

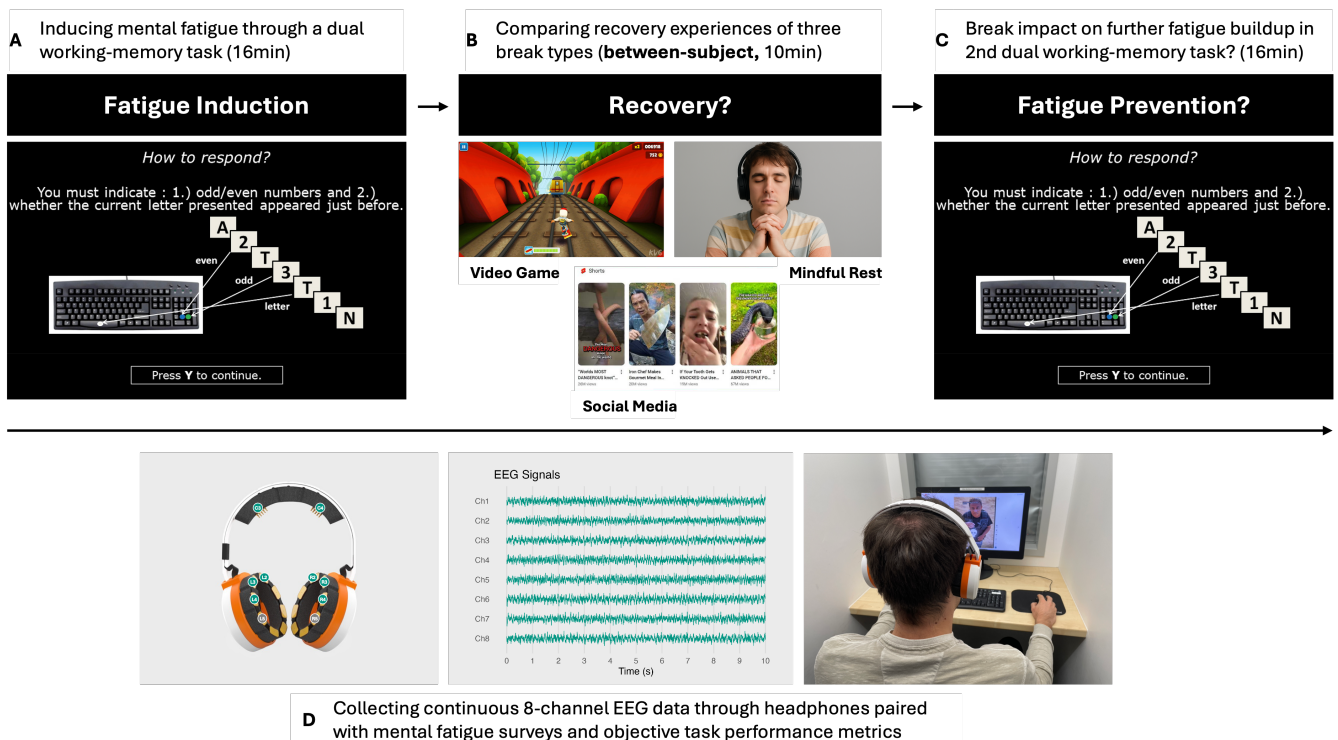
# Rest Assured: Detecting Mental Fatigue and Recovery with EEG Headphones

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**Figure 1: The study investigates how different break activities affect mental fatigue recovery by comparing neural changes tracked through headphone-EEG (D) across two demanding cognitive-task blocks (A&C) separated by one of three break conditions (B).**



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 CHI '26, Barcelona, Spain  
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 ACM ISBN 979-8-4007-2278-3/26/04  
<https://doi.org/10.1145/3772318.3791781>

## Abstract

Mental fatigue, a common consequence of cognitively demanding work, impairs concentration and well-being, posing long-term health risks. Distinct from drowsiness, mental fatigue is reliably

measured with EEG, yet conventional setups remain too cumbersome for everyday use. To overcome this barrier, this study investigates whether EEG headphones can detect mental fatigue and recovery across two common digital break activities: playing a video game and browsing social media. We conducted an experiment with consecutive task sessions and an intermittent break, collecting self-report, performance, and EEG data. Our results show that EEG headphones can detect mental fatigue and recovery dynamics via relative alpha power, and differentiate recovery effects between break types. Social media proved more restorative than gaming, with effects persisting into the subsequent task. These findings establish needed working principles for using headphone-EEG in naturalistic fatigue and recovery research, providing a foundation for future studies.

## CCS Concepts

• **Human-centered computing** → **Empirical studies in HCI; User studies.**

## Keywords

Mental Fatigue, Recovery, Digital Breaks, Headphone EEG, Open ExG Headphones, Social Media, Video Gaming, Mindfulness

### ACM Reference Format:

Lukas Schick, Emilia Frey, Felix Putze, and Michael T. Knierim. 2026. Rest Assured: Detecting Mental Fatigue and Recovery with EEG Headphones. In *Proceedings of the 2026 CHI Conference on Human Factors in Computing Systems (CHI '26)*, April 13–17, 2026, Barcelona, Spain. ACM, New York, NY, USA, 17 pages. <https://doi.org/10.1145/3772318.3791781>

## 1 Introduction

Mental fatigue, a phenomenon distinct from general sleepiness or drowsiness, is described as a feeling of exhaustion that arises from engaging in cognitively demanding tasks over extended periods. It manifests itself through losses in concentration, reduced willingness to complete the current task, and increased error proneness [10, 11]. Its negative impact on mood and mental well-being is well established and can include long-term consequences such as burnout or depression [26, 56]. Feelings of mental fatigue are highly prevalent in modern society, with over one third of workers in the Netherlands and the US [11] reporting mental fatigue episodes, and over half of adults in Japan [94] suffering from it chronically. Unfortunately, our increasingly digital world appears to exacerbate the strain [79, 101]. Correspondingly, mental fatigue has become an important area of research in HCI, covering the impact of digital technologies [15, 60, 71], the interplay of mental fatigue and other cognitive states [83], and its detection [29, 36, 47, 54].

Researchers have suggested that systems capable of continuously monitoring mental fatigue may help to counteract it, for instance through automated break interventions [47, 54]. However, mental fatigue monitoring in naturalistic settings is still inhibited by the available measurement methods. Questionnaires, the most established way of assessing mental fatigue, are subjective and interruptive. Electroencephalography (EEG) is considered the most reliable physiological marker of mental fatigue [58, 96], yet its cumbersome setup and required expertise limit everyday use [8, 72]. Recently, though, advances in ear-centered neural sensing

are leading to more practical EEG solutions. Various headphone-EEG solutions have been developed that integrate brain signal measurement with everyday devices by placing electrodes in the ear-canal [21, 42, 59], around the ears [3, 18, 23, 46, 52, 53, 62] and in headphone headbands [3, 18, 46, 53]. These systems greatly reduce setup time and complexity compared to conventional EEG devices, and allow for high-quality recordings in both laboratory and field settings [8, 53, 57, 105]. Headphone-EEG systems therefore present a promising yet untested option for monitoring mental fatigue. Moreover, headphone-EEG may also enable assessing recovery, offering insights into the quality and effectiveness of breaks.

Taking breaks, thereby allowing the brain to disengage from the activity causing strain, has been identified as a key strategy to reduce mental fatigue, especially in the work context [89]. Notably, HCI research highlights that digital breaks have become pervasive among knowledge workers [27, 80, 86], and investigates whether digital break activities help or hinder recovery, with ambiguous results [40, 108]. Thus, there is a need for comparisons of common digital break activities - examining how they provide recovery (compared to established breaks like mindful-rest), whether their impact can be measured physiologically, and how they affect mental states both in the short term and in subsequent work. Physiological assessment with headphone-EEG, in particular, could enable long-term studies of mental fatigue and recovery in naturalistic settings that were previously out of reach.

Taking the identified challenges from both perspectives into account, we pose the following research questions (RQ):

- (1) Can headphone-EEG be used to detect mental fatigue and recovery in typical work-break sequences?
- (2) How do common digital break activities influence recovery, both immediately and during subsequent work?

To answer these RQ, we designed an experiment with two consecutive task sessions and an intermittent break, in which participants experienced one of two common digital break activities: playing a video game, or browsing social media, with a mindful-rest break as a control condition. Our findings show that mental fatigue monitoring with EEG headphones is possible through between-task and on-task alpha power dynamics, providing working principles for future research on mental fatigue and recovery in naturalistic settings.

