**Article:**

Ma, S., Yan, X., Billington, J. orcid.org/0000-0003-0995-8875 et al. (2 more authors) (2024) Cognitive load during driving: EEG microstate metrics are sensitive to task difficulty and predict safety outcomes. Accident Analysis & Prevention, 207. 107769. ISSN 0001-4575

https://doi.org/10.1016/j.aap.2024.107769

# Cognitive load during driving: EEG microstate metrics are sensitive to task difficulty and predict safety outcomes

Siwei Ma[1], Xuedong Yan[1*], Jac Billington[2], Natasha Merat[3], Gustav Markkula[3]

1 MOT Key Laboratory of Transport Industry of Big Data Application Technologies for Comprehensive Transport, Beijing Jiaotong University, Beijing 100044, PR China.
2 School of Psychology, University of Leeds, Leeds LS2 9JT, U.K.
3 Institute for Transport Studies, University of Leeds, Leeds LS2 9JT, U.K.
∗ Corresponding author.
E-mail addresses: 22110287@bjtu.edu.cn (S. Ma), xdyan@bjtu.edu.cn (X. Yan), j.billington@leeds.ac.uk (J. Billington), n.merat@its.leeds.ac.uk (N. Merat), g.markkula@leeds.ac.uk (G. Markkula)

**Abstract:** Engaging in phone conversations or other cognitively challenging tasks while driving detrimentally impacts cognitive functions and has been associated with increased risk of accidents. Existing EEG methods have been shown to differentiate between load and no load, but not between different levels of cognitive load. Furthermore, it has not been investigated whether EEG measurements of load can be used to predict safety outcomes in critical events. EEG microstates analysis, categorizing EEG signals into a concise set of prototypical functional states, has been used in other task contexts with good results, but has not been applied in the driving context. Here, this gap is addressed by means of a driving simulation experiment. Three phone use conditions (no phone use, hands-free, and handheld), combined with two task difficulty levels (single- or double-digit addition and subtraction), were tested before and during a rear-end collision conflict. Both conventional EEG spectral power and EEG microstates were analyzed. The results showed that different levels of cognitive load influenced EEG microstates differently, while EEG spectral power remained unaffected. A distinct EEG pattern emerged when drivers engaged in phone tasks while driving, characterized by a simultaneous increase and decrease in two of the EEG microstates, suggesting a heightened focus on auditory information, potentially at a cost to attention reorientation ability. The increase and decrease in these two microstates follow a monotonic sequence from baseline to hands-free simple, hands-free complex, handheld simple, and finally handheld complex, showing sensitivity to task difficulty. This pattern was found both before and after the lead vehicle braked. Furthermore, EEG microstates prior to the lead vehicle braking improved predictions of safety outcomes in terms of minimum time headway after the lead vehicle braked, clearly suggesting that these microstates measure brain states which are indicative of impaired driving. Additionally, EEG microstates are more predictive of safety outcomes than task difficulty, highlighting individual differences in task effects. These findings

enhance our understanding of the neural dynamics involved in distracted driving and can be used in methods for evaluating the cognitive load induced by in-vehicle systems.

**Keywords**: Cognitive load levels; EEG microstates; Safety-critical scenario; Driving simulation

## 1 Introduction

Cognitive load, as defined by Engström et al. (2017), typically refers to the “amount” of cognitive resource demanded from the driver by a competing activity. In the context of driving, cognitive load plays a crucial role in determining a driver’s ability to effectively process information, such as observing road conditions, anticipating potential hazards, and making timely decisions. However, engaging in activities such as talking on the phone diverts drivers’ cognitive resources away from the primary task of driving. Further, the content of a conversation can influence cognitive load due to factors such as the complexity and novelty (Simmons et al., 2016; Kong et al., 2021).

There has been an ongoing debate regarding the impact of high cognitive loads on driver safety. Some studies argue that high cognitive load can be associated with increased arousal and compensatory safety measures from the driver, such as increasing headway or reducing speed (Simmons et al., 2016; Caird et al., 2017), while others demonstrate that excessive cognitive load leads to errors and impairs driving performance. The result of this can be increased reaction times, impaired situational awareness, and elevated accident risks (Klauer et al., 2014; Chan et al., 2020; Kong et al., 2021). These inconsistent observations may be influenced by the varied adaptability of individuals to different task conditions (Puma et al., 2018). In other words, different people might experience different cognitive loads even when faced with the same task, leading to varied adjustments in behavior (Goodridge et al., 2024). Therefore, gaining insights into how cognitive load influences safety outcomes can be better achieved by directly measuring the cognitive load for each individual while driving, rather than relying solely on behavioral performance (Borghini et al., 2014; Wang et al., 2015; Fan et al., 2022).

Mainstream objective measures for cognitive load include psychophysiological measurements such as eye tracking, heart rate, and electroencephalography (EEG), which have been identified as robust options for evaluating cognitive load (Charles & Nixon, 2019; Alyan et al., 2023). Among these measures, EEG has proven advantageous due to its high temporal resolution and the ability of directly representing the electrical activity of the brain, which offers a robust means of depicting the neural dynamics associated with complex cognitive tasks (Zarjam, et al., 2010; Charles & Nixon, 2019; Peng et al., 2022). This method complements behavioral analysis by offering a more direct and immediate assessment of cognitive states. Furthermore, recent research has explored alternative methods for evaluating drivers' cognitive load, such as using vehicle maneuvering data (Jang et al., 2024).

Within EEG research, theta waves, ranging from 4 to 8 Hz in frequency, have emerged as a critical component for understanding cognitive processes. Beyond the domain of driving, EEG research on cognitive load measurement has indicated that theta power is the most reliable index of cognitive load (Chikhi et al., 2022). An increase in theta power has been consistently linked to the amount of information being processed, that is, theta power tends to be higher under conditions of high cognitive load compared to low cognitive load (Deiber et al., 2007; Chikhi et al., 2022). A systematic review found a particular increase in theta power over the prefrontal cortex to be associated with increased task demands (Kabilmiharbi et al., 2022). The prefrontal area, located at the midline scalp position, is crucial for controlling the highest-order cognitive abilities. This region acts as a hub for synthesizing complex cognitive functions, including decision-making, problem-solving, and behavioral control, and is sensitive to cognitive load (Siddiqui et al., 2008; Foy & Chapman, 2018).

In the context of driving, researchers have used EEG to investigate cognitive load changes when drivers are engaged in secondary tasks while driving. Most of this work has focused on the comparison between task and no task conditions. For example, Almahasneh et al. (2014) conducted a driving simulation experiment where participants were required to drive while simultaneously responding to questions, which were designed as a mix of logical reasoning in the form of analogies and real-life problems involving math tasks. They found that the right frontal cortex region was the most affected area during distracted driving. Li et al. (2023) conducted a car-following experiment and analyzed drivers' EEG activities across three secondary tasks: a clock task, a 2-back task, and a navigation task. They observed increased activity in the theta band in the frontal lobe during all three task conditions, compared to driving without a secondary task. Some human-computer interaction-based studies have examined EEG differences across various levels of different cognitive load tasks, such as working memory tasks (Jensen and Tesche, 2002) and visual tracking tasks (Puma et al., 2018). However, it remains to be seen whether EEG has sufficient sensitivity to differentiate between different levels of cognitive load during driving and driving related tasks. The ability to recognize distinct cognitive load levels is crucial in the context of driving, as it can contribute to the development of personalized approaches in driver training, vehicle design, and interface design (Peng et al., 2022).

In addition to the insufficient number of EEG studies dedicated to differentiating between different levels of cognitive load in driving scenarios, few studies have explored drivers' EEG activity during safety-critical situations, such as when drivers are faced with an impending collision. To the best of our knowledge, only one study has attempted to analyze drivers' EEG response in a safety critical situation, where a roadside pedestrian suddenly crossed the road when the driver approached (Li et al., 2022). They found that the activities of all EEG bands (delta to beta) changed consistently, with the power increasing significantly throughout the entire pedestrian-collision avoidance process.

However, this study mainly focused on EEG changes in the collision process, without considering the impact of cognitive load.

With regards to the EEG metrics for reflecting cognitive load, EEG microstate analysis has drawn growing attention in recent years as an innovative method for investigating brain function. EEG microstate analysis assesses brain activity at a millisecond resolution by dividing the raw EEG data into quasi-stable states, often referred to as "atoms of thoughts" (Lehmann et al., 1987). Each EEG microstate remains stable for a certain duration (around 80-120 ms), and then transits into a new topography (Lehmann and Skrandies, 1980; Lehmann et al., 1998; Khanna et al., 2015). These microstates represent a recurring pattern of overall brain activation. Research has found that approximately 70-80% of EEG states could be effectively characterized by only four distinct microstates (Wackermann et al., 1993; Koenig et al., 2002), referred to as microstate A through to D. Microstate A is related to phonological processing, exhibiting a right-frontal left-posterior distribution; microstate B is related to visual processing, exhibiting a left-frontal right-posterior distribution; microstate C is a default mode, exhibiting a midline frontal-occipital orientation, and microstate D represents attention reorientation, exhibiting a midline frontal orientation (Milz et al., 2016; Michel & Koenig, 2018). The robustness and consistency of these four microstates have been demonstrated across diverse conditions, including different age groups and varying states, such as rest versus task conditions (Koenig et al., 2002; Britz et al., 2010). Therefore, the EEG microstates method holds great potential for application in measuring cognitive load during driving, which has not been attempted, to date.

This study utilizes EEG microstate analysis to evaluate cognitive load during routine and safety-critical driving scenarios, with a specific focus on the cognitive demands associated with cell phone use. Arithmetic tasks involving single- or double-digit addition and subtraction were designed to induce different levels of cognitive load. Three phone use modes (baseline, no phone; hands-free; handheld) were used alongside the two arithmetic tasks, as the manual interaction required for handheld mode could potentially affect cognitive load. Data on drivers' EEG signals and vehicle kinematics were collected simultaneously in the collision avoidance scenario.

