Fatigue in Wildland Firefighting:
Relationships Between Sleep, Shift Characteristics, and Levels of Stress and Cognitive Function.

by

Jesse E. Wallace-Webb
BSc Kinesiology (Hons), University of Victoria, 2020

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We acknowledge and respect the ləkʷəŋən peoples on whose traditional
territory the university stands and the Songhees, Esquimalt and W̱SÁNEĆ
peoples whose historical relationships with the land continue to this day.

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Abstract

Rationale: With climate change rising, the impact of wildfires is expected to increase. Wildland firefighting requires constant attention while exposed to harsh working conditions, including long working hours and sub-optimal sleep. These stressors may contribute to heightened stress and impaired cognitive function, which poses a risk to worker health and safety, respectively. **Purpose:** The current study's objective was to investigate the associations between sleep, shift characteristics and levels of stress and cognitive function in Canadian wildland firefighters. **Methods:** Employing a within-subject observational study design, we recruited a geographically diverse sample of 25 wildland firefighters from the British Columbia Wildfire Service (BCWS). Remote data collection occurred between June and September of the 2021 and 2022 fire seasons, including in participants' homes and at their work respective location. Wrist-worn actigraphy, heart rate variability (HRV), and the psychomotor vigilance task served as objective, mobile measures of sleep, stress, and cognitive function, respectively. Web-based methods were used to collect shift information, as well as subjective reports of stress and fatigue. Linear mixed effects modelling was used to statistically control for inter-individual differences. The influence of participant-factors such as age, biological sex, and years of firefighting experience was also explored. **Results:** Average sleep and shift durations on fire suppression days were 6.7 and 13.8 hours, respectively (SD: 66 mins; 108 mins). Polar sleep score was found to be the best sleep-related predictor of every outcome measure, except HRV. Poor sleep, according to sleep score, was significantly associated with increased levels of stress and fatigue across all metrics ($p<0.01$). Later evening bedtimes were non-significantly related to reduced HRV ($p<0.1$). Shift duration was found to be the best shift-related predictor of every outcome measure. Longer shift durations were significantly associated with increased levels of stress and fatigue across all metrics ($p<0.001$). No shift characteristic predicted HRV. Cross-level interactions were indicated for two relationships involving shift duration. Physical activity and meditation experience were found to moderate the relationship between shift duration and heart rate such that the strength of association tended to be stronger in individuals without meditation experience and individuals with low physical activity. Trait morning-eveningness, physical activity, and meditation experience all moderated the relationship between shift duration and subjective fatigue such that the association was stronger in morning type individuals, individuals with low physical activity, and individuals with meditation experience. **Conclusion:** Our findings show that wildland firefighters are often exposed to sub-optimal sleep and long shifts. Importantly, poor sleep and long shift durations were associated with heightened levels of stress and impaired cognitive function, which have implications for worker heath and safety. We contribute novel findings to the field of research on occupational health and safety. We also provide insight and recommendations towards improved fatigue management policy within the BCWS by supporting the development, implementation, and continuous improvement of a practical and scientifically defensible fatigue risk management system.

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List of Abbreviations

AIC = Akaike's Information Criteria

ANOVA = Analysis of Variance

B.C. = British Columbia

BCWS = British Columbia Wildfire Service

BIC = Bayes Information Criteria

FC = Fire Centre

FFMQ = Five Facet Mindfulness Questionnaire

FRMS = Fatigue Risk Management System

GLM = General Linear Models

HR = Heart Rate

HRV = Heart Rate Variability

IA = Initial Attack

ICC = Intraclass Correlation

LL = Log Likelihood

LME = Linear Mixed Effects

LRT = Likelihood Ratio Test

PA = Physical Activity

MEQ = Morningness-Eveningness Questionnaire

ML = Maximum Likelihood

PVT = Psychomotor Vigilance Test

REML = Restricted Maximum Likelihood

RMSSD = Root Mean Squares of Successive Differences

RT = Response Time

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Chapter 1: Introduction

1.1 Rationale

With climate change continuing to rise, the frequency, duration, and severity of wildfires worldwide are expected to increase (Albertson et al., 2010; Liu et al., 2010; Westerling, 2016). In British Columbia, three out of the past six years have seen record-breaking fire seasons, during which the province has spent nearly two billion dollars containing wildfires that have a combined area of over three million hectares (Government of British Columbia, 2022). With this rise in wildfire activity, so too rises the demand on the wildland firefighters whose and health, safety, and performance are required for protecting communities. As an occupation, wildland firefighting involves dangerous suppression activities that require continuous focused attention and complex decision-making. Meanwhile, workers are often exposed to harsh working conditions, including long working hours (Jeklin et al., 2021), demanding physical work (Parker et al., 2017; Rodríguez-Marroyo et al., 2011), sub-optimal sleep (Vincent et al., 2016), high ambient temperatures, dehydration, and psychological stress (Aisbett et al., 2012; Aisbett & Nichols, 2007). From the perspective of occupational health and safety, all these stressors can be seen as contributing factors to an overall state of cognitive fatigue, which poses a serious risk to worker safety on several levels, ranging from reduced awareness and impaired hazard recognition to hasty decision-making and poor judgment.

Indeed, fatigue determinants such as sub-optimal sleep have previously been linked to an increased risk of workplace injuries (Uehli et al., 2014) and driving-related accidents (Bioulac et al., 2017; Philip & Åkerstedt, 2006). These safety-related consequences are likely attributable to the known impairing effect of sleep loss on cognitive function, as has been widely established in laboratory studies (Lim et al., 2010; Lowe et al., 2017). Previous research has found sleep duration to be reduced during multi-day wildfire suppression (Vincent et al., 2018). This is concerning in light of findings that consecutive nights of partial sleep loss (<6hrs/night) can result in cognitive deficits equivalent to 24 hours of total sleep deprivation (Van Dongen et al., 2003). Possibly related to these negative impacts of sub-optimal sleep, shift and scheduling characteristics have similar implications for worker health and safety (Barger et al., 2009; Folkard & Tucker, 2003; van der Hulst, 2003). In particular, long working hours have been shown to adversely affect several dimensions of worker health (Bannai & Tamakoshi, 2014; Wong et al., 2019), including mental health (Afonso et al., 2017), risk of chronic health conditions (Rivera et al., 2020), and stress responses (Kikuchi et al., 2020). Previous research on shift-length-related fatigue has tended to focus on healthcare workers, wherein extended shifts have been shown to be associated with increased medical errors (Landrigan et al., 2004), post-shift driving accidents (Barger et al., 2005), and adverse patient outcomes (Bae, 2021; Rogers et al., 2017). Limited research in the context of wildland firefighting has found that firefighters routinely work 12 to 14 hours a day (Jeklin, Davies, et al., 2021; Jeklin et al., 2020). These extended shifts may have safety-related consequences, including an increased risk of workplace accidents and injuries (Dembe et al., 2005; Wagstaff & Lie, 2011), which is likely related to deficits in cognitive function (Leso et al., 2021).

Unfortunately, research on fatigue-related cognitive impairment in wildland firefighting is sparse (Ferguson et al., 2016; Jeklin et al., 2020) and mostly limited to the isolated effects of sleep loss (Vincent et al., 2018) and heat stress (Williams-Bell et al., 2017a). Very few studies have examined the combined effect of multiple stressors (Cvirn et al., 2019; Smith et al., 2016) and only one used the integrative framework of cognitive fatigue (Jeklin et al., 2020). Field-based research on the occupational health impacts associated with wildland firefighting is also a critically valuable, yet lacking, subject of research (Allison et al., 2022; Koopmans et al., 2022). Most of its related topics are overwhelmingly done in-laboratory (Hancock et al., 2007; Lowe et al., 2017; Shields et al., 2016; Walter & Carraretto, 2016; Wittbrodt & Millard-Stafford, 2018) and under controlled conditions that may not be realistic to the working environment.

1.2 Research Objective & Implications

The current study's objective is to investigate the incidence and potential determinants of stress and fatigue within the occupational setting of wildland firefighting by examining the cognitive and stress-related associates of sleep and shift characteristics. The approach of this project is innovative in that it is the first of the author's knowledge to (1) employ completely remote methodology and (2) use linear mixed effects modeling to control for participant-level characteristics. These novelties allowed us to extend previous research in important ways. For example, we address several gaps in the literature that were identified in past studies, including the collection of data across multiple deployments (Jeklin et al., 2020) and under naturalistic conditions (McGillis et al., 2017), as well as accounting for factors such as age, biological sex, and firefighting experience (Vincent et al., 2016).

The outcomes of this investigation entail both theoretical and applied benefits. That is, its interdisciplinary nature has the potential to contribute to and expand scientific knowledge on several fronts, including in relation to sleep, neurophysiology, and cognitive function. Meanwhile, its direct relevance to occupational health and safety could improve worker safety on two levels: (1) by providing insight and recommendations towards improved fatigue management policy within the British Columbia Wildfire Service (BCWS) and (2) by testing the practicality of mobile tools designed to monitor levels of sleep (i.e., wrist-worn actigraphy), stress (i.e., HRV monitors), and cognitive function (i.e., mobile PVT). Our remote methodology also allowed for a multi-site recruitment strategy and naturalistic collection period, both of which provided benefits to ecological validity and the real-world applicability of study findings.

1.3 Research Question & Hypotheses

1. Are indices of cognitive function or stress associated with sleep and/or shift characteristics?
    1. Ho1: Neither cognitive function nor stress indices will be associated with sleep nor shift characteristics.
2. Do participant-level characteristics such as age, biological sex, and firefighting experience moderate the relationship between sleep/shift characteristics and stress/cognitive function?
    1. Ho2: Participant level characteristics will not moderate the relationship between sleep/shift characteristics and stress/cognitive function.

1.4 Delimitations

- Only firefighters employed by the BCWS were recruited to participate in this study.
- Testing only occurred during the middle portion of the fire season (July - September).
- Data was only collected while on shift and in participants' sleeping location.

1.5 Limitations

Largely in part due to being conducted in a field setting, as opposed to a controlled laboratory environment, the current study has several limitations that should be acknowledged:

- There was an inherent selection bias due to recruitment via convenience sampling.
- Some participants began work for up to 5 months before testing started, which might have affected cumulative stress and fatigue.

- The study did not control for several factors that have been found to influence stress and cognitive function, including acute exercise (Chang et al., 2012; Marasingha-Arachchige et al., 2022), dietary habits (Gupta et al., 2019; Yoshizaki et al., 2014), acute nicotine intake (Lawrence et al., 2002), habitual cannabis (Nicholls et al., 2015) and alcohol consumption (Bijl et al., 2005), individual coping strategies like acute breathwork (Zaccaro et al., 2018) and/or specific meditation practices (Sumantry & Stewart, 2021), or sleeping location (Vincent et al., 2018).
- The sample size of this study was relatively small, and the frequency of testing was minimized to reduce participant burden and impact on wildfire preparedness and operations.
- Testing times could not be standardized due to variability in the scheduling each day.
- This study could not control for activities on participants' days off, which may have influenced their recovery from stress and fatigue.
- It was not possible to control for events experienced on shift. Some participants may have been exposed to more strenuous conditions than others, which could have impacted corresponding stress and fatigue variables.

1.6 Assumptions

This study has the following assumptions:

- Participants did not dramatically change their sleep, physical activity, hydration, or caffeine consumption habits due to being enrolled in the current study.
- The distribution of age and experience among the study population is representative of the larger pool of BCWS firefighters.
- None of the participants had pre-diagnosed mental or physical conditions.

Chapter 2: Review of the Literature

2.1 Wildfires in British Columbia

Covering nearly a million square kilometers, the province of British Columbia (B.C.) is defined by diverse geographical regions, including its vast Pacific coastline, rich forest ecosystems, rolling interior grasslands, and rugged mountainous terrain (Government of British Columbia, 2022). Recognized as a world leader in wildfire management, the B.C. Wildfire Service (BCWS) is known for skilled personnel and a focus on safety. The BCWS is responsible for coordinating the response to an average of 1,600 wildfires each year, 94 percent of which are contained within 24 hours of ignition by highly trained and specialized crews (Government of British Columbia, 2022). Despite these efforts, however, B.C. wildfires in recent years have still burned millions of hectares of land, cost billions of dollars in suppression, and tragically destroyed entire communities (Cohen & Westhaver, 2022) . Three out of the past six years (2017, 2018, and 2021) have seen record-breaking fire seasons in B.C. During these three seasons alone, the BCWS has spent nearly two billion dollars containing wildfires that have a combined area of over three million hectares (Province of British Columbia, 2022b).

Further, with climate change continuing to rise, the frequency, duration, and severity of wildfires worldwide are expected to increase (Albertson et al., 2010; Liu et al., 2010; Westerling, 2016). This trajectory towards heightened wildfire activity signals the need for fire agencies both in B.C. and globally to allocate attention to the increasing health and safety risks of wildland firefighters whose performance is critical for wildfire response.

2.1.1 Structure of BCWS

For the purposes of coordinating local wildfire response, B.C. is divided into the following six geographical areas, as shown in Figure 2.1: 1) Cariboo, 2) Coastal, 3) Kamloops, 4) Northwest, 5) Prince George, and 6) Southeast. Each fire center is responsible for wildfire management within its boundaries. The Provincial Wildfire Coordination Centre (Kamloops) and the BCWS Headquarters (Victoria) oversee and coordinate all province-wide wildfire functions (Government of British Columbia, 2022). Of interest here, different geographical areas of B.C. pose unique fatigue-related challenges. For example, firefighters in the Coastal FC are more often exposed to steep terrain and remote access areas, while those in the Kamloops FC are more likely to be exposed to heat-stress due to high ambient temperatures and reduced shade.

Figure 2.1. BCWS Fire Centre Divisions

2.1.2 Types of Response Crews

Initial attack (IA) crews consist of three to four people and are usually the first on scene to a new wildfire. Highly independent and mobile, IA crews are strategically placed on "standby" based on local fire danger ratings, which means that they are ready to be deployed quickly by helicopter or truck after a new wildfire starts. Once deployed, IA crews are often responsible for initiating fire suppression efforts at emerging incidents, which may include setting up water pumps, hose suppression, and digging fire guards. Supplied with 1-3 days of supplies and gear, IA crews may work and camp near the fire until it is fully controlled. They are often successful in containing wildfires by 10 am the following day, which translates to shorter deployment durations. Engaged in similar suppression activities as IA firefighters, unit crews consist of 20 firefighters and are usually deployed when fires grow to a size that exceeds capabilities the of initial suppression efforts. For larger, more complex fires that require a high level of response for extended periods of time, unit crew firefighters will stay often at temporary camps for up to 14 consecutive days at a time.

Aside from IA and unit crew personnel, the BCWS also has two additional crews that are more highly specialized: rappattack and parattack. Rappattack crews are a specialized type of 3-4 person IA crew who are trained to use helicopters equipped with hoist and rappel gear to access difficult-to-reach wildfires that are inaccessible by foot or vehicle, and where there are no suitable landing areas for helicopters nearby. Parattack crews are another specialized type of IA crew that are trained to parachute from fixed-wing aircraft to access wildfires in remote or difficult-to-reach locations. Like other IA crews, rappattack and parattack crews are both very versatile. Beyond initiating fire suppression at new incidents, they may also respond to medical emergencies in remote areas or be deployed to larger, more complex incidents to aid unit crew personnel in sustained action efforts across the province.

2.2 Workplace Fatigue

2.2.1 Defining Fatigue

Although an accepted definition has yet to be established, fatigue as a phenomenon is universal to all humans bound by the laws of physiology. Whether it be caused by work, school, parenting, jetlag, or other reasons, everyone confronts the experience of fatigue at some point in their life. Likely attributable to its vague symptomology and ambiguity, previously proposed definitions of fatigue are complex and wide-ranging (Phillips, 2015). The commonness of fatigue as a term in everyday use leads it to be used to describe many related yet distinct phenomena. Indeed, people seem to have trouble distinguishing fatigue from other subjective feelings with which it often co-occurs, including stress, anxiety, burnout, boredom, and sleepiness (Phillips, 2015).

The relationship between fatigue and sleepiness is especially complex (Pigeon et al., 2003; Shen et al., 2006), as the two often co-exist because of sleep loss and are often grouped together under the lay term of being "tired". In the context of occupational research, for example, sleepiness and fatigue are often used interchangeably to describe a state of reduced alertness (Satterfield & Van Dongen, 2013). Despite their interrelatedness and shared mechanisms, however, there may be practical benefits to distinguishing fatigue from sleepiness (Phillips, 2015; Pigeon et al., 2003; Shen et al., 2006). For example, sleepiness as defined by "the propensity to fall asleep" does not explain the motivational or time-on-task related performance decrements in vigilant attention that are associated with fatigue more generally; nor can sleepiness alone capture the exhausted but non-sleepy states of fatigue that are associated with stress and long-term burnout (Phillips, 2015).

In line with this integrative approach, formal definitions of fatigue can be divided into different categories according to which aspect of the construct they focus on. Some of these categories include physical, mental, acute, chronic, and behavioral. Physical fatigue can be defined as reduced maximal force-generating capacity during muscular activity due to energy depletion in the form of lacking adequate levels of neurotransmitter concentration or essential physiological substrates such as glucose (Shen et al., 2006). Mental or sometimes called “cognitive” fatigue can be defined as the temporary feeling of tiredness, exhaustion, and/or decreased cognitive function following prolonged task engagement (Boksem & Tops, 2008). Acute or “short-term” fatigue can manifest either physically or mentally but generally occurs in healthy individuals as a normal protective function (Shen et al., 2006). It has a rapid onset and is of short duration, and is usually alleviated after a period of rest, exercise, and/or stress management**.** Conversely, chronic, or “long-term” fatigue is primarily viewed as a clinical condition wherein individuals experience abnormal, unusual, or excessive levels of fatigue that persist over time (Shen et al., 2006). Chronic fatigue is often insidious in onset, multi-factorial in etiology, and generally not relieved by usual restorative techniques. Fatigue can also be viewed behaviourally as a decrement in physical or cognitive function (Phillips, 2015; Shen et al., 2006). Defining fatigue in this way is convenient for the purposes of operationalization because it lends well to objective measurement, which is particularly useful when speaking in terms of occupational risks and safety.

In light of these complexities, there have been efforts made to create a “whole definition” of fatigue that encompasses its various psychophysiological dimensions. For example, Phillip (2015) proposed the following definition:

“Fatigue is a suboptimal psychophysiological condition caused by exertion. The degree and dimensional character of the condition depends on the form, dynamics, and context of exertion. The context of exertion is described by the value and meaning of performance to the individual; rest and sleep history; circadian effects; psychosocial factors spanning work and home life; individual traits; diet; health, fitness, and other individual states; and environmental conditions. The fatigue condition results in changes in strategies or resource use such that original levels of mental processing or physical activity are maintained or reduced.”

For the purposes of this investigation, fatigue is operationally defined as the net sum of factors contributing to a state of mental tiredness and/or reduced cognitive function. Of interest here, these contributing factors may include, but are not limited to, poor sleep, long and/or irregular shift schedules, acute psychological stress, dehydration, and/or hyperthermia.

Considering the above, it’s important to note that fatigue is a complex interaction of neurological, physiological, psychological, and environmental factors. Several in-depth reviews have investigated the various contributing factors to fatigue in occupational settings (Lehrer, 2015; Lerman et al., 2012; Satterfield & Van Dongen, 2013; Williamson et al., 2011; Williamson & Friswell, 2013). Among them, circadian factors (e.g., time of day and associated light exposure), homeostatic factors (e.g., rest requirements according to recent sleep/wake patterns), and job demands (e.g., task monotony and time-on-task) appear to exert the greatest influence on cognitive function (Satterfield & van Dongen, 2013).

2.2.2 Fatigue and Safety

Although fatigue is a hypothetical construct that may not be directly observable or objectively measurable itself, its existence can be inferred from associated phenomena that are directly observable and measurable (Dawson et al., 2021; Williamson et al., 2011). Of importance to the field of occupational health and safety, these measurable phenomena include a reliable performance decrement in vigilance attention. Indeed, it is well established that fatigue determinants such as sleep loss produce impaired cognition, which has most often been studied using the psychomotor vigilance test (PVT) (Drummond et al., 2005; Lim & Dinges, 2008). Decrements in PVT performance due to sleep-loss-related fatigue are characterized by an overall slowing of response times and an increased propensity for lapses in attention, as often defined by responses time over 500ms.

However, given that workplace accidents often involve a chain of causal factors, the link between fatigue, error, and worker safety is not so straightforward (Dawson et al., 2012; Satterfield & Van Dongen, 2013). According to Reason's "Swiss Cheese" model of human error (Reason, 2000), accidents happen when multiple underlying failures coincide in space and time. In occupational settings, lapses of attention represent one such failure (Dinges, 1995; Van Dongen & Hursh, 2010). It is somewhat rare for multiple underlying failures to coincide, and thus most lapses of attention tend to pass inconspicuously, without consequence, which gives a false sense that fatigue may not be a critical risk factor. Nonetheless, it is important to recognize that lapses of attention can happen at any moment, unpredictable in time yet more frequent with greater levels of fatigue, which has implications for worker safety.

In light of these safety-related implications, considerable attention in the past 20 years has gone towards investigating potential countermeasures to occupational fatigue (Satterfield & van Dongen, 2013; Williamson & Friswell, 2013), of which the use of on-shift naps and caffeine use have emerged as promising options (Dawson et al., 2021; Patterson, Higgins, et al., 2018). There has also been an increasing trend in recent years for workplaces globally to implement more progressive fatigue management policies, the most comprehensive of which follow guidelines set by Lerman et al. (2012) description of a fatigue risk management system (FRMS). Although evidence in support of their effectiveness as a whole remains sparse, FRMS components (e.g., bio-mathematical models, countermeasures, worker education, self-report measures, performance monitoring, etc.) have been found to positively impact fatigue, safety, and performance (Sprajcer et al., 2022).

2.2.3 Fatigue in Wildland Firefighting

To conclude, occupational fatigue has previously been identified as a major concern for worker health and safety (Lerman et al., 2012; Satterfield & van Dongen, 2013; Williamson &

Friswell, 2013). This may be especially true in the setting of wildland fire, which includes many risks and hazards including fire entrapments, heat-related illnesses, dehydration, vehicle-related injuries, falls, falling trees and rocks, and exposure to smoke and noise (Aisbett et al., 2012). Wildland firefighters may be at increased risk for fatigue-related injuries due to psychosocial stress, inadequate sleep, and long work hours, however, research is lacking. Recent reviews have indicated that existing research examining fatigue-related factors in the context of wildland firefighting is sparse (Allison et al., 2022; Groot et al., 2019; Koopmans et al., 2022). In particular, very few studies have objectively measured cognitive fatigue in the context of wildland firefighting (Cvirn et al., 2019; Ferguson et al., 2016; Jeklin et al., 2020; McGillis et al., 2017; Smith et al., 2016; Williams-Bell et al., 2017b). Further, only two have objectively measured fatigue in Canada under naturalistic conditions (Jeklin et al., 2020; McGillis et al., 2017), whereas the rest were done in a different country during simulated firefighting scenarios (Cvirn et al., 2019; Ferguson et al., 2016; Smith et al., 2016; Williams-Bell et al., 2017).

2.3 Sleep Loss

Although the exact mechanisms are still unclear, it has long been known that sleep is an essential component of normal human functioning. However, despite recommendations (Watson et al., 2015b, 2015a), workers are increasingly likely to fall victim to short sleep duration (Khubchandani & Price, 2020; Luckhaupt et al., 2010). This may have significant health-related implications, as reduced sleep durations have been associated with several adverse physiological consequences, including reduced immunologic, cardiovascular, and metabolic health, as well as increased risk of cancer and all-cause mortality (Chaput et al., 2020; Watson et al., 2015a). In addition, cognitive impairments due to sleep loss pose a serious risk to worker safety on several levels, ranging from impaired decision-making ability (Harrison & Horne, 2000) and increased workplace injuries (Uehli et al., 2014), to tragic driving-related accidents (Bioulac et al., 2017;

Philip & Åkerstedt, 2006). These occupational health and safety risks of sleep loss are likely even greater in professions with non-standard work schedules, such as those involving early morning start times, long working hours, and/or shift work, as has been reviewed in healthcare (Owens, 2007), mining (Bauerle et al., 2018), and wildland firefighting (Vincent et al., 2018).

The cognitive effects of sleep loss in occupational settings have remained relatively unclear in past decades, which in part stems from the fact that most research concerning the effects of sleep loss on cognition has come from total sleep deprivation laboratory experiments wherein prolonged wakefulness occurs for at least 24 hours prior to testing. However, the effects of sleep restriction, otherwise known as partial sleep deprivation, wherein normal sleep time is reduced below baseline, has received considerably less attention in the literature, despite being a more common occurrence in occupational settings (Reynolds & Banks, 2010). Nevertheless, separate meta-analyses of total sleep deprivation (Lim et al., 2010) and sleep restriction (Lowe et al., 2017) experiments have revealed that acute sleep loss of any duration impairs performance across most cognitive domains, although there appears to be considerable variability as to the magnitude and specificity of its effects. For example, while deficits in simple cognitive abilities, such as sustained attention, have been consistently reported in the literature, there is still disagreement regarding more complex cognitive abilities, such as those that involve high-level executive control (Killgore, 2010).

One classic study by Van Dongen et al. (2003) found that participants who obtained 4-h of sleep per night for 14-days showed levels of working memory impairment compared to those who had endured two nights of total sleep deprivation, however, these deficits did not manifest until after roughly four consecutive nights of sleep restriction. Meanwhile, performance on the psychomotor vigilant task (PVT) showed impairments in the form of slowed response times after only one night of RS. According to (Lim & Dinges, 2008) reduced alertness and overall slowing of response times on the PVT due to RS may be associated with general state-related changes in brain activity, as has been investigated using electroencephalography (EEG; (Lee et al., 2003), positron emission tomography (Thomas et al., 2000) and functional magnetic resonance imaging (Drummond et al., 2005). Of concern, these findings have safety-related implications when viewed in the context of driving performance, as slowed response times translate to a slower braking response, which reduces the ability to respond quickly to hazards (Philip et al., 2003). As well, slowed response times resulting from RS have been linked to other driving impairments, including the frequency of crossing over the centerline (Philip, 2005), which also increases the risk of tragic accidents. Further, sleep loss and stress appear to have a reciprocal relationship such that stress-induced pre-bed anxiety impairs sleep quality (Åkerstedt et al., 2007; Hall et al., 2004), meanwhile impaired sleep lowers the threshold at which a person experiences events as stressful (Minkel et al., 2012).

Despite a relative paucity of research, sleep loss has previously been identified as a major occupational hazard in wildland firefighting (Vincent et al., 2018). In their review, Vincent et al. (2018) identified four studies that investigated firefighters' sleep during wildfire suppression, all of which reported shortened sleep duration on fire days (Cater et al., 2007; Gaskill & Ruby, 2004; McGillis et al., 2017; Vincent et al., 2016). Only two of the reviewed studies included objective sleep measurement via wrist-worn actigraphy (McGillis et al., 2017; Vincent et al., 2016), whereas the other two relied solely on self-report measures that may not yield sufficient accuracy (Vincent et al., 2018). Further, the reviewed studies that measured wrist-worn actigraphy data showed conflicting findings related to sleep quality, which may be attributable to differences in shift characteristics or sleeping environments between countries.

To the author's knowledge, only one study has examined sleep in wildland firefighting since the mentioned review (Jeklin et al., 2020). As the first study to examine firefighters in British Columbia (B.C), Jeklin et al. (2020) similarly found sleep time to be reduced on fire days (M = 6.6 h ± 49.2 min) compared to non-fire days (M = 6.8 h ± 92.2 min), whereas no difference was found for sleep quality. Further, Jeklin et al. (2020) found that this shortened sleep duration was associated with impaired cognitive function on the PVT and higher ratings of subjective fatigue, the latter of which is supported by other previously mentioned studies (McGillis et al., 2017; Vincent et al., 2016).

2.4 Stress

Although a clear definition has yet to reach consensus, psychophysiological stress can broadly be viewed as the physiological and subsequent behavioral response to a psychological stressor or threatening stimuli (Bhoja et al., 2020; Jarczok et al., 2020). Having been the focus of much research in recent decades, it is now well-established that prolonged or "chronic" stress can have a profound negative impact on human function through wear and tear on bodily and cognitive systems (i.e., allostatic load; McEwen, 1998, 2006; O'Connor et al., 2021). Indeed, long term exposure to stress seems to affect the body on several fronts, including at the cardiovascular, metabolic, neural, behavioral, and cellular levels; the sum of which may lead to a wide range of negative health outcomes through increasing the risk of developing diseases (McEwen, 2007; O'Connor et al., 2021). Conversely, short-term, or "acute" stress has been found to impair cognitive function in several domains (Shields et al., 2016). The prefrontal cortex seems to be especially sensitive to the effects of acute stress (McEwen & Morrison, 2013; Yu, 2016), which may explain resulting deficits in top-down cognitive control (Arnsten, 2009; Gärtner et al., 2014).

Traditionally, these health and cognitive outcomes of stress have been approached by studying the endocrine response to stress via endogenous measurement or exogenous manipulation of cortisol levels (O'Connor et al., 2021; Shields et al., 2016). More recently, heart rate variability (HRV) has emerged as a potential biomarker for measuring the autonomic response to stress (Kim et al., 2018). Although the interpretation of many of its components remains unclear (Billman, 2013; Shaffer & Ginsberg, 2017), there is general agreement that the root mean of squares of successive differences (RMSSD) and high frequency components of HRV broadly reflect the vagal (i.e. parasympathetic activity) modulation of heart rate (Shaffer & Ginsberg, 2017), thus providing a valuable tool for assessing autonomic nervous system imbalance (Kim et al., 2018). Indeed, there is strong evidence that low levels of vagally mediated HRV are associated with several health-risk factors (Thayer et al., 2010) and reduced cognitive function (Colzato et al., 2018; Forte et al., 2019; Zahn et al., 2016). Of interest here, occupational stress has been associated with HRV indicators of autonomic imbalance in a sequence of systematic reviews (Jarczok et al., 2013, 2020), thus implicating stress at work to several cardiovascular risk factors, including inflammation, hyperglycemia, hyperlipidemia, and hypertension (Jarczok et al., 2019).

Despite this growing wealth of knowledge, objective measurements of occupational stress in the context of wildland firefighting are severely lacking, with only four experiments identified in the authors' search of the literature. Of the two identified studies that examined endocrine-related stress, it was found that firefighting under simulated conditions for multiple days while sleep-restricted resulted in higher levels of cortisol (Wolkow, Ferguson, et al., 2016) and stress-related cytokines (Wolkow, Aisbett, et al., 2016), with a similar trend being found in a follow-up study that compared simulated firefighting in a temperature-controlled hot environment (Wolkow et al., 2017). To the author's knowledge, two studies have examined HRV in wildland firefighting (Jeklin, Perrotta, et al., 2021a; Robertson et al., 2017), however, only one reported a validated measure of HRV (Jeklin et al., 2021). Although HRV was not found to change over the course of a wildfire deployment, Jeklin et al. (2021) did find the RMSSD component of HRV to be associated with subjective sleepiness, fatigue, and sleep duration, whereas no association was found with reaction time.

The fact that only one study has used a validated, objective measure of stress under natural conditions in wildland firefighting is both surprising and concerning, as the reported prevalence of post-traumatic stress disorder in wildland firefighters is substantial (Groot et al., 2019). Suboptimal decisions during fire suppression that resulted in fatality have previously been attributed to impaired cognitive function due to acute psychological stress (Useem et al., 2005). Indeed, there are several potential contributing factors to occupational stress in wildland firefighters, including prolonged separation from family and friends, as well as exposure at times to human suffering and severe ecological damage. Further, the "on-call" nature of IA firefighting may induce stress-related pre-bed anxiety that reduces sleep quality (Åkerstedt et al., 2007; Hall et al., 2017), which could lead to cognitive impairment the following day (Sprajcer et al., 2018). Therefore, despite being linked to reduced health and safety on several levels, there remains to be a paucity of objective stress measurement in the occupational context of wildland firefighting.

Chapter 3 Methods

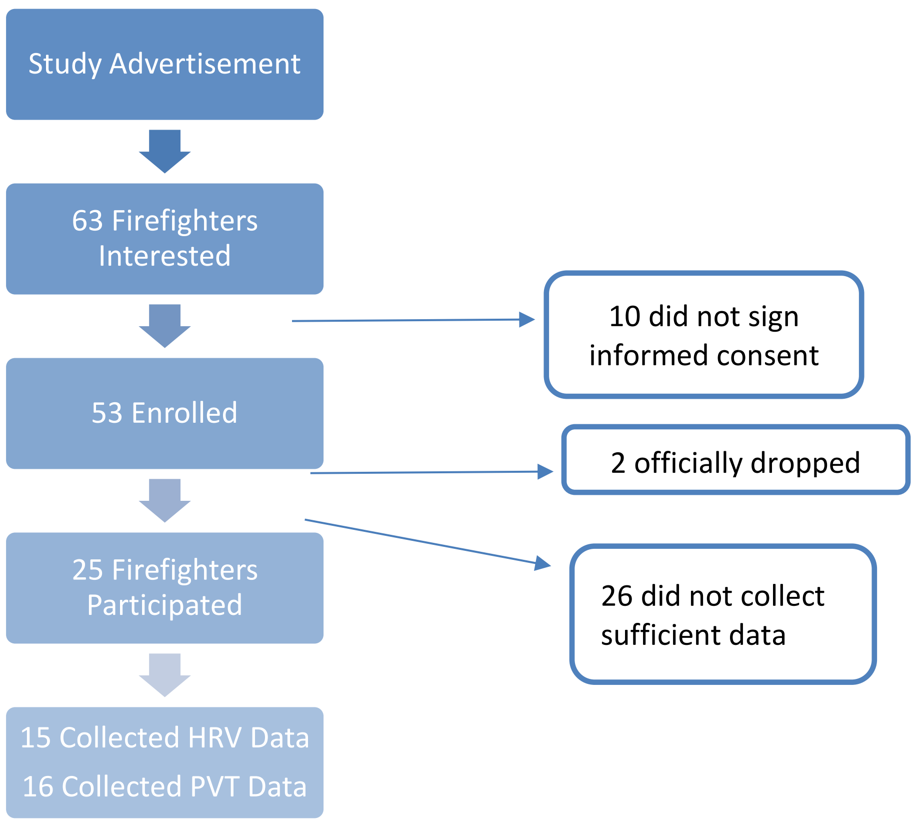
3.1 Participants

Ethical approval (#21-0124; Appendix D**)** for this study was initially granted from the human research ethics board (HREB) at the University of Victoria on July 13th, 2021. Ethics renewal for the second summer of data collection was granted on May 11th, 2022. An optimal sample of 20 participants for the 2022 collection period was determined from a statistical power analysis (GPower software, version 3.1) of pilot data collected during the 2021 fire season (N=4).

In total, 63 wildland firefighters from the British Columbia Wildfire Service (BCWS) were recruited to attend a recruitment information session. Recruitment methods included both random sampling via existing BCWS communication channels (i.e., email correspondence, an internal communications article, and advertisement at a provincial-level course), and as well convenience snowball (i.e., chain-referral) based sampling via word-of-mouth**.** Of the 63 participants that attended an information session, 53 provided written informed consent and were recruited to the study. Two of the recruited participants officially dropped out via email correspondence. Of the remaining 51 participants, 26 did not collect a sufficient amount of data (i.e., fewer than three observations per outcome measure) and so were removed from the study. Twenty-five participants were included in the final dataset (Figure 3.1).

To improve generalizability, participants were recruited from multiple BCWS crew types (i.e. initial attack, rapattack, and unit crew) and geographical areas of British Columbia according to BCWS Fire Centre (FC) divisions (i.e., Coastal, Southeast, Kamloops, Cariboo, and Prince George). The only crew type not represented was parattack, while the only FC not represented was the Northwest. Recruitment was not limited to age, gender, biological sex, ethnicity, religion, class, or experience. The only inclusion criteria, therefore, was that participants were employed as Type-1 wildland firefighters with the BCWS, either as crew leaders/supervisors (i.e., those who plan and supervise fire suppression operations) or crew members (i.e., those who directly execute fire suppression operations). This criterion was used to ensure the range of firefighting tasks across the participants were roughly similar.

Figure 3.1 *Study Recruitment Process with Number of Participants in Each Stage*



3.2 Study Design

Similar to previous methods in this domain (Jeklin et al., 2020), this study employed an observational, within-subject design to examine the associations between sleep, shift characteristics and variables related to stress and cognitive function. Data collection occurred at daily intervals between June and September of the 2021 and 2022 fire seasons. The setting of data collection was primarily in the participants' homes and their respective base locations. If deployed, data collection occurred at the participants' sleeping location (e.g., hotel, fire camp, etc.) and nearest marshaling point (i.e., wherever they started and ended their shift). All self-report measures, including the baseline and daily questionnaires, were administered through "SurveyMonkey" software. If out of service due to being deployed to a remote location, the daily questionnaire was completed using a physical form. All data collection measures were self-administered.

3.3 Procedure

3.3.1 Recruitment

Participant recruitment information sessions occurred remotely via online video meetings from May until July in 2021 and 2022. Following recruitment and informed consent, data collection materials were shipped to participants' homes and participants were instructed on data collection procedures via email.

3.3.2 Baseline Measures

Once familiar with study procedures, participants completed several baseline questionnaires (Appendix C.3) designed to capture relevant contextual information, as well as insight into potential moderators that may influence the complex relationship between sleep, stress, shift duration, and cognitive function. These included a unique, general questionnaire (i.e., individual characteristics, work history, medical history, habitual caffeine intake, physical activity habits, and experience with meditation) and previously validated questionnaires that measure trait mindfulness (10-Item Five Facet Trait Mindfulness Questionnaire; FFMQ; Baer et al., 2006), and trait morningness-eveningness (19-Item Morningness-Eveningness Questionnaire; MEQ; Horne & Östberg, 1976).

3.3.3 Daily Measures

Daily data collection began with the measurement of heart rate variability (HRV) immediately upon waking, either in the participants' home or elsewhere if deployed. Seven minute HRV recordings were collected using a 3-lead Polar H10® chest-worn monitor (Kempele, Finland). The H10 monitor was paired via Bluetooth with the Polar Ignite® Activity Tracker (Kempele, Finland) worn on the wrists of participants' hands. Participants were instructed to lay prone with their arms and legs uncrossed. HRV was also measured in the evening, directly prior to bed. A daily log was provided to participants to allow them to track any events during recording that could impact the resulting HRV profiles.

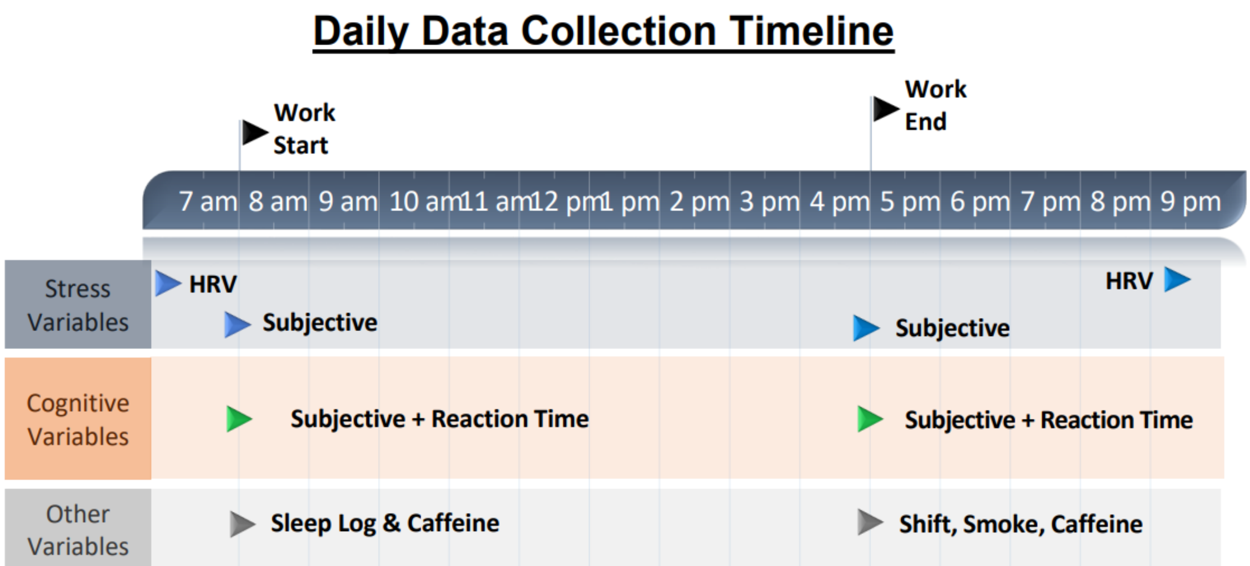
Once participants arrived at work later the same day, they completed a pre-shift questionnaire (Appendix C.1) that measured subjective sleep characteristics, stress, sleepiness, fatigue, and caffeine intake. Subjective sleep characteristics included sleep duration (i.e., bedtime; wake-up time) and sleep quality via a 5-point Likert scale wherein 1 = "Very Poor", 2 = "Poor", 3 = "Average", 4 = "Good", and 5 = "Very Good". Objective sleep measures were also measured continuously via wrist-worn actigraphy (Polar Ignite® activity tracker). Subjective stress was measured via a 4-point Likert scale wherein 1 = "Not Stressed At All", 2 = "A Little Stressed", 3 ="Fairly Stressed", and 4 = "Very Stressed". Subjective sleepiness was measured using the Stanford Sleepiness Scale (SSS) (Hoddes et al., 1973), which is 7-point scale that ranges from 1 ("feel active and vital; alert, wide awake") to 7 ("almost in reverie; sleep onset soon; lost struggle to remain awake"). Subjective fatigue was measured using the Samn-Perelli Fatigue Scale (SPS) (Samn & Perelli, 1982), which is a 7-point scale that ranges from 1 ("fully alert, wide awake") to 7 ("completely exhausted, unable to function effectively"). The SPS has previously been showed to be the most sensitive subjective assay to objective fatigue in wildland firefighting (Ferguson et al., 2016). Caffeine intake was indicated by the response "No" or "Yes (Please Specify)".

Following the pre-shift questionnaire, cognitive function was measured objectively via performance on the Psychomotor Vigilance Task (PVT). The PVT is based on simple reaction time (RT) to stimuli that occur at random intervals and therefore measures vigilant attention. The PVT is the most commonly used objective measure of cognitive function and has been shown to be sensitive to the effects of sleep loss and fatigue (Basner & Dinges, 2011; Dinges et al., 1997; Ferguson et al., 2016). 3-minute versions of the PVT have also been validated (Basner et al., 2011; Grant et al., 2017). PVT performance in this study was measured using the “Vigilance Buddy” (AppBriek) smartphone app, which is publicly available on the Apple App Store (for iPhone users) and Google Play Store (for Android users).

Participants completed a 3-minute version of the PVT (otherwise known as the PVT-Breif or PVT-B; Basner et al., 2011), each using their own personal smartphone. Participants were instructed to monitor a blank grey screen and press the screen as soon as a white stimulus counter appeared on the screen, which stopped the counter and displayed the RT in milliseconds for a 1 second period. The inter-stimulus intervals varied randomly from 0.5 to 3.5 seconds (including a 1 second RT feedback interval). Participants were instructed to press the response button as soon as each stimulus appeared, in order to keep RT as low as possible, but not to press the button too soon (which yielded a “false positive” warning on the display). The test gave a signal after a 5-second period without response, which was counted as a lapse (see below) with 5 second response time.

At the end of the shift, participants completed the PVT and a post-shift questionnaire (Appendix C.2). The post-shift questionnaire contained several of the same measures as pre-shift (i.e. subjective stress, sleepiness, fatigue, and caffeine intake), as well as additional measures that characterized that day of work. These additional measures included shift characteristics (i.e. start time, stop time and time between shifts), fire stage of control (i.e. out of control, being held, or under control), activities performed (e.g. base day, travel, patrol, etc.), and exposure to smoke (via 3-point Likert scale wherein 1 = "No Exposure", 2 = "Some Exposure", 3 = "Heavy Exposure").

