Exploring the Effects of Cognitive Load on Mental Fatigue Across the Lifespan: A Behavioral and Ocular Metrics Approach

Author Note

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Author contributions

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Abstract

Although mental fatigue is known to negatively impact performance, it remains unclear how cognitive resources interact with fatigue levels across the adult lifespan. Using a dual-task paradigm, we manipulated cognitive load (low vs. high) to induce varying levels of mental fatigue in young, middle-aged, and older adults. We assessed self-reported fatigue, sleepiness, and motivation pre- and post-task, while exploring task-related fluctuations in task accuracy and eye-metrics (pupil size, pupillary response speed, and long blinks). Younger adults reported higher subjective fatigue and had lower task performance than older adults did. There was no significant interaction effect between age and cognitive load condition on performance. Results indicated that pupil size and long blinks are useful indicators of cognitive load in younger and middle-aged adults but may be less reliable in older adults. These findings suggest exploring alternative measures to better capture cognitive and physiological responses to mental fatigue in older populations.

Keywords: mental fatigue, cognitive load, adult lifespan, eye-metrics

Mental fatigue is a prevalent issue in modern society, contributing to accidents in contexts such as driving (Akerstedt et al., 2005) and in the workplace (Sadeghniiat-Haghighi & Yazdi, 2015). Although it encompasses many definitions due to its complex multidimensional nature (Kluger et al., 2013), we opted to define mental fatigue as a normal transient psychophysiological state characterized by a subjective lack of mental energy experienced by people after prolonged or sustained cognitive activity, which can be attenuated by rest (Finsterer & Mahjoub, 2014; Jason et al., 2010). In contrast, pathological fatigue, observed in conditions such as multiple sclerosis or chronic fatigue syndrome, is more persistent and less responsive to rest (Jason et al., 2010).

Current Assessment Approaches

When assessing mental fatigue, it is important to distinguish it from other related states, such as sleepiness, boredom, lack of motivation, or depressive states, which may overlap with fatigue, mimic its associated performance impairments and enhance the subjective experience of fatigue (Kuppuswamy, 2017). Importantly, these constructs, though distinguishable, are interrelated and may serve as moderators in driving one another, even though their causal relationships remain not fully understood (Vermeylen et al., 2025). Sleepiness, for instance, is a physiological drive for sleep that can be measured objectively through indicators like EEG signals denoting the transition from wakefulness to sleep (Shen et al., 2006). In contrast, boredom is typically associated with reduced motivation and low engagement particularly in monotonous tasks (Pattyn et al., 2008), while depressive states are characterized by a lack of energy that extends beyond transient fatigue (Corfield et al., 2016). Lack of motivation in engaging in activities refers to a reduced valuation of goals or expected outcomes, further suggested to be influenced by fatigue (Müller & Apps, 2019). Furthermore, individual factors, including physical activity levels, overall health status, and the use of medications, may serve as moderators influencing the degree of mental fatigue experienced (van de Port et al., 2007). Therefore, these lifestyle and health-related factors should be carefully considered when addressing mental fatigue.

Mental fatigue is commonly assessed using subjective measures such as the Fatigue Severity Scale (FSS; Krupp et al., 1989) and visual analog scales (VAS; Lee et al., 1991). Nevertheless, fatigue can also manifest in an objective manner, evidenced by cognitive performance and efficiency declines (e.g., increased reaction times and errors) (Kluger et al., 2013) along with reduced task engagement, a phenomenon termed *fatigability* (Kluger et al., 2013). However, these performance parameters may also reflect motivational influences, such as monetary incentives (Esterman et al., 2014) or increased demotivation state (Read et al., 2026), which should therefore be controlled for in experimental designs.

Experimental induction of mental fatigue typically relies on prolonged task engagement (time-on-task paradigm) (Möckel et al., 2015) or manipulation of cognitive load, which refers to the mental resources required to perform a task (Biondi et al., 2023). Referring on the latter paradigm, the time-based resource sharing model (Barrouillet et al., 2004) provides a theoretical account of how cognitive load constraints working memory performance by limiting the time available for memory maintenance and retrieval processes. Building on this framework, Borragán et al. (2017) propose that mental fatigue and performance outcomes are directly influenced by the balance between cognitive demands and available resources. Specifically, reducing the available processing time for a cognitive task places greater demands on cognitive resources, leading to heightened fatigue and decreased accuracy.

Paradoxically, participants' subjective states correlate poorly with their cognitive performance decrement (Bailey et al., 2007). For example, performance decline can precede the onset of perceived fatigue (Zhang et al., 2011), and feelings of mental fatigue may not coincide with objective performance decrement (Muñoz-de-Escalona et al., 2020). Such disparities can be explained by compensatory processes put in place to counteract the effects of mental fatigue, allocating additional resources under high mental workload conditions to sustain task performance (Muñoz-de-Escalona et al., 2020). Based on these discrepancies, task performance and subjective fatigue measures are not sufficient to effectively assess mental fatigue.

Eye-Metrics as Fatigue Indicators

Consequently, psychophysiological techniques for evaluating fatigue have gained attention. Heart rate variability or EEG activity changes have been consistently associated with mental fatigue (Arnau et al., 2017), but ocular metrics are particularly promising (McLaughlin et al., 2023). This non-invasive approach holds advantages, as it captures a natural phenomenon influenced by the central nervous system, without requiring intentional manipulation. Notably, pupillometry provides indices of arousal and cognitive load, with larger pupil size under high cognitive load (van der Wel & van Steenbergen, 2018) and changes in pupillary dynamics in fatigued states, which can be indicative of task engagement and sleepiness (Bafna & Hansen, 2021).

Interestingly, the dynamic measures of pupil, in opposition as the static ones such as its size, appear to exhibit heightened responsiveness to fatigue compared to static ones (Bafna & Hansen, 2021) and are less influenced by individual differences, including aging, unlike pupil size, which decreases with age (Lazar et al., 2024). However, existing research has predominantly concentrated on pathological cohorts, including multiple sclerosis fatigued patients, who display disruptions in pupillary response (Guillemin et al., 2022). This insufficiency underscores the motivation of our study to better understand the links between pupillary response speed and fatigue in healthy individuals across the adult lifespan.

Blink metrics constitute another relevant indicator of assessing mental fatigue (Martins & Carvalho, 2015). Blink frequency and duration have been widely used to monitor fatigue and alertness, especially in driving and flying simulation experiments (e.g., Hu & Lodewijks, 2021). The frequency of eye blinks not only serves as a measure of fatigue; it also reflects a dynamic measure of cognitive load and cognitive processes and corresponds to adaptation in response to task complexity. However, findings regarding cognitive load and blinking are mixed, as high cognitive load has been associated with both reduced (Zheng et al., 2012) and increased (Tsai et al., 2007) blink frequency and duration. Within the temporal scope of cognitive tasks, eye blink frequency may evolve, showing an increasing frequency pattern as tasks progress and fatigue/sleepiness ensues (Tsai et al., 2007). Finally, long-duration eye-blinks (i.e., over 300ms) are also considered as relatively good markers of sleepiness, and are less affected by inter-individual variations observed in regular blinking (Schleicher et al., 2008).

Aging and Mental Fatigue

A critical gap in literature concerns the influence of aging on mental fatigue and its measurements and their effectiveness across age groups. For instance, pupillometry might not be as effective to assess fatigue in older adults due to age-related changes in pupil responsiveness, which could affect both the accuracy and the reliability of this method. Additionally, while some studies have recognized fatigue's broader impact on the older population, positioning it as a potential marker of frailty (e.g., Cohen et al., 2021), these studies have either not specifically addressed the phenomena of mental fatigue or have exclusively relied on subjective reported measures.

Cognitive aging models postulate reductions in processing speed and available cognitive resources with aging (Collette & Salmon, 2014; Salthouse & Babcock, 1991), which could increase susceptibility to fatigue under demanding conditions. This way, older adults may experience greater difficulty than younger adults when performing tasks with identical cognitive demands, potentially leading to higher fatigue. Yet, empirical findings are inconsistent. Some studies report greater extreme reaction times (i.e., delay in reaction times) in younger (Gilsoul et al., 2021) or middled-aged adults (Gilsoul et al., 2024) and worst performance decline with time-on-task in young adults (Samuel et al., 2019), whereas older adults often maintain stable performance, possibly reflecting strategic adjustments such as speed-accuracy trade-off or higher task motivation. These findings suggest a non-linear relationship between age and mental fatigue, with younger and middle-aged adults sometimes showing greater susceptibility than older adults, despite age-related declines in cognitive resources. This pattern may reflect higher resistance to monotony and greater task motivation in older individuals (Arnau et al., 2017). Additionally, age differences in performance may be partly explained by strategic variations, particularly a speed-accuracy trade-off: younger adults tend to prioritize speed, whereas older adults adopt a more error-aversive approach, leading to slower but more stable performance under fatigue (Salthouse & Babcock, 1991).

Aims and Hypotheses

The present study examines the differential impact of cognitive load on mental fatigue across young, middle-aged, and older individuals. Using an adaptative dual-task paradigm (Time Load Dual Back task) to equate task difficulty across individuals by tailoring stimulus presentation times, we manipulated cognitive load to induce varying fatigue levels. Subjective fatigue, sleepiness, and motivation were acquired pre- and post-task, alongside behavioral performance. In parallel, we recorded pupil size, pupillary response speed, and blink rate to evaluate ocular metrics as objective markers of fatigue across adulthood. Thus, our study is not restricted to the behavioral and subjective consequences of mental fatigue induction but also assesses the physiological changes inherent to the onset of mental fatigue.

We hypothesized that the higher cognitive load would elicit greater performance decline and increased subjective fatigue, with older adults, followed by middle-aged adults, showing larger decrements over time relative to younger adults. We further expected larger pupil size under high cognitive load and increased blink rate under low-load, as sleepiness may arise from the monotonous nature of the task. However, given the known effects of aging on ocular physiology, the examination of ocular metrics across age groups was considered exploratory.

Method

Participants

Participants were recruited via social media and through a database of healthy volunteers available at GIGA-CRC Human Imaging. The present study was conducted after approval of the Ethical Committee of the Faculty of Psychology, Speech Therapy and

Educational Science of Liège University. All participants provided informed consent. No financial compensation was provided.