The objectives of this study were as follows:

(a) Determine whether EEG power and microstates are influenced by cognitive load in driving scenarios and what this means in terms of our understanding of cognitive processing.

(b) Evaluate the feasibility of utilizing EEG power and microstates to classify different levels of cognitive load in driving scenarios.

(c) Assess whether EEG recorded before a safety-critical rear-end collision event can aid in predicting how the driver responds to the event.

## 2 Method

This study analyses EEG data from a previously conducted study reported by Xue et al. (2020). In Sections 2.1-3 below, we describe the experimental methods relevant to the present study. Section 2.4 outlines the EEG data analysis method, and Section 2.5 introduces the statistical analysis used.

### 2.1 Participants and apparatus

Thirty-four participants (16 females, 18 males) completed the whole experiment with valid EEG data collected. We performed a power analysis using G*Power (Faul et al., 2009), based on a medium effect size (Cohen's d = 0.5), a significance level of 0.05, and a desired power of 0.95. The medium effect size was chosen based on a series of cognitive load experiment reported by Mayer & Moreno (2003), where the observed effect sizes were greater than 0.5. With these assumptions, the minimum number of participants required was calculated to be 30, i.e., slightly less than our sample size. The participants were middle-aged adults (between 32 and 40 years, mean = 34.3, S.D. = 4.6) to minimize the potential confounding effects of age on cognitive load tasks (Trammell et al., 2017; Stacey et al., 2021). All participants possessed a valid driver's license and had a minimum of two years' driving experience. The experiment took about 30 mins, and each participant was compensated with RMB200 (approximately \$ 30) after completing the experiment. Approval was obtained from the ethics committee of Beijing Jiaotong University.

We used the high-fidelity Beijing Jiaotong University (BJTU) driving simulator equipped with an EEG system to collect simultaneous behavioral and EEG data (see **Fig.1**). The cabin of the simulator is identical to a Ford Focus with a steering wheel, brake pedal, throttle and a real operational interface. With a pre-view display system, the simulated environment is projected at a 300-degree field of view with a resolution of 1400 * 1050 pixels on each screen. To create a fully immersive driving environment, the simulator is also equipped with a vehicle dynamic simulation system, a linear motion base capable of operation with one degree of freedom in the longitudinal direction, and an environmental noise and vibration system. To acquire EEG data, the Neuroscan system with a SynAmps2™ amplifier and a 64-electrode cap was used. The electrodes were laid out according to the international 10–20 system. While collecting the EEG signals from the electrode cap, a computer connected with the amplifier showed the data with the voltages of each electrode on the screen. This alerted the experiment of any invalid data derived from errors with the cap adjustment. The EEG signals were sampled at 1000 Hz.

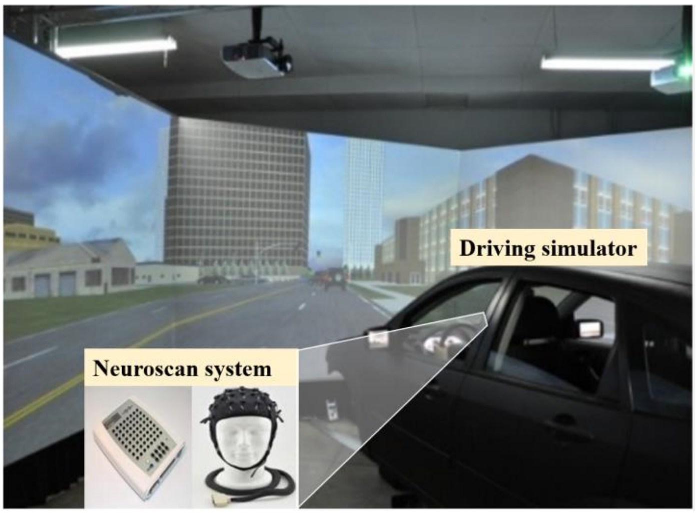



Fig. 1 Apparatus used for data collection.

2.2 Scenario design

The road was a 4 km long, contraflow, two-lane section, with no guardrail or center median divider. The speed limit was 80 km/h. The layout of the experiment scenario is shown in **Fig. 2(a)**, and the simulated road environment is shown in **Fig. 2(b).** Considering the rarity of rear-end collisions in real-world driving within a short time period, a route incorporating two intersections and two curved segments was designed prior to the rear-end collision scenario. This design aimed to provide a more varied driving experience and discourage participants from speculating about the purpose of the experiment. The rear-end collision events only occurred when participants were driving on a straight road.

The speed of the lead vehicle was predefined, as shown in the upper curve graph in **Fig. 2(c)**. The lead vehicle initially stopped on the road and began to accelerate to 50 km/h with an acceleration rate of 1 m/s$^2$ when the subject vehicle arrived at 55 m behind the lead vehicle. Then the lead vehicle kept a constant speed at 50 km/h until arriving at 465 m away from the starting point, where it decelerated to 40 km/h at 4 m/s$^2$ to shorten the headway between the lead and the subject vehicle. After that, the lead vehicle kept driving and decelerated from 40 km/h to 4 km/h at 6 m/s$^2$ when it was 675 m away from the starting point. This sudden braking was designed to create a potential rear-end collision scenario. The subject vehicle's operating speed fundamentally depended on the lead vehicle's speed profile (see the lower graph in **Fig. 2(c)**). After braking, the lead vehicle drove away with an acceleration rate of 1 m/s$^2$.

While driving, the participants were engaged in phone conversations where they had to respond to arithmetic problems. The choice of arithmetic problem-solving tasks was based on previous research demonstrating that the number of digits in arithmetic questions correlates with the perceived level of difficulty (Ryu & Myung, 2005; Molina Del Río et al., 2019). Therefore, this study designed simple and complex tasks as single- and double-digit addition or subtraction, with no phone conversation serving as the baseline. The conversation tasks were played by a sound system installed in the simulator, and they were triggered by sensors so that participants would drive under a similar mental workload in the same situation.

Participants engaged in both hands-free and handheld phone conversation, for both simple and complex versions of the task. In the handheld task, drivers had to use one hand to hold the phone to their ear and the other to operate the steering wheel, whereas, in the hands-free task, they could use both hands to operate the car. This design aimed to assess whether the handheld phone use mode would introduce additional cognitive load, due to its inherent manual demands. Therefore, each participant completed the entire 4 km drive five times, while engaged in the different cell phone tasks: baseline, hands-free simple task, hands-free complex task, handheld simple task, and handheld complex task. The tasks were performed continuously during the entire drive. Participants were required to give the answer as quickly and accurately as possible, which were recorded by an experimenter outside the simulator.

The data analysis focused on two stages of this driving scenario, just before and just after the braking event: The *normal driving* stage refers to the last 6 seconds before the lead vehicle started braking. The *critical braking* stage refers to the time from the lead vehicle's brake onset until the ego vehicle stopped braking, i.e., this stage included the entire collision avoidance process of the ego vehicle.

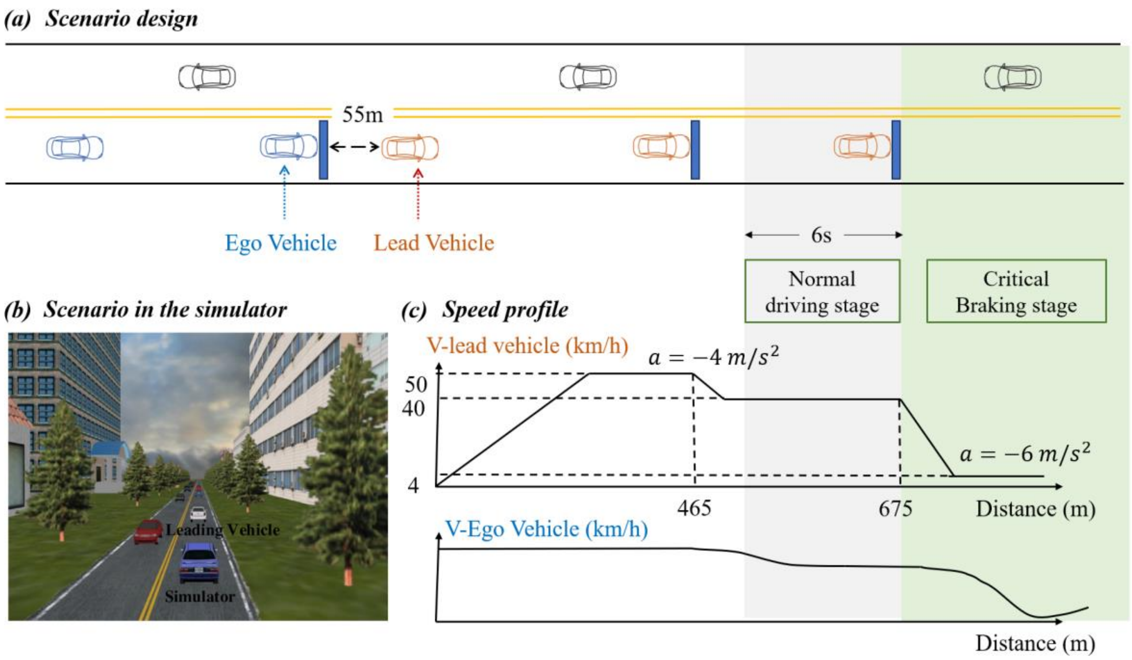



Fig. 2 Details of the experiment scenario.

## 2.3 Procedure

Participants were required to fill out and sign an informed consent form (per Institutional Review Board, IRB) upon arrival. They were instructed to drive in a manner consistent with their daily habits.

