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1 Cognitive load during driving: EEG microstate metrics are sensitive 2 to task difficulty and predict safety outcomes

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13
14 **Abstract:** Engaging in phone conversations or other cognitively challenging tasks while driving
15 detrimentally impacts cognitive functions and has been associated with increased risk of accidents.
16 Existing EEG methods have been shown to differentiate between load and no load, but not between
17 different levels of cognitive load. Furthermore, it has not been investigated whether EEG
18 measurements of load can be used to predict safety outcomes in critical events. EEG microstates
19 analysis, categorizing EEG signals into a concise set of prototypical functional states, has been used
20 in other task contexts with good results, but has not been applied in the driving context. Here, this gap
21 is addressed by means of a driving simulation experiment. Three phone use conditions (no phone use,
22 hands-free, and handheld), combined with two task difficulty levels (single- or double-digit addition
23 and subtraction), were tested before and during a rear-end collision conflict. Both conventional EEG
24 spectral power and EEG microstates were analyzed. The results showed that different levels of
25 cognitive load influenced EEG microstates differently, while EEG spectral power remained unaffected.
26 A distinct EEG pattern emerged when drivers engaged in phone tasks while driving, characterized by
27 a simultaneous increase and decrease in two of the EEG microstates, suggesting a heightened focus on
28 auditory information, potentially at a cost to attention reorientation ability. The increase and decrease
29 in these two microstates follow a monotonic sequence from baseline to hands-free simple, hands-free
30 complex, handheld simple, and finally handheld complex, showing sensitivity to task difficulty. This
31 pattern was found both before and after the lead vehicle braked. Furthermore, EEG microstates prior
32 to the lead vehicle braking improved predictions of safety outcomes in terms of minimum time
33 headway after the lead vehicle braked, clearly suggesting that these microstates measure brain states
34 which are indicative of impaired driving. Additionally, EEG microstates are more predictive of safety
35 outcomes than task difficulty, highlighting individual differences in task effects. These findings

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

3
4 **Keywords:** Cognitive load levels; EEG microstates; Safety-critical scenario; Driving simulation
5

6 **1 Introduction**

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

14 There has been an ongoing debate regarding the impact of high cognitive loads on driver safety.
15 Some studies argue that high cognitive load can be associated with increased arousal and compensatory
16 safety measures from the driver, such as increasing headway or reducing speed (Simmons et al., 2016;
17 Caird et al., 2017), while others demonstrate that excessive cognitive load leads to errors and impairs
18 driving performance. The result of this can be increased reaction times, impaired situational awareness,
19 and elevated accident risks (Klauer et al., 2014; Chan et al., 2020; Kong et al., 2021). These
20 inconsistent observations may be influenced by the varied adaptability of individuals to different task
21 conditions (Puma et al., 2018). In other words, different people might experience different cognitive
22 loads even when faced with the same task, leading to varied adjustments in behavior (Goodridge et al.,
23 2024). Therefore, gaining insights into how cognitive load influences safety outcomes can be better
24 achieved by directly measuring the cognitive load for each individual while driving, rather than relying
25 solely on behavioral performance (Borghini et al., 2014; Wang et al., 2015; Fan et al., 2022).

26 Mainstream objective measures for cognitive load include psychophysiological measurements
27 such as eye tracking, heart rate, and electroencephalography (EEG), which have been identified as
28 robust options for evaluating cognitive load (Charles & Nixon, 2019; Alyan et al., 2023). Among these
29 measures, EEG has proven advantageous due to its high temporal resolution and the ability of directly
30 representing the electrical activity of the brain, which offers a robust means of depicting the neural
31 dynamics associated with complex cognitive tasks (Zarjam, et al., 2010; Charles & Nixon, 2019; Peng
32 et al., 2022). This method complements behavioral analysis by offering a more direct and immediate
33 assessment of cognitive states. Furthermore, recent research has explored alternative methods for
34 evaluating drivers' cognitive load, such as using vehicle maneuvering data (Jang et al., 2024).
35

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

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

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

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

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

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

28 The objectives of this study were as follows:

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

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

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

1 2 Method

2 This study analyses EEG data from a previously conducted study reported by Xue et al. (2020).
3 In Sections 2.1-3 below, we describe the experimental methods relevant to the present study. Section
4 2.4 outlines the EEG data analysis method, and Section 2.5 introduces the statistical analysis used.

