Mental workLoad Accumulation Effect of Mobile Phone Distraction in L2 Autopilot Mode

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Research Article

Keywords: Distracted Driving, Mobile Phones, Autopilot, Mental Load, Electroencephalography (EEG)

Posted Date: January 12th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1209327/v1

Abstract

As self-driving vehicles become more common, there is a need for precise measurement and definition of when and in what ways a driver can use a mobile phone in autonomous driving mode, for how long it can be used, the complexity of the call content, and the accumulated psychological load. This study uses a 2 (driving mode) * 2 (call content complexity) * 6 (driving phase) three-factor mixed experimental design to investigate the effect of these factors on the driver's psychological load by measuring the driver's performance on peripheral visual detection tasks, pupil diameter, and EEG components in various brain regions in the alpha band. The results showed that drivers' mental load levels converge between manual and automatic driving modes as the duration of driving increases, regardless of the level of complexity of the mobile phone conversation. This suggests that mobile phone conversations can also disrupt the driver's cognitive resource balance in automatic driving mode, as it increases mental load while also impairing the normal functioning of brain functions such as cognitive control, problem solving, and judgment, thereby compromising driving safety.

1. Introduction

The use of mobile phones while driving is a widespread phenomenon, with various countries banning the use of mobile phones for talking while driving and drivers and the public becoming aware of the negative effects of mobile phone use while driving, yet the proportion of drivers using mobile phones while driving is still increasing every year (WHO, 2018). Mobile phone conversations contribute to reduced driving performance and increased crash probability in a number of ways (e.g. increased cognitive load on drivers, longer reaction times to events, etc.) (Caird et al., 2008; Athley et al., 2014;Saxby et al., 2017)

At the same time, despite the popularity of self-driving vehicles, there are no clear legal regulations in these countries regarding whether the use of mobile phones is allowed while driving smart vehicles. Current laws and regulations in the field of autonomous driving only govern the manufacturing technology of self-driving vehicles, the public road testing of self-driving vehicles, and the systems of ethical reasoning when conducting autonomous driving. For example, safety assessment standards for self-driving vehicles are limited within each state in the US, China has clear requirements for road specifications for testing self-driving vehicle technology, and the UK and Australia require drivers to be ready to take over and control the vehicle. (Geroge et al., 2021) The American Society of Automotive Engineers and the National Highway Traffic Safety Administration have defined six levels of autonomous vehicles from L0 to L5, based on the level of vehicle automation (SAE, 2014). The most widespread vehicles on the market today are those with L2 level of driving, also known as 'Partly automated driving', which combines both longitudinal and lateral control of the vehicle and is represented by the vehicle's adaptive cruise control (ACC) and lane center assist. L2 autonomous driving systems require the driver to continuously monitor road hazards and be ready to take over the vehicle at all times.

Rudin-Brown and Praker (2004) showed that when drivers used adaptive cruise control (ACC), they were more likely to engage in secondary tasks (e.g., making phone calls, using the radio, etc.) and they took

longer to detect hazards than when they did not use the ACC system. Llaneras et al. (2013) found that when drivers used L2 automated driving systems while engaged in secondary tasks, the duration of the driver's vision away from the road ahead increased. Research by Gasper (2019) et al. also confirms that with the use of automated driving systems, drivers will develop longer visual disengagement, spend more time with their eyes on the in-vehicle dashboard and on in-vehicle aids such as operating screens, and require longer times to take over the automated vehicle compared to traditional manual driving, with increased reaction time. These studies suggest that driver engagement in distracting tasks during L2 level driving can have a range of negative effects on driver performance. Therefore, there is a need to precisely measure and define when and in what manner drivers can use mobile phones in automated driving mode, how long they can continue to do so, as well as the complexity of the calls and the accumulated mental load, in order to provide a theoretical basis for the development of a system to regulate and classify mobile phone use in automated driving mode.

1.1 Indicators for testing the psychological load of drivers

The main methods of monitoring drivers' mental load include subjective assessment (mental load), Peripheral Detection Tasks (PDT), eye tracking, and EEG measurements. Peripheral visual detection methods assume that as drivers' mental load increases, their remaining attentional resources are significantly reduced, thus prioritizing the efficiency of central visual field gaze at the expense of attentional input from the peripheral visual field, and therefore leading to a reduction in correct target detection and increased reaction time in the peripheral visual field (Olsson et al., 2000). Other researchers have used pupil diameter to measure driver mental load (Marquart, Cabrall & de Winter, 2015), which is particularly sensitive to high levels of mental load and is a valid indicator of driver distraction (Caffier Erdmann & Ullsperger, 2003).

Changes in drivers' electrical brain activity (Electroencephalo-graph, EEG) can also be a useful indicator of their distracted state and mental load, and electroencephalographic component (EEG) measurements are the most effective means used to detect driving distractions.(Lin et al., 2009;Wang et al., 2014)Brookhuis and Waard et al. (2014) used a driving simulator to test drivers' driving performance in different road environments and recorded their ECG and EEG signals, and found that the alpha band of the EEG signal correlated well with drivers' mental load, with a significantly lower alpha wave band power spectrum at higher mental load(Klimesch et al.,1999). A study by Hossam Almahasneh (2014) et al. examined the effects of different cognitive tasks (mathematical calculations and decision problems) on driver cognitive state. It was found that the area most affected during distracted driving was the right frontal cortex region, and that activation of the right frontal cortex region was effective in examining the driver's cognitive distraction state. Additionally, changes in the right frontal alpha band may also be a better indicator, which needs to be further validated in future studies (Lin et al., 2011).

At the same time, monitoring the driver's attention-related brain resources remains a challenge for researchers in the field of cognitive brain research and human-computer interaction. (Lin et al., 2011) Frontal regions are known to be involved in impulse control, judgement, language production, working

memory, motor function, and problem solving. (Burgess et al., 2000) Activation of frontal areas is induced by the performance of mental tasks. In turn, power changes in frontal areas represent the degree of activation of intrinsic neurons when individuals allocate their attention to different task stimuli. (Missonnier et al., 2006) The prefrontal cortex in frontal areas has also been thought to play an important role in cognitive control, i.e. the coordination of thoughts and actions according to internal goals. (Miller et al., 2001) Therefore, the detection of EEG changes during a driver's mobile phone call is expected to further uncover the hazards and effects on various brain regions.

Based on the above literature review, this study used a multimodal detection method to simultaneously measure drivers' peripheral visual detection task performance, pupil diameter and EEG components across brain regions in the alpha band to comprehensively assess drivers' psychological load in both automated and manual driving conditions. This will provide guidance suggestions for the development of an EEG-based distraction detection and intervention system for drivers' mobile phones.

1.2 Effects of mobile phone distraction on driver psychological load in autonomous driving mode

Many studies have shown that drivers tend to use their mobile phones during the use of automated driving systems (Mcdonanetal et al., 2018). A study by Noble et al. (2021) found that drivers frequently engaged in high-risk secondary tasks (e.g., browsing their mobile phones, dialing numbers with their phones in hand, using their mobile phones for location, etc.) in L2-level autonomous driving mode, thereby prolonging the time their eyes are off the road. Banks et al. (2018) found that some drivers even took their hands off the steering wheel for up to 11 seconds while using their mobile phones in L2 autonomous driving mode. These studies all suggest that drivers are prone to mobile phone distractions during automated driving.

It has also been shown that drivers attempt to increase the mental load in monotonous environments to control their increasing levels of passive fatigue. Young and Stanton, in a summary of the extensive literature, defined mental load as the amount of attentional resources people give to meet objective and subjective performance criteria, which is related to task demands, external support, and the individual's experience (Dick De Waard et al., 1996). For example, Neubauer's (2012) study showed that using a mobile phone and doing something unrelated to the driving task while in the car was effective in maintaining driver engagement during autonomous driving. A study by Paul Atchley (2014) found that strategic language tasks improved driver performance and alertness during fatigue. This suggests that the additional load imposed by mobile phone conversations may be beneficial to drivers in reducing passive fatigue and helping to maintain their alertness.

However, when drivers are driving for long periods of time and are already actively fatigued, short-term strategies to increase task load and arousal levels are unlikely to have much benefit in terms of active fatigue relief. In fact, when fatigued drivers engage in mobile phone conversations, these conversations and fatigue superimpose to crowd attentional channels and the driver's psychological load increases, resulting in a cumulative effect (Regan et al., 2009). Saxby et al. (2017) showed that mobile phone

conversations do not counteract fatigue induced by autonomous driving and that mobile phone conversations in a state of passive fatigue may further impair driver driving performance. However, this study only measured driver fatigue from a subjective rating perspective and did not differentiate driver fatigue levels by stage, nor did it differentiate the complexity of the content of mobile phone calls, and therefore could not provide targeted guidance on policy recommendations for mobile phone use regulations under autonomous driving conditions.

1.3 Impact of mobile phone call task complexity on driver psychological load

Research has found that the degree of difficulty (task complexity) or emotionality of a driver making a mobile phone call while driving can affect the driver's cognitive demands, which may distract the driver from the driving task. (Horrey & Mary, 2017)

Current research on the effects of mobile phone conversation task complexity on drivers' psychological load can be broadly divided paradigmatically into two categories: computational reasoning-type tasks, represented by similar tasks such as logical reasoning and mathematical calculations, and naturalistic contextual or emotional mobile phone conversation tasks. In a study by Shinar et al. (2005), it was found that drivers performing logical reasoning tasks reduced driving performance to a greater extent than engaging in conversations involving emotional relevance. The advantages of this type of task are that the experiment is well controlled, the difficulty is clearly quantified, and the experiment is more effective. However, the disadvantage is that they lack ecological validity and are difficult to generalize to everyday contexts.

