

Fatigue in wildland firefighting: relationships between sleep, shift characteristics, and cognitive function

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Received: 10 December 2024

Accepted: 27 May 2025

Published: 4 September 2025

Cite this: Wallace-Webb J *et al.* (2025) Fatigue in wildland firefighting: relationships between sleep, shift characteristics, and cognitive function. *International Journal of Wildland Fire* **34**, WF24212. doi:[10.1071/WF24212](https://doi.org/10.1071/WF24212)

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ABSTRACT

Background. Wildland firefighting requires exposure to long shifts and poor sleep, which may pose a risk to worker safety due to impaired cognitive function. **Aims.** We investigated the associations between sleep, shift characteristics, and cognitive function in wildland firefighters.

Methods. We conducted a within-subject observational study with 25 wildland firefighters from the British Columbia Wildfire Service, Canada. Data were collected remotely during the 2021 and 2022 fire seasons. Wrist-worn actigraphy and the psychomotor vigilance task served as objective, mobile measures of sleep and cognitive function, respectively. Web-based surveys were used to collect shift information and subjective cognitive function. Linear mixed effects modeling was used to control for inter-individual differences and explore the influence of participant-factors.

Key results. Average sleep duration on fire suppression days was 6.7 h (s.d. 66 min), while average shift duration was 13.8 h (s.d. 108 min). Poor sleep and longer shift durations were both associated with reduced cognitive function across all metrics ($P < 0.01$; $P < 0.001$). **Conclusion.** Firefighters are often exposed to poor sleep and long shifts, which are both associated with impaired cognitive function. **Implications.** Our results highlight the need for fire agencies to consider fatigue-related cognitive impairment as an important factor for worker health and safety.

Keywords: cognitive function, extended shifts, fatigue management, occupational health and safety, psychomotor vigilance task, shift work, sleep deprivation, wildland firefighting.

Introduction

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). With this rise in wildfire activity, so too rises the demand and health and safety risks for the wildland firefighters whose performance is required for protecting communities. As an occupation, wildland firefighting involves dangerous suppression activities that require continuous focused attention and complex decision-making. Workers are often exposed to harsh working conditions, including long working hours (Jeklin *et al.* 2021), demanding physical work (Rodríguez-Marroyo *et al.* 2011; Parker *et al.* 2017), sub-optimal sleep (Vincent *et al.* 2018), smoke exposure (Barbosa *et al.* 2022), high ambient temperatures, dehydration, and acute psychological stress (Aisbett and Nichols 2007; Aisbett *et al.* 2012). From the perspective of occupational health and safety, all these conditions can be seen as contributing factors to a state of impaired cognitive function, which poses a serious risk to worker safety on several levels, ranging from reduced awareness (Williamson *et al.* 2011) to impaired decision-making (Harrison and Horne 2000).

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 (Philip and Åkerstedt 2006; Bioulac *et al.* 2017). 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 and Dinges 2010; Lowe *et al.* 2017). Previous research has found sleep duration to be restricted during multi-day wildfire suppression (Vincent *et al.* 2018). This is concerning in light of findings that

consecutive nights of partial sleep loss (i.e. <6 h per night) can result in cognitive deficits equivalent to 24 h 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 (Folkard and Tucker 2003; van der Hulst 2003; Barger *et al.* 2009). 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 (Rogers *et al.* 2004; Bae 2021). Limited research in the context of wildland firefighting has found that firefighters routinely work 12–14 h per day (Jeklin *et al.* 2020, 2021). These extended shifts may have safety-related consequences, including an increased risk of workplace accidents and injuries (Dembe *et al.* 2005; Wagstaff and 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.* 2017). Very few studies have examined the combined effect of multiple stressors (Smith *et al.* 2016; Cvirn *et al.* 2019) and only one used the integrative framework of cognitive fatigue (Jeklin *et al.* 2020). Field-based research on the occupational health and safety impacts associated with wildland firefighting is also a critically valuable yet lacking subject of research (Allison *et al.* 2022; Koopmans *et al.* 2022; García-Heras *et al.* 2025). Most of its related topics including sleep (Lowe *et al.* 2017), acute stress (Shields *et al.* 2016), hydration status (Wittbrodt and Millard-Stafford 2018), and heat stress (Hancock *et al.* 2007; Walter and Carraretto 2016) are mostly studied under controlled laboratory conditions that may not accurately reflect the working environment.

The aim of this study was to investigate the incidence and potential determinants of fatigue-related cognitive impairment within the occupational setting of wildland firefighting by examining the cognitive-related associates of sleep and shift characteristics. To the best of our knowledge, this was the first naturalistic study in wildland firefighters to: (1) employ completely remote methodology; and (2) use linear mixed effects modeling to investigate fatigue-related cognitive impairment while controlling 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; McGillis *et al.* 2017), and accounting for factors like age, biological sex, and firefighting experience (Vincent *et al.* 2016).

Our research questions and hypotheses were:

1. Are indices of cognitive function associated with sleep and/or shift characteristics?

Hypothesis 1: Cognitive function indices will not be associated with sleep nor shift characteristics.

2. Do participant-level characteristics such as age, biological sex, and firefighting experience moderate the relationship between cognitive function and sleep/shift characteristics?
- Hypothesis 2: Participant level characteristics will not moderate the relationship between cognitive function and sleep/shift characteristics.

Materials and methods

Study design and procedure

Study design

Similar to previous methods (Jeklin *et al.* 2020), this study employed an observational, within-subject design to examine the associations between sleep, shift characteristics, and variables related to cognitive function. Data collection occurred at daily intervals during the fire seasons between June and September in 2021 and 2022. 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 online via 'SurveyMonkey' software (SurveyMonkey Inc, San Mateo, California, USA). If participants were out of cell 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.

Procedure

Recruitment. Participant recruitment information sessions occurred remotely via online video meetings from May to 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.

Baseline measures. Once familiar with study procedures, participants completed several baseline questionnaires designed to capture relevant contextual information as well as insight into potential moderators that may influence the complex relationships between sleep, shift duration, and cognitive function. These included a unique general questionnaire (i.e. individual characteristics, work history, medical history, 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 and Östberg 1977).

Daily measures. Daily data collection began with over-night sleep measurement, either in the participants' home or elsewhere if deployed, using the wrist-worn Polar Ignite Activity Tracker (Kempele, Finland). The following sleep metrics were extracted: sleep duration, previous evening bedtime, wakeup time, and eight sleep quality metrics (i.e., number of sleep cycles, sleep continuity (/5), overall sleep score (/100), long interruptions (minutes), percentage of time asleep vs awake, and percentage of time spent in light, REM, and deep sleep). Once participants arrived at work later the same day, they completed a pre-shift questionnaire that measured subjective sleep and cognitive function metrics. Subjective sleep metrics 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'. Subjective cognitive function metrics included subjective sleepiness and subjective fatigue. 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 and 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).