5 2.1 Participants and apparatus

6 Thirty-four participants (16 females, 18 males) completed the whole experiment with valid EEG
7 data collected. We performed a power analysis using G*Power (Faul et al., 2009), based on a medium
8 effect size (Cohen's $d = 0.5$), a significance level of 0.05, and a desired power of 0.95. The medium
9 effect size was chosen based on a series of cognitive load experiment reported by Mayer & Moreno
10 (2003), where the observed effect sizes were greater than 0.5. With these assumptions, the minimum
11 number of participants required was calculated to be 30, i.e., slightly less than our sample size. The
12 participants were middle-aged adults (between 32 and 40 years, mean = 34.3, S.D. = 4.6) to minimize
13 the potential confounding effects of age on cognitive load tasks (Trammell et al., 2017; Stacey et al.,
14 2021). All participants possessed a valid driver's license and had a minimum of two years' driving
15 experience. The experiment took about 30 mins, and each participant was compensated with RMB200
16 (approximately \$ 30) after completing the experiment. Approval was obtained from the ethics
17 committee of Beijing Jiaotong University.

18 We used the high-fidelity Beijing Jiaotong University (BJTU) driving simulator equipped with an
19 EEG system to collect simultaneous behavioral and EEG data (see **Fig.1**). The cabin of the simulator
20 is identical to a Ford Focus with a steering wheel, brake pedal, throttle and a real operational interface.
21 With a pre-view display system, the simulated environment is projected at a 300-degree field of view
22 with a resolution of 1400 * 1050 pixels on each screen. To create a fully immersive driving
23 environment, the simulator is also equipped with a vehicle dynamic simulation system, a linear motion
24 base capable of operation with one degree of freedom in the longitudinal direction, and an
25 environmental noise and vibration system. To acquire EEG data, the Neuroscan system with a
26 SynAmps2TM amplifier and a 64-electrode cap was used. The electrodes were laid out according to the
27 international 10–20 system. While collecting the EEG signals from the electrode cap, a computer
28 connected with the amplifier showed the data with the voltages of each electrode on the screen. This
29 alerted the experiment of any invalid data derived from errors with the cap adjustment. The EEG
30 signals were sampled at 1000 Hz.

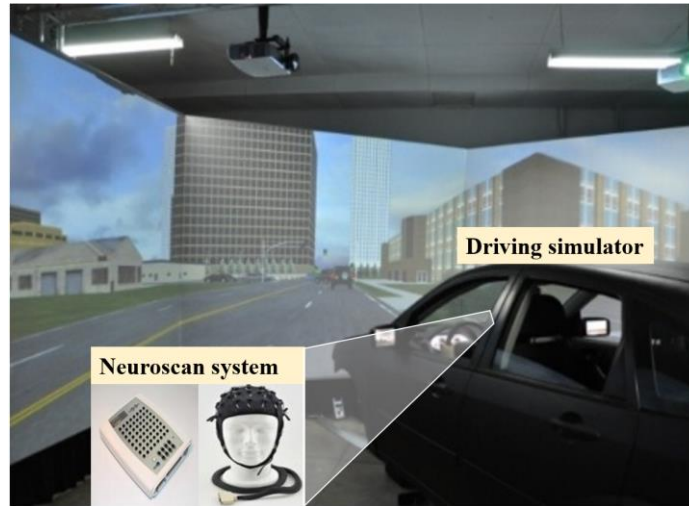


Fig. 1 Apparatus used for data collection.

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,

1 and they were triggered by sensors so that participants would drive under a similar mental workload
 2 in the same situation.

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

13
 14 The data analysis focused on two stages of this driving scenario, just before and just after the
 15 braking event: The *normal driving* stage refers to the last 6 seconds before the lead vehicle started
 16 braking. The *critical braking* stage refers to the time from the lead vehicle’s brake onset until the ego
 17 vehicle stopped braking, i.e., this stage included the entire collision avoidance process of the ego
 18 vehicle.

