Title: EEG-based Assessment of Long-Term Vigilance and Lapses of Attention using a User- Centered Frequency-Tagging Approach

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CRediT authorship contribution statement:
S. Ladouce: Conceptualization, Data collection, Data analysis, Writing. **J. J. Torre-Tresols:** Data analysis, Writing. **K. Le Goff:** Writing. **F Dehais:** Conceptualization, Writing.

Highlights

- Fluctuations in the SSVEP response to a continuous frequency-tagging flicker presented throughout a 45-minutes long vigilance task was used to characterize lapses of attention
- The frequency-tagging flicker superimposed to the task was designed to be minimally intrusive thanks to its low luminance and low contrast
- Neither the user experience nor the task performance were altered by the presence of the frequency-tagging flicker
- The SSVEP response outperformed measures of individual alpha peak and theta band activity in the distinction of attentional lapses (missed events) from successful target event identification
- The present findings have implications for the design of Human-Computer Interfaces aimed at monitoring (in)attention during the performance of monotonous routines (e.g., surveillance, driving,...)

Data availability statement

The datasets analyzed in the current study will be made publicly available in an online repository [https://www.osf.io/duzcn/]. The source code for the analysis will be available on GitHub [https://github.com/sladouce/Clock_SSVEP/].

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Conflict of interest disclosure

The authors declare that they have no known competing financial interests or personal relationships that may be construed as competing interests or could have influenced the work reported in this paper.

Ethics approval statement

The study was approved by the Ethics Committee of the University of Toulouse (CER approval number 2023-749) and conducted in accordance with the Declaration of Helsinki

EEG-based Assessment of Long-Term Vigilance and Lapses of Attention using a User-Centered Frequency-Tagging Approach

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ABSTRACT

Sustaining vigilance over extended periods is crucial for many critical operations but remains challenging due to the cognitive resources required. Fatigue and other factors contribute to fluctuations in vigilance, causing attentional focus to drift from task-relevant information. Such lapses of attention, common in prolonged tasks, lead to decreased performance and missed critical information, with potentially serious consequences. Identifying physiological markers that predict inattention is key to developing preventive strategies. Previous research has established electroencephalography (EEG) responses to periodic visual stimuli, known as steady-state visual evoked potentials (SSVEP), as sensitive markers of attention. In this study, we evaluated a minimally intrusive SSVEP-based approach for tracking vigilance in healthy participants (N = 16) during two sessions of a 45-minute sustained visual attention task (Mackworth's clock task). A 14 Hz frequency-tagging flicker was either superimposed on the task or absent. Results revealed that SSVEP responses were lower prior to lapses of attention, while other spectral EEG markers, such as frontal theta and parietal alpha activity, did not reliably distinguish between detected and missed attention probes. Importantly, the flicker did not affect task performance or participant experience. This non-intrusive frequency-tagging method provides a continuous measure of vigilance, effectively detecting attention lapses in prolonged tasks. It holds promise for integration into passive brain-computer interfaces, offering a practical solution for real-time vigilance monitoring in high-stakes settings like air traffic control or driving.

1. Introduction

Vigilance, defined as the capacity to sustain attention over prolonged periods Oken et al. (2006); Mehrabi and Kim (2022), plays a critical role in high-stakes environments where timely responses to new information are essential Mehta and Parasuraman (2013); Small et al. (2014); Lin et al. (2014); Zheng et al. (2011). However, vigilance is not a static state; it fluctuates due to various factors and typically declines over the course of extended tasks, often resulting in lapses of attention Hancock (2017). These lapses, characterized by reduced responsiveness or failure to detect critical information, can lead to serious real-world consequences, such as impaired driving performance Papadelis et al. (2007).

Two main hypotheses have been proposed to explain lapses in attention. The first posits that lapses arise from the depletion of top-down executive control resources necessary to maintain focus over time (Warm et al., 2008; Kamzanova et al., 2014; Thomson et al., 2015). As these cognitive resources diminish, sustaining attention becomes increasingly effortful. The second hypothesis suggests that lapses occur due to task monotony, which leads attention to drift away from task-relevant information and fosters a "mindless" operational mode (Manly et al., 1999). Factors such as habituation to repetitive stimuli (Möckel et al., 2015), reduced motivation (Brosowsky et al., 2023), and increased boredom (Esposito et al., 2022; Esterman et al., 2016) collectively contribute to this progressive task disengagement.

In line with these frameworks, vigilance fluctuations and lapses in attention have been linked to cognitive fatigue (Tian et al., 2018; Trejo et al., 2015; Tran et al., 2020), mental workload (Borghini et al., 2014), mind-blanking (Ward

& Wegner, 2013), mind-wandering (Chun et al., 2011; Groot et al., 2021; Andrillon et al., 2021), and distractions from task-irrelevant stimuli (Pershin et al., 2023). Furthermore, chronobiological factors such as circadian rhythms have been implicated in these fluctuations (Czisch et al., 2012; Gibbings et al., 2021; Hudson et al., 2020; Jagannathan et al., 2018; Xie et al., 2023). Regardless of the terminologies or theoretical frameworks employed, identifying predictive markers for vigilance lapses remains a critical goal for advancing neuroassistive technologies aimed at enhancing safety and performance in attention-demanding tasks.

Various sustained attention tasks have been employed to study the neural correlates of vigilance decrement, frequently revealing time-on-task effects such as increased error rates and slower reaction times (Manly et al., 1999; Robertson et al., 1997; Drummond et al., 2005; Mackworth, 1948). For instance, the Sustained Attention to Response Task (SART, Torkamani-Azar et al. (2020)), combined with experience sampling, has demonstrated that task-unrelated thoughts are related to increases in alpha, theta, and delta power, as well as an imbalance between the default mode network and its anticorrelated network (Groot et al., 2021). Similarly, Molina et al. (2019) examined EEG dynamics during a 45-minute Psychomotor Vigilance Task (PVT, Dinges and Powell (1985); Drummond et al. (2005)), finding that increases in alpha, theta, and beta power were associated with slower response times, reflecting a decline of task performance.

In another EEG study, Esposito et al. (2022) used Mackworth's Clock Task (MCT, Mackworth (1948)) to investigate vigilance decrements and found that frontal theta power positively correlated with reaction time, while parietal theta power was negatively correlated with detection rates, underscoring distinct neural correlates of vigilance lapses. Boksem et al. (2005) similarly recorded EEG data during a three-hour visual attention task, finding that subjective fatigue ratings and power in theta and lower-alpha bands increased significantly over time, reflecting fatigue accumulation. Additionally, in a four-hour EEG study, Wascher et al. (2014) observed that mental fatigue manifested through a progressive rise in alpha power within the first hour, followed by sustained increases in frontal theta activity. These increases in theta reliably reflected cognitive fatigue and changes in attentional engagement, indicating that vigilance decrements could be mapped through spectral power dynamics.

Furthermore, specific neurophysiological markers have been identified as predictors of impending lapses in vigilance. For example, O'Connell et al. (2009) reported increased alpha power in the right inferior parietal cortex up to 20 seconds before errors in a continuous temporal expectancy task, suggesting it as a neural marker for approaching lapses. Using a prolonged Flanker task, Eichele et al. (2010) documented a gradual decline in N2 amplitude starting several trials before errors. Similarly, Shou et al. (2015) found that pre-stimulus alpha activity predicted errors in a prolonged color-word matching Stroop task. In a notable study involving Mackworth's Clock Task, Martel et al. (2014) observed distinctive neural patterns preceding lapses, including increased alpha power approximately 10 seconds before a missed target, likely reflecting a shift toward an internally focused attentional state. The authors also reported a reduction in the P3 component, an indicator of attentional resource allocation, in response to prior events occurring up to five seconds before lapses, suggesting a progressive disengagement from the task.

While these findings offer valuable insights into the neural mechanisms underlying attention fluctuations, they face practical challenges for real-world monitoring Dehais et al. (2020). Although various EEG frequency indices have been linked to mind-wandering and performance decrements, they lack the specificity needed to reliably predict attentional lapses. This limitation arises because frequency bands such as alpha, theta, and beta are associated with a broad range of cognitive phenomena (Kahana, 2006), complicating efforts to isolate attentional lapses based solely on these measures. Additionally, studies suggest that these spectral markers often lack temporal stability (Roy et al., 2013, 2016), which may confound electrophysiological responses with time-on-task effects. Moreover, extracting precise, time-sensitive features like ERPs requires knowledge of specific event timings, posing significant challenges for real-time applications.