Before the formal experiment, each participant drove for at least five minutes to get accustomed to the driving simulator operation and driving environment. The order of the five experimental drives was randomized per participant, to counteract order effects. Participants had at least five minutes of self-paced rest between tasks, and they were free to quit the experiment at any time in case of motion sickness or any discomfort.

### 2.4 EEG data analysis

#### 2.4.1 Preprocessing of EEG signals

In order to obtain a stable estimation of EEG signals, preprocessing is required, to reduce noise and eliminate artifacts. In this study, the open-source toolbox EEGLAB in MATLAB 2018a was used (Delorme & Makeig, 2004). The main steps of preprocessing were as follows:

Firstly, the EEG signals underwent a 0.5–30 Hz band-pass filter across all channels, with the high-pass and low-pass filters applied separately. Then, independent component analysis (ICA) was used to decompose the EEG signals. The ADJUST plugin was used to automatically identify and remove artifacts (Mognon et al., 2011). ADJUST automatically detects and removes ocular artifacts caused by blinks, eye movements and the generic artefacts caused by the recording device. An experienced EEG analyst also manually verified the removed artifacts. Finally, the EEG data were referenced to the average reference, and baseline corrections were done by removing the mean amplitude of each channel. After completing these steps, artifact-free EEG data were prepared for further analysis.

#### 2.4.2 EEG spectral power analysis

Based on the preprocessed artifact-free EEG data, Fast Fourier Transform (FFT, Frigo and Johnson, 1998) with Hanning window was applied to convert the EEG signal from the time domain to the frequency domain. This process decomposed the signal into individual frequency components, revealing amplitude and phase details for each frequency band. Then band power was extracted by integrating the frequency spectrum within specific frequency ranges. In this study, we mainly focus on theta band (4 Hz – 7 Hz) given its dominance in reflecting cognitive states. The process of EEG spectral power analysis is a standard method used in numerous previous studies (for a review, Haghani et al., 2021).

#### 2.4.3 EEG microstate analysis

Prior to EEG microstate calculation, a band-pass FIR filter (Cetin et al., 1997) of 2 to 20 Hz was performed on the preprocessed data, which is a frequency range commonly used in microstate research (Koenig et al., 2002). Four sequential steps were then executed to estimate EEG microstates, as outlined below. The process adheres to the methodology proposed by Koenig et al. (1999), utilizing the microstate toolbox for EEGLAB developed by Koenig (2017).

(1) Compute global field power (GFP). GFP is the instantaneous spatial standard deviation of the signal potential values, which is calculated as:

$$GFP(t) = \sqrt{\left( \sum_{n=1}^{N} \left( V_n(t) - \overline{V}(t) \right)^2 \right) \Big/ N} \quad (1)$$

Where n denotes an electrode index, $N$ denotes the number of electrodes. $V_n(t)$ represents the signal potential value of electrode n at time t. $\overline{V}(t)$ represents the average potential value of all electrodes at time point t.

(2) Find the maxima of GFP. This is because the topographic maps tend to be most stable (with the optimal signal-to-noise ratio) around the maxima of the GFP (Lehmann et al., 2009).

(3) Perform k-means clustering analysis. All maps are categorized into a set of four predefined classes, based on their topographic similarities, following Koenig et al. (1999), Koenig et al. (2002) and Lehmann et al. (2009), as shown in **Fig. 3** (middle plot). According to previous research, these four prototypic topographies could represent 70%-80% maps in a multichannel recording. Even when selecting more than four cluster maps, these specific four microstates consistently stand out as the predominant ones (Khanna et al., 2015). The four classes are referred to as microstates A through D (MSA-MSD). Each class has been linked to a distinct cognitive function, namely phonological processing, visual network, default mode, and attention reorientation, respectively (Milz et al., 2016; Seitzman et al., 2016). When relating these states to driving, MSA could for example corresponds to a driver focusing on listening to the auditory content of a phone conversation; MSB could correspond to visually interpreting a traffic scene ahead; and MSD could correspond to the driver switching attention between driving and a secondary task. As for MSC, the so-called "default mode" activity of the brain refers to the type of activation observed during wakeful rest, without engagement in any external task, i.e., a priori it may not be very relevant in the driving context.

(4) Match the topographic map to four clustered microstates. Each topographic map is matched to a clustered microstate based on the highest Pearson's correlation coefficient at each time point. The correlation is calculated and compared across the four clusters to determine the microstate to which it belongs. In this way, the EEG signal can be re-expressed as a sequence of microstate classes. The global explained variance of the four clustered microstates in our dataset was 76%, within the typical reported range in previous studies (Lehmann et al., 2009).

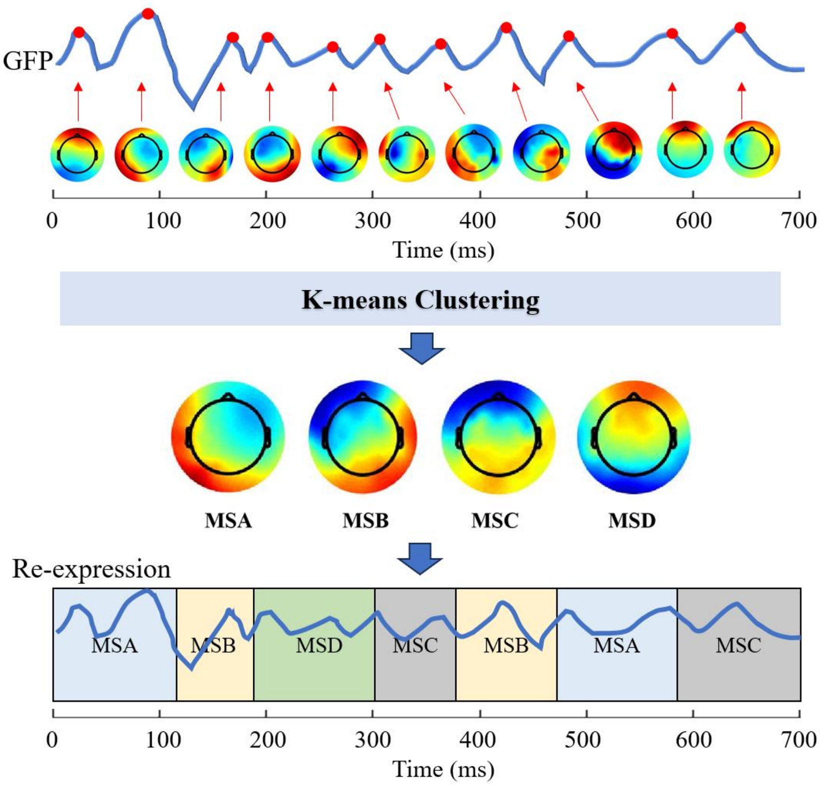



Fig. 3 Steps to get EEG microstates.

After obtaining the sequence of EEG microstates as outlined above, the following measures were calculated for each microstate (Khanna et al., 2015; Michel & Koenig, 2018):

- Duration (ms): The average duration for which each microstate remained stable before transitioning to another microstate.
- Occurrence (/s): The frequency of occurrence, representing how many times a particular microstate class appears, on average, within a one-second interval.
- Coverage (%): The proportion of the total time occupied by a specific microstate class, expressed as a percentage.
- Transition probability (%): The likelihood of transitioning from each microstate to each other microstate, presented as a percentage.

## 2.5 Statistical analysis

Linear Mixed Model analysis was employed for inferential statistical analysis due to the repeated measures in the data (IBM Corp., 2021). This method includes both fixed effects (group-level effects) and random effects (subject-specific effects), which allows the model to capture both systematic trends and individual variability. Bonferroni correction was done for multiple comparisons. In all analyses, an alpha-level of 0.05 was used to determine statistical significance.

The Linear Mixed Model analyses served two purposes. Firstly, LMMs were fitted to examine the impact of various task conditions on EEG metrics (both the spectral power metrics and the microstate metrics, which serve as the dependent variables in the LMMs). Secondly, LMMs were fitted to quantify the relationship between pre-braking parameters and safety outcomes. In the latter analysis, kinematic and EEG parameters from before the lead vehicle brake onset were used as the independent variables, and the minimum time headway (MinTh) as the dependent variable. In the safety outcome analysis, alternative models were tested, both with and without EEG metrics among the predictors, to evaluate their contribution to the prediction of the minimum time headway outcome.

## 3 Results

### 3.1 Effects of phone use on EEG power

Effects of phone use on EEG power were tested in both the normal driving stage and the critical braking stage. In the normal driving stage, drivers maintained a safe following distance behind the lead vehicle, while in the critical braking stage, drivers were required to react promptly to the sudden braking of the lead vehicle. **Fig. 4** depicts the observed EEG theta band power across task conditions, during normal driving and critical braking stages, respectively. When drivers were in task conditions, although there was a slightly higher theta power compared to baseline in normal driving stage, this result was non-significant ($F = 1.21$, $p = 0.11$). Whereas in critical braking stage, the difference between these four task conditions and the baseline is not significant ($F = 0.39$, $p = 0.43$).