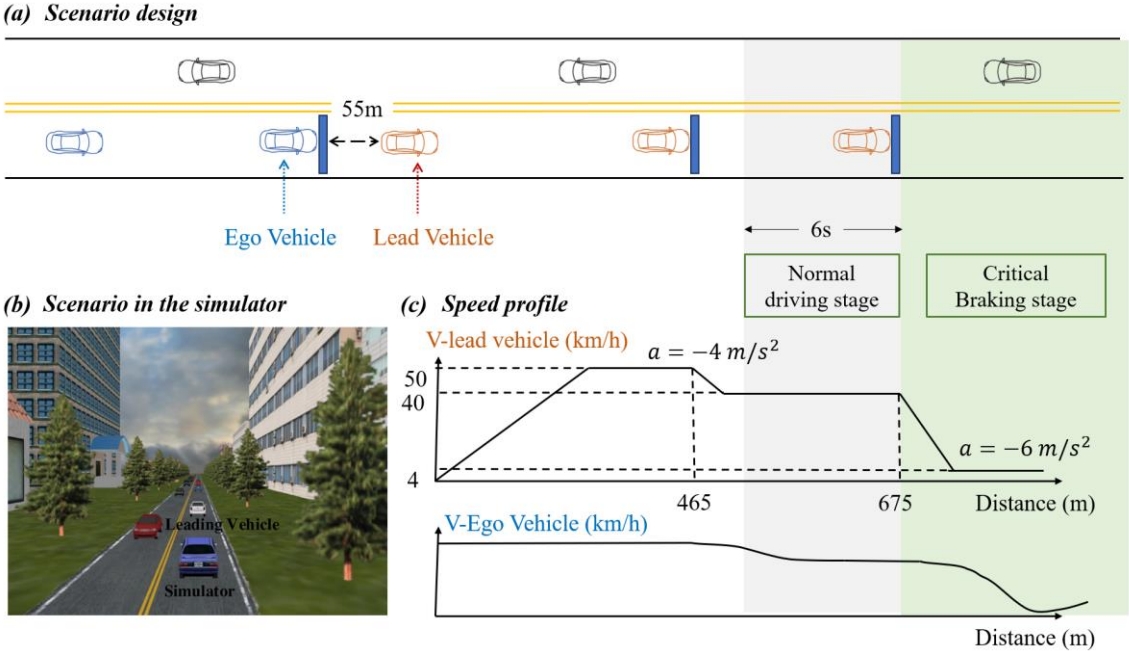


Fig. 2 Details of the experiment scenario.

21 2.3 Procedure

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

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

6 2.4 EEG data analysis

7 2.4.1 Preprocessing of EEG signals

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

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

19 2.4.2 EEG spectral power analysis

20 Based on the preprocessed artifact-free EEG data, Fast Fourier Transform (FFT, Frigo and
21 Johnson, 1998) with Hanning window was applied to convert the EEG signal from the time domain to
22 the frequency domain. This process decomposed the signal into individual frequency components,
23 revealing amplitude and phase details for each frequency band. Then band power was extracted by
24 integrating the frequency spectrum within specific frequency ranges. In this study, we mainly focus on
25 theta band (4 Hz – 7 Hz) given its dominance in reflecting cognitive states. The process of EEG spectral
26 power analysis is a standard method used in numerous previous studies (for a review, Haghani et al.,
27 2021).

28 2.4.3 EEG microstate analysis

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

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

$$3 \quad GFP(t) = \sqrt{\left(\sum_{n=1}^N (V_n(t) - \bar{V}(t))^2 \right) / N} \quad (1)$$

