigue. That is, as TOT increases, operators will generally experience a higher degree of cognitive fatigue and performance decrements (Ackerman, 2011). However, workload can vary along a bipolar continuum of underload and overload, where workload interacts with TOT to produce differing fatigue states. According to Hancock and Warm's (1989) model, the stress of fatigue is predicted to produce negative outcomes during both high and low task workloads. Task workload and TOT act as input forms of stress, which in turn propagate through the adaptive systems to reduce dynamic adaptability and negatively affect performance outcomes.

With active and passive fatigue, each fatigue state results from task demands being too high or too low, respectively, for an extended TOT. Prolonged high task demands reduce the ability of operators to adapt, resulting in a state of active fatigue. Contrastingly, in a state of underload, operators still experience a reduced capacity to adapt to stress, but in this case, a different set of behavioral performance strategies are adopted than active fatigue due to constant system monotony and passive fatigue results (Kober, Cingel, Zimmermann, & Bengler, 2015; Saxby et al., 2013).

Compensatory control model. The compensatory control model (CCM; Hockey, 1993, 1997, 2005, 2011) can be used in conjunction with the stress adaptation model proposed by Hancock and Warm (1989). This model proposes that individuals adapt via a goal-effort balance. Accounting for sustained performance under stress, the CCM assumes that operator behavior is orientated toward maintaining set task performance goals and is modified through a mental effort self-regulatory process. The self-regulation of effort is upheld by two negative feedback loops in which operators assess how well their current performance coincides with set goals and make necessary adjustments in behavior to resolve discrepancies. Two feedback loops make behavioral adjustments via effort implementation. A lower loop adjusts behavior in response to discrepancies that are relatively minor and require little effort to adapt to. This lower loop is said to be under automatic control. In contrast, an executively controlled upper loop is activated when an *effort monitor* detects large discrepancies between goals and performance (e.g., large altitude deviations). When the effort monitor detects severe inconsistencies between goals and task performance, individuals choose one of two options, via executive control, to protect from threats to a performance/goal balance. First, operators may choose to maintain task performance goals and mobilize more effort. Although task performance is preserved, a higher effort cost is experienced. Generally, this is referred to as a "strain" coping mode. Second, operators may choose to conserve effort at the cost of lowered performance standards. This option is referred to as a "disengagement" coping mode. Effort is conserved but performance will likely decline resulting from operator disengagement from the task.

Active and passive fatigue have recently been conceptualized as being the byproducts of Hockey's (1997) strain and disengagement modes of workload adaptation, respectively (Saxby et al., 2013). More specifically, continuous high workload task demands require operators to maintain/increase effort to stabilize task performance, but at a higher energetic cost (effort with distress). Strain mode operators may be able to maintain performance but will likely demonstrate elevated subjective fatigue symptoms (e.g., tiredness) and physiological markers of fatigue (van der Linden, 2011). Operators in disengagement mode would correspond to passive fatigue states and experience a decrease in goal directed effort and may exhibit withdrawal from the task, resulting in reduced performance due to maladaptive workload regulation (distress without effort; Hockey, 2011). Passive fatigue would then result in decreased subjective and physiological indicators of task engagement.

Support for stress adaptation and effort regulatory theories. Stress adaptation and effort regulatory theories of fatigue and human performance have gained support from combinations of physiological and behavioral studies. For instance, disruptions of dopaminergic pathways have shown patterns of behavior consistent with the performance outcomes of decreased effort regulation. Correa, Carlson, Wisniecki, and Salamone (2002) investigated changes in the amount of effort rats were willing to expend to receive a reinforcer after receiving antagonistic dopamine injections to the nucleus accumbens. Groups of rats were trained to receive a food pellet via low effort or higher effort interval reinforcement schedule. Rats in the low effort group were trained to receive food pellets after pressing a lever for 30 s. The high effort condition required rats to make five additional lever presses after the 30 s response interval to receive the food reward. After receiving dopamine depleting injections, rats in the high effort interval reward schedule obtained fewer food pellets than rats in the low effort condition. That is, rats in the high effort condition were no longer able to expend higher levels of effort to achieve the food reward. Van der Linden (2011) points out that the rats were still interested in food (as evidenced by their continued seeking of food in the low effort condition) but were unable to allocate effort to achieve the reward when extra effort was required. This animal model of fatigue demonstrates that although the propensity for carrying out food seeking behavior remains, disruptions in physiological systems tied to the employment of effort ultimately lead to overt behavioral deficits linked with task performance.

Manipulations of motivation have also been shown to alter effort and performance. Hopstaken et al. (2016) demonstrated that manipulations of task motivation can reverse markers of fatigue in the subjective, behavioral, and physiological domains. Participants performed an *n*-back task for 1.75 hr under normal motivational conditions. Then, for a final 15 min block, participants were told they could leave the experiment early if they could maintain high performance for the remaining block. Before the motivation manipulation, subjective fatigue ratings increased over time along with decreases in task performance, pupil diameter, P300 event related potential (ERP) amplitude, and subjective reports of engagement. After the motivation manipulation, however, ratings of subjective fatigue decreased and ratings of engagement increased. Moreover, task performance, pupil diameter, and P300 amplitude increased. Thus, the results from this study support an effort regulatory hypothesis of fatigue-performance interaction rather than a strictly resource-based explanation. If participants were experiencing fatigue-related decrements as a result of depleted attentional resources, manipulations of motivation should not have allowed for participants to re-engage in the task and increase their performance. Moreover, the behavioral changes in task performance were accompanied by changes in physiology as well, indicating a system-wide interaction between goal states and effort regulation postulated by stress adaptation and effort regulatory theory (Hancock & Warm, 1989; Hockey, 1997).

The conceptualization of active and passive fatigue also provides support for these general models. As shown by Saxby et al. (2013), active and passive fatigue can be induced experimentally by manipulating task demands. Additionally, Saxby and colleagues observed driving performance decrements during passive fatigue conditions, lending support to effort regulatory models of cognitive fatigue and human performance as opposed to a strictly resource theory account. Briefly, resource theories of cognitive fatigue and human performance conceptualize energetic cognitive resources as mechanistic “fuel” or “electric charge” utilized during task performance. As TOT increases, resources are depleted, performance decrements become evident, and subjective feelings of fatigue arise (Ackerman, 2011; Griffith, Kerr, Mayo, & Topal, 1950; Grandjean, 1968; Ryan, 1947). Only through rest and time-off-task are resources replenished and task performance returns to normal levels (Hartzler, 2014). Ackerman (2011) modeled fatigue as an electrical circuit consisting of two batteries representing an individual’s effort (resources) available for task performance. One larger battery represents an individual’s main source of resources and a smaller battery represents an individual’s reserve resources, which can be utilized once the main battery has been depleted. In this model, the main battery of resources is discharged as a function of TOT performance and off-task distractions. Individuals may choose to mobilize reserve effort once main resources are depleted. Although resource theory intuitively makes sense, it cannot adequately explain the findings relating to decreased task performance during underload conditions (Desmond & Hoyes, 1996; Desmond & Matthews, 1997; Saxby et al., 2013) or motivation manipulations that reverse subjective, physiological, and performance indicators of cognitive fatigue (Hopstaken et al., 2016).

In summary, active and passive fatigue have been shown to be experimentally induced by varying task workload. Moreover, previous studies have found active and passive fatigue to present with different performance outcomes as well as subjective operator states relating to task engagement and affect (Saxby et al., 2013). Active and passive fatigue can both be said to be fatiguing but differ in their etiology and progression of operator coping mechanisms. Adaptive theories of stress and effort regulation predict differences in the manifestation of both active and passive fatigue states via maladaptive, executively controlled workload regulation processes resulting in the adoption of task performance strategies ill-equipped for maintaining task performance. Although active and passive fatigue have been shown to differ in terms of subjective states and driving related performance, the use of psychophysiological measures to differentiate these states has yet to be explored.

Cognitive Fatigue Assessment and Electroencephalographic Correlates

The assessment of an operator's functional state utilizes a multidimensional approach (RTO, 2004; Wickens & Tsang, 2015). Although the goal of operator functional state (OFS) assessment is to monitor the operator for performance breakdowns, using task performance in isolation is not a reliable means to measure the state of the operator due to compensatory effort effects (Hockey, 1997). Therefore, OFS should be assessed with measures from multiple domains. These domains include performance-based measures (e.g., primary and secondary tasks), subjective metrics (self-report questionnaires), and psychophysiological measurements (e.g., electroencephalography; RTO, 2008; Wickens & Tsang, 2015). Performance-based and subjective metrics are lucrative if researcher experience and funds are not adequate. Moreover, performance-based metrics allow researchers to determine how primary task and secondary task performance is affected by OFS manipulations. However, these metrics also have drawbacks. For instance, individuals may report high levels of cognitive workload or fatigue, but their performance may remain within acceptable limits, demonstrating a metric disassociation (Wickens & Tsang, 2015). Subjective measures also do not allow for continuous, real-time measurement and can be subject to situational demand biases. Furthermore, subjective measures cannot be monitored by operational augmented cognition systems for real-time system adaptation.

Assessing cognitive fatigue via psychophysiological measures creates opportunities for operational environments. Compared to subjective and performance measures, psychophysiological measures operate in real-time and thus can serve as a source of input for augmented cognition systems (e.g., adaptive automation; adaptive aiding). Moreover, psychophysiological measures allow for fatigue states to be detected without the intrusion of a secondary task or disruptions in normal operational flow (Kramer, 1991; Parasuraman, 2015).

