Fatigue-Driven Declines in Cognitive and Neural Performance Across Trials

Slower Reactions, Reduced Accuracy, and EEG/ERP Changes Reveal Effects of Time-on-Task and Time-of-Day

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Abstract (RF, CH)

This study investigated the neurocognitive mechanisms of mental fatigue during repetitive tasks using EEG/ERP measures, with a focus on circadian variations and emotional processing dynamics. Participants completed three sessions of the "FaceWord" experiment, designed to examine the influence of semantic priming on emotional face perception. In each trial, participants were presented with words of varying emotional valence (positive, negative, or neutral) followed by emotionally congruent (valid) or incongruent (invalid) facial expressions. The experiment aimed to explore how fatigue influences cognitive performance, neural markers, and emotional processing. We tested four key hypotheses regarding fatigue development.

First, we predicted cognitive performance would decline across trials (H1), with reaction times increasing and accuracy decreasing; particularly for neutral word primes during low circadian alertness. Behavioral results partially supported this, showing declining accuracy in neutral trials ($\beta = -0.95$, $p = 0.021$) but stable reaction times (580 ms) and a practice effect ($\beta = -0.0005$, $p = 0.013$). Circadian modulation was not observed.

Second, we hypothesized specific EEG changes (H2): increased frontal theta ($p = 0.018$) and parietal alpha power ($p < 0.001$), along with decreased right middle frontal gyrus beta activity. While theta and alpha changes matched predictions, beta power unexpectedly increased ($p < 0.001$). P300 amplitude also paradoxically rose, potentially reflecting compensatory processes. Correlations with subjective measures were weak except for beta power's association with boredom ($r = 0.99$, $p = 0.02$).

Third, we expected attentional ERP reductions (H3), particularly for N2b amplitude. Results showed selective impairment, with N2b reduction for irrelevant stimuli ($\beta = 0.64$, $p = 0.049$) but enhanced P300 responses ($\beta = 0.73$, $p = 0.026$), suggesting complex fatigue effects on attention systems. No effects were shown for the N1 component.

Finally, we predicted emotional disengagement (H4) through LPP and N400 amplitude reductions. However, these components increased slightly, validly cued images elicited stronger N400 responses ($\beta = 0.78$, $p = 0.027$), indicating modified emotional processing. The EPN component, as expected, remained stable.

These findings reveal mental fatigue as a multidimensional phenomenon involving both expected neural markers of cognitive depletion (theta/alpha increases) and unexpected compensatory activation patterns (beta/P300/LPP/N400 enhancement). The association between objective neural measures and subjective experience highlights the importance of multimodal assessment in fatigue research, while the resilience of emotional processing suggests domain-specific fatigue effects. These results advance theoretical models by demonstrating both degenerative and adaptive neural responses to prolonged cognitive demand.

Keywords: Mental fatigue, EEG, Event-related potentials, Circadian rhythms, Time-of-day, Cognitive performance, Attentional control

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Introduction (RF, CH)

Motivation (RF)

Mental fatigue in both real-life and experimental settings are often overlooked, despite affecting how we perceive and interpret visual stimuli, and how effectively we perform tasks. More specifically it can slow down reaction times, reduce accuracy, and make it more difficult to stay focused while solving a task.

In other experiments, sustained performance on monotonous tasks has reliably produced a progressive decline in P300 amplitude and a rise in frontal theta and alpha power, established electrophysiological markers of mental fatigue (Boksem et al., 2005; Wascher et al., 2014). However, these studies usually employ neutral stimuli and do not include individual level self-reports, time of day, and do not investigate how fatigue interacts with emotional meanings or subjective state. Our experiment aims to close this gap by pairing neural markers from emotional stimuli as well as subjective measures, giving potentially a more detailed picture of cognitive dynamics of fatigue using electroencephalography (EEG) and event-related potentials (ERP).

By examining how mental fatigue accumulates during short cognitive tasks and how this interacts with circadian rhythms and emotional processing, this study contributes to a more detailed understanding of attention, cognitive effort, and neural dynamics in real time.

The Neuron (CH), EEG recordings (RF) and ERPs (CH)

First and foremost, neurons are the basic units of the nervous system, responsible for processing and transmitting information. They communicate via action potentials, which are rapid electrical impulses. This change in voltage travels down the axon to the terminals, where neurotransmitters are released (Anderson, 2020). Information is encoded by the rate of firing, or number of action potentials per second (Anderson, 2020). Electrical signals from postsynaptic potentials are strongest when neurons are aligned perpendicular to the scalp, such as in the gyri of the cerebral cortex (Bear, Connors, & Paradiso, 2020).

The electroencephalogram (EEG) is a method that measures electrical activity on the scalp. It is non-invasive and painless. Small voltage fluctuations, usually a few tens of microvolts (μV) in amplitude, are measured between selected pairs of electrodes (Bear, Connors, & Paradiso, 2020) that are placed on the scalp. One of the drawbacks of EEG is that the signal must penetrate several layers of non-neural tissue, including the meninges, fluid, the skull, and skin, to reach the electrodes. This means that the origin of the electrical signal, the number of neurons, their location, etc., is unknown (the inverse problem). Consequently, EEG has a very low spatial resolution. On the other hand, with EEG we can measure rapid fluctuations (around 1 ms resolution) in the signal that is impossible to do so by other methods such as fMRI (Bear, Connors, & Paradiso, 2020).

The amplitude of EEG signals depends on the synchronization of neuronal activity, with higher synchrony producing higher amplitude waves (Bear, Connors, & Paradiso, 2020). When EEG data are averaged across repeated presentations of a specific stimulus or event,

the resulting waveform is known as an event-related potential (ERP). The ERPs are extracted from the EEG recordings by averaging across the EEG signal through events, thus enhancing the stimulus-related neural activity and also reducing possible unrelated background noise or artifacts (Mouraux & Iannetti, 2008). Different ERP components are associated with activity in different brain regions (Luck, S. J., 2014), and these components are typically labeled based on their polarity (positive or negative) and latency (time in milliseconds after stimulus onset) (Luck, S. J., 2014).

Another way to look at brain activations in EEG is through time-frequency representation (TFR), and analyze the rate of oscillations. This means decomposing the EEG signal into its frequency components over time, which allows us to track how power in specific frequency bands (like alpha, beta, or gamma) evolve throughout an event. The reason for this is that when the cortex is engaged in information processing, the activity of neurons is high, but also relatively unsynchronised (Bear et al., 2020).

Brain rhythms and sleep (CH)

The different EEG rhythms vary depending on particular behavioral states such as sleeping, waking, attentiveness, and pathology. First, Theta rhythms (from 4 to 7 Hz), can be observed during both sleep and wakefulness. They are especially prominent in the anterior regions of the brain during states of fatigue and are thought to play a role in both sleep processes and maintaining attentiveness when individuals are tired (Trejo et al., 2015). Second, Alpha rhythms (8 to 13 Hz), are largest over the posterior, occipital cortex and are typically associated with quiet, waking states. These rhythms are also prominent in calm wakefulness but decrease as an individual engages in cognitive tasks (Corsi-Cabrera et al., 1996; Trejo et al., 2015). This relationship between EEG rhythms and behavioral states forms the basis for understanding how brainwave dynamics can reflect fatigue-induced changes in attention and performance (Trejo et al., 2015; Valdez, 2019).

Further supporting these trends, a negative correlation has been observed between alertness and EEG indices of mental fatigue, including increased frontal theta and parietal alpha power, which indicate reduced cognitive engagement and vigilance (Trejo et al., 2015). These changes, localized over anterior and parietal scalp regions corresponding to medial frontal and posterior parietal cortical sources, mirror patterns associated with reduced attentional control and declining task performance (Trejo et al., 2015).

Increased power in beta frequency bands has also been associated with elevated levels of sleepiness and exhaustion, reflecting cortical overactivation as the brain attempts to compensate for cognitive decline (Tanaka et al., 2014). The power spectral densities (PSDs) of theta, alpha, and beta bands have been found to co-vary with subjective mental fatigue, particularly across time-on-task, and are modulated by individual circadian rhythms (Trejo et al., 2015). Together, these oscillatory changes further demonstrate how EEG spectral features can correspond to both self-reported and behavioral indicators of fatigue, as well as to fluctuations in alertness related to circadian timing.

Timing differences in EEG & Circadian Rhythms (CH)

Cognitive performance can be impacted by physiological and environmental factors, which in turn can influence EEG signals. Circadian rhythms play a critical role in shaping attention and alertness throughout the day. These biological rhythms are regulated by clock genes and exposure to light or artificial illumination in experimental settings (Bear et al., 2020). For instance, an EEG study demonstrated that the waking brain exhibits changes attributable to both circadian and homeostatic (sleep-wake dependent) processes, with distinct circadian variations observed in EEG activity, particularly in the theta and high-frequency alpha bands, which may represent electrophysiological correlates of different aspects of the circadian rhythm in arousal (Aeschbach et al., 1999).

This understanding of circadian influence on EEG signals lays the groundwork for exploring specific EEG components such as the P300, which are sensitive to time-of-day variations and individual circadian patterns. For example, Geisler and Polich (1992) demonstrated that P300 amplitude and latency fluctuate depending on time of day (TOD) and circadian rhythms, with performance and attention typically declining during early morning and nighttime hours. Productivity also tends to decrease, and error rates tend to rise during these periods (Valdez, 2019). This is further supported by evidence linking self-reported sleep quality and alertness with attenuated EEG signal strength, particularly during sustained attention tasks (Komarov, Ko, & Jung, 2020).

In addition to TOD differences, individual differences in circadian rhythms also play a significant role in cognitive performance. Individual differences in chronotype, sleep patterns, and even sleep deprivation can modulate circadian rhythms, further impacting cognitive performance (Fan et al., 2023).

Fatigue: Behavioural (RF) and Neuroscientific Indicators (CH)

Behaviourally, it has been shown that reaction time and accuracy decreases over many repeated trials. Even two minutes of repetitive finger tapping is enough to introduce fatigue effects and slow reaction time. (Soto-Leon et al., 2020). When tasks become prolonged or cognitively taxing, participants may sacrifice speed to maintain accuracy or vice versa, illustrating the classic speed-accuracy trade-off (Rozand et al., 2015). Furthermore, participants become less efficient at performing tasks by time spent on the tasks, and the perceived difference between relevant and irrelevant cues becomes smaller, so the effect of priming weakens as mental fatigue increases (Lorist, 2008).

Cognitive fatigue is associated with changes in effort and reward processing in the anterior cingulate cortex (Glenn R. Wylie, et al., 2017). At the neural level, fatigue consistently shows reduction in event-related potential (ERP) amplitudes across trials. Later components, such as the P300, are associated with higher-level cognitive functions like attention allocation and stimulus evaluation. The P300 typically appears around 250-500 ms after stimulus onset and is most often recorded over parietal scalp regions, with neural sources in the posterior parietal cortex and dorsolateral prefrontal cortex (Geisler & Polich, 1992). Its amplitude and latency are used to assess decision-making efficiency and task relevance.

At a systems level, fatigue may involve a shift in brain network dynamics. Among other brain regions, the medial prefrontal cortex is a part of the default mode network (DMN), which

shows greater activation during rest compared to active tasks (Bear et al., 2020). As attention shifts from internal mentation to externally driven tasks, DMN activity typically decreases while lateral and dorsolateral cortical regions involved in sensory and motor processing increase in activation (Bear et al., 2020; Boksem, Meijman, & Lorist, 2005). [1]

Attention and information-processing (RF)

Attention plays a critical role in determining which information is processed and which is ignored, making it essential to understand how fatigue may disrupt these mechanisms. Attention is often described as a bottleneck in information processing: attended information is processed, while unattended information is discarded. Two distinct attentional systems mediate this process: exogenous and endogenous pathways (Bear et al., 2020). Bottom-up attention is generally triggered by physically salient events. In contrast, top-down attention is initiated by behavioural goals in the prefrontal cortex, from where neural signal travels to the lateral intraparietal cortex (LIP) where priority maps are formed, which guide orienting and reaction to stimuli (Bisley & Goldberg, 2010).

The endogenous control of attention also depends on the individual's ability to process the available information to make appropriate judgments later (Corbetta et al., 2002). So even when valid biasing information is provided, fatigue can induce effects that make the use of this information difficult (Boksem et al., 2005). From an attentional point of view, fatigue can be characterized as a decline in the ability to sustain endogenous control, leading to a shift toward increased responsiveness to external stimuli. In effect, fatigue reduces the capacity to suppress irrelevant input, making responses less controlled (Faber et al., 2012).

Posner's attention network (Posner & Petersen, 1990) is particularly well-suited[2] for studying the temporal dynamics of attention under fatigue. It divides attention into three distinct systems: alerting, orienting, and executive control; each associated with identifiable neural markers: N1, P300, and N2, respectively. Pauletti et al. (2024) found that increasing fatigue is linked to reduced N1 amplitude during alerting, decreased P300 during orienting, and diminished N2 amplitude during conflict resolution and executive control. Boksem et al. (2005) observed that prolonged task performance attenuates the N2b differentiation between relevant and irrelevant stimuli, indicating a shift from endogenous to exogenous attention.