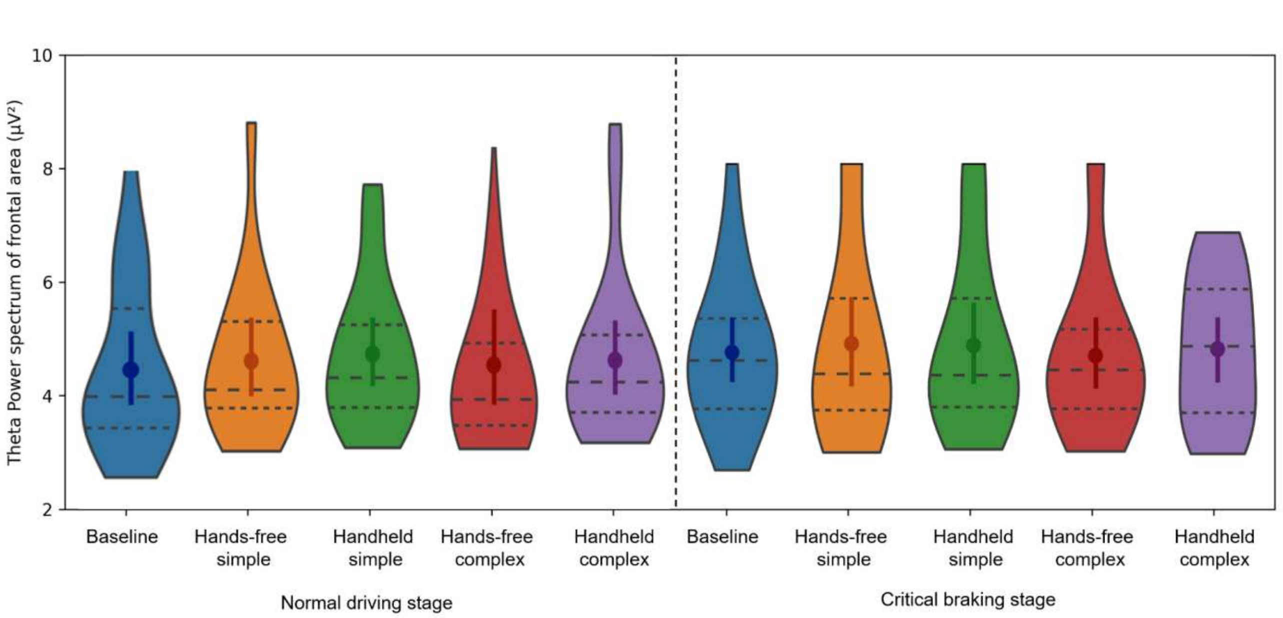



Fig. 4 Frontal theta power during normal driving and critical braking stages.

## 3.2 Effects of phone use on microstates

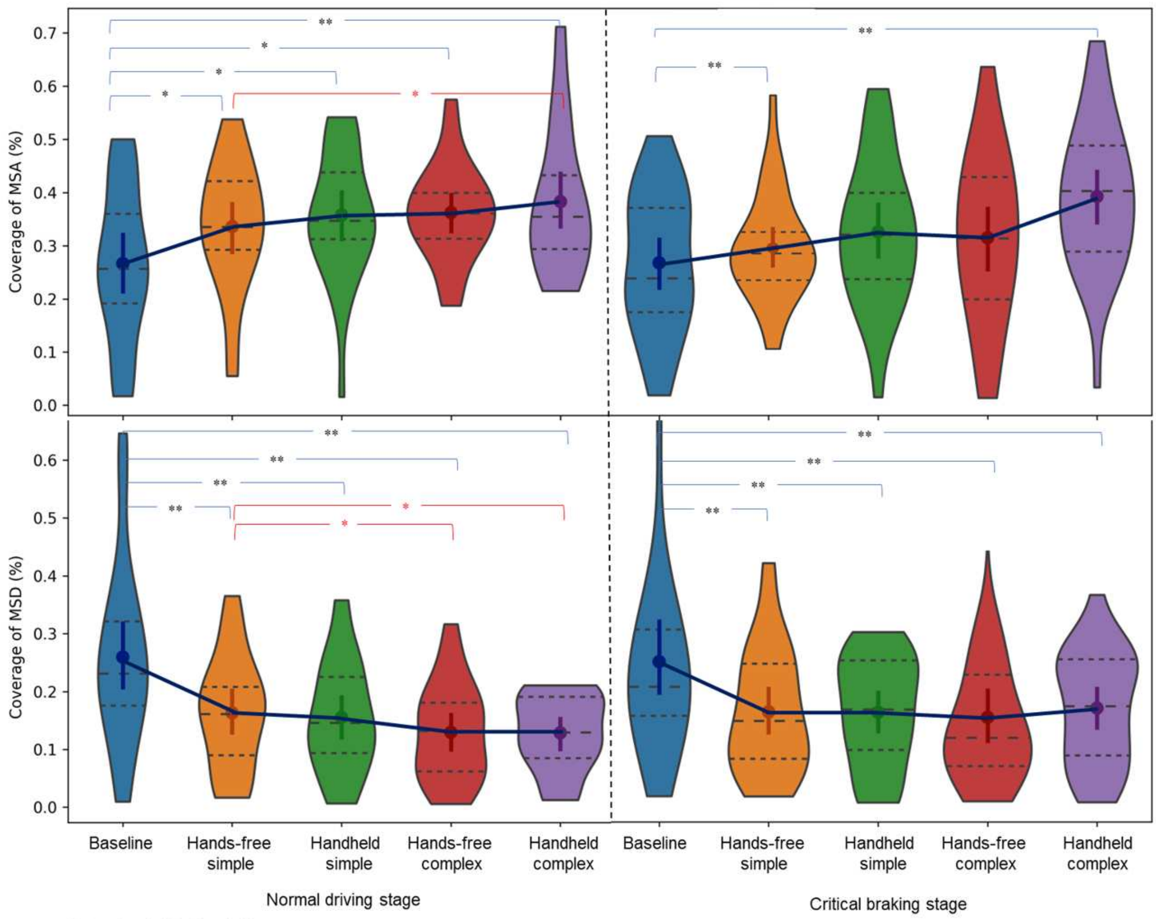
In this section, results from the impact of phone use tasks on EEG microstates and their statistical significance are reported. The occurrence, duration, coverage, and transition probability of EEG microstates were examined during normal driving and critical braking stages, respectively.

A consistent change in the coverage of MSA (related to phonological processing) and MSD (related to attentional reorientation) was observed across both normal driving and critical braking stages. As shown in **Fig. 5**, the coverage of EEG microstates suggests a clear ordered sequence, characterized by a decrease in MSD coupled with an increase in MSA. The MSD values follow the order: baseline > hands-free simple task > handheld simple task > hands-free complex task > handheld complex task, while the MSA values show the opposite trend.

To test the significance of the above sequence, post-hoc tests were done on the MSA and MSD coverage among the different task conditions, in both normal driving and critical braking stages. The results are shown in **Fig. 5**, using blue lines to represent significant differences between baseline and phone use tasks, and red lines to represent significant differences between the four phone use task conditions. Significant differences between phone use tasks and baseline are present in both normal driving and critical braking stages. In contrast, the differences among the four phone tasks are only significant in the normal driving stage. Particularly, there is a significantly lower MSA coverage and a higher MSD coverage in the hands-free simple scenario, compared to the handheld complex scenario. Moreover, a significantly lower MSD value is observed in the simple hands-free task, compared with the complex hands-free task.

In addition to these changes in the coverage of MSA and MSD, the different phone use tasks show significant impacts on some other microstates metrics. Specifically, in the normal driving stage, different tasks affect the occurrence and duration of MSD in significantly different ways. During the critical braking stage, a significant impact is found on the duration of MSA. These changes are in line with the changes of coverage of MSA and MSD. Details about the EEG microstates metrics are shown in **Table 1** for normal driving stage and **Table 2** for critical braking stage.

The significant impact of task conditions on microstate transition probability is depicted in **Fig. 6**. When drivers were engaged in the arithmetic tasks while driving, there was an observed increase in the transition probability from MSB to MSA and a concurrent decrease in the transition to MSD, aligning with the observed coverage differences across task conditions.




Note: * p<0.05; ** p<0.01

Fig. 5 Coverage of MSA and MSD in normal driving and critical braking stages. The dot in each violin represents the mean value, and error bars represent 95% confidence interval.

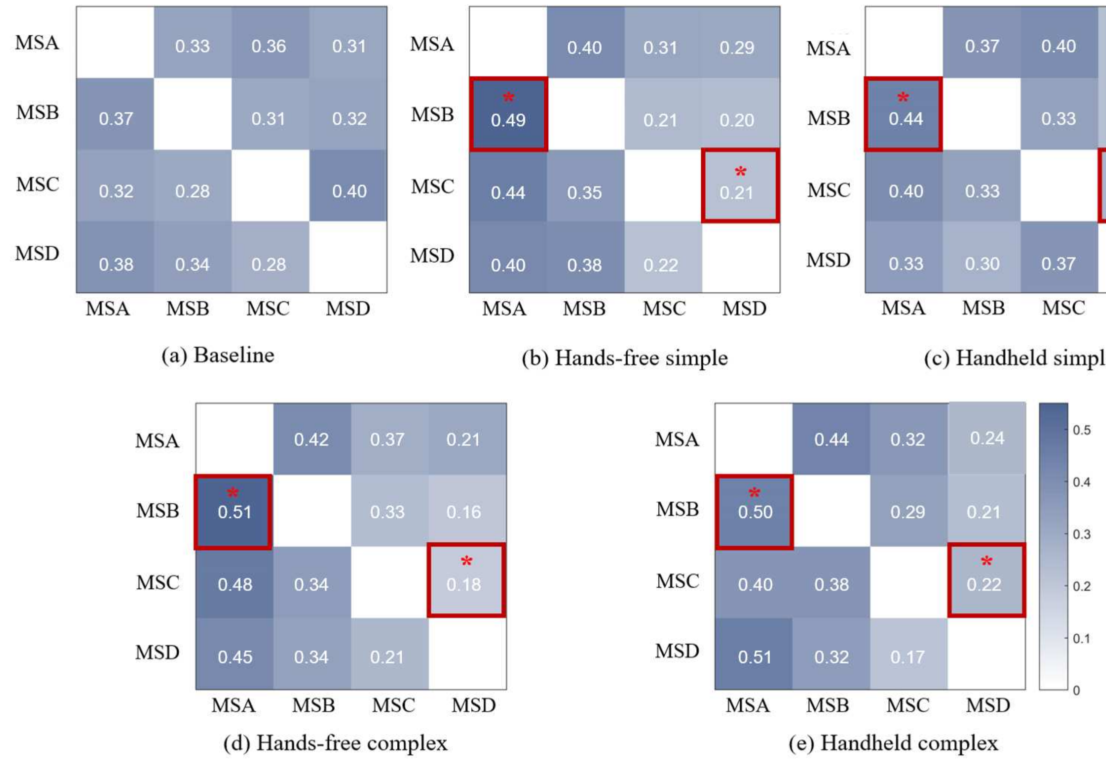



Fig. 6 Effects of phone use on microstates transition probability. The number in each cell is the transition probability from the vertical axis to the horizontal axis, and this probability is also indicated by the color of the cell. Darker colors indicate higher transition probabilities. The cells outlined in red and marked with asterisks indicate significant differences (p<0.05) between the baseline and the task condition in question.