Following the pre-shift questionnaire, cognitive function was measured objectively via performance on the Psychomotor Vigilance Task (PVT). The PVT is based on simple response time (RT) to stimuli that occur at random intervals and therefore measures vigilant attention. Within the domain of sleep research, 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 (Dinges *et al.* 1997; Basner and Dinges 2011; Ferguson *et al.* 2016). Three-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. Participants completed a 3-min version of the PVT (otherwise known as the PVT-Brief or PVT-B; Basner *et al.* 2011), each using their own personal smartphone. Participants were instructed to monitor a blank gray 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-s period. The inter-stimulus intervals varied randomly from 0.5 to 3.5-s (including a 1-s 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 start' warning on the display). The test gave a signal after a 5-s period without response, which was counted as a lapse with a 5-s RT. In accordance with standardized methods of reporting (Basner and Dinges 2011;

Basner *et al.* 2011), the following metrics were calculated in Excel and included in following analyses: (1) mean 1/RT (also called reciprocal RT); 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 1000 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).

At the end of the shift, participants completed the PVT and a post-shift questionnaire. The post-shift questionnaire contained two of the same measures as pre-shift (i.e. subjective sleepiness and fatigue) as well as shift characteristics (i.e. start time, stop time, and time between shifts).

Workdays were classified as either fire suppression or non-fire suppression days. Fire suppression days included active wildfire suppression activities, while non-fire suppression days referred to workdays without wildfire suppression. The latter included administrative tasks performed at base, project work involving physical labor (e.g. trail construction), and/or training activities. 'Deployments' refer to multiple consecutive fire suppression days, which typically involve travel away from a firefighter's home base.

Recruitment of participants

Ethical approval (#21-0124) for this study was initially granted from the human research ethics board (HREB) at the University of Victoria in July 2021. Ethics renewal for the second summer of data collection was granted in May 2022. An optimal sample of 20 participants for the 2022 collection period was determined from a statistical power analysis (GPower software, ver. 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 in any measure) and so were removed from the study. In total, 25 participants were included in the final dataset (Fig. 1).

Recruitment was not limited to age, gender, biological sex, ethnicity, religion, class, or experience. Therefore, the only inclusion criteria was that participants were employed

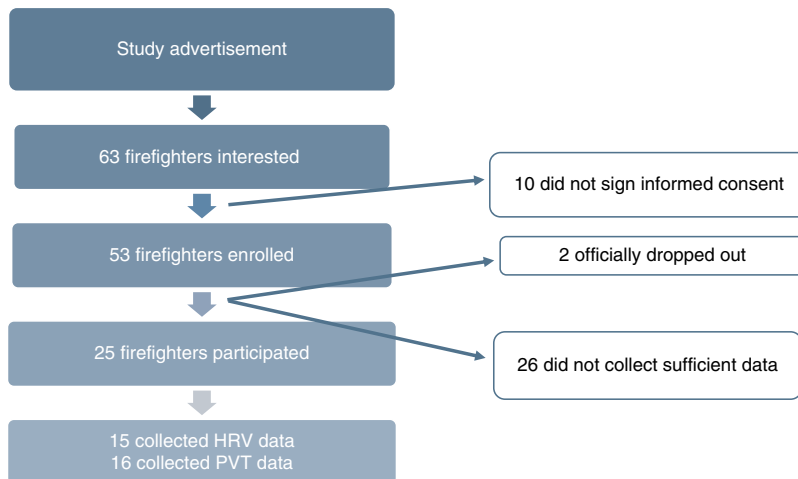


Fig. 1. Study recruitment process with number of participants in each stage.

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.

Statistical analysis

Issues with traditional statistical tests

Our study investigated the associations between sleep, shift characteristics and indices of cognitive function using an unbalanced, repeated measures design. Traditional general linear models (GLM), including 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 *et al.* 2004a, 2004b).

How linear mixed effect (LME) models circumvent these issues

In consideration of these limitations, we used LME modeling 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 , response time) in conjunction with 'random-effects' that recognize potential between-participant differences in baseline values of variable y (e.g. inter-individual differences in response time), 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 modeling accommodates hierarchical designs wherein lower, level 1 (L1) variables are clustered or 'nested' within higher, level 2 (L2) variables. In this way, LME modeling 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 modeling has previously been employed in sleep literature (Van Dongen *et al.* 2003) and is generally preferred over traditional GLMs, as they better account for autocorrelation 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. Therefore, our statistical approach used random intercepts to account for unequal numbers of observations for each participant. Although a complete discussion of LME modeling 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 *et al.* 2004b).

How LME modeling 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 (Fogt *et al.* 2011; Ferguson *et al.* 2016; Barger *et al.* 2019; Chien *et al.* 2020), the following process was followed for constructing LME models to investigate the effects of observation-level predictors of cognitive function (i.e. sleep and shift characteristics) while accounting for participant-level characteristics such as age, biological sex, and years of firefighting experience. All analyses were conducted using Jamovi software (ver. 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.

Results

Demographic variables

A total of 25 wildland firefighters (18 male, seven female) from the BCWS participated in the current study. The average age of participants was 26.4 years (± 3.2), and average BMI was 23.9 kg/m² (± 1.7) (Tables 1–3). None self-reported a sleep disorder diagnosis.

Descriptive statistics

Sleep information

In total, participants completed a combined 565 days of sleep testing. There was a total of 1410 h of sleep recorded by wrist-worn actigraphy (698 on 105 fire suppression days; 712 on 100 non-fire suppression days) and 2622 h of sleep recorded by self-report (1495 on 216 fire suppression days; 1127 on 146 non-fire suppression days). Table 4 and Fig. 2 show that actigraphy recorded bedtimes tended to be approximately 40 min earlier, on average, on fire suppression days (23:08 hours ± 68 min) compared to non-fire suppression days (23:48 hours ± 68 min). Average wakeup times tended to be over 1 h earlier on fire suppression days (05:47 hours ± 55 min vs 06:54 hours ± 50 min). Although the earlier bedtimes on fire suppression days partially compensated for early wakeup times, overall sleep durations still tended to be shorter on fire suppression days (6.7 h ± 66 min) compared to non-fire suppression days (7.1 h ± 60 min). Table 4 shows that 72% of actigraphy-recorded sleeps on fire suppression days were under 7 h in duration compared to 48% of sleeps on non-fire suppression days.

Shift information

Overall, there was a total of 5388 hours worked across 454 recorded shifts (3887 on 282 fire suppression days; 1501 on 172 non-fire suppression days). Table 5 and

Table 1. Characteristics of the participants.

Characteristic	Total population (<i>n</i> = 25)			
	Mean	s.d.	<i>N</i>	(%)
Age (years)	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 (kg/m ²)	24	1.7		
Height (cm)	177	5.5		
Weight (kg)	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 2. Work experience of the participants.