## 2 Related Work

### 2.1 Mental Fatigue

A person can be fully awake, yet simultaneously too mentally tired to concentrate on and perform voluntary activities. This is what researchers call mental fatigue [97], resulting in short-term consequences such as reduced attention, increased error-proneness, and decreased well-being, as well as serious long-term health hazards like occupational burnout [10, 11, 26, 56]. Mental fatigue accumulates during demanding tasks through two processes: cognitive resource depletion, meaning a reduction in mental resources one can expend on a task, and motivational fatigue, an unwillingness to continue working on a particular task [35].

HCI literature points out that the demands placed upon us by our increasingly digital environment can exacerbate mental fatigue. At work, digital technologies increase cognitive demands [83, 103, 106],

with video meeting systems [79] and GenAI [60] contributing to mental resource depletion. In leisure, social media [15, 40] and video games [6] can cause overstimulation. Altogether, this results in increased pressure on our mental resources throughout the day.

In previous works, subjective questionnaires and performance tasks are commonly used to assess fatigue [87, 88], but both are disruptive and impractical in naturalistic settings like the workplace. Physiological measures offer an objective, non-disruptive alternative. While ECG [22] and eye-tracking [4] are useful, neuro-physiological approaches, with EEG most prominent among them, are particularly sensitive and reliable [24, 58, 69, 96]. A clear connection between mental fatigue states and changes in the power of frequency bands of neural oscillations has been established, and meta-analyses confirm that increases in overall theta (4–8 Hz) and alpha (8–13 Hz) activity are consistent EEG biomarkers of mental fatigue [69, 96]. Theta increases are commonly linked to heightened cognitive effort and growing difficulty in maintaining control and vigilance, indexing stronger engagement of frontal control networks [50]. Alpha power, in contrast, is inversely related to cortical activation and typically rises when attention wanes or mental resources become depleted, reflecting increased functional inhibition across task-irrelevant regions [50, 69, 96].

EEG-based mental fatigue studies usually compare the cognitive state at rest, prior to and after completing a fatiguing task, or track it during the task, often aggregating data across minutes or longer intervals [41, 56, 65, 97].

## 2.2 Work Breaks and Recovery

Breaks are the primary way to restore mental resources during work [89]. Defined as periods without work demands [98], they enable recovery through activities that allow the replenishment of resources [64]. Sonnentag and Fritz propose that recovery experiences are composed of four dimensions: *Psychological Detachment*, allowing mental disengagement from work, *Relaxation*, a state of low activation and demands, *Mastery*, providing opportunities for learning and growth, and *Control*, the ability to choose which activity to pursue [90]. In later works, these dimensions have been complemented by other concepts, such as *Relatedness*, reflecting the need for social connection [14]. In addition to longer, scheduled breaks, short, often spontaneous “micro breaks” lasting no longer than ten minutes can also effectively supplement the restoration of cognitive resources throughout the workday [2, 49].

For knowledge workers, digital break activities dominate [48]. Browsing social media and playing video games are among the most common digital break activities, along with watching videos and online shopping [27, 77, 86].

HCI literature debates the efficacy of such digital breaks. It highlights both risks, like increased sedentariness, information overload, and overstimulation [39, 40, 80], and benefits, such as facilitating social connection [40], creativity [39], and detachment from work [86], if used purposefully. These contrasting findings suggest different recovery mechanisms. While no direct comparisons exist, prior studies show games foster recovery through mastery experiences [20, 108], whereas social media supports recovery via detachment and relaxation [19, 31, 40]. It should therefore be tested how such digital breaks impact recovery.

## 2.3 Ear-centered Neural Sensing

Neural sensing technologies are increasingly moving from lab to real-world use [53, 55, 72]. While several sensing modalities are being explored for wearables, EEG remains the most mature and accessible. Traditional EEG systems, however, pose barriers through large electrode arrays, conductive gels, and complex setups [8, 72], prompting efforts toward “transparent” neural sensing with everyday devices [72], such as smart glasses [55, 102] or bike helmets [81].

Ear-centered EEG has emerged as particularly promising, leveraging the ear’s proximity to neural sources while fitting within familiar wearable designs. Configurations range from in-ear systems [21, 42, 59] to around-the-ear arrays [8, 23, 52] and headphone-integrated solutions [3, 18, 44, 46, 51, 62]. Around-the-ear approaches offer larger inter-electrode distances that limit amplitude attenuation compared to in-ear designs [8, 23], primarily capturing temporal cortex activity including auditory ERPs and even distant sources like auditory brainstem responses [30, 67], but with reduced sensitivity to frontal, parietal, and motor-related potentials (20–40% attenuation for some ERP components) [67, 74]. However, headband-embedded electrodes can extend coverage toward central and frontal regions, retaining capture of oscillatory and ERP components from these regions better [53, 57]. Ear-EEG has shown applications for long-term recordings during everyday activities [37, 52], auditory attention and speech tracking (e.g., various auditory ERPs – N100, P300, N400, lateralized attention effects, and continuous speech attention [8, 23, 38]), sleep staging [93], biometric authentication [68], mental workload monitoring [46, 53, 57, 104], and mental commands (e.g., speech imagery [44]). However, no work has yet examined ear-EEG for mental fatigue detection.

## 3 Methodology

To examine recovery from mental fatigue, participants completed a fatiguing task interspersed with one of two common digital breaks (social media or video gaming), with a mindfulness rest break serving as the control condition, implemented in a between-subject design.

### 3.1 Time Load Dual-Back Task

The Time load Dual-back (*TloadDback*) task [13] has repeatedly been used for mental fatigue induction in several studies [12, 41, 73, 75]. It reliably induces mental fatigue in a short amount of time through high information processing and working memory demands, and can be individualized to account for differences in abilities between participants [73].

During the task, participants see a series of alternating stimuli, letters and numbers, and are required to work on two sub-tasks simultaneously. For letters, they perform a 1-back task. When a letter matches the letter that was shown immediately before it, the space bar should be pressed. Otherwise, no action should be taken. For numbers, they perform a parity judgment task, pressing different keys depending on whether the number is even or odd. Exemplary task screens are displayed in Figure 2. A keyboard set up for this task is shown in Figure 3. By requiring participants to pay attention to both tasks at the same time, the task creates high cognitive engagement [12]. In the standard configuration, each



Figure 2: Left: Instructions given to the participants during calibration. Center: Letter stimulus. Right: Number stimulus.

stimulus is shown for 1500 ms, but during the calibration process, this is adjusted to provide a suitable level of difficulty for each participant. The calibration phase also allows the participants to get familiar with the task, mitigating training effects later on [12].

### 3.2 Break Activities

We selected video gaming and social media browsing as break activities because they are among the most common digital break behaviors for knowledge workers [27, 78, 86] and differ markedly in the degree of active versus passive engagement – a central distinction in break research [31]. The video game represents an active, high-engagement break requiring continuous visuomotor input and rapid decisions [108], whereas the hedonic social media break provides largely passive content consumption with minimal interaction [31, 39, 40]. These two activities therefore represent realistic, yet contrastive recovery experiences, which allow us to test whether we can detect psychophysiological differences between the conditions.

For the video game break, Subway Surfers, a casual Jump n' Run game, was chosen, due to its popularity [91], easily understandable controls, and built-in tutorial. The increasing challenge level of the game is also conducive to mastery experiences [108].

For the social media break, YouTube Shorts was chosen, as short-form content has become the most common form of hedonic social media use [31], and YouTube is the most popular, openly-accessible social media platform [43, 92]. Using a browser extension, YouTube was configured to only show short-form videos (max. 30 seconds), allowing users to scroll through long sequences of videos undisturbed, aiding detachment and relaxation. Following recommendations from previous studies, participants could freely choose which videos to watch, but experiment recordings were screened for offensive, political or erotic material [31].

As a control condition, we used a mindful-rest break. Rest with minimal external stimulation has been found to be effective for short-term recovery [34, 61, 84], and brief mindfulness techniques have similarly been shown to reduce mental fatigue [7, 63]. Participants were instructed to sit with eyes closed and focus on their breathing to minimize uncontrolled mind-wandering and ensure a consistent, low-demand recovery condition against which the two digital breaks can be compared.

### 3.3 Experiment Design

A 3 x 4 mixed-effect design was chosen for the study, with *Break Types* (Video Game (VG), Social Media (SM) or Mindful Rest (MR)) as the between-subject factor, and the within-subject factor *Stage*, indicating the four stages during the experiment where self-reports were collected:  $T1_{before}$ , before the first task block,  $T1_{after}$ , between the first task block and the break,  $T2_{before}$ , after the break and before the second task block, and  $T2_{after}$ , after the second task block.