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

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

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

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

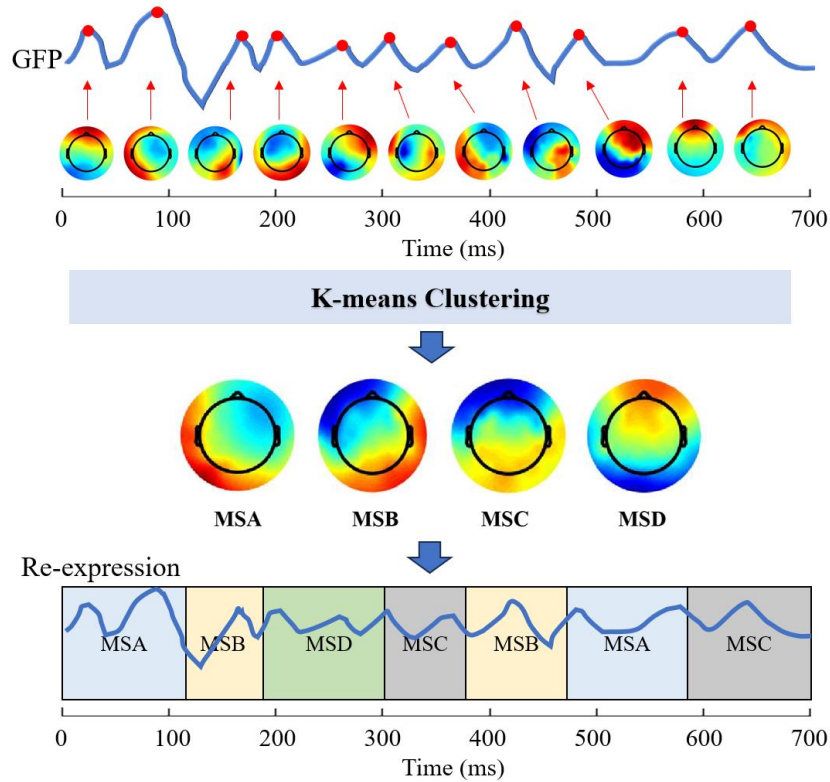


Fig. 3 Steps to get EEG microstates.

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.

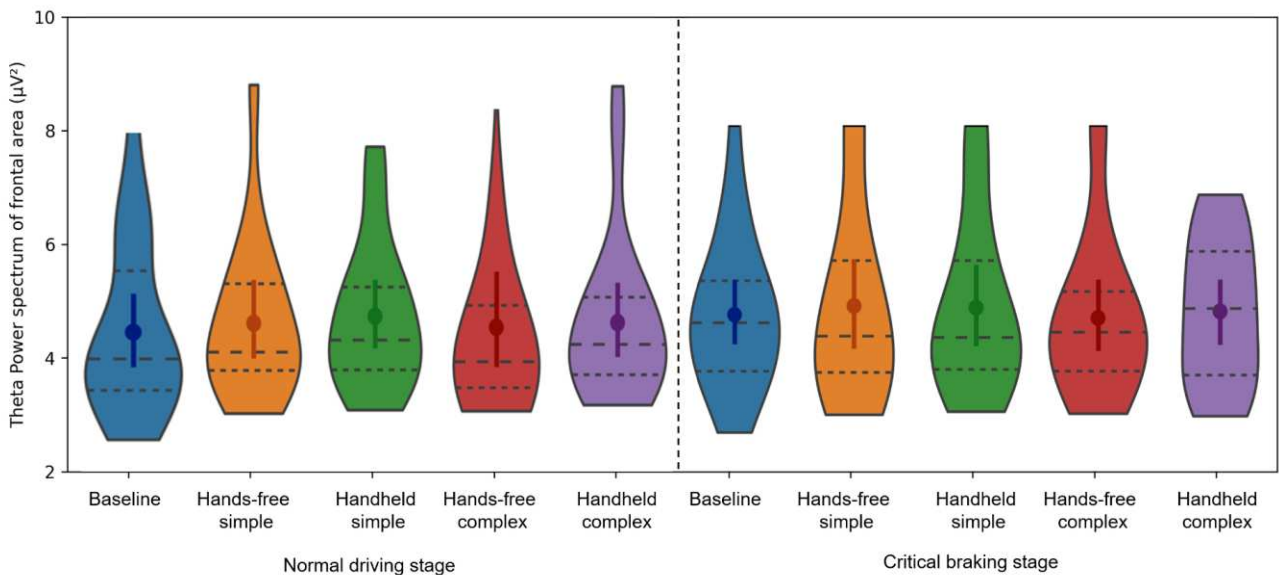
The Linear Mixed Model analyses served two purposes. Firstly, LMMs were fitted to examine the impact of various task conditions on EEG metrics (both the spectral power metrics and the

1 microstate metrics, which serve as the dependent variables in the LMMs). Secondly, LMMs were fitted
2 to quantify the relationship between pre-braking parameters and safety outcomes. In the latter analysis,
3 kinematic and EEG parameters from before the lead vehicle brake onset were used as the independent
4 variables, and the minimum time headway (MinTh) as the dependent variable. In the safety outcome
5 analysis, alternative models were tested, both with and without EEG metrics among the predictors, to
6 evaluate their contribution to the prediction of the minimum time headway outcome.