Work experience	Total population (<i>n</i> = 25)			
	Mean	s.d.	<i>N</i>	(%)
BCWS	4.2	2.7		
Contract crew	1.4	2.5		
Any	5.6	3.3		
1 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
Work history				
Days since started work that season	87	37		
Number of fire suppression days since started work that season	7	7		

Table 3. Habitual traits of the participants.

Habitual traits	Total population (n = 25)			
	Mean	s.d.	N	(%)
Baseline physical activity (min/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
Trait mindfulness (FFMQ scores/5)				
Observing	3.53	0.72		
Describing	3.5	0.78		
Awareness	3.48	0.58		
Non-judging	3.51	0.59		
Non-reactivity	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%

Fig. 3 show that shift start times tended to be approximately 1.5 h earlier, on average, on fire suppression days (06:50 hours \pm 67 min) compared to non-fire suppression days (08:15 hours \pm 48 min). Shift end times tended to be approximately 3.5 h later (20:39 hours \pm 99 min vs 17:06 hours \pm 99 min). This translated into substantially longer shifts on fire suppression days (13.8 h \pm 108 min) compared to non-fire suppression days (8.7 h \pm 100 min). Table 5 shows that 89% of shifts on fire suppression days were over

12 h in duration, while 88% of shifts on non-fire suppression days were under 10.5 h in duration.

Linear mixed model justification

As shown in Table 6, ICC values in null LME models indicated substantial within-participant correlation in every outcome variable of interest (Mean ICC = 0.49 ± 0.13 s.d.). Stated otherwise, $49 \pm 13\%$ 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 $\chi^2(1) = 128 \pm 48$ s.d., $P < 0.001$), thus warranting the need for further analysis via LME modeling over traditional statistical techniques (Field *et al.* 2012).

Sleep and cognitive function

Supplementary Tables S1–S3 summarize the results of 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 eight sleep quality metrics (i.e. number of sleep cycles, sleep continuity (/5), overall sleep score (/100), long interruptions (minutes), percentage of time asleep vs awake, and percentage of time spent in light, REM, and deep sleep). 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 355 ms) ($\gamma_{10} = -0.02$, $t(114) = -3.27$, $P < 0.001$), PVT mean reciprocal response time (RT) ($\gamma_{10} = -0.43$, $t(114) = -3.23$, $P < 0.005$), and subjective fatigue ($\gamma_{10} = -0.09$, $t(168) = -6.19$, $P < 0.001$).

Transformations

We modeled transformed data for pre-shift PVT lapses and subjective fatigue, (i.e. log and cubic root transforms, respectively) 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. A total of 11 outlier data points for mean RT were identified by visual inspection (Supplementary Fig. S1) and were replaced with mean + 2 s.d., 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.

Participant-level characteristics

Tables S1–S3 shows the results of a backward covariate selection process wherein participant characteristics were individually assessed according to their ability to predict cognitive function measures. If not contributing to model fit, the worst performing covariate was progressively eliminated

Table 4. Actigraphy recorded sleep information on fire suppression vs non-fire suppression days.

	Fire suppression day	Wakeup time	Bedtime	Overall sleep duration (h)	% of time asleep	Actual sleep duration	Sleep score (/100)		
Mean	Yes	05:47 hours	23:08 hours	6.7	93	6.2	65		
	No	06:54 hours	23:48 hours	7.1	93	6.6	68		
s.d.	Yes	0 h 55 min	1 h 8 min	1.1	3	1.0	11		
	No	0 h 50 min	1 h 8 min	1.0	3	0.9	13		
	Fire suppression day	# of sleep cycles	Sleep continuity	Long interruptions (min)	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		
s.d.	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 21:00 hours	4	4	Before 04:00 hours	5	5	Under 5 h	3	3
	21:00–22:00 hours	10	10	04:00–05:00 hours	12	11	5–6 h	22	21
	22:00–23:00 hours	27	26	05:00–06:00 hours	35	33	6–7 h	50	48
	23:00–00:00 hours	40	38	06:00–07:00 hours	47	45	7–8 h	21	21
	00:00–01:00 hours	21	20	07:00–08:00 hours	5	5	8–9 h	5	5
	After 01:00 hours	3	3	After 08:00 hours	1	1	Over 9 h	4	4
No	Before 21:00 hours	0	0	Before 04:00 hours	0	0	Under 5 h	1	1
	21:00–22:00 hours	5	5	04:00–05:00 hours	0	0	5–6 h	13	13
	22:00–23:00 hours	20	20	05:00–06:00 hours	10	10	6–7 h	34	34
	23:00–00:00 hours	32	32	06:00–07:00 hours	37	37	7–8 h	34	34
	00:00–01:00 hours	31	31	07:00–08:00 hours	42	42	8–9 h	13	13
	After 01:00 hours	12	12	After 08:00 hours	11	11	Over 9 h	5	5

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 Table 7 and Tables S1–S3, 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 trait 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

Tables S1–S3 show the results of a comparison between the final fixed slope model and two competing random slope models with differing covariance structures (i.e. independence and 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 cognitive function measures are shown in Eqns 1–3.

$$\begin{aligned} \text{Pre RT}_{ij} = & \gamma_{00} + \gamma_{10}\text{SleepScore}_{ij} + \gamma_{01}\text{Meditation}_j \\ & + \gamma_{02}\text{Age}_j + \gamma_{03}\text{ME}_j + \gamma_{04}\text{Mindfulness}_j \\ & + \mu_{0j} + \varepsilon_{ij} \end{aligned} \quad (1)$$

$$\begin{aligned} \text{Pre Lapses}_{ij} = & \gamma_{00} + \gamma_{10}\text{SleepScore}_{ij} \\ & + \gamma_{01}\text{Experience}_j + \gamma_{03}\text{ME}_j + \mu_{0j} + \varepsilon_{ij} \end{aligned} \quad (2)$$

