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Validation of Vigilance Decline Capability in a Simulated Test Environment: A Preliminary Step Towards Neuroadaptive Control

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ABSTRACT

Sustaining attention is crucial in tasks like piloting and driving, significantly impacting cognitive performance and driving safety. Addressing the issue of diminishing vigilance, it becomes imperative to develop advanced systems, including neuroadaptive technologies aiming to detect and facilitate adaptive control of vigilance states. In pursuit of this aim, the current study recruited 32 participants (21 males, 11 females) to monitor their vigilance decline during a 60-minute simulated driving task in a monotonous environment. We used the Karolinska Sleepiness Scale (KSS), Stanford Sleepiness Scale (SSS), Psychomotor Vigilance Task (PVT), along with neurophysiological specialized equipment: Enobio 8 electroencephalogram (EEG), Empatica E4, Polar H10 and Tobii Nano Pro eye tracker. Participants self-reported their loss of vigilance by pressing a marker on the steering wheel. In this study, we report the results to assess the experimental setup capacity in inducing lack of vigilance. We found that the mean KSS score significantly increased, from “fairly alert” to “some signs of sleepiness”, and the SSS increased from “being able to concentrate” up to “a somewhat foggy state”. Results from the PVT showed a significant increase in the mean reaction time as well. Participants self-reported their initial lack of vigilance within the first 18 minutes of the experiment. The study’s outcomes emphasize a consistent decline in vigilance with increased subjective sleepiness score and reaction time response post-driving. In conclusion, the study confirmed the effectiveness and validity of the simulated testbed in inducing vigilance decline and set the stage for exploring neuroadaptive control strategies to enhance task performance and safety.

Keywords: Vigilance, Simulated driving, Karolinska sleepiness scale, Stanford sleepiness scale, Psychomotor vigilance task, Driving behaviour, Driving safety, Adaptive control, Neuroadaptive technologies

INTRODUCTION

Vigilance is essential in cognitive performance, especially for tasks demanding prolonged attention, such as aviation and driving (Parasuraman, 1979; Warm, 1980). It is critical in dynamic and safety-sensitive situations where inattention can lead to severe consequences (Durmer and Dinges, 2005). The challenges of prolonged cognitive tasks are not limited to reduced operational efficiency; they involve a multifaceted interplay that can cause fatigue, slower reaction times, and a higher likelihood of errors (Campagne et al., 2004; Pattyn et al., 2008). In emergencies, where rapid and corrective decision-making is crucial to prevent harm, the decline in vigilance is especially significant. This network of cognitive dynamics is particularly noticeable in scenarios requiring quick decision-making and corrective actions. Warm and Finomore (2008) highlighted the vital link between vigilance and decision-making, noting that a decline in vigilance impairs sustained attention and adversely affects the cognitive processes necessary for fast and effective decision-making in critical scenarios.

Real-time monitoring of vigilance states is crucial for addressing challenges in various high-stakes environments. Neurophysiological indicators have become invaluable in this effort, providing insights into cognitive states associated with vigilance paving the way for neuroadaptive monitoring (Mackie, 2013; van Weelden et al., 2022). This innovative approach dynamically responds to individuals' neurophysiological signals, allowing real-time adjustments in monitoring, crucial for safety-sensitive situations. Utilizing artificial intelligence (AI) algorithms, neuroadaptive systems can understand and adapt to specific cognitive patterns, ensuring a personalized and accurate vigilance assessment. However, the success of neuroadaptive monitoring relies on robust data. Employing a multimodal approach that integrates various measures is essential, enriching the dataset for a nuanced understanding of vigilance states. Rigorous data collection methodologies are crucial to ensuring the model's effectiveness.

The potential for revolutionizing vigilance assessment lies in integrating neuroadaptive monitoring and high-quality data, offering insights to enhance safety and performance in critical domains.