Another category of naturalistic contextual or emotional phone conversation task is more reductive to real driver phone conversation content. A study by AL-Tarawneh (2004) et al. found that a recall-type phone conversation task (representing complex call content) had a much higher response latency effect on visual targets than having a simpler everyday conversation. Although the ecological validity of this type of task is high, subsequent studies are difficult to replicate, for example, Rakauskas and his colleagues (2004) used a call task in a naturalistic context to investigate the relationship between call difficulty and driver distraction. The results showed that although mobile phone use reduced driving performance, the level of call difficulty did not have a significant effect on average speed, driving performance, or psychological load. The reason for the inconsistency of this study's results with other similar studies may be that conversations in natural contexts require less cognitive load than the verbal reasoning and mathematical tasks used in other studies, and therefore the effect of increased difficulty of call content is less sensitive to driving performance. All of the above studies suggest that the effect of naturalistic contexts or emotional mobile phone call content on driving performance is limited and dependent on the experimenter's control over the difficulty of the call task. Based on these considerations, the present study selected call content related to logical reasoning to examine the effects of mobile phone distractions on driver performance on mental load and vigilance detection tasks.

In addition to the difficulty of mobile phone call content, another difficulty in the development of laws and regulations regarding the use of mobile phones for autonomous driving is the determination of call duration. The question of how long a call is beneficial for the mitigation of passive fatigue in autonomous driving mode is also a focus that this study explores. A recent study shows that the first 40 minutes of a driving task under monotonic autonomous driving conditions is a critical period for passive fatigue to develop (Zhang et al., 2021), and we thus envisage whether the driver underload problem would be alleviated if mobile phone call content is imposed during the first 40 minutes of a monotonic autonomous driving task, and as the driving duration increases, we ask whether the amount of load caused by mobile phone calls during autonomous driving differs from that of manual driving. This study thus uses a 2-(driving mode: automatic driving group, manual driving group)*2 (call content complexity: simple call content group, complex call content group)*6 (driving phase: 6 phases) three-factor mixed experimental design to examine the effects of driving mode, call content difficulty, and driving phase on driver psychological load. The following hypotheses were proposed:

During the initial phase of driving (within 40 minutes), the EEG alpha wave power values were higher in the autopilot simple talk content group than in the manual simple talk content group and tended to increase. In contrast, the EEG alpha power values in the frontal area of the autopilot complex talk content group gradually decreased. When the driving time was 60 minutes, the EEG alpha power values of mobile phone calls in the autopilot mode did not differ from those of the manual driving group.

During the initial phase of driving (within 40 minutes), when drivers were making mobile phone calls, the PDT detection response task reaction time was slower in the manual driving group than in the automatic driving group, and the PDT detection response task correctness rate was lower in the manual driving group than in the automatic driving. As the driving time increased (around 60 minutes), the PDT detection response time became slower and the correctness rate decreased in the automatic driving group, and their task performance converged with that of the manual driving group.

During the initial phase of driving (within 40 minutes), the pupil diameter was smaller in the autopilot simple talk content group than in the manual driving group. When driving for 60 minutes, there was no significant difference between the pupil diameter of the autopilot group and the manual driving group.

2. Methods

2.1 Participants

Recruiting 58 college student novice drivers with driving licenses in Dalian, 29 male and 29 female. The age range was 20-30 years (*M*=22.03, *SD*=2.08), the driving experience range was 1-5 years *(M*=1.85, *SD*=1.56) and the mileage range was 1-1000 km (*M*=329.41, *SD*=402.105). Eyeglass wearers were also questioned and were asked to participate in the experiment with both right and left eye prescriptions controlled to less than 200 degrees and without problems such as astigmatism. The subjects were randomly assigned to 15 subjects in the automatic driving mode simple talk group (AS), 15 in the

automatic driving mode difficult talk group (AC), 14 in the manual driving mode simple talk group (MS) and 14 in the manual driving mode complex talk group (MC). The EEG data of 5 subjects were excluded due to a large number of artefacts caused by large head movements and the EEG data were not collected in full at some electrode sites. The final EEG data were valid for 53 subjects, 58 for driving performance and 58 for pupil diameter. Subjects were asked to refrain from drinking alcoholic or caffeinated beverages 24 hours prior to the experiment, to get enough sleep the day before the experiment, and were given a reward at the end of the experiment.This study was approved by the Ethics Committee of Liaoning Normal University and was performed in accordance with the approved guidelines and the Declaration of Helsinki. All the participants provided written informed consent before participating, and known their identifying images will publication in an online open-access.

2.2 Experimental design

The experimental design was a 2 (driving mode: automatic driving group, manual driving group)*2 (call content difficulty: simple call content group, complex call content group)*6 (driving stages: 6 stages) three-factor mixed experimental design. The driving phases were evenly divided according to the driving duration of 1 hour into 6 phases, with 0-10 minutes as the first phase, 10-20 minutes as the second phase, 20-30 minutes as the third phase, 30-40 minutes as the fourth phase, 40-50 minutes as the fifth phase, and 50-60 minutes as the sixth phase. The driving mode and call content difficulty are between-subject factors, the driving phase is a within-subject factor, and the dependent variable is the driver's workload level, as indicated by the power of each brain region in the EEG *alpha* wave, the duration of the detection response task, the correct rate of the detection response task, and the pupil diameter size.

2.3 Experimental materials

2.3.1 Mobile phone call task design

The content of the mobile phone call task is designed to distract the driver sufficiently to cause distraction and increase the driver's workload. Mobile phone call tasks are designed for two levels of difficulty: simple and complex, and Rakauskas(2012) study suggests that the difficulty of mobile phone call content is differentiated by the level of cognitive load on the driver. The naturalistic nature of the conversation involving driver memory and recollection is considered simple, while arithmetic problems involving logical reasoning, calculation, or verbal confusion are considered difficult.

In the talk task, participants were asked to provide appropriate answers after listening to the complete question. The questions in the simple talk task were designed based on Burns' (2002) talk task. The questions asked in the simple talk task were conversational in nature in a natural context, e.g., "What is your favorite color?". The simple call task was ten questions. The complex call task, on the other hand, was designed based on the call task of Peng et al. (2014). Some arithmetic questions or some verbal confusion (requiring participants to reason logically) questions were presented to participants, e.g. "If Kris is younger than Albert and Albert is younger than Sam, then who is the youngest?" The complex call task was also a ten-question task.

The call task was played back to the participant in the form of a hands-free mobile phone (JBL wireless Bluetooth audio) during the experiment, and the subjects were asked to answer the call content question as soon as they heard it. The duration of the experiment was 60 minutes, divided equally into six phases, each phase being three minutes in length of the mobile phone call.

2.4 Driving duties

This experiment used the Xuan Ai QJ-3A1 (small) driving simulator with constituent components such as a seat belt, steering wheel, instrument panel, transmission lever, parking brake operating lever, brake pedal, and accelerator pedal, which accurately replicates the interior of a small motor vehicle cab. See Figure 1. This study kept the cognitive load low during driving with few stimuli and low driving task difficulty. A daytime, sunny urban roadway was used as the simulated driving scenario. In the manual driving mode, subjects were asked to follow the vehicle in front of them normally, travel at a speed of no more than 120km/h and maintain a safe distance (no less than 100m) from the vehicle in front of them at all times while driving. The subjects were also asked to perform a detection response task presented randomly by the screens on both sides of the driving simulator, i.e. to brake in response to a picture of a pedestrian appearing on the screen, with a randomized presentation time of between 60±40s.

In automatic driving mode, the driver was not required to steer or apply the brakes. The brakes needed to be applied only to perform the task of detecting a response, and the other experimental conditions were the same as in manual driving mode.

2.5 Pupil diameter measurement

This experiment used a head-mounted Tobii Pro Glasses II eye-tracking system (Tobii Pro Glasses II, Sweden) to record eye movement data, which allowed free head movement. The oculomotor was sampled at a frequency of 50 Hz and had an accuracy of 0.5°. The subjects' eye movement data was collected and analyzed using Tobii Studio 3.0. Pupil diameter data was mainly collected from the subjects.

2.6 Experimental procedure

2.6.1 Experimental preparation stage

To briefly introduce the procedure, the subject was given an EEG and eye-tracking device and asked to fill in basic information, including age, gender, driving age, and education level. To ensure that the subjects were familiar with the procedure, they were first provided with verbal instructions to practice using the simulator for 3-5 minutes, which included using the simulator equipment, giving braking responses to random event stimuli on the screens on both sides of the simulator, and answering talking questions played on the audio to ensure that the subjects learned how to use it.

2.6.2 Application phase

Subjects performed a 60-minute driving task and completed a call task of the corresponding group difficulty based on the assigned group. During the experiment, the driver was required to complete a peripheral visual detection response task in which 50 bursts appear randomly on both sides of the driving simulator screen, with each burst appearing at a random location and at random intervals to avoid expectation effects on the subject. The driver's eye movements and EEG data were also recorded.