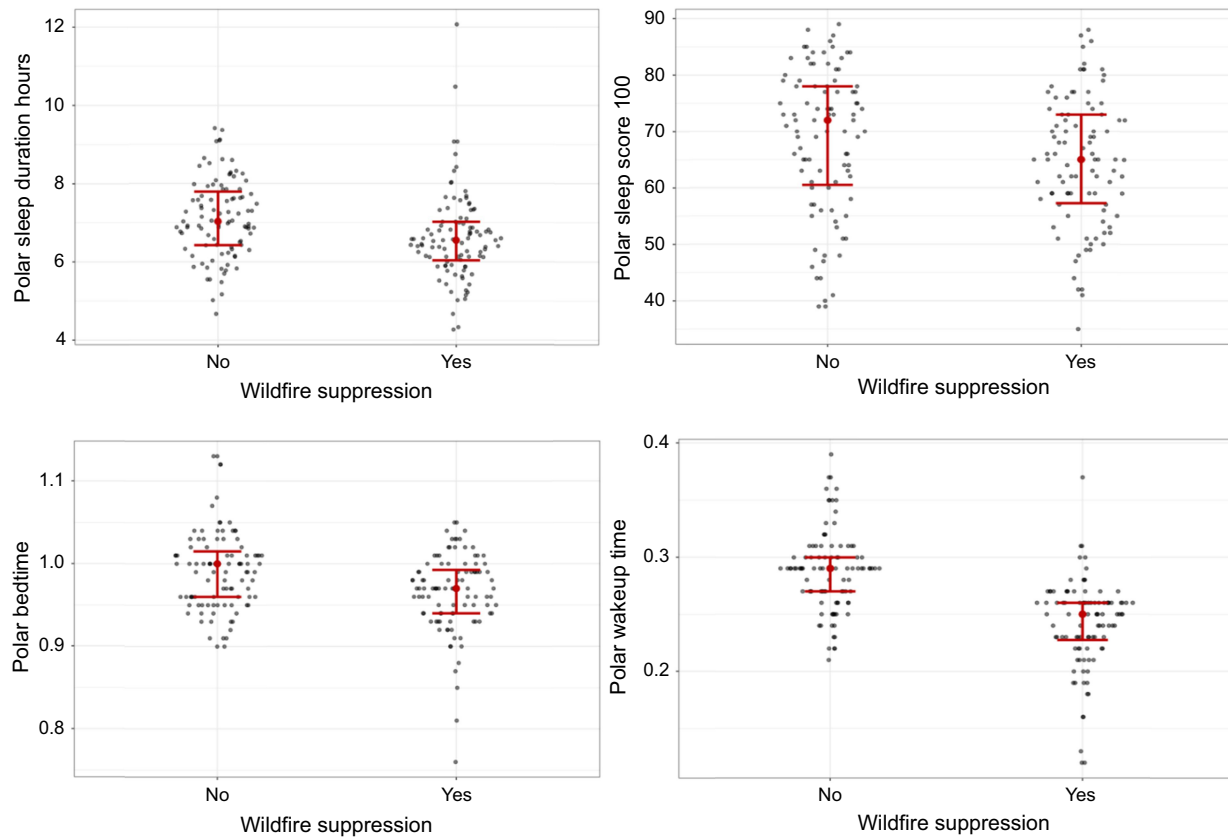


Fig. 2. Visual representation of sleep information on fire suppression vs non-fire suppression days. Note: each black dot represents an individual observation. The red center dot shows the median value, while the upper and lower bars represent the 75th and 25th percentile values, respectively. Bedtime and wakeup times were converted to decimal numbers such that 1.0 corresponds to 00:00 hours (midnight) and 0.3 corresponds to 07:12 hours. Each 0.1-unit increment represents a change of 2 h and 24 min. All figures were made using the Flexplot (Fife *et al.* 2021) module in Jamovi.

$$\text{Pre Subjective Fatigue}_{ij} = \gamma_{00} + \gamma_{10}\text{SleepScore}_{ij} + \mu_{0j} + \varepsilon_{ij} \quad (3)$$

Shift characteristics and cognitive function

Tables S4–S6 show the results of a backward variable selection process wherein 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 ($\gamma_{10} = 0.07$, $t(164) = 3.39$, $P < 0.001$), RT ($\gamma_{10} = 1.83$, $t(164) = 3.07$, $P < 0.005$), and subjective fatigue ($\gamma_{10} = 0.04$, $t(304) = 5.77$, $P < 0.001$).

Transformations

We modeled transformed data for pre-shift PVT lapses and subjective fatigue (i.e. log and square root transforms, respectively) 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 (Supplementary Fig. S2) and were replaced with mean + 2 s.d., 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 (Supplementary Fig. S3).

Participant-level characteristics

As shown in Table 7 and Tables S4–S6, contributing covariates for predicting PVT lapses included participant trait mindfulness ($P = 0.184$), ME ($P < 0.05$), and age ($P < 0.05$). Contributing covariates for RT included ME ($P < 0.001$), trait 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

Table 5. Shift information on fire suppression vs non-fire suppression days

	Fire suppression day	Start time	End time	Shift duration (h)	Time between shifts (h)
Mean	Yes	06:50 hours	20:39 hours	13.8	11.8
	No	08:15 hours	17:06 hours	8.7	20.9
s.d.	Yes	1 h 7 min	1 h 39 min	1.7	7.94
	No	0 h 48 min	1 h 39 min	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 h	4	1	Before 05:00 hours	8	3	Before 17:00 hours	14	5
	9–10 h	5	2	05:00–05:30 hours	5	2	17:00–19:00 hours	12	4
	10.5–12 h	22	8	06:00–06:30 hours	120	43	19:30–21:00 hours	145	51
	12.5–14 h	150	53	07:00–07:30 hours	99	35	21:30–23:00 hours	97	34
	14.5–16 h	84	30	08:00–08:30 hours	45	16	After 23:00 hours	14	5
	Over 16 h	17	6	After 08:30 hours	5	2			
No	Under 9 h	134	78	Before 05:00 hours	0	0			
	9–10 h	17	10	05:00–05:30 hours	0	0	Before 17:00 hours	132	77
	10.5–12 h	4	2	06:00–06:30 hours	5	3	17:00–19:00 hours	18	10
	12.5–14 h	15	9	07:00–07:30 hours	9	5	19:30–21:00 hours	14	8
	14.5–16 h	2	1	08:00–08:30 hours	151	87	21:30–21:00 hours	8	5
	Over 16 h	0	0	After 08:30 hours	9	5	After 23:00 hours	0	0

non-contributing covariates from all post-shift cognitive function models, while ME was identified as a significant contributor to model fit 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. trait mindfulness, age, and ME on PVT performance).

Interindividual variation

As shown in Tables S4–S6, 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 (s.d. = 0.07, 95% CI: [0.01, 0.14], $\chi^2(2) = 4.63$, $P < 0.05$), and subjective fatigue (s.d. = 0.02, 95% CI: [0, 0.05], $\chi^2(2) = 4.12$, $P < 0.05$), 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 8) revealed that the strength of association between shift duration and subjective fatigue was higher in individuals with low PA ($\beta_1 = 0.04$, $P < 0.05$)

compared to those with average ($\beta_1 = 0.02$, $P = 0.12$) or high PA ($\beta_{1j} = 0.003$, $P = 0.88$). The strength of association was also higher in individuals with meditation experience ($\beta_1 = 0.05$, $P < 0.005$) compared to those without meditation experience ($\beta_1 = -0.007$, $P = 0.77$). Morning-type individuals also showed higher strength of association ($\beta_1 = 0.03$, $P = 0.08$) compared to evening-type ($\beta_1 = 0.02$, $P = 0.12$) or neither-type ($\beta_1 = 0.01$, $P = 0.58$). Visual representations of each covariate's modulatory effects on the relationship between shift duration and subjective fatigue are shown in Fig. 4. No cross-level interactions were found to contribute to model fit for PVT lapses.

