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Beyond Overload: Assessing Cognitive Load to Facilitate Learning Transfer in Virtual Environments

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Abstract

Learning transfer, the ability to apply knowledge to new situations, is a foundation of effective education. It involves applying what one has learned in a previous situation to solve problems or navigate new environments. However, this process can fail when a new challenge overwhelms our cognitive resources. Because working memory has a limited capacity, extraneous mental demands can cause overload, hampering performance. This study investigates this phenomenon by measuring the cognitive load of undergraduate students during an immersive virtual reality (VR) driving simulation. We used real-time physiological indicators, pupil diameter and heart rate, to assess the students' mental workload as they performed complex driving tasks. Our analysis, which categorized different levels of cognitive load, revealed that these psychophysiological measures were directly sensitive to changes in mental demand. The results confirm that tracking physiological signals like heart rate and pupil size provides a valuable window into cognitive load, highlighting its critical role in understanding and facilitating learning transfer within realistic, simulated environments.

Keywords: *Cognitive load, psychophysiological responses, driving simulator, learning transfer.*

1.0 Introduction

Working memory inherently has a restricted capacity, which can become overloaded when extraneous tasks are introduced during cognitive processing, subsequently diminishing task performance [1, 2]. This phenomenon, known as cognitive overload, arises from the learner's need to allocate additional cognitive resources to complete complex tasks, straining their mental capacity beyond optimal levels [3]. Consequently, increased cognitive load impedes task performance, which can be systematically measured through subjective methods (e.g., perceived difficulty, self-reported effort) or objective metrics (e.g., physiological indicators and task accuracy) [4].

In the current study, cognitive load was assessed through an objective psychophysiological approach, specifically using real-time measures of heart rate and pupil diameter to ascertain the participants' cognitive demands. Psychophysiology, the study of the interplay between psychological processes and physiological responses, elucidates how cognitive and emotional processes exert a significant influence on physical responses [5]. Psychophysiological states, including cognitive processing, emotional arousal, and stress, are frequently quantified using established measures such as skin conductance, heart rate, blood pressure, brain activity (e.g., EEG), and respiratory rate. Consequently, these metrics furnish real-time, comprehensive data on cognitive load, reflecting the ongoing allocation of cognitive resources during task performance.

Existing literature demonstrates that cognitive load incrementally correlates with physiological metrics, notably heart rate (HR) and heart rate variability (HRV), which are sensitive indicators of sympathetic nervous system activity, a response that escalates under task difficulty [6, 7]. HR and HRV reflect the autonomic nervous system's response to cognitive demands, with sympathetic activation generally associated with increased HR, while parasympathetic influence results in decreased HR. This relationship underscores the utility of HR metrics in capturing cognitive load intensity, supported by findings from Gruden et al., who incorporated HR with other psychophysiological metrics to examine task-related physiological responses [8].

In addition, pupil diameter, a well-established cognitive load metric within Human-Computer Interaction (HCI), has been shown to increase in response to heightened cognitive demand, providing an index of task difficulty and mental workload [9, 2]. According to [10], this response is particularly pronounced under tasks that exceed baseline cognitive demands, indicating a direct relationship between cognitive load and pupil dilation. Furthermore, Jerčić et al. demonstrated that pupil dilation correlates with sympathetic arousal, even when induced by emotionally charged stimuli, regardless of the valence [11]. Supporting this, Kahneman & Beatty documented that larger pupil diameter is associated with higher volumes of information processing [12]. Recent studies have extended this application to domains such as driving, where pupil dilation is used to monitor cognitive load in

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simulated driving environments [13, 14]. Although fluctuations in screen illumination and gaze direction can affect the precision of pupil diameter measurements, the impact on situational awareness assessments remains negligible [14].

In this study, we used easy and difficult routes for the cognitive exercise during navigational exercise. We employed heart rate and pupil diameter as psychophysiological indices of cognitive load during the experimental task. It's hypothesized that the use of routes of different difficulty levels would elicit different cognitive loads. At the same time, high cognitive load may impede the application of knowledge acquired during the initial phase of the task. Also, it is hypothesized that elevated cognitive load is associated with an increased frequency of driving errors. To achieve the stated hypotheses, virtual reality (VR) technology was used.

Therefore, this study highlights the efficacy of psychophysiological metrics in assessing cognitive load by leveraging real-time indicators, specifically heart rate and pupil diameter, to objectively quantify cognitive workload. These metrics provide significant insight into the effects of cognitive load on task performance, reinforcing the relevance of psychophysiological assessment tools in evaluating cognitive demands across various disciplines and experimental context.