A total of 108 individuals underwent initial screening for eligibility between February 2019 and May 2022. Inclusion criteria were aged between 18 and 75 years and being a native French-speaker. Exclusion criteria included history of head injury, neurological or psychiatric disease, substance abuse or use of medication likely to affect the central nervous system functioning, cognition, or fatigue (i.e., antidepressants, anxiolytics, anticholinergics).

Eighty-seven participants met eligibility criteria and completed the study (see **Figure A1** in Supplemental Data for flowchart). Participants were categorized into three age groups: young (N = 43), middle-aged (N = 25) and older adults (N = 19). For eye-metrics analyses, a subset of 65 participants was retained based on signal quality criteria (young = 30, middle-aged = 18 and older adults = 17). Demographic characteristics of the whole sample and subsample are presented in **Table 1**.

The recommend total sample size was approximately 100 participants for regression models including seven predictors (group, condition, time, and their interactions) and assuming a medium effect size (f^2 = .15), α = .05, and 80% power. Due to recruitment constraints during the COVID-19 pandemic, particularly affecting older adults, the final sample comprised 87 participants. Therefore, a post-hoc sensitivity power analysis was performed using G°Power 3.1.9.7, revealing that the study was powered (1 – β = .80, α = .05) to detect effects of f^2 = .18 or larger, corresponding to a medium effect size.

Table 1

Sociodemographic Characteristics of the Participants

	Full sample (N = 87)			**Eye-metrics subsample (N = 65)**		
	Young (N = 43)	**Middle-aged**	**Older (N = 19)**	**Young (N = 30)**	**Middle-aged**	**Older (N = 17)**

	(*N* = 25)			**(*N* = 18)**		
Age, *years*	22.70 (2.81) [18 – 29]	53.60 (6.37) [40 – 60]	66.53 (3.92) [61 – 74]	22.40 (2.91) [18 – 29]	51.06 (6.20) [40 – 59]	65.77 (3.72) [61 – 72]
Woman, *n (%)*	32 (74.42)	18 (72.00)	14 (73.68)	21 (70.00)	13 (72.22)	13 (76.47)
Educational level, *years*	13.12 (2.13) [6 – 18]	15.12 (1.90) [11 – 18]	15.05 (1.62) [12 – 18]	12.60 (2.06) [6 – 18]	15.06 (2.04) [11 – 17]	15.06 (1.60) [12 – 18]

Note. Values are presented as mean (standard deviation) [range].

Study Design

This study used a counterbalanced within-subjects design with cognitive load (low, LCL vs. high, HCL) as a repeated-measures factor and age group (young, middle-aged, older adults) as a between-subjects factor. Participants completed three sessions scheduled one week apart (**see Figure 1** for a complete overview of the experimental procedure). The primary dependent variables were subjective fatigue, behavioral performance, and ocular metrics.

Materials and Measures

Cognitive Screening Measures

During the first session, participants underwent cognitive screening to ensure the absence of significant impairment. Measures included verbal working memory (digit span, Wechsler, 2011), alertness (TAP, Zimmermann & Fimm, 2002), and crystallized intelligence (Mill Hill, Raven & Deltour, 2007). Participants over 60 years of age additionally completed the Mattis Dementia Rating Scale (Mattis, 1976).

Questionnaires

Participants filled-in trait questionnaires that could influence the level of fatigue, namely depressive symptoms (CES-DS; Radloff, 1977), sleep quality (PSQI; Buysse et al., 1989), and sleepiness (ESS; Johns, 1991), along with demographic information.

Fatigue Induction Task: The Time Load Dual Back (TLDB)

Mental fatigue was induced using the Time Load Dual Back task (TLDB, Borragán et al., 2016), a computerized-dual task combining in parity judgments for digits and a 1-back task for letters. Stimuli were presented alternatively in a white font on a black background. Participants responded to digits using the numeric keypad (even vs. odd) and to letters by pressing the space bar when identical to the preceding letter. They were instructed to respond as quickly and accurately as possible throughout the task. The task lasted 32 minutes and was divided into four 8-minute blocks. The first 60 items considered as practice trials were excluded from analyses.

Cognitive load was manipulated by adjusting stimulus presentation time. In the high cognitive load (HCL), stimuli were presented at each participant's maximum speed allowing 85% accuracy. In the low cognitive load (LCL), presentation speed was reduced by 50%.

Individual maximum speed was determined during training and recalibrated before each experimental session. Mean stimulus duration was 1.33 s in LCL and 0.89 s in HCL, with no significant age-group differences.

Subjective Measure of Fatigue Using Self-Reported Scales

All subjective measures were administered immediately before and after completion of the TLDB task in each session. Participants rated fatigue and motivation using visual analog scales (VAS). Each VAS consisted of a 10-cm horizontal continuum displayed on a screen, ranging from 0 to 100. The participants were asked to move the cursor to the modality that best reflected their current subjective state. All questions were displayed above the corresponding scale on the screen. Instructions emphasized that ratings should reflect the participant's current state ("at this moment") and were delivered orally before the experiment and were identical across sessions.

For fatigue state, participants were asked *"How fatigued do you feel at this moment?"* The left anchor (0) was labeled "*feeling fresh*" and the right anchor (100) "*feeling exhausted*".

For motivation, participants were asked *"How motivated are you to continue the experiment right now?"*. The scale ranged from 0 "*demotivated*" to 100 "*motivated*", with midpoint representing a state of being neither motivated nor demotivated. Sleepiness was measured using the Karolinska Sleepiness Scale (KSS; Shahid et al., 2012), ranging from 1 "*not sleepy at all*", to 9 "*very sleepy*".

Physiological Measure of Fatigue Using Eye-Metrics

Ocular activity was recorded during the TLDB using the Drowsimeter R100 (Phasya©, Belgium), sampling the right eye at 120 Hz. Each recording was approximately 32 minutes long (equivalent to the duration of the TLDB task) and represented a time series of 230k points.

Signals were visually inspected for quality. Recordings containing excessive artefacts (e.g., signal loss, spikes) were excluded. Pupil size was smoothed using a 4^{th}-order low-pass Butterworth filter (4 Hz cutoff). Mean pupil speed (in pixels/ms) was computed as the first-order difference across 100-ms bins and separated into constriction and dilation phases. Blink frequency and duration were extracted, and blinks exceeding 300 ms were categorized as long blinks. Even though no official threshold exists in categorizing blinks, average time of blinks in the general population is around 100-400ms, with duration over 500ms considered to be microsleep (Kwon et al., 2013).

Testing occurred in a controlled environment (21°C; 50 lux) to minimize environmental effects on ocular measures (Piccoli, 2003).

Procedure

Participants completed three sessions approximately one week apart, as described in **Figure 1**.

During session 1, participants provided informed consent, completed cognitive screening and trait questionnaires, and underwent a 30-minute TLDB training. To minimize expectancy effects, the study was presented as investigating cognitive functioning; the focus on mental fatigue was disclosed only after study completion.

Sessions 2 and 3 involved the administration of the TLDB under either low (LCL) or high (HCL) cognitive load, with the order of the conditions counterbalanced across participants. Before and after the task, participants completed VAS ratings of fatigue and motivation and the KSS. Eye-metrics were recorded continuously during task performance.

Participants were instructed to maintain a stable sleep-wake schedule and avoid excessive caffeine consumptions before sessions. Compliance was monitored using a fatigue diary completed throughout the study period.

Figure 1

Overview of the Experimental Procedure

Session 1	• Informed consent • Global cognitive assessment • Questionnaires on demographics, mood, sleep quality, and sleepiness • Training on the fatigue-induction task (Time Load Dual Back, TLDB)
Sessions 2 & 3 *(counterbalanced according to cognitive load)*	• TLDB task for 32-min under one of the two cognitive load conditions: low (LCL) or high (HCL) • Measures of subjective fatigue, motivation and sleepiness pre- and post-task • Recording of eye-metrics throughout the task

Note. Overview of the experimental procedure. On session 1, participants were administered a global cognitive assessment (including measures of verbal working memory, alertness and crystallized intelligence) along with trait questionnaires (CES-DS, PSQI and ESS). The session ended with training for the fatigue-induction task (TLDB). On sessions 2 and 3, participants performed the TLDB task under either low (LCL) or high (HCL) condition (counterbalanced). Measures of subjective fatigue, motivation, and sleepiness were recorded before and after the task. Eye-metrics were continuously recorded throughout the task.

Alt-text: *Overview of the experimental procedure. On session 1, participants were administered informed consent, global cognitive assessment, questionnaires on demographics, mood, sleep quality, and sleepiness; and a training of the fatigue-induction task (TLDB). On sessions 2 and 3, participants performed the TLDB task under either low (LCL) or high (HCL) condition (counterbalanced). Measures of subjective fatigue, motivation, and sleepiness were recorded before and after the task. Eye-metrics were continuously recorded throughout the task.*

Statistical Analyses

Data analyses were performed on *RStudio* (Version 2023.03.0).

Population Characterization Analyses

Group differences in demographic and questionnaire variables were assessed using ANOVAs. Normality was evaluated via Q-Q plots and Shapiro-Wilk tests. When necessary, transformations were applied using the *bestNormalize* package (Peterson, 2021).

Main Analyses

Linear Mixed-Effects Models (LMEMs) were used to assess the effects of Condition [LCL vs. HCL], Time [Pre vs. Post-task or Block 1 to 4], and Group [Young, Middle-aged, Older adults] and their interactions on subjective, behavioral, and ocular outcomes using the *lme4* package (Bates et al., 2015). Subject was included as random intercept. The operationalization of Time differed depending on the outcome measure. For subjective state measures (fatigue, motivation, sleepiness), Time referred to the pre- versus post-task assessments. For behavioral performance and pupil metrics, Time reflected time-on-task and was operationalized as the four consecutive task blocks (Block 1–4).

More precisely, the model was specified as follows, using accuracy as an example:

$$Accuracy = \beta_0 + \beta_1\, Condition + \beta_2\, Time + \beta_3\, Group + \beta_4\, Condition{:}Time$$
$$+ \beta_5\, Condition{:}Group + \beta_6\, Time{:}Group + \varepsilon$$

For subjective states, LMEMs were employed separately on scores from KSS for sleepiness and scores from VAS for fatigue and motivation. For TLDB performance, separate models were conducted for letters and digits, with mean accuracy analyzed across four 8-minute blocks. Mean accuracy represented the proportion of correctly answered items (hit rate), specifically, correctly identified letters matching the previous one and accurate digits parity judgments. For ocular metrics, long-blink rate, pupil size, pupil constriction and dilation speeds were analyzed using comparable LMEM structures.