Several physiological responses have been associated with cognitive fatigue; however, electrophysiological activity of the outer cortex measured via electroencephalography (EEG) is regarded as the most reliable physiological measure of cognitive fatigue (Lal & Craig, 2001; Simon et al., 2011). Using EEG to assess cognitive fatigue has been implemented in a variety of applied settings including aviation (e.g., Caldwell et al., 2002) and driving (e.g., Zhao, Zhao, Liu, & Zheng, 2012). Changes in EEG bandwidth frequency (i.e., delta, theta, alpha, beta) power spectral densities (PSD) are associated with task performance outcomes during sustained task performance (Besserve et al., 2008), making EEG a useful means for evaluating OFS and inferring cognitive states associated with task performance (Berka et al., 2007). Reviews of the cognitive fatigue literature have shown characteristic PSD changes in EEG bandwidths associated with increased TOT and cognitive fatigue effects. For instance, Borghini et al. (2014) reviewed the literature pertaining to physiological measures of cognitive fatigue in pilots and drivers. In their review, Borghini and colleagues concluded that cognitive fatigue is associated with increased slow-wave EEG oscillations. More specifically, increases in frontal midline theta and alpha power are associated with cognitive fatigue. Increases in alpha and decreases in beta power in posterior brain regions (i.e., parietal, occipital) were also reported in several driving studies. An earlier review conducted by Lal and Craig (2001) reported similar findings relating to increased slow-wave oscillations, specifically, increased overall delta, theta, and alpha activity with the onset of cognitive fatigue.

Sleep deprivation studies in aviators have demonstrated similar trends. Caldwell et al. (2002) investigated changes in EEG power spectra in U.S. Army UH-60 Blackhawk helicopter pilots during actual flight maneuvers during 26 hr of continuous wakefulness. Pilots woke at 0700 and stayed awake through 0900 the next day. Over the course of sleep deprivation, pilots flew three, 1.5 hr flights at 2300, 0400, and 0900. Across the three flights, reliable linear increases in central and frontal midline theta power were observed. Moreover, linear increases in alpha power were observed in parietal, frontal, and central midline sites. These changes in EEG were accompanied by increases in subjective fatigue and negative affect. Continuing this line of research, Caldwell and colleagues (2004) investigated the effects of 37 hr of continuous wakefulness on EEG variables, simulated flight performance, and mood in Air Force F-117A Nighthawk pilots. Participants flew five simulated flights over the course of sleep deprivation. As sleep deprivation progressed, pilots exhibited increases in delta and theta activity at central and parietal midline sites. Progressive flight performance decrements and negative affect accompanied these changes.

Laboratory-based experiments have generally corroborated applied studies. A study examining cognitive fatigue over the course of extended of neuropsychological testing showed similar trends in the EEG power spectrum (Barwick et al., 2012). From pre to post testing, theta power in frontal regions and alpha power in parietal regions increased, while beta power decreased in parietal regions. These EEG changes were accompanied by increased subjective cognitive fatigue. Wascher et al. (2014) tracked changes in EEG PSD while participants performed a stimulus-response correspondence task for a duration of 4 hr. Results indicated that frontal theta power slowly increased with TOT and alpha power in the occipital region increased rapidly as time progressed.

Efforts have also been focused on deriving reliable indices of operator states, including cognitive fatigue, from EEG PSD markers. One such indicator is the task load index (TLI; Gevins & Smith, 2003; Smith, Gevins, Brown, Karnik, & Du, 2001). The TLI is computed by taking the ratio of frontal midline theta power to parietal alpha power (Fz theta/Pz alpha). The TLI is based on research demonstrating frontal midline theta activity is associated with executive control processing (Gevins et al., 1998; Itthipuripat, Wessel, & Aron, 2013; Kawasaki, Kitajo, & Yamaguchi, 2010) and decreased parietal alpha activity being associated with increased task load (Borghini et al., 2014; Fournier, Wilson, & Swain, 1999; Gevines et al., 1998). Cyclic changes in task demands have been shown to alter TLI ratios such that increased task difficulty resulted in increased TLI scores and unloading resulted in decreased TLI scores (Hockey, Nickel, Roberts, & Roberts, 2009). More importantly, Hockey et al. (2009) proposed the TLI could be used as a marker of cognitive fatigue because of the relationship between frontal theta activity and effort regulation responses to fatigue. Hockey and colleagues stated, "Given the basis of executive activity in frontal brain processes, the prediction is made most strongly supported for the TLI measure, where reduced use of executive control under fatigue may produce lower levels of theta activity" (p. 1012). Reduced executive control associated with cognitive fatigue would result in decreased theta activity in frontal regions responsible for executive control. Corresponding increases in parietal alpha are also expected as predicted from sleep deprivation studies (e.g., Caldwell et al., 2002). Thus, cognitive fatigue would result in a decreased TLI ratio due to disengagement from the task and maladaptive executive control effort responses. However, if participants are expending substantial effort to preserve task performance, increases in frontal midline theta may result in increased TLI ratios. Indeed, previous researchers have reported increases in frontal midline theta power after prolonged task performance, potentially as a result of increased task-directed effort (e.g., Wascher et al., 2014). The TLI ratio may, therefore, reflect either a unique effort construct or reflect executively controlled workload regulation. More research is needed to clarify the relationship between TLI ratios and fatigue states.

Overall, EEG studies generally support changes in the theta, alpha, and beta bands with cognitive fatigue. Changes in these bands are viewed as being indicative of sleepiness and on the verge of entering Stage 1 sleep (Lal & Craig, 2001; Purves et al., 2012). Thus, EEG measures provide a reliable means to evaluate the progression of cognitive fatigue over the course of advanced simulation performance. Because EEG can continually monitor an operator, EEG can potentially differentiate between active and passive fatigue states during task performance. Currently, no studies have investigated whether EEG variables demonstrated differing patterns during active or passive fatigue onset.

The Current Study

The current study had two main purposes. First, it expanded the understanding of active and passive fatigue by incorporating continuous EEG measurements throughout the fatigue induction process to monitor and differentiate between the onset of active and passive fatigue states. Previous research on active and passive fatigue has only incorporated subjective measures of task engagement and workload administered post-task (e.g., Saxby et al., 2013). Psychophysiological measures allow for engagement and workload to be tracked throughout fatigue induction and can provide potentially valuable insight into underlying executively controlled effort regulatory processes that have been theorized to be indicative of the differences between active and passive fatigue. Distinctive EEG profiles should differentiate passive and active fatigue because of physiological costs associated with strain due to continuous high workload (active fatigue) or effort under regulation due to underload, resulting in task disengagement (passive fatigue; van der Linden, 2011). In conjunction with EEG, this study incorporated subjective and performance metrics to ascertain a holistic picture of active and passive fatigue as recommended in OFS assessment (Wickens and Tsang, 2015).

Second, this study tested if manipulations of active and passive fatigue (Desmond & Hancock, 2001) exhibit similar effects on individuals outside of the driving simulator environment. Previous research has only manipulated active and passive fatigue within the context of simulated driving. If active and passive fatigue are general fatigue constructs, they should be evident across different experimental tasks and manipulations. To accomplish this goal, this study utilized the Multi-Attribute Task Battery-II (MATB; Santiago-Espada, Myer, Latorella, & Comstock, 2011), a low-cost, computer-based multitasking simulator readily available to researchers.

This study tested five hypotheses relating active and passive fatigue to overt task performance, EEG variables, and subjective ratings of workload, task engagement, and alertness:

Hypothesis 1: Active fatigue should exhibit higher ratings of subjective workload and task engagement compared to passive fatigue. This hypothesis aims to replicate the findings of Saxby et al. (2013).

Hypothesis 2: Subjective ratings of alertness should decrease in both active and passive fatigue manipulations from pre to post fatigue induction, demonstrating that each manipulation produces subjective accounts of fatigue. In other words, both conditions could be said to be fatiguing.

Hypothesis 3: Over the course of fatigue induction, active fatigue should exhibit higher EEG metrics of task engagement and workload. On the other hand, passive fatigue should demonstrate consistently low EEG engagement and workload during fatigue onset. TLI ratios will also differ between fatigue conditions, with passive fatigue potentially exhibiting lower TLI ratios due to reductions in executive control workload regulation strategies.

Hypothesis 4: Overt performance decrements will be more pronounced in participants exposed to passive fatigue compared to active fatigue due to maladaptive workload regulatory strategies adopted during fatigue induction, resulting in less effort employed during task performance evaluations. During performance evaluations, passive fatigue participants may demonstrate increased workload, but consistently low EEG indices of engagement.

Hypothesis 5: In accordance with Hypothesis 4, during performance evaluations, those exposed to prolonged passive fatigue conditions will demonstrate lowered EEG indices of engagement due to maladaptive workload regulation strategies compared to those exposed to active fatigue conditions.

The implications of this study lie in the utility for designing appropriate cognitive fatigue countermeasures within transportation vehicles. One countermeasure may be appropriate for passive fatigue conditions, but not for active fatigue conditions. Indeed, May and Baldwin (2009) stressed that differentiating between active and passive fatigue states is vital for employing the proper fatigue countermeasure. Applying automation may be useful in curtailing high workload that may lead to active fatigue but may be inadequate for counteracting passive fatigue. Countermeasures that increase engagement may be necessary for passive fatigue environments. Therefore, using EEG to identify cognitive fatigue states with augmented cognitions systems can be instrumental in deploying correct cognitive fatigue countermeasures (May & Baldwin, 2009).

CHAPTER II

METHOD

Participants

Ninety-five undergraduate students from the University of North Dakota were recruited to participate in this study. After excluding participants for not completing the study (n = 6) and not possessing 20/20 or corrected to 20/20 vision (n = 5; evaluated via self-report), a final usable sample size of 84 (25 males and 59 women) was retained. Participant ages ranged from 18-30 years (M = 19.13, SD = 1.92). No participants reported any form of traumatic brain injury within the past year. Approximately half of the participants (n = 44) completed the study during the morning (0800-1200) and the remaining participants (n = 40) completed the study during the afternoon (1200-1700).

Materials

Simulation

The Multi-Attribute Task Battery-II (MATB; Santiago-Espada, Myer, Latorella, & Comstock, 2011) was used to induce cognitive fatigue and to assess changes in performance. The MATB is a computerized multitasking workload simulator that mimics the cognitive tasks pilots frequently encounter during flight; however, the MATB was designed to be used by participants with and without aviation experience (Santiago et al., 2011). A screenshot of the MATB interface is displayed in Figure 1. The MATB is a flexible workload simulation platform that allows researchers to manipulate task demands and has been widely used in human factors research including studies investigating cognitive fatigue and workload (e.g., Caldwell et al., 2000; Caldwell et al., 2004; Caldwell & Ramspott, 1998; Fournier et al., 1999; Wilson, Caldwell, & Russell, 2007). There are four subtasks included within the MATB. These subtasks include system monitoring, communications, tracking, and resource management. The following describes each subtask.