The N1 component is observed around 140-200 ms post-stimulus, which is a component that has been linked to selective visual attention, measured at posterior-occipital electrode sites, linked to activity in the extrastriate visual cortex (Vogel & Luck, 2000). The N2b component, linked to functional selectivity, is evoked around 200-350 ms after stimulus onset (Patel & Azzam, 2005), measured in the anterior regions of the scalp, as it is considered to involve activation in medial structures like the ACC and the dlPFC (Wijers et al., 1989).

[1] See Appendix for further reading on *The Sentinel Hypothesis*
[2] See Appendix: *Supplementary notes* for further reading on attention models

Emotional investment (RF)

Emotional investment can also be an indicator of cognitive fatigue, and research has shown that time spent on a task reduces the reactivity to emotionally salient stimuli. While perceptual processes are inherently biased towards emotionally valenced information, this prioritization is mediated by attention processes, to ensure rapid reactions to changes in the environment. Hence, emotional reactivity, just as attention, diminishes greatly with fatigue (Fan et al., 2023). However, research suggests a two-stage processing of emotional stimuli. First, emotional significance is evaluated by subcortical circuits, including the amygdala. Second, emotionally significant stimuli are prioritized for selective attention (Compton, 2003). Even if attentional resources decline over time due to fatigue, that would affect the second stage of this process.

EEG evidence can support this view, Kissler et al. (2008) has shown that emotionally valenced stimuli elicit early ERPs like the early posterior negativity (EPN, around 200–300 ms after stimulus onset), measured at posterior electrode sites, reflecting the preattentive state of processing. This component is characterised by a negative deflection in the ERP waveform (Leupel, 2024). The EPN appears insensitive to attentional modulations (Kissler et al., 2008). In contrast, the late positive potential (LPP, ~300–600 ms after stimulus onset) is sensitive to motivational and attentional factors. Studies show that LPP amplitude diminishes over time or with fatigue, suggesting a progressive disengagement from emotional content (Fan et al., 2023; Zhang, 2017). The LPP has also been observed to be larger for emotionally salient faces, especially ones expressing anger (Duval et al., 2013). It is often associated with medial frontal and posterior brain regions, is longer in duration and more broadly distributed across the scalp than earlier components (Luck, 2014; Kissler et al., 2008).

The N400 component, generally measured at centro-parietal electrode sites, (Luck, 2014), around 300-450 ms post stimulus, is traditionally linked to semantic incongruity, but has been observed in relation to emotional faces, particularly in tasks involving priming. Low-arousing emotional faces can elicit larger N400 amplitudes than high-arousing ones, likely reflecting increased semantic or emotional integration demands (Li & Lu, 2014). These effects suggest that even higher-level meaning-related processing is influenced by the emotional facial stimuli. As fatigue accumulates, reduction in N400 amplitude may reflect changes in emotional processing (van Dillen, et al., 2009).

Hypotheses (RF, CH)

H1: Cognitive performance will decline across trials, with reaction times increasing and accuracy decreasing over time. This decline is expected to vary depending on participants' circadian rhythms, particularly in trials involving neutral word primes. (CH)

Neutral primes require cognitive effort to process, making them vulnerable to fatigue-related performance drops. This aligns with behavioural fatigue effects seen in prolonged tasks, where participants either slow down to preserve accuracy or show increased error rates. These changes reflect a gradual disengagement from the task and reduced motivation, especially in less stimulating conditions. Additionally, these performance drops are expected to be more significant during times of low circadian alertness, as cognitive capacity fluctuates with circadian rhythms.

H2: Mental fatigue will increase frontal theta (θ) and parietal alpha (α) power, and decrease beta-frequency power in the right middle frontal gyrus (Boksem et al., 2005). These changes will correlate with self-reported stress, boredom, and sleepiness, and vary with participants' circadian rhythms, reflected by the P300 ERP. (CH)

The change in power bands over trials will suggest declined cognitive processing due to fatigue (Boksem et al., 2005). Furthermore, the P300 ERP provides evidence that time of day can influence cognitive performance.

H3: Attentional ERP components, specifically N1 and N2b and P300, will show reduced amplitude in later trials, reflecting diminished ability for top-down attentional control.(RF)

With increasing task-induced fatigue, top-down attentional control will show progressively reduced amplitudes in later trials compared to early ones, and the N2b component will indicate the decreased capacity to prioritize relevant over irrelevant input (Faber et al., 2012).

H4: Across trials, LPP and N400 amplitudes will decline, signalling reduced neural engagement with emotionally salient facial stimuli as mental fatigue accumulates. (RF)

Specifically, LPP amplitudes, higher for negative compared to positive faces (Duval et al., 2013), should decrease over sessions. In contrast, the EPN is not expected to show systematic changes, indicating that the preattentive emotional encoding remains intact while later processing is disrupted (Kissler et al., 2008). The N400 response to neutral primes is expected to be greater than for valid primes (Li & Lu, 2014), but this difference-, and the N400 amplitude is expected to reduce with time on task.

Methods

Participant group (CH)[3]

The final sample included 8 (out of 10) university students residing in Denmark, were fluent in English, 1 participant was excluded due to incomplete session data and another due to noise. All participants had normal or corrected vision and were healthy. Most participants were right-handed, with only one left-handed. The mean age was 22.88 years (range 19-35, SD ≈ 5.11). The gender distribution was 5 females and 3 males.

In terms of productivity preferences, half of the participants (n = 4) reported feeling most productive in the morning (8:00–11:00), while 2 preferred midday (11:00–14:00), and 2 preferred the afternoon (14:00–18:00). Reported wake-up times on the day of the EEG session ranged from 05:50 to 09:30. Average survey results were the following:

Assessment	Average response	(Rating) Scale
Hours of sleep	6,5	Hours
Stress levels	5,6	1 - 10
Subjective boredom	3,5	1 - 5
Boredom on 1st trial	2,6	1 - 5
Boredom on 2nd trial	3,6	1 - 5
Boredom on 3rd trial	4,25	1 - 5

Table 1: Averaging over subjective survey answers: Sleep, Stress and Boredom

All participants consented to their data being used for analysis for an internal exam project and data was anonymized.

[3] The data from the survey can be accessed in the Appendix

Experimental procedure (RF)

The experiment was programmed using PsychoPy (v3+), an open-source application for running psychology experiments in Python. Key PsychoPy modules used included core, visual, event, monitors, and gui, for stimulus presentation, timing, user input, and display.

Participants completed 3 sessions of the "FaceWord" experiment, designed to examine the influence of semantic priming on emotional face perception. Each trial began with the presentation of a word displayed centrally for 700 milliseconds (corresponding to 42 frames at a 60 Hz refresh rate). Each word and displayed text in the experiment was written in the font: Consolas. The words carried either positive, negative, or neutral valence, based on normative affective ratings (Binder, 2016)[4]. There were 20 positive, 20 negative and 20 neutral words per session. Emotionally valenced words were always followed by matching faces (positive-happy, negative-fearful)[5], while neutral words were randomly paired with either a happy or fearful face for unpredictability. On average per session, neutral words were followed by a positive face ~ 10,3 times and a negative face ~ 9,7 times.

After the word presentation, a fixation cross was shown for a variable duration of either 2 sec (120 frames) or 3 sec (180 frames), selected randomly to reduce predictability. This was followed by an emoji-style face, centered on the screen with a black background and displayed for 700 ms. Both faces consisted of the same amount of pixels. A second fixation cross, also lasting either 2 or 3 sec randomly, concluded the trial sequence. Each session consisted of 60 trials, and participants were instructed to complete three sessions, resulting in a total experiment duration of ~ 20 min.

Participants were briefed on the experimental procedure. Instructions were given verbally and on the computer screen in front of them[6]. They were asked to remain as still as possible and avoid jaw clenching, to reduce recording noise. They completed the experiment in a dimly lit, closed room. Audible noise level was kept to the minimum. The experiment instructed them to take a break after each session, and start the experiment again, when they were ready.

Participants were instructed to press the 'b' key for happy (positive) expressions and the 'y' key for fearful (negative) expressions. Reaction time was measured from the onset of the face stimulus until a keypress response was recorded. If no response was given, the trial was logged accordingly. All stimulus onsets, offsets, and reaction times were precisely time-stamped using a monotonic clock, relative to the experiment's start, which was triggered by either a keypress or a scanner pulse signaled by the 't' key. A photodiode marker, visible as a small dot in the lower corner of the screen, was present during both word and image presentation phases to allow for synchronization with electrophysiological recordings.

[4] See the Appendix *FaceWord Stimuli - Words*
[5] See the Appendix *FaceWord Stimuli - Images*
[6] See Instructions in the Appendix

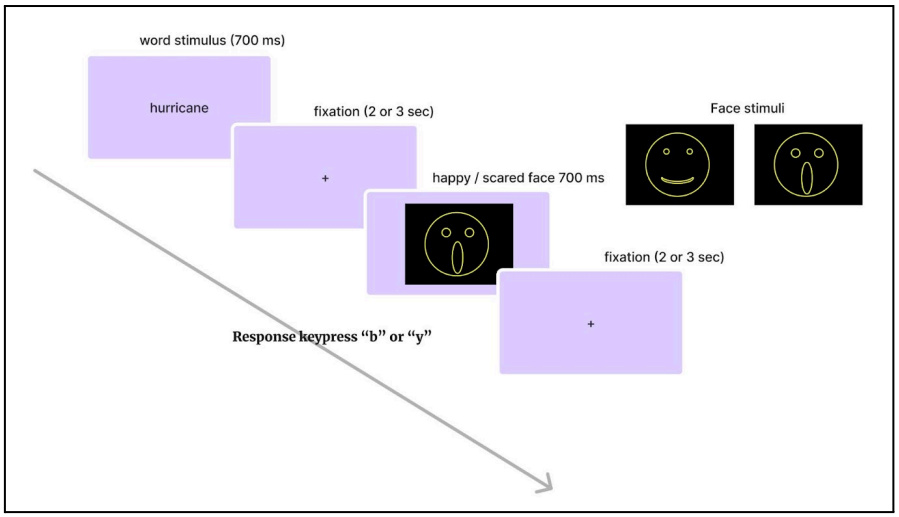


Figure 1: Experimental Procedure

EEG Methods (RF)

Out of the 8 participants, 5 arrived for the morning sessions (8:00–11:00 / 9:00–12:00) and 3 for the midday sessions (11:00–14:00 / 12:00–15:00). Participant setup took ~ one hour, meaning the actual experimental tasks began around 10:00–11:00 for the morning group and 12:00–13:00 for the midday group.

The EEG (Ag/AgCl electrodes, BrainAmp DC amplifier, sampling rate 1000 Hz) was recorded continuously from 28 scalp sites according to the international 10–20 system using ActiCap systems 32 electrode cap (Brain Products GmbH, Gilching, Germany)[7]. The reference electrode was placed at AFz, and the ground electrode was placed at FCz. The electrodes were secured to the scalp using conductive paste to ensure better electrical connection and signal quality. Two channels were used for electrooculography (EOG) to detect and later remove eye-blink artifacts from the EEG data. Activity was recorded at the right eye with one supraorbital electrode and one at the outer canthus.

Analysis methods (CH)

Continuous EEG data was preprocessed using MNE-Python (Gramfort et al., 2013). Bad channels were first identified during visual inspection and the ones either completely flat or extremely noisy were excluded from further analysis. The list of remaining 20 channels: Fz, F4, FC5, FC2, FC6, C3, Cz, C4, CP5, CP1, CP2, CP6, P7, P3, Pz, P4, P8, O1, Oz, O2. The EEG montage was aligned to the standard 10–20 system. Data were band-pass filtered using a zero-phase, two-pass FIR filter with a passband of 1–10 Hz (Hann window, transition bandwidth 0.5 Hz, 10 s filter length) (Gramfort et al., 2013), from 1 to 40 Hz and re-referenced to the average reference. Independent component analysis (ICA) was performed on the remaining channels (95% explained variance, max 800 iterations, random seed = 7) to remove artifacts, primarily ocular components.[8]

[7] Find electrode positions image in the Appendix
[8] See difference between unfiltered and filtered data in Appendix *Preprocessing*

Events were extracted from annotations, and only valid event types present in the data were retained. There were 3 sessions in total, each consisting of 60 trials, where the participant was required to respond with a keypress. Across all sessions, there were 723 events in total, avg. 241 events per session. Epochs were created from −100 ms to 700 ms relative to stimulus onset event, with baseline correction from -100 ms pre-stimulus onset to 0 ms. Epochs with EEG amplitudes exceeding 150 μV were rejected[9], this was <0.01% of the total epoch count. Finally, the data was downsampled to 250 Hz for analysis. For analysis of hypotheses 3 and 4, the first five trials of each session were discarded to minimize practice and habituation effects (Soto-Leon et al., 2020). Component values were computed as the average of the selected electrodes and time points for each epoch, then collapsed across trials within session and condition (Table 2). If not specified, events where the image stimuli was shown, is the baseline.