2.0 Methodology

2.1 Subjects and Experiments

An experimental study was conducted using a driving simulator to assess the psychophysiological responses of university undergraduate students while engaging in virtual reality (VR)-based driving tasks. The study recruited 40 undergraduate students (50% male) from Fudan University with no prior real-world driving experience. Participants were evenly divided into two groups (A and B), each comprising 10 males and 10 females. The study received approval from the University's Ethics Committee, and informed consent was obtained from all participants.

The experiment was designed with two main routes of differing difficulty levels: easy routes (Group A) and difficult routes (Group B). Each group was further subdivided into two sessions: Group A1 and Group A2 for the easy routes, and Group B1 and Group B2 for the difficult routes. The easy route (Group A) featured three landmarks, three intersections, and three traffic signals. In contrast, the difficult route (Group B) was designed with greater complexity, incorporating seven landmarks, five intersections, and five traffic signals. Thus, each participant was assigned to complete two sessions based on their respective group, either completing the easy routes (A1 and A2) or the difficult routes (B1 and B2).

The participants were tasked with independently navigating the VR driving system from start to finish, adhering to traffic laws and regulations. Before beginning the driving task, baseline data were collected from the participants. Prior to the task, all participants watched a single video tutorial illustrating their assigned route. They were instructed to memorize the landmarks and key features to facilitate subsequent navigation.

Once the video tutorial was completed, the eye-tracking and heart rate monitoring sensors were set up by the instructors to track the participants' physiological responses during the driving task. The experimental task required each participant to drive the assigned route independently. Any navigational error, such as an incorrect turn, resulted in the participant being returned to the beginning, shown the tutorial video again, and required to repeat the attempt. The performance during the tutorial and subsequent retries was recorded by the VR-driving system, but this data was not included in the final analysis of the study.

By structuring the experiment in this manner, the study aimed to investigate the impact of route difficulty on participants' cognitive load and their physiological responses, particularly pupil diameter and heart rate, while navigating the VR driving environment.

2.2 Experimental Apparatus and Measured Physiological Responses

The psychophysiological responses of the participants were measured using a range of advanced equipment, as detailed below:

a. Vive Pro Eye: This eye-tracking device was employed to record eye movement and pupil diameter data at a sampling frequency of 50 Hz [15]. It provided high precision in tracking eye movements, which was essential for measuring cognitive load via pupil dilation during driving tasks.
b. Logitech 27 Steering-Wheel Controller: The steering-wheel controller was used by the participants to control the virtual vehicle within the driving environment. This allowed for realistic interaction with the simulated driving tasks, providing data on user performance and driving behavior.
c. Esri CityEngine and Autodesk Maya: These software tools were used to design and render the virtual driving environment, including landmarks, buildings, intersections, traffic lights, and various other elements of the environment, such as roads and vehicles [16]. These tools helped to create an immersive and dynamic environment for the participants to navigate.

d. Unity3D: Unity3D was utilized to develop the game platform and integrate the interactive elements of the driving simulation. It served as the primary environment for the virtual reality driving tasks, ensuring a smooth and engaging experience for the participants.
e. Heart Rate Monitoring Device: A dedicated biosensor was used to capture electrocardiogram (ECG) data at a 500 Hz sampling rate, providing high-temporal-resolution data on cardiac responses to the driving tasks.

The driving simulation environment consisted of various components such as straightaways, intersections, multiple turns, and landmarks, including familiar objects like McDonald's, a basketball court, a convenience store, a post office, a church, a gas station, and Walmart. These features were included to make the simulation both challenging and realistic, while also offering a way to test participants' ability to navigate through complex environments.

The driving system, depicted in Figure 1, was capable of recording different physiological metrics (such as heart rate and pupil diameter) alongside performance features like task completion time and driving errors. These physiological and performance data points were crucial for analyzing the relationship between cognitive load and driving behavior in a virtual environment.

Figure1: VR driving platform: A participant (on the right) carrying out a VR driving task

3.0 Data Processing

Signals from the Vive Pro eye tracker and the heart rate monitor were pre-processed to remove artifacts and reduce noise. This was accomplished using a median filter, a non-parametric method effective for smoothing data and mitigating the influence of outliers. In addition to these physiological signals, various other user-driving performance features were recorded during the study. However, for the scope of this research, only the psychophysiological features, including heart rate and pupil diameter, were considered for analysis. This focused approach allowed for a more detailed examination of the relationship between cognitive load and psychophysiological responses during virtual reality driving tasks.

