A Longitudinal Study on the Effects of Circadian Fatigue on Sound Source Identification and Localization using a Heads-Up Display

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Abstract

Circadian fatigue, largely caused by sleep deprivation, significantly diminishes alertness and situational awareness. This issue becomes critical in environments where auditory awareness—such as responding to verbal instructions or localizing alarms—is essential for performance and safety. While head-mounted displays have demonstrated potential in enhancing situational awareness through visual cues, their effectiveness in supporting sound localization under the influence of circadian fatigue remains under-explored. This study addresses this knowledge gap through a longitudinal study (N=19) conducted over 2–4 months, tracking participants' fatigue levels through daily assessments. Participants were called in to perform non-line-of-sight sound source identification and localization tasks in a virtual environment under high- and low-fatigue conditions, both with and without head-up display assistance. The results show task-dependent effects of circadian fatigue. Unexpectedly, reaction times were shorter across all tasks under high-fatigue conditions. Yet, in sound localization, where precision is key, the HUD offered the greatest performance enhancement by reducing pointing error. The results suggest the auditory channel is a robust means of enhancing situational awareness and providing support for incorporating spatial audio cues and HUD as standard features in augmented reality platforms for fatigue-prone scenarios.

CCS Concepts

• **Human-centered computing → User studies**; **Mixed / augmented reality**; **User interface design**.

Keywords

Human-Computer Interaction, Head-Up Display, Circadian Fatigue, Multimodal Interaction, Longitudinal Study

CHI '25, Yokohama, Japan

ACM ISBN 979-8-4007-1394-1/25/04
https://doi.org/10.1145/3706598.3713402

ACM Reference Format:
Alexander G Minton, Howe Yuan Zhu, Hsiang-Ting Chen, Yu-Kai Wang, Zhuoli Zhuang, Gina Notaro, Raquel Galvan, James Allen, Matthias D

Ziegler, and Chin-Teng Lin. 2025. A Longitudinal Study on the Effects of Circadian Fatigue on Sound Source Identification and Localization using a Heads-Up Display. In *CHI Conference on Human Factors in Computing Systems (CHI '25), April 26–May 01, 2025, Yokohama, Japan.* ACM, New York, NY, USA, 12 pages. https://doi.org/10.1145/3706598.3713402

1 Introduction

Circadian fatigue, often stemming from sleep deprivation, significantly impacts human performance across physical [49, 57] and cognitive domains [27, 86]. It affects core skills, including distance estimation [5], stimulus discrimination [62], and central auditory processing [62]. This impairment is particularly critical for auditory perception [96], especially in 'non-line of sight' scenarios where visual cues are absent [10]. For professionals working extended hours (e.g., miners, hospital staff, truck drivers), circadian fatigue can lead to diminished perception capabilities, potentially resulting in physical harm and detrimental outcomes [17, 104]. Understanding and mitigating these effects on workers' environmental awareness remains an active and evolving research field [71, 85].

Recent advancements in augmented reality (AR) and head-up displays (HUD) have demonstrated significant potential to enhance workers' ability to perceive environmental hazards. Research across professions such as aviation [89], trucking [64], and mechanical repair [43] has highlighted the effectiveness of integrating real-time visual information through AR and HUD to improve hazard awareness. Complementing these findings, innovative methods like providing visual cues for 'non-line-of-sight' stimuli via acoustic localization [54] or utilizing wide camera views from wearable devices [40, 46, 107] address situations where direct visual detection is not feasible. Building on these advancements, the heads-up computing framework [110] advocates a shift from device-centered to human-centered interactions by distributing input and output functionalities across multiple sensory channels, aligning with human cognitive and perceptual capabilities to optimize situational awareness[108].

However, HUDs are not without drawbacks, as they can negatively affect perception [102] and cause VR sickness [22], a limitation that may be exacerbated by fatigue. This issue is particularly concerning in industries where HUDs are widely adopted, as these environments often involve shift work and extended hours. The Human-Computer Interaction (HCI) and AR communities have extensively explored various types of fatigue associated with AR use, including visual fatigue [58], cognitive fatigue [87], physical fatigue [55], and interaction-related fatigue [12]. Yet, there is a notable lack of research on how circadian fatigue affects HUD usage for enhancing environmental awareness, particularly in the integration of auditory perception with visual cues [38]. This gap is critical, as many workplace hazards are first detected through auditory signals, and the ability to localize and respond to these sounds rapidly is essential for maintaining safety.

To address this knowledge gap, we conducted a longitudinal study spanning 2-4 months with 19 participants to investigate the effects of circadian fatigue on sound source identification and localization tasks using a head-up display. We employed a 2x2 within-subjects design with fatigue level (low, high) and HUD guidance (on, off) as independent variables. Our methodology involved daily fatigue monitoring through smartwatches, which tracked sleep patterns and subjective fatigue assessments. We utilized the Fatigue Impairment Prediction Suite (FIPS) to estimate fatigue levels and identify suitable times for experimental sessions. Participants completed two virtual reality sessions - one in a high-fatigue state and one in a low-fatigue state on different days. In each session, the participant performed target localization and identification tasks for non-line-of-sight auditory stimuli in a virtual environment, both with and without HUD guidance, while observing and recalling environmental details to simulate real-world multitasking.