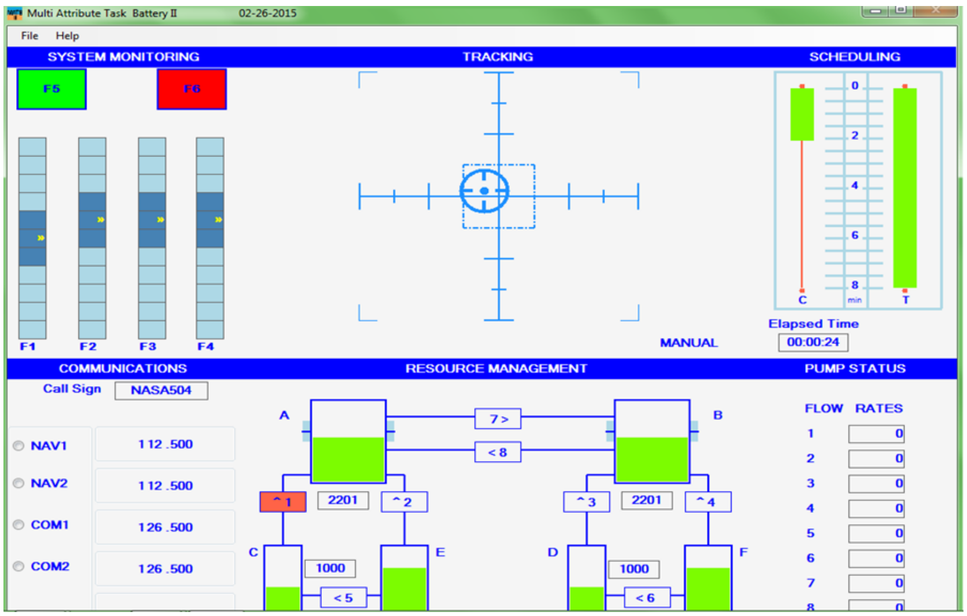

Figure 1. A screenshot of the Multi-Attribute Task Battery-II display (Santiago-Espada et al., 2011) with system monitoring (upper left), tracking (upper center), communications (lower left), and resource management (lower center) subtasks.

System monitoring. The system monitoring subtask (see Figure 1 top left) required participants to monitor lights and moving scales for changes. Responses were made via a standard keyboard. Two lights were located above four scales (see Figure 1 top left). The left light was to remain green and the right light was to remain colorless. If the green light turned grey, participants pressed the F5 key on the keyboard to bring the green light back. In a similar fashion, if the right light turned red, the participant pressed the F6 key on the keyboard to return the light back to grey. The four oscillating scales below the lights correspond to the keys F1, F2, F3, and F4 on the keyboard. When a scale deviated substantially from the center (i.e., the sliding bar touches either the top or the bottom of the scale), participants pressed the corresponding F key to bring the scale back to a normal status. A normal system state consisted of a green left light, grey right light, and center-oscillating scales. Any deviation from this normal state required participants to press the appropriate key to return the system back to stasis. No performance measures for this task were analyzed in this study.

Tracking. For the tracking subtask (see Figure 1 top center), participants attempted to keep a circular reticle inside of a box centered at the intersection of two crosshairs with the use of a joystick. The MATB program randomly pulled the circular reticle outside of the box and participants continuously compensated with the joystick to keep the reticle centered. The tracking task can be programmed to be either in automatic response mode (requiring no participant input) or manual response mode. Performance was measured in root-mean-square deviation from the center point in pixels.

Communications. The communications task required participants to respond to auditorily presented, simulated air traffic control (ATC) radio frequency change commands. Participants only responded to commands pertaining to their call sign (NASA504) and ignored all others. For example, a command may have stated, “NASA five zero four, NASA five zero four, tune your nav two radio to frequency one one two point five zero zero." The participant would use the mouse to select the nav two radio, dial in the correct frequency, and click enter when finished. Performance measures included frequency change reaction time and proportion of transmissions correctly responded to.

Resource management. The resource management task was not utilized in this study.

Simulation sequence, parameters, and conditions. Three, 62 min MATB simulations were developed during a pilot study (N = 35) to eliminate potential ceiling effects in performance. One was programmed to produce active fatigue, one to produce passive fatigue, and one as a control condition. Each simulation consisted of two, 6 min performance evaluations – one prior to fatigue induction and one post fatigue induction. These performance evaluations were consistent across conditions. Separating the two performance evaluations was a 50 min fatigue induction period. The fatigue induction periods differentiated the three fatigue conditions. Auditory cues directed participants when to perform the subtasks corresponding to either the performance evaluation or fatigue induction periods. The following describes the parameters for each simulation.

Performance evaluations. Performance evaluations required participants to perform the tracking and communications tasks simultaneously. This combination of tasks was chosen because it mimics emergency situations where pilots must respond to air traffic control commands as well as manually control the aircraft. Moreover, the communications task requires participants to use higher-order cognitive processes, including response inhibition and working memory, which have been shown to be negatively affected by cognitive fatigue (van der Linden, 2011).

Before the onset of the communications task, participants manually controlled the tracking task for 30 s in isolation. After this 30 s, 22 randomized simulated air traffic control radio calls (11 calling the participant's call sign) occurred at 10 s intervals. Participants were required to respond with correct radio frequencies for their call signs within 5 s after the conclusion of the call to avoid a timeout error. The tracking task was set at the highest difficulty.

Active fatigue induction condition. To induce active fatigue, participants performed the system monitoring and tracking subtasks together during the 50 min fatigue induction period. The system monitoring task consisted of approximately 8 to 10 events per min. Participants had 10 s to respond to these events to avoid a timeout error. The tracking task was set to the highest difficulty, requiring participants to make significant psychomotor adjustments throughout the MATB simulation. The aim of this condition was to elicit high workload and continuous perceptual-motor adjustments, the two defining characteristics of active fatigue (Desmond & Hancock, 2001; Saxby et al., 2013).

Passive fatigue induction condition. In the passive fatigue induction condition, the tracking task was automated and participants responded to only the system monitoring task. Critical system monitoring events were infrequent, occurring once approximately every 4 to 7 min. Critical signals were only the red light. This condition reflects the primarily system monitoring role of the operator that characterizes passive fatigue as proposed by Desmond and Hancock (2001).

Control condition. A control condition consisted of only the system monitoring task modified to mimic a paced psychomotor vigilance test (PVT). In this condition, the red light illuminated every 10 s throughout fatigue induction. As with the passive fatigue condition, the tracking task was automated. The justification for including this control condition was to compare the manipulations of active and passive fatigue to a common vigilance paradigm that results in task-related fatigue effects.

Subjective Measures

Subjective measures of participant alertness, task engagement, and workload were collected to replicate prior research and to achieve a comprehensive OFS assessment paradigm.

Karolinska Sleepiness Scale. The Karolinska Sleepiness Scale (KSS; Akerstedt & Gillberg, 1990) was used to track subjective ratings of alertness indicative of cognitive fatigue from pre to post fatigue induction. The KSS is a single item scale that requires participants to rate their current level of alertness ranging from 1 (*extremely alert*) to 9 (*extremely sleepy/fighting sleep*). The KSS was developed in accordance with EEG PSD markers of sleepiness and demonstrates good correlations with EEG markers of sleepiness (r = .40-.56; Akerstedt & Gillberg, 1990; Kaida et al., 2006) and PVT performance decrements (r = .57; Kaida et al., 2006). Moreover, the KSS correlates significantly with other subjective measures of sleepiness (e.g., visual analogue scale for sleepiness; r = .89; Kaida et al., 2006). A recent study examining fatigue in regional airline pilots demonstrated that the KSS shows linear increases (less reported alertness) in subjective alertness in pilots over a 14 hr flight shift (Honn, Satterfield, McCauley, Caldwell, & Van Dongen, 2016). Overall, the KSS is a reliable and valid tool for evaluating subjective alertness (Kaida et al., 2006).

Short Stress State Questionnaire. The engagement scale of the Short Stress State Questionnaire (SSSQ; Helton, 2004) was used to track subjective engagement. The SSSQ is a shorted version of the Dunde State Stress Questionnaire (DSSQ; Matthews et al., 2002) and consists of 24-items that load on the three higher order factors of task engagement, worry, and distress. The 24-items are administered prior to completing a task and immediately after. SSSQ higher order factors have been shown to have good reliability (Cronbach's α =.80-.89) and are sensitive to different types of tasks and task stressors (Helton & Näswall, 2015). Higher scores indicate more task engagement.

NASA-Task Load Index. Subjective workload was assessed with the NASA-Task Load Index (NASA-TLX; Hart & Staveland, 1988). The NASA-TLX consists of six subscales that relate to task demands (physical, mental, temporal) and to the internal state of the rater (frustration, performance, effort). An average composite workload rating is computed from these subscales ranging from 0-100, with higher scores indicating higher levels of subjective workload. The NASA-TLX was embedded within the MATB platform allowing participants to rate each scale by moving sliders with the computer mouse. The NASA-TLX has strong convergent validity with other measures of workload (r = .98-.97) and good concurrent validity with measures of task performance (r = .65-.75; Rubio, Diaz, Martin, & Puente, 2004). Internal reliability the NASA-TLX is high

(Cronbach's α = .82; De la Torre, Ramallo, & Cervantes, 2016). Composite NASA-TLX scores were used as a measure of subjective workload.