Figure 3.2 Daily data collection timeline



3.3.4 Daily Measure Collection Frequency

The collection frequency of daily measures differed slightly depending on working assignment status. To minimize participant burden, participants only collected daily measures during two-week-long "collection periods" that rotated between two or three members of the same crew. If not assigned to a fire, then daily measures were collected at the start and end of each work week (i.e., Monday and Friday). If assigned to a fire of unknown duration (e.g., an initial attack fire), then daily measures were collected every day for the first three days and then every 3rd day afterward until the end of the respective collection period). If assigned to a fire of known duration (e.g., 14-day deployment to a project fire), then the collection of daily measures rotated every two days with another participating member on the crew (i.e., one collects for two days, then another collects for the next days, etc.) until the end of the deployment. This was done to maximize the amount of data being collected, while still being mindful of participant burden. Following the deployment, participants were instructed to collect daily measures on their first day back to work after the employer's policy of 72 hours of rest. Check-ins were conducted with each participant via email in August 2022 to capture the completeness of data collection and to identify any barriers to the collection as they arose. Recognizing the realities of field data collection, flexibility was granted to participants regarding their frequency of data collection to reduce participant burden and maximize the likelihood of participation.

3.4 Main Outcome Measures

Table 3.1 Measured variables, instrumentation, and time of data collection

Variable Measured	**Data Collection Instrument**	**Collection Time (Time Required)**
INDEPENDENT VARIABLES: BASELINE MEASURES		
Individual characteristics	Medical history, age, height, weight, etc.	July (1 minute)
Work History	Years of firefighting experience, position, and weeks since started work this year	July (1 minute)
Meditation Experience	Duration of practice (years, months)	July (1 minute)
Trait Mindfulness	Five Facet Mindfulness Questionnaire (Baer et al., 2006)	July (10 minutes)
Trait Morningness-Eveningness	(Horne & Östberg, 1976)	July (10 minutes)
INDEPENDENT VARIABLES: DAILY MEASURES		
Objective Sleep Duration and Quality	Wrist-worn actigraphy (Polar Ignite activity tracker)	Automatic

Shift Characteristics	Start time, end time, shift duration, and time between shifts	End of shift (1 minute)
Subjective Sleep Log	Sleep duration (bedtime; wake-up time) and quality (5-point Likert scale)	Start of shift (1 minute)
Daily Caffeine Intake	Yes/No	Start of shift and end of shift (<1 minute)
Working conditions	Fire stage of control & activities performed	End of shift (<1 minute)
Smoke Exposure	3- point Likert scale	End of shift (<1 minute)
DEPENDENT VARIIABLES: DAILY MEASURES		
Perceived stress	4- point Likert scale	Start of shift (<1 minute)
Heart rate variability (HRV)	Chest worn monitor (Polar H10) + Polar Ignite activity tracker	Upon waking up (7 minutes)
Behavioral Alertness	Vigilance Buddy app (AppBriek)	Start of shift, mid-shift, and end of shift (3 minutes)
Subjective Fatigue	Samn-Perelli Fatigue Scale (Samn & Perelli, 1982)	Start of shift, mid-shift, and end of shift (<1 minute each)

3.5 Data Analysis

3.5.1 Data Acquisition

Psychomotor Vigilance Task

As according to standardized methods reporting (Basner et al., 2011; Basner & Dinges, 2011), the following metrics were calculated in Excel and included in following analyses: (1) mean 1/RT (also called reciprocal response time) and (2) number of lapses in attention. A response was regarded valid if RT was ≥ 100 ms. Responses without a stimulus or RTs < 100 ms were counted as false starts (errors of commission). For calculating mean 1/RT, each RT was divided by 1,000 and then reciprocally transformed.

The transformed values were then averaged. Lapses (errors of omission) were defined as RTs ≥ 355 ms. This lapse threshold was chosen over ≥ 500 ms (as is standard for both the 5-min and 10-min versions of the PVT) according to previous 3-min PVT reporting guidelines established by Basner and Dinges (2011).

Additional PVT metrics were also extracted but not analyzed, including 1) mean RT, (2) median RT, (3) slowest 10% 1/RT, (4) fastest 10% RT, (5) lapse probability (i.e., number of lapses divided by the number of valid stimuli, excluding false starts), (6) number of false starts, (7) number of lapses and false starts, and (8) performance score. The performance score was calculated as 100% minus the number of lapses and false starts divided by the number of valid stimuli (including false starts). It ranges from 100% (optimal performance, no lapses or false starts) to 0% (worst possible performance, only lapses and false starts).

Heart Rate Variability

Each participants synced their Polar Ignite Activity Tracker to their personal smartphone containing the "Polar Flow" application (Version 4.4.6, Kempele, Finland) at the end of each two-week collection period. Participants were assigned a Polar account username according to their unique participant ID, as well as a password created by the researchers to allow for data storage on their device. Researchers were then able to access data for each participant by logging into their account on the Polar Flow website. Once data collection was complete, participants returned the chest strap and activity tracker to the researchers via postage.

Heart rate data was extracted from the Polar Flow website and then converted from inter-beat R-R intervals to heart rate variability (HRV) components, prior to statistical analysis, using Kubios HRV Standard (Version 3.4.3, Kuopio, Finland) software on a secure computer. The first 120 seconds was removed from each 7-minute recording to allow for participant acclimation at the recording session. This allowed for a five-minute segment to be analyzed from 2:00-7:00, which is in line with established guidelines (Malik et al., 1996). Any large spikes in heart rate during the recording were also removed from the analysis and a filter setting of “strong” was used to remove artifacts and extraneous data points by correcting any inter-beat intervals that differed by more than 150ms at rest, replacing them with interpolated values via cubic spline interpolation (Taravainen et al., 2021). The following time-domain measures were reported to allow for comparison with previous related literature (Jeklin, Perrotta, et al., 2021): average heart rate (HR; as based on mean R-R interval) and root mean successive square difference (RMSSD). Additional HRV metrics were also extracted, which were based on Fast-Fourier-Transfer (FFT) waveforms. This process separates the original signal into distinct frequencies like VLF, LF, and HF. Though similar to an autoregressive (AR) model, FFT is more favorable as AR tends to employ a stronger filter with regard to outliers that may remove otherwise valid data (Herff & Krusienski, 2018). The following HRV frequency domain measures were extracted by not analyzed: LFms2 , LFnu, HFms2, HFnu, and LF/HF. All exported HRV measures were in line with standard methods of reporting (Shaffer & Ginsberg, 2017).

3.6.2 Statistical Analysis

Issues with Traditional Statistical Tests

The current study investigated the associations between sleep, shift characteristics and indices of stress and cognitive function using an unbalanced, repeated measures design. Traditional general linear models (GLM), including analysis of variance (ANOVA) and linear regression, are not well-suited for this type of design due to their assumption of independence, which states that each observation must come from a separate entity (Field et al., 2012). Repeated measure designs violate this assumption, as separate observations from the same participant are naturally dependant (i.e., they tend to correlate with one another). In the case of GLMs, repeated measures from the same participant will artificially increase sample size, which increases the risk of making Type 1 (i.e., false positive) errors (Field et al., 2012). Traditional repeated measures ANOVA overcomes this assumption of independence by testing within-participant effects across time, however, they still assume that the relationship between dependant variables and predictor variables are homogeneous across subjects (Van Dongen et al., 2003). Ignoring inter-individual differences in the independent variable's effects in this way is problematic here because susceptibility to sleep loss is known to exhibit trait-like variability (Van Dongen, Baynard, et al., 2004; Van Dongen, Olofsen, et al., 2004).

How LME Models Circumvent These Issues

In consideration of these limitations, we used linear mixed effects (LME) modelling to estimate the aggregated within-participant changes related to the effects of differing sleep and shift schedules in wildland firefighters. In brief, LME models are suitable for the current research design because they incorporate "fixed-effects" that assess the overall association between the independent variables (e.g., variable x, sleep duration) and dependant variables (e.g. variable y, heart rate), in conjunction with "random-effects" that recognize potential between-participant differences in baseline values of variable y (e.g., inter-individual differences in resting heart rate), as well as varying relationships with respect to variables x and y (e.g., inter-individual differences in response to sleep restriction). Familiar to their alternative name of "multi-level linear model", LME modelling accommodates hierarchical designs wherein lower, level 1 (L1) variables are clustered or "nested" within higher, level 2 (L2) variables. In this way, LME modelling is suitable for the current design because it allows for the assessment of within-subject (i.e., intra-individual; L1) effects while accounting for between-subject (i.e., inter-individual; L2) differences.

LME modelling has previously been employed in sleep literature (Van Dongen et al. 2003) and is generally preferred over traditional GLMs, as they better account for auto-correlation due to repeated measures. Further, LME models are preferable for unbalanced research designs because they automatically handle missing data by using maximum likelihood (ML) methods for parameter estimation, assuming data are missing at random. Inherent constraints of field data collection meant that not all participants in this study contributed equally to the data set. Our statistical approach, therefore, used random intercepts to account for unequal numbers of observations for each participant. Although a complete discussion of LME modelling is beyond the scope of this study, readers are encouraged to seek out the introductory textbook on the topic by Twisk (2006), as well as a detailed comparison of LME modelling and ANOVA in sleep research (Van Dongen, Olofsen, et al., 2004).

How LME Modelling was implemented in this study

As guided by established recommendations (Aguinis et al., 2013) and informed by previous examples of LME models in sleep and shift research (Barger et al., 2019; Chien et al., 2020; Ferguson et al., 2016; Fogt et al., 2011), the following process was followed for constructing LME models to investigate the effects of observation-level predictors of stress and cognitive function (i.e., sleep and shift characteristics), meanwhile accounting for participant-level characteristics such as age, biological sex, and years of firefighting experience. All analyses were conducted using Jamovi software (Version 2.0.21.0) with GAMl package (Gallucci, 2019;

jamovi, 2022) for linear mixed models. Degrees of freedom were estimated using the Satterthwaite method in all cases.

- Step 1. Confirm the Need for Random Intercepts
- Step 2: Determine the Strongest Level 1 Predictor
- Step 3: Add in Level 2 Covariates
- Step 4: Assess the Need for Random Slopes
- Step 5: Probe for Cross Level Interactions
- Step 6. Assumptions Testing

Step 1. Confirm the Need for Random Intercepts

Before proceeding with LME modelling, it's important to confirm the need for a random-effects parameter in the first place (Field et al., 2012). Thus, the first step in the model building process was to create a null LME model such that all predictors were omitted, and only model intercepts were allowed to vary across participants. This is illustrated by Equation 3.1:

(Eq. 3.1)

- Level 1: $y_{ij} = \beta_{0j} + \varepsilon_{ij}$
- Level 2: $\beta_{0j} = \gamma_{00} + \mu_{0j}$
- Combined: $y_{ij} = \gamma_{00} + \mu_{0j} + \varepsilon_{ij}$

Where:

- y_{ij}= value of outcome variable y for observation *i* in participant *j*
- β_{0j}= participant j's intercept for outcome variable y
- ε_{ij} = L1 residual associated with observation *i* in participant *j*
- γ_{00} = grand mean of intercepts across participants for outcome variable y

- μ_{0j} = L2 residual associated with the difference between participant j's intercept (β_{0j}) and the grand mean intercept (γ_{00})

Eq. 3.1 illustrates how the value of outcome variable y is a function of the grand mean intercept (i.e., aggregated across all participants, γ_{00}), a L2 residual term (μ_{0j}) that describes how each individual intercept (β_{0j}) deviates from the grand mean intercept (γ_{00}), and a L1 residual term (ε_{ij}) that describes how each observation within an individual (y_{ij}) deviates from their respective intercept (β_{0j}). Under this model, we can also assess the variance of μ_0, denoted by $\sigma^2_{\mu_0}$, which quantifies the degree of heterogeneity in intercepts across participants. As part of this first step in the model building process, an intraclass correlation (ICC) was computed, which quantifies the overall degree of within-participant correlation in variable y. Stated otherwise, the ICC is the amount of variation in intercepts ($\sigma^2_{\mu_0}$) for variable y that is accounted for by inter-individual differences. According to Field et al. (2012), ICC values above 0.05 indicate a substantial risk for Type 1 error. The significance of this inter-individual variation in intercepts was also computed using the likelihood ratio test (LRT). As described below, the LRT functions by comparing the "goodness-of-fit" between a full model (i.e., with random intercepts) and reduced model (i.e., without random intercepts). Using a chi-squared test of -2LL values, significant variation in intercepts was indicated by a p-value of less than 0.05. Restricted maximum likelihood (REML) was used for this analysis instead of the alternative, maximal likelihood ML, because REML provides better estimation of random variance components (e.g., μ_0; Twisk, 2006). However, ML was used for the estimation of log-likelihood based model fit criteria (i.e., AIC, BIC, -2LL) for congruency with later steps, as REML does not provide a valid comparison of these fit criteria between models with differing fixed effects (Twisk, 2006).

Step 2: Determine the Strongest Level 1 Predictor

Similar to previous methods (Ferguson et al., 2016), a second analysis was conducted in which all primary L1 predictors (i.e., sleep and shift characteristics) were compared in terms of their associations with each dependent variable of interest. The rationale for this analysis was to prevent creating an excessive number of models, as well as to avoid issues with multicollinearity (i.e., close linear relationships between two or more predictor variables). LME models were applied, with a random intercept for between-participant variation, and fixed slopes for the L1 predictor variables. This is illustrated by Equation 3.2:

(Eq. 3.2)

- Level 1:
  - $y_{ij} = \beta_{0j} + \beta_{1j}X_{1ij} + \beta_{1j}X_{2ij} \ldots + \varepsilon_{ij}$
  - $\widehat{y_{ij}} = \beta_{0j} + \beta_{1j}X_{1ij} + \beta_{1j}X_{2ij} \ldots$
  - $\varepsilon_{ij} = y_{ij} - \widehat{y_{ij}}$
- Level 2:
  - $\beta_{0j} = \gamma_{00} + \mu_{0j}$
  - $\mu_{0j} = \beta_{0j} - \gamma_{00}$
  - $\beta_{1j} = \gamma_{10}$
- Combined: $y_{ij} = \gamma_{00} + \gamma_{10}X_{1ij} + \gamma_{10}X_{2ij} .. \mu_{0j} + \varepsilon_{ij}$

Where:
- Level 1 Terms:
  - β_{1j} = participant j's regression slope for outcome variable y
  - X_{1ij} = value of L1 predictor X for observation ***i*** in participant ***j***
  - $\widehat{y_{ij}}$ = predicted value of outcome variable y for observation ***i*** in participant ***j,*** as based on participant j's intercept (β_{0j}) and regression slope (β_{1j})
  - ε_{ij} = L1 residual associated with the difference between $\hat{y}$ and y_{ij} for observation *i* in participant *j*
- Level 2 Terms:
  - γ_{10} = grand mean of regression slopes across participants for outcome variable y

Eq. 3.2 illustrates that the value of outcome variable y for observation i in participant j is equal to participant j's mean for measure y (β_{0j}) plus the product of their regression slope (β_{1j}) and observation i's value for variables $X_{1,2,3\ldots}$ plus L1 residual error (ε_{ij}). Further, each participant's intercept is equal to the grand mean of the intercepts (γ_{00}) plus L2 residual error (μ_{0j}), as was true in Eq. 1., that each participant's intercept is adjusted for by each predictor ($X_{1,2,3\ldots}$). Because the only random effect parameter included in the model is varying intercepts, the L2 equation for the slope β_{1j} is equal to the grand mean of the regression slopes (γ_{10}). To avoid model over-fitting with too many predictor variables, separate models were created for sleep characteristics and shift characteristics. Only pre-shift data and post-shift data were included in sleep and shift models, respectively. This was based on the rationale that post-shift observations were affected by several extraneous factors that would make difficult to isolate the effects of sleep. Similarly, it was assumed that pre-shift levels of stress and cognitive function would not be affected, at least not nearly to the same degree, by shift duration or end time, as compared to post-shift observations. Sleep characteristics included sleep duration, previous evening bedtime, wakeup time, and eight sleep quality metrics (i.e., number of sleep cycles, sleep continuity (/5), and overall sleep score (/100), long interruptions (minutes), percentage of time asleep vs awake, and percentage of time in light, REM, and deep sleep). Meanwhile, shift characteristics included shift start time, end time, shift duration, and time between shifts.

A stepwise backward variable selection process proceeded such that the worst performing predictor, as determined by the significance level of their fixed effects parameter estimates, was progressively eliminated from the model until a single best predictor remained. This was supported by an additional analysis that assessed the predictive ability of each predictor in isolation. It should be noted that only actigraphy-recorded sleep information was used in the current analysis because subjective measures exhibited differing degrees of freedom, which limited their ability to be compared with other sleep metrics. Participant with fewer than three observations in a particular measure were removed from further steps in the analysis. This was based on the assumption that associations based on only two observations would be excessively influenced by outlier data points and extraneous factors. Extreme outlier data points identified by visual inspection (i.e., via boxplot and Q-Q plots of residuals) were replaced with mean + 2SD values, as based on recommendations by Field et al. (2012). ML was used for all parameter estimates during this step because the determination of predictive ability was not based on the values of random variance components (i.e., μ_0).

Step 3: Add in Level 2 Covariates

Following identification of the single strongest shift/sleep predictor (i.e., X) for each outcome variable (y), a second stepwise regression was conducted in which participant-level (i.e., L2) covariates were individually added to the model if they improved model fit. The purpose of this step was to control for factors that may also influence outcome variable y, independent of predictor X. L2 covariates (i.e. $W_{1,2,3\ldots}$) included participant age, biological sex, years of firefighting experience, experience with meditation (binary coded as 1 for "Yes" and 2 for "No"), baseline physical activity (measured as total time in minutes spent doing moderate or vigorous intensity exercise during a typical 7-day week before the fire season started), trait mindfulness (continuous variable; 39-195), and trait morningness-eveningness (continuous variable; 16-70). LME models were applied, with a random intercept for between-participant variation, and fixed slopes for all predictor variables. This is illustrated by Equation 3.3:

(Eq. 3.3)

- Level 1:
  - $y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + \varepsilon_{ij}$
  - $\widehat{y_{ij}} = \beta_{0j} + \beta_{1j}X_{ij}$
  - $\varepsilon_{ij} = y_{ij} - \widehat{y_{ij}}$
- Level 2:
  - $\beta_{0j} = \gamma_{00} + \gamma_{01}W_{1j} + \gamma_{02}W_{2j\ldots} + \mu_{0j}$

- $\beta_{1j} = \gamma_{10}$
- $\mu_{0j} = \beta_{0j} - \widehat{\beta_{0J}}$
- $\widehat{\beta_{0J}} = \gamma_{00} + \gamma_{01}W_{1j} + \gamma_{02}W_{2j\ldots}$
- Combined:
  - $y_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + \gamma_{01}W_{1j} + \gamma_{02}W_{2j\ldots} + +\mu_{0j} + \varepsilon_{ij}$

Where:

- Level 1 Terms:
  - X_{ij} = value of L1 predictor X for observation ***i*** in participant ***j***
- Level 2 Terms:
  - W_{1j} = value of L2 covariate W_1 for participant ***j***
  - $\widehat{\beta_{0J}}$ = predicted intercept for participant j
  - $\gamma_{01}W_1$= influence of L2 covariate W_1 in accounting for variation in intercepts between participants.

Note that the LME model illustrated by Eq. 3.3 uses the same structure as Eq. 3.2 (i.e., random intercepts with fixed slopes), only with L2 covariates ($W_{1,2,3\ldots}$). In this way, Eq. 3.3 predicts the value of outcome variable y based on the grand mean intercept, γ_{00}, observation-level (L1) factors multiplied by the grand mean slope coefficient γ_{10}, and participant-level (L2) factors, reflected by their respective coefficients $\gamma_{01,02\ldots}$. As stated above, regression slopes were constant across all participants (i.e., $\beta_1 = \gamma_{10}$), whereas the regression intercepts (β_0) were allowed to vary across participants. Participant intercepts are thus shown to be a function of the grand mean intercept (γ_{00}) and a residual term (μ_{0j}) that describes how each participant intercept (e.g., β_{0j}) deviates from the grand mean intercept (γ_{00}), after controlling for the L2 covariates (i.e., $W_{1,2,3\ldots}$). Note that each participant's intercept is also adjusted for by the main predictor variable (X). The relative influence that each L2 covariate has on inter-participant difference in intercepts (e.g., W_1; γ_{01}) is interpreted as the amount of change in a participant's average value for outcome variable y associated with a 1-unit increase in W_1. In other words, L2 covariate coefficients ($\gamma_{01,02\ldots}$) assess the presence of a cross-level effect (e.g., effect of age on heart rate) while controlling for other L2 covariates (e.g., biological sex). L2 covariates can thus be shown to explain at least part of the variation in intercepts across participants ($\sigma^2_{\mu_0}$) that was identified in the first step of the model building process.

Although not shown in the above equations for the sake of simplicity, all LME analyses involved centering procedures such that all continuous predictor variables were transformed into deviations around a fixed (i.e., mean) point, as based on previous recommendations (Aguinis et al., 2013; Field et al., 2012). According to Field et al. (2012), group mean clustering for L1 variables should be used if the primary interest is between associations measured at L1 (e.g., the relationship between sleep and cognitive function). Group mean clustering is also preferable for examining cross-level interactions (e.g., the interactive effect of participant age and sleep on cognitive function, as discussed below). For this reason, all continuous L1 predictor variables in our analyses (i.e., X_1) were centered cluster-wise such that within-participant averages for each variable were subtracted from each observation value (e.g., X_{ij}- $\overline{X_j}$) so to interpret γ_{00} in reference to within-participant means (e.g., $\overline{X_j}$). Similarly, continuous L2 covariates ($W_{1,2,3..}$) were re-scaled by grand mean centering such that overall mean values across participants for each variable were subtracted from each participant value (e.g., W_{1j}- $\overline{W_1}$) so to interpret γ_{00} in reference to overall means (e.g., $\overline{W_{1,2,3..}}$). The rationale for these centering procedures was to improve the ease of interpretation for resulting parameter estimates, especially for variables that do not have a meaningful zero point (Aguinis et al., 2013; Field et al., 2012). That is, if all predictors are centred around their mean, then the grand mean intercept (γ_{00}) is the value of the outcome variable y when all predictors are at their means. More specifically, γ_{00} represents the predicted value of outcome variable y given the mean of within-particant averages for L1 predictor variables (i.e., X_1) and overall mean values, across participants, for L2 covariates

($W_{1,2,3..}$). Beyond ease of interpretation, Field et al. (2012) notes that centering is useful way to avoid multicollinearity between predictor variables.

It should be noted that the overarching goal of this analysis was to build the most predictive, yet parsimonious model possible. In this context, predictive ability was defined as maximizing model fit, while parsimony was defined as minimizing the number of parameters in the model. To achieve both these ends, an iterative, reverse selection process was employed such that all L2 covariates were initially included in the model and were then individually assessed individually assessed against model fit criteria. Non-contributing covariates (i.e., those that worsened model fit) were sequentially removed, as based on the significance level of their fixed effects parameter estimates. Each time a covariate was removed, the contribution of the remaining covariates was reassessed, and the process continued until removing any covariate caused model fit to decrease. In this way, the worst performing covariates were progressively eliminated from the model until a final set of contributing covariates remained. We chose this backward approach over a forward approach to avoid suppressor effects, which occur when a predictor has an effect but only when another variable is held constant (Field et al., 2012). As was true in step two, separate models were created for sleep characteristics and shift characteristics. Only pre-shift data and post-shift data were included in sleep and shift models, respectively.

Under this backward stepwise approach, “goodness-of-fit” for each iteration of the model building process was assessed using three different log-likelihood (LL) based criteria: AIC, BIC, and -2LL. At their core, all these criteria function to compare the likelihood (i.e., how well a model represents the observed data) of two models that differ only in terms of level of complexity. In this way, the comparisons of LL require that the models be nested such that more complex model can be transformed into the simpler model by imposing some constraint (i.e., simplification) of the former's parameters. The -2 log-likelihood (i.e., deviance statistic; -2LL) criteria is simply the of product of LL multiplied by -2. Parsimony-adjusted measures of fit criteria, termed Akaike's and Bayes information criteria (AIC; BIC), similarly use LL based criteria to assess model fit, but also consider model complexity by penalizing models that contain more parameters. For -2LL, AIC and BIC, smaller values indicate a better fit of the data. Each iteration of the LME model building process was associated with the addition or removal of a single fixed-effect or random-effect parameter. This allowed value of each parameter to be assessed in isolation by comparing log-likelihood based fit criteria (i.e., LRT, AIC, and BIC) between a full model (i.e., with the additional parameter) and a reduced model (i.e., without the additional parameter). In cases where there was disagreement between -2LL, AIC, and BIC, a likelihood ratio test (LRT) was performed, which tests whether the difference in model fit (i.e. -2LL) is significantly different between competing models, given the difference in number of parameters.

The current analysis was only conducted if step two in the analysis identified at least one significant predictor for the outcome variable of interest. Although statistical significance was generally set at $p < 0.05$, predictors that trended toward significance (i.e., p values between 0.5 and 0.1) were also included because it was assumed that these associations could still be practically significant, despite not reaching statistic significance. This was especially true for associations that were statically underpowered (e.g., sleep and heart rate). That is, these associations might have reached statistically significant with sufficient sample size of 20 participants, as identified in the power analysis mentioned above. As mentioned above, REML can only be used to compare model fit when fixed effects are held constant across models, which is not true in our case because tested models in this step specifically diffed by the addition or removal of fixed-effect parameters. Accordingly, ML was used instead REML for the estimation of log-likelihood based fit criteria (i.e., AIC, BIC, -2LL). REML was used for the estimation of random variance components (i.e., μ_{0j}). ML was used for the estimation of fixed regression parameters (i.e., γ_{10}), unless the model crashed due to issues related to the estimation of random variance components. In such cases, REML was used for the estimation of fixed regression parameters. The change in explained variance (R^2) in the model was considered as an additional indication of model predictive ability. The pseudo marginal R^2 value indicates the proportion of total variance explained through fixed effects only, while the pseudo conditional R^2 value is the proportion of total variance explained through both fixed and random effects.

Step 4: Assess the Need for Random Slopes

The next step in the modelling building process was to assess the need for a varying slope parameter. The purpose of this analysis was to determine whether the relationship between the outcome variable y (i.e., measure of stress or cognitive function) and predictor variable X (i.e., the most predictive sleep/shift characteristic identified in step two) varies across participants. To do so, a random intercept, random slope model was built such that both regression intercepts (β_0) and slopes (β_1) were allowed to vary across participants. This is illustrated by Equation 3.4:

(Eq. 3.4)

- Level 1:
    - $y_{ij} = \beta_{0j} + \beta_{1j}X_{1ij} + \varepsilon_{ij}$
    - $\widehat{y_{ij}} = \beta_{0j} + \beta_{1j}X_{1ij}$
    - $\varepsilon_{ij} = y_{ij} - \widehat{y_{ij}}$
- Level 2:
    - $\beta_{0j} = \gamma_{00} + \gamma_{01}W_{1j} + \gamma_{02}W_{2j\ldots} + \mu_{0j}$
    - $\beta_{1j} = \gamma_{10} + \mu_{1j}$
    - $\mu_{0j} = \beta_{0j} - \widehat{\beta_{0j}}$

- $\mu_{1j} = \beta_{1j} - \widehat{\beta_{1j}}$
- $\widehat{\beta_{0j}} = \gamma_{00} + \gamma_{01}W_{1j} + \gamma_{02}W_{2j\ldots}$
- $\widehat{\beta_{1j}} = \gamma_{10}$

- Combined:
  - $y_{ij} = \gamma_{00} + \gamma_{01}W_{1j} + \gamma_{02}W_{2j\ldots} + \gamma_{10}X_{ij} + \mu_{0j} + \mu_{1j}X_{ij} + \varepsilon_{ij}$
- Where:
  - $\widehat{\beta_{1j}}$= predicted regression slope for participant j
  - μ_{1j} = L2 residual associated with the difference between participant j's regression slope (β_{1j}) and the grand mean intercept (γ_{00})

Note that the LME model illustrated by Eq. 3.4 differs from Eq. 3.3 only with addition of a varying slope parameter (i.e., μ_1) which represents that the slope of predictor X's effect on outcome variable is allowed to vary across participants. Similar to the random intercept parameter in Eq. 3.3, the regression slope of predictor X's effect on variable y (β_{1j}) is a function of the grand mean slope (i.e., aggregated across all participants; γ_{10}) and a residual term μ_{1j}, that describes how each participant's slope differs from γ_{10}. Further, as was true in step three, each participant's intercept is adjusted for by the L1 main predictor variable (X_1) and each L2 covariate ($W_1, W_{2\ldots}$). It's important to recognize that the varying slope parameter μ_{1j} in Eq. 3.4 further implicates two additional parameter estimates that are not explicit in the model: the variance of slopes across participants (i.e., $\sigma^2_{\mu_1}$) and the covariance between intercepts and slopes, which is denoted by the term σ^2_{IS}. Similar to $\sigma^2_{\mu_0}$ in step one, we can assess the variance of μ_1, as denoted by $\sigma^2_{\mu_1}$, which quantifies the degree of heterogeneity in regression slopes across participants. Likewise, the variance of regression slopes across participants (i.e., $\sigma^2_{\mu_1}$) can be assessed statistically by computing a -2 log likelihood ratio test (LRT) between Eq. 3.4 (i.e., model with a random slope component) and Eq. 3.3 (i.e., model without a random slope component), with significant variation in slopes being indicated by a p-value of less than 0.05.

As the name suggests, the covariance between intercepts and slopes (σ_{IS}^2) represents the degree to which regression slopes and intercepts tend to covary together. A positive value of σ_{IS}^2 means that participants with steeper slopes (i.e., a stronger relationship) between predictor X and variable y tend to have higher values for variable y, on average. Although a complete discussion regarding the implications of covariance structures in LME modeling is beyond the scope of this study, Field et al. (2012) notes that if random effects exist within an LME model, then it's important to specify the covariance structure because its respective complexity affects the resulting parameter estimates. Several strategies exist for how to select a covariance structure (Kincaid, 2005), though there remains to be a lack of conscious on which is most appropriate. Our analysis followed the process recommended by Field et al. (2012) such that the covariance structure for each dependant variable was determined based on comparing -2 log-likelihood based fit criteria (i.e., -2LL; AIC; BIC) between competing models with differing covariance structures (i.e., independent vs. unstructured). The covariance structure associated with the best model fit was selected as most appropriate. Because these models differed only in terms of random effects (i.e., fixed-effects parameters were held constant across models), REML was used for all components of this analysis, including the estimation of random variance components (i.e., μ_0, μ_1), model fit criteria (i.e., AIC, BIC, -2LL), and fixed regression parameters (i.e., γ_{10}). Fit criteria were later re-estimated using ML to allow for comparisons between steps.

Step 5: Probe for Cross-Level Interactions

The fourth and final step in the LME model building process tested whether cross-level interactions existed between participant-level (L2) covariates (i.e., $W_{1,2,3\ldots}$) and primary observation-level (L1) predictor variables (e.g., X_1). As guided by the process set forth by

Aguinis et al. (2013), this analysis allowed us to address the question of whether participant-level (L2) characteristics (e.g., participant age) moderated the relationship between primary predictor variables (e.g., X; sleep) and outcome variable (e.g., y; cognitive function). For example, does the relationship between sleep and cognitive function differ depending on participant age? Stated otherwise, this analysis aimed to determine whether, in addition to explaining part of the variation in intercepts (i.e., $\sigma^2_{\mu_1}$), L2 covariates identified in step three were also able to explain part of the random variation in slope across participants ($\sigma^2_{\mu_1}$) that was identified in step four. To do so, a random intercept, random slope, cross-level interaction model was built such that both regression intercepts (β_0) and slopes (β_1) were allowed to vary across participants and interaction terms was added between the L1 primary predictor variable and L2 covariates of interest (i.e., $X_1 * W_{1,2,3\ldots}$). This is illustrated by Equation 3.5:

(Eq. 3.5)

- Level 1:
  - $y_{ij} = \beta_{0j} + \beta_{1j}X_{1ij} + \varepsilon_{ij}$
  - $\widehat{y_{ij}} = \beta_{0j} + \beta_{1j}X_{1ij}$
  - $\varepsilon_{ij} = y_{ij} - \widehat{y_{ij}}$
- Level 2:
  - $\beta_{0j} = \gamma_{00} + \gamma_{01}W_{1j} + \gamma_{02}W_{2j\ldots} + \mu_{0j}$
  - $\beta_{1j} = \gamma_{10} + \gamma_{11}W_{1j} + \gamma_{12}W_{2j\ldots} + \mu_{1j}$
  - $\mu_{0j} = \beta_{0j} - \widehat{\beta_{0j}}$
  - $\mu_{1j} = \beta_{1j} - \widehat{\beta_{1j}}$
  - $\widehat{\beta_{0j}} = \gamma_{00} + \gamma_{01}W_{1j} + \gamma_{02}W_{2j\ldots}$
  - $\widehat{\beta_{1j}} = \gamma_{10} + \gamma_{11}W_{1j} + \gamma_{12}W_{2j\ldots}$
- Combined:
  - $y_{ij} = \gamma_{00} + \gamma_{01}W_{1j} + \gamma_{02}W_{2j\ldots} + \gamma_{10}X_{ij} + \gamma_{11}(X_{ij})(W_{1j}) + \gamma_{12}(X_{ij})(W_{2j}) + \mu_{0j} + \mu_{1j}X_{ij} + \mu_{0j} + \varepsilon_{ij}$
- Where:
  - $\gamma_{11}(X_{ij})(W_{1j})$ = cross-level interaction term representing the interaction between predictor X and L2 covariate W_1 in predicting value of outcome variable y for observation i in participant j.

Note that Eq. 3.5 is the same as Eq. 3.4 but with the addition of interaction terms (e.g., $X{:}\,W_1$) representing participant-level (L2) characteristics (e.g., W_1) exerting a moderating role on the relationship between observation-level predictor X and outcome variable y. The moderating effect of W_1 on the relationship between X and y is captured by the coefficient term γ_{11}. That is, γ_{11} represents the change in the slope of predictor $X's$ effect on variable y across participants when W_1 increases by 1 unit. A result that γ_{11} is positive indicates that X is more strongly related to y in participants with a higher value in W_1 compared to participants with a lower value in W_1. Relating back to the scenario above, for example, this would mean that the relationship between sleep (X) and cognitive function (y) is stronger for older participants compared to younger participants. Similar to in step three, cross-level interactions were tested in a reverse stepwise fashion such that all possible interactions were included initially included in the model and then individually assessed individually assessed against model fit criteria. Interaction parameters were sequentially removed, as based on the significance level of their fixed effects parameter estimates, until the removal of any interaction decreased model fit. Cross-level interactions were further investigated using simple effects analysis.

As in line with the goal of parsimony, the current analysis was only conducted if step four in the LME model building process indicated (1) a significant variation in slopes ($\sigma^2_{\mu_j}$) between participants and (2) that L2 covariates identified in step 3 remained to have an influence on the outcome variable of interest (e.g. W_1; γ_{01}) once the varying slope parameter (μ_1) was added. As noted above in step 3, cluster-wise centering was used for all continuous L1 predictor variables (i.e., X_1) because it better allowed for the investigation of cross level interactions. This is because, if grand mean clustering was used, then the L1 component of interaction (i.e., X_1) would contain a mixture of L2 and L1 effects (Aguinis et al., 2013; Field et al., 2012). As was true in above steps, REML was used for the estimation of random variance components (i.e., μ_0, μ_1), while ML was used for the estimation of model fit criteria (i.e., AIC, BIC, -2LL). ML was also used for the estimation of fixed regression parameters (i.e., γ_{10}, $\gamma_{11\ldots}$), unless the model crashed due to issues related to the estimation of random variance components. In such cases, REML was used for the estimation of fixed regression parameters.

Step 6: Assumption Testing

There are several assumptions of LME models that must be met so that the resulting interpretations are considered valid and generalizable. First, LME models are an extension of GLMs, so many of the same assumptions apply, including the assumptions of multicollinearity and linearity. Further, model residuals (ε_i) are also assumed to be random, homoscedastic, and randomly distributed. Multicollinearity occurs when there is a close linear relationship between two or more of the predictor variables (Field et al., 2012). As recommended by Field et al. (2012), collinearity between predictor variables was assessed using the VIF and tolerance statistics (with tolerance being 1 divided by the VIF). Multicollinearity is believed to be a serious concern if (1) the largest VIF is greater than 10 or (2) tolerance values are below 0.1. The assumption of linearity states that average values of the outcome variable for each level of the predictor variable(s) should lie along a straight line (Field et al., 2012), meanwhile, the homoscedasticity of residuals assumption states that at each level of the predictor variable(s), the variance of the residuals (e.g., ε_{ij}) should be constant. As informed by Field et al. (2012), the assumptions of linearity and homoscedasticity of residuals were both assessed visually by plotting the standardized residuals (ε_{ij}) via scatterplot against the predicted outcome values (y_{ij}) for each outcome variable of interest. Field et al. (2012) notes that this residual vs predicted graph should produce a random array of data points evenly dispersed around zero; if the array appears to funnel out, then it indicates heteroscedasticity (i.e., increasing variance across the residuals), while any sort of curve indicates a non-linear relationship between the outcome and the predictor(s).

The assumption of normally distributed residuals states that model residuals should also present a normal distribution with a mean of zero. Normality of residuals was assessed statistically via the Shapiro-Wilk/Kolmogorov-Smirnov test, as well as visually, by plotting their distribution via Q-Q plot and histogram. According to Field et al. (2012), the straight line in the Q-Q plot represents a normal distribution, while the points represent individual residuals (ε_{ij}). Thus, in a dataset with perfectly normally distributed residuals, all points would lie on the line, meanwhile, data points that trend away the line at the extremes are indicative of deviations from normality (e.g., skewness). Similarly, normally distributed residuals should produce a bell-shaped curve when plotted via histogram, while asymmetries indicate non-normality. Beyond the overlapping assumptions with GLMs, LME models have additional assumptions that relate to their randomness coefficients (i.e., β_{1j}; β_{0j}). That is, these coefficients are assumed randomly vary across participants such they conform to a normal distribution when plotted visually (Field et al., 2012). For example, in a random intercept, random slope model (as illustrated in steps four and five), both the regression slopes and intercepts are assumed to be normally distributed across participants. Though difficult to assess given a the relatively small sample size in this study, the distribution of randomness coefficients was assessed visually via histogram plotting.

Normality of residuals was assessed following step two of the model building process so that any required transformations could be performed prior to adding any predictor variables, as any transformation affected resulting parameter estimates. If the assumption of normality was violated, then the outcome variable of interest was transformed using one of the following established methods: natural logarithm ($\ln y$), common logarithm ($\log_{10} y$), inverse function ($\frac{1}{y}$), square root function ($\sqrt[2]{y}$), and cubic root function ($\sqrt[3]{y}$). All transformations were tested, and whichever transformation lead to the most normal distribution was used, as based on Kolmogorov-Smirnov and Shapiro-Wilks normality tests. All other assumptions were tested following the creation of the final LME model.

Chapter 4: Results

4.1 Sample Population Characteristics

25 wildland firefighters (18 M, 7F) from the British Columbia Wildfire Service (BCWS) participated in the current study. Most participants (56%) worked out of the Southeast Fire Center (FC). Other participants worked out of the Kamloops FC (24%), Coastal FC (16%) and Prince George FC (4%). The average age of participants was 26.4 years (± 3.2), and average BMI was 23.9 kg/m2 (± 1.7) (Table 4.1.1). None were diagnosed with sleep disorders.

Table 4.1.1. *Individual Characteristics*

	Total population (n = 25)			
Characteristic	**Mean**	**SD**	**N**	**(%)**
Age	26.4	3.2		
Under 25 Years			6	25%
25-30 Years			13	54%
Over 30 Years			5	21%
Biological Sex				
Male			18	72%
Female			7	28%
BMI	24	1.7		
Height	177	5.5		
Weight	75	6.9		
Normal Weight (18.5 - <25)			17	68%
Overweight (25 - <30)			8	32%
Relevant Clinical Diagnoses				
Sleep Disorder			0	0%
Chronic Fatigue Syndrome			1	4%
Depression			1	4%

PTSD	1	4%
Hypothyroidism	1	4%
Iron deficiency anemia	1	4%
Chronic Migraines	1	4%

Table 4.1.2. *Work Experience*

	Total population (n = 25)			
Characteristic	**Mean**	**SD**	**N**	**(%)**
BCWS	4.2	2.7		
Contract Crew	1.4	2.5		
Any	5.6	3.3		
1st Year			3	12%
2-5 Years			7	28%
5-10 Years			14	56%
Over 10 Years			1	4%
Crew Member			11	44%
Crew Leader			13	52%
Crew Supervisor			1	4%
Location				
Southeast			14	56%
Kamloops			6	24%
Coastal			4	16%
Prince George			1	4%
Work History				
Days since started work that season	87	37		
Number of fire suppression days since started work that season	7	7		

Table 4.1.3. *Habitual Traits*

	Total population (n = 25)			
Characteristic	**Mean**	**SD**	**N**	**(%)**
Baseline Physical Activity (mins/day)				
Vigorous Intensity	280	152		
Moderate Intensity	264	170		
Vigorous or Moderate Intensity	543	250		
Habitual Caffeine Intake (cups/day)				
Coffee	1.7	1.1	20	80%
Tea	0.3	0.5	3	12%
Energy Drink	0.4	0.7	4	16%
Any	1.9	1.0	23	92%
Experience with Meditation				
Yes			13	52%
No			12	48%
Regular practice				
None			16	64%
Several times a month			6	24%
Several times a week			2	8%
Once a day or more			1	4%
Tait Mindfulness (FFMQ Scores /5)				
Observing	3.53	0.72		
Describing	3.5	0.78		
Awareness	3.48	0.58		
Nonjudging	3.51	0.59		
Nonreactivity	3.25	0.58		
Total	3.46	0.4		

Morning-Eveningness Chronotype (MEQ)				
Average Score	59.7	7.4		
Definite Evening Type (16-30)			0	0%
Moderately Evening Type (31–41)			0	0%
Neither Type (42–58)			13	54%
Moderate Morning Type (59–69)			8	33%
Definite Evening Type (70–86)			3	13%

4.2 Descriptive Statistics

Sleep Information

In total, participants completed a combined 674 days of testing. There was a total of 2252 hours of sleep recorded by wrist-worn actigraphy (698 on 105 fire suppression days; 712 on 100 non-fire suppression days) and 3203 hours of sleep recorded by self report (1495 on 216 fire suppression days; 1127 on 146 non-fire suppression days). Table 4.2.1 shows that actigraphy recorded bedtimes tended to be approximately 40 minutes earlier, on average, on fire suppression days (11:08AM +/- 68 mins) compared to non-fire suppression days (11:48PM +/- 68 mins). Meanwhile, average wakeup times tended to be over an hour earlier (5:47 AM +/- 55 mins vs 6:54 AM +/- 50 mins). Although earlier bedtimes on fire suppression days somewhat compensated for early wakeup times, overall sleep durations still tended to be shorter on fire suppression days (6.7hrs +/- 66 mins) compared to non-fire suppression days (7.1hrs +/- 60 mins). Table 4.2.1 shows that 72% of actigraphy-recorded sleeps on fire suppression days were under 7 hours in duration, as compared to 48% of sleeps on non-fire suppression days.