7 **3 Results**

8 3.1 Effects of phone use on EEG power

9 Effects of phone use on EEG power were tested in both the normal driving stage and the critical
10 braking stage. In the normal driving stage, drivers maintained a safe following distance behind the lead
11 vehicle, while in the critical braking stage, drivers were required to react promptly to the sudden
12 braking of the lead vehicle. **Fig. 4** depicts the observed EEG theta band power across task conditions,
13 during normal driving and critical braking stages, respectively. When drivers were in task conditions,
14 although there was a slightly higher theta power compared to baseline in normal driving stage, this
15 result was non-significant ($F = 1.21, p = 0.11$). Whereas in critical braking stage, the difference between
16 these four task conditions and the baseline is not significant ($F = 0.39, p = 0.43$).
17



18 Fig. 4 Frontal theta power during normal driving and critical braking stages.
19
20

3.2 Effects of phone use on microstates

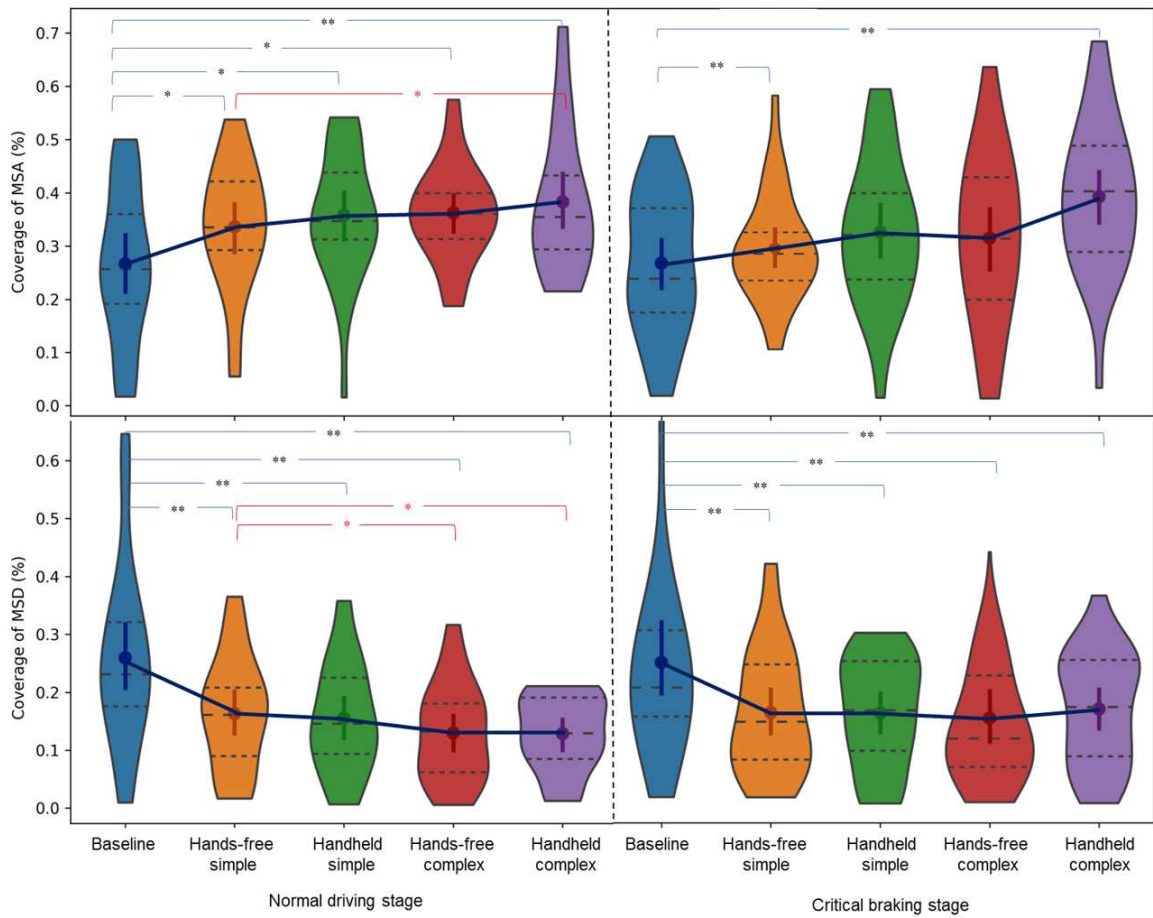
In this section, results from the impact of phone use tasks on EEG microstates and their statistical significance are reported. The occurrence, duration, coverage, and transition probability of EEG microstates were examined during normal driving and critical braking stages, respectively.

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.



1
2
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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.