At the end of the formal experiment a fee was given to the subject to verbally ask about the problems encountered in the driving simulation and the psychological situation, and to thank the subject for participating.

2.7 EEG data acquisition

The experiments were conducted using a 64-lead EEG instrument to acquire EEG data in real time, using a sampling rate of 2000 Hz to amplify and digitize the signals. The international 10-20 electrode system was used to arrange the electrode positions, with the CPz electrode as the reference electrode and the AFz electrode as the ground electrode. The resistance of all electrodes was less than 10KΩ.

2.8 EEG data pre-processing

According to the principle of resting EEG data preprocessing30, after filtering the continuous EEG data between 0.5 and 30 Hz, the EEG data of each participant during the simulated driving process were divided into six parts, corresponding to stage 1–6, respectively. Each phase lasted about 10 minutes, and the sampling rate was reduced to 250 Hz. EEG data were referenced to the average of both mastoids (M1,M2). The Independent Component Analysis (ICA) algorithm was used to correct the part of the data contaminated by eye movement or electromyography (EMG) data or by any other non-physiological diseases.

2.9 Power computation

For each participant, the pre-processed continuous EEG data were segmented into dozens of epochs, with epoch length of 2000 ms. Then the 61-channel segmented epochs were transformed to the frequency domain based on Fast Fourier transforms (FFTs) using a Hamming window with a 50% overlap, yielding FFTs ranging from 0.5 to 30 Hz with a frequency resolution of 0.5 Hz31. The power spectrum of each frequency point was averaged over the epochs. Previous studies indicated that EEG algorithm alphas showed larger increases as fatigue increased10. The power of alpha bands were the largest in parietal lobe and the power of each band was distributed symmetrically between the left hemisphere and the right hemisphere25. Therefore, this study selected the P3, Pz, P4 electrode data to implement the difference tests. Single-subject EEG spectra were averaged across subjects in each group in order to obtain group-level EEG spectra.

According to Brookhuis and Waard et al. (2014), the alpha band of the EEG signal was found to correlate well with the mental load of the driver. Accordingly, the EEG power in the alpha (8-13 Hz) band was calculated and the workload in five specific brain regions was examined and explored according to the

electrode positions corresponding to different brain regions: frontal, F3, Fz, F4; temporal, T7, T8; parietal, P3, Pz, P4; occipital, O1, Oz, O2; and prefrontal, Fp1, Fpz, Fp2.

3. Results

3.1 Results of power analysis of each brain region in the EEG alpha wave band

The single-subject EEG spectra were averaged across subjects in each group in order to obtain the group-level EEG spectra. The alpha (8–13 Hz) power topographies were displayed as four groups and six stages (Figure 2).

3.1.1 EEG prefrontal area power analysis results

Repeated-measures ANOVA tests were conducted with driving pattern and call content complexity as between-subject variables, measurement phase as within-subject variables, and alpha wave prefrontal area EEG power values as dependent variables, with Greenhouse-Geisser correction for p-values that did not satisfy the spherical hypothesis variables. Results showed a significant main effect of call content complexity $F(1, 49) = 5.507$, $p = 0.029$, $\eta p^2 = 0.094$, a significant interaction of stage with call content complexity, $F(1, 49) = 7.880$, $p = 0.007$, $\eta p^2 = 0.139$, and a significant interaction of stage with driving mode, $F(1, 49) = 7.979$, $p = 0.007$, $\eta p^2 = 0.140$). The interaction between stage, call content complexity, and driving mode was significant, $F(1, 49) = 8.234$, $p = 0.006$, $\eta p^2 = 0.144$. A simple effect test demonstrated that in automatic driving mode, there was a significant difference in brain power values in the alpha wave prefrontal area of the driver in the first stage as the difficulty of the call content varied ($p = 0.02$). In manual driving mode, driver workload levels differed significantly in stage 2 (p=0.000) and stage 3 (p=0.015) as the difficulty of the call content varied. There was a tendency for the difference to be significant in stage five (p=0.066).

For simple calls, there was a significant difference in driver workload levels in the second stage in different driving modes (p=0.006). No difference in driver workload was observed in different driving modes when complex calls were made.

Apart from this, the main effect of driving mode was not significant $F(1, 49) = 0.057$, $p = 0.812$, $\eta p^2 = 0.001$. The interaction between driving scenario and driving mode was not significant $F(1, 49) = 1.058$, $p = 0.309$, $\eta p^2 = 0.021$. See Figure 3 for detailed trends.

3.1.2 Results of power analysis of EEG frontal areas

Repeated-measures ANOVA tests were conducted with driving pattern and call content complexity as between-subject variables, measurement phase as within-subject variables, and EEG power values in alpha wave frontal regions as dependent variables, with Greenhouse-Geisser correction for p-values that did not satisfy the spherical hypothesis variables. Results showed that the three-way interaction of stage,

driving mode, and call content complexity was significant $F(1, 49) = 8.174$, $p = 0.006$, $\eta p^2 = 0.143$. A simple effect test demonstrated a significant difference of $p = 0.17$ at stage 6 as driving mode varied when making complex calls.

Apart from this, the main effect of call content complexity was not significant $F(1, 49) = 0.085$, $p = 0.771$, $\eta p^2 = 0.002$. The main effect of driving mode was not significant $F(1, 49) = 0.618$, $p = 0.436$, $\eta p^2 = 0.012$. The interaction between call content complexity and driving mode was not significant $F(1, 49) = 0.021$, $p = 0.885$, $\eta p^2 = 0.000$. The interaction between stage and call content complexity was not significant $F(1, 49) = 0.537$, $p = 0.467$, $\eta p^2 = 0.011$. The interaction between stage and driving mode was not significant $F(1, 49) = 0.329$, $p = 0.569$, $\eta p^2 = 0.007$. See Figure 4 for detailed trends.

3.1.3 Results of power analysis of the occipital region of the EEG

Repeated-measures ANOVA tests were performed with driving mode and call content complexity as between-subject variables, measurement phase as within-subject variables, and EEG power values in the occipital region of the alpha wave as the dependent variable, with Greenhouse-Geisser correction for p-values that did not satisfy the spherical hypothesis variable. Results showed a significant main effect of driving mode $F(1, 49) = 4.230$, $p = 0.045$, $\eta p^2 = 0.079$ and a significant three-factor interaction of stage, driving mode, and call content complexity $F(1, 49) = 4.687$, $p = 0.035$, $\eta p^2 = 0.087$. Simple effect tests demonstrated that when making simple calls, significant differences occurred at stages 1 and 2 in different driving modes. In the first stage, marginal significance was $p=0.057$, and in the second stage, significance was $p=0.048$. In the case of complex calls, significant differences emerged in stages 3 and 5 with different driving patterns. These were significant at stage 3, $p=0.051$, and at stage 5, $p=0.024$.

Apart from this, the main effect of call content complexity was not significant $F(1, 49) = 0.173$, $p = 0.680$, $\eta p^2 = 0.004$. The interaction between call content complexity and driving mode was not significant $F(1, 49) = 0.039$, $p = 0.844$, $\eta p^2 = 0.001$. The interaction between stage and call content complexity was not significant $F(1, 49) = 1.762$, $p = 0.191$, $\eta p^2 = 0.035$. The interaction between stage and driving mode was not significant, $F(1, 49) = 0.861$, $p = 0.358$, $\eta p^2 = 0.017$. See Figure 5 for detailed trends.

3.1.4 Results of power analysis of the parietal region of the EEG

Repeated-measures ANOVA tests were conducted with driving mode and call content complexity as between-subject variables, measurement phase as within-subject variables, and EEG power values in the alpha wave parietal region as the dependent variable, with Greenhouse-Geisser correction for p-values that did not satisfy the spherical hypothesis variable. Results showed that the main effect of call content complexity was significant $F(1, 49) = 4.844$, $p = 0.032$, $\eta p^2 = 0.090$. The main effect of driving mode was borderline significant $F(1, 49) = 3.915$, $p = 0.054$, $\eta p^2 = 0.074$.

Apart from this, the interaction between call content complexity and driving mode was not significant $F(1, 49) = 0.207$, $p = 0.651$, $\eta p^2 = 0.004$. The interaction between stage and call content complexity was not significant $F(1, 49) = 0.029$, $p = 0.866$, $\eta p^2 = 0.001$. The interaction between stage and driving mode was not significant $F(1, 49) = 1.392$, $p = 0.244$, $\eta p^2 = 0.028$. The three-factor interaction of stage, driving mode, and call content complexity was significant $F(1, 49) = 4.687$, $p = 0.035$, $\eta p^2 = 0.087$, see Figure 6 for detailed trends.

3.1.5 Results of EEG temporal lobe area power analysis

Repeated-measures ANOVA tests were conducted with driving mode and call content complexity as between-subject variables, measurement phase as within-subject variables, and EEG power values in alpha-wave temporal lobe regions as dependent variables, with Greenhouse-Geisser correction for p-values that did not satisfy the spherical hypothesis variable. Results showed a significant driving mode main effect $F(1, 49) = 4.200$, $p = 0.046$, $\eta p^2 = 0.079$.