To design and develop a robust neuroadaptive intelligent system, the foundational requirement is the acquisition of valid data that accurately represents vigilance. This data forms the basis for the subsequent development of precise prediction models essential for real-time vigilance detection. A crucial first step is establishing a validated simulated testbed capable of effectively inducing vigilance decline. In this work, we designed an ecologically-valid, controlled test environment to monitor the driver's vigilance during a driving task, using self-reporting, behavioral, and neurophysiological measures. Having a realistic simulation that can induce loss of vigilance will provide valuable data for applied research in neuroadaptive systems. This paper reports the validation check to confirm the simulation environment induced a vigilance decline.

The rest of the paper is structured as follows. The next section reviews the main vigilance measures relevant to driving. Then, the simulation environment and experimental method are presented, followed by the main results confirming the vigilance decrement. The discussion puts these results in perspective with neuroadaptive systems.

LITERATURE REVIEW

Different approaches have been explored to monitor vigilance states, particularly hypovigilance (Kerick et al., 2013; Marois et al., 2023; Oken et al., 2006). These approaches encompass various measures, including self-reports, behavioral, physiological, and neurological indicators. Self-reporting tools such as the Karolinska Sleepiness Scale (KSS) and Stanford Sleepiness Scale (SSS) capture individual perceptions of drowsiness or vigilance (Dorrian et al., 2008; Luna et al., 2022). KSS and SSS are often used as gold standard to measure vigilance in human studies (Marois et al., 2023).

Behavioral measures assess the impact of vigilance decline over a focal task (Kashevnik et al., 2021). The Psychomotor Vigilance Task (PVT), widely utilized for assessing alertness and behavioral vigilance (Dinges et al., 1997), involves measuring cognitive performance by measuring the reaction time to a visual stimulus. The Mackworth Clock Test is another behavioral technique that measures sustained attention by assessing an individual's ability to detect anomalies in a clock-like pattern (Mackworth, 1948). Furthermore, the NASA Task Load Index (NASA-TLX), initially developed for workload assessment, finds applications in evaluating vigilance demands in complex tasks, providing subjective insights into cognitive processes (Hart, 2006). In the context of driving, missing traffic signals or doing erratic manoeuvers can indicate a hypovigilant and distracted state. For instance, the Lane Change Test (LCT) is employed in driving simulations and can be used to evaluate the ability to make timely and accurate lane changes, which reflects cognitive alertness (Harbluk et al., 2007). These measures are, however, prone to biases and external influences, such as motivation, emotional states (Pessoa, 2009) and other factors that might affect the person's performance on the primary task.

Neurophysiological and physiological measures present a compelling alternative by investigating fluctuations in brain activity and autonomic responses. Physiological measures involve analysing the central or peripheral nervous system to estimate sustained attention deployment (Oken et al., 2006; Rush et al., 2019). Parameters such as heart rate variability (HRV) and electrodermal activity sensors offer valuable insights into autonomic nervous system responses and physiological arousal (Lutnyk et al., 2023; Regula et al., 2014). Pupillometry i.e., monitoring changes in pupil size, emerges as a nuanced tool providing unique perspectives on cognitive load, attention variations, and arousal levels (Granholm et al., 1996; Piquado et al., 2010). Eye-tracking technology and facial expression analysis contribute to understanding how vigilance fluctuations manifest in gaze behavior and emotional responses (Biondi et al., 2023; Bitkina et al., 2021; Rahman et al., 2020). Integrating an HD camera system enhances the exploration of cognitive workload and emotional states (Stemberger et al., 2010). Functional near-infrared spectroscopy (fNIRS) allows for the non-invasive assessment of brain activity by measuring changes in oxygenated and deoxygenated hemoglobin levels, providing real-time insights into cognitive processes (Leon-Carion and Leon-Dominguez, 2012). This imaging technique enriches the understanding of cerebral oxygenation dynamics during tasks demanding sustained attention. The rationale behind these physiological measures is deeply rooted in the significant implication of the locus coeruleus-norepinephrine (LC-NE) system in attention-related activities. The secretion of norepinephrine (NE) across multiple brain areas influences vigilance, attention orienting, arousal, and the sleep–wake cycle (Aston-Jones and Cohen, 2005; Sara and Bouret, 2012). Neurological indicators illuminate the intricate dimension of vigilance, providing real-time examination of brain activity and cognitive fluctuations (Graw et al., 2004; Mackie, 2013; Mullen et al., 2015). Electroencephalography (EEG) offers high temporal resolution of brain activity and has successfully assessed vigilance and cognitive workload (Akin et al., 2008; Zhou et al., 2022).