Table 4.2.1. *Actigraphy Recorded Sleep Information on Fire Suppression vs Non-Fire Suppression Days*

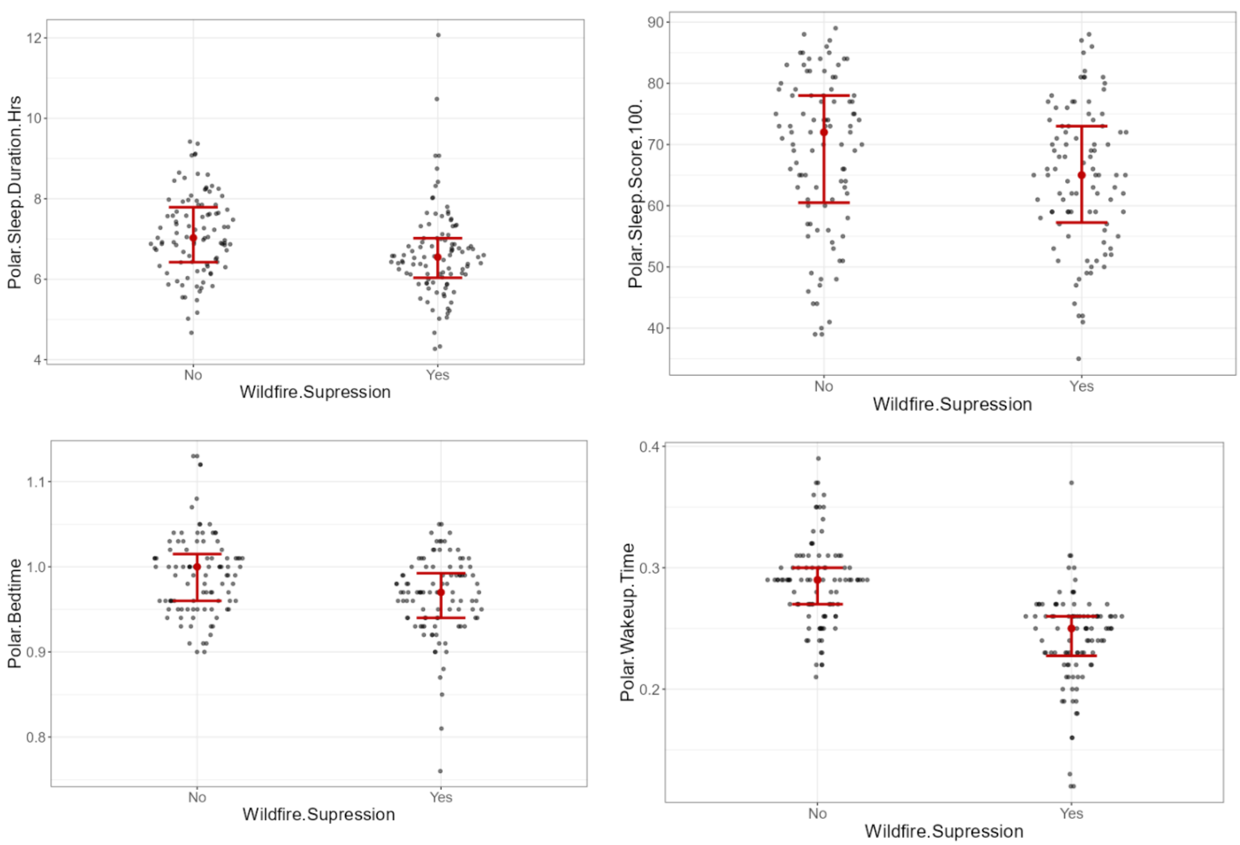
	Fire Suppression Day	Wakeup Time	Bedtime	Overall Sleep Duration (hrs)	% Of Time Asleep	Actual Sleep Duration	Sleep Score (/100)
Mean	Yes	5:47 AM	11:08 PM	6.7	93%	6.2	65
	No	6:54 AM	11:48 PM	7.1	93%	6.6	68
SD	Yes	0hr 55mins	1hr 8mins	1.1	3%	1.0	11
	No	0hr 50mins	1hr 8mins	1.0	3%	0.9	13

	Fire Suppression Day	# Of Sleep Cycles	Sleep Continuity	Long Interruptions (mins)	REM Sleep %	Deep Sleep %	Light Sleep %
Mean	Yes	4.58	2.87	13.9	20%	17%	64%
	No	4.73	2.76	14.3	20%	16%	64%
SD	Yes	0.919	0.798	10.8	6%	6%	7%
	No	1.04	0.883	10.3	6%	5%	8%

Fire Suppression Day	Bedtime	Counts	% Of Total	Wakeup Time	Counts	% Of Total	Sleep Duration	Counts	% Of Total
Yes	Before 9PM	4	4%	Before 4AM	5	5%	Under 5 Hrs	3	3%
	9PM - 10PM	10	10%	4AM - 5AM	12	11%	5-6 Hours	22	21%
	10PM - 11PM	27	26%	5AM - 6AM	35	33%	6-7 Hours	50	48%
	11PM - Midnight	40	38%	6AM - 7AM	47	45%	7-8 Hours	21	21%
	Midnight - 1AM	21	20%	7AM - 8AM	5	5%	8-9 Hours	5	5%
	After 1AM	3	3%	After 8AM	1	1%	Over 9 Hrs	4	4%

	Before 9PM	0	0%	Before 4AM	0	0%	Under 5 Hrs	1	1%
	9PM - 10PM	5	5%	4AM - 5AM	0	0%	5-6 Hours	13	13%
No	10PM - 11PM	20	20%	5AM - 6AM	10	10%	6-7 Hours	34	34%
	11PM - Midnight	32	32%	6AM - 7AM	37	37%	7-8 Hours	34	34%
	Midnight - 1AM	31	31%	7AM - 8AM	42	42%	8-9 Hours	13	13%
	After 1AM	12	12%	After 8AM	11	11%	Over 9 Hrs	5	5%

Figure 4.2.2. *Visual Representation of Sleep Information on Fire Suppression vs Non-Fire Suppression Days*



Note: Each black dot represents an individual observation. The red center dot shows the median value, while the upper and lower bars represent the 75th and 25th percentile values, respectively. Bedtime and wakeup times were converted to decimal numbers such that 1.0 corresponds to midnight am and 0.3 corresponds to 7:12 am. Each 0.1-unit increment represents a change of 2 hours and 24 minutes. All figures were made using the Flexplot (Fife et al., 2021) module in Jamovi.

Shift Information

Overall, there was a total of 5388 reported hours worked (3887 on 282 fire suppression days; 1501 on 172 non-fire suppression days). Table 4.2.2 shows that shift start times tended to be approximately 1.5 hours earlier, on average, on fire suppression days (6:50AM +/- 67 mins) compared to non-fire suppression days (8:15 AM +/- 48 mins). Meanwhile, shift end times tended to be approximately 3.5 hours later (8:39 PM +/- 99 mins vs 5:06 PM +/- 99 mins). This translated into substantially longer shifts on fire suppression days (13.8hrs +/- 108 mins) compared to non-fire suppression days (8.7hrs +/- 100 mins). Table 4.2.2 which shows that 89% of shifts on fire suppression days were over 12 hours in duration, while 88% of shifts on non-fire suppression days were under 10.5 hours in duration.

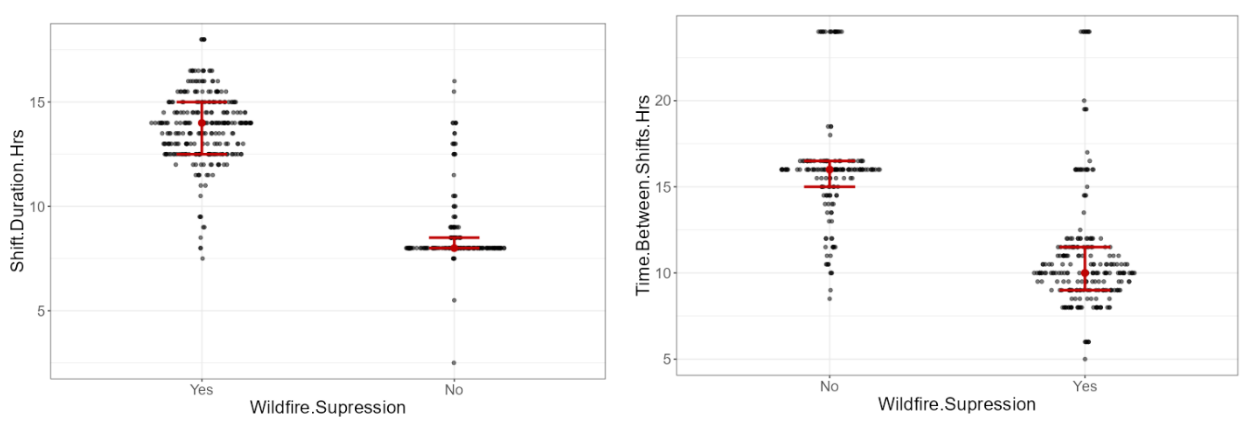
Table 4.2.2. *Shift Information on Fire Suppression vs Non-Fire Suppression Days*

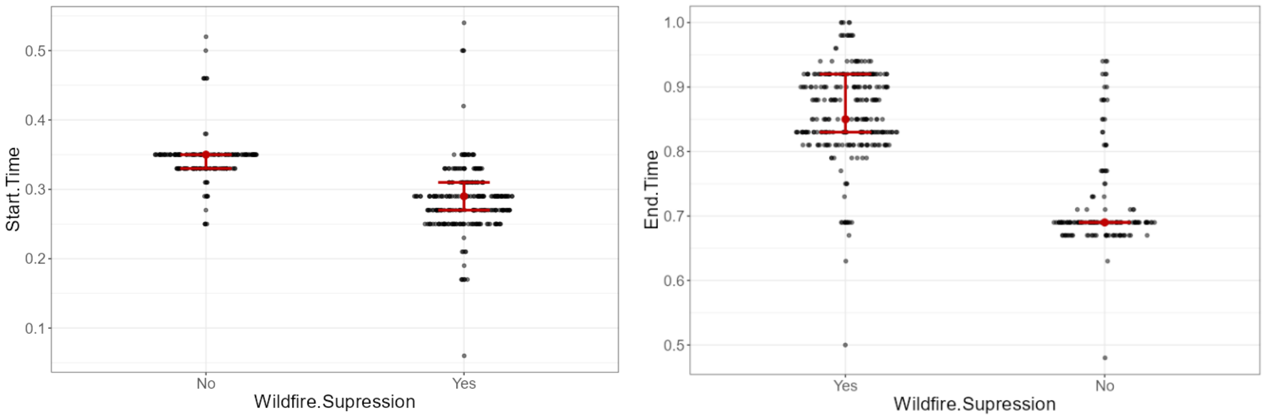
	Fire Suppression Day	Start Time	End Time	Shift Duration (hrs)	Time Between Shifts (hrs)
Mean	Yes	6:50 AM	8:39 PM	13.8	11.8
	No	8:15 AM	5:06 PM	8.7	20.9
SD	Yes	1h 7m	1h 39m	1.7	7.94
	No	0h 48m	1h 39m	1.8	17.2

Fire Suppression Day	Shift Duration	Counts	% Of Total	Start Time	Counts	% Of Total	End Time	Counts	% Of Total
Yes	Under 9 Hours	4	1%	Before 5AM	8	3%	Before 5PM	14	5%

	9 – 10 Hours	5	2%	5AM - 5:30AM	5	2%	5PM - 7PM	12	4%
	10.5 – 12 Hours	22	8%	6AM - 6:30AM	120	43%	7:30PM - 9PM	145	51%
	12.5 – 14 Hours	150	53%	7AM - 7:30AM	99	35%	9:30PM - 11PM	97	34%
	14.5 – 16 Hours	84	30%	8AM-8:30AM	45	16%	After 11PM	14	5%
	Over 16 Hours	17	6%	After 8:30 AM	5	2%			
	Under 9 Hours	134	78%	Before 5AM	0	0%			
	9 – 10 Hours	17	10%	5AM - 5:30AM	0	0%	Before 5PM	132	77%
No	10.5 – 12 Hours	4	2%	6AM - 6:30AM	5	3%	5PM - 7PM	18	10%
	12.5 – 14 Hours	15	9%	7AM - 7:30AM	9	5%	7:30PM - 9PM	14	8%
	14.5 – 16 Hours	2	1%	8AM-8:30AM	151	87%	9:30PM - 11PM	8	5%
	Over 16 Hours	0	0%	After 8:30 AM	9	5%	After 11PM	0	0%

Figure 4.2.2. *Visual Representation of Shift Information on Fire Suppression vs Non-Fire Suppression Days*





Note: Each black dot represents an individual observation. The red center dot shows the median value, while the upper and lower bars represent the 75th and 25th percentile values, respectively. Start and end times were converted to decimal numbers such that 0.3 corresponds to 7:12 am and 0.8 corresponds to 7:12 pm. Each 0.1-unit increment represents a change of 2 hours and 24 minutes. All figures were made using the Flexplot (Fife et al., 2021) module in Jamovi.

4.3 Linear Mixed Models

As shown in Table 3.1, ICC values in null LME models indicated substantial within-participant correlation in every outcome variable of interest (Mean ICC = 0.52 +/- 0.2 SD). Stated otherwise, 52% +/- 20% of total variance in outcome variables were explained through the variation in intercepts alone. Results of the likelihood ratio test (LRT) confirmed that intercepts significantly varied across participants in every outcome variable (Mean χ^2 (1) = 128 +/- 48 SD, p < .001), thus warranting the need for further analysis via LME modelling over traditional statistical techniques.

Table 4.3.0.1 *Random Intercept Assessment Criteria*

Measure	***Intercept variance***	***ICC***	***AIC***	***LRT***	***P-Value***
Pre-Shift					
Subjective Fatigue	0.552	0.315	1468	110	< .001
PVT Response Time	430	0.662	2399	234	< .001

PVT Lapses	0.439	0.549	692	180	< .001
Subjective Stress	0.123	0.273	883	83.8	< .001
Mean RR	42626	0.814	2219	183	< .001
RMSSD	412	0.632	1526	93.9	< .001
Post Shift					
Subjective Fatigue	0.772	0.359	1225	106	< .001
PVT Response Time	566	0.556	2003	119	< .001
PVT Lapses	0.508	0.514	578	106	< .001
Subjective Stress	0.106	0.197	754	63.1	< .001
Mean RR	27599	0.71	1898	130	< .001
RMSSD	561	0.711	1354	131	< .001
Mean		**0.54**		**129.98**	
SD		**0.19**		**50.31**	

Table 4.3.0.2 *Covariates Table*

Pre-Shift Models		**Post-Shift Models**	
PVT Lapses	**γ (SE)**	**Subjective Fatigue**	**γ (SE)**
Experience (γ_{01})	-0.09 (0.04) #	*Meditation (γ_{01})*	-0.22 (0.1) *
MEQ (γ_{02})	0.05 (0.01) **	*PA (γ_{02})*	-0.0004 (0.0002) #
PVT Response Time		*MEQ (γ_{03})*	0.01 (0.01)
Meditation (γ_{01})	-19.5 (4.4)	**PVT Shift Lapses**	
Age (γ_{02})	-1.13 (0.49)	*Age (γ_{01})*	-0.13 (0.04) *
FFMQ (γ_{03})	0.48 (0.24)	*MEQ (γ_{02})*	0.07 (0.01) *
MEQ (γ_{04})	2.31 (0.28)	*FFMQ (γ_{03})*	0.01 (0.01)
Subjective Stress		**PVT Response Time**	
Sex (γ_{01})	-1.54 (0.54) *	*Age (γ_{01})*	-3.91 (1.01) **
Experience (γ_{02})	0.15 (0.06) #	*FFMQ (γ_{02})*	0.55 (0.20) *
MEQ (γ_{03})	0.06 (0.03)	*MEQ (γ_{03})*	2.38 (0.37) ***
Mean RR		**Subjective Stress**	
Sex (γ_{01})	-548 (129) **	*Sex (γ_{01})*	-0.24 (0.08) **
Age (γ_{02})	48.6 (11.9) **	*Meditation (γ_{02})*	-0.21 (0.09) *
PA (γ_{03})	0.55 (0.15) **	*Age (γ_{03})*	0.03 (0.02) *

FFMQ (γ_{04})	8.03 (3.1) *	*PA (γ_{04})*	-6.54e–4 (0.0002) ***
MEQ (γ_{05})	34.7 (7.7) **		
Mean RMSSD		**Mean RR**	
MEQ (γ_{01})	2.69 (0.45) ***	*Meditation (γ_{01})*	121 (49) *
Sex (γ_{02})	-42.7 (7.45) ***	*Age (γ_{02})*	17.3 (7.8) #
PA (γ_{03})	0.03 (0.007) *	*Experience (γ_{03})*	44.4 (9.2) ***
FFMQ (γ_{04})	0.63 (0.19) *	*PA (γ_{04})*	0.568 (0.09) ***

Note: Every covariate shown contributed to improved model fit in respective models. γ values are unstandardized beta-weights, which represent the amount of change in the outcome variable per one unit change in the covariate variable. Values in parentheses are standard errors. # p < .10 *p < .05. **p < .01. ***p<.001. Negative numbers indictate negative associations. Estimates are derived from covariate models only and therefore do not take random slopes or cross-level interactions into account.

4.3.1 Pre-Shift Fatigue

Research Question 1: Are indices of cognitive function associated with sleep characteristics?

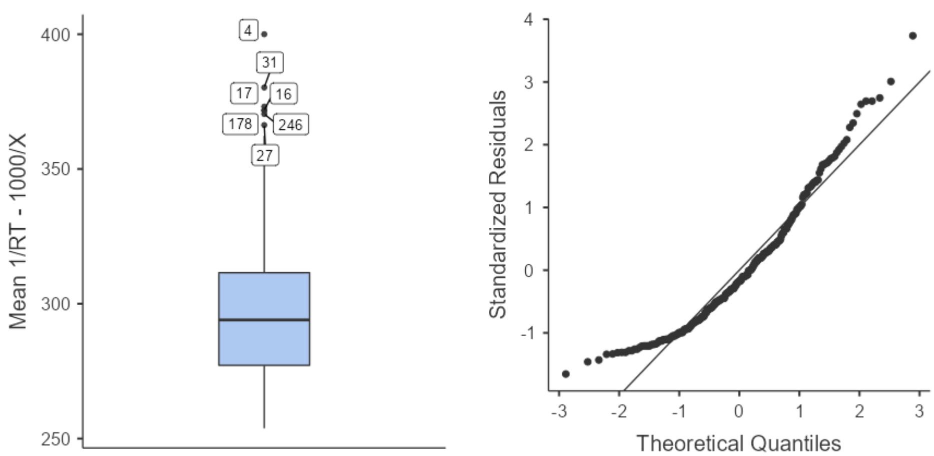
Appendix G.1 summarizes a backward variable selection process wherein sleep-related predictors were progressively eliminated from an original set including sleep duration, previous evening bedtime, wakeup time, and three sleep quality metrics (i.e., number of sleep cycles, sleep continuity (/5), and overall sleep score (/100)). This process revealed overall actigraphy-measured sleep quality (i.e., sleep score) to be the best sleep-related predictor for all measures of cognitive function, including number of PVT lapses in attention (i.e., responses time over 355ms) (γ_{10} = -0.02, t(114) = -3.27, p < 0.001), PVT mean reciprocal response time (RT) (γ_{10} = -0.43, t(114) = -3.23, p < 0.005), and subjective fatigue (γ_{10} = -0.09, t(168) = -6.19, p < 0.001).

Transformations

We modelled transformed data for pre-shift PVT lapses and subjective fatigue, (i.e., log and cubic root transforms, respectfully) because their original predictor-only models violated the assumption of normally distributed residuals. The log (x) transformation for PVT lapses had to be adapted to log (x+1) because potential values included 0. Further, cubic root values of subjective fatigue were multiplied by 10 so that their model fit criteria were interpretable. 11

outlier data points for mean RT were identified by visual inspection (Figure 4.3.1) and were replaced with mean + 2SD, as based on recommendations by Field et al. (2012). Once the above transformed were performed, residuals for all three measures met the assumption normality according to the Kolmogorov-Smirnov test, Shapiro-Wilks test, and visual inspection.

Figure 4.3.1.1 *Visual Illustration of Outlier Data Points for Pre-Shift Response Time*



Research Question 2: <u>Do participant-level characteristics moderate the relationship between sleep and cognitive function?</u>

Appendix G.1 summarizes the results of a backward covariate selection process wherein participant characteristics were individually assessed according to their effect on cognitive function measures. If not contributing to model fit, the worst performing covariate was progressively eliminated from an original set including participant age, biological sex, years of firefighting experience (hereby referred to as “experience”), experience with meditation (i.e., hereby referred to as “meditation”), baseline physical activity (PA), trait mindfulness, and trait morningness-eveningness (ME).

As shown in Appendix G.1 and Table 4.3.0.2, contributing covariates for predicting PVT lapses included ME ($p < 0.01$) and experience ($p = 0.056$). Contributing covariates for RT included participant ME (p = 0.17), meditation (p = 0.18), age (p = 0.33), and mindfulness (p = 0.4). Note that all included covariates for RT contributed to model fit, despite lacking statistical significance. All participant characteristics were removed as non-contributing covariates for predicting subjective fatigue. Thus, sex and PA were removed as non-contributing covariates from all pre-shift cognitive function models, while ME was identified as a significant contributor to model fit for both PVT lapses and RT. These results provide tentative evidence in support of a direct single-level effect (i.e., sleep score on cognitive function), as well as several cross-level effects (e.g., ME on PVT lapses and RT).

Interindividual Variation

Appendix G.1 summarizes the results of a comparison between the final fixed slope model and two competing random slope models with differing covariance structures (i.e., independence vs. unstructured). Results of the LRT indicated that the slopes of association did not significantly vary across participants in any measure of pre-shift cognitive function, so LME models were deemed complete.

Final LME models representing the relationships between sleep and pre-shift stress measures are illustrated by Equations 4.1 - 4.3.

- (Eq. 4.1) $Pre\ RT_{ij} = \gamma_{00} + \gamma_{10}SleepScore_{ij} + \gamma_{01}Meditation_j + \gamma_{02}Age_j + \gamma_{03}ME_j + \gamma_{04}Mindfulness_j + \mu_{0j} + \varepsilon_{ij}$
- (Eq. 4.2) $Pre\ Lapses_{ij} = \gamma_{00} + \gamma_{10}SleepScore_{ij} + \gamma_{01}Experience_j + \gamma_{03}ME_j + \mu_{0j} + \varepsilon_{ij}$
- (Eq. 4.3) $Pre\ Subjective\ Fatigue_{ij} = \gamma_{00} + \gamma_{10}SleepScore_{ij} + \mu_{0j} + \varepsilon_{ij}$

4.3.2 Pre-Shift Stress

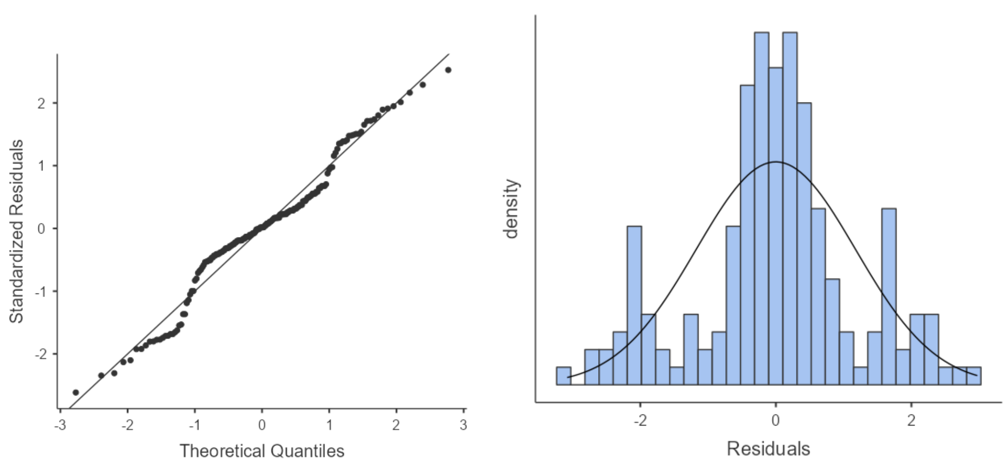
Research Question 1: Are indices of stress associated with sleep characteristics?

Appendix G.2 shows that sleep score was the best sleep-related predictor for pre-shift subjective stress (γ_{10} = -0.02, t(168) = -3.49, p < 0.001) and morning heart rate, as measured by mean R-R interval (γ_{10} = 2.31, t(109) = 2.64, p < 0.01), while evening bedtime was best predictor for morning heart rate variability (HRV), as measured by RMSSD (γ_{10} = -58, t(109) = -1.84, p = 0.07).

Transformations

We modelled cubic-root transformed data for pre-shift subjective stress because the original predictor-only model violated the assumption of normally distributed residuals. These cubic root values were multiplied by 10 so that model fit criteria were interpretable. Once the above transformations were performed, residuals met the assumption normality according to the Kolmogorov-Smirnov test. Transformed subjective stress values did not conform to a normal distribution according to the Shapiro-Wilks test but did appear to be roughly normally distributed upon visual inspection Figure (4.3.2.1).

Figure 4.3.1.1 *Visual Illustration of Outlier Residual Distribution for Post Shift Response Time*



Research Question 2: Do participant-level characteristics moderate the relationship between sleep characteristics and stress?

As shown in Appendix G.2 and Table 4.3.0.2, contributing covariates for predicting subjective stress included participant sex ($p < 0.05$), experience ($p = 0.07$), and ME ($p = 0.18$). Contributing covariates for RR included sex ($p < 0.005$), age ($p < 0.005$), PA ($p < 0.005$), mindfulness ($p < 0.05$), and ME ($p < 0.001$). Contributing covariates for RMSSD included ME ($p < 0.001$), sex ($p < 0.001$), PA ($p < 0.05$) and mindfulness ($p < 0.05$). Thus, meditation was removed as a non-contributing covariate from all pre-shift stress models, while sex and ME were identified as significant contributors to model fit for all stress indices. These results provide tentative evidence in support of several direct single-level effects (i.e., sleep score on subjective stress and heart rate; bedtime on HRV), as well as several cross-level effects (e.g., sex, experience, and ME on subjective stress).

Interindividual Variation

Results of the LRT indicated that the slopes of association did not significantly vary across participants in any pre-shift measures of stress, so LME models were deemed complete.

Final LME models representing the relationships between sleep and pre-shift cognitive function measures are illustrated by Equations 4.4 - 4.6.

- (Eq. 4.4) $Pre\ RR_{ij} = \gamma_{00} + \gamma_{10}SleepScore_{ij} + \gamma_{01}Sex_j + \gamma_{02}Age_j + \gamma_{03}PA_j + + \gamma_{04}Mindfulness_j + \gamma_{05}ME_j\ \mu_{0j} + \varepsilon_{ij}$

- (Eq. 4.5) $Pre\ RMSSD_{ij} = \gamma_{00} + \gamma_{10}Bedtime_{ij} + \gamma_{01}ME_j + \gamma_{02}Sex_j + \gamma_{03}PA_j + \gamma_{04}Mindfulness_j + \mu_{0j} + \varepsilon_{ij}$

- (Eq. 4.6) $Pre\ Subjective\ Stress_{ij} = \gamma_{00} + \gamma_{10}SleepScore_{ij} + \gamma_{01}Sex_j + \gamma_{02}Experience_j + \gamma_{03}MEQ_j\ \mu_{0j} + \varepsilon_{ij}$

4.3.3 Post-Shift Fatigue

Research Question 1: Are indices of cognitive function associated with shift characteristics?

Appendix G.3 summarizes a backward variable selection process wherein the shift-related predictors were progressively eliminated from an original set including start time, end time, shift duration, and time between shifts. This process revealed shift duration to be the best shift-related predictor for all measures of cognitive function, including number of PVT lapses (γ_{10} = 0.07, t(164) = 3.39, p < 0.001), RT (γ_{10} = 1.83, t(164) = 3.07, p < 0.005), and subjective fatigue (γ_{10} = 0.04, t(304) = 5.77, p < 0.001).

Transformations

We modelled transformed data for pre-shift PVT lapses and subjective fatigue, (i.e., log and square root transforms, respectfully) because the original predictor-only models violated the assumption of normally distributed residuals. The log (x) transformation for PVT lapses were to be adapted to log (x+1) because potential values included 0. Eight outlier data points for mean RT were identified by visual inspection (Figure 4.3.3.1) and were replaced with mean + 2SD, as based on recommendations by Field et al. (2012). Once the above transformed were performed, residuals for all three measures met the assumption normality according to the Kolmogorov-Smirnov test. Transformed RT values did not conform to a normal distribution according to the Shapiro-Wilks test but did appear to be normally distributed upon visual inspection (Figure 4.3.3.2).

Figure 4.3.3.1 *Visual Illustration of Outlier Data Points for Post-Shift Response Time*

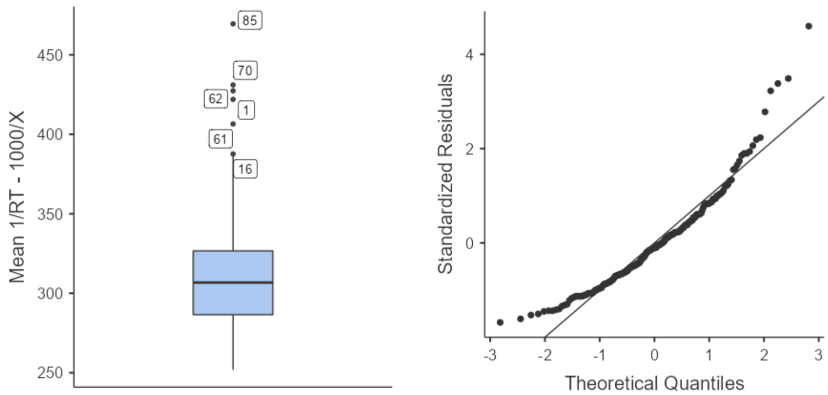
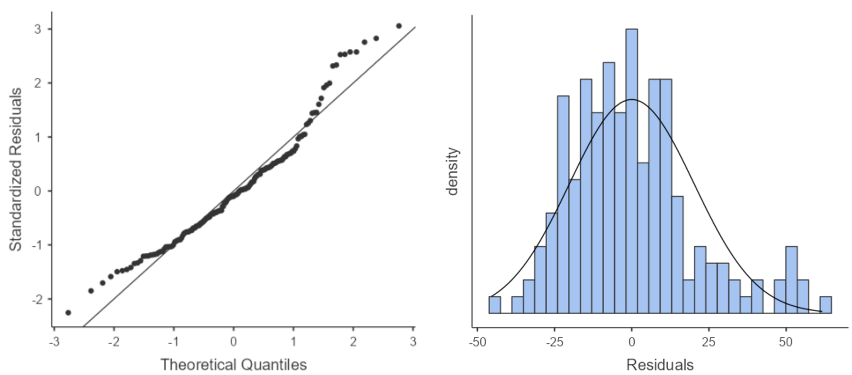


Figure 4.3.3.2 *Visual Illustration of Residusal Distribution for Post Shift Response Time*



<u>**Research Question 2:** Do participant-level characteristics moderate the relationship between shift characteristics and cognitive function?</u>

As shown in Appendix G.3 and Table 4.3.0.2, contributing covariates for predicting PVT lapses included participant mindfulness ($p = 0.184$), ME ($p < 0.05$), and age ($p < 0.05$). Contributing covariates for RT included ME ($p < 0.001$), mindfulness ($p < 0.05$), and age ($p < 0.01$). Contributing covariates for subjective fatigue included meditation ($p < 0.05$), PA ($p = 0.07$) and ME ($p = 0.16$). Thus, sex and experience were removed as non-contributing covariates from all post-shift cognitive function models, while ME was identified as a significant contributor to model for all cognitive function indices. These results provide tentative evidence in support of a direct single-level effect (i.e., shift duration on cognitive function) as well as several cross-level effects (e.g., mindfulness, age, and ME on PVT performance).

Interindividual Variation

As shown in Appendix G.3, results of the LRT indicated that the slopes of association did not significantly vary across participants in the post-shift RT model, so cross-level interactions were not investigated. However, significant variation in slope was identified for both PVT lapses (*SD* = 0.07, 95% CI: [0.01, 0.14], χ^2 (2) = 4.63, $p < .05$), and subjective fatigue (*SD* = 0.02, 95% CI: [0, 0.05], χ^2 (2) = 4.12, $p < 0.05$), with independence covariance structures resulting in the best model fit for both.

Cross-Level Interactions

Cross level interactions in the post-shift subjective fatigue model were indicated for meditation, ME and PA. Simple effects analysis (Table 4.3.3.1) revealed that the strength of association between shift duration and subjective fatigue was higher in individuals with low PA (β_1 = 0.04, $p < 0.05$) compared to those with average (β_1 = 0.02, p = 0.12) or high PA (β_{1j} = 0.003, p = 0.88). The strength of association was also higher in individuals with meditation experience (β_1 = 0.05, $p < 0.005$) compared to those with without meditation experience (β_1 = -0.007, p = 0.77). Morning-type individuals also showed higher strength of association (β_1 = 0.03, p = 0.08) compared to evening-type (β_1 = 0.02, p = 0.12) or neither-type (β_1 = 0.01, p = 0.58). Visual representations of each covariate's modulatory effects on the relationship between shift duration and subjective fatigue are shown in Figure 4.3.3.3 No cross-level interactions were found to contribute to model fit for PVT lapses.

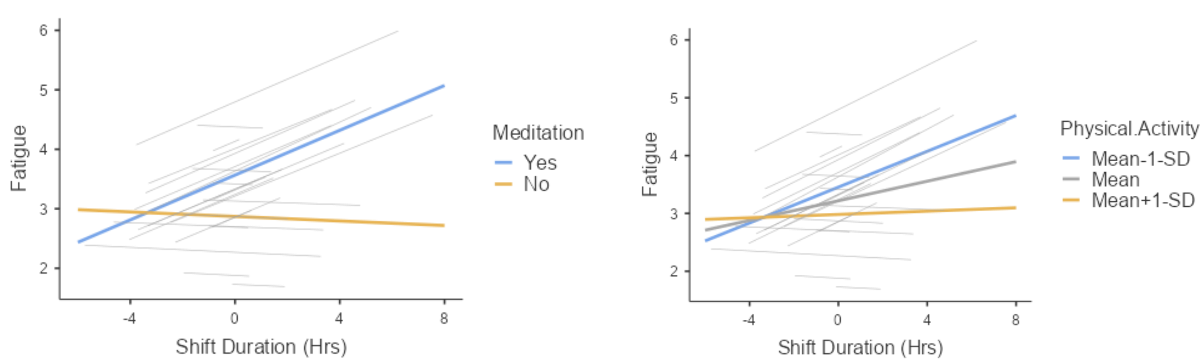
Table 4.3.3.1 *Simple Effects Analysis of Cross Level Interactions for Post-Shift Fatigue*

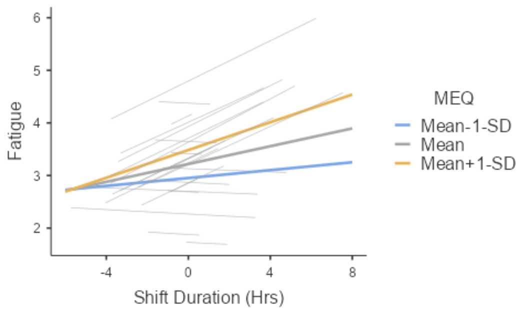
Simple effects of Shift Duration: Parameter estimates

Moderator levels			
Physical Activity	**Estimate**	**SE**	**p**
Mean-1-SD	0.041	0.02	0.025
Mean	0.022	0.01	0.119
Mean+1-SD	0.003	0.02	0.882
Meditation			
Yes	0.051	0.01	0.002
No	-0.007	0.02	0.777
MEQ			
Mean-1-SD	0.010	0.02	0.579
Mean	0.022	0.01	0.119
Mean+1-SD	0.034	0.02	0.077

Note. Simple effects are estimated keeping constant other independent variable(s) in the model

Figure 4.3.3.3 *Visual Illustration of Cross-Level Interactions for Post-Shift Fatigue*





Note: Solid colored lines represent fixed effects (across individuals), while grey lines represent random effects (within individuals). Effects are estimated keeping other independent variables constant in the model.

Final LME models representing the relationships between shift characteristics and post-shift cognitive function measures are illustrated by Equations 4.7 – 4.9:

- (Eq. 4.7) $Post\ RT_{ij} = \gamma_{00} + \gamma_{10}Shift\ Duration_{ij} + \gamma_{01}Age_j + \gamma_{02}Minfulness_j + \gamma_{03}MEQ_j + \mu_{0j} + \varepsilon_{ij}$

- (Eq. 4.8) $Post\ Lapses_{ij} = \gamma_{00} + \gamma_{10}Shift\ Duration_{ij} + \gamma_{01}Age_j + \gamma_{02}MEQ_j + \gamma_{03}Mindfulness_j + \mu_{0j} + \mu_{1j}Shift\ Duration_{ij} + \varepsilon_{ij}$

- $Post\ Subjective\ Fatigue_{ij} = \gamma_{00} + \gamma_{10}Shift\ Duration_{ij} + \gamma_{01}Meditation_j + \gamma_{02}PA_j + \gamma_{03}MEQ_j + \gamma_{11}(Shift\ Duration_{ij})(Meditation_j) + \gamma_{12}(Shift\ Duration_{ij})\left(PA_j\right) + \gamma_{12}(Shift\ Duration_{ij})\left(ME_j\right) + \mu_{0j} + \mu_{1j}Shift\ Duration_{ij} + \varepsilon_{ij}$

Additional analysis showed that shift condition significantly moderated the relationship such that the association between shift duration and cognitive function was stronger for post-shift observations compared to pre-shift. Stated otherwise, the difference between pre-shift levels of cognitive function and post-shift levels of cognitive function appeared to increase in line with longer shift durations. This is illustrated by the simple effects analysis shown in Table 4.3.3.2, as well as in Figure 4.3.3.4.

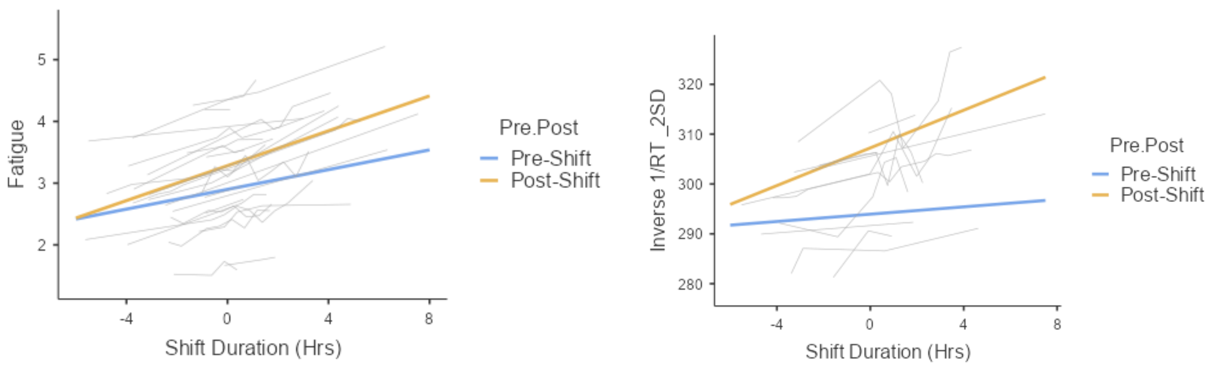
Table 4.3.3.2 *Simple Effects Analysis Comparing Pre vs Post-Shift Effects of Shift Duration on Each Measure of Cognitive Function*

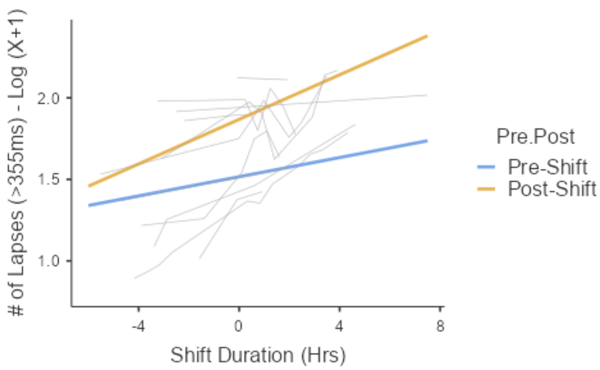
Simple effects of Shift Duration (Hrs): Parameter estimates

Measure of Cognitive Function	Moderator levels	Estimate	SE	p
Subjective Fatigue	Pre-Shift	0.019	0.014	0.177
	Post-Shift	0.034	0.014	0.024
PVT Response Time	Pre-Shift	0.367	0.520	0.481
	Post-Shift	1.890	0.528	< .001
PVT Lapses	Pre-Shift	0.029	0.031	0.358
	Post-Shift	0.068	0.032	0.045

Note. Simple effects are estimated keeping constant other independent variable(s) in the model

Figure 4.3.3.4 *Visual Illustration of Pre vs Post-Shift Associations Between Shift Duration and Each Measure of Cognitive Function*





Note: Solid colored lines represent fixed effects (across individuals), while grey lines represent random effects (within individuals). Effects are estimated keeping other independent variables constant in the model.

4.3.4 Post-Shift Stress

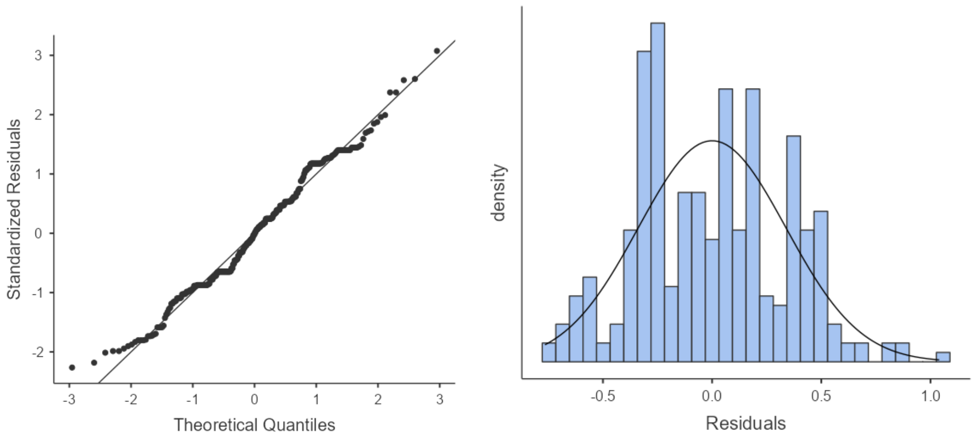
Research Question 1: Are indices of stress associated with shift characteristics?

Appendix G.4 shows that shift duration was the best shift-related predictor of heart rate, as measured by mean RR interval (γ_{10} = - 13.6, t (113) = -3.40, p<0.001) and subjective stress (γ_{10} = 0.09, t (301) = 6.43, p<0.001). No shift-related predictors were identified for RMSSD, so an LME model was not created.

Transformations

We modelled log transformed data for pre-shift subjective stress because the original predictor-only model violated the assumption of normally distributed residuals. Although this improved the normality of residual distribution, transformed values still violated met the assumption normality according to the Kolmogorov-Smirnov and Shapiro-Wilks tests. However, transformed subjective stress value residuals appear to be roughly normally distributed upon visual inspection *(*Figure 4.3.4.1)

Figure 4.3.4.1 *Visual Illustration of Outlier Residusal Distribution for Post-Shift Subjective Stress*



Research Question 2: <u>Do participant-level characteristics moderate the relationship between shift characteristics and stress?</u>

As shown in Appendix G.3 and Table 4.3.0.2, contributing covariates for predicting post-shift subjective stress included participant PA ($p < 0.001$), sex ($p < 0.005$), age ($p < 0.05$), and meditation ($p < 0.05$). Contributing covariates for RR included participant age ($p=0.06$), meditation ($p < 0.05$), experience ($p < 0.001$) and PA ($p < 0.001$). Thus, mindfulness and ME were removed as non-contributing covariates from all post-shift stress models, while meditation, age, and PA were identified as significant contributors to model fit for both stress indices. These results provide tentative evidence in support of two direct single-level effects (i.e., shift duration on subjective stress and heart rate), as well as several cross-level effects (e.g., meditation, age, and PA on subjective stress and heart rate).

Interindividual Variation

Results of the LRT indicated that the slopes of association did not significantly vary across participants in post-shift subjective stress, so cross-level interactions were not investigated. However, significant variation in slope was identified for mean RR (*SD* = 12.7, 95% CI: 4.3, 27.4], χ^2 (1) = 8.63, $p < .05$), with an unstructured covariance structure resulting in the best model fit.