Final LME models representing the relationships between shift characteristics and post-shift cognitive function measures are shown in Eqns 4–6:

$$\begin{aligned} \text{Post RT}_{ij} = & \gamma_{00} + \gamma_{10}\text{Shift Duration}_{ij} + \gamma_{01}\text{Age}_j \\ & + \gamma_{02}\text{Mindfulness}_j + \gamma_{03}\text{MEQ}_j + \mu_{0j} + \varepsilon_{ij} \end{aligned} \quad (4)$$

$$\begin{aligned} \text{Post Lapses}_{ij} = & \gamma_{00} + \gamma_{10}\text{Shift Duration}_{ij} + \gamma_{01}\text{Age}_j \\ & + \gamma_{02}\text{MEQ}_j + \gamma_{03}\text{Mindfulness}_j + \mu_{0j} \\ & + \mu_{1j}\text{Shift Duration} + \varepsilon_{ij} \end{aligned} \quad (5)$$

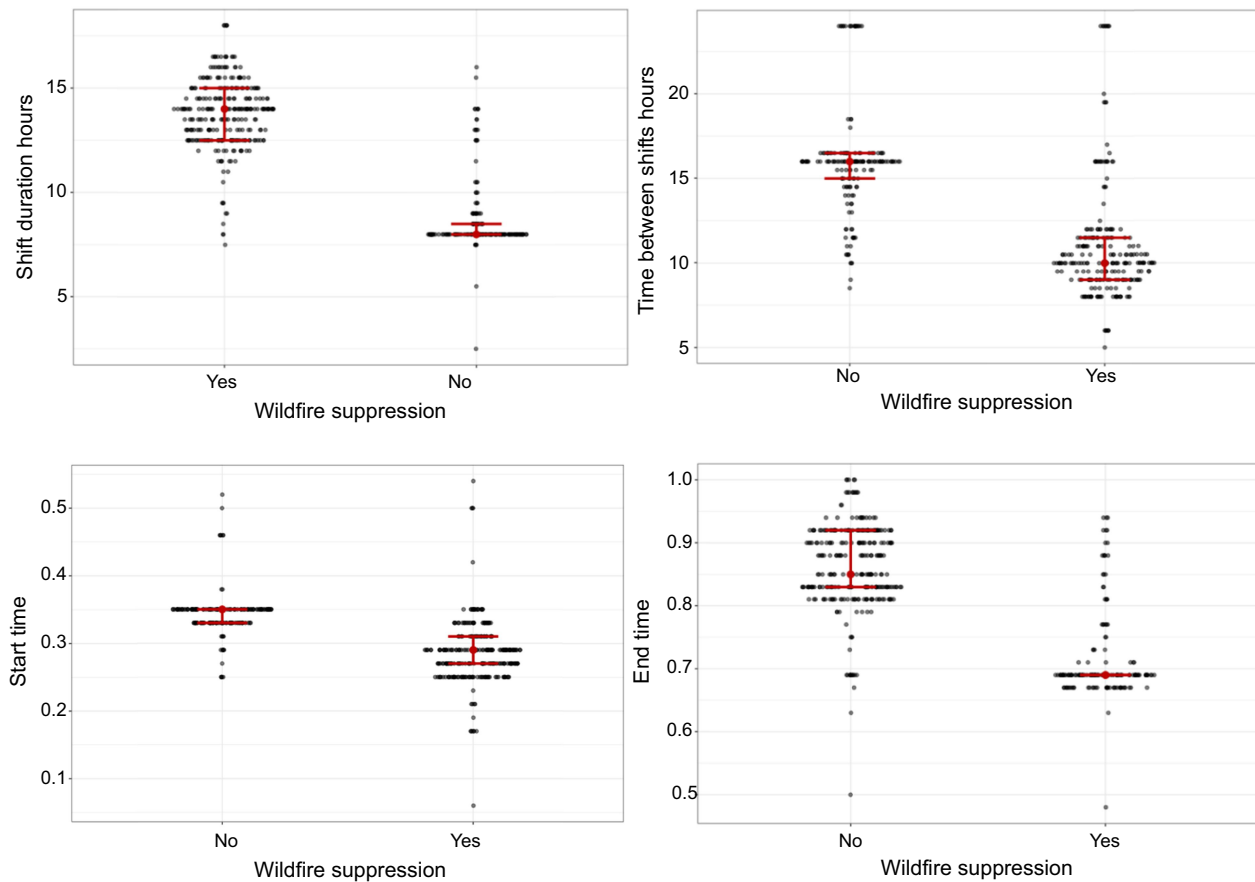


Fig. 3. Visual representation of shift information on fire suppression vs non-fire suppression days. Note: each black dot represents an individual observation. The red center dot shows the median value, while the upper and lower bars represent the 75th and 25th percentile values, respectively. Start and end times were converted to decimal numbers such that 0.3 corresponds to 07:12 hours and 0.8 corresponds to 19:12 hours. Each 0.1-unit increment represents a change of 2 h and 24 min. All figures were made using the Flexplot (Fife et al. 2021) module in Jamovi.

Table 6. Random intercept assessment criteria.

Measure	Intercept variance	ICC	AIC	LRT	P-value
Pre-shift					
Subjective fatigue	0.552	0.315	1468	110	<0.001
PVT response time	430	0.662	2399	234	<0.001
PVT lapses	0.439	0.549	692	180	<0.001
Post shift					
Subjective fatigue	0.772	0.359	1225	106	<0.001
PVT response time	566	0.556	2003	119	<0.001
PVT lapses	0.508	0.514	578	106	<0.001
Mean		0.49		142.5	
s.d.		0.13		53.01	

$$\begin{aligned}
 \text{Post Subjective Fatigue}_{ij} = & \gamma_{00} + \gamma_{10}\text{Shift Duration}_{ij} \\
 & + \gamma_{01}\text{Meditation}_j + \gamma_{02}\text{PA}_j \\
 & + \gamma_{03}\text{MEQ}_j \\
 & + \gamma_{11}(\text{Shift Duration}_{ij}) \\
 & \quad (\text{Meditation}_j) \\
 & + \gamma_{12}(\text{Shift Duration}_{ij})(\text{PA}_j) \\
 & + \gamma_{12}(\text{Shift Duration}_{ij})(\text{MEQ}_j) \\
 & + \mu_{0j} + \mu_{1j}\text{Shift Duration}_{ij} \\
 & + \varepsilon_{ij}
 \end{aligned} \quad (6)$$

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

Table 7. Covariates table.