Table 1 Effect of cell phone on EEG Microstates in normal driving stage.

| Variables | Scenario | | | | | | | | | | F |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Baseline | | Hands-free simple | | Hands-free complex | | Handheld simple | | Handheld complex | | |
| | M. | S.D. | M. | S.D. | M. | S.D. | M. | S.D. | M. | S.D. | |
| Occurrence_MSA | 2.08 | 0.84 | 2.21 | 0.71 | 2.44 | 0.72 | 2.27 | 0.59 | 2.41 | 0.63 | 1.693 |
| Occurrence_MSB | 1.93 | 0.88 | 2.17 | 0.62 | 2.08 | 0.74 | 2.10 | 0.68 | 2.14 | 0.65 | .542 |
| Occurrence_MSC | 1.88 | 0.83 | 1.94 | 0.69 | 1.93 | 0.69 | 1.87 | 0.71 | 1.88 | 0.74 | .076 |
| **Occurrence_MSD** | **2.01** | 0.77 | **1.71** | 0.73 | **1.45** | 0.77 | **1.60** | 0.68 | **1.39** | 0.55 | **3.657**** |
| Duration_MSA | 119.63 | 38.99 | 134.54 | 47.06 | 141.55 | 42.39 | 144.42 | 38.36 | 146.17 | 48.05 | 1.983 |
| Duration_MSB | 115.94 | 37.36 | 132.19 | 48.00 | 117.84 | 40.83 | 116.87 | 26.88 | 133.24 | 44.40 | 1.391 |
| Duration_MSC | 120.04 | 37.29 | 112.37 | 34.48 | 121.42 | 51.15 | 118.68 | 32.22 | 108.01 | 41.99 | .598 |
| **Duration_MSD** | **122.61** | 47.15 | **117.86** | 32.79 | **89.57** | 33.87 | **105.55** | 39.40 | **97.25** | 24.82 | **3.585**** |
| **Coverage_MSA** | **0.27** | 0.14 | **0.31** | 0.14 | **0.36** | 0.14 | **0.34** | 0.12 | **0.37** | 0.15 | **2.484*** |
| Coverage_MSB | 0.23 | 0.13 | 0.26 | 0.13 | 0.26 | 0.14 | 0.26 | 0.11 | 0.28 | 0.12 | 1.123 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Coverage_MSC | 0.24 | 0.15 | 0.24 | 0.13 | 0.24 | 0.15 | 0.24 | 0.09 | 0.22 | 0.13 | .251 |
| **Coverage_MSD** | **0.26** | 0.15 | **0.19** | 0.10 | **0.14** | 0.11 | **0.16** | 0.13 | **0.14** | 0.07 | **5.252**** |

Note: * p<0.05; ** p<0.01

Table 2 Effect of cell phone on EEG Microstates in critical braking stage.

| Variables | Scenario | | | | | | | | | | F |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Baseline | | Hands-free simple | | Hands-free complex | | Handheld simple | | Handheld complex | | |
| | M. | S.D. | M. | S.D. | M. | S.D. | M. | S.D. | M. | S.D. | |
| Occurrence_MSA | 2.11 | 0.73 | 2.24 | 0.54 | 2.33 | 0.60 | 2.24 | 0.85 | 2.54 | 0.56 | 2.352 |
| Occurrence_MSB | 1.95 | 0.84 | 2.00 | 0.73 | 2.17 | 0.57 | 1.96 | 0.87 | 2.04 | 0.76 | .415 |
| Occurrence_MSC | 1.80 | 0.91 | 1.64 | 0.76 | 1.88 | 0.65 | 2.08 | 0.49 | 1.69 | 0.66 | 1.819 |
| Occurrence_MSD | 1.88 | 0.74 | 1.61 | 0.76 | 1.42 | 0.69 | 1.55 | 0.75 | 1.60 | 0.70 | 1.574 |
| **Duration_MSA** | **121.92** | 43.20 | **127.3** | 47.79 | **138.21** | 44.54 | **137.54** | 54.39 | **155.57** | 42.90 | **2.490***  |
| Duration_MSB | 119.08 | 44.82 | 118.0 | 30.16 | 121.74 | 36.84 | 107.75 | 36.55 | 110.74 | 30.67 | .817 |
| Duration_MSC | 108.46 | 36.24 | 101.5 | 39.30 | 123.65 | 77.81 | 134.47 | 91.54 | 100.78 | 35.71 | 1.699 |
| Duration_MSD | 134.45 | 102.1 | 93.21 | 31.91 | 99.94 | 41.77 | 100.02 | 35.25 | 102.21 | 31.25 | 2.414 |
| **Coverage_MSA** | **0.27** | 0.14 | **0.31** | 0.15 | **0.33** | 0.14 | **0.32** | 0.17 | **0.41** | 0.15 | **4.241**** |
| Coverage_MSB | 0.26 | 0.16 | 0.24 | 0.11 | 0.27 | 0.13 | 0.23 | 0.13 | 0.24 | 0.13 | .467 |
| Coverage_MSC | 0.21 | 0.15 | 0.28 | 0.12 | 0.23 | 0.15 | 0.28 | 0.18 | 0.18 | 0.10 | 2.244 |
| **Coverage_MSD** | **0.26** | 0.18 | **0.17** | 0.10 | **0.16** | 0.13 | **0.17** | 0.11 | **0.17** | 0.10 | **2.872***  |

Note: * p<0.05; ** p<0.01

### 3.3 The efficacy of EEG microstates in predicting behavior

The aim of this section is to predict safety outcomes from information available before the safety critical event (i.e., before the lead vehicle braking), and see if EEG information can improve such predictions.

As a first step, we tested to what extent the type of task could predict the safety outcome, and also whether it could predict the kinematic state *before* the lead vehicle began braking, since it is known that drivers may adapt their behavior to manage changes in cognitive load (Onate-Vega et al., 2020). The speed ($V_0$) and distance headway ($H_0$) at the time when the lead vehicle braked were used to reflect the kinematic state before the critical event, and the minimum time headway (MinTh) was adopted to represent safety outcome. As described in the statistical analysis section of the Methods, a LMM was used to test the impact of task conditions on $V_0$, $H_0$, and MinTh. The differences identified as statistically significant ($p < 0.05$) in this analysis are marked with an asterisk (*) in **Fig. 7**. Phone use tasks had a significant impact on $V_0$ and $H_0$, both of which increased under task conditions. However, the influence of task conditions on MinTh was not statistically significant. This can be understood by considering the relationships between these variables: MinTh is negatively correlated with $V_0$ and positively correlated with $H_0$ (**Table 3**). Since both $V_0$ and $H_0$ increase under task conditions, their opposing effects might counteract each other, resulting in no significant impact on MinTh.

The second question to be answered is how to improve the prediction results, and to test the efficacy of EEG microstates in predicting behavior. Based on the behavioral adaptation finding, $V_0$ and $H_0$ should be included when predicting safety outcomes from pre-event information. We constructed three models: one with only $V_0$, $H_0$ (kinematics model), another extending with task information (kinematics + task), and a third extending with EEG information (kinematics + EEG). For the model with EEG information (kinematics + EEG), only EEG microstates were adopted in the prediction since the difference of EEG power under different task conditions was not significant. Specifically, EEG microstate coverage was chosen as the input variable because of its significant variations observed among different task conditions, as shown in Section **3.2**. To alleviate collinearity, only the coverage of MSA, MSB and MSD was integrated into the model, considering that the sum of the coverage of all four microstates equals one.

The model results for the second (kinematics + task) and the third extensions (kinematics + EEG microstates) are shown in **Tables 4 & 5**. The results indicate that task conditions were not statistically significant predictors in the model, with none of them differing significantly from the baseline condition ($p > 0.05$). In comparison, the coverage of EEG microstate A was a significant predictor (coefficient = -0.482, $p = 0.041$), indicating that a decrease in MSA contributes to a higher minimum time headway. Given the repeated measures design, we included random intercepts for subjects in our model to capture individual variability. The results showed that there was a significant portion of the variability in MinTh that could be attributed to differences between individuals ($p < 0.01$).

Visually, the small but noticeable improvement in model fit when adding the microstates to the kinematics-only model can be seen in **Fig. 8**. These findings suggest that EEG microstates preceding the critical event can contribute to better prediction of safety outcomes, surpassing the predictive utility of knowing the specific task the driver is engaged in. Specifically in this case, the negative correlation between the coverage of MSA and minimum time headway suggests that when drivers concentrate more on auditory information, it is detrimental to maintaining a safe time headway.