Post-hoc analyses were conducted to examine pairwise differences between levels of predictor variables, with *p*-values adjusted for multiple comparisons using the false discovery rate (FDR) method. Moreover, contrasts were established using the *emmeans* package, comparing the condition effect within each group in order to observe age-related specific effects of the cognitive load manipulation. For interactions, only comparisons of interest were examined, such as differences between the three groups within the same condition or differences within a group across two conditions. Partial eta-squared effect sizes were estimated based on the variance explained by each factor of the model.

Missing Data Management

Missing observations were noted across several assessments. Missing scores were not manually imputed as LMEM models are robust in handling missing values (Brown, 2021). The distribution of missing data across assessment periods and cognitive load conditions is as follows: subjective fatigue (N = 8), motivation (N = 8), sleepiness (N = 13), TLDB performance (missing due to technical issue: 4 Young, 1 Middle-aged, 1 Older adults; excluded for pressing incorrect keys: 2 Young, 1 Middle-aged, 2 Older adults), eye-metrics (excluded for not meeting quality standards: 13 Young, 7 Middle-aged, 2 Older adults).

Results

Questionnaires

Descriptive statistics for the questionnaires are presented in **Table 2**. Differences between groups at these questionnaires were assessed with ANOVA.

Depressive Mood. Scores at the CES-DS (Radloff, 1977) showed a significant difference between groups [$F(2,84) = 8.60$, $p < .001$, $\eta^2 = .17$], with post-hoc analysis revealing that young people have higher depressive scores than the older adult group [$t(84) = 4.06$, $p < .001$, $d = -1.20$]. More specifically, 16 young adults (37%) scored above the cutoff for depressive symptomatology (≥16), compared to 2 middle-aged adults (12%) and 1 older adult (10.5%).

Sleep Quality. A significant difference between groups was also observed at the PSQI (Buysse et al., 1989) [F(2,84) = 7.68, p < .001, η^2 = .16], with the older adult group facing more sleep disturbances than young [t(84) = - 3.71, p = .001, d = 1.03] and middle-aged people [t(84) = - 3.31, p = .004, d = -1.01]. Fourteen older participants (74%) scored above the cutoff score for sleep disturbances (>5), compared to 7 middle-aged adults (28%) and 11 young adults (26%).

Sleepiness. No difference was observed between groups at the ESS (Johns, 1991) [F(2,84) = 0.33, p = .72, η^2 = .01].

Table 2

Scores Obtained at the Questionnaires

	Young (N = 43)	**Middle-aged** (N = 25)	**Older** (N = 19)	$\boldsymbol{F}$(2,84)	$\boldsymbol{p}$	$\boldsymbol{\eta^2}$
Depression[1] [0 – 60]	14.30 (6.91) [5 – 37]	11.00 (5.17) [0 – 21]	7.47 (5.17) [0 – 20]	8.60	<.001	.17
Sleep quality[2] [0 – 21]	4.78 (3.85) [1 – 9]	4.80 (1.73) [2 – 10]	6.90 (2.92) [2 – 12]	7.68	<.001	.16
Sleepiness[3] [0 – 24]	8.40 (2.40) [3 – 15]	8.00 (4.20) [0 – 15]	7.68 (3.76) [0 – 19]	0.330	.72	.008

Note. Values are presented as mean (standard deviation) [range]. [1]Depressive mood from CES-DS (Radloff, 1977); [2]Sleep quality from PSQI (Buysse et al., 1989); [3]Sleepiness from ESS (Johns, 1991).

Subjective Level: Scores on Visual Analog Scales

Figure 2 displays the scores obtained at the visual analog scales, while **Table 3** provides an overview of the analysis findings.

Fatigue. LMEM analysis on the subjective level of fatigue revealed an effect of time [F(1,244.31) = 40.24, p < .001, η^2 = .77] and group (F(2,84.03) = 5.32, p = .007, η^2 = .10]. Participants were statistically more tired after the TLDB task than before [t(244) = -6.34, p <

.001]. Post-hoc analyses revealed that the older adult group was feeling less tired than the young [$t(84) = 3.25$, $p = .005$] and middle-aged groups [$t(84.2) = 2.21$, $p = .045$]. No effects of the condition or interaction were found.

Sleepiness. Concerning the sleepiness score assessed using KSS, LMEM analysis showed an effect of time [$F(1,240.15) = 30.36$, $p < .001$, $\eta^2 = .58$], group [$F(2,84.13) = 9.57$, $p < .001$, $\eta^2 = .18$], along with a condition*time interaction [$F(1,240.13) = 7.29$, $p = .007$, $\eta^2 = .14$]. Regarding main effects, participants felt sleepier after the task than before [$t(240) = -0.43$, $p < .001$], and older group indicated less sleepiness than the younger [$t(84.8) = 0.83$, $p < .001$], and middle-aged groups [$t(84.4) = 0.80$, $p < .001$]. Post-hoc comparisons on the interaction effect showed that the time effect was present only within the HCL condition and that sleepiness was higher post-task in the HCL condition than in the LCL.

Motivation. Concerning motivation level, LMEM analysis revealed a significant effect of time [$F(1,244.25) = 44.28$, $p < .001$, $\eta^2 = .78$] and group [$F(2,84.04) = 8.14$, $p < .001$, $\eta^2 = .14$]. Post-hoc analyses highlighted that participants felt less motivated after the task than before [$t(244) = -6.34$, $p < .001$], and that young people felt less motivated than the middle-aged [$t(84) = 2.25$, $p = .04$] and older [$t(84) = 3.91$, $p = .006$] groups. No condition or group * condition interaction effects were found.

Table 3

Linear Mixed-Effects Models on Visual Analog Scales

A. Fatigue

Predictor	*F*	*Df*	*Df res*	*p*	η^2
(Intercept)	0.89	1	84.06	.35	.02
Condition	2.31	1	247.39	.13	.04
Time	40.24	1	244.31	<.001	.77
Group	5.32	2	84.03	.007	.10
Condition:Time	1.00	1	244.31	.32	.02
Condition:Group	1.96	2	247.29	.14	.04
Time:Group	0.56	2	244.33	.57	.01
Condition:Time:Group	0.11	2	244.33	.90	.002

B. Sleepiness

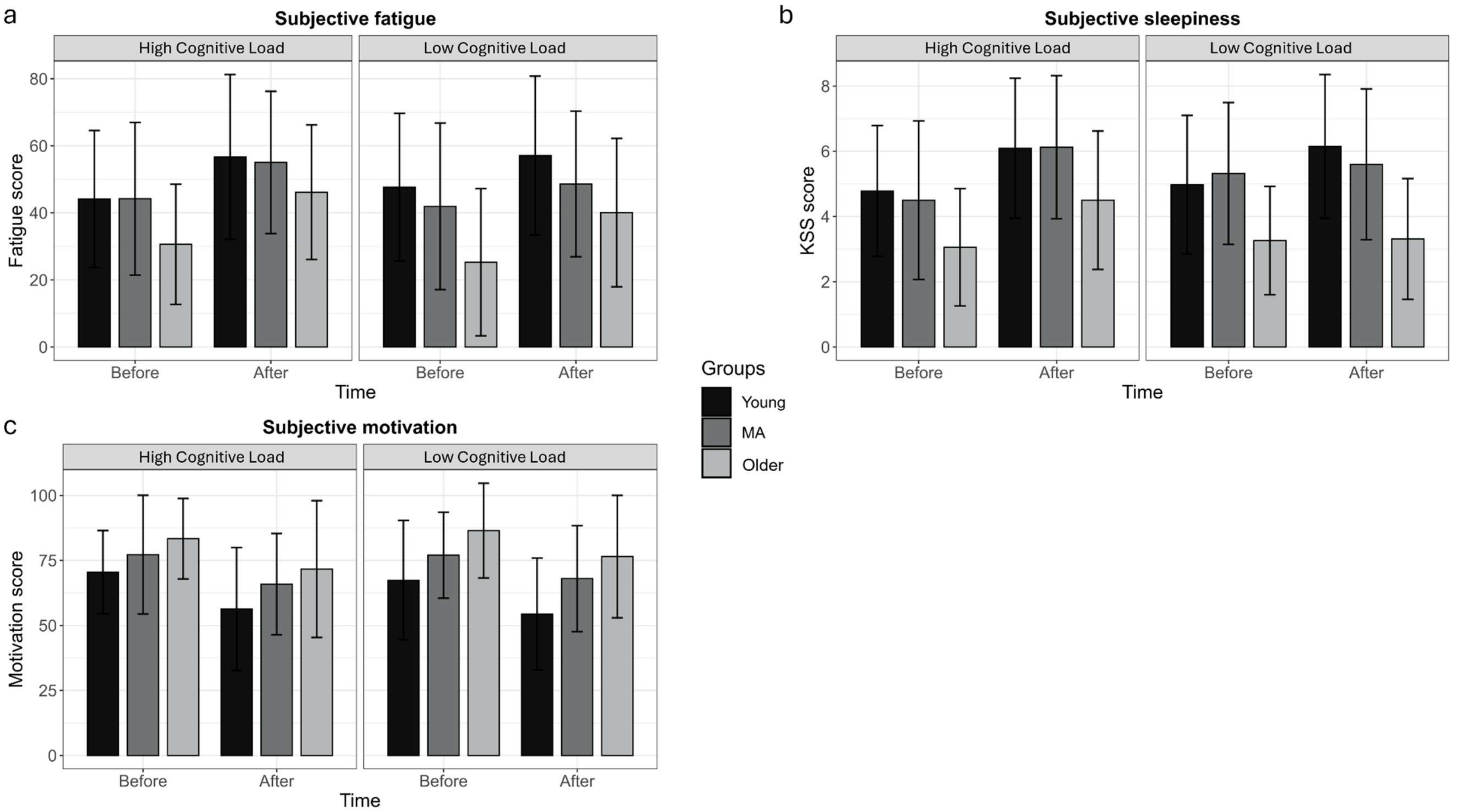
Predictor	*F*	*Df*	*Df res*	*p*	*η*²
(Intercept)	1.39	1	84.24	.24	.03
Condition	0.37	1	243.55	.54	.007
Time	30.36	1	240.15	<.001	.58
Group	9.57	2	84.13	<.001	.18
Condition:Time	7.29	1	240.13	.007	.14
Condition:Group	1.15	2	243.28	.32	.02
Time:Group	0.62	2	240.08	.54	.01
Condition:Time:Group	1.46	2	240.04	.23	.03

C. Motivation

Predictor	*F*	*Df*	*Df res*	*p*	*η*²
(Intercept)	1.79	1	84.07	.18	.03
Condition	0.41	1	246.98	.52	.007
Time	44.28	1	244.25	<.001	.78
Group	8.14	2	84.04	<.001	.14
Condition:Time	0.17	1	244.25	.68	.003
Condition:Group	1.20	2	246.89	.30	.02
Time:Group	0.01	2	244.27	.99	.0002
Condition:Time:Group	0.45	2	244.27	.64	.008

Figure 2

Scores Obtained at the Visual Analog Scales



Note. Raw data from fatigue and motivation VAS have been rescaled from 0 to 100 for visualization purpose.
a. Subjective fatigue; **b.** Subjective sleepiness; **c.** Subjective motivation.