Since this is the first time that headphone-EEG was used for mental fatigue monitoring, the experiment was conducted in a laboratory setting to ensure high internal validity. The experiment sessions were conducted in sound-proof and air-conditioned booths.

Participants were assigned to one of the three break activities. To control for circadian influences, participants were balanced across conditions at different session times [96]. In the lab booths, the headphone-EEG was set up, and the participants started by filling out demographic and fatigue trait questionnaires. After *TloadDback* calibration, participants completed the first 16-minute *TloadDback* block, then the 10-minute break, and finally the second 16-minute block. The durations for the task and break blocks were aligned with previous studies, where 16 minutes of *TloadDback* have already been shown to elicit moderate to high levels of mental fatigue [41, 73]. Moreover, the 10-minute break duration is at the upper limit of what is considered a micro-break, which are the typical breaks workers take throughout the workday [2], meaning the chosen break duration is realistic, while also providing a minimum viable contrast between recovery effects of the break activities.

These experiment stages were interspersed with questionnaires and resting phases. For each participant, a screen recording of the experiment was reviewed to confirm that the experiment instructions were followed. Figure 4 provides an overview of the experiment procedure.

### 3.4 Questionnaires

The Fatigue Instantaneous Self-Assessment (F-ISA) [32], adapted to a visual analogue scale (VAS), was used to allow for quick and sensitive mental fatigue assessments, serving as a comparison for EEG measurements. Using a VAS to measure subjective mental fatigue is recommended [88], and it has been employed in similar studies before [41]. Additionally, the NASA task load index (TLX)



Figure 3: Keyboard modified for the *TloadDback* task in accordance with [12]. The white dot should be pressed in the 1-back letter task, the blue (even) and green (odd) dots in the parity judgement task.

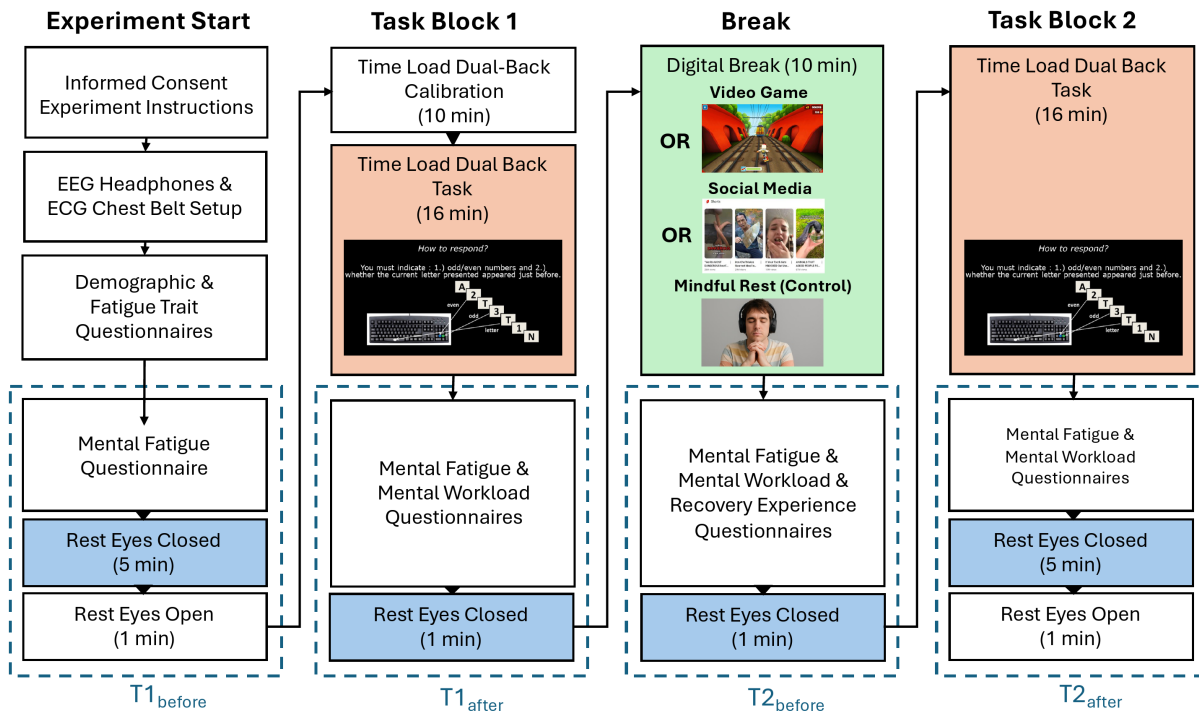


Figure 4: Overview of the experiment procedure. Tasks highlighted in red, break highlighted in green. Measurement stages framed by dashed blue line, segments of EEG measurements used for analysis highlighted in blue and red.

[33] was used to measure the perceived mental workload during the task and the break. Recovery experience was measured using the Recovery Experience Questionnaire [90], supplemented with the *Relatedness* dimension proposed by Bosch et al. [14] to capture possible social dynamics of break types. Participants were also asked how similar the break was to their usual break activities.

### 3.5 EEG Setup and Data Processing

We employed the latest OpenExG Headphones as our headphone-EEG system [51]. The device integrates an 8-channel OpenBCI Cyton amplifier (250 Hz, 24-bit resolution,  $\leq 1 \mu\text{Vpp}$  noise) [76]. Gold-plated electrodes mounted on polyurethane foam connected via FPC terminals recorded EEG at eight sites: three around each

ear (L2–L4, R2–R4) and two central (C3, C4), with reference and ground at L5 and R5 (Figure 5). Gel was applied (Ten20 paste) to electrodes, ensuring stable contact and high signal quality, and participants removed earrings or other electrode obstructions. EEG was recorded using OpenBCI GUI, with electrode signals being examined for impedances below 100 kOhm, and low and homogeneous amplitudes between  $\pm 10\text{--}20 \mu\text{Vpp}$ .

Processing was performed in Python, primarily using *mne-python*, following a fully automated and lightweight preprocessing strategy aligned with prior ear-EEG work in comparable naturalistic but controlled contexts [104]. The pipeline targets the main sources of degradation in wearable EEG: (1) slow drifts and line noise, (2) bad channels, and (3) sporadic movement artefacts [9, 25, 53, 104].



**Figure 5: ExG Headphone System (left), in use during the study (center), and schematic electrode layout (right).**

First, to remove unwanted low- and high-frequency components, experimental stage data segments were mean-centered for each participant and band-pass filtered using a 2–30 Hz linear-phase, zero-phase FIR filter (order 413) with a 1–3 Hz low-frequency and 26–33.5 Hz high-frequency transition band. These parameters yield a flat passband above 4 Hz, ensuring undistorted theta (4–8 Hz) and alpha (8–13 Hz) activity. Second, bad channels - one of the most detrimental data quality issues in EEG data [25], were detected and removed using *pyprep*'s automatic detection of near-flat signals ( $\leq 10^{-15}$   $\mu\text{V}$ ) and amplitude deviations ( $\geq 5$  SD). 9.4% of channels were removed this way. Afterwards, signals were re-referenced to linked mastoids (L4, R4), a low-noise reference commonly used in around-the-ear-EEG studies [9, 53, 104]. Theta and alpha activity have repeatedly been detected in such mastoid-referenced ear-based recordings, reflecting their wide cortical spread, which remain robustly observable around the ears despite potentially attenuated local field potentials [53, 104]. Finally, artifact subspace reconstruction (ASR) [70], was applied (bad channel fraction 0.3) using *asrpy*. ASR identifies transient, high-variance signal segments and reconstructs them from a pre-conditioned clean signal space, effectively removing short movement- and muscle-related bursts without distorting ongoing neural activity - which has been demonstrated to work well for ear-EEG [9, 53, 104]. Power Spectral Density (PSD) was then computed using 2s Welch windows with 50 % overlap, extracting normalized, relative Theta (4–8 Hz) and Alpha (8–13 Hz) band powers.

The eyes-closed vs. eyes-open contrast (Berger effect) at the beginning and the end of the experiment was used to verify signal quality. After excluding faulty or incomplete recordings, 72 valid datasets remained (26 video game, 23 social media, 23 mindful-rest break).