Apart from this, the main effect of call content complexity was not significant $F(1, 49) = 0.281$, $p = 0.599$, $\eta p^2 = 0.006$. The interaction between call content complexity and driving mode was not significant $F(1, 49) = 0.448$, $p = 0.506$, $\eta p^2 = 0.009$. The interaction between stage and call content complexity was not significant $F(1, 49) = 0.477$, $p = 0.493$, $\eta p^2 = 0.010$. The interaction between stage and driving mode was not significant $F(1, 49) = 0.094$, $p = 0.760$, $\eta p^2 = 0.002$. The three-way interaction of stage, driving mode, and call content complexity was not significant $F(1, 49) = 0.319$, $p = 0.575$, $\eta p^2 = 0.006$. See Figure 7 for detailed trends.

3.2 Results of the driving performance analysis

3.2.1 Results of the analysis of the reaction task response tests

Repeated-measures ANOVA tests were conducted with driving mode and call content complexity as between-subject variables, measurement phase as within-subject variables, and reaction time as the dependent variable, with Greenhouse-Geisser correction for p-values that did not satisfy the sphericity hypothesis variable. Results indicated a significant interaction between stage and driving mode, $F(1, 54) = 7.598$, $p = 0.008$, $\eta p^2 = 0.123$. Simple effect tests demonstrated that different driving modes appeared to differ significantly at stage 1, $p = 0.000$.

Apart from this, the main effect of driving mode was not significant $F(1, 54) = 0.307$, $p = 0.582$, $\eta p^2 = 0.006$ and the main effect of call content complexity was not significant $F(1, 54) = 0.021$, $p = 0.884$, $\eta p^2 = 0.000$. The interaction between call content complexity and driving mode was not significant $F(1, 54) = 0.040$, $p = 0.843$, $\eta p^2 = 0.001$. The interaction between stage and call content complexity was not significant $F(1, 54) = 0.019$, $p = 0.890$, $\eta p^2 = 0.000$. The three-way interaction between stage, driving mode, and call content complexity was not significant $F(1, 54) = 7.598$, $p = 0.008$, $\eta p^2 = 0.123$. See Figure 8 for detailed trends.

3.2.2 Results of the analysis of the correct rate of detection response tasks

Repeated-measures ANOVA tests were conducted with driving mode and call content complexity as between-subject variables, measurement phase as within-subject variables, and correctness as the dependent variable, with Greenhouse-Geisser correction for p-values that did not satisfy the sphericity hypothesis variable. Results showed a significant interaction between stage and driving mode, $F(1, 54) = 4.070$, $p = 0.049$, $\eta p^2 = 0.070$. Simple effect tests demonstrated that different driving modes appeared to differ significantly at stage 1, $p = 0.003$.

Apart from this, the main effect of driving mode was not significant $F(1, 54) = 0.974$, $p = 0.328$, $\eta p^2 = 0.018$ and the main effect of call content complexity was not significant $F(1, 54) = 0.015$, $p = 0.903$, $\eta p^2 = 0.000$. The interaction between call content complexity and driving mode was not significant $F(1, 54) = 0.750$, $p = 0.390$, $\eta p^2 = 0.014$. The interaction between stage and call content complexity was not significant $F(1, 54) = 0.625$, $p = 0.433$, $\eta p^2 = 0.011$. The three-factor interaction between stage, driving mode, and call content complexity was not significant $F(1, 54) = 0.315$, $p = 0.577$, $\eta p^2 = 0.006$. See Figure 9 for detailed trends.

3.3 Results of pupil diameter analysis

3.3.1 Results of left eye pupil diameter analysis

Repeated measures ANOVA tests were conducted with driving mode and call content complexity as between-subject variables, measurement phase as within-subject variables, and left eye pupil diameter as the dependent variable, with Greenhouse-Geisser correction for p-values that did not satisfy the spherical hypothesis variable. Results showed a significant interaction between stage and driving mode $F(1, 54) = 8.571$, $p = 0.005$, $\eta p^2 = 0.137$. Simple effect tests demonstrated a significant difference between driving modes at stage 1, $p = 0.004$, and a significant trend at stage 2, $p = 0.060$.

Apart from this, the main effect of driving mode was not significant $F(1, 54) = 2.492$, $p = 0.120$, $\eta p^2 = 0.044$ and the main effect of call content complexity was not significant $F(1, 54) = 0.108$, $p = 0.743$, $\eta p^2 = 0.002$. The interaction between call content complexity and driving mode was not significant $F(1, 54) = 1.406$, $p = 0.241$, $\eta p^2 = 0.025$. The interaction between stage and call content complexity was not significant $F(1, 54) =2.367$, $p = 0.130$, $\eta p^2 = 0.042$. The three-factor interaction between stage, driving mode and call content complexity was not significant $F(1, 54) =0.950$, $p = 0.344$, $\eta p^2 = 0.017$. See Figure 10 for detailed trends.

3.3.2 Results of right eye pupil diameter analysis

Repeated-measures ANOVA tests were conducted with driving mode and call content complexity as between-subject variables, measurement phase as within-subject variables, and right eye pupil diameter as the dependent variable, with Greenhouse-Geisser correction for p-values that did not satisfy the

spherical hypothesis variable. Results showed a significant main effect of driving mode $F(1, 54) = 4.050$, $p = 0.049$, $\eta p^2 = 0.070$ and a significant interaction between stage and driving mode, $F(1, 54) = 7.665$, $p = 0.008$, $\eta p^2 = 0.124$. Simple effect tests demonstrated that different driving modes appeared to be significantly different at stage 1 ($p = 0.001$) and stage 2 ($p = 0.016$). The three-way interaction of stage, driving mode, and call content complexity was significant $F(1, 54) = 5.290$, $p = 0.025$, $\eta p^2 = 0.089$. Simple effect tests demonstrated that driver pupil diameter size varied significantly with driving mode for simple call content in stage 1 ($p = 0.005$) and stage 2 ($p = 0.030$).

The size of the driver's pupil diameter varied significantly (p=0.050) in the first stage as the driving mode varied while the driver was making complex calls. Detailed trends are shown in Figure 11.

Apart from this, the main effect of driving mode was not significant $F(1, 54) = 2.492$, $p = 0.120$, $\eta p^2 = 0.044$ and the main effect of call content complexity was not significant $F(1, 54) = 0.108$, $p = 0.743$, $\eta p^2 = 0.002$. The interaction of call content complexity with driving mode was not significant $F(1, 54) = 1.406$, $p = 0.241$, $\eta p^2 = 0.025$. The interaction of stage with call content complexity was not significant $F(1,54) =2.367$, $p = 0.130$, $\eta p^2 = 0.042$. See Figure 11 for detailed trends.

4. Discussion

It should be noted that the EEG power in this study is low. It may be caused by the calculation method of power. In the research using the same power calculation method, the beta frequency band varies in the range of 0.0005–0.007, which is not high either31,32. Therefore, even if the value of Alpha power is low (basically between 0.0013 and 0.0025), we still report them objectively.

The distraction effect arises in large part due to a shift in brain resources. (Wang et al., 2014) We found a consistent trend in drivers' prefrontal, frontal, occipital, and temporal regions, i.e. a gradual decrease in alpha power values during driving phase 2.3 (20-30 minutes) for drivers in the simple talk content group in automatic driving mode. The trend was the opposite for the complex talk content group, with a gradual increase. At 20 minutes of driving, the alpha power values in the prefrontal areas of the simple talk content group were significantly lower than those of the simple talk group in the manual driving group. The prefrontal cortex has been thought to play an important role in cognitive control, i.e. the coordination of thoughts and actions according to internal goals. Cognitive control stems from the active maintenance of prefrontal cortex activity patterns that represent goals and the means to achieve those goals. (Miller et al., 2001) Thus, the results of the EEG data suggest that the mental load induced by the content of a simple mobile phone call is higher in the automatic driving mode for about 10-20 minutes of driving time than in the manual driving state during the same period, occupying more brain resources in the driver's prefrontal area and leading to a reduction in his or her cognitive control. At the same time, the trends in the detection response task performance data during this phase were consistent with the EEG data. The trend in Figure 8 shows that at a driving duration of 10 minutes, the automatic driving simple talk content group had faster response times than the manual driving simple talk content group. When driving for 20 minutes, the autopilot simplex content group's response times slowed rapidly and converged with the manual simple content group. Although the trend in Figure 9 indicates that the autopilot simple content

group was more correct during this period compared to the manual group, the EEG data shows that the overall driver load was still high during this period, as their cognitive control was reduced and the excessive attentional resources were disruptive to the driver's reaction time to detect peripheral signals, resulting in progressively slower reaction times.