The results show task-specific effects of circadian fatigue on performance. Surprisingly, reaction times (RTs) were shorter under high-fatigue conditions for all tasks. Notably, the HUD guidance provides the most performance improvement in the sound source localization task, a task that demands high precision under high-fatigue conditions. The result supports the auditory channel as a reliable modality for safety-critical AR applications and leads to our advocacy for incorporating spatial audio cues and HUD guidance as a standardized design component, particularly for AR applications intended for contexts where circadian fatigue is anticipated.

Contributions

- A novel experimental design examining the effects of circadian fatigue and HUD guidance on sound source identification and localization, addressing a critical gap in human-computer interaction research.
- A longitudinal study spanning 2-4 months, yielding rich data on daily sleep patterns and subjective fatigue assessments.
- Empirical evidence on the effects of circadian fatigue on accuracy and reaction times in sound source identification and localization tasks, informing the design of technologies for fatigue-prone environments.

2 Related Works

2.1 Fatigue in HCI and AR Research

The HCI and AR community has extensively investigated various types of fatigue associated with AR use, such as visual, cognitive, physical, and interaction-related fatigue.

AR systems often induce visual fatigue due to the vergence-accommodation conflict, where the eyes' convergence and accommodation cues misalign. This misalignment leads to eye strain, discomfort, and headaches [58]. Strategies like multifocal and gaze-adaptive displays dynamically adjust focal depth, reducing ocular strain [109]. Furthermore, Kim et al. demonstrated that dark mode graphics in optical see-through displays enhance visual acuity and reduce fatigue, particularly under varying ambient lighting conditions [31].

Cognitive fatigue refers to a state of mental and physical exhaustion marked by diminished energy and increased feelings of monotony arising from prolonged engagement in demanding cognitive tasks. This condition often improves with rest or breaks from repetitive and complex activities [87]. It is a significant factor in AR usage, stemming from the mental effort required to process augmented information. Research on cognitive fatigue in VR primarily explores the impact of virtual environments, such as environmental design [68, 90], interaction methods [100], and usage duration [100].

Researchers have also focused on physical fatigue by examining the form factor of headsets. Studies confirm that headset weight [55] and weight distribution [4] significantly affect physical and mental load, with improvements in these areas enhancing the overall VR experience [53]. Additionally, muscular fatigue, particularly from mid-air gestures, presents unique challenges. These gestures, a common AR input method, often cause gorilla arm syndrome [12], characterized by muscle fatigue in the shoulders and arms from repetitive movements. Researchers have proposed solutions such as adaptive gesture recognition systems [41] and hybrid approaches that combine gestures with voice commands or tangible inputs to alleviate physical strain [103]. Recent works also focus on quantifying muscle fatigue in mid-air interactions [44, 61].

Circadian fatigue research presents unique challenges in HCI, primarily due to the significant resources required for longitudinal investigations of sleep cycles [8] and the intricate cross-modal effects on cognitive and physical performance [45]. This study addresses these challenges by focusing on the impact of circadian fatigue on sound identification and localization during AR use. Examining the interplay between auditory processing and fatigue cycles contributes novel insights into mitigating fatigue-induced performance declines. These findings aim to inform AR system design, enhancing usability and user performance even in fatigue-prone contexts.

2.2 Effects of Circadian Fatigue on Human Performance

Circadian fatigue, or sleep deprivation, significantly impacts both physical and cognitive performance, from tasks like driving [49, 52, 57] to multi-tasking and standardized tests [27, 86], with effects even observed at the neurological level [25, 36]. Cognitive performance and fatigue levels are closely linked, with research showing potential for predicting and classifying fatigue states based on various features [13, 70]. However, physiological monitoring systems' large size and lengthy setup times have long been barriers to their widespread use [45].

Beyond biometric measures, behavioral data and self-reporting have been used to assess how fatigue affects performance. Human Factors research often employs the Three-Level Model of Situation Awareness [29], which includes Perception (Level 1), Comprehension (Level 2), and Projection (Level 3) of environmental changes. The Situation Awareness Global Assessment Technique (SAGAT) [28] is commonly used to evaluate these aspects and has been applied to study the impact of fatigue on task performance [78], recognizing fatigue as a key factor in many tasks [11, 47].

Efforts have also been made to implement effective safety practices in hazardous environments [72, 88] and establish regulations for the safe operation of dangerous equipment [76]. These initiatives aim to minimize risks by addressing factors such as fatigue and ensuring that workers maintain high levels of situational awareness, particularly in environments where errors can lead to serious consequences. Additionally, portable systems to monitor fatigue have been developed to complement these safety practices, enhancing the ability to manage fatigue in real-time and reduce the likelihood of accidents [105].

2.3 Sound Source Localization

Accurate sound identification and localization are vital for environmental awareness, especially when detecting stimuli outside the field of view, such as alarms or threats. Visual cues significantly aid auditory localization [113], with audio-visual integration playing a crucial role in perception [96]. Visual information becomes even more critical in challenging conditions like the "cone of confusion," where sounds from the side are hard to pinpoint [82, 97]. Techniques like "perceptual feedback training" [7] and "sensory augmentation" [77, 112] have been shown to improve audio-only localization and reduce errors such as misidentifying sound direction, though spontaneous reorientation using only auditory cues remains difficult [75].

When auditory stimuli are obstructed, outside the line of sight, or distorted due to reverberation [92], traditional audio-only localization struggles. In response, methods like microphone arrays have been developed to calculate sound direction based on differences in arrival times [91]. Augmenting audio cues with visual elements, such as HUDs, has improved localization accuracy [59]. However, HUDs also have drawbacks, including the potential to impair aural performance [2], cause attentional tunnelling, and lead to information overload [35, 99, 102]. These challenges are particularly relevant in designing human-support systems [30].