Descriptive caption: Plot A. *Bar graph showing an increase in subjective fatigue scores from before to after, irrespective of age groups (young, middle-aged, older adults) and conditions (HCL, LCL).* ***Plot B.*** *Bar graph depicting subjective sleepiness (KSS score) increasing over time, stratified by age groups and conditions (HCL, LCL).* ***Plot C.*** *Bar graph by age groups and conditions (HCL, LCL) illustrating a decrease in subjective motivation scores from before to after.*

Behavioral Level: Performance during TLDB

Figure 3 displays the behavioral performance at the Time Load Dual back and **Table 4** presents the summary of the analyses on performance indices. Within the text, only results from post-hoc comparisons of interest will be detailed.

Mean Accuracy. Separate LMEMs analyses showed a main effect of condition for letters [$F(1, 565.51) = 619.76$, $p < .001$, $\eta^2 = .95$] and digits [$F(1, 556.87) = 821.50$, $p <.001$, $\eta^2 = .97$], with a lower accuracy rate in HCL than LCL condition. Analysis on mean accuracy for letters [$F(3, 560.04) = 21.11$, $p < .001$, $\eta^2 = .03$] and digits [$F(3, 544.10) = 15.06$, $p < .001$, $\eta^2 = .18$] also showed a main effect of block, with accuracy in block 1 being statistically higher than in the three latter blocks for both letters and digits, and block 2 having a better accuracy compared to block 4 for digits only (post-hoc comparisons). Finally, analysis revealed a group effect for both letters [$F(2, 83.72) = 7.58$, $p < .001$, $\eta^2 = .01$] and digits [$F(2, 83.81) = 6.50$, $p = .002$, $\eta^2 = .008$], with post-hoc comparisons indicating a lower accuracy for the young group compared to middle-aged and older groups. However, no interaction was found in this model.

Table 4

Linear Mixed-Effects Models on Performance at the Time Load Dual Back

A. Mean Accuracy on Letters

Predictor	***F***	***Df***	***Df res***	***p***	***η²***
(Intercept)	0.45	1	83.68	0.51	<.001
Condition	619.76	1	565.51	<.001	.95
Block	21.11	3	560.04	<.001	.03
Group	7.58	2	83.72	<.001	.01
Condition:Block	2.06	3	560.04	.10	.003
Condition:Group	0.12	2	565.83	.89	<.001
Block:Group	0.56	6	560.04	.80	<.001
Condition:Block:Group	0.79	6	560.04	.58	.001

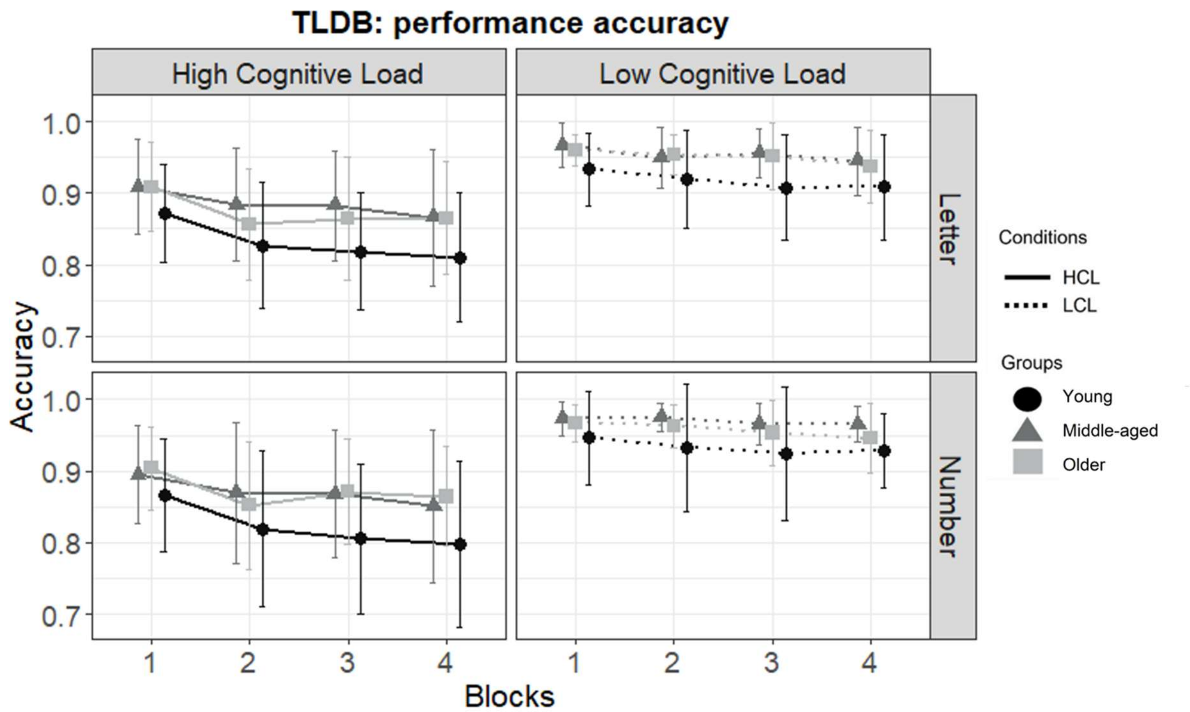
B. Mean Accuracy on Digits

Predictor	***F***	***Df***	***Df res***	***p***	***η²***

(Intercept)	0.74	1	83.80	.39	<.001
Condition	821.50	1	556.87	<.001	.97
Block	15.06	3	544.10	<.001	.18
Group	6.50	2	83.81	.002	.008
Condition:Block	2.31	3	544.10	.06	.003
Condition:Group	1.73	2	556.85	.18	.002
Block:Group	0.68	6	544.10	.66	<.001
Condition:Block:Group	0.37	6	544.10	.90	<.001

Figure 3

Scores Obtained at the Time Load Dual Back



Note. HCL, High Cognitive Load; LCL, Low Cognitive Load.

Descriptive caption: Plot. Line graph showing accuracy across four time-blocks for letter and number items, stratified by age groups (young, middle-aged, older adults) and conditions (HCL, LCL).

Physiological Level: Eye-Metrics during the Cognitive Task

Figure 4 shows the eye-metrics evolutions during the cognitive task, while **Table 5** displays the summary of the analyses on eye-metrics.

Pupil Size. LMEM analysis on the pupil diameter indicated a significant effect of group [F(2, 58.88) = 11.18, p < .001, η^2 = .39], condition [F(1, 297.58) = 10.09, p = .002, η^2 = .035] and a condition*group interaction [F(2, 291.71) = 5.87, p = .003, η^2 = .20]. More precisely, the pupil sizes were larger in the HCL condition compared to the LCL [t(298) = 3.18, p = .002]. Younger participants had a larger pupil size than middle-aged [t(59.3) = 3.29, p = .003] and older participants [t(58.4) = 4.39, p < .001]. Post-hoc comparisons on the condition*group interaction demonstrated that the pupil size was larger in the HCL condition compared to LCL in young and middle-aged, but not in older adults.

Pupil Dilation Speed. LMEM analysis on the pupil dilation speed mean showed a significant effect of group [F(2, 58.79) = 5.44, p = .007, η^2 = .30], as well as a group*condition interaction [F(2, 304.57) = 10.73, p < .001, η^2 = .58]. Post-hoc comparisons revealed that the older group had a slower dilation speed than the young group [t(57.8) = 3.27, p = .006]. Moreover, the pupil dilation speed of the older group under HCL condition was statistically slower compared to their speed under LCL, while middle-aged had faster dilation speed in HCL compared to LCL.

Pupil Constriction Speed. LMEM analysis on the pupil constriction speed mean revealed a significant effect of group [F(2, 58.77) = 4.35, p = .02, η^2 = .22], as well as a group*condition interaction [F(2, 304.22) = 10.63, p < .001, η^2 = .54]. Post-hoc comparisons showed that the older group had a slower constriction speed than the young group [t(57.8) = 2.92, p = .01]. For the group*condition interaction, similar results were observed than dilation speed. The pupil constriction speed of the older group under HCL condition was statistically slower compared to their speed under LCL. Conversely, the middle-aged group had a slower constriction speed in LCL than HCL.

Long Blink Rate. LMEM analysis revealed an effect of condition [F(1, 319.15) = 40.91, p < .001, η^2 = .61], with more long blinks recorded in the LCL condition than the HCL (t(319) = -6.40, p < .001). A block effect was also found [F(3, 275.86) = 4.05, p = 008, η^2 = .06]. Post-hoc comparisons showed that block 1 had a significantly smaller quantity of blinks than block 4 (t(276) = -2.93, p = .01), and block 2 followed the same tendency with block 4 (t(276) = -2.98,

$p < .01$). A group effect [$F(2, 58.72) = 4.63$, $p = .01$, $\eta^2 = .07$] was also revealed, with younger people having more long blinks than the older group ($t(57.6) = 3.00$, $p = .012$). Finally, a condition*group interaction [$F(2, 308.67) = 14.06$, $p < .001$, $\eta^2 = .21$] was observed. Notably, both younger and middle-aged, but not older participants had more blinks in their LCL condition compared to their own in HCL.