The results of Hossam Almahasneh's (2014) study found that the most affected brain region during distracted driving was the right frontal cortex. The present study builds on this finding by examining the complexity of drivers' secondary tasks. The most significant difference in the detection of distracted driving was found in the prefrontal regions of the frontal lobe when the complexity of the secondary task was varied, suggesting that mobile phone conversations impair cognitive control in the prefrontal regions of the driver. Meanwhile, Lin et al. (2011) suggested that changes in the alpha band in the frontal region were associated with distracted driving. The EEG results of the present study suggest that a decrease in alpha wave power values in the prefrontal region is a valid indicator for identifying increased mental load in drivers due to distracted mobile phone use. This complements another brain region band indicator for the detection of distracted driving, whereas previous studies have been limited to considering changes in theta wave band as a marker of cognitive distraction in drivers. (Dong et al, 2011; Lin et al., 2009; Victor et al., 2005)

Also, previous studies have found that drivers performing interactive cognitive tasks during prolonged driving appear to improve alertness and driving performance. (Gershon et al., 2009) We additionally found that in the autopilot mode, drivers in the complex mobile phone talk content group had significantly higher alpha wave power values in the occipital region than the manual mode complex talk content group for the same period (30-50 min), and that the complex mobile phone talk content group had significantly higher alpha wave power values in the frontal region than the manual mode complex talk content group for the same period (60 min). Since power changes in frontal regions mainly reflect the degree of activation of intrinsic neurons when individuals allocate their attention to different task stimuli (Missonnier et al., 2006), frontal areas are involved in impulse control, judgement, language production, working memory, motor function, and problem solving. (Burgess et al., 2000) This therefore suggests that activation in the occipital areas of drivers in the complex mobile phone call content group was lower in the automatic driving mode compared to the manual driving state during the same period (30-50 minutes) and that activation in the frontal areas of the complex mobile phone call content group was lower in the automatic driving compared to the manual driving mode during the same period (60 minutes). In contrast, parietal circuits, the prefrontal cortex, and corticolimbic structures were shown to be involved in the distribution of individual directed attention networks together with the medial pulvinar nucleus. (Bakeydier & Mauguiere, 1985) This nucleus projects and receives visual input from the occipital cortex and the superior colliculus, forming an important link with the hippocampus for further memory processing. (Van Hoesen& Pandya, 1975) This suggests that the effects of mobile phone conversations on activation of the occipital cortex as well as the frontal cortex are shared. When drivers engage in complex mobile phone conversations, even when on autopilot, brain functions such as problem solving, judgement and impulse control are impaired as the duration of driving increases. The present study also refines the findings of Saxby (2017) et al. by exploring the complexity of mobile phone calls, and finds

that even complex calls, in monotonous prolonged autopilot mode, are not a safe way to reduce fatigue and increase alertness, but instead can be detrimental to driver function in various brain regions.

We also found consistent trends through changes in EEG, pupil diameter, and vigilance detection response task data. The EEG data results showed that the alpha power values in the prefrontal areas of the complex talk content group were significantly lower than those of the simple talk content group at 10 minutes of driving time in automatic driving mode. For 20-30 minutes of driving time in manual driving mode, the alpha power values in the prefrontal areas of the complex talk content group were significantly lower than those of the simple talk content group. However, the difference decreased with increasing driving time, and no significant difference was observed. At 60 minutes of driving time, the prefrontal and temporal data showed a consistent trend in mental load levels regardless of the driving mode and level of complexity.

The trend in pupil diameter indicates that both simple and complex calls in manual driving mode directly lead to an increase in the driver's psychological load, with complex calls inducing a faster and deeper increase in psychological load. In the initial phase of driving (10-20 minutes), the pupil diameter of the drivers in the simple talk content group was significantly smaller in the automatic driving group than in the manual driving group. However, as the duration of driving increased, none of the differences between the pupil diameters of the autopilot group and the manual driving group were significant.

The PDT alert detection response task data showed that during the initial phase of driving (around 10 minutes), when the driver was talking on a mobile phone, the PDT detection response task reaction time was significantly slower in the manual driving group than in the automatic driving group, and the correct PDT detection response task rate was significantly lower in the manual driving group than in the automatic driving group. As the driving time increased, the PDT detection reaction time in the automatic driving group gradually became slower and converged with that of the manual driving group. There was a tendency to overtake the manual driving group after 60 minutes.

All three data results above indicate a common trend that regardless of the level of complexity of mobile phone conversations a driver engages in, the level of psychological load tends to converge between manual and automatic driving modes as the length of driving time increases, suggesting that mobile phone conversations in automatic driving modes also disrupt the driver's cognitive resource balance state, leading to reduced cognitive control and impairing driving safety. The trend of the findings also validates the previous view on the cumulative effect of psychological load (Regan et al., 2009) and refines previous findings (Atchely, et al., 2014; Saxby, et al., 2017) by further delineating the impairment of drivers' use of mobile phone calls during different driving phases in the autonomous driving mode.

For the parietal region, alpha power values were higher in the simple talk group than in the complex talk group at stage 6. In the frontal and occipital regions, the alpha power values of the simple talk group were found to be lower than those of the complex talk group at stage 6. A possible explanation for this is that the occipital component is very close to the parietal area and the left and right motor areas of the frontal lobe, and because of the interconnectedness and complexity of the brain areas, brain areas located in the

same cortical layer interact with each other while acting separately on the body (Van Hoesen & Pandya, 1975). It is also possible that at the end of the driving phase, EEG signal acquisition is affected by the driver's somatic fluctuations, resulting in variable alpha-wave brain power values during stage 6.

As automated systems move towards higher levels (L4~L5), the frequency and risk of mobile phone use by drivers remains a key safety concern. Future research needs to further explore the ecology and empirical evidence of mobile phone call content; to delineate the impact of mobile phone calls on the conversion of resources in the driver's brain area at other wave frequencies; to distinguish how the cognitive load from mobile phone calls and the psychological load from fatigue cross over to affect the driver in automated driving mode; and how the psychological load on the driver's mobile phone use changes in longer (more than 60 minutes) automated driving situations, as well as how the psychological load of mobile phone use changes in longer (more than 60 minutes) autonomous driving situations.

In summary, this study compares the safety implications of mobile phone distraction in autonomous driving mode with the use of mobile phones in conventional driving situations; provides a rough delineation of when and for how long mobile phone conversations take place; compares the changes in EEG components in various brain regions in the driver's alpha wave band during mobile phone conversations. This provides a theoretical basis for the development of laws and regulations and policy implications for the use of mobile phones in the field of autonomous driving, where autonomous driving systems require drivers to constantly monitor road hazards and be ready to take over the vehicle, and where the overload caused by mobile phone use can compromise driving safety. At the same time, mobile phone conversations are not a consistent and effective response to the problem of underload in autonomous driving, as they can impair the normal functioning of the driver's brain functions, such as cognitive control, problem solving, and judgement, while increasing the psychological load and compromising driving safety.

Conclusion

During the initial phase of driving (10-20 minutes), the mental load induced by the content of a simple mobile phone call is higher in automatic driving mode than in manual driving during the same period, occupying more brain resources in the driver's prefrontal area, leading to a reduction in his cognitive control, and making the driver slower to respond to peripheral visual detection signals.

The activation of the driver's occipital area in the complex mobile phone call content group was lower in the automatic driving mode compared to the manual driving state during the same period (30-50 minutes), and the activation of the frontal area in the complex mobile phone call content group was lower compared to the manual driving mode during the same period (60 minutes), indicating that complex mobile phone calls, even in the automatic driving state, caused a decline in the driver's problem solving, judgement, and impulse control, among other brain functions.

EEG and pupil diameter indicators together indicate that regardless of the level of complexity of mobile phone calls made by the driver, the level of psychological load tends to be the same for drivers in manual

and automatic driving modes as the duration of driving increases, suggesting that mobile phone calls in automatic driving mode also disrupt the driver's cognitive resource balance, leading to a reduction in cognitive control and impairing driving safety.

Declarations

Data Availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Acknowledgements

This work was supported by the Humanity and Social Science Youth Foundation of Ministry of Education of China (Research on Psychological Mechanism and Regulation of Passive Fatigue of L3 Autonomous Vehicle's Drivers; grant number 20YJC190015).

Declaration of Interest

We have no conflicts of interest to declare.

Author contributions

J.M. conceived the study and designed the experiments. Testing and data collection were performed by H.Z.; H.Z. and Y.Z. performed the data analysis and interpretation under the supervision of J.M.; H.Z. and J.M. wrote the main manuscript text; R.C. reviewed the manuscript and all authors approved the final version of the manuscript for submission.