3 Methodology

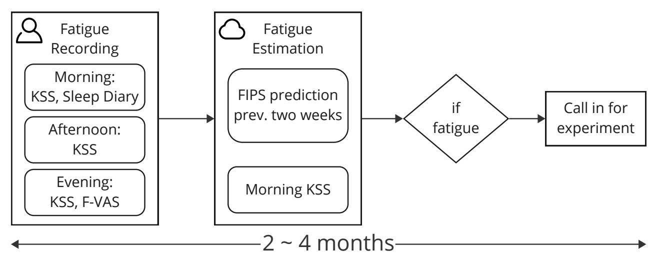

Figure 1: The longitudinal study procedure over the study duration. The blocks outline the daily fatigue measuring tasks, the method of fatigue estimation, and the call-in criteria for experiment sessions based on predicted fatigue levels.

An overview of the experimental procedure is depicted in Figure 1. We employed a 2x2 within-subjects design with two independent variables: circadian fatigue (low, high) and HUD display (on, off). Participants' fatigue levels were continuously monitored for a minimum of two months using smartwatch data and daily questionnaires to accurately predict fatigue states. Following this longitudinal monitoring phase, participants were called into two VR experiment sessions in the laboratory - one during a state of low fatigue and one during high fatigue. The fatigue state for each session was determined through a combination of predicted fatigue levels and participants' self-reported fatigue on the day of testing. During each experiment session, participants completed a sound source identification and localization task in virtual reality. The following subsections provide a detailed explanation of the experimental design and methodology.

3.1 Participants

Initially, 20 participants were recruited for the study. All participants agreed to wear a smartwatch for continuous sleep data monitoring and provide daily sleep condition reports. One participant was excluded due to non-compliance with the longitudinal protocol, resulting in a final sample of 19 participants ($N = 19$) for analysis. The participants were right-handed individuals aged 18-35 years ($M = 24.35, SD = 5.85$), including five females. All participants were healthy, with normal or corrected-to-normal visual and auditory function. Exclusion criteria included any history of psychiatric disorders, neurological diseases, sleep or fatigue-related disorders, or alcohol or drug abuse.

Participants were instructed to maintain a minimum of 6 hours of continuous sleep per night throughout the study period. They were also required to limit their caffeine intake to no more than 3 standard cups of coffee or other stimulants (200mg caffeine) in the 24 hours preceding a recording session, with no caffeine consumption in the 10 hours immediately before a session. Participants reported any use of sleep aid medications or initiation of long-term pharmaceutical treatment through a sleep diary. Compensation for participation included $80 for the experiment sessions and retention of the smartwatch used during the longitudinal phase of the study. Informed written consent was obtained from all participants prior to the experiment. The study protocol was approved by the Institutional Human Research Ethics Committee.

3.2 Circadian Fatigue Recording

We utilized multiple data sources for the estimations of the participants' circadian fatigue levels. These metrics allowed for redundancy and comparison between metrics during the study to ensure validity in the high and low-fatigue experimental sessions. We collected the following data sources:

- Nightly sleep patterns from the Fitbit Sense smartwatch (as shown in Figure 2a) [26]
- Daily questionnaires including:Karolinska Sleepiness Scale (KSS) [3, 83], Visual Analogue Scale to Evaluate Fatigue Severity (VAS-F) [60] and a customized sleep diary questionnaire
- Monthly Pittsburgh Sleep Quality Index [16] survey to assess overall sleep quality.

To ensure sufficient data points for accurate fatigue level estimation, we set a minimum data collection period of two months before scheduling participants to the laboratory. Participants received smartwatches at the start of the experiment. They responded to questionnaires via a custom smartphone application on their personal devices (an example of this application is shown in Figure 2b). An automated system monitored data collection, alerting researchers to anomalous or missing sleep data.

3.3 Circadian Fatigue Estimation

Several measures were taken to ensure the study's reliability and validity. First, two weeks of verification data were collected before participants were eligible for recording sessions to ensure FIPS' accuracy. Sleep duration data collected from participants' smartwatches over the previous two weeks was input into FIPS' biomathematical model to generate predictions of fatigue states for the following week (an example of the weekly forecast is shown in Figure 2c).

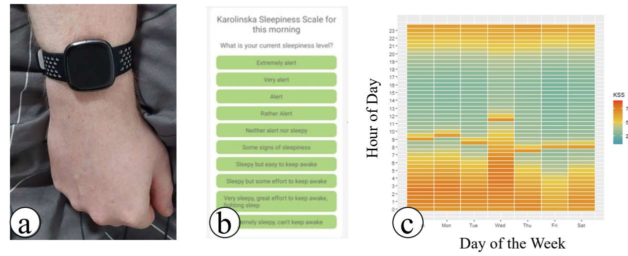

Figure 2: (a): The Fitbit Sense smartwatch used in the study. (b): A screenshot of the phone app used by participants to input daily questionnaires (the Karolinska Sleepiness Scale is shown in the image). (c): An example of a weekly forecast of fatigue levels from the FIPS model. The prediction highlights Wednesday as a potential recording session due to heightened fatigue level.

A two-fold approach was implemented to identify participant fatigue levels accurately for recording sessions using the FIPS [105] and participants' self-reported KSS scores. The FIPS predictions were cross-validated with participants' daily KSS responses to ensure a high likelihood of suitable fatigue states during recording sessions, primarily scheduled in the afternoons when peak faigue was expected.