### 3.6 Participants

The study was approved by the first author's institutional review board. Participants were recruited through a student participant pool at a technical university, receiving 18.50 EUR as base compensation, with up to 9 EUR in additional performance-based compensation. An a-priori sample size of 87 was calculated using G\*Power 3.1 (Repeated measures ANOVA, within-between interaction, effect size of 0.15 - 0.2,  $\alpha = 0.05$ , power = 0.8, correlation among repeated

measures = 0.3), conservatively following previous studies with a similar design [31].

We recruited 97 participants (34 for the video game and social media conditions, 29 for the mindful-rest break;  $M = 23.0$  years,  $SD = 3.6$ ; 63 male, 34 female) in two waves. In the first wave, participants were randomly assigned to the video game and social media conditions. During the revision process, the mindful-rest condition was added and participants were recruited separately, in the second wave. Both waves of data collection occurred at similar points of the semester, meaning the influence of the different recruitment times on the student sample should be minimal. Exclusion criteria followed prior work and required normal or corrected-to-normal vision, no sleep disorders, and no recreational drug use within 24 hours of the experiment [31, 65, 96]. Due to the faster setup of the headphone-EEG compared to conventional devices, data from four participants could be collected at the same time, and data collection was completed within seven days total.

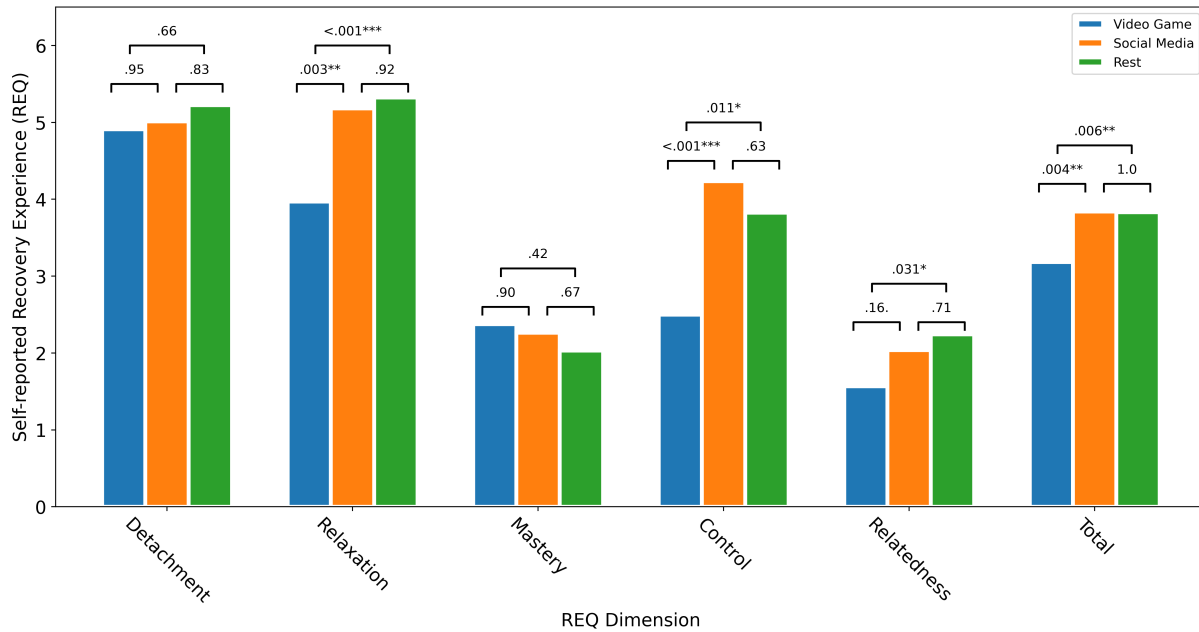
## 4 Results

As a basis for interpreting the EEG headphone recordings, we begin by assessing the break experiences, followed by established measures of mental fatigue: self-reports and task performance.

### 4.1 Break Experiences

**4.1.1 Recovery Experience.** Recovery experience is reported for each REQ dimension and as an overall mean across dimensions (see Figure 6). High values of *psychological detachment* are reported for all break conditions, with no significant difference between the groups. *Relaxation* was rated higher for the social media and mindful-rest conditions than the video game condition, as was *control*. *Relatedness* was rated as significantly higher during the mindful-rest break than during the video game break. There was no significant difference between break conditions in the *mastery* dimension. The overall recovery experience across all dimensions was also rated higher for the social media and mindful-rest break conditions, meaning participants felt that these two breaks allowed for a better recovery than the video game break.

**4.1.2 Break Demands & Familiarity.** Self-reported mental workload (avg. of all six TLX items) was significantly lower during breaks than during task blocks ( $t(96) = 16.3, p < .001$ ). A one-way



**Figure 6: Bar chart comparing the three break conditions in terms of recovery experience as queried in the recovery experience questionnaire. Values are shown for each of the five recovery dimensions, along with 'total' recovery, an average over the five dimensions. Significant differences between the conditions are highlighted as follows: \*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .001$ .**

ANOVA showed significant differences for mental workload during the break across conditions ( $F(2, 94) = 10.4, p < .001$ ). Post-hoc contrasts revealed significantly higher reported workload during the video game break compared to the other two break conditions ( $VG - SM : t(66) = 4.0, p < .001$ ;  $VG - MR : t(61) = 3.6, p < .001$ ).

Moreover, participants reported that the social media break was significantly more similar to the breaks they usually take than the other conditions ( $SM - VG : t(66) = 4.2, p < .001$ ;  $SM - MR : t(61) = 3.7, p < .001$ ).

## 4.2 Reported and Performance-Based Mental Fatigue

Based on the observation of perceived effective breaks, we pursued analyses of fatigue induction and recovery. ANOVAs based on linear mixed-effects models (LMM) with a random intercept per participant were used for statistical analysis, with Tukey-corrected pairwise post-hoc contrasts.

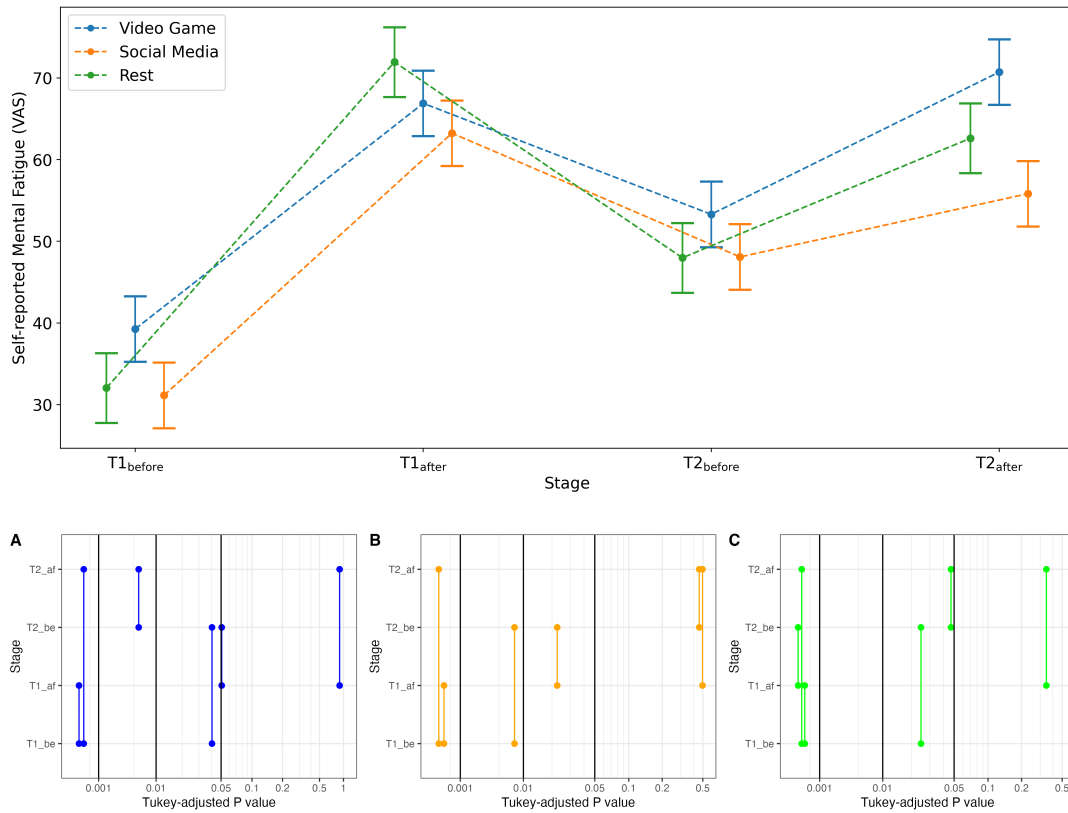
**4.2.1 Self-Reported Mental Fatigue.** Fatigue reports were collected at four stages (see Figure 7 Top): before the first task block ( $T1_{before}$ ), after the first task block ( $T1_{after}$ ), after the break / before the second task block ( $T2_{before}$ ), and after the second task block ( $T2_{after}$ ). We found no condition  $\times$  stage interaction; however, perceived fatigue showed a significant main effect of stage ( $F(3, 282) = 19.4, p < .001$ ). Post-hoc contrasts (see Figure 7 Bottom) showed significant fatigue increases during the first task block for all conditions, with a further significant increase during the second task block for the video game and mindful-rest conditions. Perceived fatigue decreased significantly after social media browsing

and mindful-rest, but not after the video game. A trend level main effect of condition ( $F(2, 94) = 2.8, p = .066$ ) was detected. Post-hoc comparisons showed no between-condition differences except after the second task block, where the video game group reported higher fatigue than the social media group ( $t(66) = -2.6, p = .025$ ).