Hypothesis	Picks	Time window (from stimulus onset)
H2	**Frontal:** Fz, F1, F2 **Parietal:** Pz, P3, P4 **rMFG:** F4, FC4, AF4	Bands: 200 ms - 400 ms P300: 250 ms - 500 ms
H3	**N1:** Oz **N2b:** Fz **P300:** Pz	140 ms - 200 ms 200 ms - 350 ms 250 ms - 500 ms
H4	**LPP:** Pz, Cz and Fz **EPN:** Oz, P3 and P4 **N400:** Cz, C3 and C4	300 ms - 600 ms 240 ms - 300 ms 300 ms - 450 ms

Table 2: Analysed components, their respective EEG electrode placements and time windows.

Paired t-tests were used to compare mean amplitudes between conditions, and ANOVA to evaluate model specifications. OLS regression was used to assess relationships between boredom ratings and predictors (wake-up time, sleep duration, stress levels), with F-statistics for model significance and t-tests for coefficients. EEG data was analyzed using linear mixed-effects models (REML) with random participant intercepts. Separate models were used to test for each frequency band (theta, alpha, beta) and ERP amplitudes, with z-statistics evaluating fixed effects and residual variance to support evaluation of model fit.

Supplementary analyses and sanity checks included Shapiro-Wilk normality tests, Pearson correlations (neural-behavioral relationships), and likelihood ratio tests (nested models). Residual plots verified assumptions. Analyses used Python 3.12 (statsmodels v0.14.0, SciPy v1.11.0; $\alpha = 0.05$), reporting β (regression) and r (correlations) and R (Core Team, 2023) with key packages including lme4 and glmmTMB (mixed-effects modeling), lmerTest (significance testing), emmeans (post-hoc comparisons). Reaction times and accuracy were also monitored to confirm plausible ranges and participant engagement, with acceptable reaction times between 200–1000 ms and accuracy rates above 70%. Visual inspection of plotted data also revealed one missing session and one case of irregular data, leading to the exclusion of two participants.

[9] See rejected epoch counts by subject in Appendix *Preprocessing*

Results

Hypothesis 1: Performance Decline with Fatigue (CH)

Across all participants and experimental trials, the task elicited highly accurate responses, with a mean accuracy of 96.2% (SD = 0.19), indicating near-ceiling performance. Reaction times were similarly consistent, averaging 580 ms (SD = 0.19).

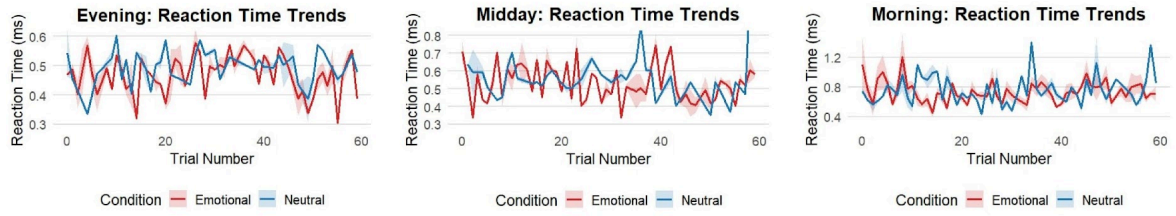


Figure 2: Reaction Time Trends Across Time of Day and Word Conditions

The evening session graph shows stable reaction times (400-600 ms) across trials, with emotional (M=520 ms) and neutral (M=540 ms) conditions showing minimal difference. The midday session displays similar consistency (emotional: M=510 ms, neutral: M=530 ms). The morning session reveals slightly greater variability, particularly in neutral trials (range: 400-1200 ms) compared to emotional trials (450-650 ms).

A linear mixed-effects model examined the effects of trial number (X), word condition (word_label: neutral, positive, negative), and time of day (tod: Morning, Middle of the Day, Afternoon) on reaction times. The model (*rt ~ X * word_label * tod + (1 | ID)*) revealed no significant main effects of trial number (β = 0.00053, p = 0.6138), word condition (neutral: p = 0.7881; positive: p = 0.9861), or time of day (Morning: p = 0.4693; Middle: p = 0.7565). None of the two-way or three-way interactions reached statistical significance (all p > 0.1).

A simplified linear mixed-effects model was fit to the RT dataset across all word conditions (*rt ~ X + (1 | ID), N = 2,400*), revealing a significant main effect of trial number (β = −0.000519, SE = 0.000209, p = 0.0133), indicating a change in RT over time. A follow-up model restricted to neutral trials (*rt ~ X * tod + (1 | ID)*) revealed no significant main effect of trial number (β = 0.0000456, p = 0.959) or interactions with time of day (X × Morning: p = 0.286; X × Middle: p = 0.817).

Accuracy for neutral trials was analyzed using a generalized linear mixed-effects model (*correct_resp ~ X * tod + (1 | ID)*), showing a significant main effect of trial number (β = −0.951, SE = 0.413, p = 0.0213).[10] No significant main effects or interactions involving time of day were found (all p > 0.1). Post-hoc estimated marginal trends showed non-significant accuracy changes across time of day (Morning: −0.00121; Afternoon: −0.0000456; Middle: +0.000253; all p > 0.4).

[10] See *Accuracy over Trials* in the Appendix

Hypothesis 2: EEG Fatigue Markers (CH)

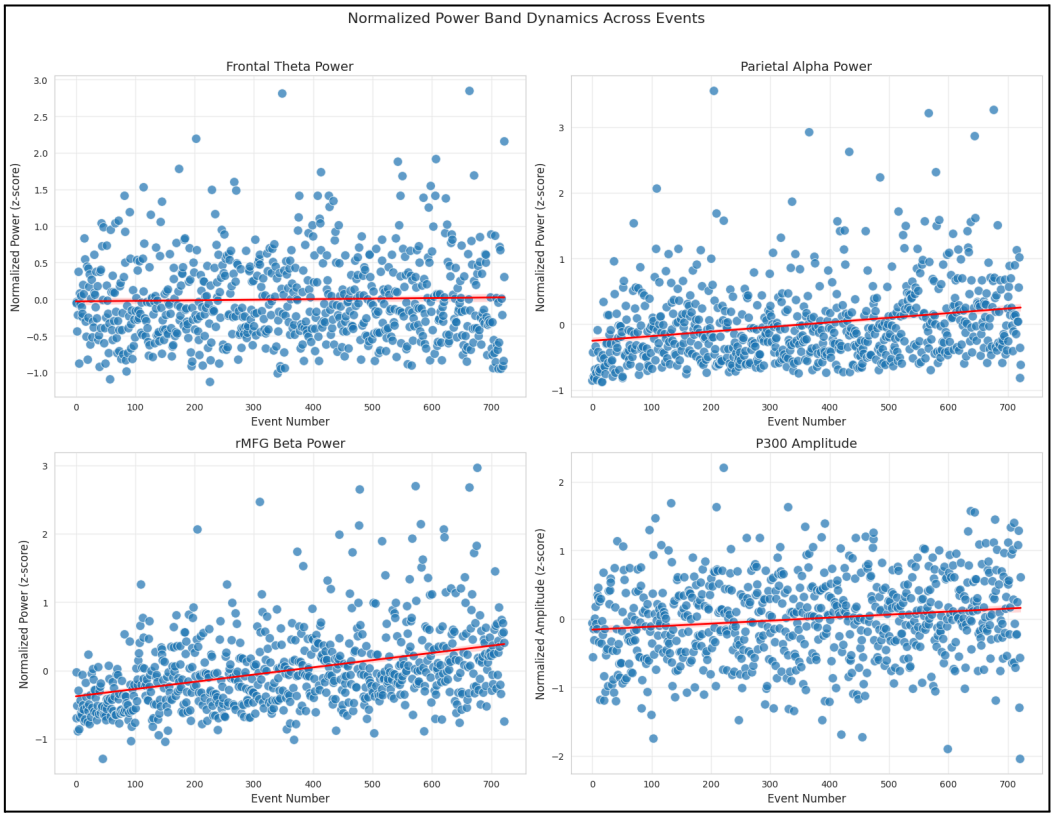


Figure 3: Time-course of neural oscillatory power and P300 amplitude across experimental events.

(A) Frontal theta (θ) increased with time (cognitive effort). (B) Parietal alpha (α) rose (inhibitory processing). (C) Right frontal beta (β) declined (reduced cognitive control). (D) P300 amplitude decreased (attenuated attention). Error bands show 95% CIs. X-axis: Event number; Y-axis: Normalized power (A-C) or amplitude (D).

Band Power and Experimental Effects

Frontal Theta power

A linear mixed-effects model using restricted maximum likelihood (REML) estimation revealed a significant positive relationship between fatigue progression and frontal theta power ($\beta = 0.000$, $z = 2.371$, $p = 0.018$). The model included random intercepts for participants and accounted for 6426 observations across 3 groups. The negligible random effects variance (0.000) and significant likelihood ratio test ($\chi^2(1) = 5.62$, $p = 0.018$) confirmed the robustness of this effect.

Parietal Alpha power

The REML-fitted mixed model for parietal alpha power showed a stronger positive association with fatigue ($\beta = 0.000$, $z = 11.352$, $p < 0.001$). Despite convergence warnings during optimization, the model explained significant variance in the 6426 observations, with a moderate random effects component (0.014). The scale parameter was estimated at 0.0744, indicating good model fit.

rMFG Beta Power

Analysis of right middle frontal gyrus beta activity using mixed modeling yielded unexpected results. The REML solution converged properly and showed significant positive coefficients ($\beta = 0.000$, $z = 12.555$, $p < 0.001$) across all 6426 trials. The model had the highest random effects variance (0.028) among all frequency bands, with a scale parameter of 0.0267 suggesting excellent fit.

P300 ERP

The P300 mixed model analysis incorporated 19,278 observations across 3 groups. REML estimation produced stable parameters showing significant positive amplitude changes ($\beta = 0.000$, $z = 13.040$, $p < 0.001$). The model accounted for minimal between-subject variability (random effects variance = 0.011) and demonstrated good convergence with a scale parameter of 0.9912.

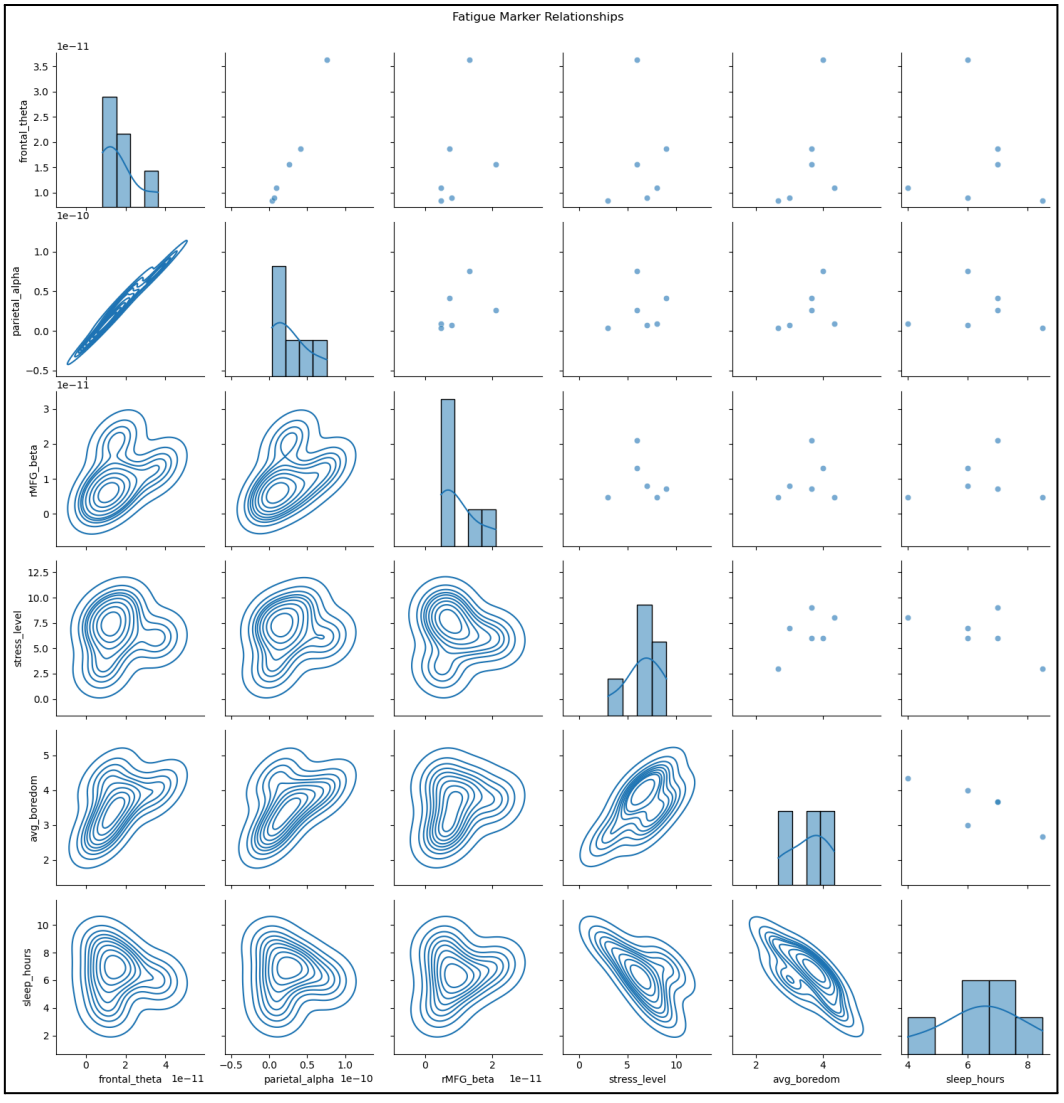


Figure 3: Fatigue Marker Relationships by EEG dynamics and behavioral correlates

(A) Normalized EEG power across trials for frontal theta, parietal alpha, and rMFG beta; error bands indicate ±2 SE. (B) Frontal theta power by chronotype (Morning vs Evening). (C) Negative association between P300 amplitude and wake-up time. (D) Pairwise relationships among EEG markers and behavioral variables (stress, boredom, sleep). (E) Sleep duration moderates the stress–frontal theta relationship.