3.4 Scheduling Participants for the Experiment Sessions

The research team contacted and scheduled the participants on the morning of the experiment sessions. The research team used the FIPS model prediction and the participant's morning KSS to schedule the high or low fatigue same-day recording session. Generally, low-fatigue experiment sessions were scheduled in the morning and high-fatigue experiment sessions in the afternoon. The sessions were scheduled based on fatigue level and participant availability over the longitudinal period. Upon arrival, participants completed another KSS compared to the prediction to confirm their fatigue level.

The research team aimed for a minimum two-week gap between sessions to limit learning effects while ensuring timely study completion. The order of fatigue conditions was counterbalanced across participants, with half the cohort performing the high fatigue condition first and half performing the low fatigue condition first.

3.5 Sound Source Identification and Localization Experiment

VR Hardware. Participants wore a Vive Pro Eye virtual reality headset (2 x 1440 x 1600 resolution, 90Hz refresh rate, 3D spatial sound, and 120 Hz eye tracker sampling rate) during recording sessions, with eye tracking calibrated before each session. The official Vive 3D Sound Spatializer Plugin [48] was used to ensure correct audio spatialization. During the experiment, participants were required to stand in a stationary position.

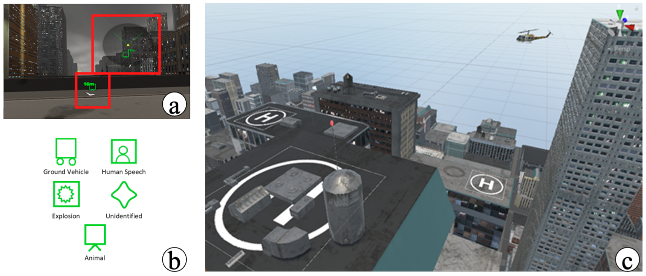

Figure 3: (a): The Heads Up Display in a first-person view. The HUD consists of a radar-style map in the top right and indicators that appear in the peripheral. (b): The 5 symbols that could appear in the experiment: Ground Vehicle, Human Speech, Explosion, Unidentified, and Animal. (c): One of the virtual environments used in the study. The image is of a rooftop of a tall urban building.

HUD design and VR Environments. The HUD design and symbols (Figure 3a and Figure 3b) were based on a usability study by Tian et al. [95]. The design (Radar+Indicator) was selected for its simplicity and emphasis on mitigating information overload in fatigued states. To maintain consistency, the same stimulus categories and associated symbols from the original study were followed in this implementation. Figure 3c shows one of the VR environments for the sound localisation task.

Procedure. Figure 4 shows a timeline of the complete procedure for an experiment session. The entire session lasted approximately 1.5-2 hours. The timing of each session varied due to the variance in the temporal performance of the task and rest period. The session began with the initial questionnaires and training session to familiarize participants with the task. The main experimental phase comprised four blocks of 20 trials each (80 per session). The HUD On and HUD Off (no visual aids) trials were evenly distributed (10 trials each) within each 20 trial block. The trials were interwoven and randomized. Between blocks, participants completed intermittent questionnaires and a rest period with a minimum of 2 minutes that can be extended upon request. The session concluded with a final questionnaire.

The primary task required participants to notice, locate, and identify non-visual audio stimuli based on previous 3D audio localization experiments that explore egocentric pointing [6] and the effects of visual environments/aids for indirect sound source localization [21, 69].

The experiment used 5 categories of auditory stimulus, including sounds from ground vehicles, human speech, explosion, unidentified and animals, as shown in Figure 3b.

At random intervals (5-7s), an auditory stimulus was presented in one of the four cardinal directions (North, South, East, West) with a variance of up to 20 degrees. Each of the 5 categories was randomly presented 4 times (2 with HUD guidance, 2 without HUD guidance) in each of the 4 directions.

The participant progressed through three sequential stages when a stimulus was presented, as shown in Figure 5. In the *notice stage*, participants pressed the left controller's trigger upon detecting an auditory stimulus. If no response was registered within 5 seconds, a visual prompt appeared and the trial automatically advanced.

The *locate stage* required participants to use the right controller to point at the perceived stimulus location and press the trigger, receiving visual feedback upon completion.

Finally, in the *identify stage*, participants selected the appropriate stimulus category from a menu presented in the virtual environment.

After completing the primary task, participants engaged in a secondary task that involved inspecting the surrounding virtual environment. This secondary task served two purposes: it simulated real-world HUD usage and mitigated attentional tunnelling effects [93, 102]. Based on the Situation Awareness Global Assessment Technique (SAGAT) [28], participants were prepared to answer unexpected questions about the environment during inter-block periods. The inclusion of this secondary task provided a more realistic context for HUD usage. It allowed for assessing participants' ability to balance attention between the HUD and the broader environment under varying fatigue conditions.

3.6 Experiment Measurements

Participant performance was measured at each task stage. During the **Notice** stage, performance was measured by *Successful Notice Rate* (reaction within 5 seconds) and *Time to Notice* (time between stimulus presentation and trigger pull). The **Locate** stage assessed *Pointing Angle Error* (difference between true and indicated location) and *Time to Locate* (time between Notice and Locate trigger pulls). Finally, the **Identify** stage measured *Successful Identification Rate* (correct stimulus category selection) and *Time to Identify* (time between Locate and Identify trigger pulls).