Pre-shift models		Post-shift models	
PVT Lapses	γ (s.e.)	Subjective fatigue	γ (s.e.)
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)
		PVT Response Time	
		Age (γ_{01})	-3.91 (1.01)**
		FFMQ (γ_{02})	0.55 (0.20)*
		MEQ (γ_{03})	2.38 (0.37)***

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 s.e. [#] $P < 0.10$; * $P < 0.05$; ** $P < 0.01$; *** $P < 0.001$. Negative numbers indicate negative associations. Estimates are derived from covariate models only and therefore do not take random slopes or cross-level interactions into account.

Table 8. Simple effects analysis of cross level interactions for post-shift fatigue.

Simple effects of shift duration: parameter estimates			
Physical activity	Estimate	s.e.	P-value
Moderator levels			
Mean - 1-s.d.	0.041	0.02	0.025
Mean	0.022	0.01	0.119
Mean + 1-s.d.	0.003	0.02	0.882
Meditation			
Yes	0.051	0.01	0.002
No	-0.007	0.02	0.777
MEQ			
Mean - 1-s.d.	0.010	0.02	0.579
Mean	0.022	0.01	0.119
Mean + 1-s.d.	0.034	0.02	0.077

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

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 in Table 9 and Fig. 5.

Discussion

Our study is the first to examine fatigue-related cognitive impairment in wildland firefighters under naturalistic conditions while utilizing LME modeling to control for participant-level characteristics. Contrary to our null hypothesis, the main finding was that poor sleep and long shifts were both associated with impaired cognitive function, which has important implications for workplace health and safety.

Sleep and cognitive function

Results indicated poor sleep to be related to reduced cognitive function, which is congruent with previous literature. Extensive laboratory research has revealed that acute sleep loss of any duration impairs performance across most cognitive domains (Lim and Dinges 2010; Lowe *et al.* 2017), though deficits in attentional ability appear to be the most susceptible (Killgore 2010). Similarly, field-based studies in this domain have shown sleep loss to impair attentional ability across several occupational groups. For example, Ferguson *et al.* (2011) found that the miners with less than 6 h of sleep in the preceding 24 h exhibited slower RT on the PVT compared to those who had over 7 h of sleep. Similarly, Flynn-Evans *et al.* (2018) found sleep duration in pilots to be over 1 h 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 in 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 best of our knowledge, only three separate studies have measured sleep and PVT performance, concurrently, in the context of wildland firefighting (Ferguson *et al.* 2016; Smith *et al.* 2016; McGillis *et al.* 2017; Jeklin *et al.* 2020). In the same study cohort, Ferguson *et al.* (2016) and Smith *et al.* (2016) measured attentional ability across 3 days of simulated wildland firefighting. Their results showed that firefighters exposed to restricted sleep opportunities (i.e. 4 h per night) had slower response times on the PVT compared to the control condition (i.e. 8-h sleep opportunity). 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 initial attack deployments were associated with less total sleep time and slower PVT RT compared to project fire deployments and base work.

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

Shift characteristics and cognitive function

Our study also found prolonged shift durations to be related to reduced cognitive function. 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 (Patterson *et al.* 2018; Ferris *et al.* 2021; Leso *et al.* 2021).

Research on air medical clinicians has indicated no difference in cognitive function when comparing 12-h shifts to 18-h shifts (Thomas *et al.* 2006) or 24 h (Manacci *et al.* 1999; Guyette *et al.* 2013; Patterson *et al.* 2019) shifts. However, many of these 12-h shifts took place overnight (Thomas *et al.* 2006; Patterson *et al.* 2019), which may have exacerbated cognitive impairment due to sleep loss and circadian misalignment (Satterfield and Van Dongen 2013).

Similar findings have been found in other healthcare professions. Yi *et al.* (2013) found no significant differences

in PVT performance between physician residents working 24-h shifts vs 12-h night shifts. Rhéaume and Mullen (2018) found that nurses working 12-h shifts did not report more cognitive errors, despite obtaining worse sleep, compared to those working 8-h shifts. Conversely, Karanovic *et al.* (2009) and Osterode *et al.* (2018) both found lower cognitive function metrics in physicians working 24-h shifts compared to 7–8-h shifts. Leso *et al.* (2021) suggests that 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 attentional ability (Killgore 2010).

Evidence from outside the healthcare sector suggests shorter shift durations benefit cognitive function (Rosa and Bonnet 1993; Amendola *et al.* 2011; Bell *et al.* 2015), although null (Lowden *et al.* 1998), and unfavorable (Hossain *et al.* 2004) effects have also been reported. Amendola *et al.* (2011) found higher subjective sleepiness and reduced alertness after 12-h shifts compared to 8-h shifts, but no differences were found in PVT performance. Bell *et al.* (2015) found 10-h shifts preferable to 13.3-h shifts across nearly all cognitive function measures.