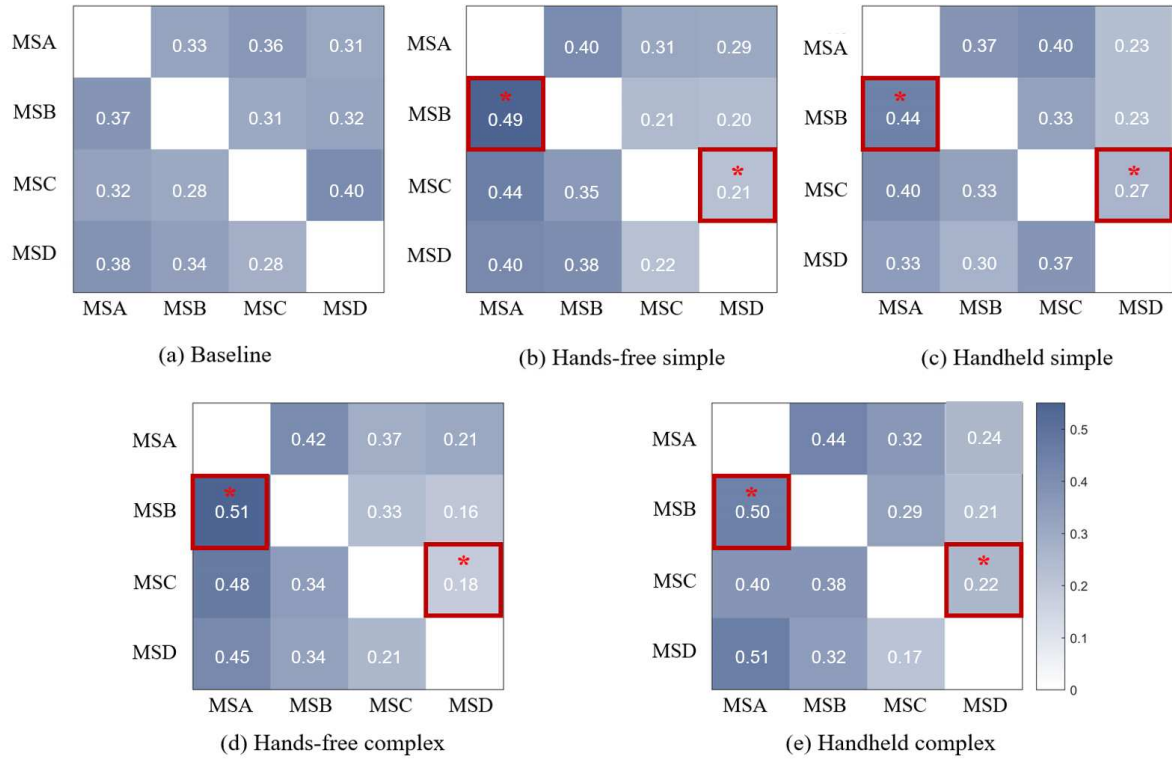


Fig. 6 Effects of phone use on microstates transition probability. The number in each cell is the transition probability from the vertical axis to the horizontal axis, and this probability is also indicated by the color of the cell. Darker colors indicate higher transition probabilities. The cells outlined 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_MS B	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_MS B	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_MS B	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

1 tasks had a significant impact on V_0 and H_0 , both of which increased under task conditions. However,
2 the influence of task conditions on MinTh was not statistically significant. This can be understood by
3 considering the relationships between these variables: MinTh is negatively correlated with V_0 and
4 positively correlated with H_0 (**Table 3**). Since both V_0 and H_0 increase under task conditions, their
5 opposing effects might counteract each other, resulting in no significant impact on MinTh.