Steady-State Visual Evoked Potentials (SSVEPs) offer unique advantages for studying cognition due to their continuous nature and high signal-to-noise ratio (Norcia et al., 2015). Typically recorded via EEG, SSVEPs are elicited by repetitive visual stimuli (or flickers) and have been widely used to investigate the relationship between brain oscillations and cognitive functions, particularly attention (Gulbinaite et al., 2019; Boremanse et al., 2013; Peterson et al., 2014). SSVEPs provide a continuous and sustained measure of visual attention, making them a promising tool

for real-time monitoring of fluctuations in vigilance.

To the best of the authors' knowledge, only two studies have specifically examined the role of SSVEPs in vigilance assessment. Silberstein et al. (1990) investigated the topographic distribution of SSVEPs using a 13 Hz flicker during a visual vigilance task, in which participants monitored a screen for rare target stimuli. Their key finding was that during periods of heightened attention, such as when participants anticipated the appearance of a target, SSVEP amplitude significantly decreased, particularly in the occipito-parietal and right prefrontal regions. This decrease was most pronounced approximately 10 seconds after stimulus onset and persisted for up to 50 seconds. However, the relatively short task duration (nine minutes split in three trials of three minutes each) may not have been sufficient to induce attentional lapses (Möckel et al., 2015; Lim and Kwok, 2016). Moreover, since no behavioral data on lapses were recorded, a direct relationship between changes in SSVEP amplitude and lapses of attention could not be established.

More recently, O'Connell et al. (2009) examined the temporal dynamics of brain activity preceding lapses of attention during a continuous temporal expectancy task. In this task, participants monitored a stream of alternating patterned stimuli flickering at 25 Hz to detect infrequent target stimuli that were 40% longer in duration than the frequent stimuli. Although changes in other electrophysiological markers, such as increased alpha activity (8–14 Hz) and reduced frontal P3, were observed to precede attentional lapses (starting 20 seconds before a missed target), variations in SSVEP amplitude were not associated with these lapses. SSVEP dynamics were computed from consecutive two-second segments and further smoothed over time, which may have reduced the sensitivity of SSVEP features. This reduced sensitivity could potentially explain the discrepancy with earlier findings that reported differences in SSVEP amplitude preceding errors and correct trials.

While these studies provide relevant insights, they do not offer conclusive evidence for using SSVEP to track attention fluctuations or predict attentional lapses. Beyond certain limitations in experimental design, one reason for the absence of significant results may be that the flickering of the stimuli was too pronounced. Prolonged exposure to flickering stimuli can negatively impact user experience due to their distracting and visually intrusive nature (Zemon and Gordon, 2006; Wu and Lakany, 2013; Duszyk et al., 2014; Ladouce et al., 2021). High contrast and luminance of flickering elements tend to capture visual attention, disrupting task-focused visual exploration strategies (Kinchla and Wolfe, 1979), and leading to issues such as eye strain (Zhu et al., 2010), mental fatigue (Makri et al., 2015), and increased drowsiness (Cao et al., 2014; Ortner et al., 2011; Patterson Gentile and Aguirre, 2020). These issues could distract participants from the task, introduce bias in their attentional state, and adversely affect vigilance.

In order to circumvent these issues and enable the use of SSVEP to tag fluctuations in attention and detect attentional lapses in a non-intrusive way, two main strategies have emerged: Rapid Invisible Frequency Tagging (RIFT) and amplitude modulation depth reduction. RIFT capitalizes on high-frequency flickers to elicit neural responses to stimuli that are imperceptible to the user, showing promise for investigating cognitive processes (Zhigalov et al., 2019; Drijvers et al., 2021; Pan et al., 2021). However, this approach requires specialized high-refresh-rate projectors and high-density neuroimaging systems, imposing significant technical constraints and limiting broader application (Arora et al., 2024). In contrast, amplitude modulation depth reduction focuses on decreasing the contrast and intensity of flickers by lowering their amplitude modulation depth (Mouli and Palaniappan, 2016). Recent research indicates that flickers of lower contrast can achieve higher classification performance in SSVEP-based Brain-Computer Interface (BCI) applications while maintaining user comfort (Ladouce et al., 2022, 2021; Cabrera-Castillos et al., 2023). Furthermore, amplitude modulation depth reduction at the threshold of conscious perception can effectively frequency-tag spatial attention with high precision (Ladouce and Dehais, 2024).

The present study aims to build on the foundation of SSVEP research by applying a minimally intrusive 14 Hz frequency-tagging flicker to monitor vigilance lapses during a 45-minute sustained attention task. We employed Mackworth's Clock Task (Mackworth, 1948) as a continuous visual attention paradigm, simulating prolonged monitoring scenarios. Unlike previous studies that have relied on extended Fourier-transformed EEG segments, potentially limiting the temporal resolution required for precise vigilance assessment, our approach harnesses advanced signal processing and feature extraction techniques. This enables us to capture moment-to-moment modulations in SSVEP responses, facilitating a continuous and detailed assessment of vigilance lapses. In addition to behavioral data, we will collect subjective reports to assess the impact of the flicker on user experience. We expect that the refined

SSVEP approach will offer a more continuous and accurate measure of vigilance compared to traditional methods, and our SNR-based analysis will be benchmarked against classical alpha and theta band measures, which have both been reported as indicators of vigilance fluctuations. We hypothesize that the signal-to-noise ratio (SNR) of the SSVEP response recorded over occipital electrodes will predict lapses of attention as indicated by behavioral performance measures (misses vs. hits).

2. Methods

2.1. Participants

Sixteen participants (mean age = 27.5 years, SD = 5; 14 right-handed; 11 males) took part in this study. The sample size was determined based on prior research investigating SSVEP responses in similar experimental contexts. Silberstein et al. (1990) used a sample of 15 participants for initial investigations of long-term SSVEP fluctuations, while subsequent studies employed sample sizes between 15 and 21 participants to explore continuous SSVEP dynamics and other EEG markers of attention lapses (Silberstein et al., 2000; O'Connell et al., 2009; Esposito et al., 2022). Participants received a 20€ voucher as compensation for their time. Written informed consent was obtained from all participants before the experiment, and they were informed of their right to withdraw at any time. Exclusion criteria included a history of epileptic seizures, visually-induced migraines, and general photosensitivity, which were screened during recruitment to ensure participant safety due to the flickering stimuli used in the study. All participants had normal or corrected-to-normal vision. The study was approved by the Ethics Committee of the University of Toulouse (CER approval number 2023-749) and conducted in accordance with the Declaration of Helsinki.

2.2. Paradigm

The well-established Mackworth Clock Task (MCT, Mackworth (1948)), renowned for its robustness in capturing behavioral markers of vigilance fluctuations and lapses of attention, was used in this study. Participants were seated comfortably in front of a monitor and instructed to maintain focus throughout the 45-minute task. The task featured a clock-like circular array of 96 linearly spaced positions displayed consistently on the screen, with a moving indicator (a red dot) that advanced in discrete steps every 800 ms (Figure 1).

Participants were required to monitor the movement of this indicator and respond as quickly and accurately as possible when the indicator skipped a step, simulating an unexpected or irregular movement. This target event could appear at any position on the circular array and followed a set of pseudorandomization rules. Specifically, the list of all 3240 steps covering the whole 45 minutes duration of the task was divided into 18 series of 180 events, within which target jumps had an occurrence rate of 4%. Target events were not allowed within the first four steps (or 3.2 seconds) of a series, and the presentation of consecutive targets were separated by at least eight regular steps. The target occurrence rate and task duration were based on previous studies that effectively induced time-on-task effects using the MCT paradigm Esposito et al. (2022).

Participants were instructed to press a designated response button (spacebar) as soon as they detected a target event. Reaction times (RTs) to target events were recorded, and if no response was made within five seconds of a target event, it was registered as a miss. Responses made without a corresponding target event were registered as false alarms, although the low incidence of false alarms in most datasets precluded further analysis of this measure. Prior to the main experimental session, participants completed a 2-minute training session to ensure understanding of the task.

The duration of each session did not exceed 90 minutes. Each session included participant briefing, EEG setup, a first resting-state recording, baseline questionnaires, completion of the 45-minute Mackworth's clock task, post-experiment questionnaires, a post-experiment resting-state recording, and a debriefing. The session order was counterbalanced across participants.