The literature on various vigilance measures is dispersed across different research approaches, posing challenges in integrating findings. Each measure category has inherent strengths and limitations, but their combined use offers a more nuanced understanding of cognitive states. Subjective measures provide valuable insights into individual perceptions of drowsiness or vigilance, yet ensuring the validity of self-reports is challenging due to susceptibility to individual variations and external influences. Behavioral measures, reflecting observable actions in diverse contexts, contribute to vigilance understanding but face challenges in interpretation, showing variations across individuals and settings, limiting broad applicability. Physiological measures, analysing the central or peripheral nervous system, offer respectively direct and indirect insights into autonomic responses and physiological arousal incurred by variations in vigilance. However, physiological responses can be influenced by individual variations, external stimuli, and emotional states, necessitating a context-sensitive and multidimensional approach for comprehensive vigilance assessment. Neurological measures enhance vigilance understanding by capturing real-time cognitive processes and emotional responses. Still, challenges arise from the intricate nature of these measures, creating difficulties in interpretation and establishing universal benchmarks for vigilance assessment.

In a recent scoping review on psychophysiological indicators of vigilance, Marois et al. (2023) found the gold standard of vigilance measurements to be the subjective questionnaires KSS and SSS along with the PVT behavioral test. Most of the studies reviewed found a strong correlation between these gold standards and EEG-derived measures. This review outlines that to comprehensively assess vigilance, an integrated approach is required combining subjective, behavioral, physiological and neurological measures. Neurophysiological measures, offering continuous quantitative data, could serve as useful indices of hypovigilance that could be fused and integrated into neuroadaptive systems relevant for monitoring operators' vigilance levels.

Objective

The overarching goal of this study is to contribute to the development of an AI-based neuroadaptive intelligent system designed to detect real-time vigilance states. To this end, we employed a multimodal approach, integrating a comprehensive array of promising behavioral and neurophysiological measures, including the Karolinska Sleepiness Scale (KSS), Stanford Sleepiness Scale (SSS), NASA-TLX, Psychomotor Vigilance Task (PVT), electroencephalography (EEG), electrodermal activity (EDA), electrocardiography (ECG), eye tracking, and facial features. The integration of these measures facilitates the assessment of vigilance states under controlled conditions. Besides, relying on both intrusive (EDA, ECG, EEG) and non-intrusive measures (eye tracking, facial analysis, behavioral) allow for the development of models that could be more easily integrated within different work contexts. It is important to note that the current study specifically assesses the simulated testbed's ability to induce vigilance decline during prolonged simulated driving. We use PVT, KSS, and SSS to analyse the testbed's effectiveness in causing vigilance decline by comparing baseline and post-driving responses. This initial phase serves as a foundation for further investigations into the development of a neuroadaptive intelligent system.

METHOD

Participants

A total of 32 participants (21 males and 11 females) were recruited for the driving experiment, aged between 18 and 35 years ($M = 26.5$, $SD = 4.9$). Eligibility criteria included having a valid driver's license, normal to corrected vision, absence of cardiovascular disorders or pacemaker usage, and no diagnosis of neurological diseases. Participants underwent a health screening questionnaire to ensure their suitability for the experiment. The study obtained approval from the Institutional Review Board [CER-2324-11-D] and all participants signed a consent form before taking part in the study. All experiments were performed before lunch, between 9 a.m. and 12 p.m., when participants were the most alert. Participants were asked to abstain from caffeine, alcohol, nicotine, and cannabis on the day of the experiment. They received a monetary compensation of $40 CAD.