Band Power by Subjective Measures

Overall, residuals from the boredom prediction model were normally distributed (Shapiro-Wilk: W = 0.892, p = 0.244), but regression coefficients were nonsignificant and confidence intervals spanned zero (R^2 = 0.552, F(3,4) = 1.643, p = 0.314).

Frontal Theta power

Despite the observed neural effects, theta power did not correlate with self-reported stress (r = 1.00, p = 1.000), and no other significant correlations were observed between EEG measures and subjective reports. This suggested a positive correlation between frontal theta power and stress level (r = 0.4946, p = 0.6706), as well as a strong positive correlation with average boredom (r = 0.8629, p = 0.3373). Similarly, a finding of a negative correlation with sleep hours (r = -0.7518, p = 0.4583) lacked statistical support when tested in a larger model. Mixed linear models confirmed the effect of experimental events on theta power (z = 2.346 to 11.900, all p < 0.05), and theta power changes were statistically significant (p = 0.019), suggesting robust experimental effects independent of subjective reports.

Parietal Alpha power

EEG spectral analyses revealed extremely strong effects for alpha power (p < 1e-15), indicating strong sensitivity to experimental manipulations. However, self-reported measures failed to show meaningful associations with parietal alpha power: a weak positive correlation with stress level (r = 0.1772, p = 0.8866), a moderate positive correlation with boredom (r = 0.6456, p = 0.5532), and a negative correlation with sleep hours (r = -0.4896, p = 0.6743). These relationships were not statistically significant.

rMFG Beta Power

Beta power exhibited extremely strong effects in EEG spectral analyses (p < 1e-27). Mixed linear models confirmed significant effects of experimental events on beta power (z = 2.346 to 11.900, all p < 0.05). Correlational analyses suggested a strong positive correlation with stress level (r = 0.8480, p = 0.3556), a very strong positive correlation with average boredom (r = 0.9994, p = 0.0223), and a strong negative correlation with sleep hours (r = -0.9748, p = 0.1433).

P300 ERP

P300 amplitude was significantly modulated (p = 1.69e-57), consistent with hypothesized sensitivity to circadian variation. Correlational findings showed a very strong positive association with wakeup hour (r = 0.9938, p = 0.0708) and a moderate negative correlation with sleep hours (r = -0.6762, p = 0.5272), though neither achieved statistical significance. This was further supported by mixed linear modeling, which showed experimental events significantly influenced amplitude (z = 2.346 to 11.900, all p < 0.05).

Hypothesis 3: Attentional ERP Decline by sessions (RF)

N1

Paired *t*-tests showed no significant differences in N1 amplitude[11] (100–200 ms) across sessions (all $p > .05$).

Amplitude ~ Session + (1 | Subject)

In the mixed-effects model, neither session 2 ($\beta = -0.31$, $p = .336$) nor session 3 ($\beta = 0.11$, $p = .735$) differed significantly from session 1. The subject-level random intercept accounted for almost no variance. Residual variance was $\sigma^2 \approx 24.3$.

N2b

Paired *t*-tests showed that N2b amplitude differed significantly between word (irrelevant) and image (relevant) stimuli in every session[12] (S1: $p = .015$; S2: $p = .009$; S3: $p = .004$). Within the word condition, amplitude means were also significantly different from session 1 to 3 and from session 2 to 3, whereas no session-to-session differences emerged for image stimuli (Figure 4).

*Amplitude ~ Session * Condition + (1 | Subject)*

In the mixed-effects model, session 3 elicited a smaller (more positive) N2b than session 1 ($\beta = 0.64$, $p = .0489$), while session 2 did not differ from session 1 ($\beta = 0.44$, $p = .1736$). Word stimuli produced substantially smaller (more positive) N2b amplitudes than images ($\beta = 2.12$, $p < .001$). Neither the session-2 × word interaction ($\beta = -0.44$, $p = .338$) nor the session-3 × word interaction ($\beta = -0.01$, $p = .980$) reached significance. The random intercept for subjects accounted for little variance. Residual variance was $\sigma^2 \approx 24.2$.

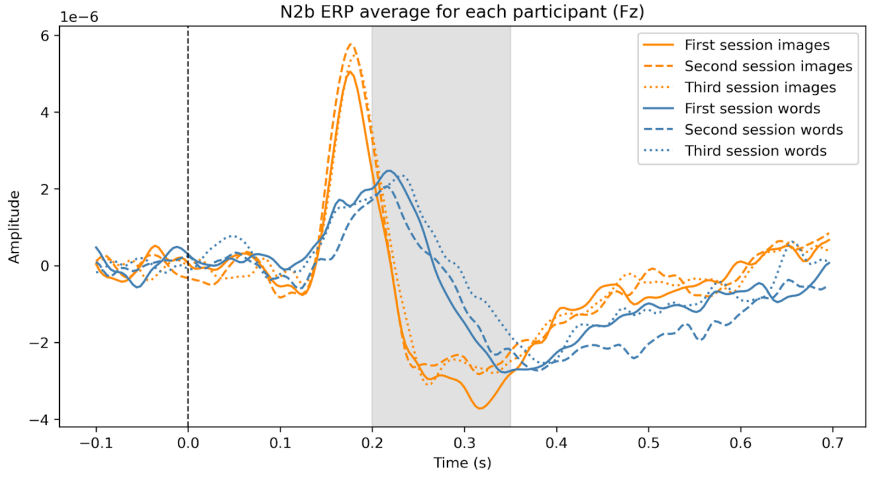


Figure 4: Difference in N2b amplitudes measured at Fz electrode, between word (blue) and image (yellow) epochs and sessions. Grey area indicates the time window of interest, 200 ms - 350 ms.

[11] See diagnostic plots in Appendix *H3: N1*
[12] See diagnostic plots in Appendix *H3 - P300*

P300

Paired *t*-tests on mean P300 amplitude (250–500 ms) revealed a marginally significant increase from session 1 to session 2 (p = .05), while neither the session 1–3 nor the session 2–3 comparisons reached significance. In the mixed-effects model predicting P300 amplitude from session with a random intercept for subject, session 2 showed a significant increase relative to session 1 (β = 0.67, p = .0386), and session 3 likewise exhibited a significant rise in amplitude compared to session 1 (β = 0.73, p = .0256)[13]. The subject-level random intercept accounted for little variance. Residual variance was: $\sigma^2 \approx 23.6$.

Hypothesis 4: Emotional reactivity by sessions (RF)

LPP amplitude

According to paired t-tests, the means of LPP amplitudes (over time window 300 ms to 600 ms post-stimulus) across all of the images show no significant difference as the time progresses (p-value > 0.05). There also seems to be no significant difference across emotional valence.[14]

With a linear mixed-effects model predicting mean amplitude from session (1, 2, 3) with a random intercept for subject, session 2 exhibited a small, but significant increase relative to session 1 (β = 0.48, p = .0144), and session 3 also shown the same effect compared to session 1 (β = 0.41, p = .0354). The subject-level random intercept did not explain much of the variance. Residual variance was $\sigma^2 \approx 8.5$. Adding emotional valence as a random intercept did not improve the model fit ($\sigma^2 \approx 8.5$, p = .399).

EPN

Paired t-tests show no significant difference in the means[15] between EPN amplitudes 240-300 ms post stimulus (all p > .05). In a linear mixed-effects model predicting EPN amplitude from session (1 = first, 2 = second, 3 = third) with a random intercept for subject, neither session 2 (β = −0.26, p = .31) nor session 3 (β = −0.31, p = .23) differed significantly from session 1. The subject-level random intercept accounted for minimal variance. Residual variance was: $\sigma^2 \approx 14.6$.

N400

Paired *t*-tests between neutrally and validly (positive or negative) cued images showed no significant differences in N400 amplitude (300–450 ms) across sessions (all p > .05).[16]

*Amplitude ~ Session * Validity + (1 | Subject)*

In the mixed-effects model both session 2 (β = 0.99, p = .0148) and session 3 (β = 0.84, p = .0381) yielded higher N400 amplitudes than session 1, and valid cues evoked more positive amplitudes overall (β = 0.78, p = .0266). Neither the session-2 × validity interaction (β = −0.55, p = .2706) nor the session-3 × validity interaction (β = −0.65, p = .1909) reached

[13] See amplitudes plot in the Appendix *H3 - P300*
[14] See amplitudes and diagnostic plots in the Appendix *H4 - LPP*
[15] See diagnostic plots in the Appendix *H4 - EPN*
[16] See diagnostic plots in the Appendix *H4 - N400*

significance. The subject-level random intercept explained minimal variance. Residual variance was $\sigma^2 \approx 12.2$.

Discussion (RF, CH)

Performance Dynamics Over Time and Word Valence (CH)

The results provide limited and partially contradictory support for H1, which proposed that cognitive performance would decline over time, with increasing reaction times and decreasing accuracy, particularly during neutral word trials and at times of low circadian alertness (Boksem et al., 2005; Lorist, 2008).

The full factorial model examining showed no significant effects or interactions. This suggests that overall response speed remained stable throughout the task, consistent with findings that habituation can mask fatigue effects in repetitive tasks (Soto-Leon et al., 2020). Contrary to the hypothesis, a simplified model collapsing across word conditions revealed a significant decrease in reaction times over trials. This pattern is more consistent with a practice or habituation effect, where participants became more efficient at the task over time, rather than exhibiting fatigue-related slowing.

However, targeted analyses of neutral word trials showed a significant decline in accuracy across trials, occurring without corresponding reaction time changes. This speed-accuracy tradeoff suggests disengagement or reduced cognitive control (Faber et al., 2012), supporting predictions that neutral primes (less salient and more effortful to process) are vulnerable to fatigue (Lorist, 2008). Notably, this decline was not moderated by time of day, suggesting task-specific fatigue (e.g., cognitive load) drove effects rather than circadian fluctuations (Valdez, 2019). All three periods; morning, midday and evening showed overlapping patterns, with no systematic circadian variation in response speeds.

Band Power and Experimental Effects (CH)

Hypothesis 2 predicted increased frontal theta (θ) and parietal alpha (α) power, and decreased right middle frontal gyrus (rMFG) beta (β) power with fatigue (Boksem et al., 2005).

The increase in frontal theta power supports H2's prediction and is consistent with prior research linking theta activity to cognitive effort and fatigue (Trejo et al., 2015; Wascher et al., 2014). The low between-subject variance suggests this effect may be relatively universal across individuals. Similarly, parietal alpha power showed a significant increase with fatigue, aligning with the hypothesis and literature suggesting that alpha enhancement reflects reduced engagement or cognitive withdrawal during mental fatigue (Trejo et al., 2015). However, convergence issues in the alpha model suggest that individual differences in alpha reactivity warrant further investigation (Komarov et al., 2020).

In contrast, the findings for the rMFG beta power directly contradict H2. Rather than decreasing, beta power significantly increased during fatigue. This may indicate compensatory cortical activation in response to fatigue, consistent with prior findings that suggest increased frontal activity under high cognitive demand (Tanaka et al., 2014). The relatively high between-subject variance here suggests notable individual variability in these responses. Similarly, P300 amplitude increased, contrary to typical fatigue-related

reductions (Geisler & Polich, 1992). This may stem from task-specific attentional engagement (Boksem et al., 2005).

Band Power and Subjective Measures (CH)

In correlation with subjective measure, H2 states that changes in EEG power bands will correlate with self-reported stress, boredom, and sleepiness, and vary with participants' circadian rhythms, reflected by the P300 ERP.

First of all, the EEG changes observed did not consistently correlate with self-reported measures of stress, boredom, or sleepiness. Although trends in the expected direction were present; for example, a positive correlation between theta power and boredom, and a negative correlation between beta power and sleep hours. These relationships did not reach statistical significance, with the exception of beta power and boredom. Notably, this correlation further contradicts H2, as rMFG beta power was expected to decrease with fatigue, not increase. Parietal alpha power showed weak and statistically nonsignificant correlations with all subjective measures, suggesting that while alpha power responds reliably to experimental manipulations, it may not directly reflect subjective fatigue experiences (Trejo et al., 2015).

The P300 amplitude showed a strong, though non-significant, positive association with wakeup time, hinting at possible circadian modulation (Santhi et al., 2016). This trend aligns with the idea that circadian alignment enhances cognitive performance, though it falls short of supporting a definitive link.