Cross-Level Interactions

Cross-level interactions in the post-shift RR model were indicated for PA and mediation. Simple effects analysis (Table 4.3.4.1) revealed that the strength of association between shift duration and mean RR was higher in individuals with average (β_1 = -19.8, p < 0.05) low (β_1 = -36.2, p = 0.06) PA compared to high PA (β_{1j} = -3.44, p = 0.72). The strength of association was also higher in individuals without meditation experience (β_1 = -29.1, p = 0.07) compared to those with meditation experience (β_1 = -10.6, p = 0.36). Visual representations of each covariate's modulatory effect on the relationship between shift duration and post-shift mean RR are shown in Figure 4.3.4.3.

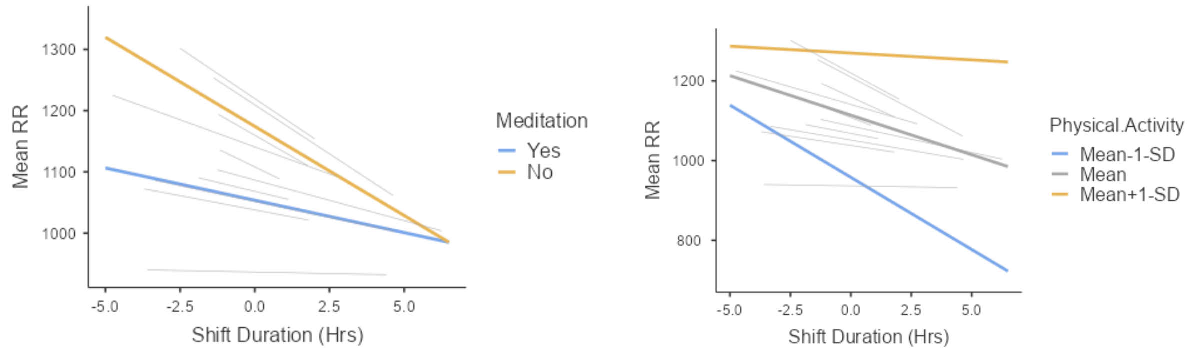
Table 4.3.4.1 *Simple Effects Analysis of Cross Level Interactions for Post-Shift RR*

Simple effects of Shift Duration (Hrs): Parameter estimates

Moderator levels			
Physical Activity	**Estimate**	**SE**	**p**
Mean-1-SD	-36.22	15.03	0.058
Mean	-19.83	8.78	0.041
Mean+1-SD	-3.44	9.31	0.718
Meditation	**Estimate**	**SE**	**p**
Yes	-10.6	7.14	0.362
No	-29.1	15.53	0.068

Note. Simple effects are estimated keeping constant other independent variable(s) in the model.

Figure 4.3.4.3 *Visual Illustration of Cross Level Interactions for Post-Shift RR*



Note: Solid colored lines represent fixed effects (across individuals), while grey lines represent random effects (within individuals). Effects are estimated keeping other independent variables constant in the model.

Final LME models representing the relationships between shift characteristics and post-shift stress measures are illustrated by Equations 4.10 and 4.11.

- (Eq. 4.10) $PostRR_{ij} = \gamma_{00} + \gamma_{01}Meditation_j + \gamma_{02}Age_j + \gamma_{03}Experience_j + \gamma_{04}PA_j + \gamma_{10}Shift\ Duration_{ij} + \gamma_{11}(Shift\ Duration_{ij})(PA_j) + \gamma_{12}(Shift\ Duration_{ij})(Meditation_j) + \mu_{0j} + \mu_{1j}Shift\ Duration_{ij} + \varepsilon_{ij}$

- (Eq. 4.11) $Post\ Subjective\ Stress_{ij} = \gamma_{00} + \gamma_{10}Shift\ Duration_{ij} + \gamma_{01}Sex_j + \gamma_{02}Meditation_j + \gamma_{03}Age_j + \gamma_{03}PA_j + \mu_{0j} + \varepsilon_{ij}$

Additional analysis showed that shift condition significantly moderated the relationships such that the associations between shift duration and stress were stronger for post-shift observations compared to pre-shift. Stated otherwise, the difference between pre-shift levels of stress and post-shift levels of stress appeared to increase in line with longer shift durations. This is illustrated by the simple effects analysis shown in Table 4.3.4.2, as well as in Figure 4.3.4.4.

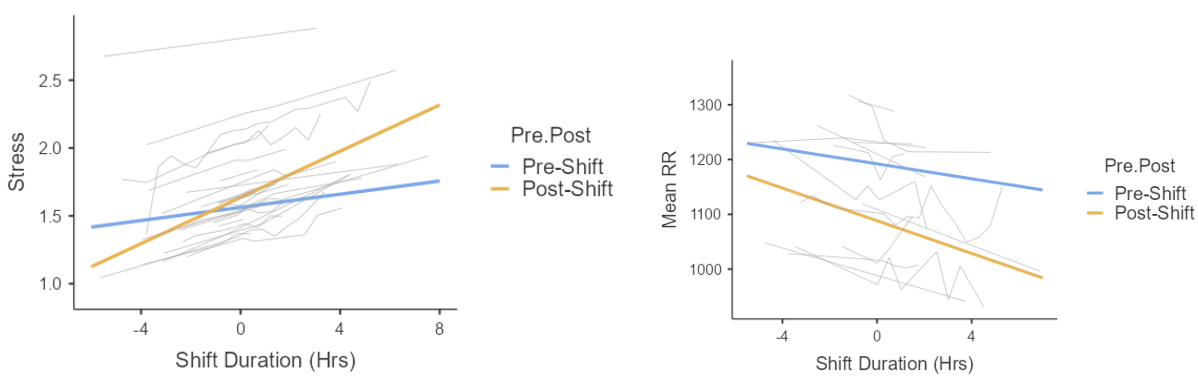
Table 4.3.4.2 *Simple Effects Analysis Comparing Pre vs Post-Shift Effects of Shift Duration on Each Measure of Stress*

Simple effects of Shift Duration (Hrs): Parameter estimates

Measure of Stress	Moderator levels	Estimate	SE	p
Subjective Stress	Pre-Shift	0.009	0.007	0.195
	Post-Shift	0.043	0.007	<0.001
R-R Interval	Pre-Shift	-6.80	6.24	0.322
	Post-Shift	-14.9	5.70	0.016

Note. Simple effects are estimated keeping constant other independent variable(s) in the model

Figure 4.3.3.4 *Visual Illustration of Pre vs Post-Shift Associations Between Shift Duration and Each Measure of Stress*



Note: Solid colored lines represent fixed effects (across individuals), while grey lines represent random effects (within individuals). Effects are estimated keeping other independent variables constant in the model.

Chapter 5: Discussion

The primary aim of this study was to investigate the relationships between sleep, shift characteristics and levels of stress and cognitive function in wildland firefighters. Contrary to our null hypothesis, the main finding was that poor sleep and long shift durations were associated with higher levels of stress and impaired cognitive function, which has implications for workplace health and safety, respectively.

5.1 Sleep and Stress

Overall actigraphy-measured sleep quality (i.e., Polar® Sleep Score; hereby referred to as "sleep score") was found to be the best sleep-related predictor for pre-shift subjective stress and morning heart rate (HR), as measured by 1-4 scale and mean R-R interval, respectively. Meanwhile, evening bedtime was the best predictor for morning heart rate variability (HRV), as measured by RMSSD. According to the Polar® website, the sleep score index is intended to summarize how much and how well one has slept. It is a 1-100 scale, calculated as the average of six components that are grouped under three themes: amount, solidity, and regeneration (Polar, 2023). Notably, impaired sleep according to the sleep score index was associated with higher resting HR, which suggests a shift in autonomic nervous system balance towards heightened sympathetic activity (Shaffer & Ginsberg, 2017). This finding is supported by previous laboratory experiments showing that sleep loss is related to increased sympathetic tone and/or reduced vagal (i.e., parasympathetic) modulation (Bourdillon et al., 2021; Dettoni et al., 2012; Grimaldi et al., 2016; Spiegel et al., 2004; Zhong et al., 2005). Evidence is mixed, however, with other laboratory studies finding prolonged wakefulness to result in reduced HR, as mediated by a decline in sympathetic activity (Holmes et al., 2002; Vaara et al., 2009), or no change at all (Pagani et al., 2009). A causal link between sleep loss and autonomic dysfunction is further evidenced by a recent meta-analysis reporting that individuals with obstructive sleep apnea exhibit impaired parasympathetic function (Wang et al., 2023), although findings are less clear for individuals with insomnia (Dodds et al., 2017).

Field studies in this domain are mostly limited to healthcare settings wherein HRV is measured across 24-hour shifts. Most of these investigations report that shift-work-related sleep impairment is associated with altered HRV parameters indicative of increased sympatric activity (Amirian et al., 2014; Arslan et al., 2019; Burch et al., 2019; Cebeci et al., 2015; Neufeld et al., 2017; Tobaldini et al., 2013), but not all (Dutheil et al., 2012; Langelotz et al., 2008; Nantsupawat et al., 2022). Notably, Nantsupawat et al. (2022) found elevated sympathetic activity and reduced parasympathetic withdrawal in physician residents classified into the long sleep group (i.e., > 307.5 mins), whereas the opposite pattern was observed in those classified as short sleepers (i.e., < 180 mins). The authors state that these divergent results may be explained by a “parasympathetic rebound” phenomenon caused by excessive levels of sleepiness.

It's important to note, however, that healthcare workers face vastly different occupational demands compared to wildland firefighters. For example, the around-the-clock nature of the healthcare sector requires nurses and physicians to routinely work 12-to-24-hour shifts, often including night-work and continuous, low-intensity physical activity while exposed to indoor fluorescent lighting and shorter, more frequent napping opportunities. Routine nightshifts in the healthcare sector may lead to unique patterns of stress (Burch et al., 2019) and fatigue (Leso et al., 2021) that are associated with extreme circadian misalignment. On the other hand, wildland firefighters in B.C. often work 12-to-16-hour shifts involving intermittent periods of intense physical activity in the outdoors while exposed to natural lighting and shortened, yet consolidated, sleep opportunities. Although 24-hour operations are not as common as in other shift-work industries, night-work is sometimes required to achieve objectives that would otherwise not be possible during the heat of the day (Vincent et al., 2018). Stepwise circadian misalignment in wildland firefighting may occur due to earlier start times and/or later end times on fire suppression days, which might explain why bedtime was a better predictor of morning HRV than overall sleep score in our study. We found that later bedtimes were associated with reduced HRV, which is indicative of heighted sympathetic activity (Shaffer & Ginsberg, 2017). This is supported by Grimaldi et al. (2016) in their finding that sleep restriction, in conjunction with circadian misalignment, led to increased HR and reduced parasympathetic tone compared to sleep restriction alone. Similarly, Faust et al. (2020) found that going to bed even 30 minutes later than one's normal bedtime was associated a higher resting HR throughout sleep, which persisted into the following day.

Unfortunately, existing research on the stress-related implications of sleep loss in wildland firefighting remains sparse. In a similar observational study involving wildfire management staff in B.C., Jeklin et al. (2021) found the RMSSD component of HRV to be associated with subjective sleepiness, fatigue, and total sleep duration. Further evidence comes from a pair of studies that examined 23 Ontario firefighters across a relatively low-hazard fire season (McGillis et al., 2017; Robertson et al., 2017). McGillis et al. (2017) found that total sleep time was reduced during initial attack (IA) deployments compared to project fires and base work. In the same group of participants, Robertson et al. (2017) found that total time spent in a state of "physiological stress" during IA deployments was higher than project fires, while time spent in a state of "physiological recovery" was lowest during IA fires compared to project fires and base work. It is important to note, however, that their determination of "physiological stress" and "physiological recovery" was based a proprietary and unvalidated measure of HRV. Two other studies examined endocrine-related markers of stress in wildland firefighting (Wolkow, Ferguson, et al., 2016; Wolkow et al., 2017). They found that simulated firefighting under conditions of sleep-restriction resulted in higher levels of cortisol and stress-related cytokines (Wolkow, Aisbett, et al., 2016), with a similar trend being found in a temperature-controlled hot environment (Wolkow et al., 2017).

In summary, our findings showed that impaired sleep was associated with higher HR and increased subjective stress. Evidence from other shift-work industries suggest that this may reflect a shift towards heightened sympathetic activity. Further research is required to elucidate the nature of this relationship, however, especially in the context of wildland firefighting.

5.2 Sleep and Fatigue

Sleep score was found to be the best sleep-related predictor for all measures of cognitive function, including number of psychomotor vigilance task (PVT) lapses in attention, mean reciprocal response time (RT), and subjective fatigue. These findings suggest that poor sleep may be related to reduced cognitive function, which is congruent with previous literature. Indeed, extensive laboratory research in recent decades has revealed that acute sleep loss of any duration impairs performance across most cognitive domains (Lim et al., 2010; Lowe et al., 2017), although deficits in attentional ability appear to be the most susceptible (Killgore et al., 2010). The PVT is a widely used and sensitive assay designed to assess neurocognitive effects of sleep loss (Basner & Dinges, 2011; Hudson et al., 2020; Lim & Dinges, 2008).

Unfortunately, field-based studies examining the effects of sleep loss on cognitive function have received less attention in the literature, despite having more real-world applicability. In general, research in this domain has shown sleep loss to impair attentional ability across several occupational groups, which supports previous laboratory research. For example, Ferguson et al. (2011) found that the miners with less than 6 hours of sleep in the preceding 24 hours exhibited slower RT on the PVT compared to those who had over 7 hours of sleep. Similarly, Flynn-Evans et al. (2018) found sleep duration in pilots to be over one hour shorter during early work shifts compared to baseline, which may explain the observed coinciding decline in PVT performance. A trend of reduced sleep durations being associated with slower RT on the PVT has also been shown police-work settings (Neylan et al., 2010) and across the healthcare sector, including in nurses (Geiger-Brown et al., 2012; Ruggiero et al., 2012), and physician interns (Basner et al., 2017; Ganesan et al., 2019).

To the authors knowledge, only three separate studies have measured sleep and PVT performance, concurrently, the context of wildland firefighting (Ferguson et al., 2016; Jeklin et al., 2020; McGillis et al., 2017; Smith et al., 2016). In the same study cohort, Ferguson et al. (2016) and Smith et al. (2016) measured attentional ability across three days of simulated wildland firefighting. Their results showed that firefighters exposed to restricted sleep opportunities (i.e., 4 hours per night) had slower response times on the PVT compared to the control condition (i.e., 8-hour sleep opportunity). Although accompanied by higher levels of subjective fatigue (Ferguson et al., 2016), firefighters were unreliable in their ability to predict declines in PVT performance following 4-hour sleep opportunities (Smith et al., 2016), which suggests that self-report may be insufficient as a fatigue risk management tool. Jeklin et al. (2020) and McGillis et al. (2017) both conducted observational, field-based studies that examined sleep and fatigue in Canadian wildland firefighters. Although neither study assessed the association between sleep and cognitive function directly, both provide evidence of impaired sleep and concurrent increased levels of fatigue during prolonged wildfire deployments. More specifically, Jeklin et al. (2020) found that firefighters reported less total sleep time, worse PVT performance and increased sleepiness toward the end of their 14-day deployment compared to day 1. Meanwhile, McGillis et al. (2017) found that IA deployments were associated with less total sleep time and slower PVT RT compared to project fire deployments and base work.

In summary, there is an extensive body of laboratory evidence showing that poor sleep induces impaired cognitive function, as often indicated by performance on the PVT. Uniquely, we extend this evidence, directly, to wildland firefighters in a naturalistic setting.

5.3 Shift and Fatigue

Possibly related to the above discussed effects of poor sleep, the current study found prolonged shift durations to be positively associated with increased levels of fatigue across all cognitive measures, including PVT lapses, RT, and subjective fatigue.

These findings sit equivocally in previous literature. There is considerable research examining the relationship between shift characteristics and fatigue-related outcomes, however, existing evidence is generally mixed, of low quality, and mostly limited to medical settings (Ferris et al., 2021; Leso et al., 2021; Patterson, Runyon, et al., 2018). In their review, Patterson, Runyon, et al. (2018) reported no clear guidance beyond shifts under 24 hours in duration being more favorable than those over 24 hours. Notably, research on air medical clinicians has indicated no difference in cognitive function when comparing 12-hour shifts to 18 hours (Thomas et al., 2006) or 24 hours (Guyette et al., 2013; Manacci et al., 1999; Patterson et al., 2019) shifts. It’s important to note, however, that many of the 12-hours shifts in these studies took place overnight (Patterson et al., 2019; Thomas et al., 2006), which may implicate secondary factors known to affect in attentional ability. That is, night-work may exacerbate cognitive impairment during prolonged shifts by layering the effects of sleep loss and circadian misalignment on top of existing prolonged wakefulness and sustained cognitive activity

(Satterfield & Van Dongen, 2013). Similar findings have been found in other healthcare professions. For example, Yi et al. (2013) did not find any significant differences in PVT performance between physician residents working 24-hour shifts versus 12-hour night shifts. Results from Rhéaume and Mullen (2018) showed that nurses working 12-hour rotations did not report making any more cognitive errors, despite obtaining worse sleep, compared to those working 8-hour day shifts. In contrast, Karanovic et al. (2009) discovered slower reaction time, though not impaired accuracy, in anesthesiologist's psychomotor performance following 24-hour shifts compared to a 7-hour normal working day. Similarly, (Osterode et al., 2018) found that hospital physicians working 24-hour shifts performed worse on a visual memory task compared to 8-hour day shifts. As supported by Leso et al. (2021), mixed findings in this domain may be attributable to heterogeneity in study designs, as above-mentioned studies differ widely in their type of shift comparisons and cognitive tasks employed. For example, both Thomas et al. (2006) and Guyette et al. (2013) employed test batteries targeting complex mental abilities like working memory, which may be more resilient to impairment compared to simple attentional ability (Killgore et al., 2010).

Evidence from outside the healthcare sector suggests a beneficial effect of shorter shift durations on cognitive function (Amendola et al., 2011; Bell et al., 2015; Rosa & Bonnet, 1993), although null (Lowden et al., 1998), and unfavorable (Hossain et al., 2004) effects have also been reported. Notably, Bell et al. (2015) and Amendola et al. (2011) both conducted comprehensive, longitudinal studies on the advantages and disadvantages of extended shift length in regard to police officer work performance, health, and safety. As they relate to cognitive function, results from Amendola et al. (2011) showed higher subjective sleepiness and reduced alertness following 12-hour shifts compared to 8-hour shifts, however, no objective differences were found in PVT performance. Bell et al. (2015) found that 10-hour shifts were preferable to 13.3 hour shifts across nearly all subjective and objective measures of cognitive function. In general, therefore, it appears that extended shift durations may have a greater impact in some occupations (e.g., police-work) compared to others (e.g., air medical clinicians). Such variability may be attributable heterogeneity in study designs and/or differing types of demands across professions. For example, Guyette et al. (2013) notes that the lack of difference observed between shift durations in their study may be due to the “nature of the shifts” in air medicine clinicians, which, in contrast to hospital physicians, “are characterized by long periods of low-intensity work interrupted by short-duration intense activity”. Different patterns of work and their associated opportunities for rest may translate to unique implications for fatigue recovery, not to mention inter-individual variability, which makes drawing conclusions from past literature difficult. To the authors knowledge, only one other study compared cognitive function by differing shifts durations in wildland firefighting (Mcgillis et al., 2017). They did not find shift length to affect subjective levels of fatigue. However, Robertson et al. (2017) found in the same subset of participants that IA deployments were associated with both longer shifts and slower RT compared to project fires and base work, which provides indirect evidence that extended shifts are related to worse cognitive function.

As illustrated in Figure 4.3.3.4, the current study also found that cognitive function tended to be worse, on average, across all measures after shift compared to before shift. This is in congruence with previous studies that employed the PVT multiple times per shift in naturalistic occupational settings (Ferris et al., 2021).

In summary, it remains unclear whether long shift durations reliably impair cognitive function compared to shorter shifts. Disagreement in this domain may stem from heterogeneity in study designs and/or differing patterns of work and rest between occupations. Nonetheless, we provide novel, direct evidence of a relationship between prolonged shift duration and impaired cognitive function in wildland firefighters.

5.4 Shift and Stress

Similar to associations with sleep, longer shift durations were related to higher levels of post-shift subjective stress and increased evening HR, as measured by 1-4 scale and mean R-R interval, respectively. No shift-related predictors were identified for HRV. However, all measures of stress, including HRV, were found to be altered after shift compared to before shift (HRV results not shown). These findings suggest that extended shifts may be associated with a shift in autonomic nervous system balance towards heightened sympathetic activity.

Available literature comparing autonomic function under differing shift conditions is mixed with incongruent findings, heterogeneous methodologies, and study designs that are most often limited to 24-hour shift-work settings (Jelmini et al., 2023). Older studies found either no relationship between working hours and HRV (Takahashi et al., 1999) or long working hours to be associated with a parasympathetic dominant state (Sasaki et al., 1999). More recently, Dutheil et al., (2012) and Thurman et al., (2017) both examined the HRV-related implications of 14-hour nights shifts compared to continuous 24-hour shifts in a healthcare setting. Dutheil et al. (2012) found that emergency physicians exposed to 24-hour shifts had higher HR and reduced HRV compared to 14-hour shifts, which suggests that prolonged shift durations may induce a state sympathetic dominance. In contrast, Thurman et al. (2017) found no significant differences in HRV between in obstetricians working 14 hours versus 24 hours in labour and delivery. These conflicting results may be attributable to differing job demands between emergency physicians and obstetricians, which highlights the above-mentioned limitations of drawing comparisons across occupational domains. Notably, Järvelin-Pasanen et al. (2013) compared HRV parameters between normal shifts (8 hours from 7:00 a.m. to 3:00 p.m.) and extended shifts (14 hours from 7:00 a.m. to 9:00 p.m.) in 60 female nurses. Their findings revealed significant differences in HRV parameters reflecting increased sympathetic control during work time compared to leisure-time. However, there were few, if any, differences in HRV parameters between normal and extended work shifts. The authors attribute this lack of different to the potential of adaptation to extended work shifts, as well the healthy status of participants (Järvelin-Pasanen et al., 2013).

The influence of shift characteristics on autonomic function can also assessed by comparing HRV before and after prolonged shifts. Similar to cognitive function (Ferris et al., 2021; Leso et al., 2021; Patterson, Runyon, et al., 2018), previous research on this topic is mixed and mostly limited to healthcare settings involving night-work. Recently, Chien et al. (2020) and Nantsupawat et al. (2022) both measured HRV before and after extended (24hr+) shifts in medical residents. Chein et al. (2020) found that parasympathetic modulation (i.e., HF power) significantly increased after shift compared to before shift, meanwhile, sympathetic activity (i.e., LF/HF) was decreased. In contrast, Nantsupawat et al. (2022) did not find any significant differences in HRV parameters between pre- and post-shift. Although commonly viewed as a beneficial "relaxation response" (Nakao, 2019), both Chien et al. (2020) and Nantsupawat et al. (2022) note that increased parasympathetic activity in the context of shift-work occupations may be indicative of excessive sleepiness or exhaustion, termed "parasympathetic rebound", which could lead to safety concerns due to diminished alertness (Furlan et al., 2000). To the authors knowledge, this was this first study to directly investigate the stress-related implications of extended shifts in wildland firefighting. Indirect evidence comes from the previously mentioned pair of studies on Ontario firefighters (McGillis et al., 2017; Robertson et al., 2017). Like sleep, Mcgillis et al. (2017) found that shift durations tended to be longer on IA fires compared to project fires and base work, while Robertson et al. (2017) found that IA deployments were associated with more total time spent in a state of "physiological stress" in the same cohort of individuals.

In summary, it remains unclear from the literature whether long shifts reliably induce increased levels of stress compared to shorter shifts. Nonetheless, we provide novel, direct evidence of a relationship between prolonged shift duration and heightened sympathetic activity in wildland firefighters.

5.5 Implications

The results of this study indicate clear relationships between sleep, shift characteristics and indices of stress and cognitive function. These findings have important implications for the domain of occupational health and safety.

For example, we found that cognitive function tended to be worse following sub-optimal sleep and prolonged shifts, which is concerning considering the established link between fatigue and worker safety (Williamson et al., 2011). Indeed, both poor sleep (Dawson & McCulloch, 2005; Wong et al., 2019) and long shift durations (Fischer et al., 2017; Gurubhagavatula et al., 2021) have been previously recognized as key risk factors for workplace accidents and injuries. Fatigue-related decrements in PVT performance have direct implications to worker safety, as slower response times while driving translates to a slower breaking response (Philip et al., 2003), while lapses in attention may result in accidents (Van Dongen & Hursh, 2010). This is especially true for workers engaged in high-risk activities, such as driving, wherein constant vigilant attention is synonymous with getting home safely.

We also found that poor sleep and long shifts were both associated with higher morning HR and increased perceived stress. Unfortunately, long-term exposure to stress has been linked to a wide range of negative health outcomes, including an increased risk of developing diseases (McEwen, 2007; O'Connor et al., 2021). This might help explain why similar health outcomes have been linked to poor sleep (Chaput et al., 2020; Watson et al., 2015b) and long working hours (Bannai & Tamakoshi, 2014; Rivera et al., 2020; Wong et al., 2019). Heightened sympathetic nervous system activity, as reflected by increased HR and/or reduced HRV, is a useful risk indicator for the negative health-related consequences of stress (Jarczok et al., 2013, 2020). For this reason, HRV has been used as a tool monitor occupational stress (Järvelin-Pasanen et al., 2018), particularly in medical (The et al., 2020; Thielmann et al., 2021; Thielmann & Boeckelmann, 2016) and military (Corrigan et al., 2021; Stephenson et al., 2021) environments.

Importantly, we found that poor sleep and long shift durations were commonplace on fire suppression days. Indeed, firefighters in the current study obtained less than 7 hours of sleep on over 70% of fire suppression days, which is below established recommendations from sleep experts (Watson et al., 2015). Reduced sleep length is commonly found in wildland firefighters (Vincent et al., 2018) and has recently been identified as a priority area for future research (Koopmans et al., 2022; Pelletier et al., 2022). Meanwhile, average fire suppression shifts were nearly 14 hours in duration (13.8 +/- 108 mins), with nearly 90% being recorded as over 12 hours. This comparable to previously reported shift durations in B.C wildfire management staff (13.8 hours ± 42 mins; Jeklin et al., 2021), but longer than previous studies on wildland firefighters in B.C. (12.8 hours ± 30 mins; Jeklin et al., 2019), Ontario (12.5 hours +/- 59 mins; McGillis et al., 2017) and Australia (11.5 hours +/− 180 mins; Vincent et al., 2016).

Therefore, given the clear connections to worker health and safety, the observed prevalence of poor sleep and long shifts in the current study make their associations with heightened stress and impaired cognitive function concerning.

5.6 Recommendations for the B.C. Wildfire Service

Although preliminary in nature, our findings point towards several actionable recommendations that have the potential to improve worker health and safety for employees of the British Columbia Wildfire Service (BCWS).

Similar to Jeklin (2019), our findings support the development, implementation, and continuous improvement and of a practical and scientifically defensible fatigue risk management system (FRMS). As described by Lerman et al. (2012), an FRMS is "a scientifically based, data-driven addition or alternative to prescriptive hours of work limitations which manages employee fatigue in a flexible manner appropriate to the level of risk exposure and the nature of the operation." Within a typical FRMS, several layers of defense exist to protect against fatigue-related accidents. In the context of wildland firefighting, these defenses could include (1) fatigue countermeasures and workplace health interventions, (2) fatigue management training and education for employees, and/or (3) fatigue incident reporting and investigation. Although evidence regarding their effectiveness as a whole remains limited, FRMS components such as these have been shown to positively impact fatigue, health, safety, and performance (Sprajcer et al., 2022). For example, workplace-based employee health interventions (e.g., physical activity, fatigue training, sleep hygiene education, and mindfulness practices) have been found to improve sleep-related outcomes (Crowther et al., 2021; Redeker et al., 2019; Robbins et al., 2021), occupational stress (Bischoff et al., 2019), and long-term health (Barger et al., 2018; Neil-Sztramko et al., 2014). Only one non-pharmacological fatigue mitigation intervention study was found in the setting of wildland firefighting (Leduc et al., 2022). They found beneficial effects following fitness and psychosocial education intervention programs. Similarly, the results of this study showed that baseline levels of physical activity moderated the relationship between shift duration and post-shift subjective fatigue, as well as between shift duration and evening heart rate. These results suggest that physical fitness may serve as a protective factor against the negative cognitive and stress-related consequences of prolonged shift durations.

With these findings in mind, we recommend that the BCWS should support new and on-going research initiatives that explore the utility of workplace-based fatigue management interventions, in addition to continuous improvement of their existing prescriptive hours of work policy. According to their recently updated 5-year (2022-2027) strategic plan (Government of British Columbia, 2022.; Figure 5.1), the first priority for the BCWS is to "promote research to enhance health, wellness, and safety within the BC Wildfire Service". Under this priority, their first objective is to "...coordinate research as required to support and evaluate shifts made to BCWS's safe work standard on staff health and fatigue management." Testing the adoption of evidence based FRMS components would fall directly in line with this stated objective, and, in doing so, would promote the BCWS as exemplars in the field of emergency services. Our findings would support the BCWS in this approach by providing valuable baseline data that could be used to evaluate iterative shifts in their fatigue management program. To ensure a continuous cycle of refinement, on-going innovations in the domain of fatigue risk management could be tested and subsequently integrated as additional elements of an increasing comprehensive FRMS. Such alignment with scientific expertise would undoubtedly secure the BCWS on the leading edge of fatigue policy and, as a result, bolster worker health and safety.

Figure 5.1 *Priorty One of BCWS 5 Year (2022-2077) Strategic Roadmap*

Promote research to enhance health, wellness, and safety within the BC Wildfire Service

Objective 1.1: Provide Research and Innovation expertise and coordinate research as required to support and evaluate shifts made to BCWS's safe work standard on staff health and fatigue management (BCWS Occupational Safe Work Standard (OSWS) #2).

Strategy	Timeline	Outcomes
Support the OSWS #2 task team in making evidence-based decisions about changes to OSWS #2 through coordination with researchers and students (ongoing).	1-3 years, beginning in 2022 and aligned with priorities and timelines of the OSWS #2 task team.	OSWS #2 Task Team has access to operationalizable research that can be used to ensure updates to OSWS #2 are science-based, where feasible.
Connect OSWS #2 task team with fatigue researchers and groups working on similar initiatives (complete and ongoing).		
Provide fatigue jurisdictional scan/literature review to Organizational Development/Task Team (complete).		

5.7 Strengths

Findings from the current study make important contributions to the field of occupational health and safety for emergency service personnel. To the authors knowledge, this was the first study in wildland firefighters to (1) employ completely remote methodology and (2) use linear mixed effects (LME) modeling to examine associates of stress and fatigue while controlling for participant-level characteristics.

Our completely remote methodology was innovative in that it allowed for a multi-site recruitment strategy and a naturalistic collection period, both of which provided benefits to the ecological validity of this study. That is, we were able to recruit from a wide range of participants, regardless of their location, by shipping data collection equipment, providing virtual training sessions, and extracting data using web-based techniques. This allowed for geographic diversity across participants, which in turn improved generalizability compared to previous studies. Removing the need for in-person contact with the research team also minimized the participants' collection burden, which allowed us to gather data across multiple deployments, including in isolated environments and without the potential for researcher interference (e.g., Hawthorne effect). Overall, these factors increased the realism of the study by allowing for data collection to occur under highly naturalistic conditions. By accurately reflecting the demands faced by firefighters in B.C., our remote methods lead to better real-world applicability compared to previous studies that were conducted under simulated firefighting conditions (Cvirn et al., 2011; Smith et al., 2016; Williams-Bell et al., 2017; Ferguson et al., 2016). In general, field studies are needed to demonstrate the ecological validity of laboratory experiments; our findings suggest that the effects of sleep loss and prolonged shifts on stress and fatigue are not masked in the operational environment. Beyond ecological validity, we also provide important proof-of-concept for anyone seeking to gather health-related information in isolated environments. More specifically, we tested the practicality of mobile tools designed to monitor levels of sleep (i.e., wrist-worn actigraphy), stress (i.e., HRV monitors), and cognitive function (i.e., mobile PVT). These tools may be useful for future studies implementing remote, web-based interventions in occupational settings, as well as for emergency service agencies that seek to incorporate fatigue monitoring into their fatigue management programs.

Additionally, linear mixed effects (LME) modeling allowed for valid association estimates, despite an unbalanced design (i.e., an unequal number of observations per subject). It also controlled for several participant-level contextual factors that have potential to influence levels of stress and fatigue, including age, biological sex, and physical activity habits (Shaffer & Ginsberg, 2017; Thielmann et al., 2021). Similar to previous research (Van Dongen, Baynard, et al., 2004), this data analytic approach revealed significant inter-individual variation and several participant-level covariates with respect to stress and fatigue. Future investigations should consider using similar LME modelling methods to account for inter-individual differences.

The novelties in this study extend previous research in important ways. We address several gaps in the literature that were identified in past studies, including (1) collecting data across multiple deployments (Jeklin et al., 2020) and under naturalistic conditions (McGillis et al., 2017), and (2) controlling for individual characteristics like age, biological sex, and firefighting experience (Vincent et al., 2016). We also expand on research by McGillis et al. (2017) by examining the associations between shift duration and objective measures of stress and fatigue, which was similarly noted as a gap by Jeklin et al. (2020). Our novel findings support shift duration, in addition to sleep length, as being an important controllable risk factor that should be considered when discussing the occupational health and safety related impacts of wildland firefighting. The nature of this investigation is also directly aligned with research priorities highlighted in recent scoping reviews (Allison et al., 2022; Koopmans et al., 2022). Similarly, Pelletier et al. (2022) found that “sleep and fatigue” and “stress” were identified as the second and fourth highest research priorities ranked by BCWS personnel (80% and 76% consensus ratings, respectively).

Thus, we believe that this study makes important and timely contributions to the growing field of literature related to occupational health and safety in first responders. We hope that our findings will help guide future studies.

5.8 Limitations and Future Directions

The current study also has several limitations that must be acknowledged. First, several observational-level covariates were not accounted for in the analysis because their inclusion led to the statistical models crashing due to excessive complexity. These included acute caffeine intake, circadian period (i.e., time of data collection), daily smoke exposure, and daily activities performed. As a result, there remains the possibility that these factors influenced the outcome variables to an unknown degree, which may have led to either under or over-estimation of the observed associations with sleep and shift characteristics. Similarly, there were several other factors that were not measured, which may have acted as extraneous (i.e., independently affects outcome variable) or even confounding (i.e., affects independent and dependant variables) variables. Indeed, stress and cognitive are influenced by many contextual factors that weren't controlled for in the current study, including acute exercise (Chang et al., 2012; Marasingha-Arachchige et al., 2022), dietary habits (Gupta et al., 2019; Yoshizaki et al., 2014), acute nicotine intake (Lawrence et al., 2002), habitual cannabis (Nicholls et al., 2015) and alcohol consumption (Bijl et al., 2005), individual coping strategies like acute breathwork (Zaccaro et al., 2018) and/or specific meditation practices (Sumantry & Stewart, 2021), sleeping location (Vincent et al., 2018), traumatic events experienced while on-shift, and various other external stressors such as co-worker conflict and personal life struggles.

Further, the nature of data collection and analysis led to only a select few of many possible associations being examined. As a result, it is possible that important relationships (e.g., between heart rate and evening bedtime) were not explicitly investigated, despite being statistically significant. We also did not investigate certain relationships that have previously been examined, despite being practically important, because they were viewed as outside the scope of the current study's objective. These include the relationship between HRV and cognitive function (Fogt et al., 2011; Henelius et al., 2014) and the associations between subjective and objective measures of sleep (Arora et al., 2013), stress (Sommerfeldt et al., 2019), and cognitive function (Ferguson et al., 2016). Subjective sleep metrics were also not incorporated into in the primary analysis because their frequency of collection did not align with objective sleep metrics. As a result, pre-shift associations might have been underestimated due to statistical models being underpowered.

The recruitment strategy included the use of both random and convenience, chain-referral based sampling methods, which may have led to a biased distribution with regard to certain demographic characteristics. For example, the nature of sampling in this study may have lead to a selection bias such that individuals who participated were already curious about the effects of stress and fatigue, which could be independently associated with health status itself. Indeed, participants reported an average of 543.4 (+/- 250.39) minutes of moderate or vigorous physical activity per week during the off-season, which is more than twice the national average of 210 minutes per week (Statistics Canada, 2021). According to Shaffer and Ginsberg (2017), better health status, including higher levels of physical activity, influences HRV metrics of autonomic function. The above-average health status in the current sample may have thus served as a protective effect against the impact of impaired sleep and extended shift durations, which limits the generalizability of findings to other populations. Future studies should consider incorporating stratified sampling methods into their recruitment strategy to improve representation across important demographic characteristics such as age, fitness, biological sex, and years of firefighting experience.

It’s also important to note that our study only tested one aspect of cognitive function, vigilant attention, which is known to be particularly sensitive to neurocognitive effects of sleep loss (Basner & Dinges, 2011). Given that both sleep loss (Killgore, 2010) and extended shift durations (Lederer et al., 2006; Manacci et al., 1999; Tadinac et al., 2014) been found to affect different cognitive domains to varying degrees, it would be interesting for future studies to investigate sleep and shift-related effects in other cognitive domains. In particular, testing more complex cognitive functions could gain insight into consequential relationships for safety in firefighting, such as between stress and decision making (Useem et al., 2005). Further, we chose to use a brief 3-minute version of the PVT, rather that the standard 10-minute version. Although the brief version has been shown to differ from the standard version across certain PVT metrics, it has still been validated as a sensitive assay for detecting neurobehavioral effects of sleep loss (Basner et al., 2011; Grant et al., 2017), which makes it suitable for time-constrained collection scenarios.

Several limitations associated with the collection of HRV should also be acknowledged. First, a considerable number of HRV recordings were unattainable because either (1) the Polar H10 was not worn or (2) the Polar H10 was not connected, or it lost synchronization, with the Polar Ignite monitor. This loss of data may be attributable to insufficient collection training, as our remote methodology meant that each participant was responsible for the collection of their own data. Despite receiving a virtual training session and several opportunities to ask questions, it is possible that some participants did not fully understand the proper procedure for recording HRV, which might explain the observed loss of data. Future studies conducting HRV research in remote settings should consider incorporating video demonstrations into their participant training to maximize data retention. Beyond participant error, we chose to use Polar H10 and Ignite monitors, which provide lower data quality compared to multi-lead and/or multi-parameter electrocardiogram (ECG) systems. For example, multi-parameter instruments like the "Equivital EQ02 Lifemonitor" have the ability to simultaneously record respiratory rate, which is known to affect HRV (Bourdillon et. al., 2021). Although multi-lead ECG instrument would have led to fewer data artifacts, Polar monitors are advantageous for field settings because of their simplicity, smaller size, and overall ease of use. Further, despite the mentioned limitations, only 4% of all HRV recordings (12/309) were removed from the current analysis due to poor data quality (as defined by over 5% of recorded heartbeats being classified as artifacts).

In terms of study design, it's worthwhile to note that testing times could not be standardized for participants due to variability in scheduling each day. Given that the time of testing is related to circadian factors, and HRV (Jeong et al., 2020) and PVT performance (Xu et al., 2021) are both influenced by circadian patterns, this factor may have influenced associations involving shift duration results, independent of shift duration itself. Another limitation was that data collection only occurred from July until September of 2021 and 2022, which were during the middle of a two high-hazard fire seasons. As such, true rested baseline measures were not able to be established, as participants likely began the study with some degree of accumulated stress and fatigue. Indeed, participants reported an average of 3 months (87 +/- 37 days) of employment before enrolling in the study, including roughly a week (6.8+/- 6.8 days) engaged in fire suppression activities. Future studies should consider employing longitudinal designs that measure sleep, stress, and fatigue over the course of an entire year, including during periods directly before and after the fire season. Such investigations of accumulated stress and fatigue, particularly as they relate to mental health, chronic burnout, and post season recovery, would address important gaps in our understanding of the long-term health impacts of wildland firefighting (Pelletier et al., 2022).

The current study did not assess the impact of successive shifts on indices of stress and cognitive function, nor the ability of firefighters to recover during rest days. Similarly, none of the collected data occurred during night shifts. Although investigated in healthcare settings (Geiger-Brown et al., 2012; Goffeng et al., 2018; Haidarimoghadam et al., 2016; Jensen et al., 2022), research on these topics is still yet to be conducted in the context of wildland firefighting.

Given the direct relevance to fatigue risk management planning, future studies should attempt to capture the physiological and psychological consequence of these scenarios. Lastly, this study was limited to a relatively small sample size, which may be due to several factors. A lack of interest during the enrollment phase may be attributable to the absence of financial incentivization. Further, the relatively high participant dropout (53%; 28/53) may have been associated with the burden of data collection, as participants were required subjects to volunteer their time during very demanding periods of the fire season. Participant burden also impacted the completeness of data collection, especially for the subset of participants that collected HRV. Ultimately, the relatively small sample size meant that analyses were under greater influence from outlier data points, which could have affected statistical power in some cases. Future studies should consider including financial incentives for participation to improve participant retention and completeness of data collection.

5.9 Conclusion

There is a pressing demand to better understand the cognitive and stress-related impacts of working conditions faced by emergency service workers. The current study sought to investigate the associations between sleep, shift characteristics and levels of stress and cognitive function in Canadian wildland firefighters. Uniquely, our completely remote methodology allowed for a multi-site recruitment strategy and naturalistic collection period. Our data analytic approach employed linear mixed effects modelling to account for inter-individual variation and participant-level characteristics that may differ with respect to stress and fatigue. Our results indicated that wildlands firefighters are often exposed to sub-optimal sleep and long shift durations. Importantly, sub-optimal sleep and long shift durations were associated with heightened levels of stress and impaired cognitive function, which have serious implications for worker heath and safety, respectively. We contribute novel findings to the growing field of research on occupational health and safety for emergency service workers. We also provide insight and recommendations towards improved fatigue management policy within the British Columbia Wildfire Service by supporting the development, implementation, and continuous improvement of a practical and scientifically defensible fatigue risk management system.

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Appendices

Appendix A: Preface

A pilot study (N=4) was conducted in July and August 2021. Information from this initial pilot study was used to inform methodology for the following data collection period (July-September 2022). Data from both 2021 and 2022 data collection periods were included in the analysis.

Appendix B: Additional Measures

Bi-Weekly Measures

To capture potential indicators of chronic stress and fatigue across the fire season, participants also completed a bi-weekly (i.e. once every two weeks) questionnaire that measured self-perceived sleep quality, burnout, resiliency, well-being, stress, fatigue, and workload. This bi-weekly questionnaire was comprised of several previously validated questionnaires, including the 9-item Pittsburgh Sleep Quality Index (Buysse et al., 1989), 13-Item Copenhagen Burnout Inventory (Kristensen et al., 2005), 10-item Connor-Davidson Resilience Scale (Campbell-Sills & Stein, 2007; Connor & Davidson, 2003), 14-Item Warwick Edinburgh Mental Wellbeing Scale (Tennant et al., 2007), 10-item Perceived Stress Scale (S. Cohen et al., 1983) and 10-item Fatigue Assessment Scale (Michielsen et al., 2003). The 10-item Perceived Stress Scale and 10-item Fatigue Assessment Scale were both adapted to capture self-perceived contributing factors to stress (e.g. co-worker conflict, and/or separation from family) and fatigue (e.g. demanding physical work, and/or reduced sleep), respectively. Workload was assessed by the following two questions: (1) " how many fire suppression days have you worked in the past 2 weeks?" and (2) "relatively speaking, how difficult has work been over the past 2 weeks?".

Subset Measures

The following measures were collected on participant subsets of as pilot investigations for future studies:

Salivary Cortisol

Salivary cortisol levels were collected by 7 participants. Directly following measurement of heart rate variability, 1.5mLsaliva samples were collected by passive drool on the mornings of data collection upon waking in participants' homes using Salimetrics validated equipment. Participants immediately placed the sample in their freezer and samples remained frozen at -

20°C until enough samples are collected to fill the entirety of the sample wells for conduction of the ELISA immunoassay.