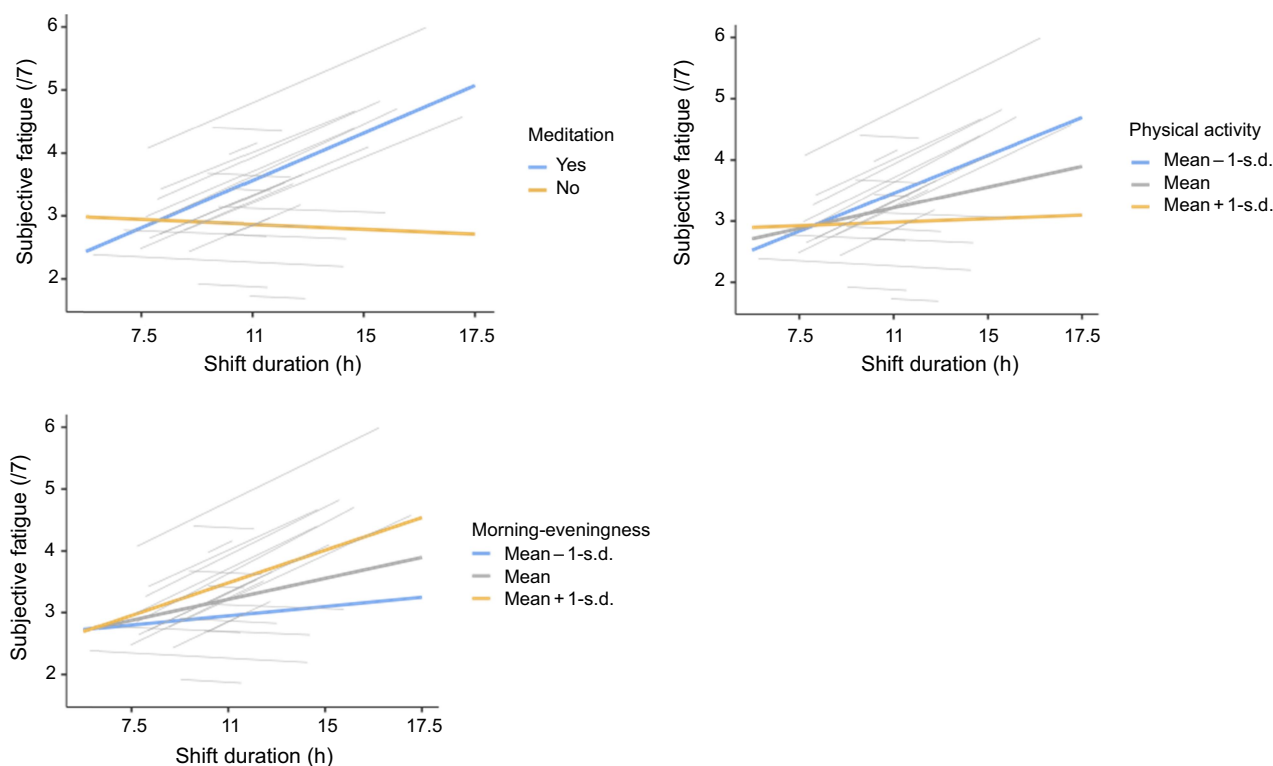


Fig. 4. Visual illustration of cross-level interactions for post-shift subjective fatigue. Note: solid colored lines represent fixed effects (across individuals); gray lines represent random effects (within individuals). Effects are estimated keeping other independent variables constant in the model.

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 to 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

Table 9. Simple effects analysis comparing pre vs post-shift effects of shift duration on each measure of cognitive function.

Measure of cognitive function	Moderator levels	Estimate	s.e.	P-value
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	<0.001
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.

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 our 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, they did find that initial attack deployments were associated with slower PVT RT compared to project fire deployments and base work. In the same study cohort, [Robertson et al. \(2017\)](#) found that initial attack deployments were also associated with longer shifts, which provides indirect evidence that extended shifts are related to worse cognitive function.

As shown in [Fig. 5](#), our 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](#)).

Thus, 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

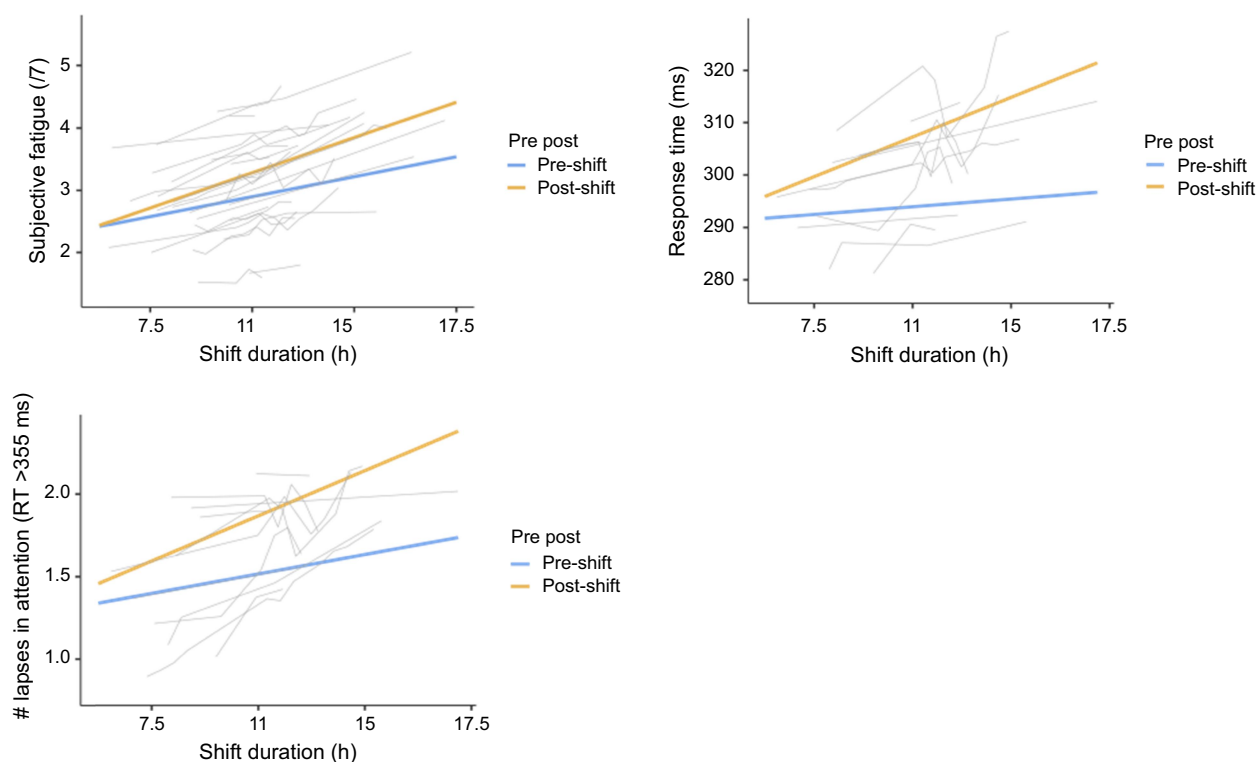


Fig. 5. Visual illustration of pre vs post-shift associations between shift duration and each measure of cognitive function. Note: solid colored lines represent fixed effects (across individuals); gray lines represent random effects (within individuals). Effects are estimated keeping other independent variables constant in the model.

evidence of a relationship between prolonged shift duration and impaired cognitive function in wildland firefighters.

Implications

The results of this study indicate clear relationships between sleep, shift characteristics and indices of cognitive function. These findings have important implications for worker 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 and 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 and Hursh 2010). This is especially true for workers engaged in high-risk activities, such as driving, wherein constant vigilant attention is required for getting home safely.

Importantly, we found that poor sleep and long shift durations were commonplace on fire suppression days. Firefighters in the current study obtained less than 7 h 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; García-Heras *et al.* 2025). Meanwhile, average fire suppression shifts were nearly 14 h in duration (13.8 ± 108 min), with nearly 90% being recorded as over 12 h. This is comparable to previously reported shift durations in BCWS management staff ($13.8 \text{ h} \pm 42$ min; Jeklin *et al.* 2021), but longer than previous studies on wildland firefighters in British Columbia, ($12.8 \text{ h} \pm 30$ min; Jeklin *et al.* 2020), Ontario ($12.5 \text{ h} \pm 59$ min; McGillis *et al.* 2017) and Australia ($11.5 \text{ h} \pm 180$ min; 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 impaired cognitive function concerning.