SAGAT questions were structured hierarchically, beginning with perception (Level 1) questions before progressing to comprehension (Level 2) and projection (Level 3) [28, 29]. This approach ensured participants had time to observe and identify environmental aspects before answering more complex questions. To prevent carry-over effects, two different virtual environments were used for the high- and low-fatigue sessions, counterbalanced across participants.

The participant also completed a Self-Assessment Manikin (SAM) [14] to measure emotional state, as emotion can impact decision-making [20, 42]. The SAM was displayed in the scene, and participants verbally responded. Subsequently, the screen was blacked out before SAGAT questions were asked in a fixed order.

4 Results

Data from 19 participants who completed the longitudinal study and two experimental sessions were analyzed. The longitudinal recording period lasted an average of 92 ± 27 days, with a mean interval of 24±4 days between the two experimental sessions. Based on G*Power [34], to achieve a power of 0.90 with an alpha level of 0.05, 19 participants should result in an anticipated effect size of 0.39 with a critical F value of 4.45.

The longitudinal data was analyzed in MATLAB using simple linear regression with Pearson correlation to identify relationships between variables. A two-tailed t-test determined significance, with α set to 0.05. Correlation plots included the first 45 days of each

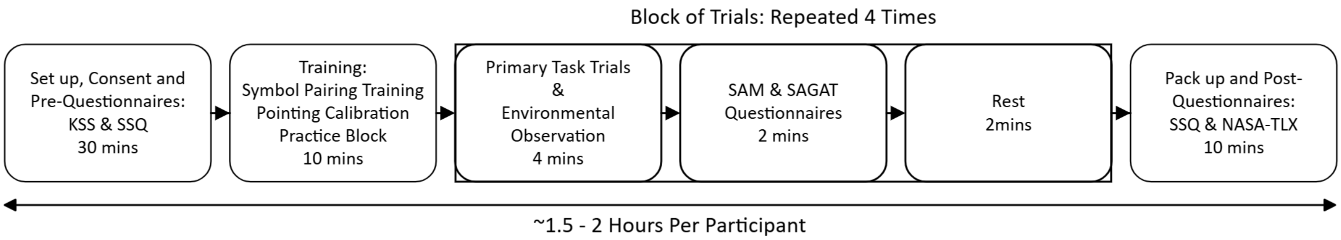

Figure 4: The timeline of the high and low fatigue experiment sessions with the participant. Each block outlines the sequence of events and the approximate duration of each section.

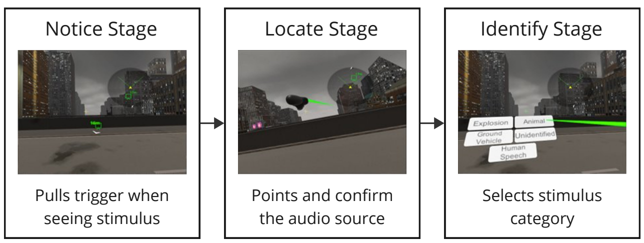

Figure 5: The procedure for a single trial of the primary task in the experiment session. Each trial consists of three stages: Notice, Locate, and Identify.

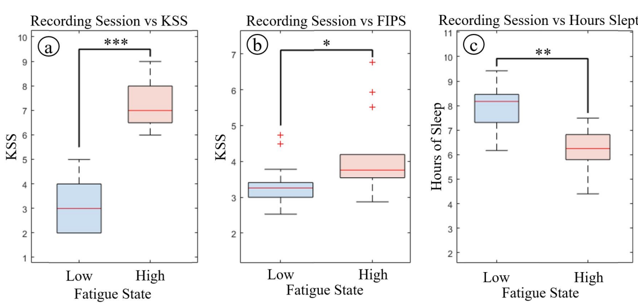

Figure 6: The fatigue measurement results indicate the high and low fatigue states for the experiment sessions. (a): The perceived fatigue levels from the KSS collected in the pre-experiment questionnaire. (b): The predicted fatigue levels by FIPS for the day of the session. (c): The average hours of sleep on the day of the session.

participant's data after a 14-day calibration period (Days 15-60) to account for repeated measures and varying study lengths.

The VR experiment data was processed in MATLAB v2020b, removing outliers beyond 3 SDs. A Shapiro-Wilk test checked normality, followed by Repeated Measures ANOVA with α set to 0.05. Bonferroni correction was applied for α inflation. Behavioural data was compared pairwise across four conditions. In all figures, * = p<0.05, ** = p<0.01, and *** = p<0.001.

4.1 Longitudinal Fatigue Measurement Results

Figure 6a shows the perceived fatigue levels from KSS, and Figure 6b shows the predicted fatigue levels from FIPS across the two fatigue

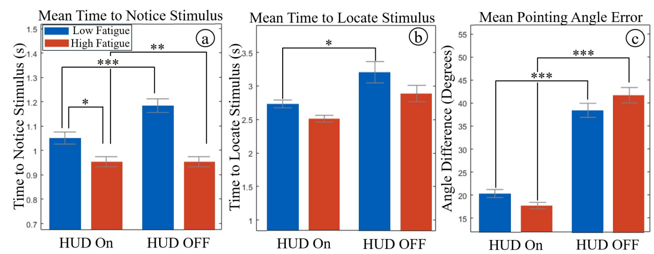

Figure 7: The performance results of the high and low fatigue experiment sessions. (a): The RT at the notice stage. (b): The RT to locate the stimulus at the locate stage. (c): The mean pointing angle error at the locate stage.

conditions. Participants' pre-experiment KSS ratings showed significant differences between the conditions (p < 0.001). FIPS-predicted KSS and participant-reported KSS had a significant but weak correlation (p < 0.001; R = 0.20). Higher FIPS-predicted fatigue generally corresponded with above-average KSS ratings, though exact matches were rare, leading to using participant-reported KSS as an additional metric for scheduling recording sessions. Sleep factors also differed significantly between conditions, with less sleep reported in the high-fatigue condition (p = 0.003), confirming distinct fatigue states for the recording sessions (as shown in Figure 6c).