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

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

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

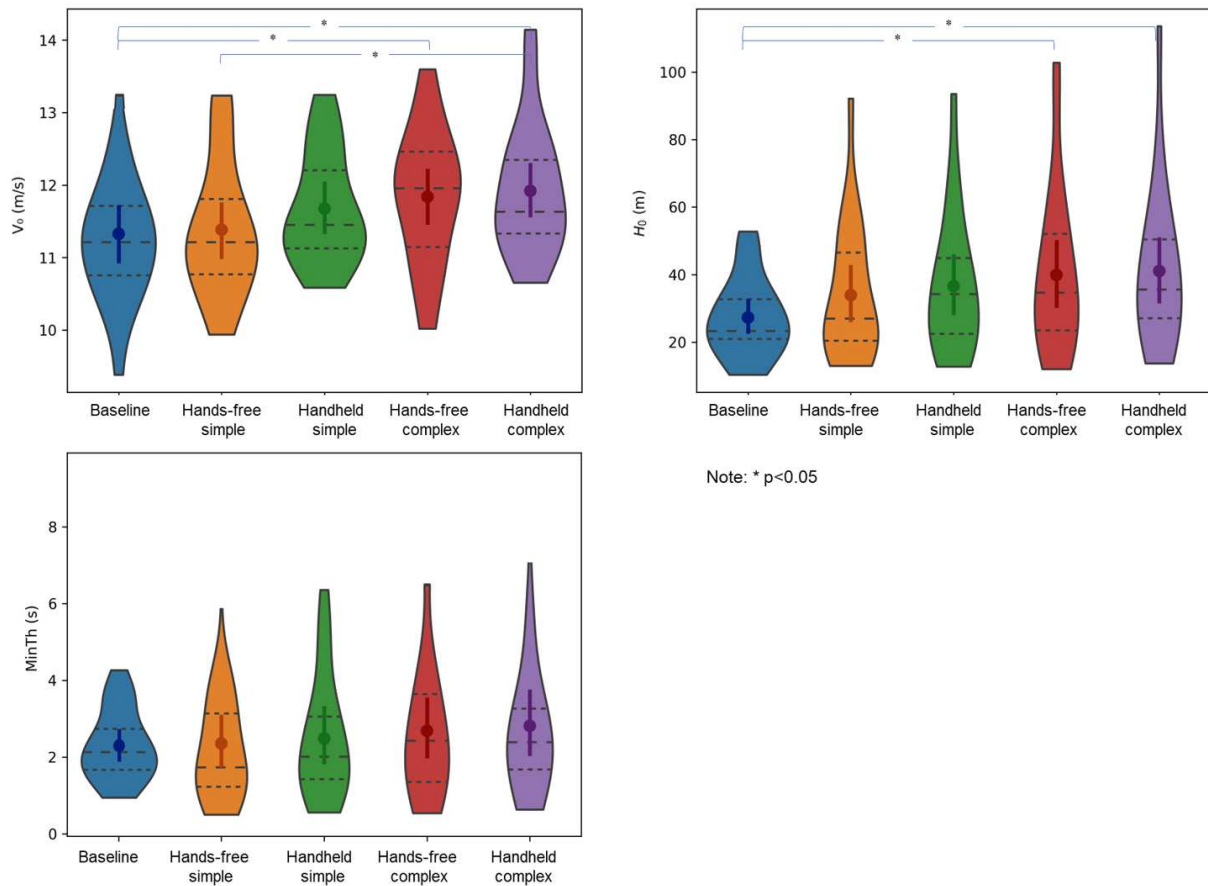


Fig. 7 The impact of task conditions on behavioral measures. Note: * $p < 0.05$.

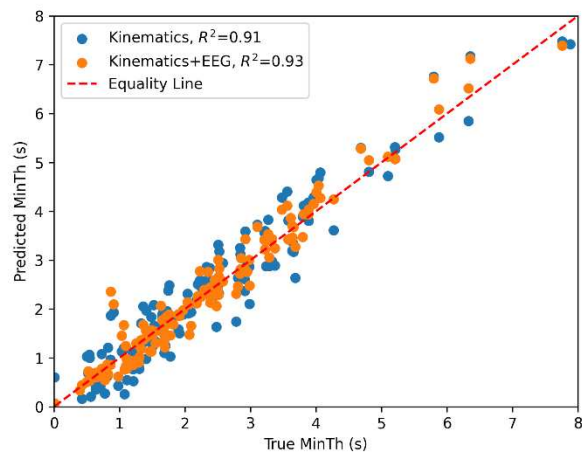


Fig. 8 Model performance.

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
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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

1 and MSA with auditory processing, this finding suggests that as drivers become more focused on
2 auditory information processing when using cell phones (associated with MSA increase), an
3 impairment of their attention reorientation ability is seen (as evidenced by MSD decrease; Milz et al.,
4 2016; Seitzman et al., 2016). These findings are in line with previous studies, suggesting that drivers
5 need to shift their attention to either problem solving, or driving rather than do these two tasks at the
6 same time (Wang et al., 2015). In addition, we found that the impact of cognitive load tasks in the
7 normal driving stage is much more significant compared to the critical braking stage. This is expected,
8 as the complexity of the critical scenario task might overshadow the impact of cell phone use,
9 prompting drivers to shift the focus of their attention to the driving task, to avoid a collision. Therefore,
10 during the critical braking stage, cognitive demands might be similar across different conditions.