**4.2.2 Task Performance.** Accuracy and reaction time in the *Tload-Back* task were analyzed across four windows per task block (see Figure 8), allowing us to track performance changes both across the experiment and within each block.

We observed main effects of window ( $F(7, 658) = 13.2, p < .001$ ) and condition ( $F(2, 94) = 3.9, p = .022$ ) on accuracy. Post-hoc contrasts showed that accuracy improved over the break, with higher accuracy in the first window of the second block than in the last window of the first block for all conditions ( $VG : t(231) = -5.4, p < .001$ ;  $SM : t(231) = -5.7, p < .001$ ;  $MR : t(196) = -5.0, p < .001$ ). Accuracy in the video game condition is significantly higher compared to the mindful-rest condition in the first three windows of the first task block ( $T1_{W1} : t(61) = -2.7, p = .017$ ;  $T1_{W2} : t(61) = -2.5, p = .032$ ;  $T1_{W3} : t(61) = -3.2, p = .004$ ). Notably, only the video game condition shows a significant decline in accuracy from the first window to the last window of the second task block ( $t(231) = 3.8, p = .004$ ).

For reaction time, main effects of window ( $F(7, 658) = 7.5, p < .001$ ) and condition ( $F(2, 94) = 66.9, p < .001$ ) were found. Post-hoc contrasts showed that participants in the video game condition had a significantly lower reaction time for all windows. Reaction times decreased over the break in all conditions, with faster responses in the first window of the second task compared to the last window of the first ( $VG : t(231) = 4.3, p < .001$ ;  $SM : t(231) = 3.8, p =$



**Figure 7: Top: Estimated marginal means of self-reported mental fatigue for each condition across the four measurement points with standard errors. Bottom: Pairwise post-hoc contrasts across stage. The x-axis shows Tukey-adjusted p-value levels with common .001, .01 and .05 significance levels as vertical lines. (A) shows the contrasts for the video game condition, (B) for the social media condition, and (C) for the mindful-rest condition.**

.004;  $MR : t(196) = 3.9, p = .003$ ). Again, only the video game condition shows a significant difference between windows during the second task block, as reaction time increased significantly from the first to the last window ( $t(231) = -3.7, p = .005$ ).

### 4.3 EEG-Based Mental Fatigue Patterns

**4.3.1 Between-Task (Tonic) EEG Changes.** We first examine EEG changes between task blocks, as the eyes-closed segments provide an uncontaminated measure of tonic fatigue that is not confounded by task engagement. For this analysis, relative theta and alpha power was computed from one-minute eyes-closed segments before and after each task block ( $T1_{before}, T1_{after}, T2_{before}, T2_{after}$ ) and averaged across all six electrodes.

For theta power, no interaction effects ( $F(6, 207) = 1.7, p = .11$ ) and no main effects of stage ( $F(3, 207) = 2.6, p = .052$ ) or condition ( $F(2, 69) = 1.5, p = .22$ ) were found.

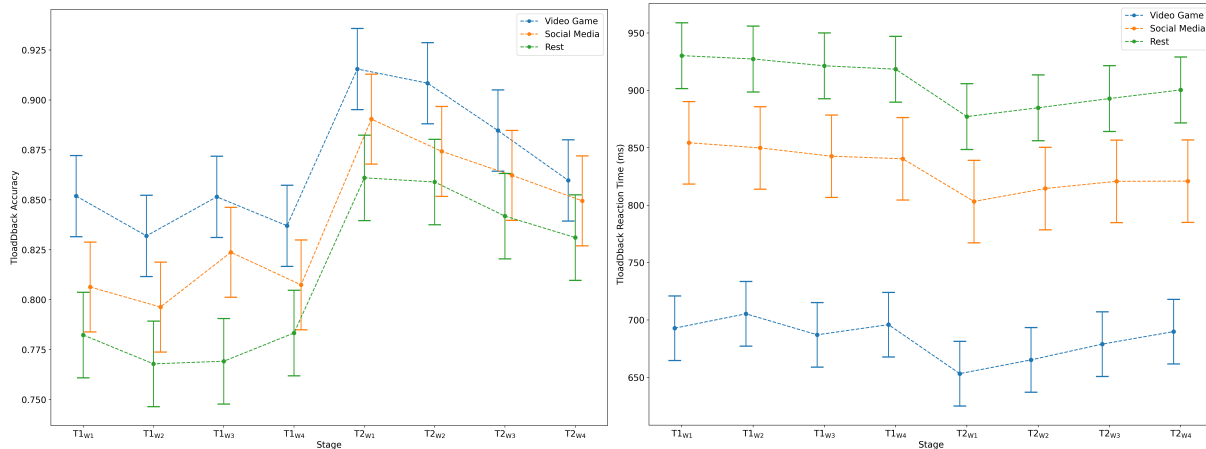
For alpha power, we found a significant condition  $\times$  stage interaction effect ( $F(6, 207) = 2.2, p = .044$ ). In all conditions, alpha increased significantly during the first task block. During the break, alpha decreased in the social media condition, but did not change

in the video game or mindful-rest conditions. During the second task block, alpha did not change significantly in any group.

Consistent with these trajectories, the break-related change ( $T2_{before} - T1_{after}$ ) differed between conditions ( $VG - SM : t(45) = 3.5, p = .007$ ;  $MR - SM : t(44) = 3.5, p = .007$ ;  $MR - VG : t(45) = -0.4, p = .89$ ), indicating a larger alpha decrease during the social media break than during the two other breaks. Notably, only the video game condition remains elevated at the end of the experiment, with no comparable change observed in the other conditions. See Figure 9 for a graphical overview.

Finally, to assess whether a more convenient setup without headband electrodes would yield comparable results - important since headband positions overlap with classic EEG sites - we repeated these analyses using only the four electrodes placed around the ears. These results largely mirror those from the full electrode setup (see Appendix A.1).

**4.3.2 On-Task EEG Dynamics.** Tonic changes show baseline fatigue, but they do not reveal whether this influences engagement once work resumes. Because alpha suppresses with attentional effort [50], its dynamics during the task blocks provide a way to



**Figure 8: Left: Estimated marginal means of achieved *ToadBack* accuracy for each condition across the two task blocks, each divided into four windows, along with standard errors. Right: Estimated marginal means of *ToadBack* reaction time for each condition across the two task blocks, each divided into four windows, along with standard errors.**

assess whether different breaks lead to measurable differences in post-break task engagement.

To explore this potential, we first compared average alpha power between the two task blocks across break conditions. Relative alpha was significantly higher in the second block for the video game and social media conditions, but not for mindful rest, which could indicate reduced attentional engagement and greater cortical idling under higher fatigue. Furthermore, pairwise comparisons show no differences between conditions in the first task block. In the second block, however, relative alpha was significantly higher in the video game condition than in the others. The left plot in Figure 10 provides statistical details.

As a follow-up, we examined the temporal progression of alpha within the second task block to determine whether post-break engagement changed gradually or remained stable over time. To do so, the block was divided into four 4-minute windows, and relative alpha power was averaged per window (see top and bottom right plots in Figure 10). Analyses of on-task alpha dynamics showed main effects of condition ( $F(2, 69) = 3.4, p = .047$ ) and window ( $F(3, 207) = 3.1, p = .017$ ). We see a significant decline in relative alpha power for the social media and mindful-rest conditions from the first to the fourth window, but not for the video game condition, which could indicate increased attentional engagement over time only in the more restorative break conditions.