Table 5

Linear Mixed-Effects Models on Eye-Metrics during the Time Load Dual Back

A. Pupil Size

Predictor	***F***	***Df***	***Df res***	***p***	***η²***
(Intercept)	0.17	1	58.90	.68	.006
Condition	10.09	1	297.58	.002	.35
Block	0.30	3	274.81	.83	.01
Group	11.18	2	58.88	<.001	.39
Condition:Block	0.06	3	274.83	.98	.002
Condition:Group	5.87	2	291.71	.003	.20
Block:Group	0.40	6	274.75	.88	.01
Condition:Block:Group	0.56	6	274.77	.76	.02

B. Dilation Speed

Predictor	***F***	***Df***	***Df res***	***p***	***η²***
(Intercept)	0.56	1	58.84	.46	.03
Condition	0.22	1	314.34	.64	.01
Block	0.24	3	274.69	.87	.01
Group	5.44	2	58.79	.007	.30
Condition:Block	0.68	3	274.73	.56	.04
Condition:Group	10.73	2	304.57	<.001	.58
Block:Group	0.45	6	274.57	.84	.02
Condition:Block:Group	0.09	6	274.61	1.00	.005

C. Constriction Speed

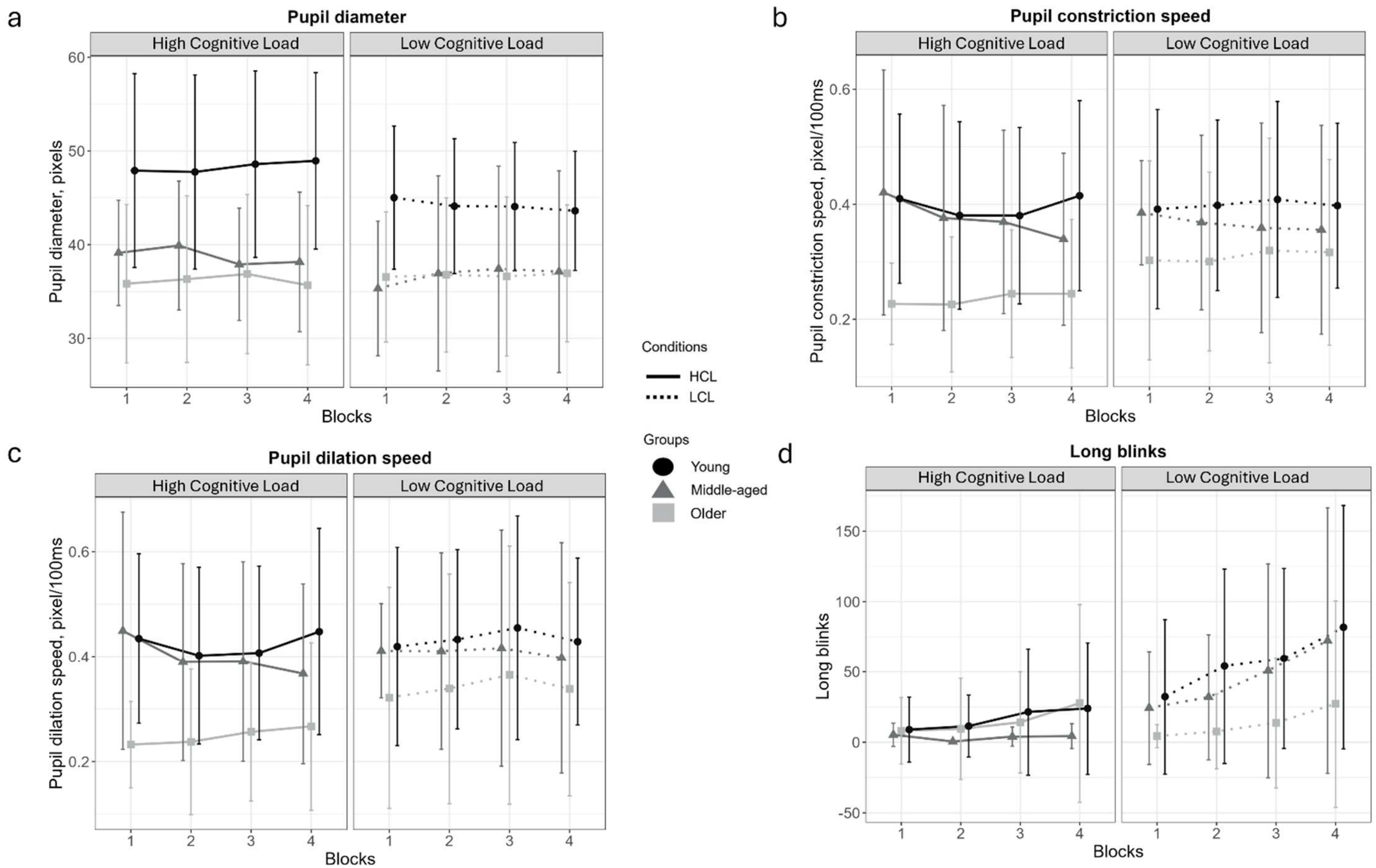
Predictor	***F***	***Df***	***Df res***	***p***	***η²***
(Intercept)	0.53	1	58.82	.50	.03
Condition	2.88	1	313.77	.09	.15
Block	0.36	3	274.61	.78	.02
Group	4.35	2	58.77	.02	.22
Condition:Block	0.36	3	274.64	.78	.02
Condition:Group	10.63	2	304.22	<.001	.54
Block:Group	0.48	6	274.48	.82	.02
Condition:Block:Group	0.08	6	274.51	1.00	.004

D. Long Blinks

Predictor	*F*	*Df*	*Df res*	*p*	η^2
(Intercept)	0.36	1	58.79	.55	.005
Condition	40.91	1	319.15	<.001	.61
Block	4.05	3	275.86	.008	.06
Group	4.63	2	58.72	.01	.07
Condition:Block	0.76	3	275.89	.52	.01
Condition:Group	14.06	2	308.67	<.001	.21
Block:Group	2.05	6	275.71	.06	.03
Condition:Block:Group	0.44	6	275.74	.85	.007

Figure 4

Eye-Metrics during the Time Load Dual Back



Note. **a.** Pupil diameter; **b.** Pupil constriction speed; **c.** Pupil dilation speed; **d.** Long blinks. HCL, High Cognitive Load; LCL, Low Cognitive Load.

Descriptive caption: *Line graph showing (A) pupil diameter, (B) pupil constrictions speed, (C) pupil dilation speed, and (D) long blinks frequency across four time-blocks, differentiated by age groups (young, middle-aged, older adults) and conditions (HCL, LCL).*

Discussion

The objectives of the present study aimed to determine whether older individuals are more sensitive to mental fatigue than younger and middle-aged adults. To explore this, we induced mental fatigue by manipulating task demands, while adapting these demands to each participant's cognitive capacity. Physiological markers (pupil size, pupillary response speed, and long blinks), along with subjective fatigue and performance, were assessed across age groups.

Even though participants reported increased fatigue following the cognitive task, increasing the cognitive load did not result in a heightened subjective sense of fatigue in either group, challenging our hypothesis that older adults would exhibit greater sensitivity to fatigue under high cognitive demands in comparison to younger cohorts. However, we identified some changes in performance accuracy and eye-metrics in response to cognitive load. Group differences also emerged: younger adults showed lower accuracy during the cognitive task and reported more fatigue than older adults in both cognitive load conditions and since the beginning of the task. This set of results will be discussed in the context of age-related differences in fatigue resistance and the utility of eye-metric physiological markers in assessing mental fatigue.

Effects of Cognitive Load Manipulation on Perceived Fatigue

We used the TLDB task to manipulate the available processing time across high and low cognitive load conditions (Barrouillet et al., 2004). All participants reported increased mental fatigue following the task. Contrary to our hypothesis, manipulating the task's cognitive load by reducing processing time did not yield discernible differences in fatigue perception (for similar results, see Smith et al., 2019). The absence of clear difference between conditions raises several possibilities: the time-constraint manipulation may have been too subtle, the metrics used may not have been sufficiently sensitive (see Wylie et al., 2021, regarding response bias), or the study underpowered to detect such effects.

Instead, subjective sleepiness increased over time under high load condition, which confirms the deleterious consequences of prolonged cognitive engagement (the temporal fatigue hypothesis, Ackerman & Kanfer, 2009; Sandry et al., 2014). This also suggests that a high cognitive load may affect mental states beyond fatigue.

Given its minimal cognitive demands and presumably more monotonous nature, the low cognitive load condition was expected to induce feelings of boredom and underload, potentially leading to increased subjective sleepiness, as described in the passive task-related fatigue phenomena (Pickering et al., 2023). The observation here of greater sleepiness with time-on-task exclusively under high load condition may be explained by the task duration (32 minutes, compared to 16 minutes in Borragán et al., 2017; for a similar interpretation, see Staiano et al., 2024). Unfortunately, without continuous VAS measurements throughout the task, we are unable to precisely determine when sleepiness began to set in. Finally, it is also possible that the low cognitive load condition, although objectively less demanding, became subjectively more effortful over time due to its insufficient workload, duration, and monotonous nature. In such contexts, maintaining engagement may require compensatory cognitive control to counteract boredom and declining motivation (Tam et al., 2021). This imbalance in the effort-reward dynamic could therefore have increased perceived effort despite low task demands, leading to reduced motivation, heightened fatigue, and impaired performance as participants progressively disengaged from the task (Boksem & Tops, 2008).

Age differences were also observed: older adults reported lower fatigue and sleepiness than young and middle-aged cohorts, while higher motivation was observed in older and middle-aged adults than in young. This pattern suggests that older individuals may possess mechanisms - such as increased motivation or reduced susceptibility to monotony - that counteract the subjective experience of mental fatigue, potentially maintaining their task performance.

Behavioral level: Performance During the Cognitive Task

Both cognitive load conditions induced fatigability, as evidenced by the overall decline in accuracy with time-on-task. While consistent with cognitive resource depletion models (Baumeister et al., 1998), mental fatigue also involves neurophysiological changes, such as glutamate accumulation (Rönnbäck & Hansson, 2004), which can influence behavior by increasing risk-taking or favoring easier, lower-reward tasks (Wiehler et al., 2022). Motivational factors and task monotony (Steward & Chib, 2024) further shape performance (Müller & Apps, 2019), potentially leading to boredom and disengagement. However, these states, fatigue, boredom, and motivation, are often difficult to disentangle through performance measures.