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

30 4.2 EEG microstates help predict driving behavior

31 The efficacy of EEG microstates for predicting safety outcomes has also been shown in this study.
32 When EEG microstates were added along with the kinematic measures in a predictive model, MSA
33 coverage was a statistically significant predictor of minimum time headway, improving the predictive
34 performance compared to using only kinematic data. An interesting finding is that to the same was not
35 true when instead adding task conditions as a predictor to the model. In other words, having
36 information about a participant's EEG microstates was more informative about safety outcomes than

1 having information about which task the participant was doing. This could be attributed to individual
2 characteristics, which means that different people might experience different amounts of distraction
3 even when performing the same task (Borghini et al., 2014). When we use task conditions in the model,
4 the details of how much cognitive load each individual is undergoing is unknown. However, our results
5 suggest that by measuring microstates, we gain a more direct insight into the level of cognitive load
6 experienced by each participant. Therefore, changes in EEG microstate measures provide a more
7 accurate reflection of how distracted individuals truly are, surpassing the information obtained solely
8 from knowing which task they are performing.

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

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

1 4.3 Possible explanations for EEG power results

2 In this study, changes of theta band power were not significantly different between different task
3 conditions, and also not so between the baseline and task conditions. This finding differs from some
4 previous EEG studies conducted during driving tasks, which report statistically significant effects on
5 theta power but typically with simpler primary driving tasks, such as free driving (Almahasneh et al.,
6 2014) and simple car-following (Li et al., 2023). The discrepancy between our studies could be
7 attributed to the more complex and demanding nature of safety-critical driving scenarios used here. In
8 these scenarios, drivers are primarily focused on collision avoidance, which may overshadow the
9 impact of phone use conditions on EEG power. According to Friston et al. (1996), the brain operates
10 through interactions among the cognitive components of a task, and altering one cognitive component
11 impacts other cognitive components. This suggests that the addition or subtraction of a cognitive
12 element within the task does not directly lead to a linear increase or decrease in brain activity; rather,
13 it entails more intricate interactions within the brain. Xiao et al. (2023) also showed that cognitive
14 control involves the complex interplay between multiple sensory inputs with task-dependent goals
15 during decision making. These studies support the notion that the impact of phone use conditions on
16 EEG power might be overshadowed by the concurrent engagement of other cognitive control processes
17 in safety-critical driving. Another possible reason for the lack of significant differences in theta power
18 might be the ceiling effect. This is supported by Chikhi et al. (2022), who found that performing two
19 tasks concurrently might not be associated with an increase in theta power, even though performing
20 one task is. This is because the theta power may already be high in the single-task condition (in our
21 case, baseline driving), with minimal increase observed during the dual-task condition (in our case,
22 driving while cognitively loaded).

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

28 **5 Conclusion**

29 This study investigated the influence of different levels of cognitive load on EEG performance in
30 safety-critical driving scenarios. The influence of three phone use conditions (no phone use, hands-
31 free, and handheld), along with two task conditions (single- or double-digit addition and subtraction),
32 were evaluated both before and during a rear-end collision conflict. EEG power and microstate
33 measures were analyzed, and the latter showed a better performance in capturing cognitive load
34 variation. A distinct EEG microstate pattern emerged when drivers were engaged in cell phone tasks
35 while driving, characterized by simultaneous increases and decreases in MSA and MSD. This suggests

1 a heightened focus on auditory information, at the expense of an ability to reorient attention. EEG
2 microstates show a higher predictive capability for safety outcomes compared to task conditions,
3 suggesting that EEG microstates can be used to measure how different drivers are affected differently
4 by a given cognitively loading task. These findings contribute to our understanding of the neural
5 dynamics involved in distracted driving, which can provide insights for policymaking related to phone
6 use while driving, and can assist in evaluating the cognitive load induced by in-vehicle systems. A
7 specific future work point that would be of interest, building on the cognitive control hypothesis, would
8 be to use EEG microstates to predict safety outcomes in the types of situations which have been
9 previously found to be most sensitive to cognitive load, i.e. complex driving situations where
10 anticipatory information needs to be held in working memory (Baumann et al., 2008; Engström et al.,
11 2017).

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