Body Temperature and Hydration Status

Body temperature and hydration status was collected at the start, middle, and end of shift on one participant. Body temperature was be measured by an in-ear thermometer (BraunThermoScan® 5), while hydration status was measured by urine specific gravity refractometer (Atago PAL-10S). Participant body weight was measured before and after shift on days of data collection as an additional measure of hydration status. Though several extraneous variables were not controlled for (e.g. food intake), change in body weight is a well-validated measure of hydration status (Sawka et al., 2007) and has been used accordingly in a similar wildland firefighting context (Cuddy et al., 2008). Further, major extraneous variables such as eating throughout the day would only lead to an underestimation of dehydration using this measure. Comparison with USG would provide insight on whether measuring a change in body weight could serve as a valuable measure for monitoring hydration status in remote occupational settings.

Mobile Electroencephalography

Electroencephalography (EEG) activity has yet to be measured in the context of wildland firefighting. Recent advances in mobile EEG have shown promising results for detecting fatigue and drowsiness (LaRocco et al., 2020), which suggests the potential for detecting workplace fatigue in remote occupational settings. Of these technologies, MUSE systems have shown EEG activity to correlate with subjective fatigue in a large sample of 1000 participants (Krigolson et al., 2021). A pilot investigation of mobile EEG activity using the MUSE headband (InteraXon, Ontario, Canada) was conducted on one participant. EEG activity was measured during performance on the Oddball and Go/No-Go Tasks in conjunction with PVT performance before and after shift on typical data collection days. Though similar in design, the Oddball and Go/No-Go tasks each measure a different aspect of cognitive function (i.e., sustained attention and response inhibition, respectively). Both tasks were administered on either an iPad (Apple Inc., California, U.S.A.). In the Go/No-Go Task, participants are instructed to respond to frequently occurring blue circles (either by tapping the iPad screen or laptop keyboard) and to withhold responding to green circles that appear less frequently. Conversely, the Oddball Task requires participants to respond to infrequently occurring green circles, but not to frequently occurring blue circles. Although the sequence order of stimuli is random in both the Oddball and Go/No-Go tasks, blue circles always appear on 70% of the trials, while green circles appear the remaining 30% of the time. Both tasks consist of 4 blocks of 50 trials and were completed while participants wore a MUSE EEG headband with pre-set collection parameters (256 Hz sampling rate, no onboard data processing: InteraXon, Ontario, Canada). The MUSE EEG headband has five electrodes (AF7, AF8, Fpz, TP9, TP10) with electrode Fpz as the reference. Data from the MUSE EEG system was streamed to and stored on the iPad or laptop computer via Bluetooth. In regard to EEG data processing, time-locked event-related potentials (ERP), including P300 & N200 components, as well as oscillatory activity from each frequency band (delta: 1–3 Hz, theta: 4–7 Hz, alpha: 8–12 Hz, beta: 13–30 Hz) were be extracted from EEG data using methods previously done and described by the Theoretical and Applied Neuroscience Laboratory at the University of Victoria (see https://www.krigolsonlab.com/muse-analysis-matlab.html).

Table A.1 Additional Measured variables, instrumentation, and time of data collection

Additional Daily Measures		
Variable Measured	**Data Collection Instrument**	**Collection Time (Time Required)**

Subjective Sleepiness	Stanford Sleepiness Scale (Hoddes et al., 1973)	Start of shift, mid-shift, and end of shift (<1 minute each)
Body Temperature	In-ear thermometer (BraunThermoScan® 5)	Start of shift, mid-shift, and end of shift (1 minute each)
Hydration Status	Urine specific gravity refractometer (Atago PAL-10S) and change in body weight (scale, 0.1lb sensitivity, model TBD)	Start of shift, mid-shift, and end of shift (4 minutes each)
Electroencephalography (EEG)	MUSE (Interaxon Inc., Canada)	Start and end of shift (concurrent with below cognitive tasks)
Sustained Attention	Oddball Task via iPad (Apple Inc., California, U.S.A.)	Start and end of shift (5 minutes)
Response Inhibition	Go/No-Go Task via iPad (Apple Inc., California, U.S.A.)	Start and end of shift (5 minutes)
Cortisol Levels	Saliva Sample (Salimetrics ELISA Immunoassay Kit)	Upon waking (2 minutes)
	Additional Bi-Weekly Measures	
Sleep Quality Index	Pittsburgh Sleep Quality Index (Buysse et al., 1989)	Every 2 weeks (5 minutes)
Workload	Number of fire suppression days; relative difficulty (1-4)	Every 2 weeks (1 minute)
Adapted Stress Scale	10-item Perceived Stress Scale (Cohen et al., 1983; Roberti et al., 2011)	Every 2 weeks (5 minutes)
Adapted Fatigue Scale	Fatigue Assessment Scale (Michielsen et al., 2004)	Every 2 weeks (5 minutes)
Resilience	Connor-Davidson Resilience Scale (Campbell-Sills & Stein, 2007; Connor & Davidson, 2003)	Every 2 weeks (5 minutes)

Wellbeing	14-Item Warwick Edinburgh Mental Wellbeing Scale (Tennant et al., 2007)	Every 2 weeks (5 minutes)
Burnout Index	Copenhagen Burnout Inventory (Kristensen et al., 2005)	Every 2 weeks (5 minutes)

Appendix C: Survey Monkey Questionnaires

Appendix C.1: Pre-Shift Daily Questionnaire

* 1. What is your participant ID?

2. How much sleep did you get last night?

What time did you go to bed last night?

Time AM/PM

hh mm -

When did you wake up this morning?

Time AM/PM

hh mm -

3. How well did you sleep last night?

Very Poor	Poor	Okay	Good	Very Good

4. How stressed did you feel when you started work this morning?

Not Stressed At All	A Little Stressed	Fairly Stressed	Very Stressed

5. How fatigued did you feel when you started work this morning?

Fully alert, wide awake	Very lively, responsive, but not at peak	Okay, somewhat fresh	A little tired, less than fresh	Moderately tired, let down	Extremely tired, very difficult to concentrate	Completely exhausted, unable to function effectivel

6. How sleepy did you feel when you started work this morning?

Feeling active, vital, alert, or	Functioning at high levels, but not at peak; able to	Awake, but relaxed; responsive but	Somewhat	Foggy; losing interest in remaining awake; slowed	Sleepy, woozy, fighting sleep; prefer to lie	No longer fighting sleep, sleep onset soon, having dream-like

wide awake	concentrate	not fully alert	foggy, let down	down	down	thoughts
○						○

7. Did you consume any caffeine this morning?

○ No

○ Yes (please specify)

8. Did you record heart rate this morning?

○ Yes

○ No

2. Describe any issues with your heart rate recording either last night or this morning (e.g. got phone call during last night's recording)

Appendix C.2: Post-Shift Daily Questionnaire

* 1. What is your participant ID?

2. How long did you work today?

What time did you start your shift?

Time hh mm

AM/PM -

What time did you end your shift?

Time		AM/PM
hh	mm	-

2. How many hours did you have between yesterdays shift and today's shift?

3. How stressed did you feel when you finished work today?

Not Stressed At All	A Little Stressed	Fairly Stressed	Very Stressed
○	○	○	○

5. How fatigued did you feel when you finished work today?

Fully alert, wide awake	Very lively, responsive, but not at peak	Okay, somewhat fresh	A little tired, less than fresh	Moderately tired, let down	Extremely tired, very difficult to concentrate	Completely exhausted, unable to function effectivel
○						○

6. How sleepy did you feel when you finished work today?

Feeling active, vital, alert, or wide awake	Functioning at high levels, but not at peak; able to concentrate	Awake, but relaxed; responsive but not fully alert	Somewhat foggy, let down	Foggy; losing interest in remaining awake; slowed down	Sleepy, woozy, fighting sleep; prefer to lie down	No longer fighting sleep, sleep onset soon, having dream-like thoughts
○						○

7. Did you consume any caffeine since starting work today?

○ No

○ Yes (please specify)

8. Were you exposed to smoke today?

No Exposure		Some Exposure	Heavy Exposure
○	○		○

9. Were you engaged in wildfire suppression today (i.e. fire suppression day) ?

- Yes
- No

10. If yes to #9, what stage of control was the fire in when you arrived?

- Out of Control
- Out
- Being Held
- N/A
- Under Control
- Other (please specify)

11. What activities were you engaged in today? (select most relevant only)

- Base Day
- Project Work / Training
- Standby
- Travel Day
- Initial Attack
- Mop-Up
- Patrol
- Equipment Demobilization
- Flood Response

\\

- Other (please specify)

Appendix C.3: Baseline Questionnaire

General Questionnaire

This questionnaire asks about individual characteristics, work history, medical history, physical activtiy habits, and experience with meditation

3.1. Please provide the following identifying characteristics (note this is for contextual purposes only; all data will be fully anonymized prior to dissemination of findings).

Name

Participant ID

Call-Sign

Employee #

2. Please provide contact and shipping-related information for yourself

Address

City/Town

Postal Code

Email Address

Phone Number

3. What is your biological sex?

- Male
- Female

4. What is your gender?

- Male
- Female
- Prefer not to say
- Other

4.

5. What is your height? (cm)

6. What is your weight? (kg)

7. How many cups of caffeinated beverage do you normally consume per day?

Coffee

Tea

Energy Drink

Other (please specify below)

8. What "other" caffeinated drinks do you normally consume?

1. 9. How many years have you worked as a wildland firefighter with the British Columbia Wildfire Service (BCWS), including 2022?

2. 10. How many years have you worked as a wildland firefighter with other agencies (e.g. contact crews)?

* 11. What is your current position within the BCWS?

- Fire Crew Member
- Fire Crew Leader
- Fire Crew Supervisor
- Other (please specify)

12. Where do work?

Crew

Fire Base

Nearest City or Town

Fire Zone

Fire Centre

s

13. Do you engage in a regular meditation practice?

- Yes
- No

5. Appoximately how long have you been practicing meditation (years, months)?

Approximately how often do you practice meditation?

- Rarely (once a month or less)
- Sometimes (several times a month)
- Often (several times a week)
- Very Often (once a day or more)

16. 4.1 What type of meditation do you normally practice?

- Focused Attention
- Open Monitoring

☐ Other (please describe below)

17. 4.1 Briefly, describe your meditation practice

General Questionnaire

* 18. When was your first day of work with BCWS in 2022?

Date

Date

MM/DD/YYYY

5. How many fire suppression days have you worked so far this year?

6. What is your other occupation when not working for BCWS?

Have you ever been diagnosed by a physician with a Sleep Disorder?

○ No

○ Yes (please describe)

22. Have you ever been diagnosed by a physician with Chronic Fatigue Syndrome?

○ Yes

○ No

23. Do you have any other relevant clinical diagnoses?

○ No

○ Yes (please describe)

7. Please indicate in the table below the amount of time (in minutes) you spend on the following activities during a typical 3-Day rest:

Vigorous exercise (Rapid heart rate, heavy perspiration. e.g., running, hockey, soccer, long-distance bicycling, resistance training)	
Moderate exercise (Not exhausting, light perspiration. e.g., fast walking, baseball, easy bicycling)	

1. Before the forest firefighting season started, over a typical 7-day week, how much time on average (in minutes) do you engage in the following activities

Vigorous exercise (Rapid heart rate, heavy perspiration. e.g., running, hockey, soccer, long-distance bicycling, resistance training)

Moderate exercise (Not exhausting, light perspiration. e.g., fast walking, baseball, easy bicycling)

4. Before the forest firefighting season started, over a typical 7-day week, how many times on average do you engage in the following types of exercise for more than 15 minutes?

Resistance training

Aerobic training (e.g. long distance running/cycling)

High intensity (e.g. sprint) interval training

5. What are the names and participant IDs of the other members of your crew that whom you will be sharing equipment with?

Co-worker 1 Name

Co-worker 1 Participant ID

Co-worker 2 Name

Co-worker 2 Participant

Five Facet Mindfulness Questionnaire

Please rate each of the following statements with the number that best describes your own opinion of what is generally true for you.

28. Please rate each of the following statements with the number that best describes your own opinion of what is generally true for you.

	Never or very rarely true	Rarely true	Sometimes true	Often true	Very often or always true
1. When I'm walking, I deliberately notice the sensations of my body moving.					
2. I'm good at finding words to describe my feelings.					
3. I criticize myself for having irrational or inappropriate emotions.					
4. I perceive my feelings and emotions without having to react to them.					
5. When I do things, my mind wanders off and I'm easily distracted.					
6. When I take a shower or bath, I stay alert to the sensations of water on my body.					
7. I can easily put my beliefs, opinions, and expectations into words.					
8. I don't pay attention to what I'm doing because I'm daydreaming, worrying, or otherwise distracted.					
7. I watch my feelings without getting lost in them.					
8. I tell myself I shouldn't be feeling the way I'm feeling.					
9. I notice how foods and drinks affect my thoughts, bodily sensations, and emotions.					
10. It's hard for me to find the words to describe what I'm thinking.					
13. I am easily distracted.					
14. I believe some of my thoughts are abnormal or bad and I shouldn't think that way.					
10. I pay attention to sensations, such as the wind in my hair or sun on my face.					

11. I have trouble thinking of the right words to express how I feel about things
12. I make judgments about whether my thoughts are good or bad.
13. I find it difficult to stay focused on what's happening in the present.
14. When I have distressing thoughts or images, I "step back" and am aware of the thought or image without getting taken over by it.
15. I pay attention to sounds, such as clocks ticking, birds chirping, or cars passing.
16. In difficult situations, I can pause without immediately reacting.

8. When I have a sensation in my body, it's difficult for me to describe it because I can't find the right words.
9. It seems I am "running on automatic" without much awareness of what I'm doing.
10. When I have distressing thoughts or images, I feel calm soon after.
11. I tell myself that I shouldn't be thinking the way I'm thinking.

26. I notice the smells and aromas of things.

11. Even when I'm feeling terribly upset, I can find a way to put it into words.
12. I rush through activities without being really attentive to them.
13. When I have distressing thoughts or images I am able just to notice them without reacting.
16. I think some of my emotions are bad or inappropriate and I shouldn't feel them.
17. I notice visual elements in art or nature, such as colors, shapes, textures, or patterns of light and shadow.

1. My natural tendency is to put my experiences into words.
2. When I have distressing thoughts or images, I just notice them and let them go.
3. I do jobs or tasks automatically without being aware of what I'm doing.
4. When I have distressing thoughts or images, I judge myself as good or bad, depending what the thought/image is about.

3. I pay attention to how my emotions affect my thoughts and behavior.
4. I can usually describe how I feel at the moment in considerable detail.
5. I find myself doing things without paying attention.
6. I disapprove of myself when I have irrational ideas.

Reference: Baer, R. A., Smith, G. T., Hopkins, J., Krietemeyer, J., & Toney, L. (2006). Using self-report assessment methods to explore facets of mindfulness. *Assessment, 13,* 27-45.

Baseline Questionnaires

Morningness-Eveningness Questionnaire

This questionnaire assessees whether or not you are a night owl, a morning lark, or somewhere in-between, and to what extent.

29. What time would you get up if you were entirely free to plan your day?

5:00 – 6:30 AM	6:30 – 7:45 AM	7:45 – 9:45 AM	9:45 – 11:00 AM	11:00 AM – 12 PM (Noon)	12 PM (Noon) – 5:00 AM
○					○

30. What time would you go to bed if you were entirely free to plan your evening?

8:00 – 9:00 PM	9:00 – 10:15 PM	10:15 PM – 12:30 AM	12:30 – 1:45 AM	1:45 – 3:00 AM	3:00 AM – 8:00 PM
○					○

5. If there is a specific time at which you have to get up in the morning, to what extent do you depend on being woken up by an alarm clock?

Not at all	Slightly	Somewhat	Very much
○	○	○	○

9. How easy do you find it to get up in the morning (when you are not woken up unexpectedly)?

Not at all easy	Not very easy	Fairly easy	Very easy
○	○	○	○

33. How alert do you feel during the first half hour after you wake up in the morning?

Not at all alert	Slightly alert	Fairly alert	Very alert
○	○	○	○

34. How hungry do you feel during the first half-hour after you wake up in the morning?

Not at all hungry	Slightly hungry	Fairly hungry	Very hungry
○	○	○	○

35. During the first half-hour after you wake up in the morning, how tired do you feel?

Very tired	Fairly tired	Fairly refreshed	Very refreshed
○	○	○	○

10. If you have no commitments the next day, what time would you go to bed compared to your usual bedtime?

Neldom or never later	Less than one hour later	1-2 hours later	More than two hours later
○	○	○	○

17. You have decided to engage in some physical exercise. A friend suggests that you do this for one hour twice a week and the best time for him is between 7:00 – 8:00 am. Bearing in mind nothing but your own internal "clock", how do you think you would perform?

Would be in good form	Would be in reasonable form	Would find it difficult	Would find it very difficult
○	○	○	○

38. At what time of day do you feel you become tired as a result of need for sleep?

8:00 – 9:00 PM	9:00 – 10:15 PM	10:15 PM – 12:45 AM	12:45 – 2:00 AM	2:00 – 3:00 AM
○	○	○	○	○

1. You want to be at your peak performance for a test that you know is going to be mentally exhausting and will last for two hours. You are entirely free to plan your day. Considering only your own internal "clock", which ONE of the four testing times would you choose?

8:00 AM – 10:00 AM	11:00 AM – 1:00 PM	3:00 PM – 5:00 PM	7:00 PM – 9:00 PM
○	○	○	○

40. If you got into bed at 11:00 PM, how tired would you be?

Not at all tired	A little tired	Fairly tired	Very tired
○	○	○	○

5. For some reason you have gone to bed several hours later than usual, but there is no need to get up at any particular time the next morning. Which ONE of the following are you most likely to do?

Wake up at usual time and NOT fall back asleep	Wake up at usual time, but doze thereafter	Wake up at usual time, but fall asleep again	Not wake up until later than usual
○			○

8. One night you have to remain awake between 4:00 – 6:00 AM in order to carry out a night watch. You have no commitments the next day. Which ONE of the alternatives would suite you best?

NOT going to bed until after the watch was over	Taking a nap before and sleep after	Taking a good sleep before and nap after	Sleeping only before the watch
○			○

10. You have to do two hours of hard physical work. You are entirely free to plan your day and considering only your own internal "clock" which ONE of the following time would you choose?

8:00 AM – 10:00 AM	11:00 AM – 1:00 PM	3:00 PM – 5:00 PM	7:00 PM – 9:00 PM
○	○	○	○

12. You have decided to engage in hard physical exercise. A friend suggests that you do this for one hour twice a week and the best time for him is between 10:00 – 11:00 PM. Bearing in mind nothing else but your own internal “clock” how well do you think you would perform?

Would be in good form	Would be in reasonable form	Would find it difficult	Would find it very difficult
○	○	○	○

17. Suppose that you can choose your own work hours. Assume that you worked a **five-hour day** (including breaks) and that your job was interesting and paid by results). At what time would you choose to begin?

5 hours starting between 4–8 AM	5 hours starting between 8–9 AM	5 hours starting between 9 AM–2 PM	5 hours starting between 2–5 PM	5 hours starting between 5 PM–4 AM
○				○

46. At what time of the day do you think that you reach your “feeling best” peak?

5:00 – 8:00 AM	8:00 – 10:00 AM	10:00 AM – 5:00 PM	5:00 – 10:00 PM	10:00 PM – 5:00 AM
○	○	○	○	○

18. One hears about “morning” and “evening” types of people. Which ONE of these types do you consider yourself to be?

Definitely a “morning” type	Rather more a “morning” than an “evening” type	Rather more an “evening” than a “morning” type	Definitely an “evening” type
○			○

Reference: Horne, J. A., & Östberg, O. (1976). A self-assessment questionnaire to determine morningness-eveningness in human circadian rhythms. *International Journal of Chronobiology, 4,* 97–110.

Appendix C.4: Bi-Weekly Questionnaire

Work History

This survey asks about your general working conditions during the past 2 weeks

* 1. Participant ID

[   ]

4. How many fire suppression days have you worked during the past 2 weeks?

[   ]

5. Relatively speaking, how difficult has the past 2 weeks been?

Very difficult, much	Somewhat difficult, relatively higher than	Neither difficult nor	Somewhat easy,	Very easy, much

higher workload than normal, several 16 hour+ days.	normal workload, several 14-16 hour days.	easy, near normal workload, several 12-14 hour days	relatively lighter than normal workload, few shifts over 10 hours	lighter than normal workload, no shifts longer than 10 hours
○				○

Other (please describe)

Fatigue Assessment Scale

The questions in this scale ask you about your feelings and thoughts during the past 2 weeks. In each case, you will be asked to indicate how often you felt or thought a certain way.

8. Please select the answer to each question that is most applicable to you. Answer each question, even if you do not have any complaints at the moment.

	Never	Rarely	ometimes	Often	Very Often
3. I am bothered by fatigue	○	○	○	○	○
4. I get tired very quickly					
5. I don't do much	○	○	○	○	○
during the day	○	○	○	○	○
6. I have enough energy for everyday life	○	○	○	○	○
6. Physically, I feel exhausted	○	○	○	○	○
7. I have problems to start things	○	○	○	○	○
8. I have problems thinking clearly	○	○	○	○	○
9. I feel no desire to do anything	○	○	○	○	○
10. Mentally, I feel exhausted	○	○	○	○	○
11. When I am doing something, I can concentrate quite well	○	○	○	○	○

7. What do you feel were the biggest contributors to fatigue over the past 2 weeks? Rank as many or as few as relevant.

- Poor sleep
- Long shifts
- Co-worker conflict
- High levels of responsibility
- Demanding physical work
- Other (please specify below)

6. Please specify the "other" contributing factor(s) to fatigue you listed in Question #5

Reference: Michielsen, H. J., De Vries, J., & Van Heck, G. L. (2003). Psychometric qualities of a brief self-rated fatigue measure: The Fatigue Assessment Scale. *Journal of Psychosomatic Research, 54*(4), 345–352. https://doi.org/10.1016/S0022-3999(02)00392-6\

Perceived Stress Scale

The questions in this scale ask you about your feelings and thoughts during the past 2 weeks. In each case, you will be asked to indicate how often you felt or thought a certain way.

8. Please select the answer to each question that is most applicable to you. Answer each question, even if you do not have any complaints at the moment.

	Never	Rarely	Sometimes	Often	Very often
2. How often have you been upset because of something that happened unexpectedly?	○	○	○	○	○
3. How often have you felt that you were unable to control the important things in your life?	○	○	○	○	○
4. How often have you felt nervous and "stressed"?	○	○	○	○	○
5. How often have you felt confident about your ability to handle your personal problems?	○	○	○	○	○
6. How often have you felt that things were going your way?	○	○	○	○	○
7. How often have you found that you could not cope with all the things that you had to do?	○	○	○	○	○
11. How often have you been able to control irritations in your life?	○	○	○	○	○
12. How often have you					

felt that you were on top of things?	○	○	○	○	○
13. How often have you been angered because of things that were outside of your control?	○	○	○	○	○
17. How often have you felt difficulties were piling up so high that you could not overcome them?	○	○	○	○	○

8. What do you feel were the biggest contributors to stress over the past 2 weeks? Rank as many or as few as relevant.

- Lack of communication with loved ones
- Lack of support from supervisor(s)
- Lack of time to do things that are important
- Co-worker conflict
- High levels of responsibility
- Poor sleep
- Long shifts
- Other (please specify below)

9. Please specify the "other" contributing factor(s) to stress you listed in Question #8

Reference: Cohen, S., Kamarck, T., & Mermelstein, R. (1983). A global measure of perceived stress. J*ournal of Health and Social Behavior, 24*(4), 385–396. https://doi.org/10.2307/2136404

The Pittsburgh Sleep Quality Index

The following questions relate to your usual sleep habits during the past 2 weeks only. Your answers should indicate the most accurate reply for the majority of days and nights in the past 2 weeks. Please answer all questions.

10. During the past two months,

When have you usually gone to bed at night?

Time AM/PM

hh mm -

When have you usually gotten up in the morning?

Time AM/PM

hh mm -

11. How long (in minutes) has it taken you to fall asleep each night?

12. How many hours of actual sleep do you get at night? (This may be different than the number of hours you spend in bed)

13. During the past month, how often have you had trouble sleeping because you...

	Not during the past month	Less than once a week	Once or twice a week	Three or more times a week
Cannot get to sleep within 30 minutes	○	○	○	○
Wake up in the middle of the night or early morning	○	○	○	○
Have to get up to use the bathroom	○	○	○	○
Cannot breathe comfortably	○	○	○	○
Cough or snore loudly	○	○	○	○
Feel too cold	○	○	○	○
Feel too hot	○	○	○	○
Have bad dreams	○	○	○	○
Have pain	○	○	○	○

Other reason(s), please describe, including how often you have had trouble sleeping because of this reason(s):	○	○	○	○

Other (please specify)

14. During the past month, how often have you...

	Not during the past month	Less than once a week	Once or twice a week	Three or more times a week
Taken medicine (prescribed or “over the counter”) to help you sleep?	○	○	○	○
Had problems keeping up enthusiasm to get things done?	○	○	○	○
Had trouble staying awake while driving, eating meals, or engaging in social activity?	○	○	○	○

15. During the past month, how would you rate your sleep quality overall?

- ◯ Very Good
- ◯ Fairly Good
- ◯ Fairly Bad
- ◯ Very Bad

Reference: Buysse, D.J., Reynolds III, C.F., Monk, T.H., Berman, S.R., & Kupfer, D.J. (1989). The Pittsburgh Sleep Quality Index: A new instrument for psychiatric practice and research. *Journal of Psychiatric Research, 28* (2), 193-213.

Connor-Davidson Resilience Scale

The questions in this scale ask you about your thoughts and feelings during the past 2 weeks. In each case, you will be asked to indicate how much you relate to a certain senitiment.

18. Please indicate how much you agree with the following statements as they apply to you during the past 2 weeks. If a particular situation has not occurred recently, answer according to how you think you would have felt.

	Not true at all	Rarely true	Sometimes ture	Often true	True nearly all the time
5. I am able to adapt when changes occur.	◯	◯	◯	◯	◯
6. I can deal with whatever comes my way.	◯	◯	◯	◯	◯
7. I try to see the humorous side of things when I am faced with problems.	◯	◯	◯	◯	◯
8. Having to cope with stress can make me stronger.	◯	◯	◯	◯	◯
I tend to bounce back after illness, injury, or other	◯	◯	◯	◯	◯

6. hardships.					
7. I believe I can achieve my goals, even if there are obstacles.	◯	◯	◯	◯	◯
8. Under pressure, I stay focused and think clearly.	◯	◯	◯	◯	◯
8. I am not easily discouraged by failure.	◯	◯	◯	◯	◯
10. I think of myself as a strong person when dealing with life's challenges and difficulties.	◯	◯	◯	◯	◯
11. I am able to handle unpleasant or painful feelings like sadness, fear, and anger.	◯	◯	◯	◯	◯

Reference: Campbell-Sills L and Stein MB. (2007). Psychometric analysis and refinement of the Connor–Davidson resilience scale (CD-RISC): Validation of a 10-item measure of resilience. *Journal of Traumatic Stress, 20,* 1019–28. doi: 10.1002/JTS.20271

Copenhagen Burnout Inventory

The questions in this scale ask you about your thoughts and feelings during the past 2 weeks. In each case, you will be asked to indicate how often you've felt a certain way.

18. Please select the answer to each question that is most applicable to you. Answer each question, even if you do not have any complaints at the moment.

	Never	Rarely (once per week or less)	Sometimes (a few times per week)	Often (about once per day)	Very often (more than once per day)
2. How often do you feel tired?	◯	◯	◯	◯	◯

2.How often are you physically exhausted?					
3. How often are you emotionally exhausted?					
4. How often do you think: "I can't take it anymore"?					
6. How often do you feel worn out?					
7. How often do you feel weak and susceptible to illness?					
8. Do you feel worn out at the end of the working day?					
9. Are you exhausted in the morning at the thought of another day at work?					
10. Do you feel that every working hour is tiring for you?					
11. Do you have enough energy for family and friends during leisure time?					
12. Is your work emotionally exhausting?					
13. Does your work frustrate you?					
14. Do you feel burnt out because of your work?					
14. Do you find it hard to work with co-workers					
15. Does it drain your energy to work with co-workers?					

16. Do you find it frustrating to work with co-workers?	◯	◯	◯	◯	◯
17. Do you feel that you give more than you get back whenyou work with co-workers?	◯	◯	◯	◯	◯
18. Are you tired of working with co-workers?	◯	◯	◯	◯	◯

Reference: Kristensen T.S., Borritz M., Villadsen E., Christensen K.B. The Copenhagen Burnout Inventory: A new tool for the assessment of burnout. (2005).*Work Stress, 19*,192–207. doi: 10.1080/02678370500297720

Warwick Edinburgh Mental Wellbeing Scale

The questions in this scale ask you about your thoughts and feelings during the past 2 weeks. In each case, you will be asked to indicate how often you've felt a certain way.

19. Please select the answer to each question that best describes your experience of each over the last 2 weeks

	Never	Rarely (once per week or less)	Sometimes (a few times per week)	Often (about once per day)	Very often (more than once per day)
I've been feeling optimistic about the future	◯	◯	◯	◯	◯
I've been feeling useful	◯	◯	◯	◯	◯
I've been feeling relaxed	◯	◯	◯	◯	◯
I've been feeling interested in other people	◯	◯	◯	◯	◯
I've had energy to spare	◯	◯	◯	◯	◯
I've been dealing with problems well	◯	◯	◯	◯	◯
I've been thinking clearly	◯	◯	◯	◯	◯
I've been feeling good about myself	◯	◯	◯	◯	◯
I've been feeling close to other people	◯	◯	◯	◯	◯

I’ve been feeling confident	◯	◯	◯	◯	◯
I’ve been able to make up my own mind about things	◯	◯	◯	◯	◯
I’ve been feeling loved	◯	◯	◯	◯	◯
I’ve been interested in new things	◯	◯	◯	◯	◯
I’ve been feeling cheerful	◯	◯	◯	◯	◯

Reference: Tennant, R., Hiller, L., Fishwick, R., Platt, S., Joseph, S., Weich, S., Parkinson, J., Secker, J., & Stewart-Brown, S. (2007). The Warwick-Edinburgh Mental Well-being Scale (WEMWBS): Development and UK validation. *Health and Quality of Life Outcomes*, *5* (63). doi: 10.1186/1477-7525-5-63

Appendix D: Certificate of Ethical Approval

University of Victoria

Office of Research Services | Human Research Ethics Board
Michael Williams Building Rm B202 PO Box 1700 STN CSC Victoria BC V8W 2Y2 Canada
T 250-472-4545 | F 250-721-8960 | uvic.ca/research | ethics@uvic.ca

Certificate of Approval

PRINCIPAL INVESTIGATOR	**Lynneth Stuart-Hill** (Supervisor)	**ETHICS PROTOCOL NUMBER** Expedited review - delegated	**21-0124**
PRINCIPAL APPLICANT	**Jesse Wallace-Webb** **Master's student**	ORIGINAL APPROVAL DATE	29-Oct-2021
		APPROVED ON	29-Oct-2021
UVIC DEPARTMENT	**Exercise Science, Physical and Health Education EPHE**	APPROVAL EXPIRY DATE	28-Oct-2022

PROJECT TITLE **Cognitive fatigue in wildland firefighting**

RESEARCH TEAM MEMBERS
Cory Coehoorn - Committee member, LSU
Olav Krigolson - Committee member, UVic

DECLARED PROJECT FUNDING **None**

DOCUMENTS INCLUDED IN THIS APPROVAL
tcps2_core_certificate.pdf - 09-Apr-2021
Baseline Five Facet Mindfulness Questionnaire.pdf - 06-May-2021
Baseline Get Active Questionnaire.pdf - 06-May-2021
Baseline Get Active Questionnaire Reference Document.pdf - 06-May-2021
Baseline Morning-Eveningness Questionnaire.pdf - 06-May-2021
Daily Perceived Stress Likert Scale.pdf - 06-May-2021
Daily Samn-Perelli Fatigue Scale.pdf - 06-May-2021
Daily Smoke Exposure Likert Scale.pdf - 06-May-2021
Daily Stanford Sleepiness Scale.pdf - 06-May-2021
Daily Subjective Sleep Quality Likert Scale.pdf - 06-May-2021
Monthly Fatigue Assessment Scale.pdf - 06-May-2021
Monthly Perceived Stress Scale.pdf - 06-May-2021
Monthly Pittsburgh Sleep Quality Index.pdf - 06-May-2021
Description of Data Collection Measures.pdf - 07-May-2021
Haig Fire Base Letter of Approval.pdf - 11-May-2021
Study Specific Assessment.pdf - 07-Jun-2021
Daily Data Collection Timeline - Unit Crew.pdf - 23-Jun-2021
Daily Data Collection Timeline - Initial Attack.pdf - 23-Jun-2021
Overall Data Collection Timeline.pdf - 23-Jun-2021
General Baseline Questionnaire Version 2.pdf - 06-Jul-2021
Recruitment Script (IA Program) - Version 3.pdf - 06-Jul-2021
Recruitment Script (Trailblazer Program) - Version 3.pdf - 06-Jul-2021
Recruitement Information Presentation - Unit Crew Version 2.pdf - 06-Jul-2021
Recruitement Information Presentation Initial Attack Version 2.pdf - 06-Jul-2021
Cognitive Fatigue in Wildland Firefighting Consent Form (IA Program) - Version 4.pdf - 06-Jul-2021
Cognitive Fatigue in Wildland Firefighting Consent Form (Trailblazer Program) - Version 4.pdf - 06-Jul-2021
Fatigue in Wildfire Data Collection - Version 2.xlsx - 06-Jul-2021
Ethics Response Document #2.pdf - 06-Jul-2021
Verification_of_Registration Stuart-Hill.pdf - 28-Oct-2021
Verification_of_Registration Stuart-Hill.pdf - 28-Oct-2021

CONDITIONS OF APPROVAL

This Certificate of Approval is valid for the above term provided there is no change in the protocol.

Modifications
To make any changes to the approved research procedures in your study, please submit a "Request for Modification" form. You must receive ethics approval before proceeding with your modified protocol.

Renewals
Your ethics approval must be current for the period during which you are recruiting participants or collecting data. To renew your protocol, please submit a "Request for Renewal" form before the expiry date on your certificate. You will be sent an emailed reminder prompting you to renew your protocol about six weeks before your expiry date.

Project Closures
When you have completed all data collection activities and will have no further contact with participants, please notify the Human Research Ethics Board by submitting a "Notice of Project Completion" form.

Certification

This certifies that the UVic Human Research Ethics Board has examined this research protocol and concluded that, in all respects, the proposed research meets the appropiate standards of ethcis as outlines by the University of Victoria Research Regulations Involving Human Participants.

Dr. Rachael Scarth
Associate VP Research Operations

Certificate Issued On: 29-Oct-2021

Appendix E: Study Advertisement Material

University of Victoria research on cognitive fatigue is seeking participation from BCWS firefighters

May 4, 2022

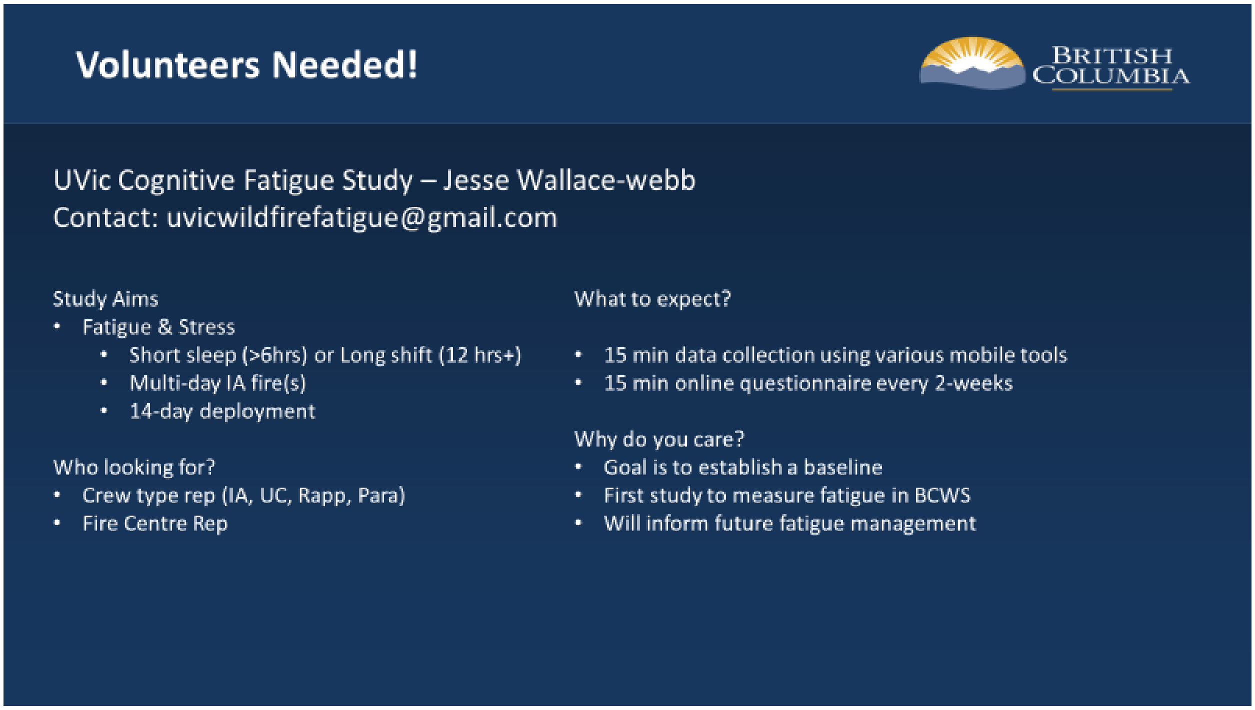
The University of Victoria (UVic) is conducting a study on cognitive fatigue in BC Wildfire Service firefighters in collaboration with BCWS. The UVic research team hopes to recruit participants across all BCWS fire centres and crew types. Recruitment will not be limited by age, gender, biological sex, ethnicity, religion, class or experience, but is limited to firefighters. Other fatigue initiatives will include a broader diversity of staff. This study aims to examine whether short nights of sleep (less than 6 hours) or long shifts (12 hours +) negatively impact measures of stress or cognitive function. A secondary aim is to determine whether measures of fatigue increase throughout a (1) multi-day initial attack fire, (2) 14-day deployment and (3) fire season, as well how well one can recover after the current policy of 72 hours of rest.

The aims of this study will build on data collected during a pilot study during the 2021 fire season. For an overview of work conducted by the Uvic research team in 2021, visit the Innovation Platform.

This year, those who sign up as participants should expect to collect data on themselves at regular intervals throughout the 2022 fire season using several mobile tools that measure sleep, stress and cognitive function. Daily data collection will take approximately 10 minutes at home in the morning and evening, and 5 minutes at the start and end of shift. Daily data collection will ideally rotate between two or three members of the same crew to minimize the burden on each person. Participants will also complete a 15-minute online questionnaire every 2 weeks.

This study aims to better understand what kind of working conditions lead to stress and impaired brain function. Doing so will help improve worker health and safety by providing insight towards improved fatigue management strategies for you and the BCWS. Considering findings from research such as this is one of the ways that the BCWS Occupational Safe Work Standard #2 task team will be able to recommend science-backed shifts to BCWS's current OSWS #2. If interested in participating in this research study, please contact the UVic Research Team at uvicwildfirefatigue@gmail.com.

1. Internal communications article sent to all BCWS staff via email correspondence.



2. PowerPoint study advertisement delivered at provincial level course.

Appendix F: Participant Consent Form

Research Study Consent Form: Cognitive Fatigue in Wildland Firefighting

Primary Contact: Jesse Wallace-Webb, MSc Kinesiology, University of Victoria

Study Supervisor: Dr. Lynneth Stuart-Hill, Occupational Physiology Researcher

Study Description
You are being invited to participate in a study called "Cognitive Fatigue in Wildland Firefighting" that is being conducted by Jesse Wallace-Webb, Dr. Lynneth Stuart-Hill, Dr. Olav Krigolson, and Dr. Cory Coehoorn. Jesse Wallace-Webb is a graduate student in the MSc Kinesiology program at the University of Victoria; Lynneth Stuart-Hill and Olav Krigolosn are faculty members in the School of Exercise Science, Physical and Health Education at the University of Victoria; Cory Coehoorn is a faculty member in the Department of Kinesiology & Health Sciences at Louisiana State University, Shreveport. If you have any questions or concerns about the study, you may contact one of the researchers using the information listed above.

As funded by the University of Victoria, the purpose of this research project is to investigate the factors that contribute to cognitive fatigue in the occupation of wildland firefighting. The variables of interest include cognitive function, sleep, stress, and shift characteristics. These variables will be measured daily. To minimize participant burden, each participant will only complete daily data collection during two-week-long "collection periods" that will rotate between two or three members of the same crew.

Cognitive fatigue is the state of reduced awareness and impaired decision-making ability. Awareness will be assessed in this study using the psychomotor vigilance task (PVT). The PVT is a short, 3-minute test that measures reaction time.

Sleep quality and quantity will be measured by a wrist-worn monitor (Polar Ignite®)

Stress is the body's combined physical and mental response to stressful situations. It will be measured by heart rate variability.

Heart rate variability is the beat-to-beat change in heart rate. It is a non-invasive way to measure nervous system activity. It will be measured using a chest-worn monitor (Polar H10® Heart Rate Sensor).

You will also be asked to complete several questionnaires throughout the fire season. First, baseline questionnaires will be given at the start of the season that ask questions related to trait mindfulness, morningness-eveningness, work history, medical history, individual characteristics, meditation experience, and exercise habits. Bi-weekly questionnaires will also be given that measure stress, fatigue, sleep quality, burnout, resiliency, and overall well-being. Subjective reports of perceived stress, fatigue, and sleepiness will be recorded daily. Participants will also be asked to report a daily log of sleep, caffeine intake, activity (i.e. what they did that day), and shift information (i.e start time, duration and time between shifts).

For participants on initial attack (IA), rapattack (RA), or parattack (PA), data will be collected at the start and end of each week (i.e. Monday & Friday), regardless of whether they are on base or assigned to a fire. If assigned to a fire, they will collect every day for the first three days and then every third day afterward until the end of their two week collection period. For participants on unit crew (UC), data will only be collected if assigned to a wildfire deployment. If deployed, they will collect data every day for the first three days of the deployment and then every third day afterward until end of their 14 day deployment. Participants will also collect data on their first day back to work after the employer's policy of 72 hours rest. Check-ins will be conducted via phone call with each participant at the end of each two-week collection period to ensure completeness of collected data and to resolve any equipment-related issues as they arise. All data collection procedures will taught to participants and self-administered throughout the fire season.

The primary aim of this study is to assess whether short sleeps (<6hrs) and/or long shifts (12hrs+) impact stress or cognitive function. We also want to determine whether fatigue increases over the course of a (1) multi-day initial attack fire, (2) 14-day deployment, and/or (3) fire season, as well how well one is able to recover after the employer's current policy of 72 hours of rest. The goal of this study is to improve worker safety by informing fatigue management policy. You are being asked to participate because you are a wildland firefighter employed by the British Columbia Wildfire Service (BCWS). If you agree to participate in this study, you will be asked to collect data on yourself throughout the fire season (May to August 2022), including nearest at your sleeping location (i.e. home, tent, hotel room, etc.) and nearest marshalling point (i.e. wherever you start work).

Risks & Benefits of Participation
Participating in this study may cause some inconvenience to you, primarily in the time required for data collection. This will include approximately 10 minutes at home in the morning and evening, and 5 minutes at the start and end of shift. Baseline questionnaires will take approximately 20 minutes to complete. Bi-weekly questionnaires will take approximately 15 minutes to complete. Potential benefits of your participation include improving your ability to self-assess personal levels of stress and fatigue-related cognitive impairment. It may also benefit your future health and safety by providing opportunities for worker education and informing government policy related to firefighter fatigue management.

Confidentiality and Anonymity
In order to protect your confidentiality, participant IDs will be created and listed on data spreadsheets instead of full names, and identifiable characteristics will not be included in the dissemination of findings. However, due to the nature of this research, you will not be anonymous to some members of the research team or other participants on your crew. Also, be advised that this research study includes data storage in U.S.A. As such, there is a possibility that information about you that is gathered for this research study may be accessed without your knowledge or consent by the U.S. government, in compliance with the U.S. Freedom Act. Once data collection is complete, data will be stored on a password-protected computer. The master list of participants, corresponding ID numbers, and the password-protected computer will only be seen and used by members of the research team. Any data provided to other researchers will be fully anonymous. It is anticipated that the findings from this study will be analyzed and disseminated both academically, through research conferences and scholarly publications (either

by the primary researcher or by other researchers), and occupationally, through worker education and collaboration with the BCWS.