4.2 VR Experiment Performance Results

Notice Stage: For response time (Figure 7a), the results were: Low-Fatigue HUD-On (1.05±0.025s), High-Fatigue HUD-On (0.95±0.021s), Low-Fatigue HUD-Off (1.19±0.028s), and High-Fatigue HUD-Off (1.07±0.022s). HUD guidance significantly improved response time in both fatigue conditions (p < 0.001 & p = 0.006). Fatigue also significantly affected performance in both HUD-On and HUD-Off conditions (p = 0.02 & p = 0.003). ANOVA confirmed significant effects of both HUD guidance (F(1,2983) = 26.2, p < 0.001) and fatigue (F(1,2983) = 20.22, p < 0.001) on task performance.

For success rate, the results were: Low-Fatigue HUD-On (98.7±0.67%), High-Fatigue HUD-On (99.5±0.24%), Low-Fatigue HUD-Off (97.4±0.96%), and High-Fatigue HUD-Off (97.0±0.41%). Participants in the high-fatigue condition performed significantly better with HUD guidance (p = 0.04). ANOVA showed that HUD

Metric	Effect of Fatigue	Effect of HUD	Interaction Effect
Notice			
Notice Time	*** | p <0.001	*** | p <0.001	NS | p = 0.664
Notice Success	NS | p = 0.757	** | p = 0.004	NS | p = 0.354
Locate			
Locate Time	* | p = 0.013	*** | p <0.001	NS | p = 0.663
Pointing Angle Error	NS | p = 0.799	*** | p <0.001	* | p = 0.02
Identify			
Identify Time	* | p = 0.029	** | p = 0.008	NS | p = 0.526
Category Identification Accuracy	NS | p = 0.232	* | p = 0.012	NS | p = 0.793

Table 1: The statistical analysis of the performance results for the experiment sessions.

guidance significantly improved performance (F(1,75) = 9.05, p = 0.004).

Locate Stage: For response time (Figure 7b), the results were: Low-Fatigue HUD-On (2.73±0.058s), High-Fatigue HUD-On (2.51±0.051s), Low-Fatigue HUD-Off (3.21±0.16s), and High-Fatigue HUD-Off (2.89±0.12s). HUD guidance improved performance, with significance seen in the low-fatigue condition (p = 0.011) but not in high-fatigue (p = 0.07). ANOVA revealed significant effects of HUD guidance (F(1,3041) = 15.86, p < 0.001) and fatigue (F(1,3041) = 6.21, p = 0.013), with performance improving under guidance and high fatigue.

For angle error (Figure 7c), the results were: Low-Fatigue HUD-On (20.38±0.87°), High-Fatigue HUD-On (17.74±0.70°), Low-Fatigue HUD-Off (38.52±1.53°), and High-Fatigue HUD-Off (41.80±1.68°). Both fatigue conditions showed significantly improved accuracy with HUD guidance (p < 0.001). ANOVA confirmed the significant effect of HUD guidance (F(1,3041) = 278, p < 0.001) and its interaction with fatigue (F(1,3041) = 5.46, p = 0.02).

Identify Stage: For the response time, the results were: Low-Fatigue HUD-On(1.62±0.86s), High-Fatigue HUD-On (1.55±0.56s), Low-Fatigue HUD-Off (1.54±0.75s), and High-Fatigue HUD-Off (1.49±0.67s). ANOVA showed significant effect in both HUD guidance (F(1,2983) = 7.03, p = 0.008) and fatigue (F(1,2983) = 4.81, p = 0.029), but there was no significant interaction. An interaction effect on the time taken was found in trials where participants failed to notice the stimulus and needed prompting (F(1,57) = 4.13, p = 0.047).

For the success rate in symbol identification, the results were: Low-Fatigue HUD-On (95.41±4.49%), High-Fatigue HUD-On (97.25±3.77%), Low-Fatigue HUD-Off (92.5±6.77%), and High-Fatigue HUD-Off (93.68±6.31%). There was a significant effect of HUD guidance (F(1,75) = 6.64, p = 0.012) on the identification of the stimulus category. A complete table of ANOVA p values for HUD guidance and fatigue across all stages is shown in Table 1.

4.3 VR Questionnaires & Environmental Awareness

For the SAM result, both fatigue and environmental effects were investigated. The environment had no significant impact (p>0.104) except after the first block, where participants in the building condition reported lower valence (p=0.007), but this effect did not persist.