2.3. Frequency-tagging flicker design

A flickering visual stimulus (or frequency-tagging probe) was presented continuously throughout the task, covering the entire screen (LCD, 26.3 inches, 1920 × 1080 pixels, maximal luminance: 400cd/m^2, 120 Hz refresh rate). The flicker frequency was set to 14 Hz, based on prior studies (Ladouce et al., 2022, 2021), which found that flickering rates between 10 and 20 Hz reliably evoke SSVEP responses with a high signal-to-noise ratio (SNR). The choice of 14 Hz was also intended to avoid overlap with frequency bands commonly linked to sustained attention, such as theta, alpha, and gamma bands Clayton et al. (2015). Specifically, the 14 Hz flicker was chosen to minimize interference with the alpha band (8-12 Hz), reducing potential confounds when comparing SSVEP with ongoing alpha-band activity.

Since the analysis focused on the characterization of the spectral response at the fundamental stimulation frequency, a square-shaped waveform was preferred (Teng et al., 2011; Chen et al., 2019). The flicker was implemented using the FlickersOnTop (v1.0) software [https://github.com/neuroergoISAE/FlickersOnTop], which was chosen for its ability to overlay flickering stimuli seamlessly on top of other software windows, ensuring precise control over the flicker's presentation without interrupting the experimental task. In the low luminance phase (flicker completely transparent), the task environment was composed of a grey background (value of 130 on the gray scale) whose luminance was 124cd/m² (measured using a digital light meter from Extech Instruments). During the high luminance phase of the flicker period, the slightly brighter (155 on the gray scale) screen- wide flicker was presented on top of the window running the experimental task with 80% transparency. As such, the luminance of the grey background alternated between 124 and 146cd/m² across the phases of the transparent flicker period (see Figure 1.D). The decision to use a relatively low contrast level was made to minimize potential eye strain and ensure participant comfort during prolonged exposure, while still maintaining a detectable SSVEP response. This decision was informed by our previous work on optimizing user experience and SSVEP signal for BCI applications (Ladouce et al., 2021, 2022).

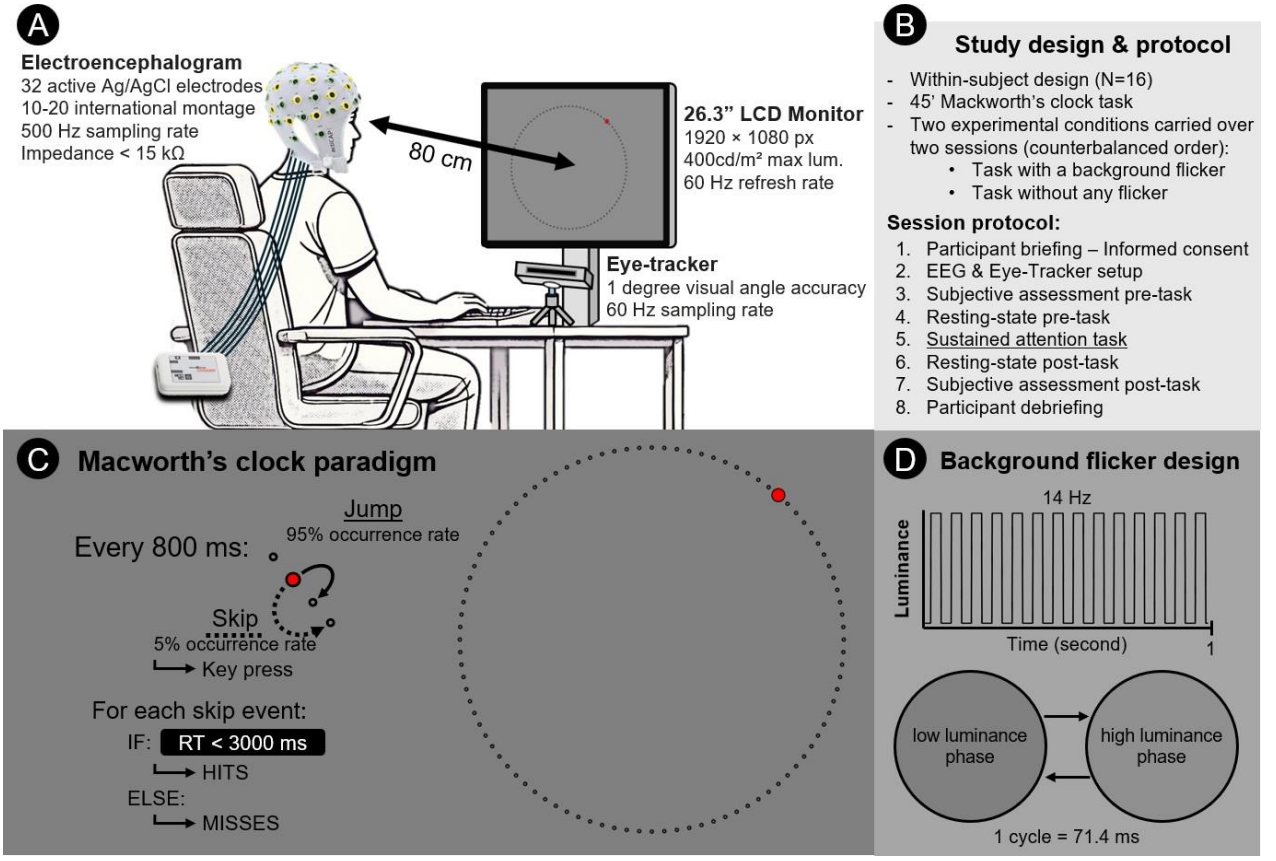

Figure 1: A. Experimental setup: Participants were seated comfortably in front of a 26.3" LCD monitor where the experimental task was presented. They were equipped with 32 electrodes for EEG recording, and their gaze was tracked using a head-mounted eye-tracker. B. Study design and protocol: Information regarding the design and procedure of an experimental session. C. Experimental paradigm: The Mackworth Clock Task was used to investigate vigilance fluctuations and lapses of attention in a long-term sustained attention context. Participants monitored a red dot moving clockwise around a 96-position clock. When the dot skipped a position (double jump), participants were instructed to press a button within five seconds (hit trials); otherwise, the trial was considered a miss. D. Flicker design: The transparent flicker was superimposed on the task, modulating the luminance of the entire screen at a rate of 14 Hz using a square wave function. The low and high luminance phases are shown below.

2.4. EEG data acquisition and processing

The EEG data were acquired using 32 active (Ag/AgCl) electrodes fitted according to the 10-20 international montage in an elastic cap, connected to a LiveAmp amplifier (Brain Products, Munich, Germany). All electrodes were referenced to the FCz electrode, with the Fpz electrode used as ground. The impedance of all electrodes was brought below 15 kΩ using conductive gel. EEG data were recorded at a sampling rate of 500 Hz with an online digital band-pass filter ranging from 0.1 to 250 Hz. At the onset of every experimental event (frequent jumps, infrequent double jumps), an event trigger was generated by the stimulus presentation program (MATLAB code available) and synchronized to the EEG data stream through the Lab Streaming Layer (LSL, Kothe et al., 2024) data synchronization framework.

After data acquisition, the following signal processing pipeline was applied to all EEG datasets. First, the raw continuous EEG data underwent an offline 1 to 40 Hz bandpass filtering (zero phase, acausal, filter order: 1651, -6 dB cut-off frequencies at 0.5 and 40.5 Hz). The data were then re-referenced to the average of all channels. An infomax Independent Component Analysis (ICA, Makeig et al., 1995) was then performed on the continuous data. The number of Independent Components (ICs) to compute was adjusted to match data rank deficiency stemming from the average referencing (Delorme and Makeig, 2023). Artifactual ICs were identified based on classification confidence scores provided by the IClabel algorithm (Pion-Tonachini et al., 2019). ICs whose classification confidence scores were above 80% for the ocular, muscular, heart rate, line noise, electrode, and other artifact classes were discarded. As a result of this pruning, a mean of 13.4 (SD = 2.45) ICs were discarded, resulting in an average of 18.6 (58%) remaining components per dataset. This artifactual IC pruning strategy is relatively conservative compared to the guidelines regarding the ratio of bad ICs proposed in (Klug and Gramann, 2021).