Attentional declines over sessions (RF)

We hypothesized that with increasing fatigue over sessions, top-down attentional control will diminish, and this will show in the ERP components N1, N2b and N400. The unexpected pattern of ERP findings offers several insights into how fatigue reshapes attentional dynamics over time. First, the absence of any reliable change in the N1 amplitude across sessions suggests that early sensory-perceptual processing remains relatively resilient to the levels of cognitive fatigue induced in this experiment (Vogel & Luck, 2000; Patel & Azzam, 2005).

In contrast, the P300 component showed a clear, progressive increase in amplitude; a direction opposite to the classic fatigue-related effect (Geisler & Polich, 1992; Glenn et al., 2017). One plausible interpretation is that participants recruited compensatory resources: as fatigue grew, the anterior cingulate and dorsolateral prefrontal networks may have over-engaged to uphold performance goals, thereby amplifying late evaluative processing (Rozand et al., 2015; Boksem et al., 2005).

By contrast, the findings related to the N2b component supported our hypothesis: relevant (images), irrelevant (word) stimuli differentiation was strong in Session 1 but declined significantly by Sessions 2 and 3, mirroring diminished executive-control capacity with mounting fatigue (Faber et al., 2012; Boksem et al., 2005). This reduction in N2b differentiation indicates a shift from sustained, top-down biasing by the lateral intraparietal and prefrontal cortices toward a more reflexive, stimulus-driven mode (Bisley & Goldberg, 2010; Corbetta et al., 2002). It also further supports Pauletti et al. 's (2024) observation of

reduced N2 amplitudes under high-fatigue conditions, underscoring that conflict resolution of the attention model (Posner & Petersen, 1990) suffers most as cognitive resources decrease.

Emotional disengagement through sessions (RF)

We expected that with increasing fatigue, emotional investment would decrease as reflected in EPN, LPP and N400. Consistent with the two-stage model of emotional processing (Compton, 2003), we found no change in EPN amplitude across sessions. Our null effect confirms that the earliest, preattentive stage of emotional valence remains intact even as participants tire (Kissler et al., 2008). This stability underscores that any decline in emotional engagement under fatigue does not originate in disrupted early sensory encoding.

Contrary to our hypothesis and prior reports of LPP decrease under fatigue, we observed an increase in LPP amplitude in Sessions 2 and 3 relative to Session 1. Because the LPP is sensitive to attentional factors, this upward drift may reflect a practice or habituation effect, with participants becoming more efficient at allocating attention to emotional faces (Fan et al., 2023; Zhang, 2017). This suggests later evaluative processing can be maintained or even enhanced under moderate fatigue.

The N400 component also showed an unexpected upward shift across sessions, with validly cued faces evoking larger amplitudes overall, contradicting the usual reduction in integration load when affective context matches (Li & Lu, 2014). As the session–validity interaction was non-significant, both cue types increased similarly, thus suggesting fatigue uniformly elevates integration demands across conditions.

Limitations (RF) and Further Research (CH)

This study had several notable limitations. First, task habituation from repetition may have led to faster reaction times driven by automaticity rather than true cognitive changes, complicating fatigue interpretation. Dim or dark lighting conditions and uncontrolled caffeine intake may have disrupted circadian rhythms, introducing variability in alertness unrelated to the task. Second, the facial expression stimulus may have resembled surprise more than clear negative emotion, possibly affecting emotional processing. The small, predominantly female sample (N=8) limited statistical power and generalizability, especially for detecting subtle effects like circadian interactions. Third, EEG data quality may have been compromised by artifacts (e.g., eye blinks, muscle movements) and inconsistencies in electrode placement, as setup was conducted by bachelor students.

Additional limitations include uncontrolled gender-related circadian differences, unstandardized nutritional states, and reliance on self-reported measures susceptible to bias. External factors such as sleep, food intake, and stress were recorded but not used as exclusion criteria. These limitations warrant cautious interpretation but do not diminish the study's contribution to understanding mental fatigue mechanisms.

Future research should extend task durations beyond 20 minutes to capture more pronounced fatigue effects and include larger, more demographically diverse samples to improve generalizability and statistical power. Studies comparing extreme chronotypes could clarify how circadian factors influence fatigue onset and performance decline across the day.

Conclusion (RF, CH)

In summary, while performance declined under sustained task demands, circadian timing showed no significant influence. Fatigue effects were primarily task-related, with neutral trials contributing most, consistent with prior findings that neutral stimuli amplify fatigue (Boksem et al., 2005).

EEG results supported this interpretation. Increases in theta and alpha activity aligned with H2, while deviations in beta and P300 suggested compensatory mechanisms. Individual differences in neural responses further highlighted individual effects of fatigue.

It seems, mental fatigue alters brain activity, particularly in the theta and alpha bands. However, the mismatch between EEG markers and subjective reports suggests these signals reflect objective fatigue that may not always be consciously perceived, likely influenced by individual variability and task design.

Overall, findings support a multi-level model of fatigue: sensory-perceptual processing remains stable, executive control declines, and evaluative networks show increased activation, likely reflecting compensatory engagement of cognitive resources. Emotion-related patterns mirrored these effects, reinforcing the model's broader applicability. Although, these results should be viewed critically, as discussed in limitations.

References

GitHub repository for data preprocessing and analysis:

https://github.com/RekaForgo/Fatigue-in-EEG-Cognitive-Neuroscience-2025-.git

Experiment:

PsychoPy code from: Mikkel Wallentin & Roberta Rocca, 2019 https://github.com/lindeloev/psychopy-course/blob/master/ppc_template.py, with some of the code adapted from Jonas Lindeløv.

Research:

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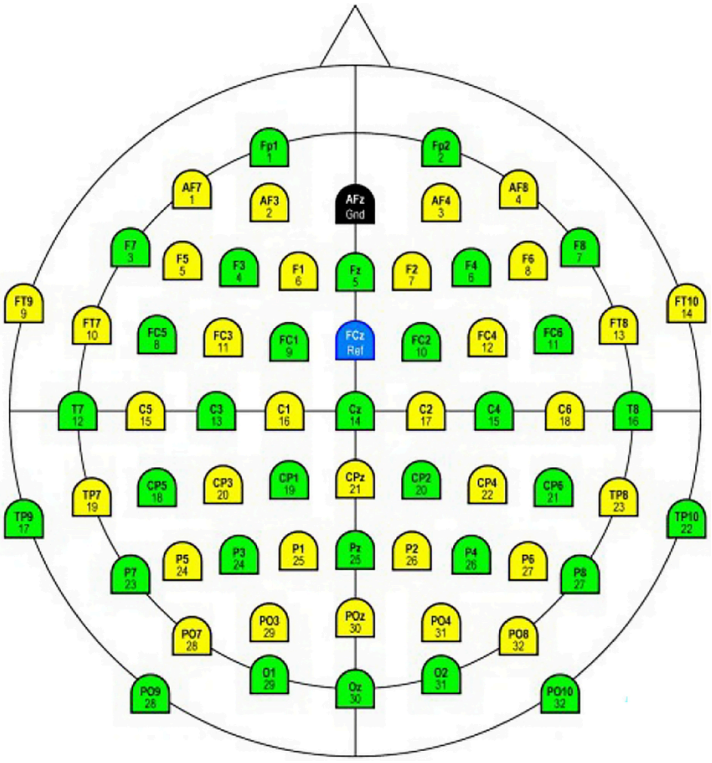
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Appendix

Standard electrode positions



FaceWord Stimuli

Words

The stimulus wordset was constructed using semantic ratings from Binder et al. (2016), where regular english words (nouns, verbs, adjectives) were rated on 60 cognitive and emotional dimensions. A subset of affect-related dimensions (pleasant, unpleasant, happy, sad) was used to extract a principal valence component via principal component analysis (PCA). Words were further cross-validated using valence scores from the Warriner et al. (2013) affective norms, using the package *pliers* (McNamara et al., 2017). Based on these combined metrics, words were classified into positive, negative, and neutral categories. For each valence category, 120 words were selected and divided into six experimental sessions, each containing 60 words (20 per category). This ensured balanced affective distribution across sessions and consistency in semantic valence.

Negative face



Positive face



The faces were outlined in yellow (HEX code : #FFFF33) on a black background.

FaceWord Instructions

"In this experiment you read words and look at faces,
Words can be used to predict facial expression,
Press "B" with INDEX finger if face is POSITIVE',
Press "Y" with MIDDLE finger if face is NEGATIVE',
The experiment starts when you press "T"."

Trial-Level Variables

- ID, age, gender, scan day, session, condition = Participant/session metadata.
- word, word_label, word_score_pc, word_score_warriner = Word stimulus details.
- img = Face image used (positive or negative).
- onset_word, offset_word, duration_measured_word = Word stimulus timing.
- onset_img, offset_img, duration_measured_img = Image stimulus timing.
- delay_frames_before, delay_frames_after = Jittering delays before/after image.
- duration_frames = Stimulus display duration.
- response, key_t, rt = Participant response, timestamp, and reaction time.
- correct_resp = Whether the response was correct.
- no = Trial number.

Supplementary notes

The sentinel hypothesis

The sentinel hypothesis suggests that the DMN remains partially active to maintain environmental awareness, which may interfere with focused attention under conditions of fatigue (Bear et al., 2020; Fan et al., 2023). This interaction between default and task-positive networks helps explain why sustained cognitive effort becomes more difficult as mental fatigue progresses (Lorist et al., 2008; Tanaka, Ishii, & Watanabe, 2014). Additionally, the internal mentation hypothesis suggests that DMN regions are involved in processing emotionally salient and memory-based stimuli, which aligns with observed reductions in LPP amplitude across trials as mental fatigue accumulates (Bear, Connors, & Paradiso, 2020). Given that fatigue alters cognitive functioning on multiple levels, its impact on attentional processes becomes particularly relevant.

Food and mental fatigue

In terms of eating before engaging in cognitively demanding tasks, it is important to eat breakfast, but after eating lunch mental fatigue is more prominent. In both a laboratory study and real-life study, mental fatigue ratings were significantly higher when exercise was undertaken fasted rather than following breakfast (Veasey et al., 2012). Additionally, post-lunch impairments in efficiency have been observed in various settings, with a maximal dip in performance occurring one to two hours after lunch (Khanna & Gupta, 2012). Not eating at all or fasting for extended periods of time before participating in a cognitively demanding study, is also a problem that can lead to increased mental fatigue. Zajac et al. (2020) noted no cognitive impairment, but increased subjective mental fatigue during fasting. Furthermore, Marcora et al. (2009) showed that mental fatigue from prolonged cognitive tasks reduced physical performance by increasing perceived exertion.

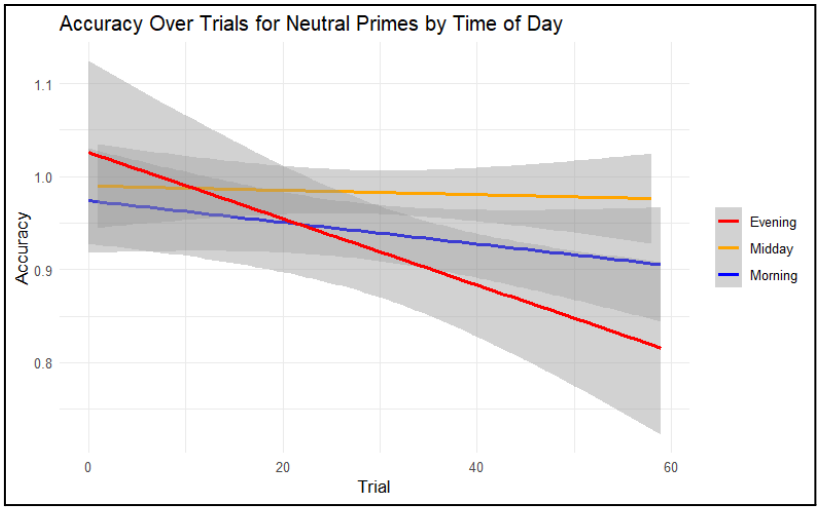
Participants were also asked whether they had eaten within 2 hours before participating in the experiment. Here, 5 participants (62%) had eaten within 2 hours before their session, 2 had not, and 1 was unsure. This meal timing likely aligned with breakfast or lunch depending on the session time.

Attention models

There are multiple models that describe attentional processes, each emphasizing different mechanisms of selection and control. Biased-competition theory suggests that sensory inputs compete for neural representation, with top-down signals biasing this competition toward goal-relevant stimuli (Desimone & Duncan, 1995). Guided Search theory synthesizes these dynamics into a priority map that integrates both bottom-up salience and top-down goals to guide attention during visual search (Wolfe, 2007). While these models account for attentional processes, such as selection and competition, Posner's attention model has directly observable EEG correlates (Pauletti et al., 2024).