Our findings also revealed performance differences between the two conditions. The high cognitive load condition was associated with lower accuracy compared to the low cognitive load condition. While this pattern is consistent with the assumption that tasks with higher cognitive demands are more taxing, an alternative interpretation is that reduced accuracy simply reflects greater task difficulty, rather than accelerated cognitive resource depletion *per se*. This interpretation is particularly relevant given the absence of differences in subjective fatigue between conditions. Thus, the behavioral results alone do not allow us to conclusively attribute performance decrements to differential fatigue processes. Nevertheless, we observed larger pupil diameter in the high cognitive load condition, a finding commonly interpreted as reflecting increased cognitive effort (Kahneman & Beatty, 1966).

Importantly, we did not find any significant interaction between time-on-task and cognitive load manipulation on accuracy, where a high cognitive load condition would have led to a more pronounced decline in accuracy over time. In the exploratory analyses restricted to the first 16 minutes of the task (see online supplemental analyses), we nevertheless observed a decrease of accuracy from the first to the second block in the HCL – but no LCL condition. These results are in agreement with Shigihara et al. (2013), who observed that active fatigue in their high-load condition led to an increased error rate while participants remained engaged in the task, as evidenced by their stable reaction times. However, we were unable to replicate the results they attributed to passive fatigue in the low cognitive load condition, specifically the pattern of increasing error rates over time. Consequently, the extended duration of the task may have confounded the influences of active fatigue associated with high cognitive load and passive fatigue, which is related to the prolonged task length across the two conditions.

Even though we did not manage to demonstrate a clear behavioral difference between the two cognitive load conditions, the time-on-task effect still indicates the presence of fatigue. Therefore, we examine whether fatigability manifests similarly across the three age-groups.

Younger participants had a higher error rate during the task (irrespective of cognitive load condition) compared to the middle-aged and older cohorts, despite task adaptation to individual maximal speed. This finding is difficult to interpret. One possibility is a different speed-accuracy trade-off across groups, with younger adults prioritizing speed over accuracy. Participants were instructed to respond as quickly and accurately as possible, but age-related differences in how this instruction was implemented may have shaped performance strategies. Alternatively, age-related differences in fatigability mechanisms may be involved. Younger participants may be more susceptible to task monotony (Wascher et al., 2016), consistent with their lower self-reported motivation. Motivation to participate in research experiment may also differ between younger (often student) and older samples (Ryan & Campbell, 2021). Another explanation of the age discrepancy in error rate relates to affective factor. Younger participants reported higher depressive symptoms (CES-D), and fatigue and depression are known to overlap and co-occur in both clinical (Heitmann et al., 2022) and healthy populations (Corfield et al., 2016). Both depression and fatigue have been associated with reduced cognitive performance (McDermott & Ebmeier, 2009), and show moderate intercorrelations (Miller et al., 2008). Overall, the lower accuracy observed in younger adults likely reflects an interaction between fatigue, depression, lack of effort, and motivation (Müller & Apps, 2019) and differential performance strategies, rather than a single underlying factor.

Middle-aged and older adults are often perceived as allocating more cognitive resources to perform the same task, aiming to match the performance levels achieved by their younger counterpart (Klaassen et al., 2016). However, in our study, their accuracy scores during the task even outperformed those of the younger group. Nonetheless, with no interaction between group and task-specificity (duration or cognitive load level), it is therefore difficult to conclude to any middle-aged or older people's greater sensitivity to either time-on-task (in opposition to Gilsoul et al., 2024) or cognitive load manipulation paradigms on fatigability measures.

Nevertheless, pupillometric data indicated larger pupil diameter in the high cognitive load condition, particularly in younger adults, suggesting increased cognitive effort in response to higher task demands. When considered alongside their lower accuracy, this pattern may indicate that younger adults experienced greater difficulty or reduced efficiency when demands increased in contrast to older people. Although this pattern may suggest greater cognitive effort, alternative explanations remain possible. In particular, differences in effort allocation or performance strategy (e.g., prioritizing speed over accuracy) cannot be ruled out, even though the pupillary findings do not fully align with the previous interpretations. Further studies specifically targeting cognitive effort and strategy would be needed to clarify this.

Physiological level: Pupillary Responses and Long-Blink Rate

We examined the pupil size, pupillary response speed and long-blink rate as ocular markers of fatigue. These measures revealed distinct patterns of change.

In young and middle-aged participants, higher cognitive load was associated with greater pupil dilation, consistent with increased sympathetic activation under higher task demands (Kahneman & Beatty, 1966). However, this effect was not observed in older adults. One explanation is that pupil diameter may reach a stabilization threshold under high demand in older adults (Peavler, 1974), or reflect age-related reductions in sympathetic activity (senile miosis; Pozzessere et al., 1997). These findings suggest that static pupil size may be less suitable for assessing cognitive load in aging, although some studies have reported preserved load-related dilation in older adults (e.g., El Haj et al., 2023).

Young and middle-aged participants exhibited more long-blinks in the low cognitive load condition, which was interpreted as heightened sleepiness due to the monotonous nature of the task (Schleicher et al., 2008). Interestingly, this physiological marker of sleepiness contrasted with the subjective reports from participants, who indicated a greater sense of sleepiness under high cognitive load conditions. This pattern may reflect general task difficulty or monotony rather than differences in cognitive load *per se*, in which the high cognitive load condition may lead to a stronger conscious experience of sleepiness.

Regarding pupillary dynamics, middle-aged adults showed faster dilation and constriction under high load compared to low load, consistent with heightened cognitive and autonomic activity (Kahneman & Beatty, 1966; Van Gerven et al., 2004). Conversely, older adults exhibited faster pupillary responses under low load, possibly reflecting age-related alterations in the autonomic nervous system efficiency (Pozzessere et al., 1997; Van Gerven et al., 2004). This age-related inversion in pupillary response speeds further highlights the complexity of interpreting physiological markers across different age groups.

Overall, our findings demonstrate that while certain ocular markers like pupil size and blink rates are useful indicators of cognitive load in younger and middle-aged adults, they may not be as reliable in older adults, potentially due to age-related autonomic changes (Van Gerven et al., 2004). Future research should consider complementary indices to better capture fatigue-related processes across the lifespan.

Limitations and Future Perspectives

Several limitations should be considered. Although pupil and eyelid measures were recoded, ocular saccades were not captured, despite their utility in assessing fatigue through peak speed decline (Zargari Marandi et al., 2018). The incorporation of ocular saccade measurements in future research endeavors may enrich our understanding of mental fatigue dynamics. Additionally, substantial data loss due to technical issues reduced the sample available for physiological and correlational analyses. Contextual factors, including recruitment during the COVID-19 period, may have influenced fatigue and mood scores (Charonitis et al., 2024) and limited older participant inclusion, resulting in unequal distribution across age groups. Physiological states such as sleepiness, boredom, depression, or medication effects can mimic fatigue, complicating interpretation (Corfield et al., 2016; Pattyn et al., 2008; Shen et al., 2006). While motivation was assessed, perceived effort was not explicitly measured, and no reward mechanism was included, which may have affected engagement. Chronobiological factors, which vary across age and influence alertness and cognitive performance (Schmidt et al., 2015) were not controlled. Finally, the lack of standardized thresholds for mental fatigue in terms of performance decrement of physiological arousal (Schleicher et al., 2008) complicates comparisons across studies. Future research would benefit from incorporating these measures to better interpret behavioral and physiological effects.

Conclusion

Our study explored the effects of mental fatigue induction on subjective states, behavioral performance, and eye-metrics across distinct age cohorts. We observed age-related differences, with younger adults reporting higher levels of fatigue yet having more task errors than older adults. However, our findings did not show significant age-based differences in response to varying cognitive loads. Notably, while increased cognitive load appears to induce subjective sleepiness, physiological markers of sleepiness, such as long blinks, were paradoxically more pronounced under low load conditions. Finally, our results demonstrate that while certain ocular markers like pupil size and blink rates are useful indicators of cognitive load in younger and middle-aged adults, they may not be as reliable in older adults, potentially due to age-related changes in the autonomic nervous system. Future research should explore alternative or additional measures that can more accurately capture cognitive and physiological responses to building-up of mental fatigue in older populations. Furthermore, other factors that can influence fatigue, such as motivation, effort, and monotony should be considered when designing or selecting tasks for experimental fatigue studies.

Data Availability

The raw dataset, extended descriptive statistics, detailed assumption checks, and additional exploratory analyses (including the results from post hoc tests) can be accessed on the OSF repository: https://osf.io/wqegf/?view_only=64a8d0870a214cbcbcc5c1d1ab1be9b9.

Declaration of Generative AI Technologies in the Writing Process

This work has utilized ChatGPT (version 3.5) for language improvement, as the authors are non-native English speakers.

Declaration of Interest Statement

The authors have no competing interests to declare.