Measures

The study adopted a multimodal approach, integrating an extensive range of measures to capture the participant's subjective, behavioral and neurophysiological responses during the driving task. We used the Enobio 8 headset for EEG, Empatica E4 wristband for EDA activity monitoring, Tobii Nano Pro eye tracker for oculometry, Polar H10 chest strap for ECG, and a 1080p USB webcam for facial features analysis (see Figure 1).

Figure 1: Illustration of the experimental set-up with neurophysiological equipment.

We used three gold standard measures (see Marois et al., 2023): KSS on a 9-point scale, SSS on a 7-point scale and PVT. We used the PVT implementation provided by PC-PVT 2.0 (Reifman et al., 2018) that consists of reacting as fast as possible to a stimulus onset for 10 minutes. The main results obtained from the PVT are the mean and median reaction time (RT), mean 1/RT (also called reciprocal response time or response speed in seconds), and the number of minor lapses, which is the number of stimuli answered with RT > 500 ms. This methodological approach ensures a thorough examination of both subjective experiences and objective performance during the simulated driving task, all within the predefined scope of this study. It is important to note that this study presents solely the KSS, SSS and PVT results to validate the experimental task to induce lack of vigilance. Neurophysiological data will be analysed in future work.

Experimental Procedure

Participants were provided with a comprehensive briefing outlining the study's objectives, the driving task and the utilized measures. Subsequently, they were guided through the placement of the chest strap, the EEG headset, the EDA wristband, along with a calibration of the eye tracker, ensuring precise positioning. Following equipment preparation, participants underwent a pre-driving assessment, comprising the KSS, SSS, and PVT to establish performance baselines. A 10-minute practice driving session familiarized participants with the task and the controls. The main driving task was conducted in BeamNG.tech (BeamNG, 2021), a physics-based driving simulator, featuring a highway with sunny weather conditions, low traffic, and no pedestrians—only cars. Participants navigated the highway for 60 minutes with an exterior field camera view and a speedometer (see Figure 2) while adhering to a speed limit of approximately 80km/h.

Several checkpoints were added on the road serving as visual cues, ensuring adherence to the designated route. The highway included two different biomes: a green area and a desert area, both consisting of empty fields of grass and sand as shown in Figure 2 (a) and (b), respectively. The scenario begins in a green biome, transitions into the desert and concludes in the green biome. The intentionally chosen low traffic conditions and limited buildings aimed to create a monotonous driving environment. The desert biome, characterized by its monotonous scenery, was selected to have the longest duration. A secondary visual attention task involving billboards was implemented to assess vigilance during the driving task. Twenty billboards were dispersed evenly on the path and contained three letters, each enclosed by a shape (see Figure 2 (c)). Participants were instructed to press the R2 button on the steering wheel when the billboard showed the letter "A" inside the star symbol. Ten of the 20 billboards contained the target and their order of appearance were randomized between participants. Additionally, participants indicated their moments of perceived loss of vigilance, boredom, or drowsiness by pressing the vigilance marker L2 button on the steering wheel (see Figure 2 (d)). After 60 minutes, the driving task was ended and participants responded to the PVT, KSS and SSS for the post-drive assessment.

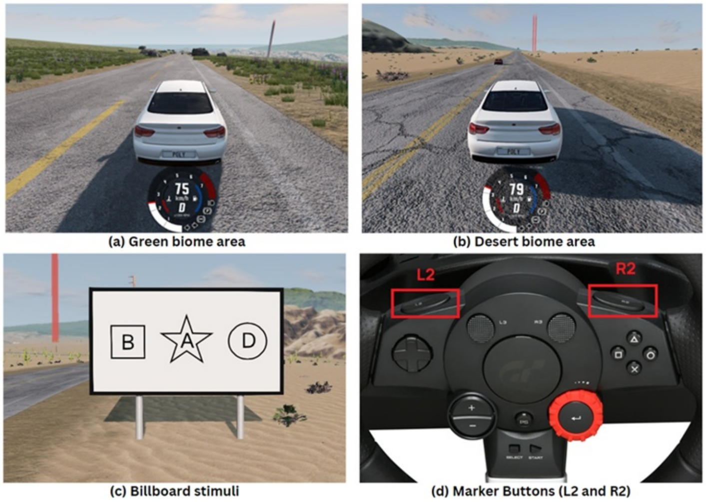

Figure 2: Visualization of (a) green biome; (b) desert biome; (c) billboard stimuli; and (d) marker buttons.