2.5. Measures

2.5.1. User experience assessment measures

Several subjective experience measures were collected both before and after the task to evaluate whether the flicker influenced sleepiness, eye strain, general fatigue, and perceived task difficulty. For measures that violated the normality assumption (tested using the Shapiro-Wilk test), a Wilcoxon signed-rank test was employed instead of a paired-sample Student's t-test.

- **Karolinska Sleepiness Scale (KSS), Akerstedt and Gillberg (1990)** was used to assess sleepiness, consisting of a single item measuring participants' subjective alertness/sleepiness on a 9-point Likert scale. Sleepiness induced by the task was indexed by the difference between pre- and post-task scores.

- **Digital Eye Strain Questionnaire (DESQ), Mylona et al. (2022)** was administered before and after the task in both sessions. This binary (yes/no) screening questionnaire evaluates eye discomfort and vision problems related to prolonged screen exposure. The DESQ includes 12 items (e.g., blurry vision, watery eyes, headaches, sensitivity to light), with each reported symptom adding one point to the scale. The difference in the total symptom scores pre- and post-task was compared between conditions.

- **Visual Analog Scale-Fatigue (VAS-F), Lee et al. (1991)** was used to assess general fatigue, both physical and mental. The difference between pre- and post-task scores served as the primary index of task-induced fatigue.

- **NASA Task Load Index (NASA-TLX), Hart (2006)** was used to assess workload after the task. Participants rated their workload experience across six dimensions on a 100-point scale with 5-point increments. Raw scores were averaged across items due to increase their test-retest reliability (Bustamante and Spain, 2008), and differences between conditions were compared.

2.5.2. Behavioural analysis

The accuracy and speed of participants' responses to the double jump events were measured based on space bar key presses recorded during data collection. A failure to press the key within 3 seconds after a target event was classified as a miss. Any key press recorded between this 3-second window and the next target event was considered accidental and excluded from further analysis. To examine time-on-task effects, the number of missed target events and the median reaction time were calculated for each of the six consecutive time periods. These measures were compared across the two experimental sessions to evaluate the effect of flicker presence on task performance.

2.5.3. SSVEP analysis

The continuous SSVEP response elicited by the 14Hz minimally intrusive flicker superimposed on the task was extracted using the Rhythmic Entrainment Source Separation (RESS; Cohen and Gulbinaite, 2016) method. RESS computes a spatial filter that maximizes the signal-to-noise ratio (SNR) of the SSVEP response at a specific frequency. First, channel-to-channel covariance matrices were computed from narrow-band filtered data centered around the 14Hz stimulation frequency (using a Gaussian-shaped filter with a full-width half maximum (FWHM) of 1 Hz) as well as from neighboring frequencies. These neighboring frequencies (1 Hz away from the stimulation frequency, with a FWHM of 1 Hz) provided reference covariance matrices (R matrices). A generalized eigendecomposition was then applied between the stimulation frequency and the average of the neighboring frequencies' covariance matrices. The eigenvector corresponding to the largest eigenvalue was selected as the main RESS component and back-projected onto the EEG time series. Since the RESS method optimizes the SNR at the stimulation frequency, caution is necessary when interpreting the filtered data, as overfitting is possible (Cohen and Gulbinaite, 2016). To verify that the 14Hz RESS component was not merely a by-product of this optimization process, the 14Hz RESS component was also computed on EEG data recorded during the no-flicker condition.

2.5.4. Alpha power analysis

Although historically regarded as a marker of an "idling brain," recent research suggests a more nuanced role for alpha oscillations. Rhythmic activity around 10 Hz is now understood to facilitate effective communication between brain regions, playing a crucial role in inhibition and gating processes that suppress irrelevant activity. Rather than averaging across the entire alpha range (8–12 Hz), focusing on the individual alpha peak frequency (IAPF) provides a more sensitive measure of neural dynamics, such as processing speed (Klimesch et al., 1996), and is linked to various cognitive functions (Haegens et al., 2014; Hülsdünker et al., 2016). As the IAPF can vary significantly across individuals (Grandy et al., 2013), accounting for these individual differences is essential for more accurate analysis.

In this study, the IAPF was calculated from 150 seconds of resting-state data recorded before the experimental task, during which participants had their eyes closed. The IAPF was identified using the algorithm proposed by Corcoran et al. (2018), with the recommended parameters (Fw = 11, k = 5). This individualized alpha frequency was then used to design filters for generalized eigendecomposition (GED), which enhances the contrast between signal components centered around the IAPF and broader, broadband activity. GED decomposes the data by comparing two covariance matrices: one representing the signal of interest (centered on the IAPF with a FWHM of 0.5 Hz) and the other representing broadband noise (within the 1 to 40 Hz bandpass-filtered signal) Parra and Sajda (2003). The eigenvector corresponding to the largest eigenvalue was selected as the primary component, effectively serving as a spatial filter (Cheveigné and Arzounian, 2015; Cohen, 2022). The filtered continuous data was then segmented into epochs of 1, 3, 5, and 10 seconds preceding hits and misses trials. Mean alpha peak activity for each time window was extracted and compared across events.

2.5.5. Theta power analysis

Frontal theta activity has been shown to gradually increase during prolonged tasks (Laukka et al., 1995) and is positively associated with task demands (Onton et al., 2005). Its consistent relationship with time-on-task effects, regardless of modality or task, suggests it reflects the rising cost of mental fatigue (Strijkstra et al., 2003) and executive control (Wascher et al., 2014; Arnau et al., 2017), leading to its recognition as a marker of mental effort. In this study, midfrontal theta was isolated using spatial filters designed to maximize theta-band power. The spatial filter was constructed by optimizing channel weights to maximize the distinction between theta-band (4–8 Hz) and broadband activity. A temporal filter centered around 6 Hz with a full-width half maximum (FWHM) of 2 Hz was applied, while broadband activity was filtered within the 1 to 40 Hz range. As with the alpha analysis, the filtered continuous data was segmented into epochs of 1, 3, 5, and 10 seconds preceding hits and misses trials. Mean theta activity for each time window was extracted and compared across events.

2.6. Statistical analyses

The primary objective of this study was to evaluate the effectiveness of a low-intensity flicker stimulus in eliciting SSVEP responses and to determine whether the amplitude of these responses could predict lapses of attention. To do so, we compared SSVEP amplitudes recorded during the periods preceding correct target detections (hits) and missed target detections (misses). In the first analysis, various time intervals preceding these events (1, 3, 5, and 10 seconds) were explored to identify the optimal temporal scale for detecting attentional lapses. A repeated measures Analysis of

Variance (ANOVA) was conducted, with time window (1, 3, 5, and 10 seconds), experimental condition (flicker, no flicker), and trial outcome (hits, misses) as independent factors, to examine their effects on SSVEP amplitude. Similar analyses were conducted on theta and alpha power. Holm corrections for multiple comparisons were applied to all post-hoc paired-sample t-tests investigating main effects and interactions between the factors in the repeated measures ANOVAs. In cases where Mauchly's test indicated a violation of the sphericity assumption, a Greenhouse-Geisser correction was applied.

The second aim of this study was to assess the impact of the flicker probe on subjective experience and task performance. Subjective measures of eye strain, fatigue, sleepiness, and mental workload, along with hit rate and median reaction time to target stimuli, were compared between the flicker and no-flicker conditions. For this analysis, two-tailed paired-samples t-tests were performed on task performance measures and the raw scores of the NASA-TLX questionnaire, as well as the pre-post task difference scores of other scales. A Shapiro-Wilk test of normality was conducted for each measure. If the assumption of normality was violated, Wilcoxon signed-rank tests were used in place of paired-samples t-tests.

3. Results

3.1. User experience

The differences in terms of user experience between the flicker and no flicker sessions were investigated across four dimensions: sleepiness, fatigue, eye strain, and perceived task load. The comparison of the pre-post difference scores on the Karolinska Sleepiness Scale did not reveal significant difference in sleepiness between the flicker and no flicker conditions [$t(15) = .513$, $p > .05$, $d = .128$]. The subjective assessment of fatigue induced by the performance of the task did not significantly vary across conditions [$W = 61.00$, $z = .362$, $p > .05$, corr = - .103]. Similarly, the DES questionnaires administered during both sessions did not reveal a significant difference related to the presence of a flicker in terms of eye strain [$W = 34.5$, $z = .714$, $p > .05$, corr = .255]. The perceived task load assessed through the NASA-TLX questionnaire was similar across conditions [$t(15) = .068$, $p > .05$, $d = .017$]. A summary of the data can be visualized in the left panel of Figure 2.