Right to Withdraw
It must be emphasized that **you are under no obligation to participate in this research study,** and your decision regarding whether or not to participate will in no way affect your employment status or review of productivity. Furthermore, if you do choose to participate, you will be able to withdraw at any time without any consequences or explanation by contacting any member of the research team. If you do withdraw from the study, your data will not be used in the analysis unless you give permission to do so. If permission is not given, your data will be deleted.

In addition to being able to contact the above listed researchers, you may also verify the ethical approval of this study or raise any concerns you may have by contacting the Research Ethics Office at the University of Victoria (250-472-4545) or via email at ethics@uvic.ca.

Your signature below indicates that you understand the above-mentioned risks, benefits, requirements of being involved with this study, that you have had the opportunity to have your questions answered by the researcher, and that you consent to participate in this research project.

______________________	______________________	______________________
Name of Participant	*Signature*	*Date*

Please keep copy of this consent form for your records and email a copy "uvicwildfirefatigue@gmail.com"

Appendix G: LME Model Building Step Tables

3.5.2 Appendix G.1.a: Pre-Shift Subjective Fatigue Model

Overview

Model Outputs	Null Model	Predictor Model
Regression Coefficients		
Level 1 (L1)		
Intercept (γ_{00})	14 (0.28) ***	14.2 (0.33) ***
Sleep Score (γ_{10})		-0.09 (0.02) ***
Fit Criteria		
AIC	1810.3	719.3
BIC	1822.5	732.0
LogLikel	-902.1	-355.6
Pseudo R^2 Marginal	0.00	0.14
Pseudo R^2 Conditional	0.31	0.35
- 2LL	1804.3	711.3
Variance Components		
Intercept (L2) variance ($\sigma^2_{\mu 0}$)	1.62	1.03
Within-participant (L1) variance (σ^2_j)	3.42	2.85
Slope (L2) variance ($\sigma^2_{\mu 1}$)	N/A	N/A
Intercept-slope (L2) covariance (σ^2_{IS})	N/A	N/A
ICC	0.322	0.267
Additional Information		
Number of estimated parameters	2	3

Note: *p < .05. **p < .01. ***p<.001. *N* = 179 and L2 sample size = 12. Coefficient values are unstandardized beta-weights. Values in parentheses are standard errors. T-statistics were computed as the ratio of each regression coefficient divided by its standard error. Variance components were estimated using REML, while regression coefficients and model fit criteria were estimated using ML. Standard deviation (SD) was calculated as the square root of shown variance. Sleep score was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom.

Step 2: Determine the Strongest L1 Predictor

	Model 1			Model 2			Model 3		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	3.04	0.21	< .001	3.04	0.21	< .001	3.04	0.21	< .001
Sleep Score (/100)	-0.05	0.02	0.03	-0.05	0.02	0.03	-0.05	0.02	0.03
Sleep Continuity (/5)	0.28	0.22	0.22	0.27	0.21	0.20	0.28	0.21	0.20
Deep Sleep %	-3.57	1.60	0.03	-3.24	2.24	0.15	-3.23	2.23	0.15
% Asleep	21.59	20.97	0.31	21.42	12.35	0.09	21.42	12.35	0.09
Long Interruptions (mins)	0.04	0.03	0.13	0.05	0.03	0.09	0.05	0.03	0.09
Wakeup time	-2.76	19.72	0.89	-2.78	19.68	0.89	-2.40	2.32	0.30

Overall Sleep Duration (hrs)	-0.10	3.23	0.98	-0.13	0.81	0.88	-0.14	0.18	0.42
Number of Sleep Cycles	-0.03	0.12	0.83	-0.03	0.12	0.83	-0.03	0.12	0.83
Light Sleep %	3.24	2.24	0.15	0.33	1.78	0.85	0.33	1.78	0.85
Bedtime	0.36	19.31	0.99	0.37	19.29	0.99			
REM Sleep % [#]	-0.33	1.79	0.85						
Actual Sleep Duration (hrs)	-0.03	3.38	0.99						
Fit Criteria									
AIC	512.261			510.26			508.26		
BIC	556.162			551.03			545.89		
LogLikel	-242.131			-242.13			-242.13		
Pseudo R^2 Marginal	0.182			0.182			0.182		
R^2 Conditional	0.435			0.435			0.435		
- 2LL	484.26			484.26			484.26		

	Model 4			Model 5			Model 6		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	3.04	0.21	< .001	3.04	0.21	< .001	3.04	0.21	< .001
Sleep Score (/100)	-0.05	0.02	0.01	-0.05	0.02	0.01	-0.06	0.01	< .001
Sleep Continuity (/5)	0.28	0.21	0.19	0.29	0.21	0.17	0.36	0.19	0.07
Deep Sleep %	-3.53	1.58	0.03	-3.46	1.56	0.03	-3.45	1.56	0.03
% Asleep	21.40	12.35	0.09	21.17	12.31	0.09	18.16	11.78	0.13
Long Interruptions	0.04	0.03	0.09	0.04	0.03	0.09	0.03	0.02	0.13
Wakeup time	-2.34	2.30	0.31	-2.33	2.30	0.31	-2.82	2.23	0.21
Overall Duration	-0.13	0.16	0.43	-0.13	0.16	0.41			
Number of Cycles	-0.03	0.12	0.82						
Fit Criteria									
AIC	506.30			504.35			503.03		
BIC	540.79			535.71			531.25		
LogLikel	-242.15			-242.17			-242.51		
Pseudo R^2 Marginal	0.182			0.182			0.180		
Pseudo R^2 Conditional	0.435			0.434			0.432		
- 2LL	484.30			484.35			485.03		

	Model 7			Model 8			Model 9		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	3.04	0.21	< .001	3.02	0.21	< .001	3.03	0.21	< .001
Sleep Score (/100)	-0.06	0.01	< .001	-0.06	0.01	< .001	-0.05	0.01	< .001
Sleep Continuity (/5)	0.39	0.19	0.04	0.43	0.18	0.02	0.46	0.15	0.00
Deep Sleep %	-3.59	1.56	0.02	-3.18	1.57	0.04	-3.47	1.59	0.03
% Asleep	19.33	11.81	0.10	3.63	7.15	0.61			
Long Interruptions (mins)	0.03	0.02	0.16						
Fit Criteria									
AIC	502.61			522.44			531.22		
BIC	527.70			544.59			550.24		
LogLikel	-243.31			-254.22			-259.61		
Pseudo R^2 Marginal	0.175			0.152			0.144		

Predictor	Estimate	SE	p	Estimate	SE	t	Estimate	SE	t
Pseudo R² Conditional	0.426			0.396			0.383		
- 2LL	486.61			508.44			519.22		

	Model 10			Model 11*			Model 12		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**t**	**Estimate**	**SE**	**t**
Intercept (γ00)	3.05	0.21	< .001	3.05	0.21	14.30			
Sleep Score (/100)	-0.05	0.01	< .001	-0.05	0.01	-5.53			
Sleep Continuity (/5)	0.37	0.14	0.01				0.27	0.14	1.85
Deep Sleep %							-1.67	1.67	-1.00
% Asleep							-3.13	4.99	-0.63
Long Interruptions (mins)							0.01	0.01	1.29
Wakeup time							-7.36	2.04	-3.60
Overall Sleep Duration (hrs)							-0.37	0.08	-4.55
Number of Sleep Cycles							-0.30	0.10	-3.01
Light Sleep %							2.57	1.27	2.03
Bedtime							1.70	2.02	0.84
REM Sleep % #							-2.67	1.65	-1.61
Actual Sleep Duration (hrs)							-0.41	0.09	-4.81
Fit Criteria									
AIC	541.05			546.10					
BIC	556.99			558.85					
LogLikel	-265.53			-269.05					
Pseudo R² Marginal	0.136			0.111					
Pseudo R² Conditional	0.378			0.350					
- 2LL	531.05			538.10					

Note: * = Final model. Model 12 shows each removed predictor in isolation. Table estimates are unstandardized beta-weights. All predictors were rescaled via cluster-wise centering. ML method was used for all parameter estimates, including fit criteria. Satterthwaite method was used for estimating degrees of freedom. ML method was used for all parameter estimates, including fit criteria. # REM sleep was removed during first iteration due to issues of perfect multicollinearity with other sleep stage metrics.

Step 3: Add in Covariates

	Model 1			Model 2			Model 3		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	13.840	0.437	< .001	13.824	0.398	< .001	13.763	0.353	< .001
Sleep Score (/100)	-0.093	0.015	< .001	-0.093	0.015	< .001	-0.093	0.015	< .001
FFMQ	-0.028	0.029	0.349	-0.029	0.026	0.280	-0.031	0.025	0.225
PA	0.002	0.001	0.145	0.002	0.001	0.093	0.002	0.001	0.098

Age	0.084	0.129	0.530	0.087	0.124	0.502	0.116	0.092	0.238
MEQ	0.075	0.056	0.208	0.074	0.055	0.204	0.072	0.054	0.208
Biological Sex	-0.813	0.972	0.419	-0.794	0.951	0.419	-0.904	0.885	0.324
Experience	0.049	0.135	0.723	0.046	0.132	0.732			
Meditation	0.068	0.744	0.928						
Fit Criteria									
AIC	727.709			725.72			723.84		
BIC	762.77			757.59			752.52		
LogLikel	-352.85			-352.86			-352.92		
Pseudo R^2 Marginal	0.24			0.23			0.24		
Pseudo R^2 Conditional	0.34			0.34			0.34		
- 2LL	705.71			705.72			705.84		
	Model 4			Model 5			Model 6		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	13.977	0.290	< .001	14.072	0.284	< .001	14.097	0.296	< .001
Sleep Score (/100)	-0.093	0.015	< .001	-0.093	0.015	< .001	-0.093	0.015	< .001
FFMQ	-0.039	0.024	0.135	-0.045	0.024	0.087	-0.038	0.023	0.136
PA	0.002	0.001	0.152	0.002	0.001	0.183	0.001	0.001	0.298
Age	0.074	0.084	0.399	0.077	0.088	0.402			
MEQ	0.029	0.034	0.428						
Fit Criteria									
AIC	722.88			721.53			720.26		
BIC	748.38			743.85			739.39		
LogLikel	-353.44			-353.77			-354.13		
Pseudo R^2 Marginal	0.23			0.20			0.20		
Pseudo R^2 Conditional	0.33			0.33			0.34		
- 2LL	706.88			707.53			708.26		
	Model 7			Model 8*					
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**			
Intercept (γ00)	14.186	0.300	< .001	14.223	0.331	< .001			
Sleep Score (/100)	-0.093	0.015	< .001	-0.093	0.015	< .001			
FFMQ	-0.035	0.024	0.179						
Fit Criteria									
AIC	719.394			719.25					
BIC	735.331			732.00					
LogLikel	-354.697			-355.63					
Pseudo R^2 Marginal	0.187			0.14					
Pseudo R^2 Conditional	0.347			0.35					
- 2LL	709.39			711.25					

Note: * = Final model. Table estimates are unstandardized beta-weights. Sleep score was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. ML method was used for all parameter estimates, including fit criteria. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire, PA = baseline physical activity

Step 4: Assess the Need for Random Slopes

	Fixed Slope Model*	Independence Structure	Unstructured Structure

Predictor	Estimate	SE	p	Estimate	SE	p	Estimate	SE	p
Intercept (γ00)	14.2238	0.3473	< .001	14.2238	0.3473	< .001	14.2363	0.3494	< .001
Sleep Score	-0.0927	0.015	< .001	-0.0881	0.0182	0.023	-0.0755	0.0195	0.004
Random Variance Components									
Intercept (L2) variance ($\sigma^2_{\mu 0}$)			1.03			1.04			1.07
Intercept (L2) variance (95% CL)			[0.29, 2.91]			[0.29, 2.91]			[0.35, 2.98]
ICC			0.267			0.269			0.278
Slope (L2) variance ($\sigma^2_{\mu 1}$)			N/A			5E-04			0.002
Slope (L2) variance (95% CL)			N/A			[0, 0.007]			[0, 0.008]
LRT Statistic			N/A			0.18			3.53
LRT P-Value			N/A			0.671			0.171
Intercept-slope (L2) covariance (σ^2_{IS})			N/A			0			1
Fit Criteria									
AIC			719.3			721.3			719.8
BIC			738.9			743.9			745.7
LogLikel			-359			-359			-357
Pseudo R² Marginal			0.136			0.124			0.093
Pseudo R² Conditional			0.366			0.366			0.363
- 2LL			718.1			718			714.6

Note: * = Final model. Table estimates are unstandardized beta-weights. Sleep Score was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. REML was used for all parameter estimates.

3.5.3 Appendix G.1.b: Pre-Shift PVT Lapses Time Model

Overview

Model Outputs	Null Model	Predictor Model	Covariate Model
Regression Coefficients			
Level 1 (L1)			
Intercept (γ_{00})	1.72 (0.19) ***	1.69 (0.25) ***	1.28 (0.13) ***
Sleep Score (γ_{10})		-0.02 (0.006) ***	-0.02 (0.006) ***
Level 2 (L2)			
Experience (γ_{01})			-0.09 (0.04) #
MEQ (γ_{02})			0.05 (0.01) **
Fit Criteria			
AIC	512.3	237.9	231.0
BIC	522.9	249.1	247.8
LogLikel	-253.1	-114.9	-109.5
Pseudo R² Marginal	0.00	0.04	0.5220
Pseudo R² Conditional	0.53	0.560	0.603
- 2LL	506.3	229.9	219.0
Variance Components			
Intercept (L2) variance ($\sigma^2_{\mu 0}$)	0.439	0.443	0.132

Within-participant (L1) variance (σ^2_j)	0.361	0.328	0.328
Slope (L2) variance ($\sigma^2_{\mu 1}$)	N/A	N/A	N/A
Intercept-slope (L2) covariance (σ^2_{IS})	N/A	N/A	N/A
ICC	0.549	0.574	0.287
Additional Information			
Number of estimated parameters	2	3	5

Note: $^{\#}$ p < .10 *p < .05. **p < .01. ***p<.001. *N* = 122 and L2 sample size = 8. Coefficient values are unstandardized beta-weights. Values in parentheses are standard errors. T-statistics were computed as the ratio of each regression coefficient divided by its standard error. Variance components were estimated using REML, while regression coefficients and model fit criteria were estimated using ML. Standard deviation (SD) was calculated as the square root of shown variance. Sleep score was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. MEQ = morningness-eveningness questionnaire.

Step 2: Determine the Strongest L1 Predictor

	Model 1			Model 2			Model 3		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1.701	0.231	< .001	1.701	0.231	< .001	1.701	0.231	< .001
Sleep Score (/100)	-0.034	0.014	0.013	-0.033	0.013	0.014	-0.033	0.013	0.015
Light Sleep %	2.080	1.476	0.162	1.377	1.150	0.234	1.331	1.146	0.248
Overall Sleep Duration	-2.072	2.785	0.459	-3.038	1.579	0.057	-2.773	1.446	0.058
Actual Sleep Duration	1.952	2.900	0.502	2.996	1.509	0.050	2.963	1.509	0.052
Bedtime	-8.157	13.677	0.552	-7.968	13.681	0.562	-2.346	1.973	0.237
Deep Sleep %	-3.401	1.166	0.004	-1.981	1.458	0.177	-2.049	1.450	0.160
Number of Sleep Cycles	-0.101	0.087	0.250	-0.101	0.087	0.248	-0.103	0.087	0.239
Long Interruptions (mins)	0.021	0.022	0.350	0.022	0.022	0.319	0.022	0.022	0.319
Sleep Continuity (/5)	-0.107	0.145	0.464	-0.108	0.145	0.460	-0.112	0.145	0.443
Wakeup time	6.061	13.728	0.660	5.694	13.711	0.679			
% Asleep	7.192	17.076	0.674						
REM Sleep % $^{\#}$	-1.321	1.157	0.256						
Fit Criteria									
AIC	234.03			232.21			230.38		
BIC	272.46			267.89			263.32		
LogLikel	-103.01			-103.10			-103.19		
Pseudo R² Marginal	0.092			0.091			0.091		
Pseudo R² Conditional	0.609			0.608			0.608		
- 2LL	206.03			206.21			206.38		

	Model 4			Model 5			Model 6		

Predictor	Estimate	SE	p	Estimate	SE	p	Estimate	SE	p
Intercept (γ00)	1.700	0.231	< .001	1.694	0.231	< .001	1.694	0.231	< .001
Sleep Score (/100)	-0.034	0.013	0.013	-0.036	0.013	0.005	-0.038	0.013	0.003
Light Sleep %	1.353	1.149	0.241	1.507	1.100	0.173	1.691	1.094	0.125
Overall Sleep Duration	-2.018	1.065	0.061	-1.382	0.610	0.026	-1.504	0.605	0.014
Actual Sleep Duration	2.187	1.126	0.055	1.545	0.701	0.030	1.628	0.701	0.022
Bedtime	-2.295	1.977	0.248	-2.366	1.900	0.216	-2.394	1.911	0.213
Deep Sleep %	-2.165	1.446	0.137	-1.659	1.378	0.231	-1.262	1.342	0.349
Number of Sleep Cycles	-0.097	0.087	0.268	-0.097	0.084	0.252			
Long Interruptions (mins)	0.012	0.018	0.498						
Fit Criteria									
AIC	228.97			233.60			232.91		
BIC	259.16			261.47			258.00		
LogLikel	-103.48			-106.80			-107.46		
Pseudo R² Marginal	0.089			0.091			0.086		
Pseudo R² Conditional	0.606			0.610			0.605		
- 2LL	206.97			213.60			214.91		

	Model 7			Model 8			Model 9		
Predictor	Estimate	SE	p	Estimate	SE	p	Estimate	SE	p
Intercept (γ00)	1.694	0.231	< .001	1.693	0.231	< .001	1.693	0.231	< .001
Sleep Score (/100)	-0.034	0.012	0.005	-0.035	0.012	0.004	-0.015	0.008	0.049
Light Sleep %	2.317	0.872	0.009	2.300	0.878	0.010	2.182	0.894	0.016
Overall Sleep Duration (hrs)	-1.359	0.587	0.022	-1.290	0.589	0.031	-0.043	0.075	0.564
Actual Sleep Duration (hrs)	1.458	0.680	0.034	1.462	0.685	0.035			
Bedtime	-2.507	1.915	0.193						
Fit Criteria									
AIC	231.79			231.50			233.96		
BIC	254.09			251.01			250.68		
LogLikel	-107.90			-108.75			-110.98		
Pseudo R² Marginal	0.083			0.078			0.062		
Pseudo R² Conditional	0.602			0.596			0.580		
- 2LL	215.79			217.50			221.96		

	Model 10			Model 11*			Model 12		
Predictor	Estimate	SE	p	Estimate	SE	p	Estimate	SE	p
Intercept (γ00)	1.693	0.231	< .001	1.691	0.231	< .001			
Sleep Score (/100)	-0.018	0.006	0.004	-0.020	0.006	0.001			
Light Sleep %	2.027	0.854	0.019				2.480	0.872	0.005
Overall Sleep Duration							-0.093	0.058	0.113
Actual Sleep Duration							-0.108	0.062	0.083

Bedtime							-0.016	1.554	0.992
Deep Sleep %							-0.734	0.824	0.375
Number of Sleep Cycles							-0.141	0.066	0.034
Long Interruptions (mins)							0.005	0.007	0.533
Sleep Continuity (/5)							-0.073	0.094	0.438
Wakeup time							-3.120	1.683	0.066
% Asleep							-3.060	3.124	0.329
REM Sleep % #							-2.110	1.020	0.04
Fit Criteria									
AIC	232.29			237.87					
BIC	246.23			249.09					
LogLikel	-111.14			-114.94					
Pseudo R^2 Marginal	0.061			0.039					
Pseudo R^2 Conditional	0.578			0.560					
- 2LL	222.29			229.87					

Note: * = Final model. Model 12 shows each removed predictor in isolation. Table estimates are unstandardized beta-weights. All predictors were rescaled via cluster-wise centering. Satterthwaite method was used for estimating degrees of freedom. ML method was used for all parameter estimates, including fit criteria. # REM was removed during first iteration due to issues of perfect multicollinearity with other sleep stage metrics.

Step 3: Add in L2 Covariates

	Model 1			Model 2			Model 3		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1.559	0.140	< .001	1.558	0.139	< .001	1.563	0.134	< .001
Sleep Score									
Experience	-0.073	0.055	0.209	-0.073	0.054	0.201	-0.070	0.051	0.188
MEQ	0.053	0.016	0.004	0.053	0.015	0.004	0.053	0.015	0.003
Age	-0.060	0.050	0.248	-0.060	0.050	0.248	-0.062	0.048	0.216
FFMQ	0.006	0.011	0.607	0.006	0.011	0.606	0.006	0.009	0.505
Biological Sex	0.114	0.296	0.707	0.110	0.267	0.688	0.114	0.265	0.675
Meditation	-0.031	0.256	0.906	-0.032	0.253	0.901			
PA	1.60E-05	0.001	0.977						
Fit Criteria									
AIC	511.974			509.974			507.991		
BIC	547.503			541.951			536.414		
LogLikel	-245.987			-245.987			-245.995		
Pseudo R^2 Marginal	0.420			0.420			0.422		
Pseudo R^2 Conditional	0.562			0.562			0.563		
- 2LL	491.974			491.974			491.990		

	Model 4			Model 5			Model 6*		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1.534	0.115	< .001	1.521	0.115	< .001	1.522	0.121	< .001
Sleep Score									

Experience	-0.078	0.047	0.122	-0.091	0.042	0.052	-0.124	0.033	0.003
MEQ	0.055	0.014	0.002	0.052	0.014	0.003	0.052	0.014	0.003
Age	-0.055	0.044	0.241	-0.051	0.045	0.273			
FFMQ	0.005	0.009	0.566						
Fit Criteria									
AIC	506.174			504.519			503.767		
BIC	531.045			525.837			521.532		
LogLikel	-246.087			-246.259			-246.883		
Pseudo R^2 Marginal	0.426			0.439			0.429		
Pseudo R^2 Conditional	0.566			0.578			0.584		
- 2LL	492.174			492.518			493.766		
	Model 7			Model 8			Model 9**		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1.675	0.161	< .001	1.606	0.173	< .001	1.282	0.133	< .001
Sleep Score							-0.020	0.006	0.001
Experience	-0.089	0.045	0.071				-0.087	0.040	0.056
MEQ				0.039	0.020	0.082	0.051	0.013	0.008
Age									
FFMQ									
Biological Sex									
Meditation									
PA									
Fit Criteria									
AIC	510.930			511.106			230.953		
BIC	525.142			525.318			247.777		
LogLikel	-251.465			-251.553			-109.476		
Pseudo R^2 Marginal	0.138			0.129			0.522		
Pseudo R^2 Conditional	0.529			0.533			0.603		
- 2LL	502.930			503.106			218.952		
	Model 10			Model 11					
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**			
Intercept (γ00)	1.380	0.163	< .001	1.472	0.225	< .001			
Sleep Score	-0.020	0.006	0.001	-0.020	0.006	0.001			
Experience				-0.120	0.065	0.099			
MEQ	0.058	0.016	0.015						
Age									
FFMQ									
Biological Sex									
Meditation									
PA									
Fit Criteria									
AIC	232.942			237.022					
BIC	246.962			251.042					
LogLikel	-111.471			-113.511					
Pseudo R^2 Marginal	0.441			0.161					
Pseudo R^2 Conditional	0.594			0.532					
- 2LL									

Note: * = Final covariate only model. **=Final model. Models 1-5 included covariates only because inclusion of sleep score caused model to crash under both ML and REML due to excessive complexity. All covariates removed during iterations 1-5 were re-tested for contribution once sleep score was added; none improved model fit (not shown). Table estimates are unstandardized beta-weights. Sleep Score was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. ML method was used for all parameter estimates, including fit criteria. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire, PA = baseline physical activity

Step 4: Assess the Need for Random Slopes

	Fixed Slope Model*			Independence Structure			Unstructured Structure		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1.282	0.133	< .001	1.282	0.133	< .001	1.238	0.134	< .001
Sleep Score	-0.020	0.006	0.001	-0.020	0.006	0.001	-0.018	0.007	0.017
Experience	-0.087	0.040	0.056	-0.087	0.040	0.056	-0.099	0.040	0.032
MEQ	0.051	0.013	0.008	0.051	0.013	0.008	0.054	0.013	0.005
Random Variance Components									
Intercept (L2) variance ($\sigma^2_{\mu 0}$)			0.067			0.067			0.0711
Intercept (L2) variance (95% CI)			[0.01, 0.3]			[0.01, 0.3]			[0.013, 0.26]
ICC			0.17			0.17			0.18
Slope (L2) variance			N/A			4E-05			3.6E-05
Slope (L2) variance (95% CI)			N/A			[0, 6.75E-04]			[0, 5.95E-04]
LRT Statistic			N/A			3E-14			0.673
LRT P-Value			N/A			1			0.714
Intercept-slope (L2) covariance (σ^2_{IS})			N/A			0			-1
Fit Criteria									
AIC			231			233			234.28
BIC			247.8			252.6			256.712
LogLikel			-109			-109			-109.14
Pseudo R² Marginal			0.522			0.522			0.553
Pseudo R² Conditional			0.603			0.603			0.636
- 2LL			219			219			218.28

Note: Note: * = Final covariate only model. Table estimates are unstandardized beta-weights. Sleep core was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. ML was used for all parameter estimates. MEQ = morningness-eveningness questionnaire.

3.5.4 Appendix G.1.c: Pre-Shift PVT Response Time Model

Overview

Model Outputs	Null Model		Predictor Model	Covariate Model
Regression Coefficients				
Level 1 (L1)				
Intercept (γ_{00})	301 (5.9) ***		300 (6.8) ***	283 (2.4) *
Sleep Score (γ_{10})			-0.43 (0.13) **	-0.43 (0.13) **
Level 2 (L2)				
Meditation (γ_{01})				-19.5 (4.4)
Age (γ_{02})				-1.13 (0.49)
FFMQ (γ_{03})				0.48 (0.24)
MEQ (γ_{04})				2.31 (0.28)
Fit Criteria				
AIC	2172.7		996.8	976.5
BIC	2183.3		1008.1	998.9
LogLikel	-1083.3		-494.4	-480.2
Pseudo R^2 Marginal	0.00		0.02	0.69
Pseudo R^2 Conditional	0.66		0.72	0.71
- 2LL	2166.7		988.8	960.5
Variance Components				
Intercept (L2) variance ($\sigma^2_{\mu 0}$)	430		403	11.3
Within-participant (L1) variance (σ^2_{j})	220		159	160
Slope (L2) variance ($\sigma^2_{\mu 1}$)	N/A	N/A	N/A	N/A
Intercept-slope (L2) covariance (σ^2_{IS})	N/A	N/A	N/A	N/A
ICC	0.662		0.717	0.0659
Additional Information				
Number of estimated parameters	2		3	7

Note: $^{\#}$ p < .10 *p < .05. **p < .01. ***p<.001. *N* = 122 and L2 sample size = 8. Coefficient values are unstandardized beta-weights. Values in parentheses are standard errors. T-statistics were computed as the ratio of each regression coefficient divided by its standard error. Regression coefficients, variance components, and R^2 were estimated using REML, while AIC, BIC, LogLikel, and -2LL model fit criteria were estimated using ML. Standard deviation (SD) was calculated as the square root of shown variance. Sleep score was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire.

Step 2: Determine the Strongest L1 Predictor

	Model 1			Model 2			Model 3		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	300.330	6.750	< .001	300.330	6.750	< .001	300.330	6.751	< .001
Sleep Score (/100)	-0.480	0.306	0.120	-0.480	0.306	0.120	-0.475	0.290	0.104
Number of Sleep Cycles	-3.510	1.978	0.079	-3.504	1.976	0.079	-3.484	1.928	0.074

Light Sleep %	-29.817	26.504	0.263	28.395	26.084	0.279	29.133	20.358	0.155
% Asleep	214.788	388.199	0.581	235.964	219.991	0.286	235.121	219.202	0.286
Sleep Continuity (/5)	-3.892	3.303	0.241	-3.815	3.092	0.220	-3.823	3.087	0.218
Long Interruptions	0.350	0.507	0.491	0.331	0.420	0.433	0.331	0.420	0.433
Wakeup time	-185.755	312.085	0.553	-189.391	307.221	0.539	-188.294	306.264	0.540
Actual Sleep Duration	12.650	65.932	0.848	8.380	13.700	0.542	8.302	13.591	0.543
Bedtime	163.646	310.933	0.600	167.984	303.956	0.582	166.738	302.707	0.583
Deep Sleep %	-28.618	26.299	0.279	-1.503	33.235	0.964			
Overall Sleep Duration	-4.191	63.303	0.947						
REM Sleep % #	-1.199	33.550	0.972						
Fit Criteria									
AIC	956.55			954.55			952.56		
BIC	994.98			990.24			985.50		
LogLikel	-464.28			-464.28			-464.28		
Pseudo R^2 Marginal	0.054			0.054			0.053		
Pseudo R^2 Conditional	0.711			0.711			0.711		
- 2LL	928.55			928.55			928.56		

	Model 4			Model 5			Model 6		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	300.330	6.751	< .001	300.329	6.751	< .001	300.329	6.751	< .001
Sleep Score (/100)	-0.487	0.289	0.095	-0.424	0.225	0.063	-0.454	0.214	0.036
Number of Sleep Cycles	-3.448	1.929	0.077	-3.298	1.882	0.083	-3.283	1.883	0.084
Light Sleep %	29.419	20.380	0.152	30.735	20.043	0.128	30.265	20.029	0.134
% Asleep	281.409	202.740	0.168	300.163	195.665	0.128	298.646	195.797	0.130
Sleep Continuity (/5)	-3.565	3.056	0.246	-3.872	2.929	0.189	-3.871	2.931	0.189
Long Interruptions	0.303	0.418	0.470	0.373	0.368	0.313	0.346	0.362	0.342
Wakeup time	-21.395	44.664	0.633	-18.705	44.025	0.672			
Actual Sleep Duration	0.973	2.776	0.727						
Fit Criteria									
AIC	950.86			948.98			947.16		
BIC	981.05			976.43			971.87		
LogLikel	-464.43			-464.49			-464.58		
Pseudo R^2 Marginal	0.053			0.052			0.052		
Pseudo R^2 Conditional	0.710			0.710			0.710		
- 2LL	928.86			928.98			929.16		

	Model 7			Model 8			Model 9		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	300.343	6.804	< .001	300.341	6.805	< .001	300.339	6.805	< .001
Sleep Score (/100)	-0.456	0.210	0.032	-0.421	0.208	0.045	-0.284	0.150	0.061
Number of Sleep Cycles	-2.272	1.713	0.187	-2.227	1.720	0.198	-2.901	1.572	0.068
Light Sleep %	31.665	19.661	0.110	35.976	19.254	0.064	32.814	19.038	0.088
% Asleep	146.210	110.219	0.187	89.440	94.473	0.346			
Sleep Continuity (/5)	-2.598	2.628	0.325						
Fit Criteria									
AIC	982.23			981.20			980.10		
BIC	1004.53			1000.72			996.82		
LogLikel	-483.12			-483.60			-484.05		
Pseudo R² Marginal	0.046			0.044			0.042		
Pseudo R² Conditional	0.716			0.714			0.711		
- 2LL	966.23			967.20			968.10		

Predictor	Model 10			Model 11*			Model 12		
Intercept (γ00)	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Sleep Score (/100)	300.287	6.822	< .001	300.240	6.826	< .001			
Number of Sleep Cycles	-2.281	1.536	0.140	-0.426	0.132	0.002			
Light Sleep %	-0.354	0.146	0.016				-3.890	1.420	0.007
% Asleep							37.000	19.470	0.060
Sleep Continuity (/5)							-77.600	68.650	0.261
Long Interruptions							-1.980	2.060	0.337
Wakeup time							0.110	0.164	0.503
Actual Sleep Duration							-57.300	37.200	0.126
Bedtime							-2.970	1.360	0.031
Deep Sleep %							28.700	34.080	0.402
Overall Sleep Duration							-3.490	18.140	0.848
REM Sleep % #							-2.560	1.280	0.047
Fit Criteria							-51.800	22.620	0.024
AIC									
BIC	988.24			996.84					
LogLikel	1002.22			1008.06					
Pseudo R² Marginal	-489.12			-494.42					
Pseudo R² Conditional	0.034			0.026					
- 2LL	0.706			0.699					

978.24	988.84	

Note: * = Final model. Model 12 shows each removed predictor in isolation. Table estimates are unstandardized beta-weights. All predictors were rescaled via cluster-wise centering. Satterthwaite method was used for estimating degrees of freedom. ML method was used for all parameter estimates, including fit criteria. # REM was removed during first iteration due to issues of perfect multicollinearity with other sleep stage metrics.

Step 3: Add in L2 Covariates

	Model 1			Model 2			Model 3		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	288.014	14.325	< .001	287.965	2.712	< .001	285.299	3.280	0.009
Sleep Score (/100)	-0.426	0.133	0.002	-0.426	0.132	0.002	-0.426	0.132	0.002
MEQ	1.798	1.990	0.368	1.682	0.373	< .001	1.838	0.499	0.112
Meditation	-15.522	19.958	0.438	-16.003	4.806	0.001	-20.477	5.020	0.094
Age	-2.006	2.542	0.432	-1.764	0.518	< .001	-1.739	0.732	0.186
FFMQ	0.949	2.049	0.644	0.723	0.260	0.006	0.343	0.291	0.450
Biological Sex	12.859	26.463	0.628	13.299	7.026	0.061	10.101	8.222	0.324
Experience	2.055	5.246	0.696	1.864	1.145	0.106			
PA	-0.014	0.064	0.829						
Fit Criteria									
AIC	977.32			975.88			976.68		
BIC	1008.16			1003.92			1001.92		
LogLikel	-477.66			-477.94			-479.34		
Pseudo R² Marginal	0.40			0.70			0.69		
Pseudo R² Conditional	0.83			0.70			0.72		
- 2LL	955.32			955.88			958.68		

	Model 4			Model 5*			Model 6		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	286.668	3.546	< .001	283.108	2.354	0.056	283.683	3.611	< .001
Sleep Score (/100)	-0.426	0.132	0.002	-0.426	0.133	0.002	-0.426	0.132	0.002
MEQ	1.437	0.408	0.027	2.308	0.279	0.167	1.955	0.317	0.013
Meditation	-20.739	5.628	0.023	-19.521	4.432	0.176	-19.345	6.408	0.048
Age	-2.013	0.788	0.056	-1.130	0.487	0.331	-1.264	0.721	0.173
FFMQ				0.478	0.239	0.400			
Biological Sex	13.837	8.356	0.148						
Fit Criteria									
AIC	980.14			976.48			982.38		
BIC	1002.57			998.91			1002.01		
LogLikel	-482.07			-480.24			-484.19		
Pseudo R² Marginal	0.69			0.69			0.68		
Pseudo R² Conditional	0.74			0.71			0.75		
- 2LL	964.14			960.48			968.38		

	Model 7			Model 8			Model 9		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	283.313	4.095	< .001	287.395	5.868	< .001	293.147	9.362	< .001
Sleep Score (/100)	-0.426	0.133	0.002	-0.426	0.132	0.002	-0.426	0.132	0.002

MEQ	2.421	0.467	0.016	2.259	0.742	0.042			
Meditation	-19.421	7.080	0.066				-16.889	18	0.402
Age				-1.252	1.263	0.381	-1.897	2.073	0.412
FFMQ	0.544	0.400	0.268	0.567	0.632	0.423	-0.812	0.812	0.375
Biological Sex									
Experience									
PA									
Fit Criteria									
AIC	983.82			991.09			999.26		
BIC	1003.44			1010.72			1018.89		
LogLikel	-484.91			-488.55			-492.63		
Pseudo R^2 Marginal	0.61			0.54			0.29		
Pseudo R^2 Conditional	0.71			0.77			0.81		
- 2LL	969.82			977.09			985.26		

Note: * = Final model. Table estimates are unstandardized beta-weights. Sleep score was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. REML was used for parameter estimates due to model crashing under ML estimation. ML used for used for likelihood-based fit criteria in all cases. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire, PA = baseline physical activity

Step 4: Assess the Need for Random Slopes

Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept ($\gamma 00$)	283.108	2.35	0.06	283.083	2.410	0.046	282.664	2.676	0.003
Sleep Score	-0.426	0.13	0.002	-0.364	0.172	0.091	-0.326	0.180	0.126
Meditation	2.308	0.28	0.17	-19.473	4.502	0.166	-18.003	4.637	0.06
Age	-19.521	4.43	0.18	-1.133	0.496	0.321	-0.777	0.500	0.267
FFMQ	-1.13	0.49	0.33	0.477	0.244	0.388	0.66	0.235	0.112
MEQ	0.478	0.24	0.40	2.309	0.285	0.153	2.537	0.292	0.024
Random Variance Components									
Intercept (L2) variance ($\sigma^2_{\mu 0}$)			11.30			12.50			20.30
Intercept (L2) variance (95% CL)			[0, 10.8]			[0, 10.9]			[0, 25.2]
ICC			0.066			0.074			0.116
Slope (L2) variance ($\sigma^2_{\mu 1}$)			N/A			0.06			0.07
Slope (L2) variance (95% CL)			N/A			[0, 0.44]			[0, Inf]
LRT Statistic			N/A			0.71			1.35
LRT P-Value			N/A			0.40			0.51
Intercept-slope (L2) covariance (σ^2_{IS})			N/A			0.00			-1.00
Fit Criteria									
AIC			976.48			978.13			980.11

BIC	999.35	1003.45	1007.61
LogLikel	-480.46	-480.10	-479.79
Pseudo R² Marginal	0.69	0.68	0.67
Pseudo R² Conditional	0.71	0.71	0.72
- 2LL	960.92	960.21	959.57

Note: * = Final model. Table estimates are unstandardized beta-weights. Sleep score was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. REML was used for all parameter estimates. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire.

3.5.5 Appendix G.2.a: Pre-Shift Subjective Stress

Overview

Model Outputs	Null Model	Predictor Model	Covariate Model
Regression Coefficients			
Level 1 (L1)			
Intercept (γ_{00})	11.6 (0.2) ***	11.8 (0.3) ***	11.8 (0.2) ***
Sleep score (γ_{10})		-0.04 (0.01) ***	-0.04 (0.01) ***
Level 2 (L2)			
Sex (γ_{01})			-1.54 (0.54) *
Experience (γ_{02})			0.15 (0.06) #
MEQ			0.06 (0.03)
Fit Criteria			
AIC	1519.8	604.924	596.7
BIC	1532.0	617.6735	619.0
LogLikel	-756.9	-298.462	-291.4
Pseudo R² Marginal	0.00	0.04	0.264
Pseudo R² Conditional	0.29	0.39	0.371
- 2LL	1513.8	596.9	582.7
Variance Components			
Intercept (L2) variance ($\sigma^2_{\mu 0}$)	0.69	0.835	0.253
Within-participant (L1) variance (σ^2_{i})	1.713	1.469	1.481
Slope (L2) variance ($\sigma^2_{\mu 1}$)	N/A	N/A	N/A
Intercept-slope (L2) covariance (σ^2_{IS})	N/A	N/A	N/A
ICC	0.287	0.363	0.146
Additional Information			
Number of estimated parameters	2	3	6

Note: # $p < .10$ * $p < .05$. ** $p < .01$. *** $p<.001$. *N* = 179 and L2 sample size = 12. Coefficient values are unstandardized beta-weights. Values in parentheses are standard errors. T-statistics were computed as the ratio of each regression coefficient divided by its standard error. Regression coefficients, variance components, and R^2 were estimated using REML, while AIC, BIC, LogLikel, and -2LL model fit criteria were estimated using ML. Standard deviation (SD) was calculated as the square root of shown variance. Sleep score was rescaled via cluster wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. MEQ = morningness-eveningness questionnaire.

Step 2: Determine the Strongest L1 Predictor

	Model 1			Model 2			Model 3		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1.75	0.12	< .001	1.75	0.12	< .001	1.75	0.12	< .001
Sleep Score (/100)	-0.01	0.01	0.28	-0.01	0.01	0.28	-0.01	0.01	0.19
Wakeup time	-20.55	10.68	0.06	-20.64	10.50	0.05	-20.65	10.50	0.05
Actual Sleep Duration (hrs)	0.94	1.83	0.61	0.86	0.46	0.06	0.87	0.45	0.06
Bedtime	17.30	10.46	0.10	17.40	10.25	0.09	17.42	10.25	0.09
% Asleep	-13.73	11.36	0.23	-13.33	7.19	0.07	-13.35	7.19	0.07
Number of Sleep Cycles	-0.04	0.07	0.54	-0.04	0.07	0.54	-0.04	0.07	0.53
Sleep Continuity (/5)	0.13	0.12	0.30	0.13	0.12	0.27	0.13	0.12	0.27
Long Interruptions (mins)	-0.01	0.02	0.67	-0.01	0.01	0.62	-0.01	0.01	0.60
Deep Sleep %	-0.28	0.87	0.75	-0.22	1.21	0.85	-0.27	0.86	0.75
Light Sleep %	0.22	1.21	0.85	0.06	0.97	0.95			
Overall Sleep Duration (hrs)	-0.08	1.75	0.96						
REM Sleep % #	-0.05	0.97	0.96						
Fit Criteria									
AIC	304.68			302.68			300.69		
BIC	348.58			343.45			338.32		
LogLikel	-138.34			-138.34			-138.34		
Pseudo R² Marginal	0.082			0.082			0.082		
Pseudo R² Conditional	0.383			0.383			0.383		
- 2LL	276.68			276.68			276.69		

	Model 4			Model 5			Model 6		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1.75	0.12	< .001	1.75	0.12	< .001	1.75	0.12	< .001
Sleep Score (/100)	-0.01	0.01	0.19	-0.01	0.01	0.26	-0.01	0.01	0.25
Wakeup time	-20.44	10.49	0.05	-21.63	10.18	0.04	-22.32	10.16	0.03
Actual Sleep Duration (hrs)	0.86	0.45	0.06	0.88	0.45	0.05	0.90	0.45	0.05
Bedtime	17.19	10.23	0.10	18.35	9.90	0.07	18.93	9.88	0.06
% Asleep	-13.50	7.17	0.06	-11.08	5.19	0.03	-9.76	4.89	0.05
Number of Sleep Cycles	-0.04	0.07	0.56	-0.05	0.06	0.39	-0.06	0.06	0.33
Sleep Continuity (/5)	0.12	0.11	0.28	0.07	0.10	0.45			

Long Interruptions (mins)	-0.01	0.01	0.58						
Fit Criteria									
AIC	298.79			303.42			301.98		
BIC	333.28			335.06			330.46		
LogLikel	-138.39			-141.71			-141.99		
Pseudo R² Marginal	0.081			0.081			0.079		
Pseudo R² Conditional	0.383			0.380			0.378		
- 2LL	276.79			283.42			283.98		

	Model 7			Model 8			Model 9		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1.75	0.12	< .001	1.75	0.12	< .001	1.75	0.12	< .001
Sleep Score (/100)	-0.02	0.01	0.05	-0.02	0.01	0.01	-0.02	0.01	0.003
Wakeup time	-17.93	10.40	0.09	-7.41	7.38	0.32	-2.84	1.25	0.03
Actual Sleep Duration (hrs)	0.72	0.46	0.12	0.30	0.35	0.41	0.08	0.07	0.25
Bedtime	14.68	10.13	0.15	4.59	7.30	0.53			
% Asleep	-6.77	4.74	0.16						
Fit Criteria									
AIC	317.60			317.62			316.02		
BIC	343.05			339.89			335.11		
LogLikel	-150.80			-151.81			-152.01		
Pseudo R² Marginal	0.074			0.066			0.065		
Pseudo R² Conditional	0.360			0.352			0.351		
- 2LL	301.60			303.62			304.02		

	Model 10			Model 11*			Model 12		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1.75	0.12	< .001	1.75	0.12	< .001			
Sleep Score (/100)	-0.01	0.005	0.003	-0.02	0.005	< .001			
Wakeup time	-2.20	1.13	0.05				-2.65	1.05	0.01
Actual Sleep Duration (hrs)							-0.10	0.05	0.03
Bedtime							-0.46	1.02	0.65
% Asleep							-5.04	2.53	0.05
Number of Sleep Cycles							-0.11	0.05	0.02
Sleep Continuity (/5)							0.03	0.07	0.70
Long Interruptions (mins)							0.01	0.01	0.24
Deep Sleep %							0.21	0.82	0.80
Light Sleep %							0.59	0.63	0.34
Overall Sleep Duration (hrs)							-0.08	0.04	0.05
REM Sleep % [#]							-1.21	0.81	0.14
Fit Criteria									
AIC	316.15			317.89					
BIC	332.09			330.64					
LogLikel	-153.07			-154.94					
Pseudo R² Marginal	0.060			0.046					

Pseudo R² Conditional	0.349	0.334
- 2LL	306.15	

Note: * = Final model. Model 12 shows each removed predictor in isolation. Table estimates are unstandardized beta-weights. All predictors were rescaled via cluster-wise centering. ML method was used for all parameter estimates, including fit criteria. Satterthwaite method was used for estimating degrees of freedom. # Deep sleep was removed during first iteration due to issues of perfect multicollinearity with other sleep stage metrics.