Covariates. Potentially confounding results was an individual's pattern of daily sleepiness while performing certain activities. The Epworth Sleepiness Scale (ESS; Johns, 1991) was used as a self-report measure of daytime sleepiness. The ESS is an 8-item questionnaire that asks participants to rate their chances of dozing when completing various activities (e.g., sitting and reading) during daily life on a scale from 0 (*would never doze*) to 3 (*high chance of dozing*). Higher total scores indicate higher levels of daytime sleepiness. The ESS has a high internal reliability (Cronbach's α = .73-.88) and a high test-retest reliability (r = .82; Johns, 1992). In addition to daytime sleepiness, participant sleep quality and sleep duration from the previous night were recorded. Participants rated their previous night's sleep quality on a scale from 1 (*very poor*) to 5 (*very good*). Participant sleep duration was evaluated with self-report bed and wake times.

Furthermore, participants were evaluated for oculomotor symptoms characteristic of convergence insufficiency (CI). Individuals with CI often experience increased fatigue, eye-strain, and blurred vision during close tasks such as reading (Arnoldi & Reynolds, 2007), which could potentially confound task performance and subjective accounts of fatigue and engagement. The Convergence Insufficiency Symptom Survey (CISS; Borsting, Rouse, & De Land, 1999) was used to measure oculomotor symptoms characteristic of CI. The CISS is a 15-item questionnaire that asks participants to rate how their eyes feel when reading or doing close work on a scale of *never*, *infrequently,* *sometimes, fairly often, and always*. Higher scores indicate more CI symptom endorsement. The CISS has been shown to be both a valid and reliable tool for identifying CI (Borsting et al., 2003; Rouse et al., 2004), but is used in conjunction with other measures to formally evaluate CI. Thus, this tool only allowed for a general assessment of oculomotor symptoms characteristic of CI.

Prior night's sleep duration and sleep quality sleep quality, total ESS scores, and total CISS scores were explored as continuous covariates in main analyses.

Electroencephalography (EEG) Recordings

Changes in cortical electrical activity were recorded using the Advanced Brain Monitoring (ABM) X-10 and X-24 wireless Bluetooth systems. Forty-six participants were tested with the X-10 and 36 were tested with the X-24. These EEG platforms are well suited for recording EEG in complex operational environments and have been implemented in human factors studies involving simulations (e.g., Matthews, Reinerman-Jones, & Barber, 2015). The X-10 and X-24 are identical systems except the X-24 supports more electrodes than the X-10. The X-10 incorporates a 9-channel electrode strip with electrode locations placed according to the international 10/20 system: F3, Fz, F4, C3, Cz, C4, P3, POz, and P4. The X-24 incorporates a 20-channel electrode strip with electrodes placed at Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, POz, O1, and O2. Reference electrodes for both systems were placed at the mastoids. Despite the differences in the number of channels, these systems output the same variables from the shared electrode sites.

Data were sampled at 256 Hz and filtered with 50, 60, 100, and 120 Hz notch filters as well as a Low Pass FIR filter online during the data collection process. Power spectral density (PSD) was then calculated on a second-by-second epoch frequency by applying a 50% overlapping Kaiser window for data smoothing to three data point windows consisting of 256 decontaminated data points each. These data were then subject to Fast Fourier Transformation to acquire four standard bandwidths of delta (1-2 Hz), theta (3-7 Hz), alpha (8-13 Hz) and beta (13-29 Hz) with PSD values produced on a second-by-second epoch basis. Prior to computing PSD values, raw signals were processed to eliminate known artifacts (e.g., electrooculographic signals) by the B-Alert live software (ABM, 2009).

ABM algorithms using discriminant function analysis (Berka et al., 2007) then computed cognitive state metric probabilities of high engagement and workload, ranging from 0.00 to 1.00, based on subsets of absolute and relative PSD values from specific electrode sites. Higher values indicated a higher probability of being in an engaged or overload state, respectively. Additionally, the task load index (TLI; Gevins & Smith, 2003; Smith, et al., 2001) was computed for each epoch by taking the ratio of frontal midline theta (Fz) PSD to parietal-occipital midline alpha PSD (POz). That is, the relative power of Fz theta divided by the relative power of POz alpha. This metric was proposed by Hockey et al. (2009) as a potential indicator of cognitive fatigue. It should be noted that the TLI was initially defined as the ratio of Fz theta to Pz alpha (Fz theta/Pz alpha) However, because the X-10 does not include a Pz electrode site, POz was used instead.

Summary of Outcome Measures

To summarize, performance measures, EEG metrics, and subjective ratings were used as outcome measures. Workload was measured with NASA-Task Load Index composite scores and Advanced Brain Monitoring's EEG workload metric. Task engagement was measured with the SSSQ task engagement scale and Advanced Brain Monitoring's EEG engagement metric. Additionally, the TLI (defined as the ratio of Fz theta power to POz alpha power) was used as a candidate marker of cognitive fatigue. Subjective alertness was evaluated with the KSS. Overt task performance measures included MATB communications subtask reaction times, proportion of communications task correct responses, and tracking subtask root-mean-square deviations. Potential covariates included trait daytime sleepiness (measured via the ESS), oculomotor symptoms characteristic of CI (measured via the CISS), previous night's sleep duration, and previous night's sleep quality (each measured via self-report).

Procedure

After arriving at the laboratory, participants provided written consent and then completed a demographics questionnaire, which included questions regarding sleep quality and duration. After this questionnaire, participants completed the CISS, ESS, and pre-task versions of the SSSQ and KSS. A research assistant then applied the EEG system to the participant's head and tested electrode impedances. Any electrodes exceeding the manufacture's recommended impedance threshold of 80 KΩ (ABM, 2009) were adjusted. Then, participants performed three neurocognitive benchmark tests (3-choice vigilance task, visual psychomotor vigilance task, auditory psychomotor vigilance task) provided by the B-Alert Live software to normalize ABM's engagement metric.

Participants then watched an instructional video describing how to complete the MATB. After this video, participants completed a 12 min, research assistant facilitated, MATB practice session. During the practice session, participants completed each MATB subtask individually for 3 min each followed by a 3 min performance evaluation. Baseline EEG data were recorded throughout the MATB training and practice sessions to obtain a large sample of possible EEG responses for experimental data normalization (Fishel, Muth, & Hoover, 2007). This period included periods of both high activation and low activation to reduce bias in detecting changes in cognitive states. Once the practice session was complete, participants were randomly assigned to either the passive (n = 31), active (n = 26), or control (n = 27) conditions and given an appropriate briefing for their condition. Then, the 62 min MATB simulation commenced, following a pre-fatigue induction performance evaluation (6 min), fatigue induction (50 min), post-fatigue induction performance evaluation (6 min) simulation sequence. During the simulation, participants completed the NASA-TLX 25 min into the fatigue induction period and at the end of the fatigue induction period. After the MATB testing session, participants completed post-task versions of the KSS and SSSQ.

Data Processing and Analytics

EEG data during the MATB scenario performance evaluations and fatigue induction were sectioned off using timed markers. Fatigue induction was separated into 10 min intervals. For each 10 min fatigue induction interval and both performance evaluations, 5% trimmed means were computed for EEG indices to improve distribution normality. EEG indices were then individually baseline adjusted for each participant using *z*-scores.

Outcome measures were analyzed with multilevel linear models (Field, Miles, & Field, 2012) using the *nlme* package (Pinheiro, Bates, DebRoy, Sarker, & R Core Team, 2017) for R (R Core Team, 2017). For these models, Time served as a within-subjects factor and Fatigue Condition served as a between-subjects factor. Running a mixed model designs as multilevel linear models instead of an ANOVA approach has several advantages. First, multilevel linear models handle missing data without the need for list-wise deletion. Second, multilevel linear models do not require the assumptions of homogeneity of variance or sphericity. Third, continuous covariates are handled appropriately across within-subjects factors. Finally, the relative contribution of each predictor variable can be assessed with model fit comparison statistics (Field et al., 2012).

Models were specified iteratively adding one parameter at a time to successive models (West, Welch, & Alecki, 2015). Model parameters were computed using maximum likelihood estimation to allow for model comparison. Likelihood ratio tests using the Δ-2log likelihood between successive models were used to evaluate changes in model fit. Δ-2log likelihood is evaluated on a χ^2 distribution with degrees of freedom equal to the change in degrees of freedom between models being compared. A significant χ^2 statistic indicates that the added predictor has a significant effect on the dependent variable and improved model fit.

First, an intercept only null model was specified. Then, predictors were added one at a time to create successive models. For model specification, Time was added first followed by Condition and then the Time x Condition interaction. Finally, potential covariates (sleep quality, sleep duration, ESS total scores, CISS total scores) were added to the models to determine if their inclusion improved model fit. Where appropriate, Tukey post-hoc tests were conducted for significant effects using the *emmeans* package (Lenth, 2018) for R. Effect sizes (η^2) are reported for post hoc comparisons. Statistical significance was set at $\alpha = .05$.

Missing data were excluded pairwise for analyses where possible. Normality was assessed with boxplots and Shapiro-Wilk tests. Outliers were screened with a combination of z-scores ($z = \pm 3.29$; Field et al., 2012) and boxplots. Moreover, Cook's Distances were used to identify influential data points for constructed models. Potential outliers for an analysis were removed and the analysis was conducted again. No differences in any analyses were found with the removal of potential outliers (i.e., non-significant results turning significant or vice versa). No Cook's Distances for analyses exceeded 1.00, indicating no unduly influential data points in models (Field et al., 2012).

CHAPTER III

RESULTS

Preliminary Analyses

Means and standard deviations for the ESS, CISS, sleep quality, and sleep duration by fatigue condition are displayed in Table 1. Between-subjects, one-way ANOVAs revealed no differences between the fatigue conditions on potential covariate measures.