Once more, an analysis of only the ear-based electrode regions (see Appendix A.2) shows highly similar results.

## 5 Discussion

### 5.1 Mental Fatigue State Detection using EEG Headphones

All break types were reported as having some recovery effect, though it was more pronounced for the social media and mindful-rest conditions. Consequently, we would expect to see recovery

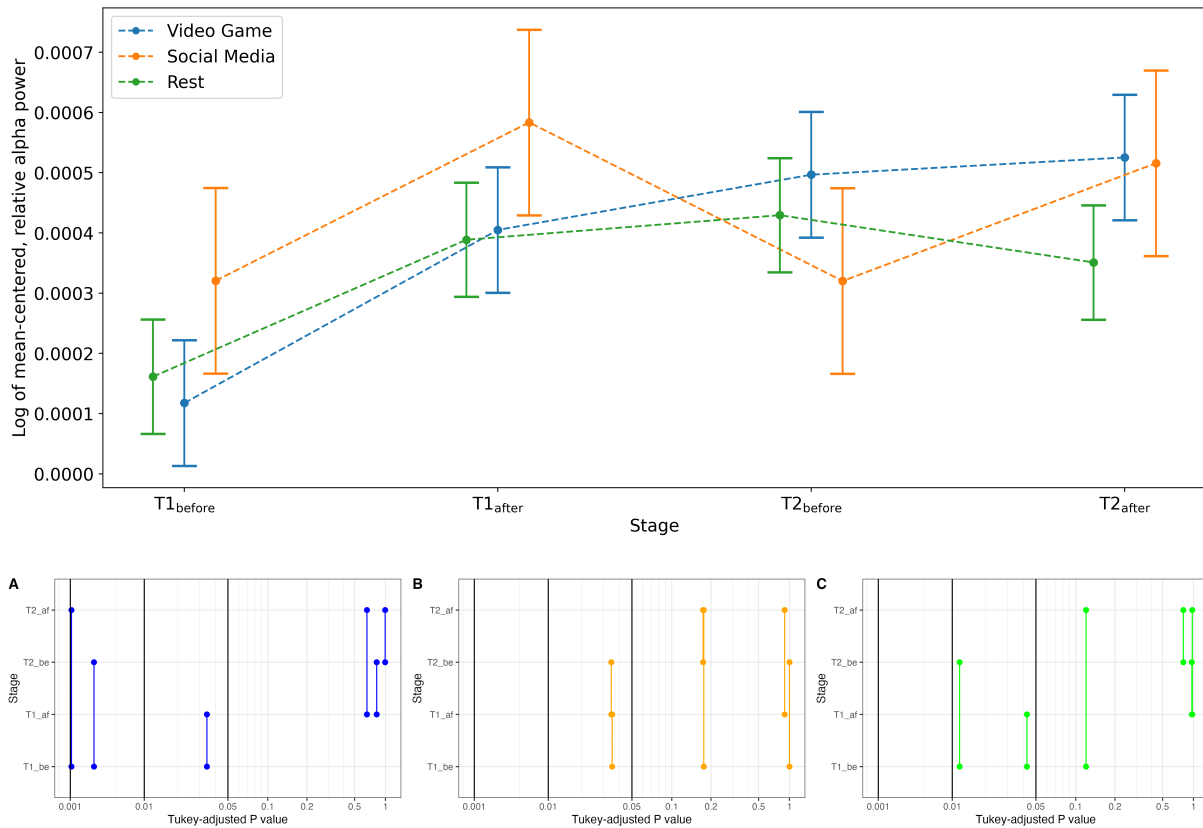
effects reflected in subjective, behavioral, and physiological measures. Self-reported mental fatigue data support this expectation, showing significantly decreased fatigue over the break for the social media and mindful-rest conditions, but not for the video game condition.

Performance data also indicate recovery, as accuracy increases and reaction times decrease after the breaks across conditions. However, as we observe improvements beyond the levels in the first task block, these metrics are likely confounded by learning effects. More importantly though, accuracy and reaction times deteriorate again over time specifically in the video game condition, suggesting that this break type did not provide lasting recovery benefits.

Our EEG findings largely corroborate these observations. We see a clear increase in relative alpha power after the first task block in all conditions, likely reflecting increased cortical idling due to elevated levels of fatigue, in line with previous work [69, 96]. Furthermore, after the first task, the tonic change observations show that the video game break does not appear to have caused effective recovery, as alpha remains elevated in that condition compared to social media and mindful-rest.

For the social media and mindful-rest conditions, the picture from the between-task EEG is less clear, as we only observe a decline in alpha power in the social media condition. It is possible that the prolonged eyes-closed mindfulness rest led to elevated alpha levels that carried over into the subsequent measurement segment. Such alpha power spillover from eyes-closed rest has been previously documented [1]. More generally, our decision to detect tonic fatigue changes through eyes-closed phases may have caused ceiling effects in measurement sensitivity beyond the first fatigue induction.

For this reason, we also investigated whether fatigue and recovery effects can be detected during the second task. This analysis further strengthens the measurement aptitude of headphone-EEG, as we find elevated alpha levels in the second task round. Initially, we considered that this elevation may represent reduced attentional



**Figure 9: Top: Estimated marginal means of the mean-centered, relative alpha power as an average of all electrodes for each condition plotted across the four stages, with standard errors. Bottom: Pairwise post-hoc contrasts across stages. The x-axis shows Tukey-adjusted p-value levels with common .001, .01 and .05 significance levels as vertical lines. (A) shows the contrasts for the video game condition, (B) for the social media condition, and (C) for the mindful-rest condition.**

requirements in line with the aforementioned learning effects – possibly, less attentional effort was required to perform the now-familiar task. However, if this were the case, we would have expected similar effect magnitudes after all three break types. Instead, the effects align with the self-reported results: social media and mindful-rest conditions showed low to no alpha increases on-task after the break. Moreover, we observe a reduction of alpha power over time in those two conditions, but not in the video game break group. This pattern most likely indicates a progression of attentional engagement. While re-engaging with the demanding task may have been harder for all groups at the start of the second task round, only in the video game condition does the expected on-task alpha suppression fail to emerge - likely because elevated fatigue made top-down attentional engagement control more difficult [50].

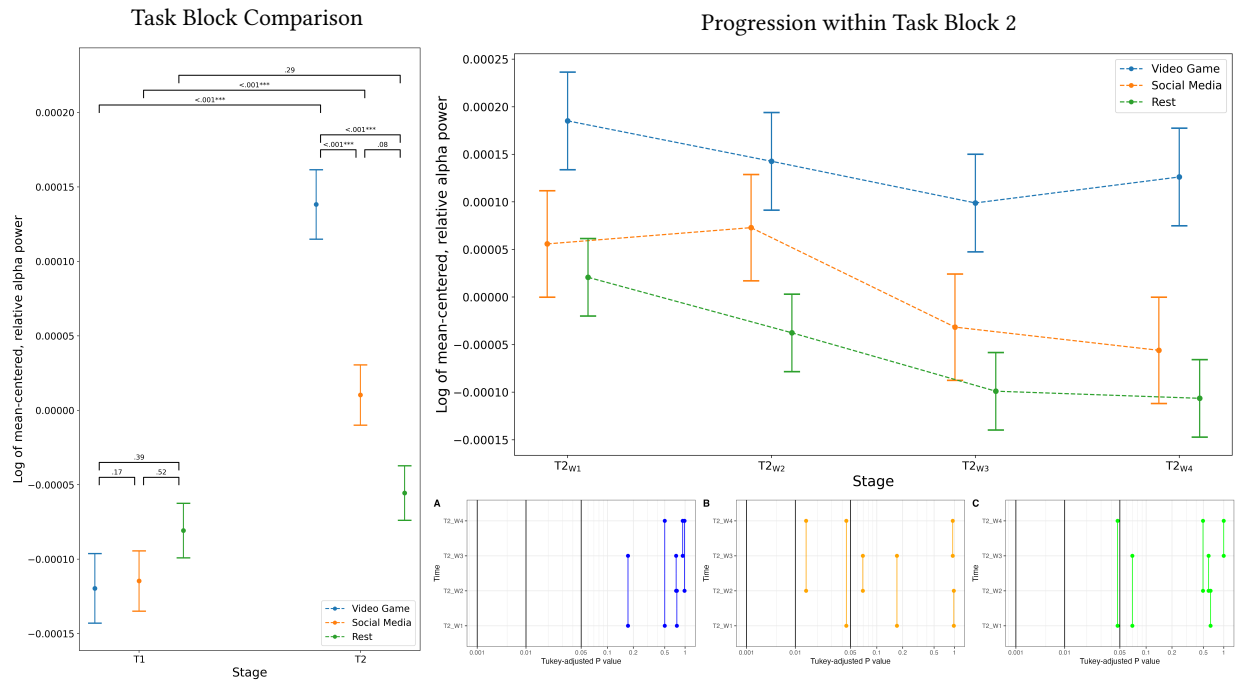
It should be noted, that while both theta and alpha activity are typically cited as biomarkers of mental fatigue [69, 96], only alpha reflected the expected changes in our study. This likely stems from two factors: (1) prior work using the *TloadDback* task reports minimal or decreasing theta over time due to its high engagement demands [41, 65], and (2) around-the-ear EEG generally captures

alpha more reliably than theta, which is strongest at central scalp sites [23, 53, 104]. These factors together may explain why fatigue-related changes emerged only in alpha activity in our study.