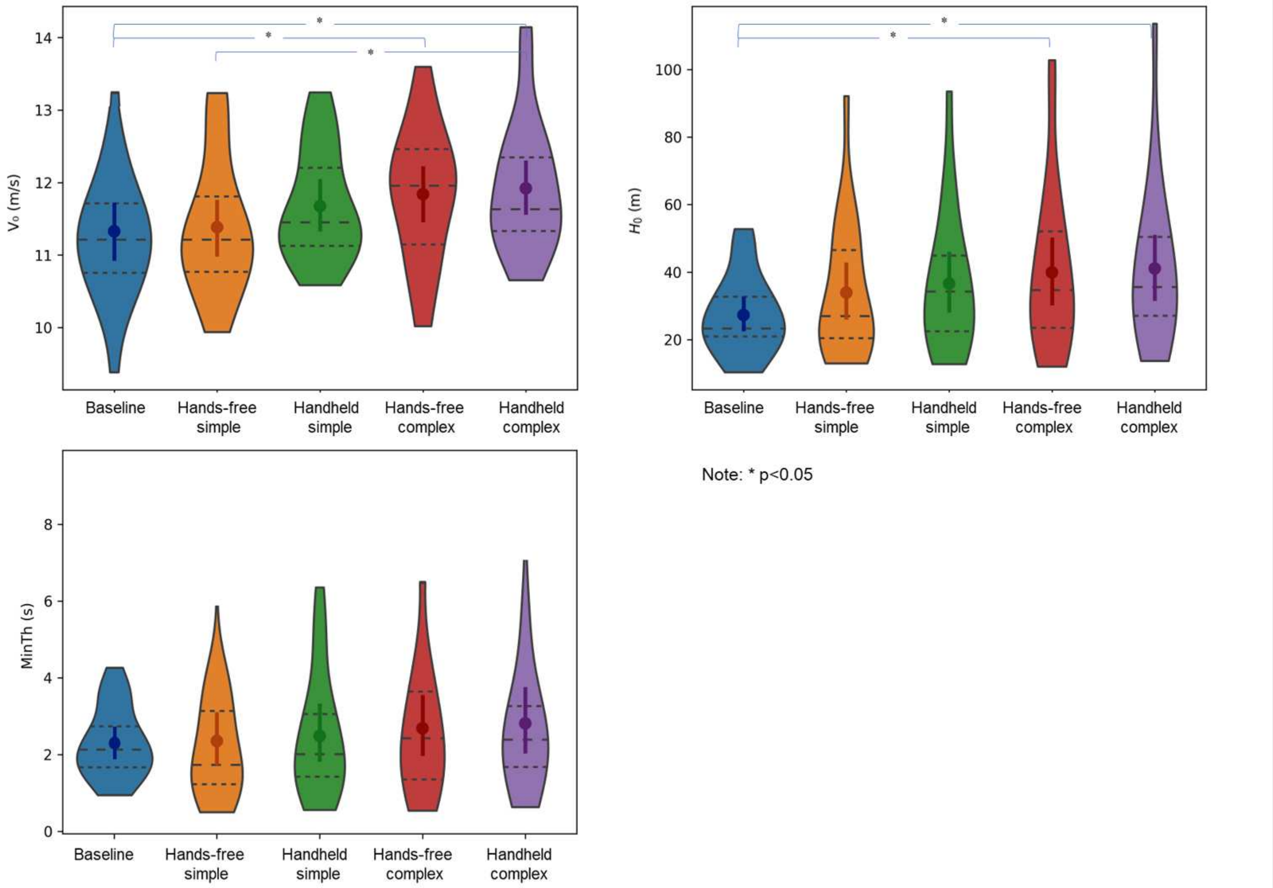



Fig. 7 The impact of task conditions on behavioral measures. Note: * $p < 0.05$.

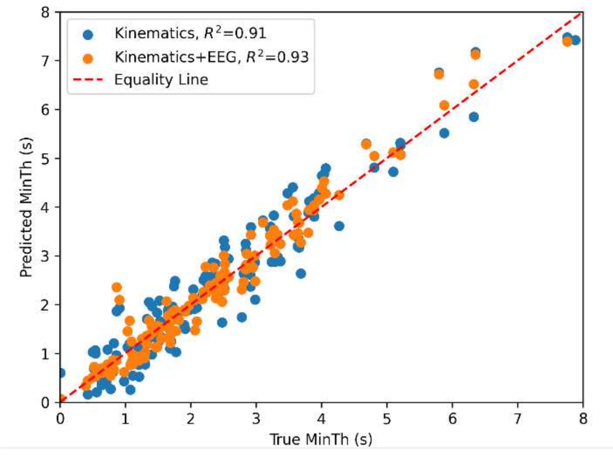



Fig. 8 Model performance.

Table 3 Results of linear mixed model using only behavioral measures.

| Variables | Coefficient | S.D. | t | p |
|---|---|---|---|---|
| Intercept | 1.656 | 0.437 | 1.609 | **<0.001** |
| $V_0$ | -0.196 | 0.026 | -6.89 | **<0.001** |

| | | | | |
|---|---|---|---|---|
| $H_0$ | 0.085 | 0.001 | 40.159 | **<0.001** |

Table 4 Results of linear mixed model using behavioral and task conditions.

| Variables | Coefficient | S.D. | t | p |
|---|---|---|---|---|
| Intercept | 1.899 | 0.317 | 5.980 | <**0.001** |
| $V_0$ | -0.216 | 0.027 | -7.922 | **<0.001** |
| $H_0$ | 0.082 | 0.001 | 79.343 | **<0.001** |
| Hands-free simple | 0.046 | 0.103 | 0.447 | .656 |
| Hands-free complex | 0.076 | 0.097 | 0.779 | .437 |
| Handheld simple | 0.008 | 0.096 | 0.839 | .403 |
| Handheld complex | 0.123 | 0.097 | 1.274 | .205 |
| Baseline | $0^a$ | | | |

Note: [a] reference category.

Table 5 Results of linear mixed model using behavioral and EEG measures.

| Variables | Coefficient | S.D. | t | p |
|---|---|---|---|---|
| Intercept | 2.131 | 0.399 | 5.342 | <**0.001** |
| $V_0$ | -0.197 | 0.026 | -7.529 | **<0.001** |
| $H_0$ | 0.084 | 0.001 | 99.258 | **<0.001** |
| Coverage_MSA | -0.482 | 0.233 | -2.063 | **0.041** |
| Coverage_MSB | -0.480 | 0.256 | -1.876 | 0.063 |
| Coverage_MSD | -0.579 | 0.305 | -1.879 | 0.060 |

## 4 Discussion

This study aimed to investigate the impact of cognitive load levels on EEG microstates in safety-critical driving scenarios. Cognitive load was induced by arithmetic tasks in combination with phone use modes in a driving simulation experiment. The efficacy of EEG in helping to predict safety critical behaviors was tested.

### 4.1 EEG microstates change significantly under different cognitive load levels

This study found significant influences of cognitive load levels on EEG microstates in a safety critical driving scenario, which has not been previously investigated. Results showed that EEG microstates changed significantly between no task and task conditions. Specifically, the coverage of MSA in task conditions was significantly higher than in baseline (baseline, MSA = 0.27; task conditions, MSA > 0.31), while the coverage of MSD in task conditions was lower than in baseline (baseline, MSD = 0.26; task conditions, MSD < 0.19). Given that MSD is associated with attention and MSA with auditory processing, this finding suggests that as drivers become more focused on auditory information processing when using cell phones (associated with MSA increase), an impairment of their attention reorientation ability is seen (as evidenced by MSD decrease; Milz et al., 2016; Seitzman et al., 2016). These findings are in line with previous studies, suggesting that drivers need to shift their attention to either problem solving, or driving rather than do these two tasks at the same time (Wang et al., 2015). In addition, we found that the impact of cognitive load tasks in the normal driving stage is much more significant compared to the critical braking stage. This is expected, as the complexity of the critical scenario task might overshadow the impact of cell phone use, prompting drivers to shift the focus of their attention to the driving task, to avoid a collision. Therefore, during the critical braking stage, cognitive demands might be similar across different conditions.

This study also found EEG microstates to be a sensitive measure of cognitive load, suggesting them to be a promising method not only for distinguishing between cognitive load and baseline conditions (no load), but also between different levels of cognitive load. A clear pattern was seen in this study: The trend in MSD values followed a decreasing order for baseline > hands-free simple task > handheld simple task > hands-free complex task > handheld complex task, whereas the trend in MSA values demonstrated the opposite trend. This observation suggests that as the difficulty level of the task increases, more cognitive load is required. This increased load leads drivers to allocate additional brain resources to process the task, resulting in a trade-off where the ability to reorient attention decreases. It should be noted, however, that within this pattern of monotonous change between conditions, the microstates changes between task conditions were not always statistically significant, and need to be interpreted carefully. The results indicate significant differences between simple and complex tasks in both MSA and MSD values. However, the significance becomes more complex when combining arithmetic tasks with phone use modes. Specifically, there appears to be a significant difference between hands-free simple tasks and handheld complex tasks. Yet, when comparing handheld simple tasks with hands-free complex tasks, the significance is not evident. These results could be explained by previous research findings, which have demonstrated that the content of the conversation exerts a greater impact on distracted driving than the method of phone conversation (Patten et al., 2004). Consequently, despite the manual demands introduced by the handheld phone use mode, it may not have led to a clear increase in cognitive load in this study.

### 4.2 EEG microstates help predict driving behavior

The efficacy of EEG microstates for predicting safety outcomes has also been shown in this study. When EEG microstates were added along with the kinematic measures in a predictive model, MSA coverage was a statistically significant predictor of minimum time headway, improving the predictive performance compared to using only kinematic data. An interesting finding is that to the same was not true when instead adding task conditions as a predictor to the model. In other words, having information about a participant's EEG microstates was more informative about safety outcomes than having information about which task the participant was doing. This could be attributed to individual characteristics, which means that different people might experience different amounts of distraction even when performing the same task (Borghini et al., 2014). When we use task conditions in the model, the details of how much cognitive load each individual is undergoing is unknown. However, our results suggest that by measuring microstates, we gain a more direct insight into the level of cognitive load experienced by each participant. Therefore, changes in EEG microstate measures provide a more accurate reflection of how distracted individuals truly are, surpassing the information obtained solely from knowing which task they are performing.