Significant negative correlations were found between sleep duration and NASA-TLX scores, indicating the longer participants slept the previous night, the lower they rated scenario workload at 25 min, $r(82) = -.32$, $p = .003$, and 50 min, $r(82) = -.35$, $p = .001$. A similar negative correlation between sleep quality and NASA-TLX rating was found, but only for ratings at 50 min, $r(82) = -.25$, $p = .020$. Furthermore, the CISS correlated positively with ESS scores, $r(82) = .38$, $p < .001$, and negatively with pre, $r(81) = -.29$, $p = .007$, and post, $r(78) = -.24$, $p = .031$, SSSQ engagement scores. The endorsement of more symptoms characteristic of CI was generally accompanied by higher daytime sleepiness and reduced reports of task engagement both pre and post MATB. Pre-KSS scores negatively correlated with pre, $r(82) = -.33$, $p = .002$, and post, $r(78) = -.30$, $p = .007$, SSSQ engagement scores, indicating the less alert participants reported being initially, the less engaged in the task they were (note that higher KSS scores indicated less alertness). Finally, a notable and consistent correlation was found between pre-KSS scores and TLI ratios for all time intervals of the fatigue induction period, average $r = .29$, $ps < .05$. This correlation indicates that the less alert participants felt before fatigue induction, the higher their TLI ratios throughout fatigue induction tended to be.

Table 1

Descriptive Statistics for the Epworth Sleepiness Scale (ESS), Convergence Insufficiency Symptom Survey (CISS), Sleep Duration, and Sleep Quality by Fatigue Condition

	Active		Passive		Control	
Measure	*M*	*SD*	*M*	*SD*	*M*	*SD*
ESS	7.50	3.50	7.32	3.65	6.74	3.72
CISS	14.50	7.50	16.20	8.13	15.78	6.19
Sleep Duration (hr)	6.77	1.26	7.39	0.87	7.35	1.27
Sleep Quality	3.38	0.75	3.65	0.61	3.70	0.78

Subjective Measures

Workload (NASA-TLX)

There was a significant main effect of Time, $\chi^2(1) = 13.31$, $p < .001$, and Condition, $\chi^2(2) = 28.08$, $p < .001$, on composite NASA-TLX scores. These main effects were qualified by a significant Time by Condition interaction, $\chi^2(2) = 11.88$, $p = .003$. The inclusion of ESS, CISS, sleep duration, and sleep quality as covariates did not improve model fit, $ps > .05$. Table 2 displays NASA-TLX descriptive statistics with post-hoc tests. Tukey post-hoc comparisons at each level of fatigue condition revealed that mean composite NASA-TLX scores for those in the active condition did not change from 25 min to 50 min. However, participants in the passive and control conditions rated workload as significantly lower at 50 min compared 25 min (see Figure 2). It should be noted that the effect size for the passive condition was substantially larger than that of the control condition. Additionally, NASA-TLX scores for the passive and control conditions were significantly lower at both rating periods compared to the active condition.

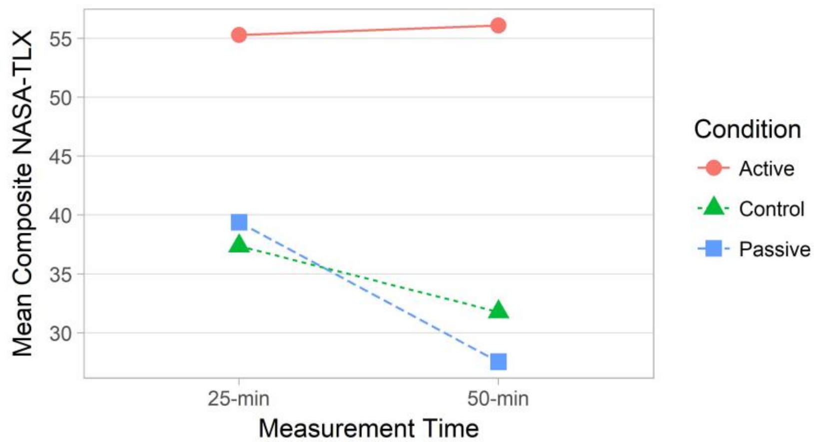

Figure 2. Mean composite NASA-TLX scores by fatigue condition and measurement time.

Alertness (KSS)

Initial analysis of KSS scores showed significant deviations from normality. To improve normality, KSS scores were $\log_{10}$ transformed. Transformed data were used in analyses, but untransformed means and standard deviations are reported. A significant main effect of Time was found, $\chi^2(1) = 25.02$, $p < .001$. This main effect was qualified by a significant Time by Condition interaction, $\chi^2(2) = 6.12$, $p = .047$. Tukey post-hoc tests at each level of condition (see Table 2) revealed that for the active condition, no significant changes were observed from pre to post MATB. Participants in the passive and control conditions reported significant increases in KSS scores, indicating a reduction in alertness. Importantly, the effect size for the passive condition was larger than the control group. This interaction is plotted in Figure 3. The main effect of Condition, $\chi^2(2) = 4.93$, $p = .085$ was not significant. Additionally, the inclusion of ESS, CISS, sleep duration, and sleep quality did not improve model fit, *ps* > .05.

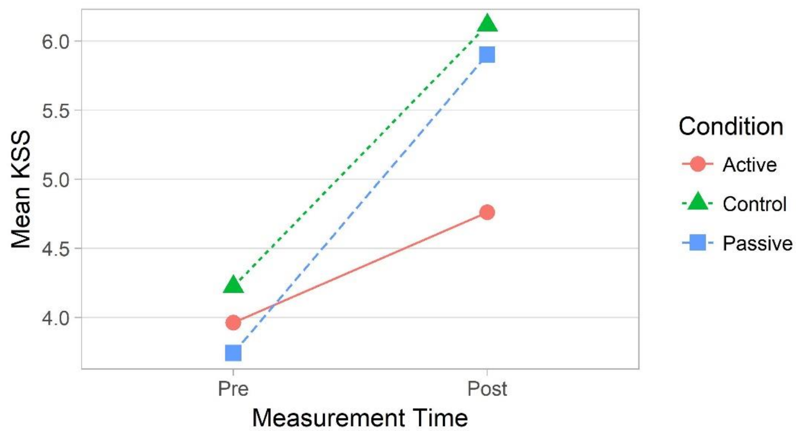

Figure 3. Mean Karolinska Sleepiness Scale (KSS) scores by fatigue condition and measurement time. Higher scores indicate less alertness.

Table 2

Descriptive Statistics and Pairwise Comparisons for NASA-TLX and Karolinska Sleepiness Scale (KSS) Scores by Fatigue Condition and Time

	Pre		Post				
Measure	*M*	*SD*	*M*	*SD*	*t*	*p*	η^2
NASA-TLX							
Active	55.29	13.84	56.09	17.32	-0.30	.766	.00
Passive	39.38	15.61	27.54	17.59	4.76	<.001	.23
Control	37.37	19.67	31.78	20.78	2.14	.035	.05
KSS							
Active	3.96	1.40	4.76	2.05	-1.06	.292	.01
Passive	3.74	1.41	5.90	1.92	-4.79	< .001	.22
Control	4.22	1.48	6.11	1.95	-3.51	< .001	.13

Note. Higher KSS scores indicate less alertness.

Engagement (SSSQ)

The main effect of Time was significant for SSSQ engagement scores, $\chi^2(1) = 25.62$, $p < .001$. The main effect of Condition, $\chi^2(2) = 3.32$, $p = .190$, and the Time by Condition interaction, $\chi^2(2) = 2.25$, $p = .325$, were not significant. However, the inclusion of CISS total scores as a covariate significantly improved model fit, $\chi^2(1) = 8.26$, $p = .004$. Estimated marginal means showed that engagement pre-MATB ($M = 3.65$, $SE = .07$) was significantly higher than post-MATB ($M = 3.27$, $SE = .07$), $t(78) = 5.32$, $p < .001$, $\eta^2 = .27$. Model parameters for the CISS covariate showed a negative relationship between engagement ratings and CISS total scores, $b = -0.02$, $SE = .01$. That is, the higher individuals scored on the CISS, generally the less engagement individuals reported, supporting preliminary analyses.

MATB Performance

Three participants were excluded from MATB performance analyses because of extremely poor performance. These participants responded correctly to less than 50% of the communications task radio calls.

Communications Task

Outcome measures for the communications task included reaction times and the proportion of correct responses. For reaction times, there was a significant main effect of Time, $\chi^2(1) = 9.54$, $p = .010$. Participant reaction times to correctly respond to radio calls significantly increased from pre-fatigue induction ($M = 2.93$, $SD = 1.05$) to post-fatigue induction ($M = 3.06$, $SD = 1.05$), $t(80) = -2.63$, $p = .010$, $\eta^2 = .08$. Neither the main effect of Condition, $\chi^2(2) = 5.25$, $p = .072$, nor the Time by Condition interaction were significant, $\chi^2(2) = 0.16$, $p = .925$. The inclusion of the ESS, CISS, sleep duration, and sleep quality did not improve model fit, *p*s > .05.

For the proportion of correct responses, there was a significant main effect of Time, $\chi^2(1) = 14.99$, $p < .001$. Overall, participants increased their accuracy from the first performance evaluation ($M = 0.85$, $SD = 0.12$) to the second performance evaluation ($M = 0.89$, $SD = 0.11$), $t(80) = -4.03$, $p < .001$, $\eta^2 = .17$. No significant effects for Condition, $\chi^2(2) = 3.42$, $p = .182$, or the Time by Condition interaction, $\chi^2(2) = 3.46$, $p = .184$, were found. The inclusion of the ESS, CISS, sleep duration, and sleep quality did not improve model fit, *p*s > .05.

In combination with the increased reaction times, these results suggest a speed-accuracy trade-off resulting from prolonged task performance. In other words, participants increased their response times in favor of higher accuracy.

Tracking Task

A significant main effect of Time was found for tracking RMSD values, $\chi^2(1) = 14.28$, $p < .001$. Tracking performance improved from the first performance evaluation ($M = 41.63$, $SD = 9.26$) to the second performance evaluation ($M = 38.87$, $SD = 7.91$), $t(80) = 3.93$, $p < .001$, $\eta^2 = .16$. No significant effects for Condition, $\chi^2(2) = 1.93$, $p = .380$, nor the Condition by Time interaction, $\chi^2(2) = 0.64$, $p = .727$, were found. No significant effects for the covariates were found, *p*s > .05. These tracking results further support a speed-accuracy trade-off in performance.