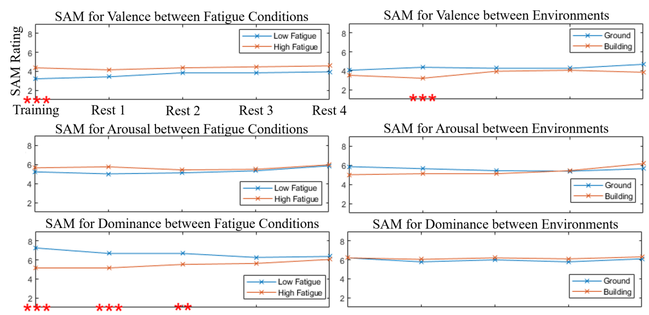

Figure 8: The SAM ratings for Valence, Arousal, and Dominance. The average rating for each category is plotted over the training and rest blocks throughout the experiment. The statistical significance is denoted by ** = p < 0.01 and *** = p < 0.001

Fatigue significantly affected both valence (p=0.007) and dominance (p<0.016). Participants in the high-fatigue condition had a more pleasant experience after the training block but felt less control during the first half of the experiment, with control levels converging by the third block (Figure 8).

Figure 9 presents the SAGAT results, showing no statistically significant differences in perception (p=0.430), comprehension (p=0.440), and projection (p=0.130) levels between the low-fatigue and high-fatigue groups. However, the data suggests that participants were more accurate in the perception and comprehension stages of situational awareness, while performance declined in the projection stage under high fatigue. This pattern indicates that while basic perception and comprehension remained relatively stable, the ability to anticipate future environmental changes was negatively affected by increased fatigue.

5 Discussion

5.1 Effect of Circadian Fatigue is Task Dependent

Fatigue and HUDs have significant main effects across most measurements in the three stages of the sound source localization and identification tasks. Still, the interaction between these factors varies depending on the task. For example, while HUD guidance improves performance for both low- and high-fatigue conditions

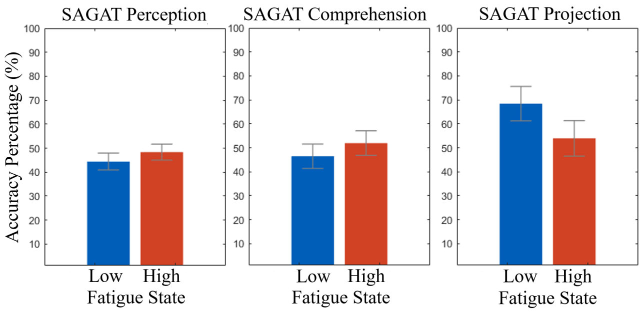

Figure 9: The average SAGAT scores calculated from the questionnaire during the experiment. The participants' SAGAT scores are expressed as a percentage.

across all tasks, its most notable impact is observed in reducing pointing angle error, the most precision-demanding task in our experiment, during high-fatigue states.

The variance in effectiveness appears to depend on the cognitive demands of the task. While fatigue reduces overall cognitive capacity [13], tasks requiring spatial accuracy benefit more from HUD assistance in high-fatigue conditions, whereas tasks focused on speed, such as noticing stimuli, show less improvement [73]. These findings suggest the importance of task-specific design considerations when implementing HUD in fatigue-prone environments, ensuring that systems are optimized for the cognitive demands of particular tasks to maintain performance under varying fatigue levels.

A surprising finding was participants' shorter RT under high-fatigue conditions, contrary to the expected performance decline. Previous studies [39, 65] have also reported similar improvements in fatigued states, attributing this to individuals becoming more alert due to their awareness of fatigue. This heightened awareness may result in compensatory effort, with participants exerting more energy to complete the task. However, the poorer performance on tasks requiring higher accuracy (e.g., pointing angle) supports the notion that fatigue more severely affects tasks with greater cognitive demands.

Another possible explanation for the shorter RT in the high-fatigue condition is the "Wake Maintenance Zone," a period in the circadian rhythm, typically in the afternoon, when individuals may experience enhanced performance even while fatigued [73]. Since most participants were called in during the afternoon, their performance likely benefited from this wake maintenance zone. Research shows that the wake maintenance zone positively impacts neurobehavioral performance, especially under conditions of sleep deprivation [24, 84]. This effect is less pronounced when individuals are well-rested but may explain the performance boost observed in the high-fatigue condition.

5.2 Implication on Multimodal Interaction in AR Systems

The result provides practical insight into the design of multimodal interaction in AR systems [15, 98], echoing the vision of heads-up computing framework [110], which emphasizes a shift from device-centered to human-centered interaction by distributing input and output functionalities across multiple channels to match human sensory and cognitive capabilities.

One key finding of our study is that reaction times for sound source notification and identification remain stable despite circadian fatigue and, in some cases, even improve. This suggests that the auditory channel could be reliable for AR systems designed for fatigue-prone contexts. Moreover, the observed improvement in sound source localization (as measured by pointing angle error) with HUD assistance is most pronounced under high circadian fatigue, further suggesting the role of incorporating auditory channels with HUD guidance in supporting precise and rapid responses.

While previous works have often utilized roughly directional sound cues, such as left or right, to nudge users' attention toward an object [46, 106], our findings further suggest a more nuanced approach is possible. Specifically, the result suggests that users can discern finer directional information even under high-fatigue conditions, especially when assisted by HUDs. Building on this, we propose establishing spatial audio cues as a standardized native UI element for future AR applications or toolkits [33]. To further enhance adaptability, developers should be provided with options to adjust the granularity of these cues, enabling customization for domain-specific applications.

This capability also presents opportunities to expand existing interface paradigms. For instance, integrating directional sound cues into glanceable user interface frameworks [66, 67] could enable multiple views of widgets positioned in various directions, enhancing multitasking capabilities. Additionally, these audio cues could be incorporated into peripheral awareness frameworks [51, 56] to improve users' ability to monitor and respond to events outside their immediate focus. These innovations would enhance situational awareness and responsiveness, particularly in dynamic and high-stakes environments.