It is worth noting here that the repeated nature of the rear-end scenario in this study is likely to have affected the observed pre-event behavioral adaptation, and also responses to the events. It is very interesting that while the drivers probably expected the lead vehicle to brake to some extent, their brain state still exhibited predictive changes related to the event outcome. This can be understood in terms of the "cognitive control hypothesis" of how cognitive load affects driving (Engström et al., 2017): Drivers had learned during the experiment that the lead vehicle would brake, and that they would need to respond to this, but since this novel insight was not automatized, it was seen to be impaired under cognitive load. This finding suggests that EEG microstates could serve as a measure specifically of the type of working memory impairment from cognitive load suggested by the cognitive control hypothesis. It is well known that working memory capacity is inherently limited, and studies have shown that an increase in cognitive load can occupy these limited attentional resources, leaving fewer resources available for primary driving tasks (Conway et al., 2003; Wickens and McCaarley, 2008; Zhang et al., 2023). The cognitive control hypothesis suggests that this becomes problematic in driving only when the primary driving task itself requires working memory, which is the case when encountering novel or complex driving situations, for which the driver does not possess automatized responses. In such situations, if the driver is cognitively loaded by a secondary task, the driver's ability to effectively perceive and process the necessary information from the environment diminishes. This deterioration in performance heightens the risk of traffic conflicts and accidents, underscoring the importance of minimizing distractions and managing cognitive load for safe driving, especially in driving situations which tax drivers' working memory.

From a real-world application perspective, due to the intrusive nature of EEG recording, the primary objective is not to equip drivers with EEG caps for monitoring during everyday driving at scale. Instead, EEG serves as a critical research and development tool aimed at understanding cognitive load and developing reliable measurement techniques. For instance, it can be used to estimate the distraction potential of in-vehicle systems through controlled experiments, thereby informing the design of safer and more efficient automotive interfaces.

### 4.3 Possible explanations for EEG power results

In this study, changes of theta band power were not significantly different between different task conditions, and also not so between the baseline and task conditions. This finding differs from some previous EEG studies conducted during driving tasks, which report statistically significant effects on theta power but typically with simpler primary driving tasks, such as free driving (Almahasneh et al., 2014) and simple car-following (Li et al., 2023). The discrepancy between our studies could be attributed to the more complex and demanding nature of safety-critical driving scenarios used here. In these scenarios, drivers are primarily focused on collision avoidance, which may overshadow the impact of phone use conditions on EEG power. According to Friston et al. (1996), the brain operates through interactions among the cognitive components of a task, and altering one cognitive component impacts other cognitive components. This suggests that the addition or subtraction of a cognitive element within the task does not directly lead to a linear increase or decrease in brain activity; rather, it entails more intricate interactions within the brain. Xiao et al. (2023) also showed that cognitive control involves the complex interplay between multiple sensory inputs with task-dependent goals during decision making. These studies support the notion that the impact of phone use conditions on EEG power might be overshadowed by the concurrent engagement of other cognitive control processes in safety-critical driving. Another possible reason for the lack of significant differences in theta power might be the ceiling effect. This is supported by Chikhi et al. (2022), who found that performing two tasks concurrently might not be associated with an increase in theta power, even though performing one task is. This is because the theta power may already be high in the single-task condition (in our case, baseline driving), with minimal increase observed during the dual-task condition (in our case, driving while cognitively loaded).

In comparison, one possible explanation for why EEG microstates can discern differences in complex driving task conditions is their capacity to capture the interactions and parallel processing between different brain areas. This is supported by research demonstrating that cognition depends on coordinated neural activations that link functional networks across multiple brain regions (Bressler and Menon, 2010; Meehan and Bressler, 2012).

## 5 Conclusion

This study investigated the influence of different levels of cognitive load on EEG performance in safety-critical driving scenarios. The influence of three phone use conditions (no phone use, hands-free, and handheld), along with two task conditions (single- or double-digit addition and subtraction), were evaluated both before and during a rear-end collision conflict. EEG power and microstate measures were analyzed, and the latter showed a better performance in capturing cognitive load variation. A distinct EEG microstate pattern emerged when drivers were engaged in cell phone tasks while driving, characterized by simultaneous increases and decreases in MSA and MSD. This suggests a heightened focus on auditory information, at the expense of an ability to reorient attention. EEG microstates show a higher predictive capability for safety outcomes compared to task conditions, suggesting that EEG microstates can be used to measure how different drivers are affected differently by a given cognitively loading task. These findings contribute to our understanding of the neural dynamics involved in distracted driving, which can provide insights for policymaking related to phone use while driving, and can assist in evaluating the cognitive load induced by in-vehicle systems. A specific future work point that would be of interest, building on the cognitive control hypothesis, would be to use EEG microstates to predict safety outcomes in the types of situations which have been previously found to be most sensitive to cognitive load, i.e. complex driving situations where anticipatory information needs to be held in working memory (Baumann et al., 2008; Engström et al., 2017).

## Acknowledgements

This work is financially supported by the National Natural Science Foundation (72171017).

## References

Almahasneh, H., Chooi, W. T., Kamel, N., & Malik, A. S. (2014). Deep in thought while driving: An EEG study on drivers' cognitive distraction. Transportation research part F: traffic psychology and behaviour, 26, 218-226.

Alyan, E., Arnau, S., Reiser, J. E., Getzmann, S., Karthaus, M., & Wascher, E. (2023). Decoding eye blink and related eeg activity in realistic working environments. IEEE Journal of Biomedical and Health Informatics.

Baumann, M. R., Petzoldt, T., Groenewoud, C., Hogema, J., & Krems, J. F. (2008, April). The effect of cognitive tasks on predicting events in traffic. In Proceedings of the European Conference on Human Centred Design for Intelligent Transport Systems (pp. 3-11). HUMANIST: Lyon, France.

Borghini, G., Astolfi, L., Vecchiato, G., Mattia, D., & Babiloni, F. (2014). Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness. Neuroscience & Biobehavioral Reviews, 44, 58-75. http://doi.org/10.1016/j.neubiorev.2012.10.003

Bressler, S. L., & Menon, V. (2010). Large-scale brain networks in cognition: emerging methods and principles. Trends in Cognitive Sciences, 14, 277–290.

Britz, J., Van De Ville, D., & Michel, C. M. (2010). BOLD correlates of EEG topography reveal rapid resting-state network dynamics. Neuroimage, 52(4), 1162-1170.

Caird, J. K., Simmons, S. M., Wiley, K., Johnston, K. A., & Horrey, W. J. (2017). Does Talking on a Cell Phone, With a Passenger, or Dialing Affect Driving Performance? An Updated Systematic

Review and Meta-Analysis of Experimental Studies. Human Factors: The Journal of the Human Factors and Ergonomics Society, 60(1), 101-133. http://doi.org/10.1177/0018720817748145

Cetin, A. E., Gerek, O. N., & Yardimci, Y. (1997). Equiripple FIR filter design by the FFT algorithm. Signal Processing Magazine, 14(2), 60-64.

Chan, T. K., Chin, C. S., Chen, H., & Zhong, X. (2020). A Comprehensive Review of Driver Behavior Analysis Utilizing Smartphones. IEEE Transactions On Intelligent Transportation Systems, 21(10), 4444-4475. http://doi.org/10.1109/TITS.2019.2940481

Charles, R. L., & Nixon, J. (2019). Measuring mental workload using physiological measures: A systematic review. Applied Ergonomics, 74, 221-232. http://doi.org/10.1016/j.apergo.2018.08.028

Chikhi, S., Matton, N., & Blanchet, S. (2022). EEG power spectral measures of cognitive workload: A meta‐analysis. Psychophysiology, 59(6). http://doi.org/10.1111/psyp.14009

Conway, A. R., Kane, M. J., & Engle, R. W. (2003). Working memory capacity and its relation to general intelligence. Trends in cognitive sciences, 7(12), 547-552.

Deiber, M. P., Missonnier, P., Bertrand, O., Gold, G., Fazio-Costa, L., Ibanez, V., & Giannakopoulos, P. (2007). Distinction between perceptual and attentional processing in working memory tasks: a study of phase-locked and induced oscillatory brain dynamics. Journal of cognitive neuroscience, 19(1), 158-172.

Delorme, A., & Makeig, S. (2004). EEGLAB: An open-source toolbox for analysis of single-trial EEG dynamics. Journal of Neuroscience Methods, 134, 9-21.

Engström, J., Markkula, G., Victor, T., & Merat, N. (2017). Effects of Cognitive Load on Driving Performance: The Cognitive Control Hypothesis. Human Factors, 59(5), 734–764. https://doi.org/10.1177/0018720817690639

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. Behavior Research Methods, 41, 1149-1160.

Foy, H. J., & Chapman, P. (2018). Mental workload is reflected in driver behaviour, physiology, eye movements and prefrontal cortex activation. Applied ergonomics, 73, 90-99.

Frigo, M., & Johnson, S. G. (1998). FFTW: An adaptive software architecture for the FFT. In Proceedings of the International Conference on Acoustics, Speech, and Signal Processing (Vol. 3, pp. 1381-1384).