Step 3: Add in L2 Covariates

	Model 1			Model 2			Model 3		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	11.613	0.554	< .001	11.627	0.457	< .001	11.674	0.373	< .001
Sleep Score	-0.037	0.011	< .001	-0.037	0.011	< .001	-0.037	0.011	< .001
Biological Sex	-1.781	1.310	0.257	-1.783	0.950	0.135	-1.843	0.829	0.087
Experience	0.097	0.169	0.598	0.103	0.129	0.468	0.109	0.113	0.389
MEQ	0.061	0.071	0.458	0.062	0.052	0.312	0.065	0.045	0.234
Age	0.085	0.153	0.609	0.080	0.123	0.558	0.073	0.107	0.539
PA	0.001	0.002	0.727	0.001	0.001	0.701	0.0004	0.001	0.739
Meditation	-0.256	0.782	0.760	-0.209	0.655	0.764			
FFMQ	-0.003	0.093	0.975						
Fit Criteria									
AIC	602.35			600.39			598.66		
BIC	637.41			632.26			627.34		
LogLikel	-290.18			-290.19			-290.33		
Pseudo R² Marginal	0.20			0.22			0.23		
Pseudo R² Conditional	0.50			0.45			0.41		
- 2LL	580.35			580.39			580.66		

	Model 4			Model 5*			Model 6		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	11.699	0.328	< .001	11.805	0.249	< .001	12.013	0.220	< .001
Sleep Score	-0.037	0.011	< .001	-0.037	0.011	< .001	-0.037	0.011	< .001
Biological Sex	-1.820	0.752	0.064	-1.544	0.540	0.037	-0.924	0.400	0.040
Experience	0.100	0.098	0.368	0.148	0.060	0.068	0.136	0.060	0.046
MEQ	0.062	0.039	0.193	0.056	0.033	0.177			
Age	0.063	0.096	0.548						
Fit Criteria									
AIC	597.23			596.72			600.39		
BIC	622.73			619.03			619.51		
LogLikel	-290.62			-291.36			-294.19		
Pseudo R² Marginal	0.25			0.26			0.25		
Pseudo R² Conditional	0.39			0.37			0.41		
- 2LL	581.23			582.72			588.39		

	Model 7			Model 8		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	11.589	0.327	< .001	12.173	0.335	< .001
Sleep Score	-0.037	0.011	< .001	-0.037	0.011	< .001

Biological Sex	-1.526	0.715	0.064			
Experience				0.155	0.087	0.113
MEQ	0.041	0.045	0.403	-0.015	0.036	0.700
Fit Criteria						
AIC	603.46			604.69		
BIC	622.58			623.81		
LogLikel	-295.73			-296.35		
Pseudo R^2 Marginal	0.15			0.16		
Pseudo R^2 Conditional	0.39			0.43		
- 2LL	591.46			592.69		

Note: * = Final model. Table estimates are unstandardized beta-weights. Sleep score was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. REML was used for parameter estimates due to model crashing under ML estimation. ML used for used for likelihood-based fit criteria in all cases. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire, PA = baseline physical activity

Step 4: Assess the Need for Random Slopes

	Fixed Slope Model*			Independence Structure			Unstructured Structure		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept ($\gamma00$)	11.805	0.249	< .001	11.806	0.25	< .001	0.114	11.510	< .001
Sleep Score	-0.037	0.011	< .001	-0.033	0.0134	0.079	0.013	-0.059	0.077
Biological Sex	-1.544	0.540	0.037	-1.541	0.5415	0.037	0.297	-2.243	< .001
Experience	0.148	0.060	0.068	0.148	0.0597	0.068	0.034	0.085	< .001
MEQ	0.056	0.033	0.177	0.056	0.0331	0.178	0.016	0.037	< .001
Random Variance Components									
Intercept (L2) variance ($\sigma^2_{\mu0}$)			0.253			0.257			0.077
Intercept (L2) variance (95% CL)			[0, 0.35]			[0, 0.35]			[0.01, 0.22]
ICC			0.146			0.149			0.0505
Slope (L2) variance ($\sigma^2_{\mu1}$)			N/A			0.0003			0.0008
Slope (L2) variance (95% CL)			N/A			[0, 0.003]			[0, 0.004]
LRT Statistic			N/A			0.32			1.34
LRT P-Value			N/A			0.572			0.511
Intercept-slope (L2) covariance (σ^2_{IS})			N/A			0.00			1.00
Fit Criteria									
AIC			596.718			598.7			600.7

BIC	639.417	644.28	652.09
LogLikel	-301.552	-301.39	-302.7
Pseudo R² Marginal	0.264	0.26	0.288
Pseudo R² Conditional	0.371	0.38	0.297
- 2LL	603.104	602.78	605.4

Note: * = Final model. Table estimates are unstandardized beta-weights. Sleep was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. # = random variance components were unable to be computed for the unstructured model under REML, so ML was used. REML was used for all other parameter estimates, including fit criteria. MEQ = morningness-eveningness questionnaire.

3.5.6 Appendix G.2.b: Pre-Shift Mean RR

Overview

Model Outputs	Null Model	Predictor Model	Covariate Model
Regression Coefficients			
Level 1 (L1)			
Intercept (γ_{00})	1183 (56) ***	1142 (59) ***	1005 (41) ***
Sleep Score (γ_{10})		2.31 (0.88) **	2.31 (0.88) **
Level 2 (L2)			
Sex (γ_{01})			-548 (129) **
Age (γ_{02})			48.6 (11.9) **
PA (γ_{03})			0.55 (0.15) **
FFMQ (γ_{04})			8.03 (3.1) *
MEQ (γ_{05})			34.7 (7.7) **
Fit Criteria			
AIC	2047.8	1424.3	1421.1
BIC	2057.1	1435.5	1446.1
LogLikel	-1020.9	-708.2	-701.6
Pseudo R² Marginal	0.00	0.01	0.61
Pseudo R² Conditional	0.80	0.84	0.831
- 2LL	2041.8	1416.3	1403.1
Variance Components			
Intercept (L2) variance ($\sigma^2_{\mu 0}$)	42626	37708	22283
Within-participant (L1) variance (σ^2_{j})	9764	6364	6364
Slope (L2) variance ($\sigma^2_{\mu 1}$)	N/A	N/A	N/A

Intercept-slope (L2) covariance (σ^2_{IS})	N/A	N/A	N/A
ICC	0.814	0.856	0.778
Additional Information			
Number of estimated parameters	2	3	8

Note: # p < .10 *p < .05. **p < .01. ***p<.001. *N* = 119 and L2 sample size = 10. Coefficient values are unstandardized beta-weights. Values in parentheses are standard errors. T-statistics were computed as the ratio of each regression coefficient divided by its standard error. Variance components were estimated using REML, while regression coefficients and model fit criteria were estimated using ML. Standard deviation (SD) was calculated as the square root of shown variance. Sleep score was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire, PA = baseline physical activity

Step 2: Determine the Strongest L1 Predictor

	Model 1			Model 2			Model 3		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1147.44	56.92	< .001	1148.13	57.10	< .001	1148.13	57.10	< .001
Sleep Score (/100)	3.38	2.16	0.12	3.26	1.98	0.10	3.29	1.97	0.10
Wakeup time	-1366.04	2117.75	0.52	-1243.91	2035.02	0.54	-1238.37	2034.70	0.54
Sleep Continuity	15.89	22.75	0.49	15.42	19.18	0.42	15.60	19.14	0.42
REM Sleep %	-123.14	187.74	0.51	-134.27	193.98	0.49	-122.46	169.68	0.47
Overall Duration	-92.10	298.85	0.76	-139.62	264.71	0.60	-141.34	264.38	0.59
Actual Duration	135.92	310.35	0.66	183.15	268.15	0.50	184.59	267.93	0.49
% Asleep	-868.69	1961.56	0.66	-1001.86	1935.38	0.61	-996.49	1935.05	0.61
Bedtime	903.22	2055.32	0.66	788.33	1973.51	0.69	782.57	1973.13	0.69
Number of Cycles	4.64	10.66	0.67	3.51	10.54	0.74	3.35	10.45	0.75
Light Sleep %	-133.81	210.27	0.53	-17.75	141.36	0.90			
Long Interruptions	-0.26	3.27	0.94						
Deep Sleep %#	10.67	143.90	0.94						
Fit Criteria									
AIC	1374.1452			1405.29			1403.31		
BIC	1412.45			1441.20			1436.45		
LogLikel	-673.07			-689.65			-689.65		
R² Marginal	0.024			0.024			0.024		
R² Conditional	0.850			0.853			0.853		
- 2LL	1346.15			1379.29			1379.31		

	Model 4	Model 5	Model 6

Predictor	Estimate	SE	p	Estimate	SE	p	Estimate	SE	p
Intercept (γ00)	1148.13	57.10	< .001	1148.13	57.10	< .001	1148.14	57.10	< .001
Sleep Score (/100)	3.32	1.97	0.10	3.41	1.96	0.08	3.32	1.95	0.09
Wakeup time	-1294.10	2028.21	0.53	-442.63	235.31	0.06	-408.38	227.55	0.08
Sleep Continuity	15.29	19.12	0.43	15.10	19.13	0.43	12.84	18.73	0.50
REM Sleep %	-110.71	165.74	0.51	-120.33	164.31	0.47	-125.11	164.33	0.45
Overall Duration	-144.96	264.26	0.58	-186.06	245.92	0.45	-63.40	111.68	0.57
Actual Duration	192.48	266.92	0.47	198.50	266.76	0.46	66.32	124.18	0.59
% Asleep	-1058.08	1926.39	0.58	-1078.64	1927.39	0.58			
Bedtime	831.83	1968.06	0.67						
Fit Criteria									
AIC	1401.41			1399.59			1397.90		
BIC	1431.79			1427.21			1422.76		
LogLikel	-689.70			-689.79			-689.95		
R^2 Marginal	0.024			0.024			0.023		
R^2 Conditional	0.853			0.853			0.852		
- 2LL	1379.41			1379.59			1379.90		

	Model 7			Model 8			Model 9		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1148.14	57.10	< .001	1148.14	57.10	< .001	1142.00	59.09	< .001
Sleep Score (/100)	3.85	1.69	0.02	3.47	1.02	< .001	2.96	0.94	0.00
Wakeup time	-410.12	227.83	0.08	-433.39	212.46	0.04	-384.46	216.15	0.08
Sleep Continuity	18.06	16.00	0.26	20.52	13.41	0.13	14.14	13.55	0.30
REM Sleep %	-153.40	155.77	0.33	-136.08	143.22	0.34			
Overall Duration	-4.32	15.30	0.78						
Fit Criteria									
AIC	1396.18			1394.26			1421.96		
BIC	1418.28			1413.60			1438.64		
LogLikel	-690.09			-690.13			-704.98		
R^2 Marginal	0.023			0.023			0.017		
R^2 Conditional	0.852			0.852			0.853		
- 2LL	1380.18			1380.26			1409.96		

	Model 10			Model 11*			Model 12		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1142.01	59.09	< .001	1142.05	59.103	< .001			
Sleep Score (/100)	3.13	0.93	< .001	2.31	0.877	0.01			
Wakeup time	-469.09	201.37	0.02				-191	186.2	0.306
Sleep Continuity							20.6	12.9	0.114
REM Sleep %							89.7	137.3	0.515
Overall Duration							8.62	7.83	0.273
Actual Duration							11.8	8.46	0.166

% Asleep			1442	561.9	0.012
Bedtime			-432	194.6	0.028
Number of Cycles			7.44	8.52	0.385
Light Sleep %			-153	110.3	0.169
Long Interruptions			-2.55	1.54	0.101
Deep Sleep %[#]			138	134.4	0.306
Fit Criteria					
AIC	1421.04	1424.34			
BIC	1434.94	1435.46			
LogLikel	-705.52	-708.17			
R^2 Marginal	0.016	0.009			
R^2 Conditional	0.852	0.844			
- 2LL	1411.05	1416.34			

Note: * = Final model. Model 12 shows each removed predictor in isolation. Table estimates are unstandardized beta-weights. All predictors were rescaled via cluster-wise centering. ML method was used for all parameter estimates, including fit criteria. Satterthwaite method was used for estimating degrees of freedom. ML method was used for all parameter estimates, including fit criteria. # Deep sleep was removed during first iteration due to issues of perfect multicollinearity with other sleep stage metrics.

Step 3: Add in L2 Covariates

	Model 1			Model 2			Model 3*		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	990.78	86.22	< .001	985.01	43.62	< .001	1004.56	40.56	< .001
Sleep Score (/100)	2.31	0.88	0.01	2.31	0.88	0.010	2.31	0.88	0.010
Biological Sex	-556.84	232.35	0.04	-571.95	126.37	< .001	-547.67	128.79	0.002
Age	51.203	15.88	0.01	52.02	11.90	0.001	48.59	11.86	0.002
PA	0.655	0.19	0.01	0.66	0.18	0.004	0.55	0.15	0.004
FFMQ	7.8	3.02	0.03	7.84	2.97	0.024	8.03	3.08	0.026
MEQ	35.36	14.43	0.03	36.31	7.58	< .001	34.69	7.69	0.001
Meditation	-72.992	92.94	0.45	-77.09	76.79	0.336			
Experience	1.982	25.55	0.94						
Fit Criteria									
AIC	1424.14			1422.15			1421.13		
BIC	1454.71			1449.94			1446.14		
LogLikel	-701.07			-701.07			-701.56		
Pseudo R^2 Marginal	0.62			0.62			0.61		
Pseudo R^2 Conditional	0.83			0.83			0.83		
- 2LL	1402.14			1402.15			1403.13		

	Model 4			Model 5			Model 6		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1097.103	60.70	< .001	1032.596	50.66	< .001	1081.13	53.93	< .001
Sleep Score (/100)	2.311	0.88	0.01	2.311	0.88	0.01	2.31	0.88	0.01
Biological Sex	-52.841	115.65	0.66	-389.761	147.16	0.02	-348.45	180.30	0.082
Age	22.073	18.21	0.25	48.576	15.45	0.01	19.86	14.24	0.194

PA	0.257	0.23	0.30	0.555	0.19	0.02			
FFMQ	1.357	4.71	0.78				8.18	4.77	0.118
MEQ				24.955	8.74	0.02	22.05	10.70	0.067
Fit Criteria									
AIC	1430.20			1424.32			1427.80		
BIC	1452.43			1446.55			1450.03		
LogLikel	-707.10			-704.16			-705.90		
Pseudo R² Marginal	0.15			0.49			0.26		
Pseudo R² Conditional	0.84			0.84			0.83		
- 2LL	1414.19			1408.32			1411.80		

	Model 7			Model 8		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1096.062	54.60	< .001	1091.627	58.59	< .001
Sleep Score (/100)	2.311	0.88	0.01			
Biological Sex	-258.751	173.32	0.165	2.311	0.88	0.01
Age				19.711	16.63	0.264
PA	0.172	0.19	0.379	0.291	0.23	0.23
FFMQ	8.232	5.03	0.132	1.965	4.59	0.678
MEQ	19.79	11.02	0.102	6.643	6.72	0.346
Fit Criteria						
AIC	1428.75			1429.47		
BIC	1450.98			1451.70		
LogLikel	-706.38			-706.74		
Pseudo R² Marginal	0.19			0.28		
Pseudo R² Conditional	0.83			0.86		
- 2LL	1412.75			1413.47		

Note: * = Final model. Table estimates are unstandardized beta-weights. Sleep score was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. ML method was used for all parameter estimates, including fit criteria. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire, PA = baseline physical activity

Step 4: Assess the Need for Random Slopes

	Fixed Slope Model*			Independence Structure			Unstructured Structure		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1004.56	40.56	< .001	1004.56	40.555	< .001	1011.882	40.471	< .001
Sleep Score (/100)	2.31	0.88	0.010	2.31	0.877	0.01	1.946	0.975	0.067
Biological Sex	-547.67	128.79	0.002	-547.67	128.787	0.002	-533.922	127.651	0.002
Age	48.59	11.86	0.002	48.59	11.864	0.002	43.712	11.553	0.003
PA	0.55	0.15	0.004	0.55	0.148	0.004	0.513	0.142	0.005
FFMQ	8.03	3.08	0.026	8.03	3.077	0.026	8.631	2.986	0.015
MEQ	34.69	7.69	0.001	34.69	7.694	0.001	33.881	7.655	0.001

Random Variance Components			
Intercept (L2) variance ($\sigma^2_{\mu 0}$)	8232	8232	8448
Intercept (L2) variance (95% CL)	[3310, 24814]	[3310, 24813]	[3363, 26629]
ICC	0.0566	0.0566	0.576
Slope (L2) variance ($\sigma^2_{\mu 1}$)	N/A	0	1.06
Slope (L2) variance (95% CL)	N/A	[0, 11]	[0, 18.3]
LRT Statistic	N/A	4.6E-13	1.24
LRT P-Value	N/A	1	0.537
Intercept-slope (L2) covariance (σ^2_{IS})	N/A	0	1
Fit Criteria			
AIC	1421.13	1423.13	1423.88
BIC	1446.14	1450.92	1454.45
LogLikel	-701.56	-701.56	-700.94
Pseudo R² Marginal	0.61	0.61	0.577
Pseudo R² Conditional	0.831	0.831	0.821
- 2LL	1403.13	1403.13	1401.88

Note: * = Final model. Table estimates are unstandardized beta-weights. Sleep score was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. ML was used for all parameter estimates, including fit criteria. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire, PA = baseline physical activity.

3.5.7 Appendix G.2.c: Pre-Shift Mean RMSSD

Overview

Model Outputs	Null Model	Predictor Model	Covariate Model
Regression Coefficients			
Level 1 (L1)			
Intercept (γ_{00})	66.2 (5.75) ***	63.2 (4.81) ***	55.7 (2.29) ***
Bedtime (γ_{10})		-58 (31.56) #	-58.1 (31.66) #
Level 2 (L2)			
MEQ (γ_{01})			2.69 (0.45) ***

Sex (γ_{02})			-42.7 (7.45) ***
PA (γ_{03})			0.03 (0.007) *
FFMQ (γ_{04})			0.63 (0.19) *
Fit Criteria			
AIC	1439.0	1059.5	1041.6
BIC	1448.4	1070.9	1064.4
LogLikel	-716.5	-525.8	-512.8
Pseudo R^2 Marginal	0.00	0.01	0.337
Pseudo R^2 Conditional	0.61	0.56	0.398
- 2LL	1433.0	1051.5	1025.6
Variance Components			
Intercept (L2) variance ($\sigma^2_{\mu 0}$)	412	232	18.2
Within-participant (L1) variance (σ^2_j)	240	179	179.2
Additional Information			
ICC	0.632	0.564	0.092
Number of estimated parameters	2	3	7

Note: $^{\#}$ $p < .10$ *$p < .05$. **$p < .01$. ***$p<.001$. N = 126 and L2 sample size = 10. Coefficient values are unstandardized beta-weights. Values in parentheses are standard errors. T-statistics were computed as the ratio of each regression coefficient divided by its standard error. Regression coefficients, variance components, and R^2 were estimated using REML, while AIC, BIC, LogLikel, and -2LL model fit criteria were estimated using ML. Standard deviation (SD) was calculated as the square root of shown variance. Bedtime was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire, PA = baseline physical activity

Step 2: Determine the Strongest L1 Predictor

	Model 1			Model 2			Model 3		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept ($\gamma 00$)	63.91	4.29	< .001	63.91	4.29	< .001	63.91	4.29	< .001
Bedtime	166.03	365.42	0.65	166.00	365.39	0.65	166.87	362.91	0.65
Actual Sleep Duration (hrs)	34.02	55.18	0.54	34.03	55.17	0.54	34.35	52.78	0.52
Overall Sleep Duration (hrs)	-24.03	53.13	0.65	-24.06	53.00	0.65	-24.35	51.04	0.63
Long Interruptions (mins)	0.64	0.58	0.28	0.64	0.55	0.25	0.64	0.48	0.18
Light Sleep %	18.67	25.58	0.47	16.31	25.80	0.53	16.25	25.64	0.53

Wakeup time	-247.00	376.52	0.51	-246.97	376.48	0.51	-247.86	373.95	0.51
% Asleep	49.53	348.75	0.89	49.37	347.91	0.89	50.83	340.50	0.88
Number of Sleep Cycles	-0.18	1.90	0.93	-0.18	1.89	0.93	-0.18	1.89	0.92
Deep Sleep %	16.17	33.38	0.63	-2.38	32.04	0.94	-2.39	32.03	0.94
Sleep Continuity (/5)	0.09	4.05	0.98	0.08	3.94	0.98			
REM Sleep % [#]	2.50	37.38	0.95						
Sleep Score (/100)	0.00	0.38	1.00						
Fit Criteria									
AIC	981.77			979.77			977.77		
BIC	1020.32			1015.57			1010.81		
LogLikel	-476.88			-476.88			-476.89		
Pseudo R² Marginal	0.032			0.032			0.032		
Pseudo R² Conditional	0.509			0.509			0.509		
- 2LL	953.77			953.77			953.77		

	Model 4			Model 5			Model 6		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	63.91	4.29	< .001	63.91	4.29	< .001	63.91	4.29	< .001
Bedtime	165.63	362.54	0.65	163.88	361.83	0.65	162.91	361.83	0.65
Actual Sleep Duration (hrs)	33.86	52.37	0.52	33.56	52.23	0.52	41.05	25.67	0.11
Overall Sleep Duration (hrs)	-23.96	50.77	0.64	-23.84	50.75	0.64	-30.82	27.86	0.27
Long Interruptions (mins)	0.64	0.48	0.18	0.64	0.48	0.18	0.65	0.48	0.18
Light Sleep %	17.46	19.89	0.38	17.59	19.82	0.38	17.13	19.63	0.39
Wakeup time	-246.30	373.38	0.51	-244.36	372.54	0.51	-245.22	372.55	0.51
% Asleep	53.48	338.66	0.88	55.56	337.58	0.87			
Number of Sleep Cycles	-0.14	1.80	0.94						
Fit Criteria									
AIC	975.78			973.78			971.81		
BIC	1006.07			1001.32			996.59		

LogLikel	-476.89			-476.89			-476.90		
Pseudo R² Marginal	0.032			0.032			0.032		
Pseudo R² Conditional	0.509			0.509			0.509		
- 2LL	953.78			953.78			953.81		

	Model 7			Model 8			Model 9		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	63.91	4.29	< .001	63.17	4.60	< .001	63.18	4.59	< .001
Bedtime	-73.83	39.51	0.07	-72.54	35.48	0.04	-70.05	35.18	0.049
Actual Sleep Duration	-39.78	24.36	0.11	-34.52	22.59	0.13	-6.76	12.3	0.584
Overall Sleep Duration (hrs)	40.07	25.68	0.12	34.72	23.78	0.15	6.07	13.37	0.651
Long Interruptions (mins)	0.57	0.47	0.22	0.58	0.45	0.19			
Light Sleep %	17.88	19.63	0.37						
Fit Criteria									
AIC	970.24			1023.82			1062.57		
BIC	992.27			1043.50			1079.68		
LogLikel	-477.12			-504.91			-525.29		
Pseudo R² Marginal	0.030			0.025			0.016		
Pseudo R² Conditional	0.507			0.555			0.548		
- 2LL	954.24			1009.82			1050.57		

	Model 10			Model 11*			Model 12		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	63.18	4.59	< .001	63.2	4.59	< .001			
Bedtime	-71.53	35.06	0.044	-58	31.56	0.068			
Actual Sleep Duration (hrs)	-1.21	1.39	0.386				0.133	1.38	0.923
Overall Sleep Duration (hrs)							0.0419	1.27	0.974
Long Interruptions (mins)							0.0253	0.251	0.92

Light Sleep %	8.68	18.82	0.646
Wakeup time	-50.2	29.77	0.094
% Asleep	62.2	92.9	0.504
Number of Sleep Cycles	-0.229	1.37	0.868
Deep Sleep %	1.28	22.86	0.955
Sleep Continuity (/5)	1.51	2.1	0.473
REM Sleep % #	-14.6	23.25	0.532
Sleep Score (/100)	-0.0272	0.152	0.858

Note: * = Final model. Model 12 shows each removed predictor in isolation. Table estimates are unstandardized beta-weights. All predictors were rescaled via cluster-wise centering. ML method was used for all parameter estimates, including fit criteria. Satterthwaite method was used for estimating degrees of freedom. ML method was used for all parameter estimates, including fit criteria. # REM sleep was removed during first iteration due to issues of perfect multicollinearity with other sleep stage metrics.

Step 3: Add in L2 Covariates

	Model 1			Model 2			Model 3		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	51.74	6.21	0.01	52.99	3.94	0.05	54.23	3.04	0.002
Bedtime	-58.05	31.67	0.07	-58.05	31.71	0.07	-58.05	31.66	0.07
MEQ	3.45	1.05	0.05	3.30	0.79	0.06	3.07	0.65	0.01
Biological Sex	-55.10	16.98	0.04	-52.64	13.06	0.06	-48.12	10.02	0.01
PA	0.03	0.01	0.08	0.03	0.01	0.08	0.03	0.01	0.03
FFMQ	0.59	0.23	0.10	0.62	0.20	0.07	0.64	0.19	0.02
Experience	-1.92	2.09	0.44	-1.54	1.57	0.44	-1.14	1.36	0.45
Age	0.58	1.12	0.65	0.50	0.87	0.64			
Meditation	-3.67	7.42	0.65						
Fit Criteria									
AIC	1044.14			1042.28			1042.19		
BIC	1075.51			1070.80			1067.86		
LogLikel	-511.07			-511.14			-512.10		
Pseudo R² Marginal	0.40			0.40			0.39		
Pseudo R² Conditional	0.40			0.40			0.39		
- 2LL	1022.14			1022.28			1024.19		

	Model 4*			Model 5			Model 6		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**

Predictor	Estimate	SE	p	Estimate	SE	p	Estimate	SE	p
Intercept (γ00)	55.72	2.29	< .001	58.54	3.49	< .001	59.54	3.77	< .001
Bedtime	-58.05	31.66	0.07	-58.05	31.50	0.07	-58.05	31.59	0.07
MEQ	2.69	0.45	< .001	2.01	0.62	0.01	2.36	0.76	0.02
Biological Sex	-42.68	7.45	0.00	-30.76	9.74	0.01	-41.97	12.62	0.01
PA	0.03	0.01	0.01	0.03	0.01	0.02			
FFMQ	0.63	0.19	0.01				0.65	0.30	0.06
Fit Criteria									
AIC	1041.61			1051.52			1054.39		
BIC	1064.43			1071.49			1074.36		
LogLikel	-512.81			-518.76			-520.20		
Pseudo R² Marginal	0.38			0.28			0.27		
Pseudo R² Conditional	0.38			0.44			0.47		
- 2LL	1025.61			1037.52			1040.39		

	Model 7			Model 8		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	60.84	5.05	< .001	60.63	5.10	< .001
Bedtime	-58.05	31.62	0.07	-58.05	31.60	0.07
MEQ	0.53	0.64	0.43			
Biological Sex				-9.13	10.51	0.41
PA	0.03	0.02	0.13	0.02	0.02	0.21
FFMQ	-0.03	0.35	0.94	0.07	0.37	0.85
Fit Criteria						
AIC	1061.50			1061.53		
BIC	1081.47			1081.49		
LogLikel	-523.75			-523.77		
Pseudo R² Marginal	0.17			0.13		
Pseudo R² Conditional	0.54			0.53		
- 2LL	1047.50			1047.53		

Note: Table estimates are unstandardized beta-weights. Bedtime was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. REML was used for parameter estimates due to model crashing under ML estimation. ML used for used for likelihood-based fit criteria in all cases. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire, PA = baseline physical activity

Step 4: Assess the Need for Random Slopes

	Fixed Slope Model*			Unstructured Structure			Independence Structure		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	55.725	2.288	< .001	55.745	2.410	< .001	55.741	2.290	< .001
Bedtime	-58.050	31.663	0.069	-34.250	38.369	0.423	-59.988	36.756	0.238
MEQ	2.689	0.453	< .001	2.606	0.467	< .001	2.689	0.453	< .001

Sex	-42.683	7.453	0.001	-40.998	7.658	0.001	-42.681	7.454	0.001
PA	0.030	0.007	0.012	0.034	0.007	0.005	0.030	0.007	0.012
FFMQ	0.625	0.187	0.014	0.534	0.190	0.024	0.624	0.187	0.014
Random Variance Components									
Intercept (L2) variance ($\sigma^2_{\mu0}$)			18.2			24.2			18.4
Intercept (L2) variance (95% CL)			[0, 28.8]			[0, 29]			[0, 28.5]
ICC			0.0921			0.121			0.0936
Slope (L2) variance ($\sigma^2_{\mu1}$)			N/A			2385.9			1141.8
Slope (L2) variance (95% CL)			N/A			[0, 24851]			[0, 19585]
LRT Statistic						0.357			0.0789
LRT P-Value						0.836			0.779
Intercept-slope (L2) covariance (σ^2_{IS})						1			0
Fit Criteria									
AIC			1041.6			1045.6			1043.6
BIC			1060.2			1069.6			1065
LogLikel			-510.71			-510.5			-510.7
Pseudo R² Marginal			0.337			0.331			0.336
Pseudo R² Conditional			0.398			0.421			0.403
- 2LL			1021.4			1021.1			1021.3

Note: *= Final Model Table estimates are unstandardized beta-weights. Bedtime was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. REML was used for all parameter estimates. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire, PA = baseline physical activity

3.5.8 Appendix G.3.a: Post Shift Subjective Fatigue

Overview

Model Outputs	Null Model	Predictor Model	-	Covariate Model
Regression Coefficients				
Level 1 (L1)				
Intercept (γ_{00})	1.76 (0.06) ***	1.77 (0.06) ***		1.77 (0.05) ***

Shift Duration (γ_{10})		0.04 (.01) ***	0.04 (.01) ***
Level 2 (L2)			
Meditation (γ_{01})			-0.22 (0.1) *
PA (γ_{02})			-0.0004 (0.0002) $^{\#}$
MEQ (γ_{03})			0.01 (0.01)
Fit Criteria			
AIC	279.0	232.1	230.76
BIC	290.5	247.3	257.25
LogLikel	-136.5	-112.1	-108.38
Pseudo R² Marginal	0.00	0.06	0.17
Pseudo R² Conditional	0.36	0.44	0.44
- 2LL	273.0	224.1	216.76
Variance Components			
Intercept (L2) variance ($\sigma^2_{\mu 0}$)	0.069	0.072	0.060
Within-participant (L1) variance (σ^2_{j})	0.115	0.102	0.102
Slope (L2) variance ($\sigma^2_{\mu 1}$)	N/A	N/A	N/A
Intercept-slope (L2) covariance (σ^2_{IS})	N/A	N/A	N/A
ICC	0.376	0.414	0.360
Additional Information			
Number of estimated parameters	2	3	6

Regression Coefficients	Random Slope Model	Interaction Model
Level 1 (L1)		
Intercept (γ_{00})	1.75 (0.05) ***	1.75 (0.05) ***
Shift Duration (γ_{10})	0.04 (.01) ***	0.02 (.01) $^{\#}$
Level 2 (L2)		
Meditation (γ_{01})	-0.21 (0.1) *	-0.21 (0.1) *
PA (γ_{02})	-0.0004 (0.0002) $^{\#}$	-0.0003 (0.0002) $^{\#}$
MEQ (γ_{03})	0.01 (0.01)	0.01 (0.01)
Cross-Level Interactions		
Shift Duration: Meditation (γ_{11})		-0.06 (0.02) *
Shift Duration: PA (γ_{12})		-8.9e−5 (3.8e-05) *
Shift Duration: MEQ (γ_{13})		0.002 (0.001) $^{\#}$
Fit Criteria		
AIC		
BIC	230.8	227.8
LogLikel	257.2	269.4
Pseudo R² Marginal	-108.4	-102.9
Pseudo R² Conditional	0.173	0.19
- 2LL	0.435	0.46
Variance Components	216.76	205.8
Intercept (L2) variance ($\sigma^2_{\mu 0}$)		

Within-participant (L1) variance (σ^2_j)	0.0577	0.0575
Slope (L2) variance ($\sigma^2_{\mu 1}$)	0.0984	0.0979
Intercept-slope (L2) covariance (σ^2_{IS})	5.79E-04	3.64E-04
ICC	0.00	0.00
Additional Information	0.370	0.370
Number of estimated parameters	7	10

Note: [#] p < .10 *p < .05. **p < .01. ***p<.001. *N* = 325 and L2 sample size = 23. Coefficient values are unstandardized beta-weights. Values in parentheses are standard errors. T-statistics were computed as the ratio of each regression coefficient divided by its standard error. Variance components were estimated using REML, while regression coefficients and model fit criteria were estimated using ML. Standard deviation (SD) was calculated as the square root of shown variance. Shift duration was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. PA = baseline physical activity

Step 2: Determine the Strongest L1 Predictor

	Model 1				Model 2			
Predictor	**Estimate**	**SE**	**t**	**p**	**Estimate**	**SE**	**t**	**p**
Intercept (γ00)	1.77	0.060	29.401	< .001	1.77	0.06	29.42	< .001
Start Time	-1.91	7.070	-0.271	0.79	-1.73	0.45	-3.82	< .001
End Time	1.00	7.024	0.143	0.89	0.83	0.21	3.86	< .001
Time Between Shifts	-2.25e−4	0.001	-0.028	0.87	-1.96e−4	0.00	-0.14	0.89
Shift Duration	-0.01	0.290	-0.158	0.98				
Fit Criteria								
AIC	230.13				227.86			
BIC	256.38				250.38			
LogLikel	-108.07				-107.93			
Pseudo R² Marginal	0.062				0.066			
Pseudo R² Conditional	0.446				0.448			
- 2LL	216.13				215.86			

	Model 3				Model 4			
Predictor	**Estimate**	**SE**	**t**	**p**	**Estimate**	**SE**	**t**	**p**
Intercept (γ00)	1.77	0.06	29.72	< .001	0.0598	1.66	29.66	< .001
Start Time	-1.76	0.42	-4.20	< .001	0.4235	- 2.87	-4.82	< .001
End Time	0.82	0.21	3.91	< .001				
Fit Criteria								
AIC	230.27				243.19			
BIC	249.20				258.34			
LogLikel	-110.13				-117.60			
Pseudo R² Marginal	0.068				0.042			

	Estimate	SE	t	p	Estimate	SE	t	p
Pseudo R² Conditional	0.446				0.419			
- 2LL	220.27				235.19			

	Model 5				Model 6			
Predictor	**Estimate**	**SE**	**t**	**p**	**Estimate**	**SE**	**t**	**p**
Intercept (γ00)	1.77	0.06	29.65	< .001	1.77	0.06	29.28	< .001
Start Time								
End Time	0.967	0.21	4.56	< .001				
Time Between Shifts					-0.002	0.00	-1.52	0.13
Shift Duration								
Fit Criteria								
AIC	245.41				256.66			
BIC	260.56				271.67			
LogLikel	-118.71				-124.33			
Pseudo R² Marginal	0.038				0.005			
Pseudo R² Conditional	0.414				0.383			
- 2LL	237.41				248.66			

	Model 7*			
Predictor	**Estimate**	**SE**	**t**	**p**
Intercept (γ00)	1.77	0.06	29.69	< .001
Start Time				
End Time				
Time Between Shifts				
Shift Duration	0.04	0.01	5.77	< .001
Fit Criteria				
AIC	232.13			
BIC	247.26			
LogLikel	-112.06			
Pseudo R² Marginal	0.058			
Pseudo R² Conditional	0.437			
- 2LL	224.13			

Note: * = Final model. Models 4-7 show each removed predictor in isolation. Table estimates are unstandardized beta-weights. All predictors were rescaled via cluster-wise centering. ML method was used for all parameter estimates, including fit criteria. Satterthwaite method was used for estimating degrees of freedom. ML method was used for all parameter estimates, including fit criteria.

Step 3: Add in L2 Covariates

	Model 1	Model 2	Model 3

Predictor	Estimate	SE	p	Estimate	SE	p	Estimate	SE	p
Intercept (γ00)	1.72	0.06	< .001	1.72	0.06	< .001	1.74	0.05	< .001
Shift Duration	0.04	0.01	< .001	0.04	0.01	< .001	0.04	0.01	< .001
Meditation	-0.23	0.10	0.03	-0.23	0.10	0.04	-0.22	0.10	0.04
PA	-6.14e−4	2.50E-04	0.02	-5.67e−4	2.29E-04	0.02	-5.27e−4	2.19E-04	0.02
MEQ	0.01	0.01	0.13	0.01	0.01	0.15	0.01	0.01	0.18
Experience	-0.03	0.02	0.17	-0.03	0.02	0.16	-0.02	0.02	0.17
Age	0.02	0.02	0.49	0.02	0.02	0.50	0.01	0.02	0.64
Biological Sex	-0.08	0.13	0.51	-0.07	0.12	0.56			
FFMQ	0.002	0.00	0.65						
Fit Criteria									
AIC	236.11			234.33			232.68		
BIC	277.74			272.17			266.74		
LogLikel	-107.06			-107.17			-107.34		
Pseudo R² Marginal	0.18			0.18			0.18		
Pseudo R² Conditional	0.42			0.42			0.42		
- 2LL	214.11			214.33			214.68		

	Model 4			Model 5*			Model 6		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1.74	0.05	< .001	1.75	0.05	< .001	1.77	0.05	< .001
Shift Duration	0.04	0.01	< .001	0.04	0.01	< .001	0.04	0.01	< .001
Meditation	-0.21	0.10	0.05	-0.21	0.10	0.05	-0.22	0.11	0.05
PA	-4.96e−4	0.00	0.03	-3.50e−4	1.85E-04	0.07	-2.81e−4	1.84E-04	0.13
MEQ	0.01	0.01	0.15	0.01	0.01	0.16			
Experience	-0.02	0.01	0.18						
Fit Criteria									
AIC	230.908			230.76			230.789		
BIC	261.178			257.25			253.492		
LogLikel	-107.454			-108.38			-109.395		
Pseudo R² Marginal	0.18			0.17			0.144		
Pseudo R² Conditional	0.426			0.44			0.432		
- 2LL	214.91			216.76			218.79		

	Model 7			Model 8		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1.75	0.06	< .001	1.76	0.06	< .001
Shift Duration	0.04	0.01	< .001	0.04	0.01	< .001

Meditation						
PA	-0.20	0.11	0.08	-3.28e−4	1.98E-04	0.10
MEQ	0.01	0.01	0.36	0.01	0.01	0.15
Fit Criteria						
AIC	232.168			232.52		
BIC	254.871			255.22		
LogLikel	-110.084			-110.26		
Pseudo R² Marginal	0.124			0.12		
Pseudo R² Conditional	0.428			0.44		
- 2LL	220.17			220.52		

Note: * = Final model. Table estimates are unstandardized beta-weights. Shift duration was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. ML was used for all parameter estimates, including fit criteria. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire, PA = baseline physical activity.

Step 4: Assess the Need for Random Slopes

	Fixed Slope Model			Independence Structure*			Unstructured Structure		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept ($\gamma 00$)	1.75	0.06	< .001	1.74	0.06	< .001	1.74	0.06	< .001
Shift Duration	0.04	0.01	< .001	0.03	0.01	0.02	0.03	0.01	0.03
Meditation	-0.21	0.11	0.08	-0.20	0.11	0.08	-0.17	0.11	0.14
PA	-3.49e−4	1.97E-04	0.09	-2.94e−4	1.98E-04	0.15	-2.58e−4	1.96E-04	0.20
MEQ	0.01	0.01	0.19	0.01	0.01	0.15	0.01	0.01	0.17
Random Variance Components									
Intercept (L2) variance ($\sigma^2_{\mu 0}$)			0.06			0.06			0.06
Intercept (L2) variance (95% CL)			[0.02, 0.1]			[0.02, 0.1]			[0.02, 0.1]
ICC			0.360			0.37			0.370
Slope (L2) variance ($\sigma^2_{\mu 1}$)			N/A			6E-04			0.0007
Slope (L2) variance (95% CL)			N/A			[0, 0.003]			[0, 0.004]
LRT Statistic			N/A			4.14			4.61
LRT P-Value			N/A			0.42			0.100
Intercept-slope (L2) covariance (σ^2_{IS})			N/A			0			0.45
Fit Criteria									
AIC			230.76			229.5			230.90
BIC			295.4			297.0			302.3
LogLikel			-127.4			-125.4			-125.1
Pseudo R² Marginal			0.16			0.139			0.12
Pseudo R² Conditional			0.46			0.47			0.46
- 2LL			254.90			250.76			250.28

Note: * = Final model. Table estimates are unstandardized beta-weights. Shift duration was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. REML was used for all parameter estimates. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire, PA = baseline physical activity

Step 5: Probe for Cross Level Interactions

	Model 1*			Model 2		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1.75	0.05	< .001	1.75	0.05	< .001
Shift Duration	0.02	0.01	0.06	0.02	0.01	0.14
Meditation	-0.21	0.10	0.05	-0.21	0.10	0.05
PA	-3.41e−4	1.85E-04	0.07	-3.37e−4	1.86E-04	0.08
MEQ	0.01	0.01	0.15	0.01	0.01	0.15
Shift Duration: Meditation	-0.06	0.02	0.02	-0.05	0.03	0.05
Shift Duration: PA	-8.91e−5	3.87E-05	0.02	-7.24e−5	4.17E-05	0.09
Shift Duration; MEQ	0.002	0.001	0.094			
Fit Criteria						
AIC	227.8			227.3		
BIC	269.4			265.2		
LogLikel	-102.9			-103.7		
Pseudo R² Marginal	0.19			0.19		
Pseudo R² Conditional	0.46			0.46		
- 2LL	205.8			207.3		
	Model 3			Model 4		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1.74	0.05	< .001	1.74	0.05	< .001
Shift Duration	0.02	0.01	0.11	0.04	0.01	0.01
Meditation	-0.21	0.10	0.06	-0.21	0.10	0.06
PA	-3.01e−4	1.86E-04	0.11	-3.33e−4	1.86E-04	0.08
MEQ	0.01	0.01	0.13	0.01	0.01	0.15
Shift Duration: Meditation	-0.05	0.03	0.07			
Shift Duration: PA				-6.95e−5	4.38E-05	0.13
Shift Duration; MEQ	0.0004	0.001	0.709	0.001	0.001	0.590
Fit Criteria						
AIC	230.17			231.114		
BIC	268.01			268.952		
LogLikel	-105.09			-105.557		
Pseudo R² Marginal	0.17			0.165		
Pseudo R² Conditional	0.45			0.443		
- 2LL	210.2			211.1		

Note: * = Final model. Table estimates are unstandardized beta-weights. Shift duration was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. ML was used for all parameter estimates, including fit criteria. PA = baseline physical activity

3.5.9 Appendix G.3.b: Post Shift PVT Lapses

Overview

Model Outputs	Null Model	Predictor Model

Regression Coefficients		
Level 1 (L1)		
Intercept (γ_{00})	2.02 (0.22) ***	1.99 (0.24) ***
Shift duration (γ_{10})		0.07 (0.02) ***
Fit Criteria		
AIC	472.7	391.6
BIC	482.7	404.2
LogLikel	-233.3	-191.8
Pseudo R^2 Marginal	0.00	0.03
Pseudo R^2 Conditional	0.51	0.56
- 2LL	466.7	383.6
Variance Components		
Intercept (L2) variance ($\sigma^2_{\mu 0}$)	0.508	0.533
Within-participant (L1) variance (σ^2_j)	0.481	0.451
Slope (L2) variance ($\sigma^2_{\mu 1}$)	N/A	N/A
Intercept-slope (L2) covariance (σ^2_{IS})	N/A	N/A
ICC	0.514	0.542
Additional Information		
Number of estimated parameters	2	3

	Covariate Model	Random Slope Model
Regression Coefficients		
Level 1 (L1)		
Intercept (γ_{00})	1.84 (0.12) ***	1.84 (0.13) ***
Shift duration (γ_{10})	0.07 (0.02) ***	0.054 (0.04)
Level 2 (L2)		
Age (γ_{01})	-0.13 (0.04) *	-0.13 (0.04) *
MEQ (γ_{02})	0.07 (0.01) *	0.07 (0.01) *
FFMQ (γ_{03})	0.01 (0.01)	0.01 (0.01)
Fit Criteria		
AIC	378.9	375.9
BIC	401.1	401.2
LogLikel	-182.5	-179.9
Pseudo R^2 Marginal	0.471	0.466
Pseudo R^2 Conditional	0.566	0.595
- 2LL	364.9	359.9
Variance Components		
Intercept (L2) variance ($\sigma^2_{\mu 0}$)	0.099	0.10534
Within-participant (L1) variance (σ^2_j)	0.453	0.423
Slope (L2) variance ($\sigma^2_{\mu 1}$)	N/A	0.004
Intercept-slope (L2) covariance (σ^2_{IS})	N/A	0
ICC	0.179	0.199
Additional Information		
Number of estimated parameters	6	7

Note: *p < .05. **p < .01. ***p<.001. *N* = 175 and L2 sample size = 10. Coefficient values are unstandardized beta-weights. Values in parentheses are standard errors. T-statistics were computed as the ratio of each regression coefficient divided by its standard error. Regression coefficients, variance components, and R^2 were estimated using REML. AIC, BIC, LogLikel, and -2LL model fit criteria were estimated using ML. Standard deviation (SD) was calculated as the square root of shown variance. Shift duration was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire.