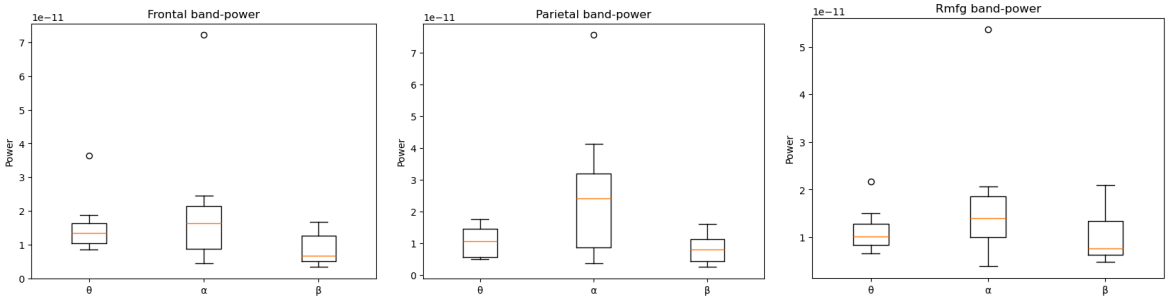
Extra Visualizations

Hypothesis 1

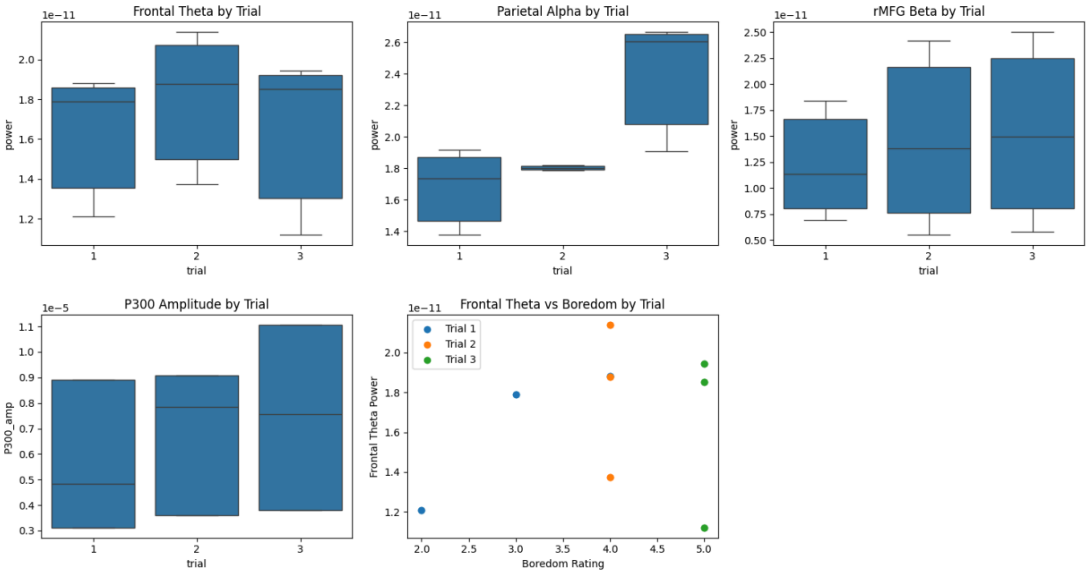


Accuracy Over Trials for Neutral Primes by Time of Day

Hypothesis 2



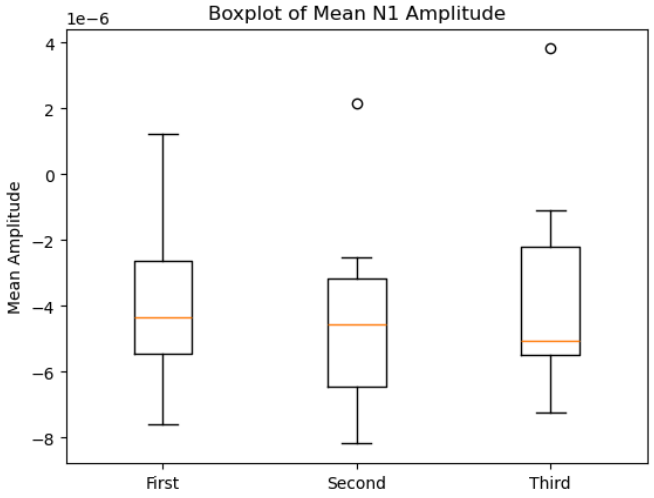
Boxplots of power by ROI & band

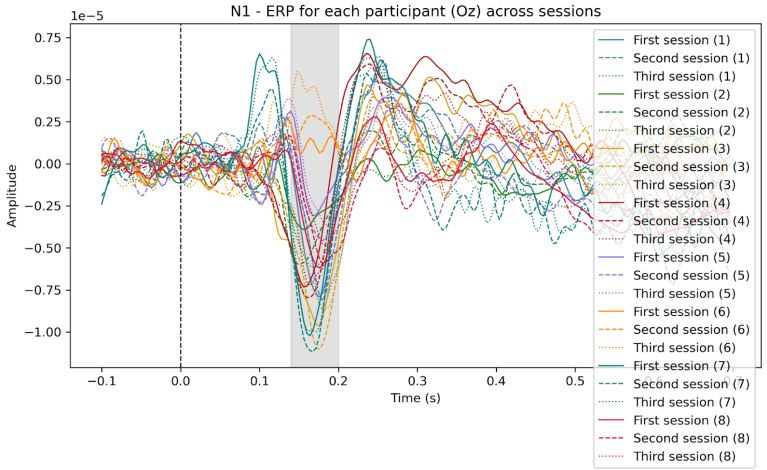


Power bands on trial + boredom & power bands on trial

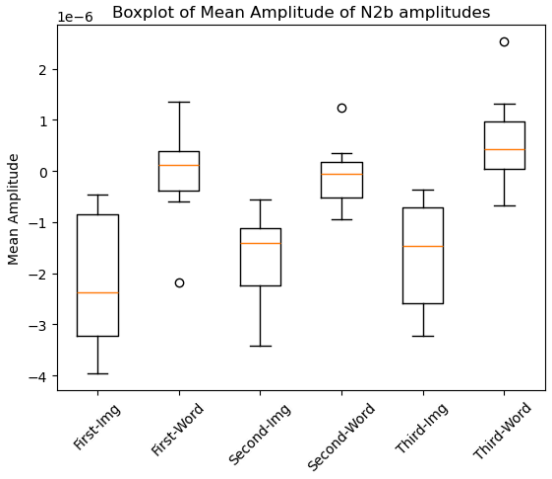
Hypothesis 3

N1

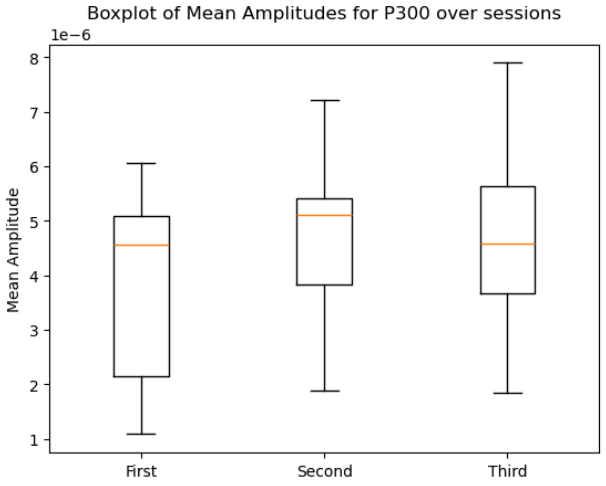


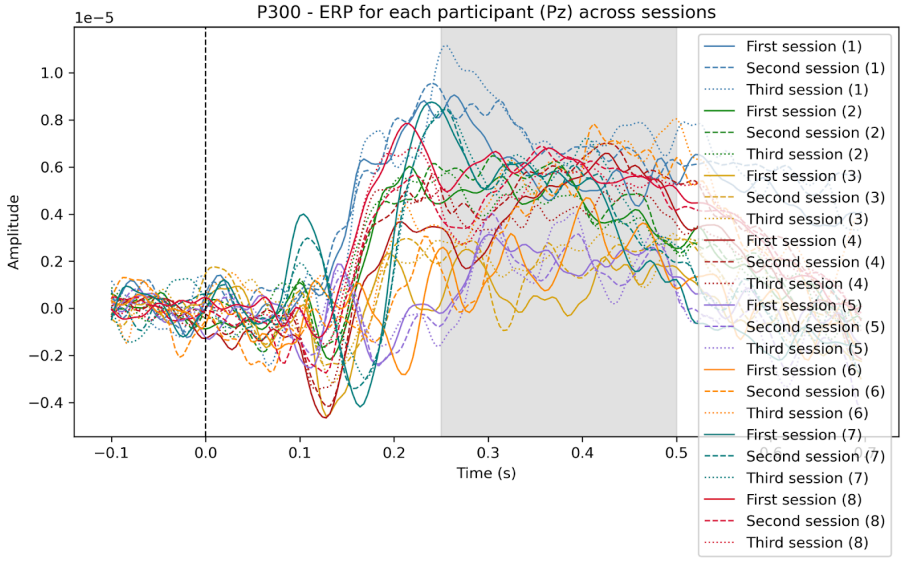


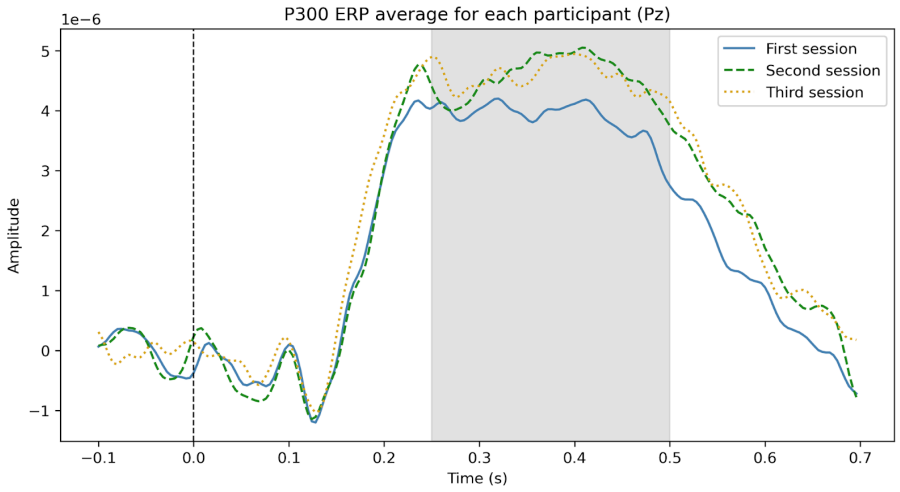
N2b


Boxplot of Mean Amplitude of N2b amplitudes
1e−6
Mean Amplitude
First-Img
First-Word
Second-Img
Second-Word
Third-Img
Third-Word

P300

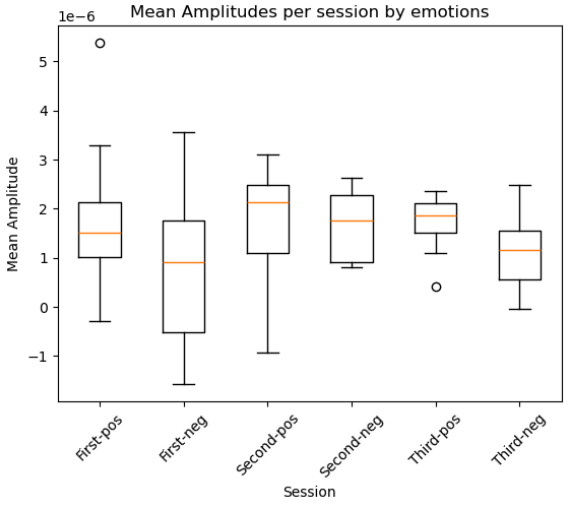

Boxplot of Mean Amplitudes for P300 over sessions
1e−6
Mean Amplitude
First
Second
Third


P300 - ERP for each participant (Pz) across sessions
1e−5
Amplitude
Time (s)
First session (1)
Second session (1)
Third session (1)
First session (2)
Second session (2)
Third session (2)
First session (3)
Second session (3)
Third session (3)
First session (4)
Second session (4)
Third session (4)
First session (5)
Second session (5)
Third session (5)
First session (6)
Second session (6)
Third session (6)
First session (7)
Second session (7)
Third session (7)
First session (8)
Second session (8)
Third session (8)