3.2. Behavioural performance

Task performance was assessed in terms of reaction time and number of missed targets. No difference was found between the flicker and control conditions in terms of median reaction time [$W = 47$, $z = 1.086$, $p = .298$, corr = 1.294] and total number of missed targets [$t(1,15) = .09$, $p > .05$, $d = .023$]. These results suggest that the presence of the flicker did not affect task performance.

In order to investigate whether measures reflecting the time on task effect were affected by the presence of a flicker, the continuous data was split into six consecutive windows of 7.5 minutes, from which outcome measures were extracted. The behavioural measures (median reaction time and number of errors per period) were analyzed through 2-by-6 repeated-measures ANOVAs with task on time (first to sixth time period) and condition (flicker, no flicker) as main factors.

There was no effect of the condition (presence or absence of the transparent flicker) on the number of missed events [$F(1,15) = 0.051$, $p > .05$, $n^2_p = .003$]. The time on task however had a main effect on the number of missed events [$F(5,75) = 15.699$, $p < .001$, $n^2_p = .511$]. The interaction between the two factors did not yield a main effect on the number of errors commited [$F(5,75) = 0.786$, $p > .05$, $n^2_p = .050$]. Post-hoc test showed that a significantly lower number of events were missed during the first two periods (from 0 to 15 minutes) than over the rest of the task (see Figure 2 and Figure 5). There was no significant difference in terms of number of missed events between the following periods.

Similarly, reaction time was not found to be mainly affected by the presence or absence of the transparent flicker [$F(1,15) = 0.933$, $p > .05$, $n^2_p = .059$]. A main effect of the time on task was also observed on reaction time [$F(1.723,25.838) = 4.896$, $p < .05$, n2p = .246]. The interaction of the two factors did not alter the reaction time significantly [$F(2.237,33.559) = 0.726$, $p > .05$, $n^2_p = .046$]. Post-hoc paired-sample t-tests revealed that reaction time significantly increased during the last period (37.5 to 45 minutes) when compared to the first and second time periods (from 0 to 15 minutes into the task) [$t(1,15) = 4.764$, $p < .001$, $d = .531$ and $t(1,15) = 3.363$, $p < .05$, $d = .375$, respectively]. No significant difference in reaction time was observed between the first two periods, nor between the following periods when compared amongst themselves (see Figure 2).

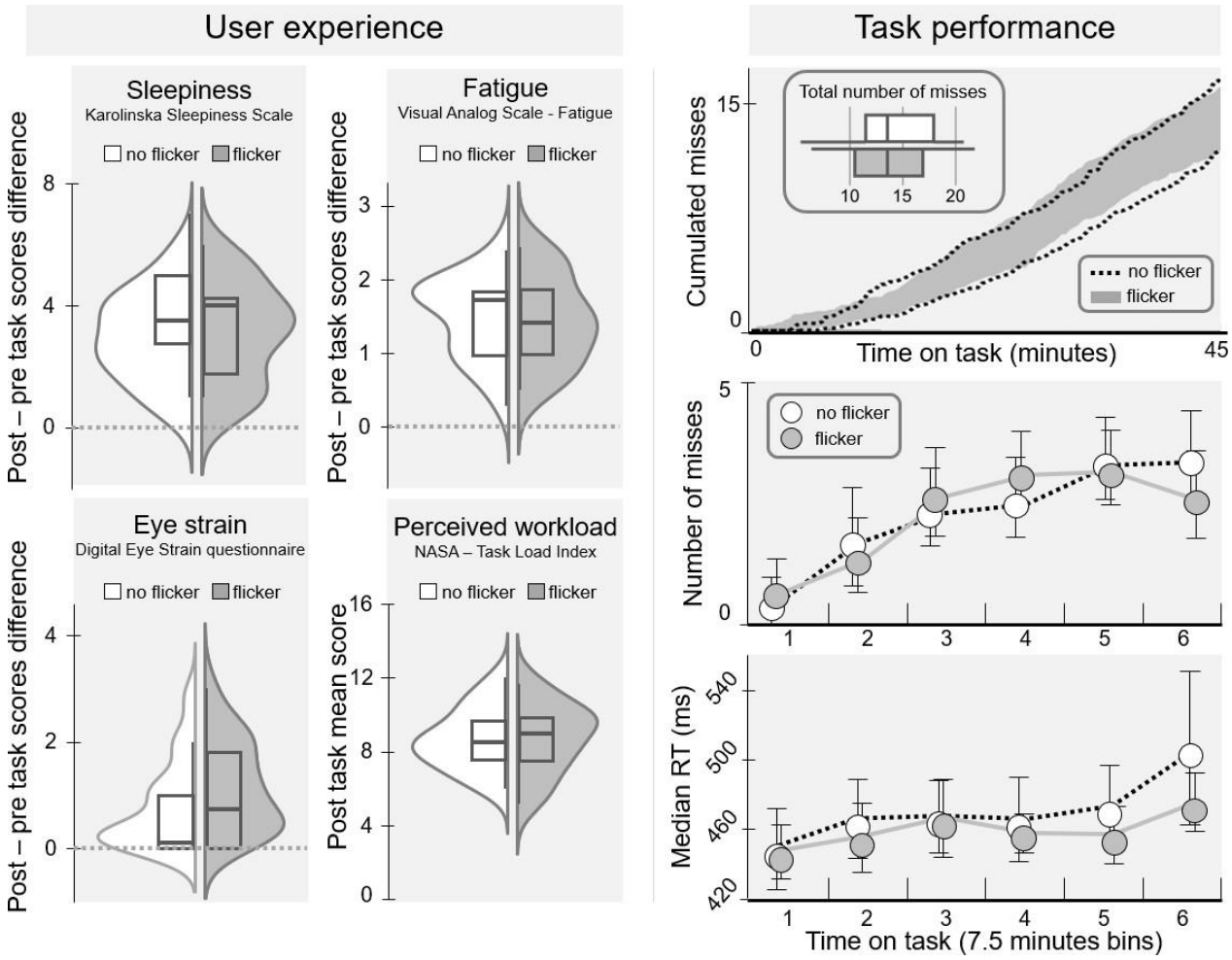

Figure 2: Comparison of user experience and task performance measures between the experimental conditions (with or without the 14 Hz transparent flicker) recorded in separate sessions. Left: Differences between pre- and post-task measures of sleepiness, fatigue, and eye strain (flicker in gray, no flicker in white) were compared to evaluate the impact of the transparent flicker on participants' subjective experiences. Perceived workload was measured at the end of each session. Right: Task performance measures, including the cumulative number of missed events over time-on-task, as well as the median number of missed events and median reaction times (RT) per 7.5-minute period, were compared across conditions to assess time-on-task effects.

3.3. EEG analysis

This study aimed to evaluate the validity of a continuous yet minimally intrusive SSVEP frequency-tagging approach for measuring lapses of attention during a sustained visual attention task. SSVEP measures were compared with other commonly used markers of attention and vigilance, including pre-stimulus theta and alpha band power. As a first validation step, we examined the effects of flicker presence and time-on-task on these EEG measures to assess both their reliability and potential interference with the proposed approach. This analysis was performed on the median signal features computed across six consecutive time periods of 7.5 minutes, comparing the two experimental sessions where participants performed the clock task with and without the 14 Hz flicker. Next, to determine which EEG features could differentiate between successful target detections (hit trials) and missed detections (miss trials), EEG features preceding these events were extracted from the continuous signals recorded during the flicker condition and compared. Additionally, to identify the optimal time window for distinguishing hit and miss trials using band-specific features, spectral power measures were computed for varying temporal windows (1, 3, 5, 10, and 30 seconds) preceding each event.

3.3.1. Steady-States Visually Evoked Potentials (SSVEP)

As expected, the presence of the transparent flicker had a main effect on the strength of the SSVEP signal extracted [$F(1,15) = 16.454$, $p < .001$, $n^2_p = .523$]. The time on task also had a main effect on SSVEP response [$F(5, 75) = 2.809$, $p < .05$, $n^2_p = .158$]. The interaction between flicker presence and time on task yielded a main effect on SSVEP response [$F(5, 75) = 4.661$, $p < .001$, $n^2_p = .237$]. Post-hoc tests revealed that the strength of the SSVEP signal was higher when the flicker was present than absent [$t(1,15) = 3.390$, $p < .001$, $d = .736$]. Moreover, the amplitude of the SSVEP response elicited by the presence of the transparent flicker was significantly higher at the end of the task than at its start (see Figure 3).