EEG Measures

Six participants were excluded from EEG analyses because of corrupt files. Three were excluded from the active condition, two were excluded from the control condition, and one from the passive condition.

EEG Engagement Metric

During the performance evaluations, no significant differences in the EEG engagement metric were found between the pre and post-fatigue induction performance evaluations, $\chi^2(1) = 0.05$, $p = .823$. Moreover, no significant differences were found between the fatigue conditions, $\chi^2(2) = 1.23$, $p = .540$. Finally, EEG engagement did not vary as a function of pre-post performance evaluation and Condition, $\chi^2(2) = 1.40$, $p = .497$. The inclusion of covariates did not increase model fit, *p*s > .05.

During the 50 min fatigue induction period, a significant main effect of Time was found, $\chi^2(1) = 37.21$, $p < .001$. Post hoc comparisons (see Table 3) showed that the 20-30, 30-40, and 40-50 min intervals had significantly lower EEG engagement than the 0-10 min interval. Moreover, the 30-40 and 40-50 min intervals had lower engagement than 10-20 min interval. In other words, EEG engagement tended to decrease throughout the fatigue induction period. A significant main effect for Condition was also found for EEG engagement, $\chi^2(2) = 11.72$, $p = .003$. Participants in the passive condition exhibited significantly less EEG engagement ($M = -0.21$, $SD = 0.23$) than participants in the active condition ($M = 0.00$, $SD = 0.19$), $t(75) = 3.52$, $p = .002$, $\eta^2 = .14$. The control ($M = -0.12$, $SD = 0.31$) and passive conditions did not differ. Figure 4 displays these trends. Lastly, the Time by Condition interaction was not significant, $\chi^2(8) = 7.85$, $p = .448$, and the inclusion of covariates did not increase model fit, *p*s > .05.

Table 3

EEG Engagement Probability Pairwise Comparisons and Descriptive Statistics by Fatigue Induction Time Interval

Time	0-10 (min)	10-20 (min)	20-30 (min)	30-40 (min)	40-50 (min)
0-10	*-0.05 (0.23)*				
10-20	2.15	*-0.09 (0.25)*			
20-30	3.79^{**}(.04)	1.64	*-0.13 (0.24)*		
30-40	5.23^{***}(.08)	3.08^{*}(.03)	1.44	*-0.16 (0.29)*	
40-50	5.13^{***}(.08)	2.98^{*}(.03)	1.34	-0.10	*-.16 (0.28)*

Note. Means (standard deviations) are on the diagonals and *t*-statistics with effect sizes for significant comparisons (η^2) are on the off diagonals. EEG engagement probabilities are z-score baseline corrected.

$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$

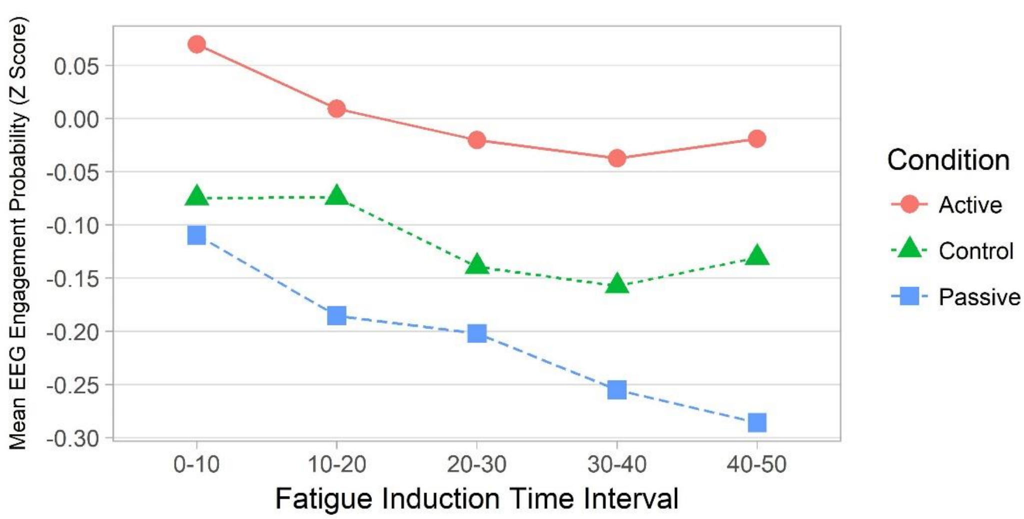

Figure 4. Mean EEG engagement probability by fatigue condition and fatigue induction time interval.

EEG Workload Metric

During the performance evaluations, a significant effect for Time was found for the EEG workload metric, $\chi^2(1) = 11.25$, $p < .001$. EEG workload was significantly higher during the first performance evaluation, ($M = 0.07$, $SD = 0.19$) than second performance evaluation ($M = -0.03$, $SD = 0.24$), $t(77) = 3.46$, $p < .001$, $\eta^2 = .13$. No significant effect for Condition, $\chi^2(2) = 1.73$, $p = .420$, or the Condition by Time interaction, $\chi^2(2) = 0.84$, $p = .657$, were found. The inclusion of covariates did not improve model fit, *p*s > .05.

During the fatigue induction period, no significant effects for Time, $\chi^2(4) = 6.34$, $p = .175$, Condition, $\chi^2(2) = 5.35$, $p = .069$, or the Time by Condition interaction, $\chi^2(8) = 13.22$, $p = .105$, were found. Additionally, the inclusion of covariates did not improve model fit, *p*s > .05.

TLI Ratios

Analysis of TLI ratios at during the performance evaluations revealed a significant main effect for Time, $\chi^2(1) = 7.47$, $p = .006$. TLI ratios were significantly higher during the second performance evaluation ($M = -0.06$, $SD = 0.33$) compared to the first performance evaluation ($M = -0.14$, $SD = 0.19$), $t(77)$, $p = .007$, $\eta^2 = .09$. No significant effects for Condition, $\chi^2(2) = 1.19$, $p = .0551$, nor the Time by Condition interaction, $\chi^2(2) = 4.39$, $p = .111$, were found. The inclusion of covariates did not significantly improve model fit, *p*s > .05.

Figure 5 displays mean TLI ratios across the five 10 min time intervals during fatigue induction. A significant main effect for Time was found on TLI ratios during the fatigue induction period, $\chi^2(4) = 49.85$, $p < .001$. However, this main effect was qualified by a significant Time by Condition interaction, $\chi^2(8) = 20$, $p = .008$. Post hoc comparisons at each level of Condition (see Table 4) revealed TLI ratios for the active condition were significantly higher during the 20-30, 30-40, and 40-50 min intervals than the 0-10 min interval. Additionally, the 30-40 and 40-50 min intervals were significantly higher than the 10-20 min interval. For the passive condition, time intervals 10-20, 20-30, 30-40, and 40-50 were significantly higher than the 0-10 min interval. No significant differences were found across the time intervals for the control condition. In other words, TLI ratios for the active condition steadily increased throughout fatigue induction until stabilizing, while TLI ratios for the passive and control conditions stabilized early during fatigue induction. The inclusion of covariates did not improve model fit, *p*s > .05.

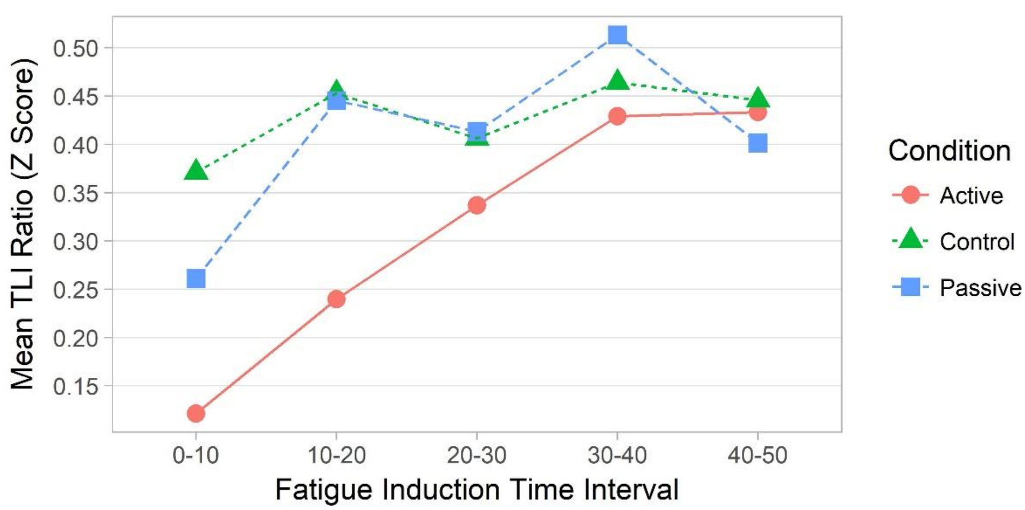

Figure 5. Mean TLI ratios by fatigue condition and fatigue induction time interval.

Table 4

TLI Ratio Pairwise Comparisons and Descriptive Statistics by Condition and Fatigue Induction Time Interval

Condition	0-10 (min)	10-20 (min)	20-30 (min)	30-40 (min)	40-50 (min)
Active					
0-10	*0.12 (0.23)*				
10-20	-2.10	*0.24 (0.35)*			
20-30	-3.82** (.05)	-1.72	*0.34 (0.34)*		
30-40	-5.44*** (.06)	-3.35* (.04)	-1.63	*0.43 (0.34)*	
40-50	-5.52*** (.08)	-3.43** (.04)	-1.71	-0.08	*0.44 (0.31)*
Passive					
0-10	*0.26 (0.37)*				
10-20	-3.72** (.04)	*0.45 (0.39)*			
20-30	-3.07* (.03)	0.65	*0.41 (0.35)*		
30-40	-5.10*** (.08)	-1.37	-2.02	*0.51 (0.50)*	
40-50	-2.84* (.03)	0.88	0.24	2.26	*0.40 (0.42)*
Control					
0-10	*0.37 (0.26)*				
10-20	-1.51	*0.45 (0.30)*			
20-30	-0.65	0.86	*0.41 (0.30)*		
30-40	-1.71	-0.21	-1.07	*0.46 (0.33)*	
40-50	-1.38	0.13	-0.73	0.34	*0.45 (0.34)*

Note. Means (standard deviations) are on the diagonals and t-statistics with effect sizes for significant comparisons (η^2) are on the off diagonals. TLI ratios are z-score baseline corrected.