References

Ackerman, P. L., & Kanfer, R. (2009). Test length and cognitive fatigue: An empirical examination of effects on performance and test-taker reactions. *Journal of Experimental Psychology: Applied*, *15*(2), 163-181. https://doi.org/10.1037/a0015719

Akerstedt, T., Peters, B., Anund, A., & Kecklund, G. (2005). Impaired alertness and performance driving home from the night shift: A driving simulator study. *Journal of Sleep Research*, *14*(1), 17-20. https://doi.org/10.1111/j.1365-2869.2004.00437.x

Arnau, S., Möckel, T., Rinkenauer, G., & Wascher, E. (2017). The interconnection of mental fatigue and aging: An EEG study. *International Journal of Psychophysiology*, *117*, 17-25. https://doi.org/10.1016/j.ijpsycho.2017.04.003

Bafna, T., & Hansen, J. P. (2021). Mental fatigue measurement using eye metrics: A systematic literature review. *Psychophysiology*, *58*(6), e13828. https://doi.org/10.1111/psyp.13828

Bailey, A., Channon, S., & Beaumont, J. G. (2007). The relationship between subjective fatigue and cognitive fatigue in advanced multiple sclerosis. *Multiple Sclerosis Journal*, *13*(1), 73-80. https://doi.org/10.1177/1352458506071162

Barrouillet, P., Bernardin, S., & Camos, V. (2004). Time constraints and resource sharing in adults' working memory spans. *Journal of Experimental Psychology: General*, *133*(1), 83-100. https://doi.org/10.1037/0096-3445.133.1.83

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), 1-48. https://doi.org/10.18637/jss.v067.i01

Baumeister, R. F., Bratslavsky, E., Muraven, M., & Tice, D. M. (1998). Ego depletion: Is the active self a limited resource? *Journal of Personality and Social Psychology*, *74*(5), 1252-1265. https://doi.org/10.1037/0022-3514.74.5.1252

Biondi, F. N., Graf, F., Pillai, P., & Balasingam, B. (2023). On validating a generic camera-based blink detection system for cognitive load assessment. *Cognitive Computation and Systems*, *5*(4), 255-264. https://doi.org/10.1049/ccs2.12088

Boksem, M. A. S., & Tops, M. (2008). Mental fatigue: Costs and benefits. *Brain Research Reviews*, *59*(1), 125-139. https://doi.org/10.1016/j.brainresrev.2008.07.001

Borragán, G., Slama, H., Bartolomei, M., & Peigneux, P. (2017). Cognitive fatigue: A Time-based resource-sharing account. *Cortex*, *89*, 71-84. https://doi.org/10.1016/j.cortex.2017.01.023

Borragán, G., Slama, H., Destrebecqz, A., & Peigneux, P. (2016). Cognitive fatigue facilitates procedural sequence learning. *Frontiers in Human Neuroscience*, *10,* Article 86. https://doi.org/10.3389/fnhum.2016.00086

Brown, V. A. (2021). An Introduction to Linear Mixed-Effects Modeling in R. *Advances in Methods and Practices in Psychological Science*, *4*(1). https://doi.org/10.1177/2515245920960351

Buysse, D. J., Reynolds, 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. *Psychiatry Research*, *28*(2), 193-213. https://doi.org/10.1016/0165-1781(89)90047-4

Charonitis, M., Requier, F., Guillemin, C., Reyt, M., Folville, A., Geurten, M., Bastin, C., Willems, S., Muto, V., Schmidt, C., & Collette, F. (2024). The influence of changes in daily life habits and well-being on fatigue level during COVID-19 pandemic. *Psychologica Belgica*, *64*(1), 85-107. https://doi.org/10.5334/pb.1259

Cohen, R. W., Meinhardt, A. J., Gmelin, T., Qiao, Y., Moored, K. D., Katz, R. D., Renner, S. W., Glynn, N. W., & for the LLFS Research Group. (2021). Prevalence and severity of perceived mental fatigability in older adults: The Long Life Family Study. *Journal of the American Geriatrics Society*, *69*(5), 1401-1403. https://doi.org/10.1111/jgs.17075

Collette, F., & Salmon, E. (2014). Les modifications du fonctionnement exécutif dans le vieillissement normal. *Psychologie Française*, *59*(1), 41-58. https://doi.org/10.1016/j.psfr.2013.03.006

Corfield, E. C., Martin, N. G., & Nyholt, D. R. (2016). Co-occurrence and symptomatology of fatigue and depression. *Comprehensive Psychiatry*, *71*, 1-10. https://doi.org/10.1016/j.comppsych.2016.08.004

El Haj, M., Boutoleau-Bretonnière, C., & Chapelet, G. (2023). The pupil knows: Pupil dilation indexes and their inhibitory ability in normal aging. *Journal of Clinical Medicine*, *12*(14), 4778. https://doi.org/10.3390/jcm12144778

Esterman, M., Reagan, A., Liu, G., Turner, C., & DeGutis, J. (2014). Reward reveals dissociable aspects of sustained attention. *Journal of Experimental Psychology: General*, *143*(6), 2287-2295. https://doi.org/10.1037/xge0000019

Finsterer, J., & Mahjoub, S. Z. (2014). Fatigue in healthy and diseased individuals. *American Journal of Hospice and Palliative Medicine*, *31*(5), 562-575. https://doi.org/10.1177/1049909113494748

Gilsoul, J., Libertiaux, V., & Collette, F. (2021). Cognitive fatigue in young, middle-aged, and older: Breaks as a way to recover. *Applied Psychology*, 71(4), 1565-1597. https://doi.org/10.1111/apps.12358

Gilsoul, J., Libertiaux, V., Depierreux, F., & Collette, F. (2024). Cognitive fatigue in young, middle-aged, and older adults: A response time distribution approach. *Journal of Adult Development*, 31, 279-292. https://doi.org/10.1007/s10804-023-09471-6

Guillemin, C., Hammad, G., Read, J., Requier, F., Charonitis, M., Delrue, G., Vandeleene, N., Lommers, E., Maquet, P., & Collette, F. (2022). Pupil response speed as a marker of cognitive fatigue in early multiple sclerosis. *Multiple Sclerosis and Related Disorders*, *65*, 104001. https://doi.org/10.1016/j.msard.2022.104001

Heitmann, H., Andlauer, T. F. M., Korn, T., Mühlau, M., Henningsen, P., Hemmer, B., & Ploner, M. (2022). Fatigue, depression, and pain in multiple sclerosis: How neuroinflammation translates into dysfunctional reward processing and anhedonic symptoms. *Multiple Sclerosis Journal*, 28(7), 1020-1027. https://doi.org/10.1177/1352458520972279

Hu, X., & Lodewijks, G. (2021). Exploration of the effects of task-related fatigue on eye-motion features and its value in improving driver fatigue-related technology. *Transportation Research Part F: Traffic Psychology and Behaviour*, *80*, 150-171. https://doi.org/10.1016/j.trf.2021.03.014

Jason, L. A., Evans, M., Brown, M., & Porter, N. (2010). What is fatigue? Pathological and nonpathological fatigue. *PM&R*, *2*(5), 327-331. https://doi.org/10.1016/j.pmrj.2010.03.028

Johns, M. W. (1991). A new method for measuring daytime sleepiness: The Epworth Sleepiness Scale. *Sleep*, *14*(6), 540-545. https://doi.org/10.1093/sleep/14.6.540

Kahneman, D., & Beatty, J. (1966). Pupil diameter and load on memory. *Science*, *154*(3756), 1583-1585. https://doi.org/10.1126/science.154.3756.1583

Klaassen, E. B., Plukaard, S., Evers, E. A. T., De Groot, R. H. M., Backes, W. H., Veltman, D. J., & Jolles, J. (2016). Young and middle-aged schoolteachers differ in the neural correlates of memory encoding and cognitive fatigue: A functional MRI study. *Frontiers in Human Neuroscience*, *10,* Article 148. https://doi.org/10.3389/fnhum.2016.00148

Kluger, B. M., Krupp, L. B., & Enoka, R. M. (2013). Fatigue and fatigability in neurologic illnesses: Proposal for a unified taxonomy. *Neurology*, *80*(4), 409-416. https://doi.org/10.1212/WNL.0b013e31827f07be

Krupp, L. B., LaRocca, N. G., Muir-Nash, J., & Steinberg, A. D. (1989). The Fatigue Severity Scale: Application to patients with multiple sclerosis and systemic lupus erythematosus. *Archives of Neurology*, *46*(10), 1121-1123. https://doi.org/10.1001/archneur.1989.00520460115022

Kuppuswamy, A. (2017). The fatigue conundrum. *Brain*, *140*(8), 2240-2245. https://doi.org/10.1093/brain/awx153

Kwon, K.-A., Shipley, R. J., Edirisinghe, M., Ezra, D. G., Rose, G., Best, S. M., & Cameron, R. E. (2013). High-speed camera characterization of voluntary eye blinking kinematics. *Journal of the Royal Society Interface*, *10*(85), 20130227. https://doi.org/10.1098/rsif.2013.0227

Lazar, R., Degen, J., Fiechter, A.-S., Monticelli, A., & Spitschan, M. (2024). Regulation of pupil size in natural vision across the human lifespan. *Royal Society Open Science*, *11*(6), 191613. https://doi.org/10.1098/rsos.191613

Lee, K. A., Hicks, G., & Nino-Murcia, G. (1991). Validity and reliability of a scale to assess fatigue. *Psychiatry Research*, *36*(3), 291-298. https://doi.org/10.1016/0165-1781(91)90027-M

Martins, R., & Carvalho, J. (2015). Eye blinking as an indicator of fatigue and mental load—A systematic review. In P. M. Arezes, J. S. Baptista, M. P. Barroso, P. Carneiro, P. Cordeiro, N. Costa, R. B. Melo, A. S. Miguel, & G. Perestrelo (Eds.), *Occupational safety and hygiene III* (pp. 231–235). CRC Press. https://doi.org/10.1201/b18042-48

Mattis, S. (1976). Mental status examination for organic mental syndrome in the elderly patient. In L. Bellak & T. B. Karasu (Eds.), *Geriatric psychiatry: A handbook for psychiatrists and primary care physicians* (pp. 77-121). Grune & Stratton.