The detection of the event (hits or miss) had a main effect on SSVEP signal strength [$F(1, 15) = 148.35$, $p < .001$, $n^2_p = .908$]. The temporal window length over which the mean signal was extracted had a main effect on SSVEP power [$F(1.764, 26.455) = 29.732$, $p < .001$, $n^2_p = .665$]. The interaction between window length and detection factors affected the amplitude of the SSVEP [$F(1.437, 21.559) = 53.918$, $p < .001$, $n^2_p = .782$]. Post-hoc tests revealed that, across time windows of different lengths, the SSVEP signal strength was significantly higher when participants detected the target events than when they missed them [$t(15) = 12.180$, $p < .001$, $d = 4.069$]. More precisely, these analyses revealed that a one second time window led to the highest contrast between SSVEP signals preceding hits and misses [$t(15)= 15.507$, $p < .001$, $d = 6.475$] (see Figure **4**), although the SSVEP response over three [$t(15) = 12.300$, $p < .001$, $d = 5.136$], five [$t(15) = 10.656$, $p < .001$, $d = 4.450$], and ten [$t(15) = 10.762$, $p < .001$, $d = 3.241$] seconds were also significantly different between hits and misses trials. This higher contrast for the one second window is mainly explained by a significant reduction in SSVEP signal amplitude during the last second preceding the missed target events than with using any of the longer time windows whereas the amplitude of the SSVEP response preceding the successfully detected target events did not vary across time windows. The extraction of mean SSVEP signal over a 30 second window preceding the events did not lead to a significant difference between hits and misses trials [$t(15) = 2.495$, $p > .05$, $d = 1.042$].

3.3.2. Alpha peak power

Effect of flicker presence on overall alpha signal strength [$F(1,15) = 0.012$, $p > .05$, $n^2_p < .001$]. The time on task did not affect absolute alpha peak signal [$F(5, 75) = 1.666$, $p > .05$, $n^2_p = .100$]. There was no interaction between flicker presence and time on task did not affect alpha peak signal [$F(5, 75) = 2.204$, $p > .05$, $n^2_p = .128$]. These results indicate that neither the presence of the transparent flicker nor the time on task did not affect the absolute alpha peak signal strength. The detection of the event (hits or miss) did not have a main effect on alpha peak signal strength [$F(1, 15) = 1.392$, $p > .05$, $n^2_p = .085$]. The temporal window length over which the mean signal was extracted did not have a main effect on alpha signal strength [$F(2.589, 38.838) = 34.705$, $p < .001$, $n^2_p = .698$]. The interaction between window length and detection factors did not affect the amplitude of the alpha signal recorded [$F(2.437, 36.550) = 1.217$, $p > .05$, $n^2_p = .075$]. Post-hoc tests revealed that shorter time windows preceding onset of events had significantly lower alpha peak signal than longer time bins (see Figure 4).

3.3.3. Theta power

Effect of flicker presence on overall theta signal strength [$F(1,15) = 0.288$, $p > .05$, $n^2_p < .019$]. The time on task did not affect absolute theta signal [$F(3.014, 45.207) = 1.372$, $p > .05$, $n^2_p = .084$]. There was no interaction between flicker presence and time on task did not affect theta signal [$F(5, 75) = 1.284$, $p > .05$, $n^2_p = .079$]. These results indicate that neither the presence of the transparent flicker nor the time on task did not affect the absolute theta signal strength. The detection of the event (hits or miss) did not have a main effect on theta signal strength [$F(1, 15) = 1.846$, $p > .05$, $n^2_p = .110$]. The temporal window length over which the mean signal was extracted did not have a main effect on theta signal strength [$F(2.570, 38.554) = 12.023$, $p < .001$, $n^2_p = .445$]. The interaction between window length and detection factors did not affect the amplitude of the theta signal recorded [$F(2.458, 36.876) = 0.079$, $p > .05$, $n^2_p = .005$]. Post-hoc tests revealed that shorter time windows preceding onset of events had significantly lower theta signal than longer time bins (see Figure 4).

3.3.4. Correlation between task performance and EEG features

The SSVEP signal amplitude preceding both the detected and the overlooked target events were negatively correlated with the total number of missed target events [detected: $r(15) = -.736$, $p < .01$, $z = -.942$; undetected:

r(15) = -.703, p < .01, z = -.873]. There was however no significant relationship between the median reaction time and neither the SSVEP amplitude preceding detected [r(15) = -.102, p > .05] and undetected target events [r(15) = -.174, p > .05]. Moreover, the SSVEP signal amplitude preceding detected and overlooked target events was strongly correlated [r(15) = .870, p < .001, z = 1.335]. For the other frequency band features, the median reaction time was not significantly correlated with peak alpha signal preceding hits [r(15) = .206, p > .05] and missed trials [r(15) = -.171, p > .05]. There was no significant relationship between the total number of errors and peak alpha signal recorded before the occurrence of hits [r(15) = .118, p > .05] but with missed trials [r(15) = .537, p < .05, z = .600]. The measures of task performance were not significantly correlated with theta activity recorded before the detection or oversight of target events.

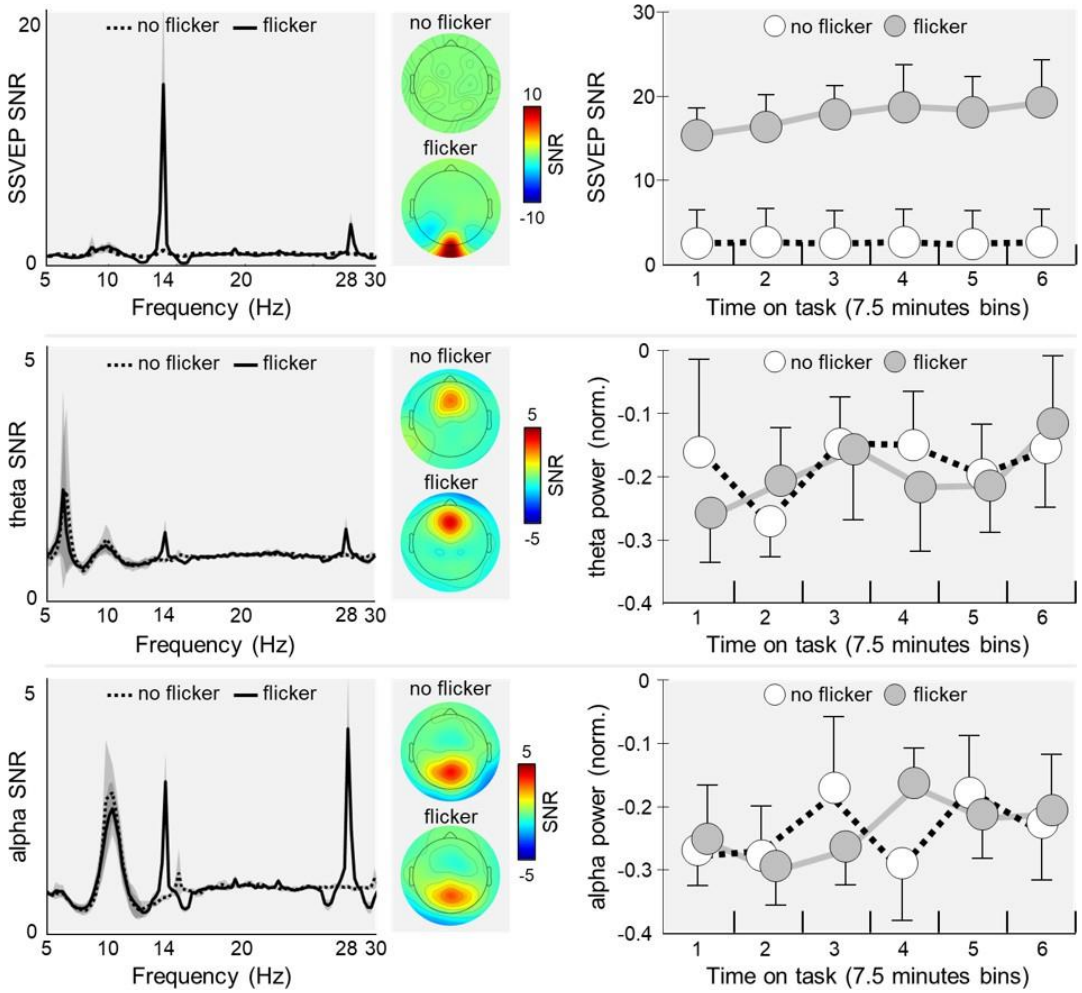

Figure 3: Grand average (N=16) power spectral density, topography, and time-on-task modulations of the different EEG features investigated: top row shows SSVEP, middle row shows theta, and bottom row shows alpha peak, across both experimental sessions (with and without a 14 Hz minimally intrusive transparent flicker). Left: Spectral power density of the spatially filtered data recorded over the entire 45-minute task (solid lines for flicker condition, dotted lines for no-flicker condition). Center: Mean spatial distribution of the spatial filters corresponding to the signals of interest across participants for both conditions. Right: Signal fluctuations over the 45-minute task, with mean signal strength extracted within six consecutive 7.5-minute time periods to assess the effects of flicker presence and time-on-task on the different signals.