Friston, K. J., Price, C. J., Fletcher, P., Moore, C., Frackowiak, R. S., & Dolan, R. J. (1996). The trouble with cognitive subtraction. NeuroImage, 4(2), 97–104. https://doi.org/10.1006/nimg.1996.0033

Goodridge, C. M., Gonçalves, R. C., Arabian, A., Horrobin, A., Solernou, A., Lee, Y. T., Lee, Y. M., Madigan, R., & Merat, N. (2024). Gaze entropy metrics for mental workload estimation are heterogenous during hands-off level 2 automation. Accident; analysis and prevention, 202, 107560. Advance online publication. https://doi.org/10.1016/j.aap.2024.107560

Haghani, M., Bliemer, M. C. J., Farooq, B., Kim, I., Li, Z., Oh, C., ... & MacDougall, H. (2021). Applications of brain imaging methods in driving behaviour research. Accident Analysis & Prevention, 154, 106093. http://doi.org/10.1016/j.aap.2021.106093

IBM Corp. (2021). IBM SPSS Statistics for Windows, Version 28.0. Armonk, NY: IBM Corp.

Jang, J., Jung, A., Oh, C., Park, J., & Yun, D. (2024). Evaluating Driving Safety of Road Alignment Conditions by Predicted Driver's Psychophysiological Workload Using Vehicle Maneuvering Data. Transportation research record, 2678(5), 479-490.

Jensen, O., & Tesche, C. D. (2002). Frontal theta activity in humans increases with memory load in a working memory task. European Journal of Neuroscience, 15(8), 1395–1399. https://doi.org/10.1046/j.1460-9568.2002.01975.x

Kabilmiharbi, N., Khamis, N. K., & Noh, N. A. (2022). Commonly Used Assessment Method to Evaluate Mental Workload for Multiple Driving Distractions: A Systematic Review. Iranian Journal of Public Health, 51(3), 482.

Khanna, A., Pascual-Leone, A., Michel, C. M., & Farzan, F. (2015). Microstates in resting-state EEG: Current status and future directions. Neuroscience & Biobehavioral Reviews, 49, 105-113. http://doi.org/10.1016/j.neubiorev.2014.12.010

Klauer, S. G., Guo, F., Simons-Morton, B. G., Ouimet, M. C., Lee, S. E., & Dingus, T. A. (2014). Distracted driving and risk of road crashes among novice and experienced drivers. The New England Journal of Medicine, 370(1), 54–59. https://doi.org/10.1056/NEJMsa1204142

Koenig, T. (2017). EEGLAB microstate plugin. In Microstates EEGLAB. Retrieved from https://www.thomaskoenig.ch/index.php/software/microstates-in-eeglab/getting-started

Koenig, T., Lehmann, D., Merlo, M. C. G., Kochi, K., Hell, D., & Koukkou, M. (1999). A deviant EEG brain microstate in acute, neuroleptic-naive schizophrenics at rest. European Archives of Psychiatry and Clinical Neuroscience, 249, 205–211. http://dx.doi.org/10.1007/

Koenig, T., Prichep, L., Lehmann, D., Sosa, P. V., Braeker, E., Kleinlogel, H., ... & John, E. R. (2002). Millisecond by millisecond, year by year: Normative EEG microstates and developmental stages. NeuroImage, 16(1), 41-48.

Kong, X., Das, S., Zhou, H., & Zhang, Y. (2021). Characterizing phone usage while driving: Safety impact from road and operational perspectives using factor analysis. Accident Analysis & Prevention, 152, 106012. http://doi.org/10.1016/j.aap.2021.106012

Lehmann, D., Ozaki, H., & Pal, I. (1987). EEG alpha map series: Brain micro-states by space-oriented adaptive segmentation. Electroencephalography and Clinical Neurophysiology, 67, 271–288.

Lehmann, D., Pascual-Marqui, R. D., & Michel, C. M. (2009). EEG microstates. Scholarpedia, 4(3), 7632.

Lehmann, D., Skrandies, W. (1980). Reference-free identification of components of checkerboard-evoked multichannel potential fields. Electroencephalogr. Clin. Neurophysiol., 48, 609–621. http://dx.doi.org/10.1016/0013-4694(80)90419-8.

Li, G., Wu, X., Eichberger, A., Green, P., Olaverri-Monreal, C., Yan, W., ... & Li, Y. (2023). Drivers' EEG Responses to Different Distraction Tasks. Automotive Innovation. http://doi.org/10.1007/s42154-022-00206-z

Li, X., Yang, L., & Yan, X. (2022). An exploratory study of drivers' EEG response during emergent collision avoidance. Journal of Safety Research, 82, 241-250. http://doi.org/10.1016/j.jsr.2022.05.015

Mayer, R. E., & Moreno, R. (2003). Nine ways to reduce cognitive load in multimedia learning. Educational psychologist, 38(1), 43-52

Meehan, T. P., & Bressler, S. L. (2012). Neurocognitive networks: Findings, models, and theory. Neuroscience & Biobehavioral Reviews, 36, 2232–2247.

Michel, C. M., & Koenig, T. (2018). EEG microstates as a tool for studying the temporal dynamics of whole-brain neuronal networks: a review. Neuroimage, 180, 577-593.

Milz, P., Faber, P., Lehmann, D., Koenig, T., Kochi, K., & Pascual-Marqui, R. (2016). The functional significance of EEG microstates—Associations with modalities of thinking. Neuroimage, 125, 643-656.

Mognon, A., Jovicich, J., Bruzzone, L., & Buiatti, M. (2011). ADJUST: an automatic EEG artifact detector based on the joint use of spatial and temporal features. Psychophysiology, 48(2), 229–240.

Molina Del Río, J., Guevara, M. A., Hernández González, M., Hidalgo Aguirre, R. M., & Cruz Aguilar, M. A. (2019). EEG correlation during the solving of simple and complex logical–mathematical problems. Cognitive, Affective, & Behavioral Neuroscience, 19(4), 1036-1046. http://doi.org/10.3758/s13415-019-00703-5

Onate-Vega, D., Oviedo-Trespalacios, O., & King, M. J. (2020). How drivers adapt their behaviour to changes in task complexity: The role of secondary task demands and road environment factors. Transportation Research Part F: Traffic Psychology and Behaviour, 71, 145-156.

Patten, C. J., Kircher, A., Ostlund, J., & Nilsson, L. (2004). Using mobile telephones: Cognitive workload and attention resource allocation. Accident Analysis & Prevention, 36(3), 341–350. https://doi.org/10.1016/S0001-4575(03)00014-9

Peng, Y., Xu, Q., Lin, S., Wang, X., Xiang, G., Huang, S., ... & Fan, C. (2022). The Application of Electroencephalogram in Driving Safety: Current Status and Future Prospects. Frontiers in Psychology, 13, 919695. http://doi.org/10.3389/fpsyg.2022.919695

Puma, S., Matton, N., Paubel, P., Raufaste, É., & El-Yagoubi, R. (2018). Using theta and alpha band power to assess cognitive workload in multitasking environments. International Journal of Psychophysiology, 123, 111-120. http://doi.org/10.1016/j.ijpsycho.2017.10.004

Ryu, K., & Myung, R. (2005). Evaluation of mental workload with a combined measure based on physiological indices during a dual task of tracking and mental arithmetic. International Journal of Industrial Ergonomics, 35(11), 991-1009. http://doi.org/10.1016/j.ergon.2005.04.005

Seitzman, B. A., Abell, M., Bartley, S. C., Erickson, M. A., Bolbecker, A. R., & Hetrick, W. P. (2016). Cognitive manipulation of brain electric microstates. Neuroimage.

Siddiqui, S. V., Chatterjee, U., Kumar, D., Siddiqui, A., & Goyal, N. (2008). Neuropsychology of prefrontal cortex. Indian journal of psychiatry, 50(3), 202–208. https://doi.org/10.4103/0019-5545.43634

Simmons, S. M., Hicks, A., & Caird, J. K. (2016). Safety-critical event risk associated with cell phone tasks as measured in naturalistic driving studies: A systematic review and meta-analysis. Accident Analysis & Prevention, 87, 161-169. http://doi.org/10.1016/j.aap.2015.11.015

Stacey, J. E., Crook-Rumsey, M., Sumich, A., Howard, C. J., Crawford, T., Livne, K., ... & Badham, S. (2021). Age differences in resting state EEG and their relation to eye movements and cognitive performance. Neuropsychologia, 157, 107887.

Trammell, J. P., MacRae, P. G., Davis, G., Bergstedt, D., & Anderson, A. E. (2017). The relationship of cognitive performance and the theta-alpha power ratio is age-dependent: an EEG study of short term memory and reasoning during task and resting-state in healthy young and old adults. Frontiers in aging neuroscience, 9, 364.

Wackermann, J., Lehmann, D., Michel, C. M., & Strik, W. K. (1993). Adaptive segmentation of spontaneous EEG map series into spatially defined microstates. International Journal of Psychophysiology, 14, 269–283.

Wang, Y., Jung, T., & Lin, C. (2015). EEG-Based Attention Tracking During Distracted Driving. Ieee Transactions On Neural Systems and Rehabilitation Engineering, 23(6), 1085-1094. http://doi.org/10.1109/TNSRE.2015.2415520

Xiao, Y., Chou, C. C., Cosgrove, G. R., Crone, N. E., Stone, S., Madsen, J. R., Reucroft, I., Shih, Y. C., Weisholtz, D., Yu, H. Y., Anderson, W. S., & Kreiman, G. (2023). Cross-task specificity and within-task invariance of cognitive control processes. Cell reports, 42(1), 111919. https://doi.org/10.1016/j.celrep.2022.111919

Xu, J., Pan, Y., Zhou, S., Zou, G., Liu, J., Su, Z., ... & Gao, J. (2020). EEG microstates are correlated with brain functional networks during slow-wave sleep. Neuroimage, 215, 116786. http://doi.org/10.1016/j.neuroimage.2020.116786

Zarjam, P., Epps, J., & Chen, F. (2010). Evaluation of working memory load using EEG signals. In Proc. APSIPA Annual Summit and Conference (pp. 715-719).

Zhang, H., Guo, Y., Yuan, W., & Li, K. (2023). On the importance of working memory in the driving safety field: a systematic review. Accident Analysis & Prevention, 187, 107071.