Taken together, our findings provide convincing evidence that headphone-EEG can detect changes in mental fatigue across different break types and capture how these fatigue states manifest during subsequent task performance. This offers an important methodological insight: fatigue can be monitored during ongoing work without needing prior knowledge of the preceding break activity. To conclude, our results show that mental fatigue states can be monitored using EEG headphones, answering RQ1.

## 5.2 Impact of Digital Breaks on Recovery

At this point, we want to discuss the effectiveness of the investigated breaks, which led to some interesting findings. In terms of recovery experience, the social media and mindful-rest breaks were rated more restorative than the video game break. All activities enabled psychological detachment, but social media and mindful rest scored higher in relaxation and control. This may reflect their more passive nature, which is consistent with previous work on social media use



**Figure 10: Left: Estimated marginal means of mean-centered, relative alpha power for each condition plotted by task block. Top Right: Estimated marginal means of the mean-centered, relative alpha power for each condition plotted in the second task block, split into four windows of four minutes each, along with standard errors. Bottom Right: Pairwise post-hoc contrasts across windows. The x-axis shows Tukey-adjusted p-value levels with common .001, .01 and .05 significance levels as vertical lines. (A) shows the contrasts for the video game condition, (B) for the social media condition, and (C) for the mindful-rest condition.**

and mindful-rest [19, 34, 39, 40, 63]. For the social media condition, participants’ autonomy in selecting content may explain the higher rating for control, while existing research suggests that mindfulness exercises can strengthen executive control [95]. The video game break, in contrast, did not show superior recovery in any dimension, despite its popularity in related work [108].

It is useful to consider why the video game break—often described as a promising recovery activity—appeared less effective here. Prior work highlights two properties of games that may support recovery: their ability to promote psychological detachment through immersive engagement and their potential to elicit mastery experiences [108]. In our study, however, participants engaged with a popular but unfamiliar game, meaning that sufficient mastery may not have been achievable during the short break. This could have made the activity demanding without offering the motivational benefits typically associated with gameplay. In addition, earlier research demonstrating restorative gaming effects has generally examined longer play durations, where deeper immersion and detachment can develop [99, 100]. The relatively short break in our design may therefore have limited the extent to which these mechanisms could unfold. As our goal was not to systematically test such parameters but rather to contrast three common break types, future work is needed to clarify how familiarity and duration shape the restorative potential of game-based breaks.

The second interesting finding is the effectiveness of the social media break, which appears similarly restorative as the mindful-rest break across several fatigue indicators. The social media break showed lower mental workload than the video game, and similar workload as the mindful-rest break, but the highest familiarity among the break types. Its effectiveness may stem from the passive, low-effort nature of watching videos compared to the active sensorimotor engagement required in gaming. According to the Effort–Recovery Model [66], recovery occurs when work demands are removed; because gaming requires sustained engagement and similar motor actions as the *TloadDback* task, recovery may be less complete. Attention Restoration Theory [45] further suggests that “softly fascinating” activities promote recovery. Browsing videos may provide such effortless digital fascination. Such “soft fascination” draws attention without demanding executive control, facilitating immediate relaxation [5]. In contrast, mindful-rest relies on deliberate attentional control and parasympathetic regulation, which may yield restorative benefits that emerge more gradually over time [17, 82]. This might explain why the well-known, effective [34, 61, 84] mindful-rest break did not show stronger recovery.

In any case, the surprising effectiveness of the social media break in our study should be interpreted with caution. Many adverse outcomes associated with social media, such as reduced well-being [28], technostress [16] or social-media-induced fatigue [85], typically

emerge over longer time scales or under unregulated use - situations that are very different from an isolated 10-minute lab break. Moreover, while social media can serve as a restorative micro-break, it can also act as a disruption [39, 40] and may facilitate cyberloafing without appropriate boundary management [107]. Thus, the effectiveness of social media as a short-term break likely depends on contextual factors, such as an individual's ability to self-regulate [48], their mindset toward social media [28], and the specific type of content and interaction involved [40].

Thus, in response to RQ2, both digital breaks enable recovery, but to varying degrees: social media offers strong immediate recovery through relaxation and low effort stimulation, which persists into subsequent work, whereas video games provide quickly diminishing, short-term benefits.

## 6 Limitations

Like most related experiments, our measurements span only 60–90 minutes, which is sufficient to capture changes in mental fatigue and recovery processes, but likely induces only moderate fatigue compared to what accumulates during demanding real-world work. As a result, our findings may reflect boundary effects, and stronger or more prolonged fatigue states could produce clearer or larger differences between break types. Longer-term studies - covering full workdays or multiple days - will therefore be essential to more comprehensively assess the impact of digital break activities.

Relatedly, this study was conducted in a controlled laboratory setting, with gel-based electrodes and participants seated throughout, to maximize EEG data quality for establishing fundamental working principles. Follow-up work must assess whether headphone-EEG remains feasible under more naturalistic, real-world conditions. While our findings demonstrate its value for research, further development is needed before such systems can actively support workers in everyday environments. At the same time, related research is consistently moving towards everyday EEG applications [53, 72] and demonstrates that principles like tonic alpha power changes and on-task alpha suppression may reliably be observed in everyday context, given that alpha modulations represent some of the most large-effect neural oscillations [50, 53].

In terms of the break effects found in the study, the different demands of the break types may have influenced EEG recordings immediately after the break due to possible spillover effects, while the higher similarity of the social media break to usual break activities of the participants may have influenced the self-reports.

## 7 Conclusion and Outlook

This study investigated mental fatigue detection and recovery using headphone-EEG in a between-subject design with the *TloadDback* task and three break activities: video games, social media, and mindful-rest. We found converging evidence that through changes in alpha activity between- and on-task, mental fatigue monitoring with headphone-EEG is possible, allowing the detection of task-induced mental fatigue increases, the differentiation of recovery experience quality between break activities, and the impact of poor recovery on attentional task engagement after a break. These EEG-based results align with self-reports and performance data, where

social media and mindful-rest were perceived as more restorative than gameplay.

For HCI, these findings have several major implications: (1) Importantly, mental fatigue detection with EEG-headphones opens new possibilities for future studies, allowing for faster and easier physiological data collection in lab settings (we could collect data from four participants at the same time, which greatly sped up the data collection), or enabling more naturalistic research designs, which are crucial for understanding how fatigue and recovery unfold during everyday life. The method also opens the door to studying how different break interaction designs—such as more physically engaging or interactive activities [64] shape the recovery process. (2) The fact that around-the-ear electrodes are sufficient for mental fatigue detection - and that the effects are visible in alpha power dynamics, a large-effect neural feature - indicate that even more convenient ear-EEG systems (e.g. using textile electrodes or in-ear systems) may also be promising.

In sum, these findings lay the groundwork for future work that investigates personal needs and individual responses to specific break types through ear-EEG, enabling more tailored approaches to fatigue management.

## Acknowledgments

Funded by the German Research Foundation (Deutsche Forschungsgemeinschaft - DFG) – GRK2739/1 – Project Nr. 447089431 – Research Training Group: KD<sup>2</sup>School – Designing Adaptive Systems for Economic Decisions.

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## A Additional EEG Analyses

### A.1 Tonic Fatigue Changes - Ear electrodes only

To assess whether a more convenient setup without headband electrodes would yield comparable results - important since headband positions overlap with classic EEG sites - we repeated the analysis for tonic fatigue changes using only the four electrodes placed around the ears (L2, L3, R2, R3). The EEG patterns for ear-electrodes largely mirror those from the full electrode setup. No main effects are found for theta activity. Again, for alpha activity, a significant condition x stage interaction effect is visible ( $F(6, 207) = 2.3, p = .034$ ).