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Figures

Figure 1

Driving tasks and simulated driving scenarios

Figure 2

EEG alpha wave band brain topography

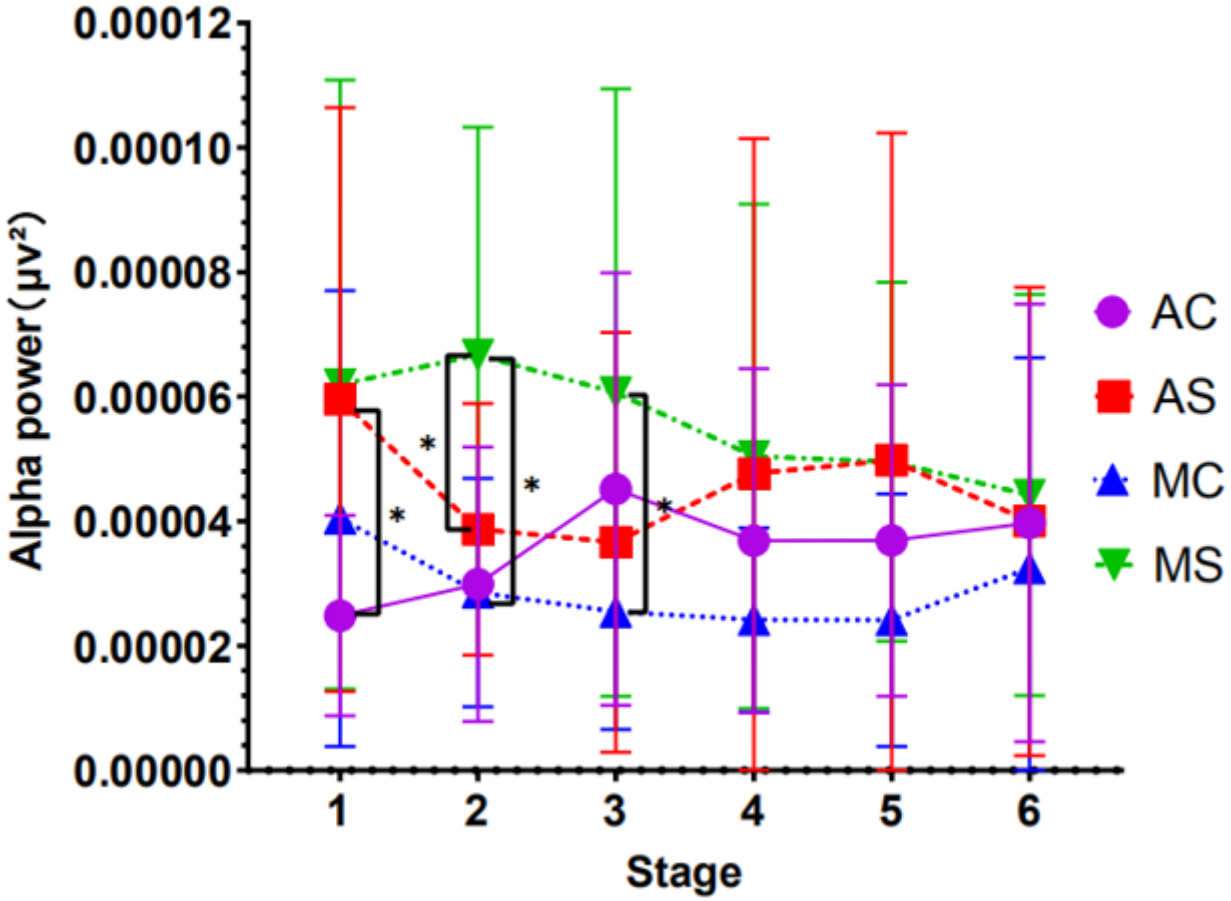

Figure 3

EEG alpha wave power in the prefrontal region (Note: *p<0.05)

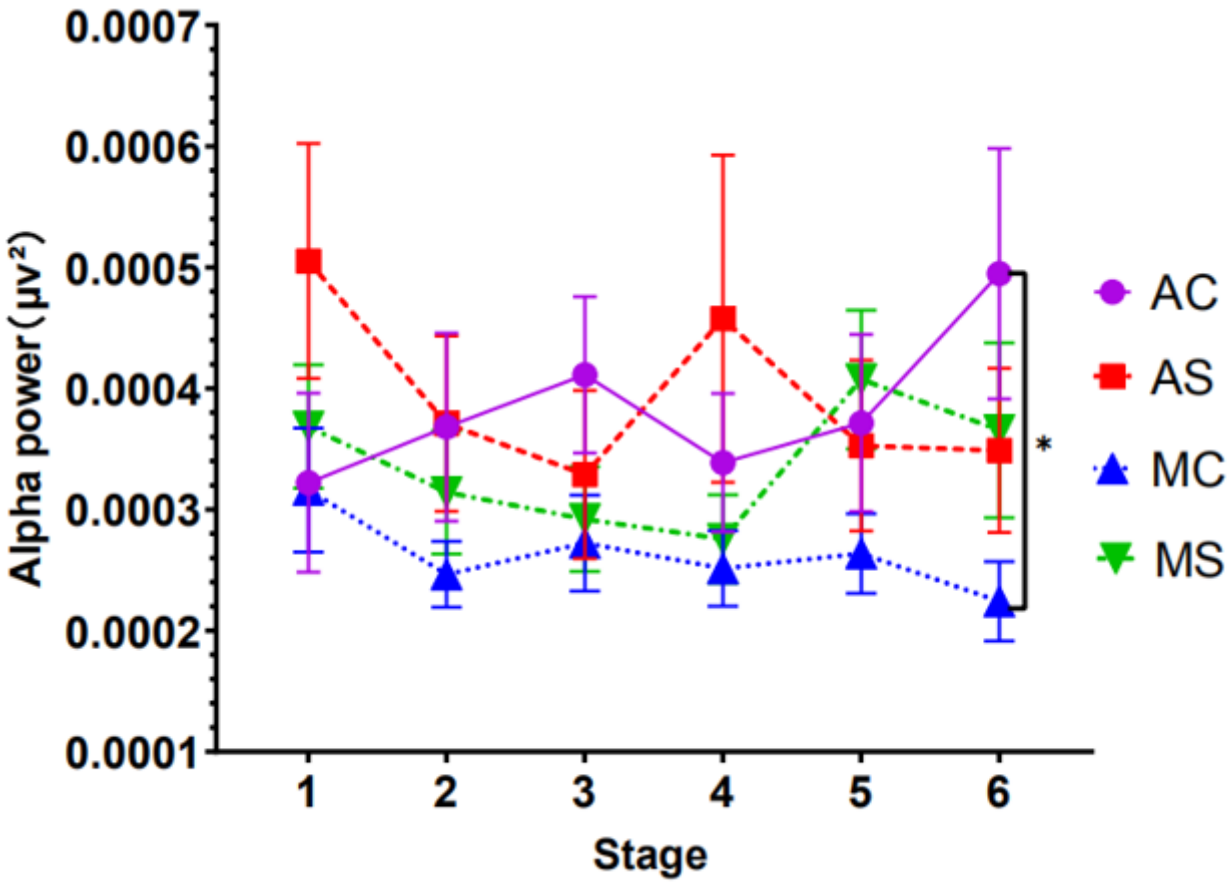

Figure 4

EEG frontal area alpha wave power (Note: *p<0.05)

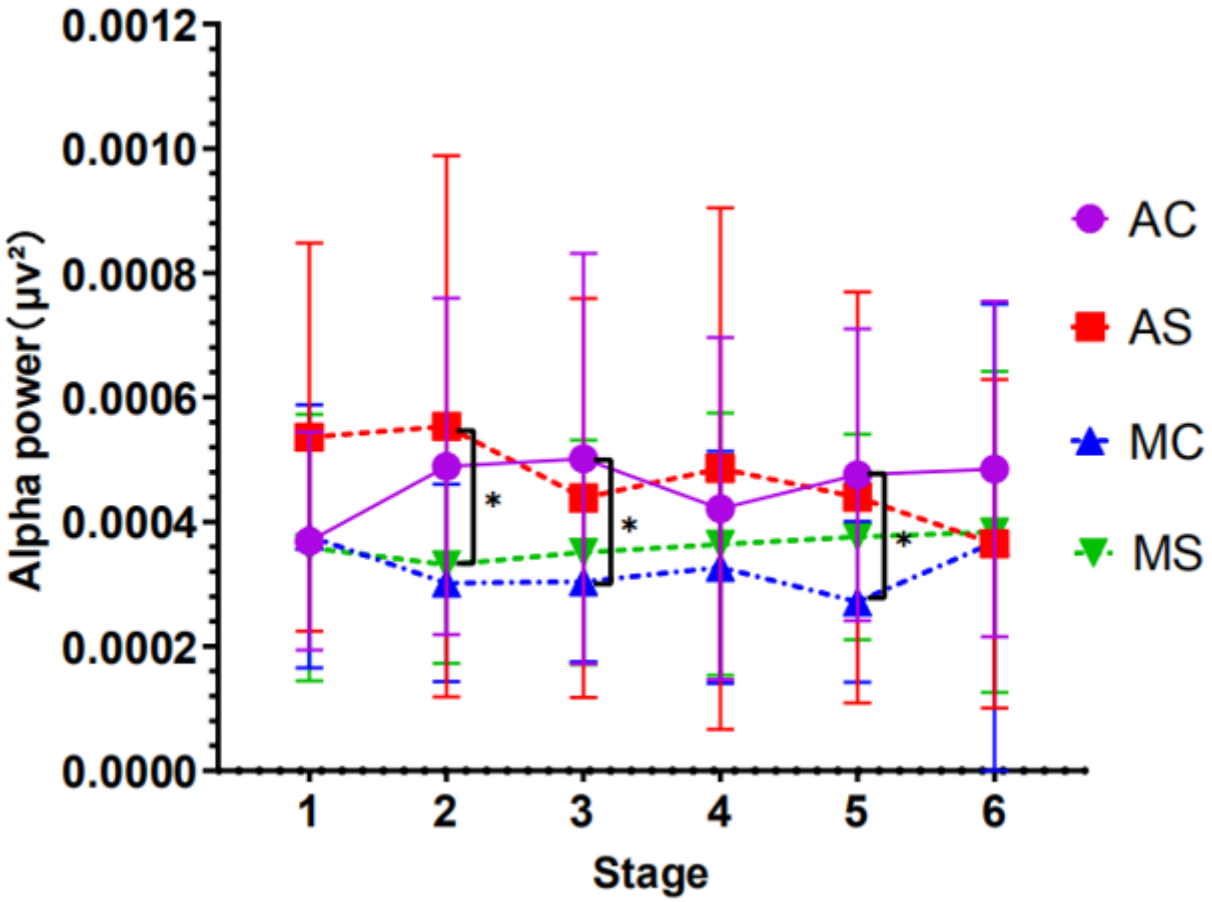

Figure 5

EEG alpha wave power in the occipital region (Note: *p<0.05)