RESULTS

The collected data related to vigilance measures, including KSS, SSS, and PVT, was analysed utilizing various statistical methods to assess the impact of the test setup on vigilance decline. The methods employed included descriptive statistics, paired *t*-tests, and correlation coefficients.

Data from the 32 participants was analyzed except for the PVT performance which, due to data loss, comprised only 31 participants. The analysis performed on the self-reports of decline in vigilance revealed that, on average, the first marker press occurred at 18 minutes, suggesting an initial lapse in vigilance within the first half-hour of driving. Notably, over 70% of these first marker presses were clustered during the segment corresponding to the desert biome.

The analysis of subjective sleepiness scores and PVT performance for baseline and post-driving is summarized in Figure 3 and Table 1. The table presents key measures such as mean, standard deviation, 95% confidence interval (CI) lower and upper limits, *p*-values, Pearson correlation coefficient (r) and Cohen's d.

Subjective Sleepiness Assessment

Participants exhibited a baseline mean KSS level of 4.3 ($SD = 1.8$), labelled as "rather alert". The post-driving mean score was of 6.1 ($SD = 1.9$), labelled as "some signs of sleepiness". This difference was significant $t(31) = 5.4$, p <0.0001. Cohen's $d = 0.98$, raising a large effect size. The correlation coefficient ($r = 0.47$) indicated a moderately strong positive relationship between baseline and post-driving sleepiness scores.

Similar to the KSS response, the participants reported a baseline mean SSS of 2.7 ($SD = 1.1$), described as "able to concentrate", initially suggesting relatively low sleepiness levels. Post-driving, the mean SSS score increased to 4.1 ($SD = 1.3$), described as "somewhat foggy, let down". The paired t-test demonstrated a significant difference in subjective sleepiness levels before and after the simulated driving task $t(31) = 7.9$, p <0.0001, Cohen's $d = 1.15$. The substantial effect size emphasized the meaningful increase in perceived sleepiness after the simulated driving task. The correlation coefficient ($r = 0.67$) suggested a moderately strong positive relationship between baseline and post-driving sleepiness scores.

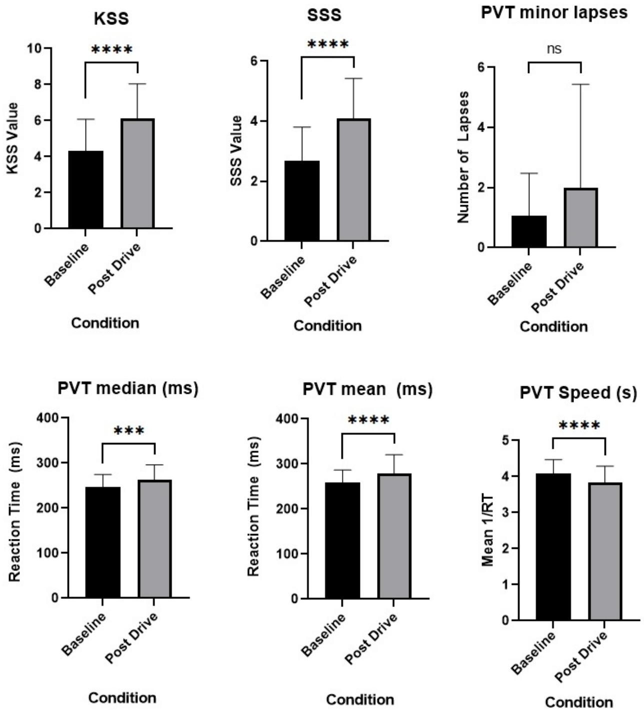

Figure 3: Comparative analysis of sleepiness score and psychomotor performance for baseline and post-driving. Confidence intervals represent the standard deviation. *n.s. = non-significant,* ***p <0.001, ****p <0.0001.