McDermott, L. M., & Ebmeier, K. P. (2009). A meta-analysis of depression severity and cognitive function. *Journal of Affective Disorders*, *119*(1-3), 1-8. https://doi.org/10.1016/j.jad.2009.04.022

McLaughlin, D. J., Zink, M. E., Gaunt, L., Reilly, J., Sommers, M. S., Van Engen, K. J., & Peelle, J. E. (2023). Give me a break! Unavoidable fatigue effects in cognitive pupillometry. *Psychophysiology*, *60*(7), e14256. https://doi.org/10.1111/psyp.14256

Miller, W. C., Anton, H. A., & Townson, A. F. (2008). Measurement properties of the CESD scale among individuals with spinal cord injury. *Spinal Cord*, *46*(4), 287-292. https://doi.org/10.1038/sj.sc.3102127

Möckel, T., Beste, C., & Wascher, E. (2015). The effects of time on task in response selection—An ERP study of mental fatigue. *Scientific Reports*, *5*(1), 10113. https://doi.org/10.1038/srep10113

Müller, T., & Apps, M. A. J. (2019). Motivational fatigue: A neurocognitive framework for the impact of effortful exertion on subsequent motivation. *Neuropsychologia*, *123*, 141-151. https://doi.org/10.1016/j.neuropsychologia.2018.04.030

Muñoz-de-Escalona, E., Cañas, J. J., & Noriega, P. (2020). Inconsistencies between mental fatigue measures under compensatory control theories. *Psicológica*, *41*(2), 103-126. https://doi.org/10.2478/psicolj-2020-0006

Pattyn, N., Neyt, X., Henderickx, D., & Soetens, E. (2008). Psychophysiological investigation of vigilance decrement: Boredom or cognitive fatigue? *Physiology & Behavior*, *93*(1-2), 369-378. https://doi.org/10.1016/j.physbeh.2007.09.016

Peavler, W. S. (1974). Pupil size, information overload, and performance differences. *Psychophysiology*, *11*(5), 559-566. https://doi.org/10.1111/j.1469-8986.1974.tb01114.x

Peterson, R. A. (2021). Finding optimal normalizing transformations via bestNormalize. *The R Journal*, *13*(1), 310-329. https://doi.org/10.32614/RJ-2021-041

Piccoli, B. (2003). A critical appraisal of current knowledge and future directions of ergophthalmology: Consensus document of the ICOH Committee on “Work and Vision”. *Ergonomics*, *46*(4), 348-406. https://doi.org/10.1080/00140130310000067473

Pickering, T., Wright, B., Schücker, L., & MacMahon, C. (2023). Active or passive? Investigating different types of cognitive fatigue. *Canadian Journal of Experimental Psychology / Revue Canadienne de Psychologie Expérimentale*, 78(1), 50-65. https://doi.org/10.1037/cep0000312

Pozzessere, G., Rossi, P., Valle, E., Froio, C. P., Petrucci, A. F. G., & Morocutti, C. (1997). Autonomic involvement in multiple sclerosis: A pupillometric study. *Clinical Autonomic Research*, *7*(6), 315-319. https://doi.org/10.1007/BF02267724

Radloff, L. S. (1977). The CES-D scale: A self-report depression scale for research in the general population. *Applied Psychological Measurement*, *1*(3), 385-401. https://doi.org/10.1177/014662167700100306

Raven, J. C., & Deltour, J.-J. (2007). *Échelle de vocabulaire Mill Hill*. [Manual]. Oxford Psychologists Press; ECPA.

Read, J., Guillemin, C., Charonitis, M., Requier, F., Beliy, N., Bahri, M. A., Vandewalle, G., & Collette, F. (2026). Effort and motivation to characterize mental fatigue: Behavior and functional connectivity. *Motivation Science*. Advance online publication. https://doi.org/10.1037/mot0000421

Rönnbäck, L., & Hansson, E. (2004). On the potential role of glutamate transport in mental fatigue. *Journal of Neuroinflammation*, *1*(1), 22. https://doi.org/10.1186/1742-2094-1-22

Ryan, A. D., & Campbell, K. L. (2021). The ironic effect of older adults’ increased task motivation: Implications for neurocognitive aging. *Psychonomic Bulletin & Review*, *28*(6), 1743-1754. https://doi.org/10.3758/s13423-021-01963-4

Sadeghniiat-Haghighi, K., & Yazdi, Z. (2015). Fatigue management in the workplace. *Industrial Psychiatry Journal*, *24*(1), 12-17. https://doi.org/10.4103/0972-6748.160915

Salthouse, T. A., & Babcock, R. L. (1991). Decomposing adult age differences in working memory. *Developmental Psychology*, *27*(5), 763-776. https://doi.org/10.1037/0012-1649.27.5.763

Samuel, I. B. H., Wang, C., Burke, S. E., Kluger, B., & Ding, M. (2019). Compensatory neural responses to cognitive fatigue in young and older adults. *Frontiers in Neural Circuits*, *13*, Article 12. https://doi.org/10.3389/fncir.2019.00012

Sandry, J., Genova, H. M., Dobryakova, E., DeLuca, J., & Wylie, G. (2014). Subjective cognitive fatigue in multiple sclerosis depends on task length. *Frontiers in Neurology*, *5,* Article 214. https://doi.org/10.3389/fneur.2014.00214

Schleicher, R., Galley, N., Briest, S., & Galley, L. (2008). Blinks and saccades as indicators of fatigue in sleepiness warnings: Looking tired? *Ergonomics*, *51*(7), 982-1010. https://doi.org/10.1080/00140130701817062

Schmidt, C., Collette, F., Reichert, C. F., Maire, M., Vandewalle, G., Peigneux, P., & Cajochen, C. (2015). Pushing the limits: Chronotype and time of day modulate working memory-dependent cerebral activity. *Frontiers in Neurology*, *6*, Article 199. https://doi.org/10.3389/fneur.2015.00199

Shahid, A., Wilkinson, K., Marcu, S., & Shapiro, C. M. (2012). Karolinska Sleepiness Scale (KSS). In A. Shahid, K. Wilkinson, S. Marcu, & C. M. Shapiro (Eds.), *STOP, THAT and one hundred other sleep scales* (pp. 209-210). Springer. https://doi.org/10.1007/978-1-4419-9893-4_47

Shen, J., Barbera, J., & Shapiro, C. M. (2006). Distinguishing sleepiness and fatigue: Focus on definition and measurement. *Sleep Medicine Reviews*, *10*(1), 63-76. https://doi.org/10.1016/j.smrv.2005.05.004

Shigihara, Y., Tanaka, M., Ishii, A., Tajima, S., Kanai, E., Funakura, M., & Watanabe, Y. (2013). Two different types of mental fatigue produce different styles of task performance. *Neurology, Psychiatry and Brain Research*, *19*(1), 5-11. https://doi.org/10.1016/j.npbr.2012.07.002

Smith, M. R., Chai, R., Nguyen, H. T., Marcora, S. M., & Coutts, A. J. (2019). Comparing the effects of three cognitive tasks on indicators of mental fatigue. *The Journal of Psychology*, *153*(8), 759-783. https://doi.org/10.1080/00223980.2019.1611530

Staiano, W., Romagnoli, M., Salazar Bonet, L. R., & Ferri-Caruana, A. (2024). Adaptive cognitive tasks for mental fatigue: An innovative paradigm for cognitive loading in human performance. *Journal of Science and Medicine in Sport*, *27*(12), 883-889. https://doi.org/10.1016/j.jsams.2024.08.199

Steward, G., & Chib, V. S. (2024). The neurobiology of cognitive fatigue and its influence on effort-based choice. *Journal of Neuroscience, 45*(24), e16122402025. https://doi.org/10.1523/JNEUROSCI.1612-24.2025

Tam, K. Y. Y., van Tilburg, W. A. P., Chan, C. S., Igou, E. R., & Lau, H. (2021). Attention drifting in and out: The boredom feedback model. *Personality and Social Psychology Review*, *25*(3), 251-272. https://doi.org/10.1177/10888683211010297

Tsai, Y., Viirre, E., Strychacz, C., Chase, B., & Jung, T.-P. (2007). Task performance and eye activity: Predicting behavior relating to cognitive workload. *Aviation Space and Environmental Medicine*, *78*(5 Suppl), B176-B185.

van de Port, I. G. L., Kwakkel, G., Schepers, V. P. M., Heinemans, C. T. I., & Lindeman, E. (2007). Is fatigue an independent factor associated with activities of daily living, instrumental activities of daily living and health-related quality of life in chronic stroke? *Cerebrovascular Diseases*, *23*(1), 40-45. https://doi.org/10.1159/000095757

van der Wel, P., & van Steenbergen, H. (2018). Pupil dilation as an index of effort in cognitive control tasks: A review. *Psychonomic Bulletin & Review*, *25*(6), 2005-2015. https://doi.org/10.3758/s13423-018-1432-y

Van Gerven, P. W. M., Paas, F., Van Merriënboer, J. J. G., & Schmidt, H. G. (2004). Memory load and the cognitive pupillary response in aging. *Psychophysiology*, *41*(2), 167-174. https://doi.org/10.1111/j.1469-8986.2003.00148.x

Vermeylen, L., Braem, S., Ivanchei, I. I., Desender, K., García-Román, J. M., González-García, C., Ruz, M., & Notebaert, W. (2025). The temporal dynamics of metacognitive experiences track rational adaptations in task performance. *Communications Psychology, 3*(1), 96. https://doi.org/10.1038/s44271-025-00282-x

Wascher, E., Heppner, H., Kobald, S. O., Arnau, S., Getzmann, S., & Möckel, T. (2016). Age-sensitive effects of enduring work with alternating cognitive and physical load. A study applying mobile EEG in a real life working scenario. *Frontiers in Human Neuroscience*, *9,* Article 711. https://doi.org/10.3389/fnhum.2015.00711

Wechsler, D. (2011). *WAIS-IV: Echelle d'intelligence de Wechsler pour adultes* [Manual]. Pearson.

Wiehler, A., Branzoli, F., Adanyeguh, I., Mochel, F., & Pessiglione, M. (2022). A neuro-metabolic account of why daylong cognitive work alters the control of economic decisions. *Current Biology*, *32*(16), 3564-3575.e5. https://doi.org/10.1016/j.cub.2022.07.010

Wylie, G. R., Yao, B., Sandry, J., & DeLuca, J. (2021). Using signal detection theory to better understand cognitive fatigue. *Frontiers in Psychology*, *11*, Article 579188. https://doi.org/10.3389/fpsyg.2020.579188

Zargari Marandi, R., Madeleine, P., Omland, Ø., Vuillerme, N., & Samani, A. (2018). Eye movement characteristics reflected fatigue development in both young and elderly individuals. *Scientific Reports*, *8*(1), 13148. https://doi.org/10.1038/s41598-018-31577-1

Zhang, Y., Gong, J., Miao, D., Zhu, X., & Yang, Y. (2011). Subjective evaluation of mental fatigue and characteristics of attention during a driving simulation. *Social Behavior and Personality: An International Journal*, *39*(1), 15-20. https://doi.org/10.2224/sbp.2011.39.1.15

Zheng, B., Jiang, X., Tien, G., Meneghetti, A., Panton, O. N. M., & Atkins, M. S. (2012). Workload assessment of surgeons: Correlation between NASA TLX and blinks. *Surgical Endoscopy*, *26*(10), 2746-2750. https://doi.org/10.1007/s00464-012-2268-6

Zimmermann, P., & Fimm, B. (2002). A test battery for attentional performance. In M. Leclercq & P. Zimmermann (Eds.), *Applied neuropsychology of attention: Theory, diagnosis and rehabilitation* (pp. 110-151). Psychology Press. https://doi.org/10.4324/9780203307014