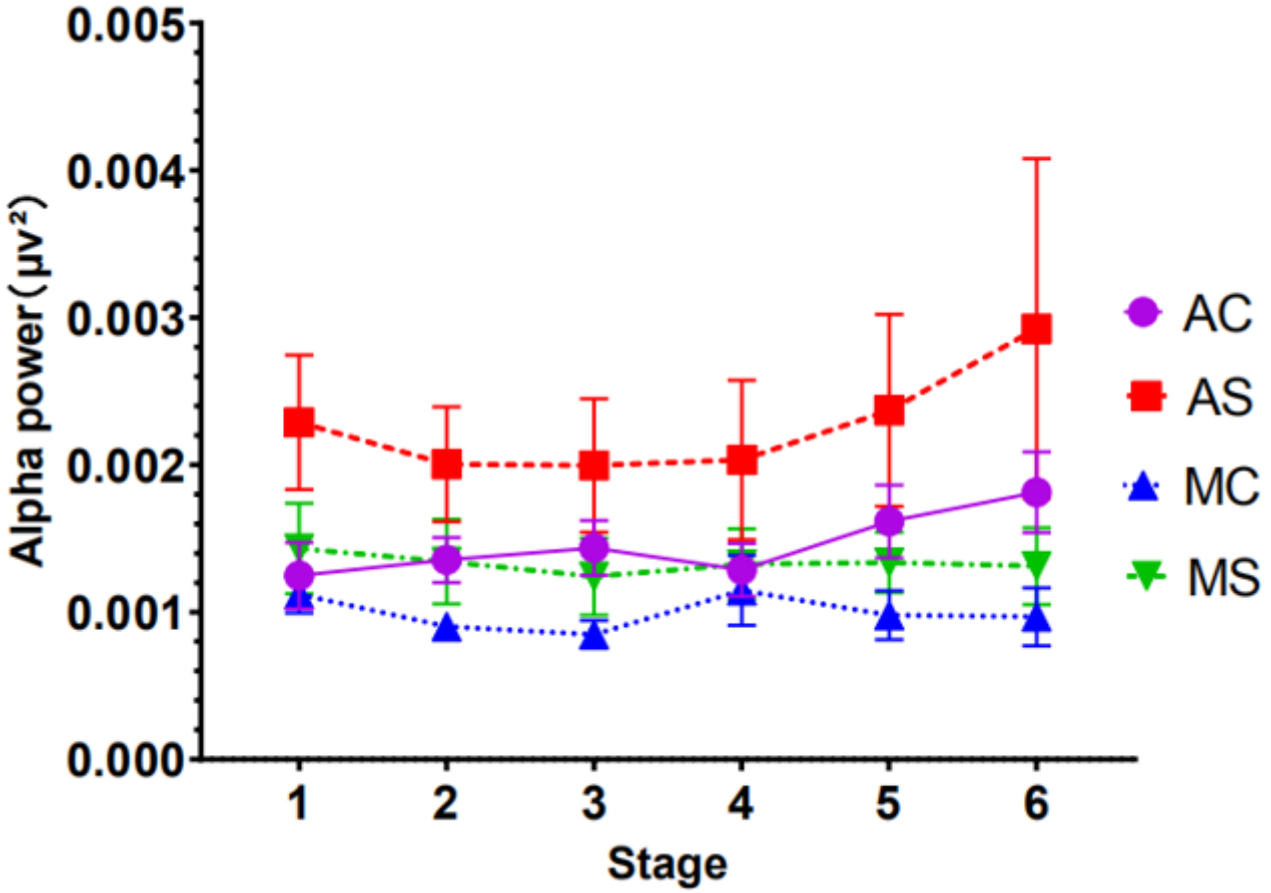

Figure 6

EEG parietal region alpha wave power (Note: *p<0.05)

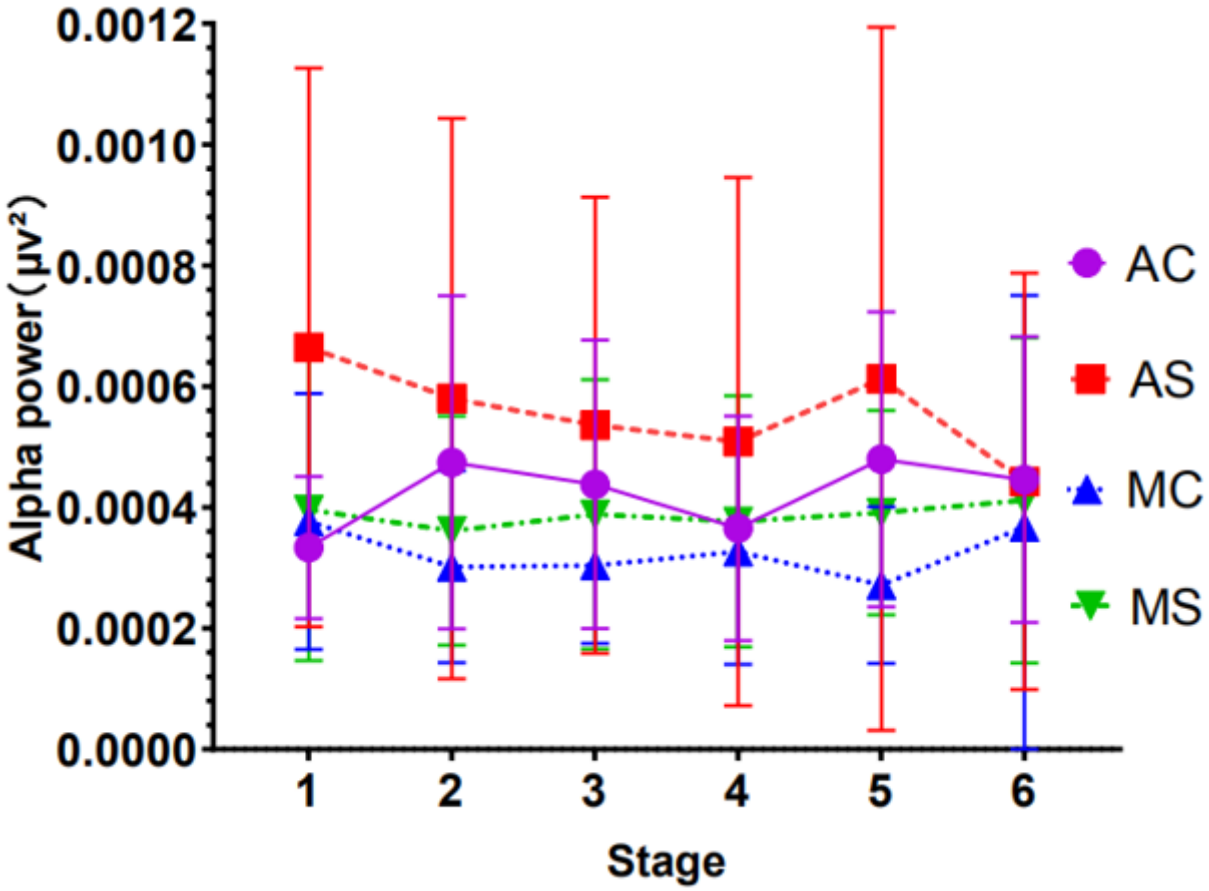

Figure 7

EEG alpha wave power in the temporal lobe region (Note: *p<0.05)