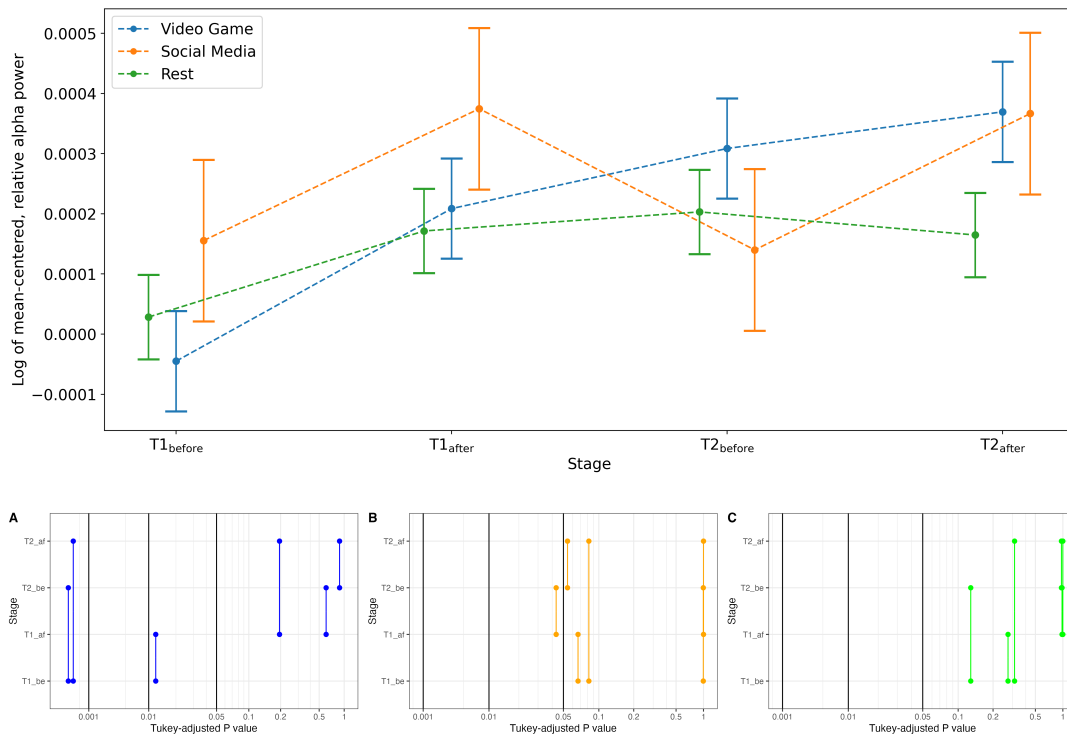
Post-hoc contrasts showed a significant increase in alpha activity during the first task block for the video game condition, with a significant decrease during the break for the social media condition, and staying stable for all conditions during the second task block. Further post-hoc contrasts yielded a difference in alpha activity change during the break ( $T2_{before} - T1_{after}$ ) between the video game and social media conditions (VG-SM:  $t(45) = 3.3, p = .013$ ; MR-SM:  $t(44) = 2.1, p = .071$ ; MR-VG:  $t(45) = -0.6, p = .82$ ). Similarly to the full electrode setup, the social media and mindful-rest conditions return to the baseline at the end of the experiment, whereas the video game condition stays elevated. In addition, a significant difference in alpha change over the second task block ( $T2_{after} - T2_{before}$ ) between the social media and mindful-rest conditions was found (MR-SM:  $t(44) = -2.3, p = .049$ ; VG-SM:  $t(45) = -1.5, p = .147$ ; MR-VG:  $t(45) = -1.0, p = .31$ ). Figure 11 shows the estimated marginal means across conditions and measurement points, along with post-hoc contrasts.

### A.2 On-Task EEG Dynamics - Ear electrodes only

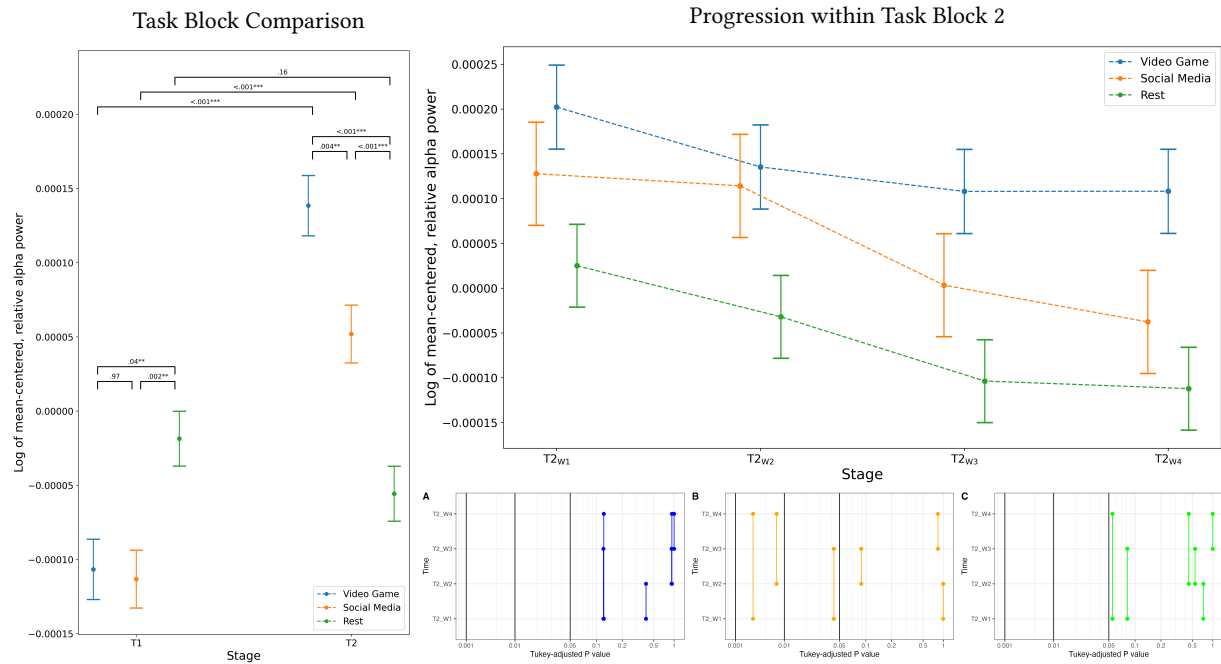
As for the tonic fatigue changes, we also repeated the on-task EEG analyses using only the four electrodes placed around the ears (L2, L3, R2, R3). Again, we see very similar results to those with the full setup.

Relative alpha was significantly higher in the second task block for the video game and social media conditions, but not for mindful rest. Pairwise comparisons show higher levels of relative alpha power in the first task block for mindful-rest compared to the other conditions. In the second block, relative alpha was significantly higher in the video game condition than in the others, with mindful-rest also lower than social media. See the left plot in Figure 12 for details.

Again using four windows in the second task block, analyses of on-task alpha dynamics showed main effects of condition ( $F(2, 69) = 3.2, p = .045$ ) and window ( $F(3, 207) = 3.5, p = .015$ ). Comparing just the four windows during the second task block, we see a significant decline in relative alpha power for the social media condition, with a trend-level effect for the mindful-rest condition, from the first to the fourth window, but not for the video game condition. This is visualized in the top and bottom right plots of Figure 10.



**Figure 11: Top: Estimated marginal means of the mean-centered, relative alpha power as an average of the four near-ear electrodes for each condition plotted across the four stages, with standard errors. Bottom: Pairwise post-hoc contrasts across stages. The x-axis shows Tukey-adjusted p-value levels with common .001, .01 and .05 significance levels as vertical lines. (A) shows the contrasts for the video game condition, (B) for the social media condition, and (C) for the mindful-rest condition.**



**Figure 12: Left: Estimated marginal means of mean-centered, relative alpha power averaged over the four near-ear electrodes, for each condition plotted by task block. Top Right: Estimated marginal means of the mean-centered, relative alpha power for each condition plotted in the second task block, split into four windows of four minutes each, along with standard errors. Bottom Right: Pairwise post-hoc contrasts across windows. The x-axis shows Tukey-adjusted p-value levels with common .001, .01 and .05 significance levels as vertical lines. (A) shows the contrasts for the video game condition, (B) for the social media condition, and (C) for the mindful-rest condition.**