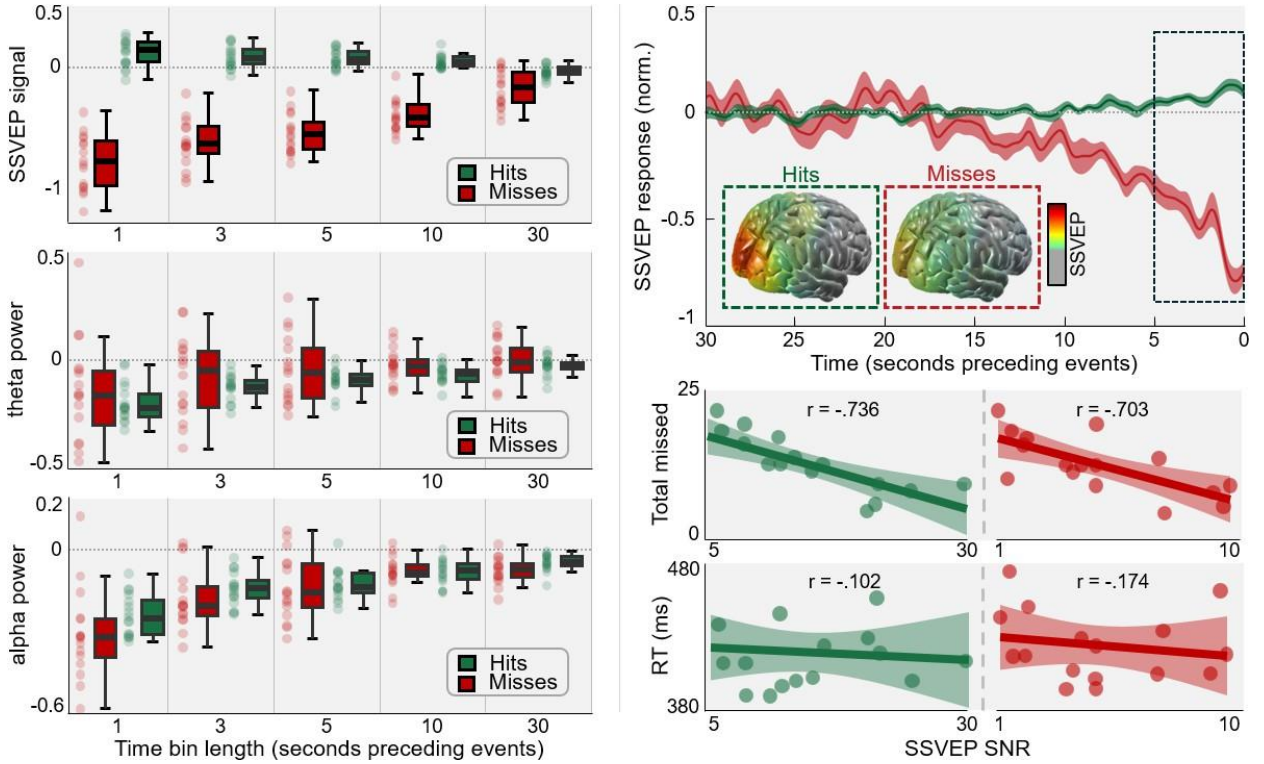

Figure 4: Left: Distribution of mean SSVEP responses preceding hit (green) and missed (red) events, extracted from time bins of varying lengths (1, 3, 5, 10, and 30 seconds). Upper right: Grand average (N=16) SSVEP response waveforms preceding hit and missed events. The topographical maps in the dotted insets show the SSVEP responses recorded during the last five seconds preceding hit and missed events. Lower right: Correlation between the mean SSVEP response recorded one second prior to hit and missed events with the total number of missed trials and the median reaction time (RT) across participants.

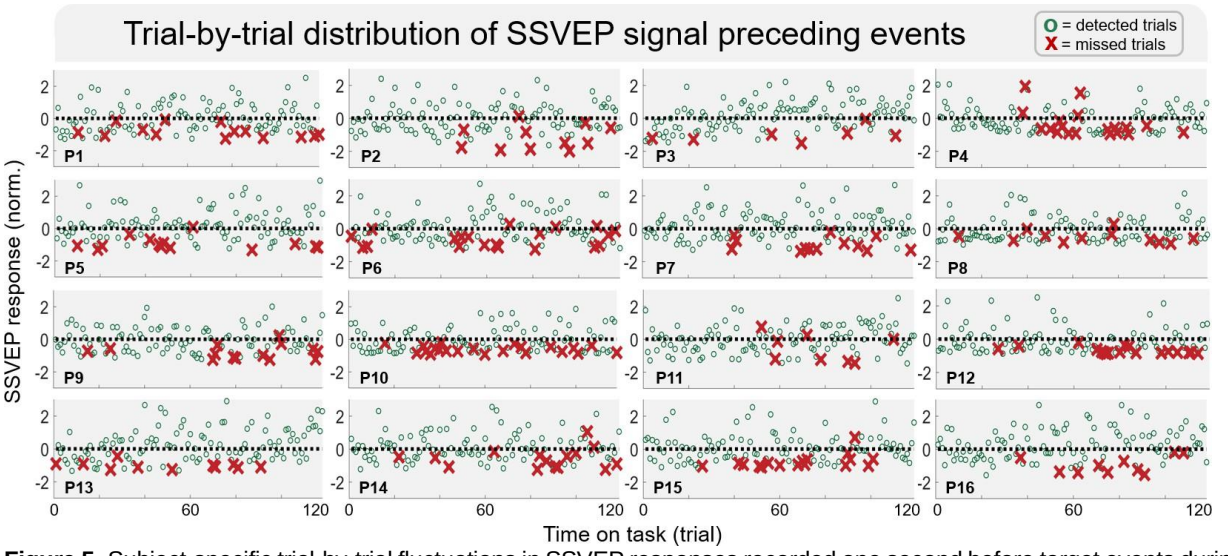

Figure 5: Subject-specific trial-by-trial fluctuations in SSVEP responses recorded one second before target events during the 45-minute clock task, with a 14 Hz transparent flicker superimposed. Green circles represent SSVEP responses recorded prior to detected trials, while red crosses represent responses preceding missed trials. The SSVEP responses were z-score normalized based on the entire recording. The dotted line represents the mean SSVEP response across the 45-minute task.

4. Discussion

This study investigated whether a minimally intrusive SSVEP frequency-tagging approach could effectively monitor vigilance fluctuations and predict lapses of attention during a prolonged sustained attention task. A 14 Hz low-luminance, low-contrast flicker was superimposed onto the Mackworth Clock Task, a well-established paradigm for simulating real-world monitoring scenarios. This design aimed to capture reliable neural markers of attentional lapses while minimizing sensory disruption. A control condition, in which participants performed the task without the flicker, confirmed that SSVEP measures were specifically modulated by the flicker without affecting user experience or task performance.

4.1. Behavioral Performance and Subjective Experience

The primary aim of our analyses was to verify whether the experimental paradigm effectively induced attentional lapses. The behavioral data clearly demonstrated a time-on-task effect: as the task progressed, participants' performance deteriorated, evidenced by an increase in missed target events and slower reaction times. These findings align with established research on vigilance lapses (Mackworth, 1948; Martel et al., 2014; Durantin et al., 2015; Braboszcz and Delorme, 2011; Manly et al., 1999; Robertson et al., 1997; Drummond et al., 2005), confirming that sustained attention tasks lead to performance declines over time. Importantly, the presence of the low-intensity flicker did not affect task performance. Reaction times and accuracy were comparable between the control condition (without flicker) and the experimental condition (with flicker), indicating that the flicker did not interfere with participants' ability to perform the task.