5.3 Fatigue and Environmental Awareness during AR Use

Our findings have substantial implications for enhancing safety in AR systems, particularly in scenarios where maintaining peripheral awareness and rapid decision-making are critical. For example, HUDs have been increasingly adopted in the automotive industry to provide drivers with critical information while maintaining their focus on the road [23, 79]. However, most existing implementations rely heavily on visual modalities, often overlooking the integration of auditory cues, with only a few notable works exploring the use of auditory feedback [19, 94]. Our findings suggest that auditory reaction times remain unaffected by circadian fatigue, making sound-based alerts a reliable modality for safety-critical information. For instance, integrating spatially localized auditory cues with HUDs could help drivers identify the direction of approaching hazards, such as an ambulance or other emergency vehicles, without diverting visual attention.

Similarly, integrating auditory and visual modalities in HUDs has direct implications for pedestrian safety, particularly in urban environments [1, 18]. The HCI community has a long history of utilizing different modalities such as haptic feedback from gloves [81], belts [32], and shoes [37], as well as emerging technologies such as electrical muscle stimulation for assisting with obstacle avoidance [80]. Our findings emphasize the utility of using spatial audio cues to alert users to the direction of oncoming traffic or other hazards, such as bicycles or emergency vehicles, even under high-fatigue conditions.

Future research should explore the potential of dynamically balancing sensory inputs in AR systems to optimize performance and mitigate fatigue-related risks, guided by principles such as Multiple Resource Theory (MRT)[101]. MRT suggests that distributing tasks across sensory modalities, like visual and auditory channels, can reduce cognitive load and enhance information processing. This aligns with resource-aware interaction models[110], which advocate for adaptive multimodal systems. For example, in high-fatigue states, the system may prioritize the auditory channels for critical tasks while reserving visual resources for precise spatial processing, which could significantly improve usability. Building on initiatives like Human-IO [63], which detect situational impairments, future advancements in adaptive interfaces promise to accommodate user limitations and maintain seamless functionality across diverse conditions.

6 Limitations and Future Works

6.1 Number of Fatigue Levels and Experiment Sessions

A key limitation of this study is the restricted number of fatigue levels and experiment sessions (two per participant). While the extreme conditions of high and low fatigue were sufficient to investigate the effects of circadian fatigue, including additional intermediate fatigue levels and more sessions could provide a richer understanding of how fatigue impacts AR usage over time. Such insights would be valuable for translating findings into real-world, longitudinal AR applications.

This limitation arises primarily from the constraints of fatigue prediction methods available at the time of the study. The FIPS model offered a reliable baseline for predicting fatigue states based on sleep data. However, its reliance on sleep patterns alone does not fully account for individual variations in circadian rhythms or wake maintenance zones. Although KSS scores collected before each session partially addressed this limitation, the precision and scope of fatigue forecasting remained constrained.

Future research could address this gap by integrating biometric measures and subjective assessments. This multimodal approach could significantly enhance the accuracy and forecast window of the FIPS model, enabling more precise predictions of individual fatigue states. Improved forecasting would facilitate better scheduling of fatigue-dependent sessions, potentially reducing the overall duration of longitudinal studies while yielding more granular insights into the effects of varying fatigue levels.

6.2 Distinguishing Circadian Fatigue from Cognitive and Physical Fatigue in the Experiment

One of the key challenges in fatigue research is distinguishing circadian fatigue from physical and cognitive fatigue [8]. Circadian fatigue, caused by disruptions to the body's natural sleep-wake cycle, can influence and amplify physical and cognitive fatigue resulting from prolonged activity, such as the tasks performed during the experiment sessions. To mitigate this overlap, the experimental design included consistent rest periods, limited physical movement, and cross-comparisons of various fatigue measures to ensure that the primary focus remained on circadian fatigue. However, these efforts were inherently limited by the complexity of disentangling circadian fatigue from other types of fatigue, particularly in real-world scenarios where these factors often coexist.

Future research could address this limitation by incorporating multimodal and real-time fatigue monitoring techniques to better capture and differentiate between various sources of fatigue. For instance, tools like Electroencephalography (EEG) [50, 111], Heart Rate Variability (HRV) [47], Eye Tracking [74], and environmental measures [9] could provide more detailed insights into the context and causes of fatigue.

Combining these measurements could improve our understanding of fatigue in daily life and build towards an adaptive AR system that is more resilient to multiple types of fatigue, enhancing its usability and effectiveness in diverse situations.

7 Conclusion

This paper presents the first longitudinal study exploring the impact of circadian fatigue on HUD-supported auditory localization and identification tasks, addressing a knowledge gap in HCI research. Through a novel experimental design spanning 2–4 months, the study captures rich data on daily sleep patterns, subjective fatigue assessments, and task performance, revealing the nuanced effects of fatigue on accuracy and reaction times. The findings show that while reaction times remain consistent and even improve under high-fatigue conditions, HUD guidance significantly enhances performance in precision-demanding tasks such as sound source localization. These results highlight the auditory channel as a robust means of enhancing situational awareness and supporting the integration of spatial audio cues and HUD as standard features in augmented reality platforms for fatigue-prone environments, informing the design of adaptive technologies to maintain usability and safety in such scenarios.

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