4.0 Results

This study sought to characterize the psychophysiological profile of undergraduate students during performance of a virtual reality driving task. The dataset consisted of 80 entries, with 40 data points collected from participants navigating easy routes (group A1 and A2) and 40 data points from those navigating difficult routes (group B1 and B2). The data were then analyzed using a statistical approach to assess the impact of route difficulty on cognitive load.

As hypothesized, difficult routes induced greater psychophysiological activation, which was reflected in significantly elevated heart rates and pupil dilation, as detailed in Table 1. These results indicate that participants required greater cognitive resources to complete their tasks on more challenging routes. The significant increase in heart rate and pupil diameter suggests that the higher cognitive load associated with navigating difficult routes was reflected in measurable physiological responses. This supports the notion that task complexity, in this case, route difficulty, directly influences cognitive workload during virtual reality driving tasks.

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Table 1: Psychophysiological measures

Group	Baseline	A1	A2	B1	B2
Heart rate (in bpm)	68.9(7.9)	71.3(5.1)	72.9(5.5)	74.3(9.1)	75.8(3.4)
Pupil diameter (in mm)	3.61(0.24)	3.76(0.53)	4.27(0.39)	5.26(0.21)	5.74(0.23)

Note: The entries are means and standard deviations in parentheses.

Table 2: Performance metrics

Performance Features	Group			
	A1	A2	B1	B2
Task completion time (sec)	187.32	228.74	289.32	374.87
Number of wrong turns	2.3	2.6	3.6	4.2
Number of collisions on the edge of the road	1.7	1.9	3.4	3.6

5.0 Data Analysis

To assess the effect of route difficulty on neurocognitive load, an independent samples t-test was performed. This analysis revealed a statistically significant effect:

5.1 Influence of Cognitive Load on Heart Rate

A t-test was conducted to examine the differences in heart rate between the groups. As shown in Table 1, the results indicate a significant difference in heart rate between Group A and Group B (t = -228.10, p = 1.67E-27), with Group B exhibiting a higher average heart rate (M = 75.05, SD = 6.25) compared to Group A (M = 71.3, SD = 5.1). This suggests that participants navigating the more challenging routes (Group B) experienced a higher cognitive load, as reflected by the increased heart rate.

Further analysis within the groups revealed significant differences in heart rate between subgroups within Group A and Group B. In Group A, the heart rate of Group A2 (M = 72.9, SD = 5.5) was significantly higher than that of Group A1 (M = 71.3, SD = 5.1), with a t-value of -151.45 and a p-value of 1.29E-13. Similarly, within Group B, the heart rate of Group B2 (M = 75.8, SD = 3.4) was significantly higher than that of Group B1 (M = 74.3, SD = 9.1), with a t-value of 161.32 and a p-value of 1.37E-15.

These findings further corroborate the hypothesis that more complex routes elicit higher cognitive load, as evidenced by the increased heart rate. The results demonstrate that both heart rate and pupil diameter are reliable psychophysiological indicators of cognitive load, with higher values reflecting increased mental effort and task difficulty. These findings support the use of heart rate as an effective physiological metric for assessing cognitive workload in real- time driving tasks, particularly in environments where task complexity can vary.

5.2 Influence of Cognitive Load on Pupil Diameter

Table 1 reveals significant differences in pupil diameter between participants navigating easy and difficult routes, indicating variations in cognitive load based on route complexity. Specifically, participants in Group B, who drove difficult routes, showed a larger pupil diameter (M = 5.5, SD = 0.22) compared to those in Group A, who drove easier routes (M = 3.67, SD = 0.39), with a significant t-value of -18.89 and p-value of 3.96E-14. This marked difference suggests an increase in cognitive load when driving on complex routes, as reflected by the greater pupil dilation in Group B.

Further analysis within each group highlights significant differences between subgroups. Within Group A, Group A2 displayed a significantly larger pupil diameter (M = 4.27, SD = 0.39) than Group A1 (M = 3.76, SD = 0.53), with a statistical difference of t = -16.80, p = 4.1E-13. Similarly, a paired comparison within Group B revealed a significant increase in pupil diameter for B2 (M = 5.74, SD = 0.23) compared to B1 (M = 5.26, SD = 0.21), with t = -16.87 and p = 5.2E-12.

These results suggest that route complexity affects cognitive load, with more challenging routes inducing greater cognitive demands. The increased pupil dilation observed in more complex conditions underscores the sensitivity of pupil diameter as a psychophysiological marker for real-time cognitive load assessment, particularly within virtual reality driving simulations. This pattern aligns with existing research, affirming the reliability of pupil diameter as a metric for gauging cognitive demands in dynamic environments and enhancing our understanding of the relationship between task complexity and cognitive processing.