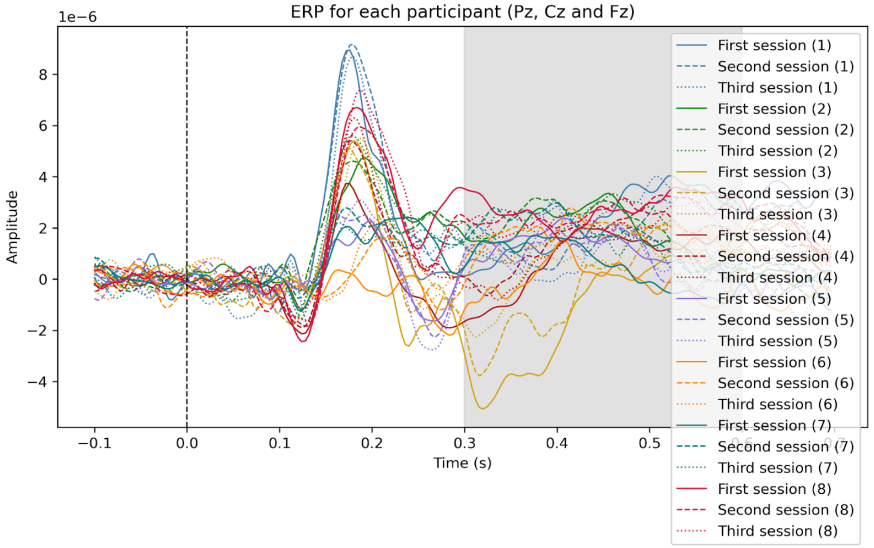


Hypothesis 4

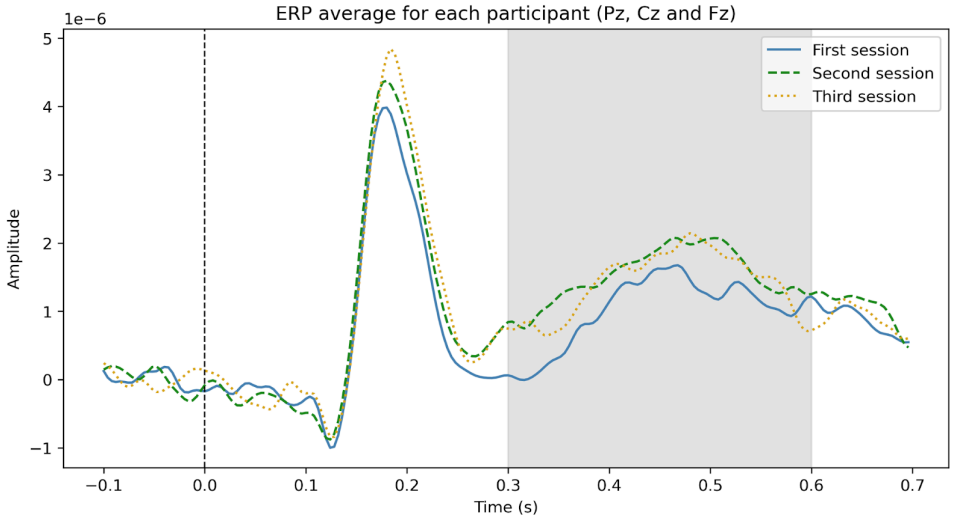
LPP



Boxplot of mean LPP amplitudes by sessions and by emotional valence of stimuli

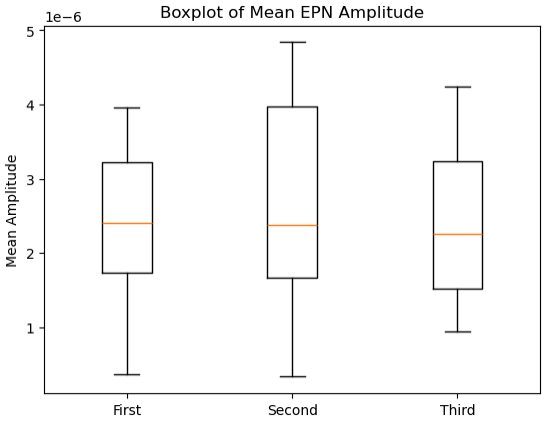


Subject level variability for LPP amplitudes across sensors Pz, Fz and Cz

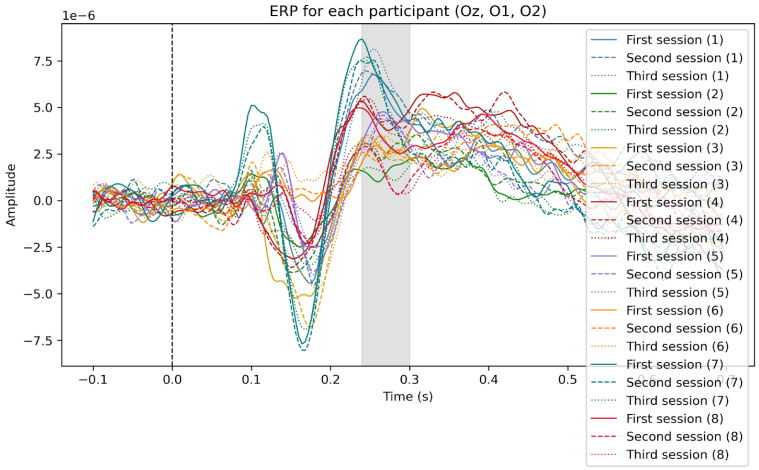


LPP amplitudes averaged over Pz, Cz and Fz electrodes, and all participants. Grey area indicates the time window 300 ms - 600 ms. The blue line is amplitudes from first session (5-60 trials), green from the second (65 - 120) and yellow from the third (125- 180)

EPN

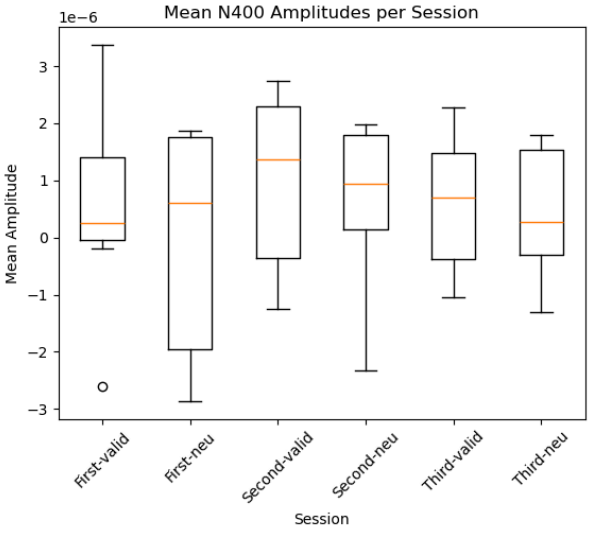


Boxplot of mean EPN amplitudes between sessions

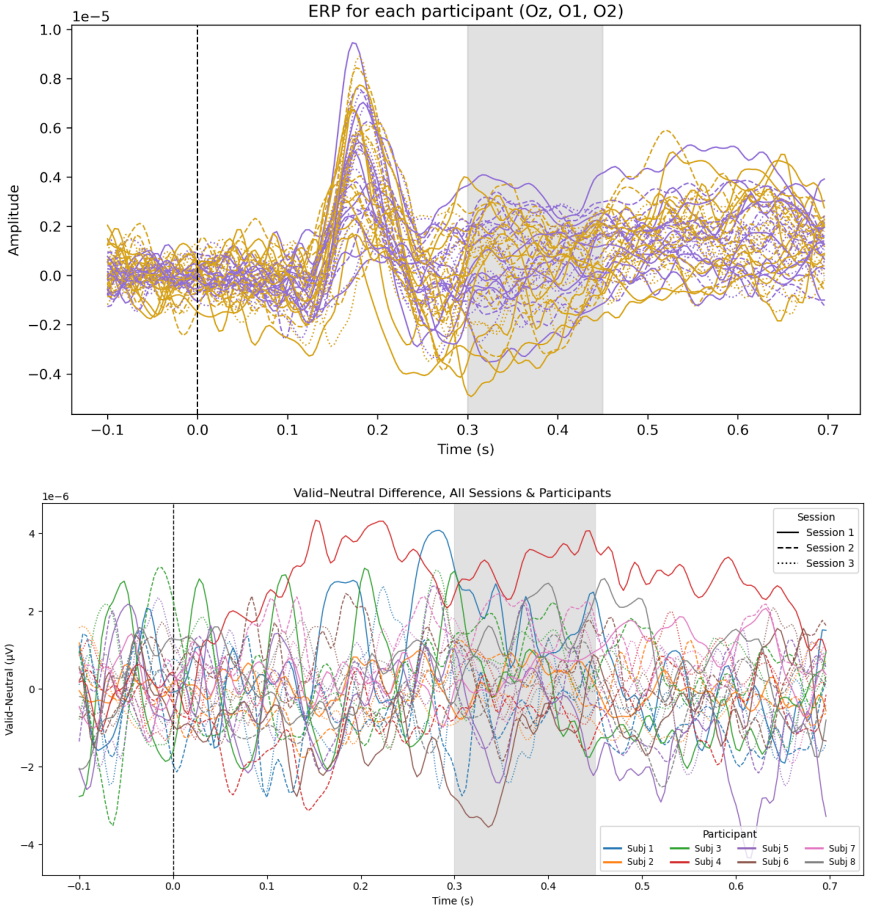


Subject level variability in EPN responses across sensors Oz, O1 and O2

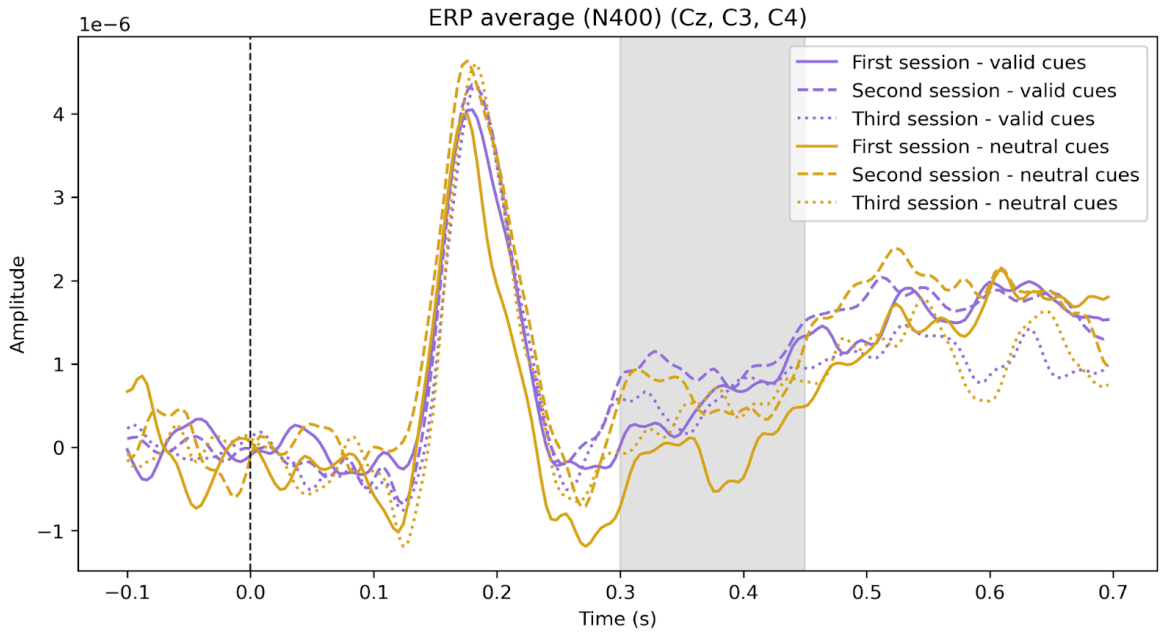
N400



Mean N400 Amplitudes by session and validity of priming cues

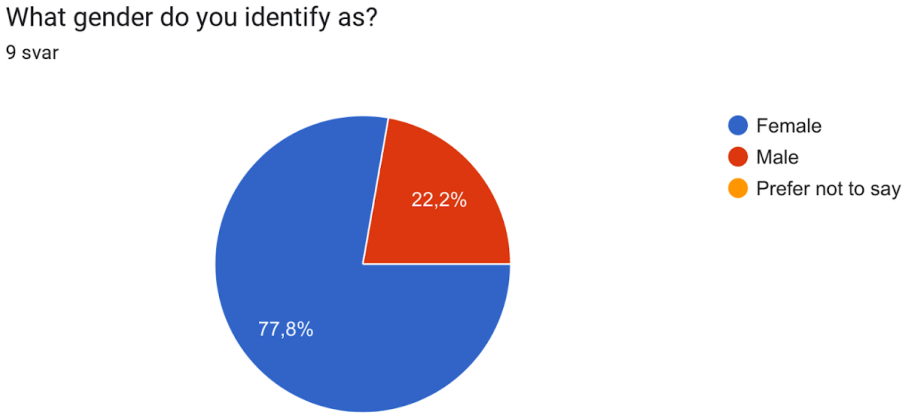


Subject level variability. Plot 1) shows lines for each subject, colored by either valid or neutral. Plot 2) shows the difference in amplitude between valid-neutral conditions on a subject level.



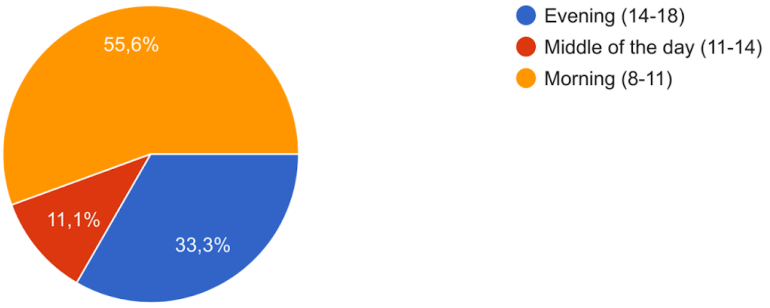
N400 amplitudes across sessions (1-3), colored by if the images were validly (purple) or invalidly cued (mustard).