PVT

Participants demonstrated mean reaction time of 258 ms ($SD = 29$) at baseline, increasing to 279 ms ($SD = 42$) post-drive. The difference was significant $t(30) = 5.0$, $p < 0.0001$ with a medium effect size, Cohen's $d = 0.61$, and showed a strong positive relationship between baseline and post-driving ($r = 0.85$). The median reaction time was 246 ms ($SD = 28$) at baseline and increased to 262 ms ($SD = 34$) post-drive. The difference observed was significant $t(30) = 4.2$, $p < 0.001$ with a medium effect size ($d = 0.50$) and depicted a positive correlation between baseline and post-driving with $r = 0.79$. The analysis of PVT speed revealed a baseline mean speed of 4.1 s^{-1} ($SD = 0.4$) that decreased to 3.8 s^{-1} ($SD = 0.4$) post-driving. The difference was significant, $t(30) = 4.8$, $p < 0.0001$ with effect size $d = 0.56$, along with a positive correlation between baseline and post-driving ($r = 0.80$). While the mean number of minor lapses (i.e., RT > 500ms) increased from 1.1 ($SD = 1.4$) during baseline to 2.0 ($SD = 3.4$) post-driving, the difference was not significant $t(30) = 1.8$, p > .05 with a small effect size ($d = 0.36$). The correlation coefficient ($r = 0.54$) indicates a moderate positive relationship between baseline and post-driving minor lapses.

Table 1. Paired t-test results for KSS, SSS, and PVT measures.

Measure		Mean (std)	95% CI	*t*	*r*	*d*
KSS	Baseline	4.3 (1.8)	[3.7 – 5.0]	5.4 ****	0.47	0.98
	Post-drive	6.1 (1.9)	[5.4 – 6.8]			
SSS	Baseline	2.7 (1.1)	[2.1 – 3.1]	7.9 ****	0.67	1.15
	Post-drive	4.1 (1.3)	[3.6 – 4.6]			
PVT mean	Baseline	258 (29)	[247 – 268]	5.0 ****	0.85	0.61
	Post-drive	279 (42)	[263 – 294]			
PVT median	Baseline	246 (28)	[236 – 257]	4.2 ***	0.79	0.50
	Post-drive	262 (34)	[249 – 274]			
PVT speed	Baseline	4.1 (0.4)	[3.9 – 4.2]	4.8 ****	0.80	0.56
	Post-drive	3.8 (0.4)	[3.7 – 4.0]			
PVT minor lapses	Baseline	1.1 (1.4)	[0.5 – 1.6]	1.8 *n.s.*	0.54	0.36
	Post-drive	2.0 (3.4)	[0.7 - 3.3]			

n.s. non-significant ***$p < 0.001$ ****$p < 0.0001$

DISCUSSION

The study highlighted an early onset of vigilance lapses, with participants reporting the first lapse within the initial 18 minutes of driving. These lapses were predominantly clustered in the desert biome segment. This points to a notable decline in vigilance during the early driving phase under the developed driving environment. Moreover, these lapses suggested a potential linkage between the driving environmental conditions and the lapses in attention. Subjective sleepiness assessment, as indicated by increased KSS and SSS scores post-driving compared to the baseline, emphasized the profound impact of the driving task (monotonous nature, environment, duration, etc.)

on the vigilance level. The paired *t*-test demonstrated significant differences that led to strengthening the impact of the driving task in declining the vigilance. In addition, the substantial effect size (i.e., Cohen's *d*) underscored the practical significance of driving tasks in altering subjective sleepiness. The increase in mean and median PVT reaction times post-driving, supported by the paired *t*-test, drew attention to the impact of driving task on the psychomotor performance among the participants.

Additionally, the decrease in PVT speed, while statistically significant (p <.0001) exhibited a complex interplay of driving-related factors on influencing the driving behaviour. It means that there was a significant decrease in response to the PVT stimuli post driving among participants. The Cohen's *d* for PVT speed showed a noticeable drop, indicating potential adaptive changes in driving behavior. This emphasizes a clear deterioration in psychomotor vigilance following the driving task.