Step 2: Determine the Strongest L1 Predictor

	Model 1			Model 2			Model 3		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	2.01	0.22	< .001	2.01	0.22	< .001	1.99	0.23	< .001
Shift Duration	0.26	0.96	0.79	0.14	0.09	0.11	0.11	0.08	0.18
End Time	-5.11	23.13	0.83	-2.38	2.62	0.37	-1.35	2.41	0.58
Time Between Shifts	0.001	0.004	0.80	0.001	0.004	0.80			
Start Time	2.81	23.63	0.91						
Fit Criteria									
AIC	380.53			378.55			393.24		
BIC	402.44			397.33			409.07		
LogLikel	-183.27			-183.27			-191.62		
Pseudo R² Marginal	0.035			0.034			0.032		
Pseudo R² Conditional	0.517			0.517			0.530		
- 2LL	366.53			366.55			383.24		

	Model 4*			Model 5		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1.99	0.23	< .001			
Shift Duration	0.07	0.02	< .001			
End Time				1.84	0.59	0.00
Time Between Shifts				0.004	-0.01	0.43
Start Time				-4.75	1.62	0.00
Fit Criteria						
AIC	391.55					
BIC	404.21					
LogLikel	-191.78					
Pseudo R² Marginal	0.031					
Pseudo R² Conditional	0.529					
- 2LL	383.55					

Note: * = Final model. Model 5 shows each removed predictor in isolation. ML method was used for all parameter estimates, including fit criteria. Table estimates are unstandardized beta-weights. All predictors were rescaled via cluster-wise centering. Satterthwaite method was used for estimating degrees of freedom.

Step 3: Add in L2 Covariates

Predictor	Model 1 Estimate	Model 1 SE	Model 1 p	Model 2 Estimate	Model 2 SE	Model 2 p	Model 3 Estimate	Model 3 SE	Model 3 p
Intercept (γ00)	1.951	0.348	0.040	1.940	0.240	0.009	1.909	0.193	0.004
Shift Duration	0.065	0.019	< .001	0.065	0.019	< .001	0.065	0.019	< .001
Age	-0.129	0.084	0.284	-0.130	0.062	0.150	-0.136	0.050	0.078
MEQ	0.058	0.035	0.249	0.060	0.023	0.094	0.064	0.019	0.046
FFMQ	0.032	0.035	0.469	0.030	0.026	0.343	0.024	0.019	0.294
Experience	0.166	0.260	0.590	0.150	0.190	0.489	0.089	0.117	0.503
Meditation	0.519	0.968	0.652	0.480	0.726	0.565	0.292	0.492	0.598
PA	0.001	0.002	0.767	0.000	0.001	0.693			
Biological Sex	0.047	0.623	0.948						
Fit Criteria									
AIC	384.16			382.28			380.28		
BIC	418.98			413.93			408.76		
LogLikel	-181.08			-181.14			-181.14		
Pseudo R² Marginal	0.40			0.45			0.47		
Pseudo R² Conditional	0.69			0.64			0.61		
- 2LL	362.16			362.28			362.28		

Predictor	Model 4 Estimate	Model 4 SE	Model 4 p	Model 5 Estimate	Model 5 SE	Model 5 p	Model 6* Estimate	Model 6* SE	Model 6* p
Intercept (γ00)	1.850	0.147	< .001	1.836	0.147	< .001	1.839	0.124	< .001
Shift Duration	0.065	0.019	< .001	0.065	0.019	< .001	0.065	0.019	< .001
Age	-0.131	0.046	0.052	-0.136	0.046	0.055	-0.131	0.039	0.033
MEQ	0.064	0.017	0.025	0.066	0.017	0.026	0.066	0.014	0.012
FFMQ	0.016	0.011	0.243	0.013	0.010	0.276	0.013	0.008	0.184
Experience	0.037	0.076	0.654						
Meditation				0.038	0.317	0.912			
Fit Criteria									
AIC	380.92			379.71			378.92		
BIC	406.23			405.03			401.07		
LogLikel	-182.46			-181.85			-182.46		
Pseudo R² Marginal	0.46			0.46			0.47		
Pseudo R² Conditional	0.59			0.59			0.57		
- 2LL	364.91			363.71			364.92		

Predictor	Model 7 Estimate	Model 7 SE	Model 7 p	Model 8 Estimate	Model 8 SE	Model 8 p	Model 9 Estimate	Model 9 SE	Model 9 p
Intercept (γ00)	1.832	0.147	< .001	1.820	0.211	< .001	2.015	0.240	< .001
Shift Duration	0.065	0.019	< .001	0.065	0.019	< .001	0.065	0.019	< .001
Age	-0.148	0.045	0.016				-0.120	0.079	0.173
MEQ	0.057	0.016	0.012	0.059	0.024	0.054			
FFMQ				0.018	0.013	0.217	-0.002	0.015	0.878
Fit Criteria									

AIC	381.91	389.21	392.60
BIC	400.90	408.20	411.58
LogLikel	-184.96	-188.60	-190.30
Pseudo R² Marginal	0.48	0.22	0.15
Pseudo R² Conditional	0.61	0.55	0.61
- 2LL	369.91	377.21	380.60

Note: * = Final model. Table estimates are unstandardized beta-weights. Shift duration was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. REML was used for parameter estimates due to model crashing under ML estimation. ML used for used for log likelihood-based fit criteria in all cases. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire, PA = baseline physical activity

Step 4: Assess the Need for Random Slopes

	Fixed Slope Model			Independence Structure*			Unstructured Structure		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1.839	0.124	< .001	1.836	0.126	< .001	1.836	0.126	< .001
Shift Duration	0.065	0.019	< .001	0.054	0.036	0.170	0.056	0.035	0.158
Age	-0.131	0.039	0.033	-0.133	0.040	0.031	-0.138	0.040	0.027
MEQ	0.066	0.014	0.012	0.066	0.015	0.012	0.066	0.015	0.011
FFMQ	0.013	0.008	0.184	0.013	0.008	0.190	0.012	0.008	0.207
Random Variance Components									
Intercept (L2) variance ($\sigma^2_{\mu 0}$)			0.10			0.1053			0.11
Intercept (L2) variance (95% CL)			[0, 0.15]			[0, 0.169]			[0.007, 0.008]
ICC			0.18			0.199			0.201
Slope (L2) variance ($\sigma^2_{\mu 1}$)			N/A			0.0044			0.004
Slope (L2) variance (95% CL)			N/A			[0.0002, 0.02]			[0.0002, 0.018]
LRT Statistic			N/A			4.63			6.81
LRT P-Value			N/A			0.031			0.033
Intercept-slope (L2) covariance (σ^2_{IS})			N/A			0			-0.22
Fit Criteria									
AIC			378.92			375.77			377.46
BIC			431.38			429.83			434.90
LogLikel			-197.61			-194.3			-194.21
Pseudo R² Marginal			0.47			0.466			0.48
Pseudo R² Conditional			0.57			0.595			0.61
- 2LL			395.23			388.51			388.41

Note: * = Final model. Table estimates are unstandardized beta-weights. Shift duration was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. REML was used for all parameter estimates, including fit criteria. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire, PA = baseline physical activity

Step 5: Probe for Cross Level Interactions

	Model 1			Model 2		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1.836	0.126	< .001	1.84	0.13	< .001
Shift Duration	0.050	0.041	0.33	0.05	0.04	0.232
Age	-0.133	0.040	0.03	-0.13	0.04	0.031
MEQ	0.066	0.015	0.012	0.07	0.01	0.012
FFMQ	0.013	0.008	0.189	0.01	0.01	0.19
Shift Duration: Age	-0.007	0.014	0.652	-0.01	0.01	0.526
Shift Duration: FFMQ	-8.98e−4	0.00	0.759	-8.86e−4	0.00	0.719
Shift Duration: MEQ	0.00	0.00	0.989			
Fit Criteria						
AIC	379.04			377.4		
BIC	413.86			409.0		
LogLikel	-178.52			-178.7		
Pseudo R² Marginal	0.456			0.465		
Pseudo R² Conditional	0.60			0.59		
- 2LL	357.0			357.4		

	Model 3			Model 4*		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1.84	0.13	< .001	1.836	0.126	< .001
Shift Duration	0.05	0.03	0.184	0.054	0.036	0.17
Age	-0.13	0.04	0.031	-0.133	0.040	0.031
MEQ	0.07	0.01	0.012	0.066	0.015	0.012
FFMQ	0.01	0.01	0.19	0.013	0.008	0.19
Shift Duration: Age	-0.01	0.01	0.392			
Fit Criteria						
AIC	375.6			375.9		
BIC	404.0			401.2		
LogLikel	-178.8			-179.9		
Pseudo R² Marginal	0.471			0.466		
Pseudo R² Conditional	0.59			0.60		
- 2LL	357.6			359.9		

Note: *= Final model. Table estimates are unstandardized beta-weights. Shift duration was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. REML was used for parameter estimates due to model crashing under ML estimation. ML used for used for log likelihood-based fit criteria in all cases. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire

3.5.10 Appendix G.3.c: Post Shift PVT Response Time

Overview

Model Outputs	Null Model	Predictor Model	Covariate Model
Regression Coefficients			
Level 1 (L1)			
Intercept (γ_{00})	312 (6.9) ***	313 (7.8) ***	308 (3.2) ***
Shift Duration (γ_{10})		1.83 (0.60) **	1.83 (0.60) **
Level 2 (L2)			
Age (γ_{01})			-3.91 (1.01) **
FFMQ (γ_{02})			0.55 (0.20) *
MEQ (γ_{03})			2.38 (0.37) ***
Fit Criteria			
AIC	1891.7	1594.4	1582.8
BIC	1901.7	1607.0	1605.0
LogLikel	-942.8	-793.2	-784.4
Pseudo R^2 Marginal	0.00	0.02	0.521
Pseudo R^2 Conditional	0.53	0.58	0.577
- 2LL	1885.7	1586.4	1568.8
Variance Components			
Intercept (L2) variance ($\sigma^2_{\mu 0}$)	566	567	57.2
Within-participant (L1) variance (σ^2_{j})	452	428	431
Slope (L2) variance ($\sigma^2_{\mu 1}$)	N/A	N/A	N/A
Intercept-slope (L2) covariance (σ^2_{IS})	N/A	N/A	N/A
ICC	0.549	0.57	0.117
Additional Information			
Number of estimated parameters	2	3	6

Note: $^{\#}$ p < .10 *p < .05. **p < .01. ***p<.001. *N* = 175 and L2 sample size = 10. Coefficient values are unstandardized beta-weights. Values in parentheses are standard errors. T-statistics were computed as the ratio of each regression coefficient divided by its standard error. Variance components were estimated using REML, while regression coefficients and model fit criteria were estimated using ML. Standard deviation (SD) was calculated as the square root of shown variance. Shift duration was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire.

Step 2: Determine the Strongest L1 Predictor

	Model 1			Model 2			Model 3		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	313.46	7.49	< .001	313.46	7.49	< .001	313.46	7.49	< .001
Shift Duration	11.56	29.91	0.70	3.30	2.76	0.24	1.64	0.63	0.01
Time Between Shifts	-0.09	0.13	0.48	-0.09	0.13	0.48	-0.11	0.13	0.39

Predictor	Estimate	SE	p	Estimate	SE	p	Estimate	SE	p
End Time	-250.08	723.07	0.73	-50.62	82.06	0.54			
Start Time	205.08	738.63	0.78						
Fit Criteria									
AIC	1545.82			1543.90			1542.28		
BIC	1567.73			1562.68			1557.93		
LogLikel	-765.91			-765.95			-766.14		
Pseudo R² Marginal	0.026			0.025			0.024		
Pseudo R² Conditional	0.560			0.559			0.558		
- 2LL	1531.82			1531.90			1532.28		

	Model 4*			Model 5		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	313.09	7.79	< .001			
Shift Duration	1.83	0.60	0.00			
Time Between Shifts				-0.20	0.13	0.12
End Time				50.60	18.09	0.01
Start Time				-138.00	49.98	0.01
Fit Criteria						
AIC	1594.37					
BIC	1607.03					
LogLikel	-793.19					
Pseudo R² Marginal	0.023					
Pseudo R² Conditional	0.580					
- 2LL	1586.37					

Note: * = Final model. Model 5 shows each removed predictor in isolation. ML method was used for all parameter estimates, including fit criteria. Table estimates are unstandardized beta-weights. All predictors were rescaled via cluster-wise centering. Satterthwaite method was used for estimating degrees of freedom.

Step 3: Add in L2 Covariates

	Model 1			Model 2			Model 3		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	307.244	3.650	< .001	307.369	3.064	< .001	308.276	2.785	< .001
Shift Duration	1.827	0.603	0.003	1.827	0.603	0.003	1.827	0.600	0.003
Age	-3.989	0.836	0.062	-3.978	0.813	0.043	-3.900	0.856	0.014
FFMQ	0.410	0.385	0.373	0.418	0.367	0.340	0.613	0.193	0.027
MEQ	2.539	0.385	0.008	2.527	0.341	0.003	2.430	0.326	< .001
PA	-0.025	0.019	0.278	-0.024	0.016	0.196	-0.016	0.011	0.202
Meditation	-7.941	10.025	0.509	-7.756	9.740	0.499	-2.601	5.934	0.684
Experience	-1.956	3.157	0.569	-1.876	2.971	0.557			
Biological Sex	-0.410	6.407	0.955						
Fit Criteria									
AIC	1588.65			1586.66			1584.97		
BIC	1623.47			1618.31			1613.45		

LogLikel	-783.33			-783.33			-783.48		
Pseudo R² Marginal	0.52			0.52			0.53		
Pseudo R² Conditional	0.54			0.54			0.56		
- 2LL	1566.65			1566.66			1566.97		

	Model 4			Model 5*			Model 6		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	308.625	2.695	< .001	307.661	3.160	< .001	307.170	4.492	< .001
Shift Duration	1.827	0.600	0.003	1.827	0.598	0.003	1.830	0.595	0.003
Age	-3.978	0.863	0.010	-3.906	1.006	0.007	-4.670	1.384	0.007
FFMQ	0.645	0.181	0.014	0.552	0.199	0.028			
MEQ	2.453	0.328	< .001	2.377	0.373	< .001	2.000	0.476	0.002
PA	-0.016	0.012	0.206						
Fit Criteria									
AIC	1583.16			1582.83			1585.97		
BIC	1608.48			1604.98			1604.96		
LogLikel	-783.58			-784.41			-786.99		
Pseudo R² Marginal	0.53			0.52			0.52		
Pseudo R² Conditional	0.56			0.58			0.64		
- 2LL	1567.16			1568.83			1573.97		

	Model 6			Model 7			Model 8		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	307.170	4.492	< .001	307.054	5.364	< .001	314.103	7.126	< .001
Shift Duration	1.830	0.595	0.003	1.827	0.597	0.003	1.827	0.596	0.003
Age	-4.670	1.384	0.007				-3.368	2.340	0.180
FFMQ				0.706	0.324	0.059	0.019	0.434	0.965
MEQ	2.000	0.476	0.002	2.216	0.614	0.006			
Fit Criteria									
AIC	1585.97			1590.191			1596.27		
BIC	1604.96			1609.179			1615.26		
LogLikel	-786.99			-789.095			-792.13		
Pseudo R² Marginal	0.52			0.313			0.13		
Pseudo R² Conditional	0.64			0.539			0.58		
- 2LL	1573.97			1578.19			1584.27		

Note: * = Final model. Table estimates are unstandardized beta-weights. Shift duration was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. ML method was used for all parameter estimates, including fit criteria. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire, PA = baseline physical activity.

Step 4: Assess the Need for Random Slopes

	Fixed Slope Model*			Independence Structure			Unstructured Structure		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	307.661	3.160	< .001	307.648	3.166	< .001	307.882	3.081	< .001

Shift Duration	1.827	0.598	0.003	1.798	0.705	0.065	1.467	0.753	0.101
Age	-3.906	1.006	0.01	-3.910	1.008	0.007	-3.029	0.846	0.013
FFMQ	0.552	0.199	0.03	0.552	0.199	0.028	0.659	0.185	0.009
MEQ	2.377	0.373	< .001	2.378	0.374	< .001	2.319	0.344	< .001
Random Variance Components									
Intercept (L2) variance ($\sigma^2_{\mu 0}$)			57.2			57.6			55.65
Intercept (L2) variance (95% CL)			[4.81, 245]			[1.53, 245]			[1.51, 270]
ICC			0.117			0.119			0.115
Slope (L2) variance ($\sigma^2_{\mu 1}$)			N/A			0.477			1.07
Slope (L2) variance (95% CL)			N/A			[0, 8.62]			[0, 10.1]
LRT Statistic			N/A			0.209			0.503
LRT P-Value			N/A			0.647			0.778
Intercept-slope (L2) covariance (σ^2_{IS})			N/A			0			0.206
Fit Criteria									
AIC			1582.829			1584.6			1586.326
BIC			1604.983			1609.9			1614.809
LogLikel			-784.414			-784.3			-784.163
Pseudo R² Marginal			0.521			0.521			0.465
Pseudo R² Conditional			0.577			0.581			0.533
- 2LL			1568.828			1568.6			1568.326

Note: * = Final model. Table estimates are unstandardized beta-weights. Shift duration was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. ML method was used for all parameter estimates and fit criteria. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire.

3.5.11 Appendix G.4.a: Post Shift Subjective Stress

Overview

Model Outputs	Null Model	Predictor Model	Covariate Model
Regression Coefficients			
Level 1 (L1)			
Intercept (γ_{00})	0.43 (0.05) ***	0.43 (0.05) ***	0.41 (0.05) ***
Shift duration (γ_{10})		0.05 (0.01) ***	0.04 (0.01) ***
Level 2 (L2)			
Sex (γ_{01})			-0.24 (0.08) **
Meditation (γ_{02})			-0.21 (0.09) *
Age (γ_{03})			0.03 (0.02) *
PA (γ_{04})			-6.54e−4 (0.0002) ***
Fit Criteria			
AIC	308.2	272.7	245.6

BIC	319.6	287.7	275.7
LogLikel	-151.1	-132.3	-114.8
Pseudo R² Marginal	0.00	0.08	0.293
Pseudo R² Conditional	0.24	0.31	0.457
- 2LL	302.2	264.7	229.6
Variance Components			
Intercept (L2) variance ($\sigma^2_{\mu 0}$)	0.043	0.0429	0.0445
Within-participant (L1) variance (σ^2_j)	0.132	0.1209	0.1091
Slope (L2) variance ($\sigma^2_{\mu 1}$)	N/A	N/A	N/A
Intercept-slope (L2) covariance (σ^2_{IS})	N/A	N/A	N/A
ICC	0.246	0.262	0.29
Additional Information			
Number of estimated parameters	2	3	7

Note: # p < .10 *p < .05. **p < .01. ***p<.001. *N* = 320 and L2 sample size = 23. Coefficient values are unstandardized beta-weights. Values in parentheses are standard errors. T-statistics were computed as the ratio of each regression coefficient divided by its standard error. Variance components were estimated using REML, while regression coefficients and model fit criteria were estimated using ML. Standard deviation (SD) was calculated as the square root of shown variance. Shift duration was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. PA = baseline physical activity

Step 2: Determine the Strongest L1 Predictor

	Model 1				Model 2			
Predictor	**Estimate**	**SE**	**t**	**p**	**Estimate**	**SE**	**t**	**p**
Intercept (γ00)	1.684	0.081	20.770	< .001	1.683	0.081	20.790	< .001
End Time	21.528	13.812	1.560	0.120	1.948	0.429	4.550	< .001
Start Time	-23.611	13.927	-1.700	0.091	-3.941	0.946	-4.160	< .001
Time Between Shifts	0.005	0.003	1.670	0.095	0.005	0.003	1.640	0.103
Shift Duration	-0.807	0.571	-1.410	0.159				
Fit Criteria								
AIC	625.90				627.40			
BIC	652.08				649.86			
LogLikel	-305.95				-307.70			
Pseudo R² Marginal	0.11				0.109			
Pseudo R² Conditional	0.30				0.297			
- 2LL	611.90				615.40			

	Model 3				Model 4			
Predictor	**Estimate**	**SE**	**t**	**p**	**Estimate**	**SE**	**t**	**p**
Intercept (γ00)	1.680	0.081	20.750	< .001	1.680	0.081	20.690	< .001
End Time	1.840	0.422	4.350	< .001	2.230	0.418	5.340	< .001
Start Time	-3.420	0.912	-3.750	< .001				
Fit Criteria								
AIC	645.11				656.85			

BIC	663.97				671.94			
LogLikel	-317.56				-324.43			
Pseudo R² Marginal	0.098				0.067			
Pseudo R² Conditional	0.287				0.254			
- 2LL	635.11				648.85			

	Model 5				Model 6			
Predictor	**Estimate**	**SE**	**t**	**p**	**Estimate**	**SE**	**t**	**p**
Intercept (γ00)	1.680	0.081	20.670	< .001	1.690	0.082	20.589	< .001
Start Time	-4.410	0.911	-4.850	< .001				
Time Between Shifts					-6.74e−5	0.003	-0.023	0.981
Fit Criteria								
AIC	661.4943				668.11			
BIC	676.58				683.08			
LogLikel	-326.75				-330.05			
Pseudo R² Marginal	0.056				0.000			
Pseudo R² Conditional	0.242				0.182			
- 2LL	653.49				660.11			

	Model 7*			
Predictor	**Estimate**	**SE**	**t**	**p**
Intercept (γ00)	1.679	0.081	20.710	< .001
End Time	0.093	0.014	6.430	< .001
Fit Criteria				
AIC	644.11			
BIC	659.18			
LogLikel	-318.05			
Pseudo R² Marginal	0.093			
Pseudo R² Conditional	0.282			
- 2LL	636.11			

Note: * = Final model. Models 4-7 show each predictor in isolation. Table estimates are unstandardized beta-weights. All predictors were rescaled via cluster-wise centering. ML method was used for all parameter estimates, including fit criteria. Satterthwaite method was used for estimating degrees of freedom.

Step 3: Add in L2 Covariates

	Model 1			Model 2			Model 3		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	0.408	0.050	< .001	0.408	0.050	< .001	0.411	0.046	< .001
Shift Duration	0.042	0.008	< .001	0.042	0.008	< .001	0.042	0.008	< .001
PA	-5.86e−4	2.09E-04	0.01	-5.75e−4	1.94E-04	0.01	-5.66e−4	1.87E-04	0.01
Biological Sex	-0.222	0.100	0.036	-0.220	0.098	0.034	-0.210	0.079	0.013
Age	0.032	0.015	0.052	0.032	0.015	0.052	0.032	0.015	0.052
Meditation	-0.195	0.091	0.043	-0.195	0.091	0.044	-0.195	0.091	0.044
Experience	0.016	0.019	0.412	0.015	0.018	0.419	0.016	0.017	0.351

MEQ	0.001	0.007	0.847	0.001	0.007	0.868			
FFMQ	0.000	0.003	0.887						
Fit Criteria									
AIC	250.67			248.69			246.72		
BIC	292.12			286.37			280.63		
LogLikel	-114.34			-114.35			-114.36		
Pseudo R² Marginal	0.29			0.28			0.29		
Pseudo R² Conditional	0.44			0.44			0.44		
- 2LL	228.67			228.69			228.72		

	Model 4*			Model 5			Model 6		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	0.409	0.047	< .001	0.420	0.050	< .001	0.411	0.049	< .001
Shift Duration	0.042	0.008	< .001	0.042	0.008	< .001	0.043	0.008	< .001
PA	-6.54e−4	1.69E-04	< .001	-6.50e−4	1.82E-04	0.001	-6.69e−4	1.75E-04	< .001
Biological Sex	-0.238	0.076	0.003	-0.233	0.080	0.006	-0.237	0.078	0.005
Age	0.035	0.015	0.034	0.031	0.017	0.072			
Meditation	-0.207	0.092	0.036				-0.176	0.095	0.083
Fit Criteria									
AIC	245.60			248.27			248.66		
BIC	275.75			274.65			275.03		
LogLikel	-114.80			-117.13			-117.33		
Pseudo R² Marginal	0.29			0.25			0.26		
Pseudo R² Conditional	0.46			0.45			0.45		
- 2LL	229.60			234.27			234.66		

	Model 7			Model 8		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	0.440	0.048	< .001	0.379	0.056	< .001
Shift Duration	0.045	0.008	< .001	0.044	0.008	< .001
PA	-7.74e−4	1.72E-04	< .001			
Biological Sex				-0.350	0.083	< .001
Age	0.034	0.016	0.048	0.041	0.019	0.043
Meditation	-0.179	0.096	0.079	-0.198	0.113	0.097
Fit Criteria						
AIC	253.29			257.03		
BIC	279.67			283.41		
LogLikel	-119.64			-121.52		
Pseudo R² Marginal	0.27			0.25		
Pseudo R² Conditional	0.45			0.50		
- 2LL	239.29			243.03		

Note: * = Final model. Table estimates are unstandardized beta-weights. Shift duration was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. ML method was used for all parameter estimates, including fit criteria. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire, PA = baseline physical activity

Step 4: Assess the Need for Random Slopes

	Fixed Slope Model*			Independence Structure			Unstructured Structure		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	0.406	0.052	< .001	0.407	0.052	< .001	0.408	0.052	< .001
Shift Duration	0.042	0.008	< .001	0.050	0.012	0.008	0.051	0.012	0.015
Biological Sex	-0.252	0.082	0.004	-0.243	0.082	0.005	-0.242	0.082	0.006
Meditation	-0.212	0.104	0.057	-0.210	0.103	0.057	-0.206	0.103	0.062
Age	0.037	0.017	0.044	0.037	0.017	0.045	0.037	0.017	0.046
PA	-6.77e−4	0.0002	0.001	-6.63e−4	0.0002	0.002	-6.67e−4	0.0002	0.002
Random Variance Components									
Intercept (L2) variance ($\sigma^2_{\mu0}$)			0.0445			0.0437			0.0438
Intercept (L2) variance (95% CL)			[0.01, 0.08]			[0.01, 0.07]			[0.01, 0.07]
ICC			0.29			0.29			0.291
Slope (L2) variance ($\sigma^2_{\mu1}$)			N/A			0.0005			0.0006
Slope (L2) variance (95% CL)			N/A			[0, 0.003]			[0,0.003]
LRT Statistic			N/A			1.23			1.24
LRT P-Value			N/A			0.27			0.59
Intercept-slope (L2) covariance (σ^2_{IS})			N/A			0.00			-0.05
Fit Criteria									
AIC			245.60			247.03			248.62
BIC			315.90			320.44			326.20
LogLikel			-134.9			-134.26			-134.26
Pseudo R² Marginal			0.29			0.30			0.30
Pseudo R² Conditional			0.50			0.51			0.51
- 2LL			269.75			268.52			268.52

Note: * = Final model. Table estimates are unstandardized beta-weights. Shift duration was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. REML was used for all parameter estimates. PA = baseline physical activity

3.5.12 Appendix G.4.b: Post Shift Mean RR

Overview

Model Outputs	Null Model	Predictor Model	Covariate Model
Regression Coefficients			
Level 1 (L1)			

Intercept (γ_{00})	1082 (48) ***	1085 (57) ***	1114 (27) ***
Shift Duration (γ_{10})		-13.6 (4.0) ***	-13.6 (4.0) ***
Level 2 (L2)			
Meditation (γ_{01})			121 (49) *
Age (γ_{02})			17.3 (7.8) #
Experience (γ_{03})			44.4 (9.2) ***
PA (γ_{04})			0.568 (0.09) ***
Fit Criteria			
AIC	1780.5	1527.35	1517.95
BIC	1789.4	1538.60	1540.45
LogLikel	-887.2	-759.68	-750.98
Pseudo R^2 Marginal	0.00	0.024	0.57
Pseudo R^2 Conditional	0.69	0.746	0.69
- 2LL	1774.5	1519.35	1501.95
Variance Components			
Intercept (L2) variance ($\sigma^2_{\mu 0}$)	25250	29471	3788
Within-participant (L1) variance (σ^2_{j})	11266	10382	10424
Slope (L2) variance ($\sigma^2_{\mu 1}$)	N/A	N/A	N/A
Intercept-slope (L2) covariance (σ^2_{IS})	N/A	N/A	N/A
Additional Information			
ICC	0.691	0.739	0.267
Number of estimated parameters	2	3	7

	Random Slope Model	Interaction Model
Regression Coefficients		
Level 1 (L1)		
Intercept (γ_{00})	1108 (27) ***	1114 (27) ***
Shift Duration (γ_{10})	-14.8 (6.3) *	-19.8 (7.2) **
Level 2 (L2)		
Meditation (γ_{01})	119 (46) *	121 (49) *
Age (γ_{02})	18.1 (6.2) *	17.3 (7.4) *
Experience (γ_{03})	39.4 (7.7) ***	43.8 (8.9) ***
PA (γ_{04})	0.603 (0.08) ***	0.563 (0.09) ***
Cross-Level Interactions		
Shift Duration: PA (γ_{11})		0.059 (0.02) **
Shift Duration: Meditating (γ_{12})		-18.5 (15)
Fit Criteria		
AIC	1513.32	1512.9
BIC	1541.44	1546.6
LogLikel	-746.66	-744.4
Pseudo R^2 Marginal	0.59	0.60
Pseudo R^2 Conditional	0.74	0.72
- 2LL	1493.32	1488.9

Variance Components		
Intercept (L2) variance ($\sigma^2_{\mu 0}$)	4400	3979.00
Within-participant (L1) variance (σ^2_j)	9479	9230.00
Slope (L2) variance ($\sigma^2_{\mu 1}$)	161	26.6
Intercept-slope (L2) covariance (σ^2_{IS})	-1.00	-1.00
Additional Information		
ICC	0.317	
Number of estimated parameters	8	10

Note: $^{\#}$ p < .10 *p < .05. **p < .01. ***p<.001. *N* = 123 and L2 sample size = 10. Coefficient values are unstandardized beta-weights. Values in parentheses are standard errors. T-statistics were computed as the ratio of each regression coefficient divided by its standard error. ML was used for all parameter estimates, including regression coefficients, variance components, and model fit criteria. Standard deviation (SD) was calculated as the square root of shown variance. Shift duration was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. PA = baseline physical activity

Step 2: Determine the Strongest L1 Predictor

	Model 1			Model 2			Model 3		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1086.53	55.99	< .001	1085.30	55.60	< .001	1085.30	55.60	< .001
Shift Duration	-202.96	144.81	0.16	-97.20	133.20	0.47	-15.20	4.45	< .001
Start Time	-4654.06	3502.46	0.19	-2148.40	3248.40	0.51	-148.60	190.63	0.44
End Time	4509.179	3492.09	0.20	1980.90	3212.10	0.54			
Time Between Shifts	-0.60	1.79	0.74						
Fit Criteria									
AIC	1385.00			1530.36			1528.74		
BIC	1403.96			1547.24			1542.81		
LogLikel	-685.50			-759.18			-759.37		
Pseudo R² Marginal	0.032			0.026			0.025		
Pseudo R² Conditional	0.752			0.748			0.747		
- 2LL	1371.00			1518.36			1518.74		

	Model 4*			Model 5		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1085.3	55.60	< .001			
Shift Duration	-13.6	4.01	< .001			
Start Time				138	179.70	0.446
End Time				-344	107.2	0.002
Time Between Shifts				1.22	1.70	0.47
Fit Criteria						
AIC	1527.35					
BIC	1538.60					
LogLikel	-759.68					

Pseudo R² Marginal	0.024
Pseudo R² Conditional	0.746
- 2LL	1519.35

Note: * = Final model. Model 5 shows each removed predictor in isolation. Table estimates are unstandardized beta-weights. ML method was used for all parameter estimates, including fit criteria. All predictors were rescaled via cluster-wise centering. Satterthwaite method was used for estimating degrees of freedom.

Step 3: Add in L2 Covariates

	Model 1			Model 2			Model 3		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1121.54	24.43	< .001	1120.54	25.10	< .001	1117.068	24.97	< .001
Shift Duration	-13.64	4.03	< .001	-13.64	4.02	< .001	-13.641	4.02	< .001
Meditation	158.283	51.56	0.012	152.81	52.48	0.01	135.784	46.99	0.02
Age	19.617	6.94	0.026	18.79	7.10	0.03	18.617	7.25	0.04
Experience	35.117	11.43	0.013	39.46	9.74	0.003	42.57	8.67	0.001
PA	0.57	0.08	< .001	0.55	0.08	< .001	0.56	0.08	< .001
Biological Sex	-120.689	82.46	0.186	-92.66	74.32	0.24	-53.168	46.35	0.29
MEQ	3.879	4.35	0.40	2.78	4.16	0.52			
FFMQ	-1.46	2.09	0.505						
Fit Criteria									
AIC	1521.86			1520.33			1518.77		
BIC	1552.79			1548.45			1544.08		
LogLikel	-749.93			-750.16			-750.38		
Pseudo R² Marginal	0.61			0.60			0.59		
Pseudo R² Conditional	0.69			0.68			0.68		
- 2LL	1499.86			1500.33			1500.77		

	Model 4*			Model 5			Model 6		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1113.511	26.74	< .001	1134.311	31.42	< .001	1095.728	32.46	< .001
Shift Duration	-13.641	4.02	< .001	-13.641	4.00	< .001	-13.641	4.01	< .001
Meditation	120.929	49.01	0.03	141.43	59.09	0.035			
Age	17.279	7.85	0.06				20.543	9.88	0.07
Experience	44.414	9.19	< .001	41.518	11.34	0.004	42.118	11.71	0.01
PA	0.568	0.09	< .001	0.519	0.11	< .001	0.546	0.11	< .001
Fit Criteria									
AIC	1517.95			1519.54			1520.63		
BIC	1540.45			1539.22			1540.32		
LogLikel	-750.98			-752.77			-753.32		
Pseudo R² Marginal	0.57			0.47			0.49		
Pseudo R² Conditional	0.69			0.67			0.70		

- 2LL	1501.95	1505.54	1506.63

	Model 7			Model 8		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1080.212	46.3	< .001	1110.56	59.55	< .001
Shift Duration	-13.641	4.01	< .001	-13.64	4.01	< .001
Meditation	107.356	87.9	0.249	96.84	108	0.389
Age	10.287	14.3	0.489	3.68	17.33	0.836
Experience				17.41	18.34	0.365
PA	0.366	0.14	0.029			
Fit Criteria						
AIC	1527.54			1531.655		
BIC	1547.23			1551.34		
LogLikel	-756.77			-758.827		
Pseudo R² Marginal	0.36			0.106		
Pseudo R² Conditional	0.75			0.736		
- 2LL	1513.54			1517.65		

Note: * = Final model. Table estimates are unstandardized beta-weights. Shift duration was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. ML method was used for all parameter estimates, including fit criteria. MEQ = morningness-eveningness questionnaire, FFMQ = five facet mindfulness questionnaire, PA = baseline physical activity

Step 4: Assess the Need for Random Slopes

	Fixed Slope Model			Unstructured Structure*			Independence Structure		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1113.51	26.74	< .001	1107.98	26.31	< .001	1114.12	26.83	< .001
Shift Duration	-13.64	4.02	< .001	-14.83	6.35	0.04	-15.74	7.12	0.08
Meditation	120.93	49.01	0.03	119.34	45.76	0.02	120.58	49.08	0.03
Age	17.28	7.85	0.06	18.11	6.24	0.01	17.08	7.89	0.06
Experience	44.41	9.19	< .001	39.39	7.72	< .001	44.28	9.22	< .001
PA	0.57	0.09	< .001	0.60	0.08	< .001	0.57	0.09	< .001
Random Variance Components									
Intercept (L2) variance ($\sigma^2_{\mu 0}$)			3788			4400			3939
Intercept (L2) variance (95% CL)			[917, 13433]			[1161.2, 16491]			[1047, 13622]
ICC			0.27			0.317			0.292
Slope (L2) variance ($\sigma^2_{\mu 1}$)						161.00			205
Slope (L2) variance (95% CL)						[18.1, 753]			[0, 1395]
LRT Statistic						8.63			3.27
LRT P-Value						0.013			0.071
Intercept-slope (L2) covariance (σ^2_{IS})						-1.00			0
Fit Criteria									
AIC			1517.95			1513.3			1516.7
BIC			1540.45			1541.4			1542
LogLikel			-750.98			-746.7			-749.3
Pseudo R² Marginal			0.57			0.59			0.57

Pseudo R² Conditional	0.69	0.736	0.718
- 2LL	1501.95	1493.3	1498.7

Note: * = Final Model. Table estimates are unstandardized beta-weights. Shift duration was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. ML method was used for parameter estimates PA = baseline physical activity

Step 5: Probe for Cross Level Interactions

	Model 1			Model 2			Model 3*		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1115.43	26.88	< .001	1114.88	26.63	< .001	1113.99	26.42	< .001
Shift Duration	-19.88	7.31	0.01	-19.81	7.26	0.01	-19.83	7.23	0.01
Meditation	121.30	49.16	0.03	120.82	49.01	0.03	120.68	48.95	0.03
Age	16.87	7.91	0.06	17.29	7.37	0.05	17.25	7.40	0.05
Experience	44.45	9.24	< .001	44.49	9.22	< .001	43.77	8.85	< .001
PA	0.56	0.09	< .001	0.57	0.09	< .001	0.56	0.09	< .001
Shift Duration: PA	0.05	0.03	0.08	0.05	0.03	0.07	0.06	0.02	0.01
Shift Duration: Meditation	-18.11	16.01	0.26	-17.69	15.34	0.25	-18.55	15.20	0.23
Shift Duration: Experience	-0.61	2.14	0.78	-0.61	2.12	0.78			
Shift Duration: Age	0.24	1.59	0.88						
Fit Criteria									
AIC	1516.8			1514.8			1512.9		
BIC	1556.2			1551.4			1546.6		
LogLikel	-744.4			-744.4			-744.4		
Pseudo R² Marginal	0.60			0.60			0.60		
Pseudo R² Conditional	0.72			0.72			0.72		
- 2LL	1488.8			1488.8			1488.9		

	Model 4			Model 5			Model 6		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	1112.20	26.26	< .001	1108.22	26.38	< .001	1107.98	26.31	< .001
Shift Duration	-13.72	5.01	0.02	-15.82	8.24	0.06	-14.83	6.35	0.04
Meditation	107.80	47.58	0.04	123.40	50.72	0.04	119.34	45.76	0.02
Age	17.07	6.99	0.04	18.22	6.29	0.01	18.11	6.24	0.01
Experience	42.76	8.54	< .001	39.42	7.74	< .001	39.39	7.72	< .001
PA	0.56	0.09	< .001	0.61	0.08	< .001	0.60	0.08	< .001
Shift Duration: PA	0.05	0.02	0.04						
Shift Duration: Meditation				-3.15	16.73	0.85			

Fit Criteria			
AIC	1512.097	1515.284	1513.32
BIC	1543.031	1546.217	1541.44
LogLikel	-745.049	-746.642	-746.66
Pseudo R² Marginal	0.579	0.593	0.59
Pseudo R² Conditional	0.713	0.738	0.74
- 2LL	1490.1	1493.3	1493.32

Note: * = Final Model. Table estimates are unstandardized beta-weights. Shift duration was rescaled via cluster-wise centering. All covariates were rescaled via grand mean centering. Satterthwaite method was used for estimating degrees of freedom. ML method was used for parameter estimates and fit criteria. PA = baseline physical activity

3.5.13 Appendix G.4.c: Post Shift RMSSD

Step 2: Determine the Strongest L1 Predictor

	Model 1			Model 2			Model 3		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	56.43	7.90	< .001	56.50	7.85	< .001	56.55	7.85	< .001
Shift Duration	-25.09	22.098	0.26	-11.40	20.11	0.57	-0.40	1.07	0.71
End Time	595.631	532.90	0.27	270.60	485.11	0.58	6.01	28.47	0.83
Start Time	-586.35	534.48	0.28	-268.10	490.57	0.59			
Time Between Shifts	-0.18	0.27	0.51						
Fit Criteria									
AIC	966.08			1072.42			1070.72		
BIC	985.05			1089.34			1084.82		
LogLikel	-476.04			-530.21			-530.36		
Pseudo R² Marginal	0.005			0.001			0.000		
Pseudo R² Conditional	0.712			0.713			0.712		
- 2LL	952.08			1060.42			1060.72		

	Model 4			Model 5			Model 6		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept (γ00)	56.547	7.85	< .001	56.55	7.85	< .001	56.55	7.85	< .001
Shift Duration	-0.218	0.60	0.72						
End Time				-2.91	15.97	0.86			
Start Time							8.29	25.83	0.749
Fit Criteria									
AIC	1068.76			1068.86			1068.79		
BIC	1080.05			1080.14			1080.07		
LogLikel	-530.38			-530.43			-530.40		
Pseudo R² Marginal	0.000			0.000			0.000		
Pseudo R² Conditional	0.712			0.712			0.712		
	1060.76			1060.86			1060.79		

	Model 7			Model 8*		
Predictor	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**

Intercept (γ00)	56.4294	7.90	< .001	56	6.84	< .001
Time Between Shifts	-0.0467	0.25	0.849			
Fit Criteria						
AIC	961.93			1230.79		
BIC	972.76			1239.70		
LogLikel	-476.96			-612.40		
Pseudo R^2 Marginal	0.000			0.000		
Pseudo R^2 Conditional	0.707			0.693		
- 2LL	953.93					

Note: * = Final model. Models 4-7 show each predictor in isolation. Table estimates are unstandardized beta-weights. All predictors were rescaled via cluster-wise centering. ML method was used for all parameter estimates, including fit criteria. Satterthwaite method was used for estimating degrees of freedom. ML method was used for all parameter estimates, including fit criteria.