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6.0 Discussion

The present study demonstrates that route difficulty significantly influences participants' cognitive load, as evidenced by both psychophysiological measures and performance results. Consistent with our hypothesis, driving on complex routes elevated cognitive demands, leading to an increase in driving errors. This was observed through heightened psychophysiological markers, specifically pupil dilation and heart rate, as shown in Table 1. These physiological responses indicate an elevated cognitive load under challenging conditions, which correlated with a higher frequency of driving errors, as detailed in Table 2. These results align with prior research showing that increased task complexity augments cognitive load, often manifesting in physiological arousal and increased error rates [17, 5, and 18].

Previous studies, such as that by [18], suggest that navigational aids, like landmarks, facilitate route-finding by assisting spatial orientation and reducing navigational errors. In their research, landmarks were shown to mitigate common errors, such as failing to turn at key intersections, by supporting cognitive mapping. Similarly, our findings suggest that the absence of sufficient navigational cues on difficult routes contributed to a higher cognitive load, as reflected in increased pupil dilation. Pupil size, a recognized indicator of cognitive load, is known to increase in response to heightened demands on working memory [5].

Additionally, our results support [19] findings that increased cognitive demands are associated with decreased heart rate variability and increased heart rate. In our study, elevated heart rate readings likely reflect participants' compensatory response to the increased demands posed by complex routes, requiring higher cognitive resources for successful navigation.

Moreover, participants navigating simpler routes demonstrated greater efficiency in task performance than those on more complex routes. Table 2 shows that Group A participants, assigned to easier routes, completed the driving task significantly faster (average of 198.21 seconds) than Group B, who navigated more challenging routes (average of 363.67 seconds). These results align with the findings of [20], which showed that participants provided with maps containing only essential landmarks completed tasks more quickly than those with more complex or redundant cues. In our study, the complexity of Group B's route likely imposed additional cognitive processing requirements, reflected in prolonged task completion times and increased errors.

Additionally, those on more challenging routes exhibited higher incidences of specific errors, such as roadside collisions and incorrect turns, when compared to participants on simpler routes. These performance outcomes suggest that complex routes impose substantial cognitive demands, necessitating greater mental resources for accurate navigation. Such elevated cognitive load could impair decision-making processes, leading to an increased frequency of errors in demanding contexts.

Therefore, this study provides evidence that cognitive load varies with task complexity, as demonstrated by significant differences in psychophysiological responses and performance metrics across driving conditions. Challenging routes necessitate higher cognitive resources, a finding reflected in both physiological activation and decreased task performance. These insights underscore the importance of optimizing task environments, such as by integrating clear navigational cues or minimizing unnecessary cognitive demands, to improve performance and reduce error rates in high-stakes, cognitively demanding tasks like driving.

7.0 Conclusion

The present study aimed to quantify the psychophysiological responses of university undergraduate students engaged in virtual reality-based driving tasks, specifically examining how cognitive workload varied with route difficulty. Through comprehensive analysis, all research objectives were achieved, providing valuable insights into the cognitive demands associated with complex navigation tasks. Findings demonstrated that difficult routes significantly increased cognitive load, impacting participants' ability to apply prior knowledge effectively. This elevated cognitive workload correlated with a higher rate of driving errors, indicating that cognitive strain may reduce task performance by overloading participants' processing capabilities.

The psychophysiological responses, particularly heart rate and pupil diameter, provided objective measures of cognitive load. Increased heart rate and pupil dilation during challenging tasks revealed the heightened mental effort exerted by participants. These physiological markers validated the use of psychophysiological measurement as a reliable approach for assessing cognitive workload. This study thus highlights the importance of monitoring psychophysiological responses to better understand how cognitive load affects real-time task performance and learning outcomes.

These findings underscore the potential value of psychophysiological metrics in designing educational and training programs, particularly in high-stakes environments where task complexity can easily induce cognitive overload. By leveraging these metrics, educators and trainers can develop optimized training pathways that balance cognitive demands with task difficulty, enhancing both learning transfer and performance accuracy. The study also underscores the broader utility of virtual reality as an immersive tool for examining cognitive workload, offering a controlled yet realistic setting that can simulate complex environments. Future research could explore further refinement of cognitive workload metrics to apply these insights across diverse learning and performance contexts, ultimately advancing our understanding of cognitive load management in dynamic, task-intensive environments.

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