Subjective reports further supported these findings. The contrast between pre- and post-task self-reports of sleepiness, eye strain, and fatigue did not differ between the flicker and non-flicker conditions, suggesting that the flicker did not negatively impact participants' experience. Moreover, participants' perception of task difficulty remained consistent across both conditions, reinforcing the minimal effect of the flicker on task performance and user comfort. These results are particularly relevant given the well-documented issues with traditional flicker stimuli, which are often associated with visual discomfort and distraction (Zhu et al., 2010; Makri et al., 2015; Cao et al., 2014; Ortner et al., 2011; Patterson Gentile and Aguirre, 2020).

4.2. Neural Response and SSVEP Modulation

While subjective assessments confirmed that the flicker was visually comfortable and did not impair task performance, it was critical to assess whether it could elicit measurable neural responses in the visual cortex and track fluctuations in vigilance, potentially predicting attentional lapses. Given the reduced saliency of the stimuli, it was initially anticipated that detecting neural variations might be challenging. However, signal-to-noise ratio (SNR) analyses revealed that even low-contrast flickers successfully triggered cortical responses, as demonstrated by measurable SNR values.

Moreover, the SSVEP signal at the target frequency was significantly modulated by the presence of the subtle flicker, increasing monotonically with time-on-task. Post-hoc analyses confirmed that SSVEP amplitude was significantly higher at the end of the task than at its onset, reinforcing this trend. These findings may seem counterintuitive, particularly in light of previous research showing a reduction in SSVEP SNR with prolonged task engagement and presumed mental fatigue (Lamti et al., 2014; Xie et al., 2016). However, it is important to note that in these studies, participants were not engaged in a vigilance task but were focused solely on the flicker stimuli, which likely induced visual fatigue and eye strain, rather than mental fatigue.

An alternative explanation for our results is that prolonged time-on-task induces mental fatigue, which paradoxically triggers stronger neural responses as a compensatory mechanism to offset reduced cognitive efficiency. This heightened neural activity could explain the increased SSVEP SNR observed in our study. Indeed, several studies suggest the existence of compensatory neural mechanisms that counteract cognitive fatigue. For example, Wang et al. (2016) found that during the initial phase of a task (lasting up to approximately 80 minutes, termed the "compensation phase"), the brain adapts to cognitive fatigue by increasing neural activity. Beyond this phase, in the "decompensation phase," the brain's ability to compensate diminishes as fatigue intensifies. This compensation model is relevant to our study, as the task duration of approximately 40 minutes aligns with the compensation phase, where compensatory mechanisms are likely to be active. The lack of changes in traditional markers such as alpha and theta rhythms which

are generally known to index time-on-task effects, as reported in several studies (Groot et al., 2021; Molina et al., 2019; Dinges and Powell, 1985; Drummond et al., 2005; Esposito et al., 2022) may further suggest that the task duration was insufficient to trigger the decompensation phase. This, in turn, supports the hypothesis that SSVEP may serve as a more sensitive indicator of attentional fluctuations compared to other neural markers.

Another possible explanation is that, during prolonged tasks, the brain may adapt to the flicker stimulus, amplifying the SSVEP response to maintain vigilance. This adaptation could involve greater engagement of the occipital cortex, as participants increase their effort to remain attentive, reflecting an adaptive neural strategy. Future studies should explore longer task durations as in (Boksem et al., 2005; Wascher et al., 2014), potentially using the Mackworth Clock Test, to further investigate these hypotheses. This would clarify the impact of extended time-on-task on SSVEP SNR under conditions of prolonged fatigue and provide deeper insights into the role of compensatory mechanisms in sustaining attention.

4.3. SSVEP Response as a Predictor of Attentional Lapses

An additional objective of this study was to determine whether steady-state visual evoked potentials (SSVEP) could act as sensitive markers for predicting lapses in attention. Our findings reveal that the SSVEP signal-to-noise ratio (SNR) was significantly lower in the moments preceding missed target events compared to those correctly detected. This result suggests that SSVEP amplitude may serve as a reliable indicator of vigilance, with the potential to distinguish between episodes of inattention and effective attentional engagement as early as 15 seconds before a response. Notably, shorter time windows (e.g., 1 second) prior to target events yielded the most robust discrimination between hits and misses, highlighting the temporal precision of SSVEP as a continuous measure of attention. Further correlational analyses reinforced the predictive value of SSVEP, as these measures were linked to both correct detections and misses. Together, these results indicate that SSVEP is not only sensitive to attentional lapses but also functions as a reliable predictor of performance outcomes.

A potential confound considered was the possibility that these SSVEP changes could reflect shifts in endogenous brain rhythms, particularly the alpha rhythm (around 14 Hz), which is close to the flicker frequency. However, no such modulations were observed in a control condition without flicker stimulation, ruling out the influence of endogenous alpha activity and confirming that the observed SSVEP variations were specific to the flicker stimulus. Moreover, both alpha and theta band activity did not show significant differences between hit and miss trials during event detection as previously shown by Shou et al. (2015); Martel et al. (2014); O'Connell et al. (2009). Nevertheless, further analyses revealed a positive correlation between alpha power and missed trials. This finding aligns with existing literature, where elevated alpha activity is often associated with attentional disengagement and performance lapses (Groot et al., 2021; Molina et al., 2019; Dinges and Powell, 1985; Drummond et al., 2005; Esposito et al., 2022).

However, alpha power was not correlated with hit trials, suggesting that SSVEP provides a more specific predictor of attentional engagement. Overall, these results underscore the utility of SSVEP as a distinct and reliable indicator of attention that is not confounded by endogenous rhythms such as alpha, which remained unaffected by flicker in control conditions. Taken together, the findings highlight the potential of SSVEP for long-term vigilance monitoring, offering advantages over traditional spectral markers like theta and alpha activity. In particular, the lack of temporal stability and specificity of these traditional markers, especially in real-world applications, reinforces the superiority of SSVEP as a tool for continuous vigilance assessment. These findings provide a strong basis for the application of SSVEP in monitoring sustained attention across various contexts.

4.4. Limitations and Future Directions

While our findings demonstrate the efficacy of SSVEP for detecting attentional lapses, several limitations should be addressed in future research. First, our sample size of 16 participants, though sufficient for exploratory purposes, may limit the generalizability of the results. Larger and more diverse samples are needed to ensure the robustness of these findings. Additionally, this study used a single flicker frequency (14 Hz) to avoid interference with endogenous alpha rhythms. Future work could explore the efficacy of other flicker frequencies and modulation depths to optimize both user comfort and signal reliability.

Moreover, while our study focused primarily on neural markers, integrating additional behavioral data such as eye-tracking measures could provide a more comprehensive understanding of attentional dynamics. Combining SSVEP with other behavioral indices may offer deeper insights into how neural activity corresponds to task performance.

4.5. Conclusion

In conclusion, this study demonstrates the effectiveness of a minimally intrusive SSVEP frequency-tagging approach for real-time monitoring of vigilance decrements. SSVEP responses, triggered by a low-luminance, low-contrast 14 Hz flicker, accurately predicted lapses in attention and outperformed traditional alpha-band EEG markers. Crucially, the flicker stimulus did not disrupt task performance or user comfort, making it highly suitable for high-stakes industries like aviation and healthcare. These findings pave the way for developing human-computer interfaces (HCIs) capable of continuously monitoring cognitive states in environments where attentional lapses could have critical consequences. By detecting vigilance lapses in real time, such HCIs could trigger adaptive interventions, such as task reminders or automated assistance, to maintain optimal performance.

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6. Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that may be construed as competing interests or could have influenced the work reported in this paper.

7. Data and Code Availability

The datasets analyzed in the current study will be made publicly available in an online repository. The source code for the analysis will also be available on GitHub.

CRediT authorship contribution statement

S. Ladouce: Conceptualization, Data collection, Data analysis, Writing. **J. J. Torre-Tresols:** Data analysis, Writing. **K. Le Goff:** Writing. **F Dehais:** Conceptualization, Writing.

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