*p < .05. **p < .01. ***p < .001

CHAPTER IV

DISCUSSION

Automated systems positively and negatively affect human operators. While automation reduces operator workload, the overreliance on automation can also lead to detrimental operator behaviors like automation bias and complacency (Parasuraman & Manzey, 2010). Additionally, researchers have proposed that increasingly automated operational environments can lead to a special case of cognitive fatigue, which may be more detrimental than cognitive fatigue that develops with continuous time on task without automation (Desmond & Hancock, 2001). These two fatigue states have been dubbed passive and active fatigue, respectively. Prior research has shown that passive and active fatigue demonstrate different patterns of subjective engagement, subjective workload, and task performance; however, no studies have used psychophysiological measures to differentiate these fatigue states.

The purpose of this study was to utilize EEG measures of cognitive workload, engagement, a candidate marker of strain under fatigue as part of a comprehensive operator functional state (OFS) framework, which includes psychophysiological, subjective, and task performance measures, to differentiate theorized active and passive fatigue states. Participants performed a 62 min flight simulator task in conditions conducive to either active or passive fatigue (or a control condition) as defined by Desmond and Hancock (2001). Results of this study generally support and extend the findings of Saxby and colleagues (2013) and the theoretical distinction between active and passive fatigue postulated by Desmond and Hancock. Specifically, subjective and physiological measures exhibited different patterns of change over the course of fatigue induction as a function of active and passive fatigue simulation conditions. The results of each type of measure (subjective, performance, EEG) are discussed in turn followed by a general synthesis discussion.

Subjective Measures

Subjective measures of participant cognitive states generally supported Hypotheses 1 and 2. Subjective measures of workload and alertness differentiated active and passive fatigue. From 25 min to 50 min into fatigue induction, NASA-TLX ratings for the active condition did not change. However, aside from being consistently lower than the active condition, both the passive and control conditions showed reduced workload ratings from 25 min to 50 min during fatigue induction. Notably, the effect size for the passive condition was substantially larger than that of the control condition. These results support those reported by Saxby et al. (2013) – operational conditions conducive to passive fatigue result in lower perceived workload. In terms of dynamic operator stability, prolonged underload conditions may result in maladaptive workload regulation strategies that result in a loss of task engagement or performance standards (Desmond & Hancock, 2001; Saxby et al., 2013).

Moreover, participants in the passive and control conditions, but not the active condition, reported reductions in alertness ratings from pre to post MATB. With prolonged task performance in underload conditions, according to Desmond and Hancock

(2001), conditions conducive to passive fatigue result in sustained attention shifting from external stimuli to internal states. Therefore, it would be expected that reduced alertness to outward stimuli would be present in severe underload conditions. As with NASA-TLX ratings, the effect size for the passive condition was much larger than that of the control condition.

Although measures of workload and alertness support the claims made by Saxby et al. (2013) and Desmond and Hancock (2001), SSSQ engagement scores did not vary as a function of fatigue condition and time on task (i.e., pre to post MATB); thus, failing to replicate the findings by Saxby and colleagues showing passive fatigue to result in reduced subjective engagement across task durations. All three conditions in this study reported similar reductions in subjective engagement from pre to post MATB. This finding may have resulted from the task environment used. This study employed a generalized flight simulator with a relatively low fidelity (i.e., no video depicting an actual flight or joystick feedback), while Saxby and colleagues used a high-fidelity driving simulator (i.e., with steering wheel feedback and moving driving scenery). This higher fidelity simulation used by Saxby and colleagues may have buffered against reduced engagement in their active fatigue manipulation. Additionally, Saxby and colleagues used the full Dunde Stress State Questionnaire (DSSQ) to measure task engagement, while this study used the shortened version of this questionnaire (SSSQ). The more comprehensive DSSQ may have been more sensitive to differentiating active and passive fatigue engagement changes than the shorter SSSQ.

Two important findings were the relationships found between the CISS and ESS as well as the CISS and SSSQ task engagement scores. The CISS positively correlated with the ESS and negatively correlated with pre and post SSSQ engagement scores. It should be noted that the correlation between the CISS and ESS was also found in the pilot study of 35 participants conducted before this main study. These correlations indicate that individuals with more severe oculomotor symptoms characteristic of convergence insufficiency generally experience more daytime sleepiness and reduced task engagement. Previous experimental studies have shown that the induction of accommodative-vergence stress in healthy individuals can produce reductions in sustained attention performance similar to those observed with attention-deficit hyperactivity disorder (Poltavski, Biberdorf, & Petros, 2012). Moreover, those diagnosed with convergence insufficiency experience greater fatigue, blurred vision while completing close tasks, and eye strain (Arnoldi & Reynolds, 2007). Thus, participants endorsing more symptoms characteristic of convergence insufficiency may have more difficulties maintaining engagement on sustained attention tasks.

In summary, subjective measures of workload and alertness differentiated active fatigue from both the control and passive fatigue conditions. Moreover, although the passive and control conditions demonstrated similar patterns of workload and alertness, reductions in these measures over time were stronger for the passive condition than the control condition. Therefore, one hallmark of passive fatigue that should be stressed is low critical signal density. Although the control and passive conditions only used the systems monitoring task, the low critical signal density of the passive condition likely resulted in larger decreases in alertness and workload ratings compared to the control condition. Subjective engagement decreased from pre to post MATB simulation similarly for all conditions. Finally, more symptoms characteristic of convergence insufficiency (e.g., double vision when reading or doing close work, eye fatigue when reading or doing close work) were positively associated with daytime sleepiness and negatively associated with subjective task engagement.

Performance Measures

Performance data did not support Hypothesis 4. In contrast to the results obtained by Saxby et al. (2013), performance results did not reveal any significant differences between the fatigue conditions. In their study, Saxby and colleagues found passive fatigue to increase both steering and breaking reaction times to an unexpected driving hazard compared to active fatigue. In the current study, reaction times to respond to own ship radio calls significantly increased from the first performance evaluation to the second performance evaluation after fatigue induction, regardless of condition. However, communications and tracking task accuracy improved from pre to post fatigue induction. Thus, it appears that participants incurred a speed-accuracy trade-off during the post-fatigue induction performance evaluation. Indeed, Hopstaken et al. (2016) also reported a speed-accuracy trade-off in participants completing an *n*-back task over the course of 1.75 hr. From a broader perspective, van der Linden (2011) proposed that fatigue effects on performance are more substantial for tasks involving executive functioning. Therefore, it is likely that the fatigue effects participants experienced in this study compromised executive functioning, requiring participants to sacrifice communication task response times for improved accuracy.

It should be noted that the effect sizes obtained by Saxby et al. (2013) for performance differences between fatigue conditions in the driving simulator were small (partial $\eta^2 = .05$) and medium (partial $\eta^2 = .08$), making it likely that the current study lacked statistical power for detecting between-subjects performance effects. Additionally, the performance metrics utilized by Saxby and colleagues were single instance reaction times for steering and breaking. In contrast, participants in this study made multiple responses to simulated radio calls under high workload. These metrics were subsequently averaged over trials. Therefore, it may be the case that passive fatigue may only be detrimental to initial events directly following prolonged fatigue induction. Additionally, researchers (Ackerman, 2011; Hockey, 2011; van der Linden, 2011) suggest that fatigue effects may not manifest in performance at the aggregate level (i.e., average group performance) because of individual differences (e.g., compensatory effort, adopting different task strategies) in combatting fatigue effects. These individual differences also likely reduced statistical power in the current study to find between-groups effects despite the inclusion of several covariates.

Overall, performance results indicated a speed-accuracy trade-off after fatigue induction that did not vary by fatigue condition. These results failed to replicate the performance differences observed between active and passive fatigue obtained by Saxby et al. (2013).

EEG Measures

EEG measures of cognitive workload and engagement disassociated from subjective measures. While NASA-TLX scores revealed significant differences between fatigue conditions as a function of time on task, no significant effects for EEG workload (measured by ABM's average workload metric) were found during fatigue induction. However, decreases in EEG workload were observed for all conditions during the second performance evaluation. This likely reflects a slight learning effect or the reduced workload that may have accompanied participants reducing goals directed toward task speed to retain accuracy.

EEG engagement (as measured by ABM's high engagement metric) showed significant decreases from pre to post fatigue induction for all conditions. This result mirrors that of SSSQ task engagement scores. Additionally, the main effect of Condition indicated that those in the passive condition exhibited significantly less engagement than those in the active condition across the fatigue induction. Although the Time by Condition interaction was not significant for EEG engagement, visual examination of means across the 10 min intervals reveals an interaction trend, with the passive condition demonstrating a more negative trend compared to the shallow trend for the active condition and the intermediate negative trend for the control condition. These results support partially Hypothesis 3. Whereas SSSQ task engagement results do not support the results obtained by Saxby et al. (2013), the EEG engagement results obtained in this study do – passive fatigue was characterized by less engagement compared to active fatigue. This finding further supports the role of using multiple measures of a construct when evaluating operator functional states.

Although significant effects were observed during fatigue induction, no effects were found on EEG engagement during performance evaluations, failing to support Hypothesis 5. The increase in task demands during the post-fatigue induction performance evaluation likely re-engaged participants in the task and returned their engagement to baseline. Like performance measures, engagement may have only been initially lower during initial portions of the performance evaluation, but then increased due to repeated instances of radio calls. More finite analyses of these segments of data would be needed to determine if any differences between conditions are present at different performance evaluation time points.