Survey results



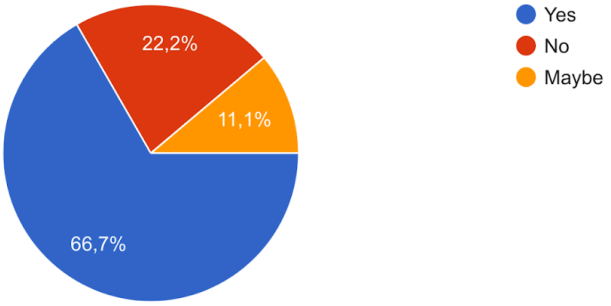
What time of the day, do you feel most productive, out of the following options:

9 svar



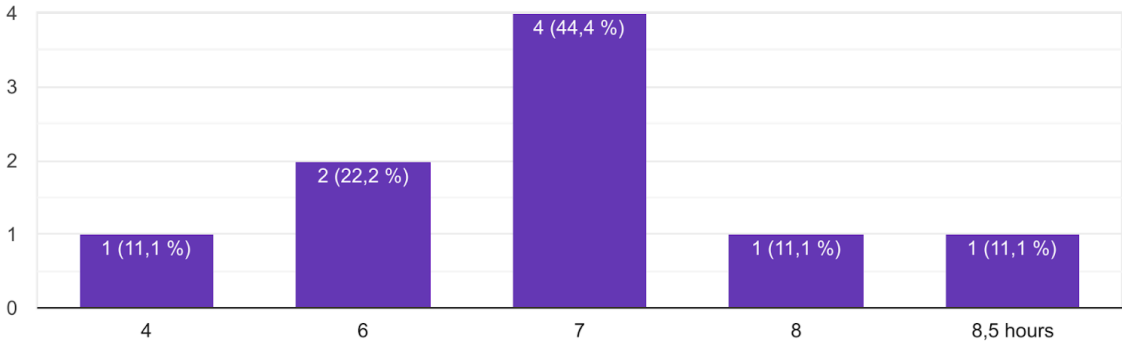
Did you eat within 2 hours before participating in the EEG experiment?

9 svar



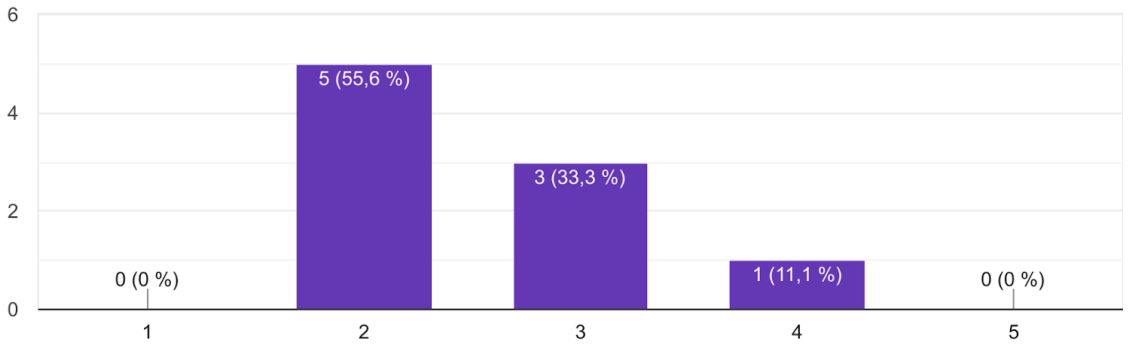
How many hours of sleep did you get the night before participating in the EEG experiment? (approximately)

9 svar



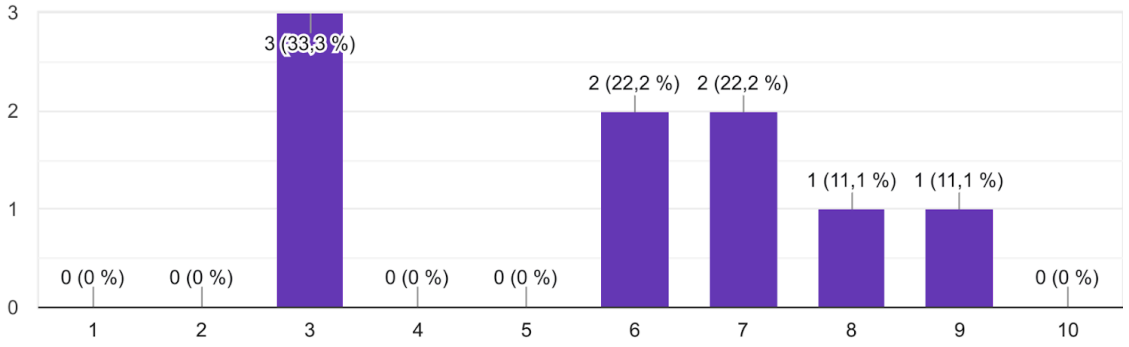
How bored did you feel on the first trial? (Faceword)

9 svar



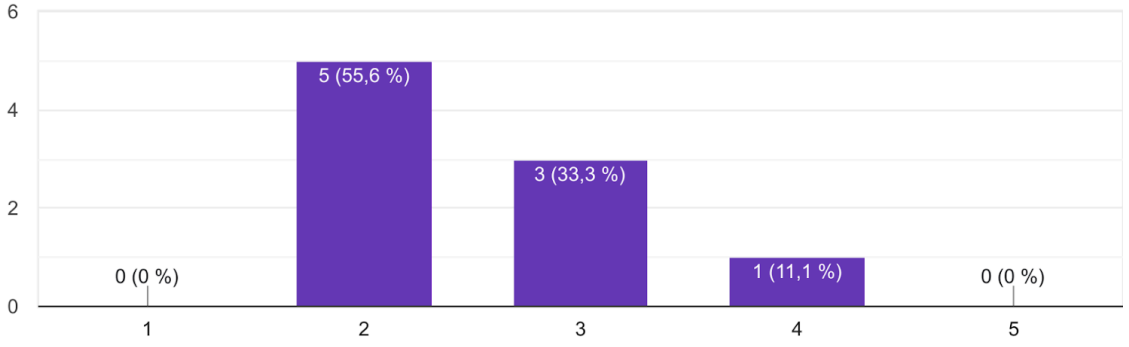
How stressed did you feel during the week of the EEG experiment?

9 svar



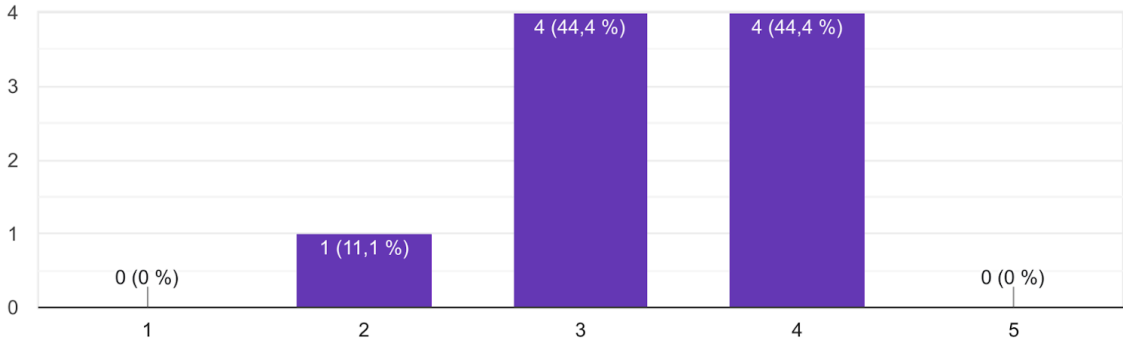
How bored did you feel on the first trial? (Faceword)

9 svar



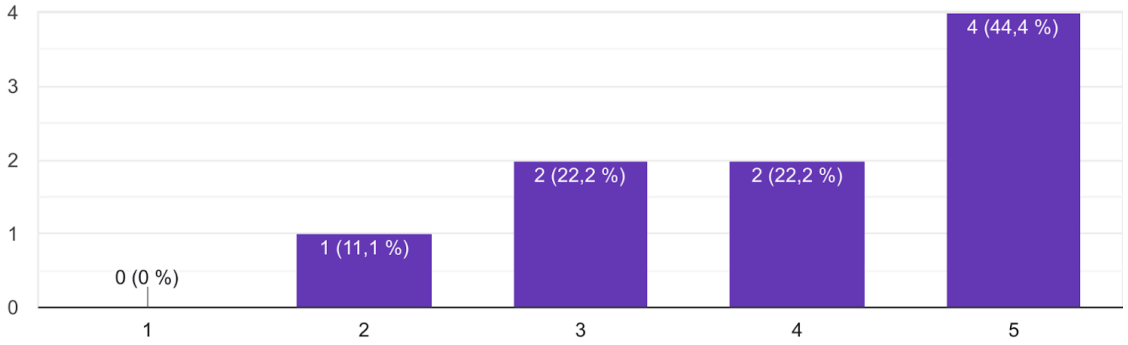
How bored did you feel on the second trial? (Faceword)

9 svar



How bored did you feel on the third (last) trial? (Faceword)

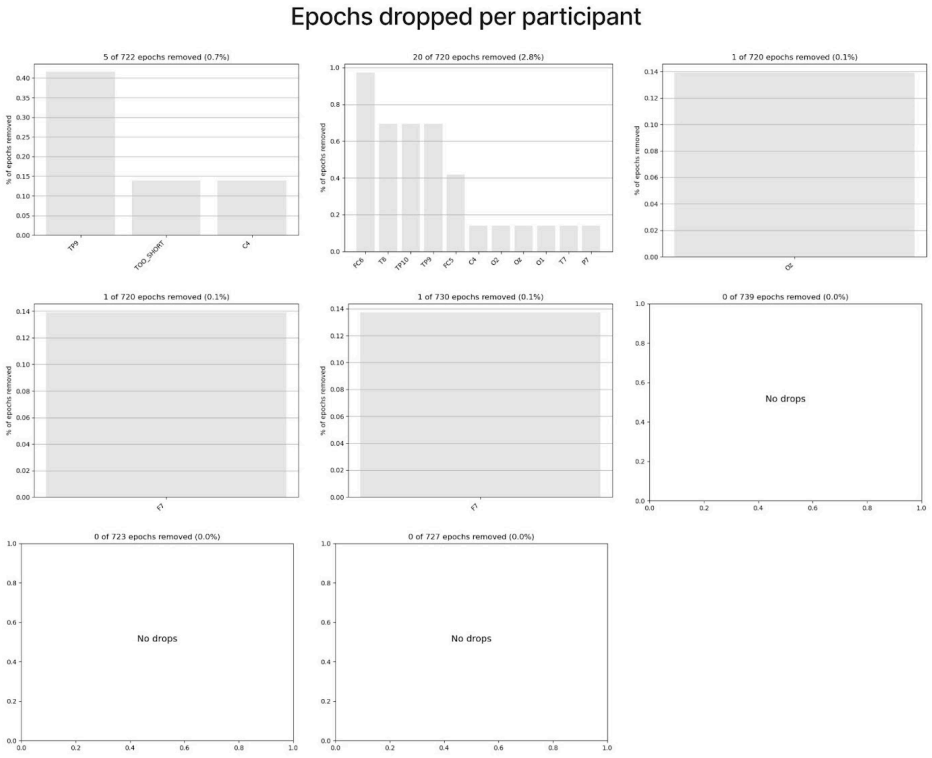
9 svar



Timestamp	Gender	Age	Productive (TOD)	Food intake	Wake up time	Sleep (H)	Stress (1-10)	Boredom (1st)	Boredom (2nd)	Boredom (3rd)	Participant EEG session	TOD (experiment)
2025.04.05. 15:25:15	Female	21	Morning (8-11)	Yes	6:30:00	7	6	2	4	5	Thursday 8-11	Morning
2025.04.05. 15:40:07	Female	19	Evening (14-18)	Yes	7:00:00	4	8	4	4	5	Tuesday 8-11	Morning
2025.04.05. 15:53:07	Female	23	Morning (8-11)	No	5:50:00	6	6	3	4	5	Thursday 11-14	Middle of the day
2025.04.05. 16:51:02	Female	22	Morning (8-11)	Yes	6:30:00	6	7	2	3	4	Thursday 8-11	Morning
2025.04.10. 12:17:02	Female	35	Evening (14-18)	No	6:40:00	7	9	3	4	4	Tuesday 8-11	Morning
2025.04.10. 12:37:04	Male	20	Evening (14-18)	Yes	8:00:00	8.5	3	2	3	3	Wednesday 12-15	Middle of the day
2025.04.13. 12:19:53	Female	20	Middle of the day (11-14)	Yes	7:00:00	7	3	2	3	3	Wednesday 9-12	Morning
2025.05.02. 11:01:04	Male	23	Middle of the day (11-14)	Maybe	9:30:00	7	3	3	4	5	Tuesday 11-14	Middle of the day
Average scores						6,5625	5,625	2,625	3,625	4,25		
Excluded participants												
~~2025.04.06. 17:58:47~~	~~Male~~	~~28~~	~~Morning (8-11)~~	~~Maybe~~	~~6:30:00~~	~~7~~	~~7~~	~~2~~	~~2~~	~~2~~	~~Tuesday 14-17~~	~~Afternoon~~
~~2025.04.07. 14:03:16~~	~~Female~~	~~24~~	~~Morning (8-11)~~	~~Yes~~	~~6:45:00~~	~~8~~	~~3~~	~~3~~	~~3~~	~~6~~	~~Wednesday 9-12~~	~~Morning~~

Preprocessing

Dropped Epochs



ICA Filtering