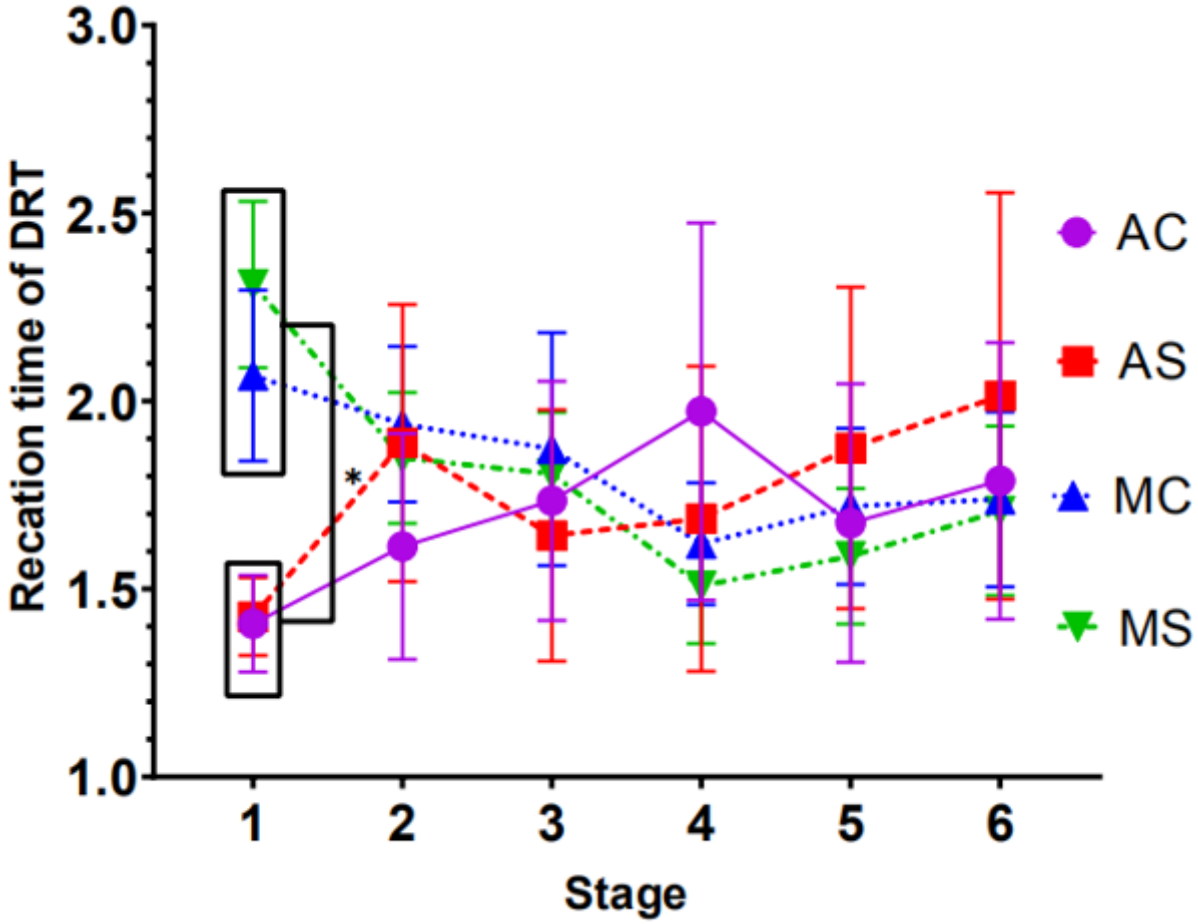

Figure 8

Trend in response time for detection response tasks (Note: *p<0.05)

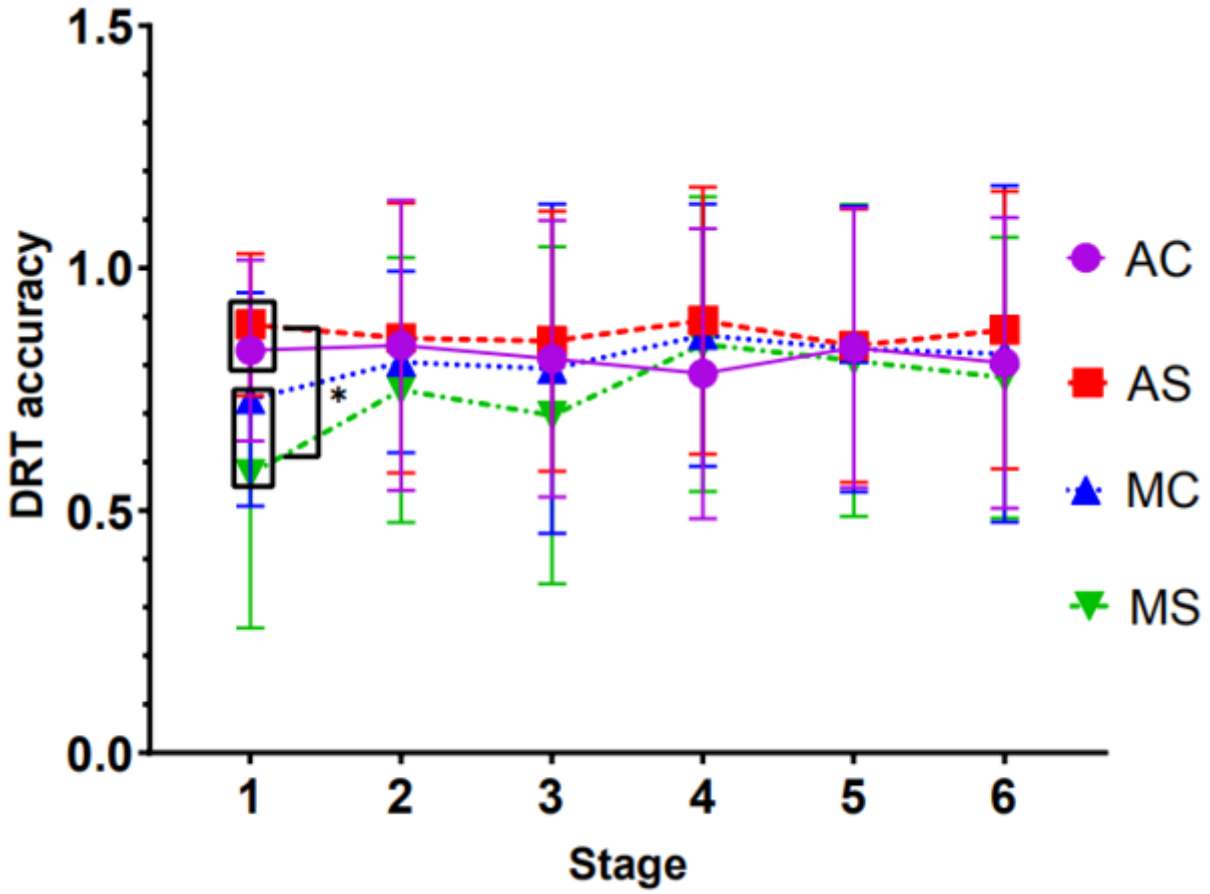

Figure 9

Trends in correct detection response task rates (Note: *p<0.05)

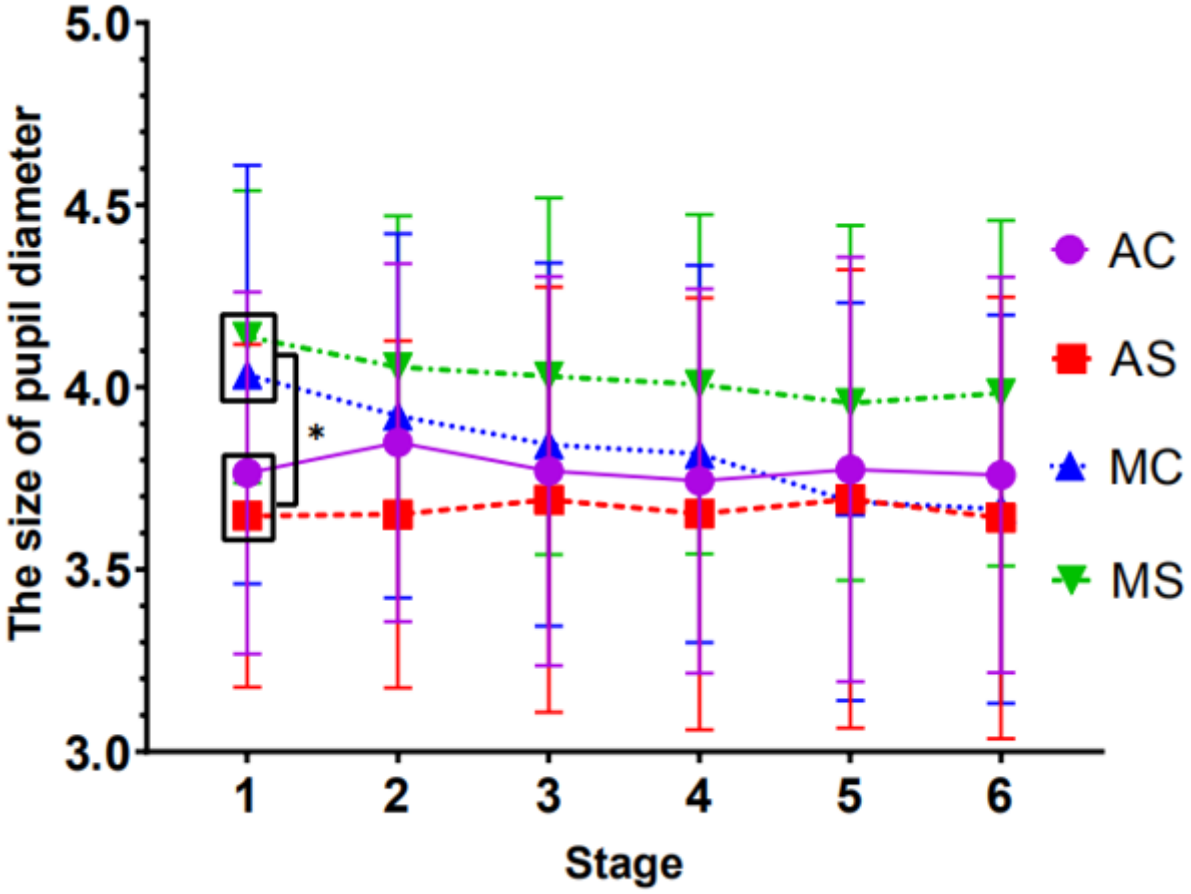

Figure 10

Trend in pupil diameter in the left eye (Note: *p<0.05)

Figure 11

Trend in pupil diameter in the right eye (Note: *p<0.05)