Study strengths and limitations

Strengths

To our knowledge, this was the first naturalistic study in wildland firefighters to: (1) employ completely remote methodology; and (2) use linear mixed effects (LME) modeling to examine fatigue-related cognitive impairment while controlling for participant-level characteristics. While previous studies (e.g. Rodríguez-Marroyo *et al.* 2011; Vincent *et al.* 2016) on

wildland firefighters have employed remote methodologies, they also included in-person components.

These novelties allowed us to extend previous research in important ways.

First, our completely remote methodology supported a multi-site recruitment strategy and a naturalistic collection period, both of which provided benefits to ecological validity. 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 British Columbia, our remote methods led to better real-world applicability compared to previous studies that were conducted under simulated firefighting conditions (Ferguson *et al.* 2016; Smith *et al.* 2016; Williams-Bell *et al.* 2017; Cvirn *et al.* 2019). 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 cognitive function are not masked in the operational environment.

Additionally, 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 fatigue, including age, biological sex, and physical activity habits (Shaffer and Ginsberg 2017; Thielmann *et al.* 2021). Similar to previous research (Van Dongen *et al.* 2004a), this data analytic approach revealed significant inter-individual variation and several participant-level covariates with respect to fatigue. Future investigations should consider using similar LME modeling methods to account for inter-individual differences. 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; McGillis *et al.* 2017), as well as accounting for factors 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 fatigue, which was similarly noted as a gap by Jeklin *et al.* (2020). Our novel findings support shift duration, in addition to sleep, as being an important controllable risk factor that should be considered when discussing the occupational health and safety related impacts of wildland firefighting. Findings from the current study thus make important contributions to the field of occupational health and safety for emergency service personnel.

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. These factors may have influenced the outcome variables to an unknown degree, which could have resulted in either under or over-estimation of the observed associations with sleep and shift characteristics. Similarly, several other contextual factors were not measured in the current study, despite having a known influence on cognitive function. These include acute exercise (Chang *et al.* 2012), dietary habits (Gupta *et al.* 2019), nicotine intake (Lawrence *et al.* 2002), habitual cannabis (Nicholls *et al.* 2015) and alcohol consumption (Bijl *et al.* 2005), and individual coping strategies like acute breathwork (Zaccaro *et al.* 2018) and meditation (Sumantry and Stewart 2021).

Further, the recruitment strategy included convenience sampling methods, which may have introduced bias, potentially affecting the generalizability of the findings. For example, participants in this study reported higher-than-average physical activity levels, which might have served as a protective factor against the impacts of impaired sleep and extended shifts. Future studies should consider incorporating stratified sampling methods into their recruitment strategy to improve representation across important demographic characteristics such as age, physical activity levels, biological sex, and years of firefighting experience.

Another limitation was that only vigilant attention was tested, despite other aspects of cognitive function being variably affected by sleep loss (Killgore 2010) and extended shift durations (Manacci *et al.* 1999; Lederer *et al.* 2006; Tadinac *et al.* 2014). Future research should explore other cognitive domains, including executive functions, to gain insight into consequential relationships for safety in firefighting, such as the between stress and decision-making (Useem *et al.* 2005).

Further, 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 PVT performance (Xu *et al.* 2021) is influenced by circadian patterns, this factor may have influenced associations involving shift duration results, independently of shift duration itself. Also, participants were not given instructions regarding the environment of PVT testing, which may have contributed to measurement noise.

Subjective sleep questions were completed on arrival at work rather than immediately upon waking, which may have introduced minor recall bias. Additionally, differences in collection frequency between subjective and objective sleep metrics prevented the inclusion of subjective sleep metrics in the primary analyses, potentially leading to underpowered models and underestimated pre-shift associations.

Another limitation was that data collection occurred from July to September during two high-hazard fire seasons, which prevented the establishment of true rested baselines. Participants likely began the study with some degree of accumulated fatigue, having already been employed and engaged in fire suppression activities for several months. Longitudinal studies measuring sleep, stress, and fatigue across an entire year, including pre- and post-fire season, are needed to better understand the long-term health impacts on wildland firefighters. The months from July to September also falls outside the typical planned burn season in British Columbia; accordingly, only one recorded shift in the dataset was classified as a planned burn.

The current study did not assess the impact of successive shifts on 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 health-care settings (Geiger-Brown *et al.* 2012; Haidarimoghadam *et al.* 2017; Goffeng *et al.* 2018; Jensen *et al.* 2022), research on these topics remains unexplored in wildland firefighters. Given the direct relevance to fatigue risk management planning, future studies should investigate the physiological and psychological consequence of these scenarios.

Lastly, the relatively small sample size and relatively high participant dropout rate (53%) may have impacted the study's statistical power. The lack of financial incentives and the demanding nature of the fire season likely contributed to this dropout. Future studies should consider providing financial incentives to improve participant retention and completeness of data collection.

Recommendations

Although preliminary, our findings point towards several actionable recommendations that have the potential to improve worker health and safety.

Similar to Jeklin (2019), our findings support the development, implementation, and continuous improvement and of practical and scientifically defensible fatigue risk management systems (FRMS). As described by Lerman *et al.* (2012), a 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 (Redeker et al. 2019; Crowther et al. 2021; Robbins et al. 2021), occupational stress (Bischoff et al. 2019), and long-term health (Neil-Sztramko et al. 2014; Barger et al. 2018). 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. These results suggest that physical fitness may serve as a protective factor against the negative cognitive-related consequences of prolonged shift durations.

With this in mind, we recommend that fire agencies should support new and ongoing 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. 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 on-going insights would bolster worker health and safety.

Conclusion

There is a pressing demand to better understand the cognitive-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 cognitive function in Canadian wildland firefighters. Uniquely, our completely remote methodology supported a multi-site recruitment strategy and naturalistic collection period, which benefited ecological validity. Our data analytic approach employed linear mixed effects modeling to account for inter-individual variation and participant-level characteristics that may differ with respect to cognitive function. Our results indicated that wildlands firefighters are often exposed to sub-optimal sleep and long shift durations. Importantly, both sub-optimal sleep and long shift durations were associated with impaired cognitive function, which has serious implications for worker health and safety. 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 in fire agencies by supporting the development, implementation, and continuous improvement of practical and scientifically defensible fatigue risk management systems.

Supplementary material

Supplementary material is available [online](#).

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Data availability. Data that form the results reported in this article are available upon reasonable request from the corresponding author.

Conflicts of interest. The authors declare no conflicts of interest.

Declaration of funding. This research did not receive any specific funding.

Acknowledgements. The authors thank the B.C. Wildfire Service Research and Innovation team, including Mike McCulley and Natasha Broznitsky, for their contribution to the design of the study protocol, as well as Marisa Harrington for their technical support with the use of the Polar monitors. Appreciation is also extended to all the BCWS staff who assisted during the recruitment phase, as well as all the participants who devoted their time to this study.

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