The simulation environment that we validated in this study can serve other researchers in their work on vigilance. Methods to induce hypovigilance in previous work involved sleep deprivation (Ahn et al., 2016; Nguyen et al., 2017), prolonged task engagement from 2h to 4h (Naeeri et al., 2019), varying workload demands (Gateau et al., 2015) or monotonous driving (Li et al., 2008). In this study, we showed that a 1-h monotonous drive using a low-cost driving simulator was sufficient to induce a notable lack of vigilance within the first 30 minutes. This setup offered a realistic microworld simulation for participants to remain engaged in the task while controlling the environmental factors to induce lack of vigilance – alternating between green and desert biomes – and having a secondary detection task embedded as an accurate world element; see (Cooke and Shope, 2004) for a discussion on the advantages of realistic simulations and microworlds.

The findings of this study serve as an advancement in the initial stage towards developing a neuroadaptive system for detecting vigilance decline to augment driving safety. This research effectively substantiates the efficacy of the designed driving task system in inducing vigilance decline, thus establishing a foundational understanding of its operational effectiveness. This observation is pivotal for the progression of the neuroadaptive system development, ensuring that the driving task is a reliable inducer of vigilance decline. It is acknowledged that a comprehensive understanding of vigilance necessitates a multimodal approach considering neurophysiological measures along with subjective and behavioral measures (cf. Marois et al., 2023). While this study successfully establishes the effectiveness of driving task in inducing vigilance decline, the next phases of research will focus on analysing the various neurophysiological measures collected. This includes utilizing experimental data related to EEG signals, EDA, oculometry, ECG, and facial feature recognition under similar driving conditions. The ultimate goal is to use the data to develop prediction models. These models will play a pivotal role in accurately detecting vigilance decline. Such neurophysiological prediction models exist, as raised in Marois et al. (2023). Most of them have been specifically developed for driving use cases (see, e.g., Awais et al., 2017; Guo et al., 2016; Leng et al., 2015; Li et al., 2015; Salvati et al., 2021). Yet, most of these models rely on a set of intrusive sensors, including, for instance, ECG, EEG and EDA. Such measures impose one to wear electrodes, garments or other types of apparel that directly collect signal from the head or the body, which can also be prone to movement artifacts, thus reducing their potential for real-life implementations. Given the variety in neurophysiological markers collected in this study, further work will aim at producing prediction models from all the fused neurophysiological signals, but also to develop models based solely on the nonintrusive sensors used through the extraction of several features related to hypovigilance. Intrusive markers, along with behavioral markers of hypovigilance such as those analyzed in the current study, will serve as ground truth measures to improve the validity and granularity of the vigilance state predictions for real-time applications (e.g., using the Karolinsa Drowsiness Test classifications from the EEG signal, Akerstedt et al., 2010). Such model could then ultimately be integrated into low-intrusion closed-loop attention management systems, deployable in several contexts and capable of providing countermeasures when periods of hypovigilance are detected (see, e.g., St. John et al., 2006).

This study is subject to the following limitations. First, participants were younger, with the oldest participant being at most 35 years old. Replicating the testbed with a larger and more diverse population could provide a more comprehensive understanding of vigilance decline induction. Second, we conducted the test in the morning in a controlled environment. Investigating the temporal aspects of driving, particularly the effect of driving in the morning versus the afternoon, may provide better insights into vigilance decline patterns.

CONCLUSION

Our study successfully tested and confirmed the simulated driving testbed's ability to induce vigilance decline. Through comprehensive subjective assessments and psychomotor performance metrics, we observed a significant reduction in vigilance level after the driving task. The testbed promptly triggered vigilance lapses within the first 18 minutes, particularly in the desert biome segment. This validation of testbed's efficacy holds practical importance by paving the way for future investigations into neuroadaptive control strategies. These insights offer promising avenues for refining our understanding and application of vigilance management, marking a significant step forward in developing a non-invasive intelligent neuroadaptive system capable of detecting vigilance states in extreme and challenging operational situations.

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