The results of TLI ratios did not support Hypothesis 4. It was hypothesized that TLI ratios would be lower for those exposed to a passive environment compared to an active environment. TLI ratios were higher during the second performance evaluation compared to the first performance evaluation, but no differences between the conditions were found. Moreover, during fatigue induction, TLI ratios varied as a function of time and condition. Specifically, the active condition exhibited sustained increases in TLI ratios beginning at the 20-30 min interval, while the passive condition demonstrated increases during the 0-10 min interval. The control condition exhibited no differences across time. During the final 40-50 min interval, TLI ratios for all conditions converged. This differing pattern of TLI ratios during fatigue induction indicates that the ratio of Fz theta to POz alpha may be used to track the initial development of different fatigue states.

Hockey et al. (2009) suggested that the TLI can be used to index cognitive strain and fatigue when maintaining performance reaches the boundaries of compensatory control. In their study, Hockey and colleagues found systematic increases in TLI ratios with task load manipulations requiring sustained effort. Furthermore, Barwick et al. (2012) found increases in frontal theta activity with corresponding decreases in alertness ratings while participants performed an effortful Stroop task. The authors concluded that this increased theta activity may be a compensatory mechanism for reduced vigilance and engagement. In the current study, increased TLI ratios, coupled with reduced engagement, likely represented a mechanism for coping with prolonged time on task and increasing effort to maintain task-related goal standards.

In terms of differentiating fatigue conditions, participants in the passive condition showed a mean increase in TLI ratios about 10 min into fatigue induction, which subsequently stabilized at 20 min into fatigue induction. Participants in the active fatigue condition exhibited a significant mean increase in TLI ratios at 20 min, which continued to increase until stabilizing at 40 min into the simulation. Within the context of dynamic models of stress and sustained attention (Handcock & Warm, 1989), the onset of reductions in operator physiological and psychological adaptation may occur earlier for passive fatigue conditions compared to active fatigue. The extreme underload of the passive condition likely reduced the operator's adaptability, which manifested in increased TLI ratios early in the scenario. Moreover, the delayed increase in mean TLI ratios for the active group likely resulted from participants initially employing proper workload adaptation regulation strategies but losing this adaptivity as time on task became a significant stressor over prolonged task performance, thus requiring the employment of more effort under strain. If TLI ratios are an indication of strain due to fatigue, then the differences observed between conditions over time found here may imply that passive fatigue onset is faster than that of active fatigue.

Although TLI ratios showed different patterns between fatigue conditions, ABM's workload metric did not. This dissociation may be due the TLI measuring a different construct compared to ABM's workload metric. Specifically, the TLI ratio may be measuring facets of operator strain associated with operators employing more effort to maintain performance on a task, while ABM's workload metric measures a general workload construct of executive function resource allocation. In other words, ABM's metric is more sensitive to changes in task demands requiring increased executive functioning, while the TLI is sensitive to the implementation of effort under the strain of fatigue to maintain performance outcomes.

TLI results may also aid in explaining the speed-accuracy trade off observed during performance evaluations. While no formal statistical comparisons were made between performance evaluation TLI ratios and fatigue induction TLI ratios, examination of TLI ratio means revealed that mean ratios during the post-MATB performance evaluation were substantially lower than TLI ratios during fatigue induction. Using Hockey's compensatory control model and assuming the TLI represents a coping mechanism for goal directed effort under strain, participants may have reduced task goals, resulting in the conservation of a reduced effort threshold. This reduction in task goals with the preservation of effort may have manifested as the speed-accuracy trade-off observed in performance data. Therefore, the progressively increasing TLI ratios over the course of fatigue induction may have indicated a build-up of strain due to fatigue, where participants subsequently adopted a non-optimal performance strategy ultimately resulting in the preservation of effort at the cost of reduced performance outcomes. However, more research is needed to determine if indeed TLI ratios correspond to the employment of effort under strain.

Overall, EEG measures indicate that passive fatigue is characterized by less engagement than active fatigue. Trends in the EEG engagement metric also indicate that loss of engagement over prolonged task performance was more severe for the passive fatigue condition than the control and active conditions. Those in the active condition exhibited sustained TLI ratio increases compared to the passive condition and control conditions, providing preliminary support for the TLI ratio being an index of operator strain due to fatigue. Engagement and TLI results also indicate two potential EEG markers indicative of active-passive fatigue differentiation that correspond to dynamic models of stress adaptation.

General Discussion

The results of the subjective measures generally support the findings and conclusions made by Saxby and colleagues (2013) – passive fatigue is characterized by a loss of engagement and alertness under conditions of prolonged underload, while active fatigue is characterized by little to no changes in alertness or engagement under sustained higher workloads. Researchers have argued that passive fatigue presents more of a threat to task performance than active fatigue conditions (e.g., Desmond & Hancock, 2001;

Saxby et al., 2013); however, performance measures in this study failed to find any differences between fatigue conditions. Importantly, this study extended previous research into fatigue types by incorporating continuous measures of central nervous system activity throughout fatigue induction and the performance of cognitively demanding performance evaluations. To date, no published studies have used any physiological measures to differentiate these fatigue states.

The combination of EEG and subjective results obtained in this study augment the understanding of operator state changes during sustained underload and high workload conditions. Saxby and colleagues (2013) suggested that responses to different fatigue states may be: 1) qualitatively distinctive modes, or 2) a gradated response mixing adaptive strategies. Results of this study likely support the latter. The inclusion of a control condition that was qualitatively similar to the passive condition supports this assertion. Both conditions involved only monitoring a system for changes; however, critical signals in the passive condition were far less frequent than critical signals in the control condition. The effect size for reduction in alertness ratings were larger for the passive condition than the control condition. Moreover, a visual examination of Figure 4 showing mean EEG engagement measurements over the fatigue induction period shows a graded-like response between conditions (i.e., the control condition was between the passive and active conditions). Thus, it appears that operator responses to different prolonged workload-related stress vectors are continuous. Additionally, it appears that the structure of the task in terms of stimuli presentation rate may be the driving factor for passive fatigue conditions that results in a smooth change in operator responses over task performance.

Although no performance differences were observed between the active and passive conditions, the strong loss of alertness and task engagement in the underload conditions characteristic of passive fatigue present safety concerns for operators. Specifically, operators becoming disengaged from a task prior to emergency situations where fast responses are required. As automation continues to be integrated in several operational environments, the probability of severe underload conditions will also increase.

One application of the current research is to develop fatigue countermeasures that are tailored to active and passive operational conditions. Whereas increased automation may alleviate sustained overload conditions, this intervention would not be suitable for underload conditions. Indeed, May and Baldwin (2009) stressed that technologies developed for combating fatigue need to be evaluated for their appropriateness within the operational environment and take into consideration different fatigue states.

Limitations and Future Research

One limitation to the current study was the low-fidelity simulation used to induce differing fatigue states. As previously mentioned, Saxby and colleagues (2013) utilized a high-fidelity driving simulation that may have maintained participant engagement more than the MATB. Participants could have disengaged from the MATB simply because it lacked realism. In true operational settings, stimuli such as scenery and noise make the environment more dynamic. Although one goal of this study was to “distill” the differences between active and passive fatigue down to their essence in a controlled setting, it is difficult to generalize low-fidelity results to situations experienced by operators such as UAV pilots. Despite this, several of the results obtained in this study support, as well as extend, those found in previous research. Thus, differences between active and passive fatigue can manifest in cost-effective tasks readily available to researchers. Relatedly, the MATB fatigue induction duration used in this study was relatively short. Operational settings like long-haul drives, UAV missions, and baggage security screening agent shifts are much longer. Continued EEG monitoring for longer durations may have revealed further reductions or plateaus in EEG indices. However, the EEG results of the current study’s short duration generally support past research using subjective measures.

Another limitation to this study was how participants responded to own ship communications task radio calls. Participants were instructed to maintain contact with the joystick until the radio call ended and then subsequently move their hand to the mouse and adjust the proper radio frequency. Unfortunately, some participants adhered to this instruction more than others, potentially introducing unwanted variability in performance resulting in reduced statistical power.

Additionally, some authors (e.g., van den Linden, 2011) have suggested that the act of switching tasks can reverse fatigue effects. In this study, participants transitioned from a stable workload, to a more demanding, emergency-like workload that spanned several minutes. This workload transition may have alleviated some effects from the relatively short fatigue induction period.

Future research on active and passive fatigue states should utilize several physiological measures simultaneously over the course of longer fatigue induction periods. For instance, one could combine time-locked ERP signals to critical system stimuli with continuous cerebral hemodynamic recordings. ERP recordings could reveal changes in electrophysical responses to discrete stimuli with different fatigue induction environments. P300 waveform amplitudes have been shown to attenuate with extended vigilance task performance (Hoptaken et al., 2016). However, no studies have examined P300 amplitude as a function of fatigue conditions. Moreover, the higher spatial resolution of many cerebral hemodynamic measures (e.g., functional near-infrared spectroscopy) could be used to determine if there are hemodynamic changes that occur at different regions as a function of fatigue conditions. Brain stimulation techniques (e.g., transcranial direct current stimulation) could then be explored as possible fatigue countermeasure strategies.

Future research should also examine the role of oculomotor functioning, specifically the accommodative-vergence response, on task engagement in operational settings. While this study revealed modest correlations between the CISS and SSSQ engagement scores, a more systematic and experimental approach could be used to explore how oculomotor functioning relates to operational conditions characteristic of active and passive fatigue. In conjunction, other measures of individual differences (e.g., automation trust, susceptibility to boredom) may also improve the understanding of different fatigue states.

Finally, since the current study, along with Saxby and colleagues (2013), provided support for differentiated fatigue states, future studies should begin to examine effective fatigue countermeasure technologies. Some avenues may be cortical stimulation via transcranial direction current stimulation (tDCS) and dynamic augmented cognition systems.

Conclusion

This study demonstrated that EEG can be used within a comprehensive OFS framework to differentiate active and passive fatigue states. Passive fatigue conditions resulted in reduced EEG engagement and elevated TLI ratios early in fatigue induction. Moreover, passive fatigue conditions resulted in reduced ratings of alertness and workload relative to active fatigue. The reduced engagement and alertness observed in passive fatigue conditions exemplifies the need for fatigue countermeasures to be tailored to specific operational environments and special safety considerations to be given to highly automated environments with human operators.

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