

Towards Modelling Distracted Human Driving: Sensor Fusion and Driver Status Monitoring in a VR Simulator

Jiacheng Liu

School of Advanced Technology
Xi'an Jiaotong-Liverpool University
Suzhou, Jiangsu, China
Jiacheng.Liu23@alumni.xjtlu.edu.cn

Yue Li

School of Advanced Technology
Xi'an Jiaotong-Liverpool University
Suzhou, Jiangsu, China
Yue.Li@xjtlu.edu.cn

Fan Zhang

School of Robotics
Xi'an Jiaotong-Liverpool University
Suzhou, Jiangsu, China
Fan.Zhang@xjtlu.edu.cn

Abstract

Various driver monitoring systems have been deployed to understand human driving behaviours in complex scenarios, contributing to the development of automated vehicles that meet technical and legal requirements. However, commercial systems are often overpriced, and there is still limited understanding of how driving behaviour, distractions, and scenarios interact to influence decision-making and performance. This study addresses the gap by collecting behavioural and physiological data in different driving tasks and modelling human decision-making. In a between-subject design, participants were instructed to drive safely or aggressively through three simulated scenes, namely the crossroads, the T-junction, and the roundabout, under five distraction conditions: 1) no distraction, 2) audio-cognitive, 3) audio-action, 4) visual-cognitive, and 5) visual-action. Each participant completed forty-five trials, lasting 30-40 minutes. The driving scene was developed in Unreal Engine 4, using Microsoft AirSim. The experiment setup included a multi-sensor driver monitoring system, a driving simulator with wheel and pedals, and a VIVE Pro 2 VR display, to collect behavioural (e.g., head movements, steering) and physiological (e.g., heart rate, skin conductance) data. ANOVA was performed to explore behavioural patterns and physiological responses, including differences between safe and aggressive driving, distractions, and scenarios. Significant differences across conditions were revealed. Specifically, the throttle, steering, acceleration, the speed of the vehicle, the heart rate, and the head turning of participants in aggressive driving are significantly different from those in safe driving. Distraction conditions had a significant impact on the steering and head turning ranges. Our contributions include setting up a realistic driving simulation environment with affordable solutions and creating a human driving data collection pipeline for modelling driving performance. Future work will focus on improving data acquisition, modelling human decision-making, and integrating these models into the planning and control of automated vehicles to enhance AI transparency and public acceptance of autonomous driving.

CCS Concepts

• **Human-centered computing** → **HCI theory, concepts and models.**



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Keywords

Driver Monitoring System, Driving Simulator, Decision-making, Virtual Reality (VR), Distraction

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1 Introduction

With the rapid development of autonomous driving technology, how to effectively monitor and understand the driver's driving behaviour in complex scenarios has become an important issue in promoting technological progress and adoption. Currently, various types of driver monitoring systems have been deployed in real driving tests to observe and analyse the characteristics of human driving behaviour.

Existing research shows that driving behaviour is affected by multiple factors, such as visual and audio distractions [17] and road conditions [26]. Especially in the context of different driving modes (safe driving and aggressive driving), drivers' driving behaviours were found to differ significantly [38]. However, most studies focused on the impact of a single factor and lack in-depth research on the interaction of these factors. It is important to further reveal the joint impacts of the factors on driving decisions and performance through comprehensive data collection for optimising autonomous driving technology and increasing public acceptance of automated vehicles.

To fill this gap, the goal of this study is to understand how distraction types, driving scenarios and driving modes interact to influence driving behaviour. To answer the question, we developed a driving simulator with customised sensors and immersive Virtual Reality (VR) displays and collected human behavioural and physiological data in different driving tasks, combined with vehicle state information. This will also help the development of Explainable AI for autonomous driving in the future [3].

The core focus of the current research lies in developing a driving simulation environment and analysing driver behaviour alongside physiological data. With the rapid advancements in autonomous driving technology, building an accurate and efficient simulation environment has become increasingly essential. Researchers rely on such environments for repeated testing of vehicles and driving behaviours under various scenarios. Additionally, collecting both behavioural and physiological data is crucial for understanding

driver responses in different driving modes. These data are invaluable in developing more intelligent and adaptive human-computer interaction systems.

The contributions of the current work are three-fold. First, we present an experimental setup of a driving simulator, adopting immersive VR head-mounted display and gaming steering wheels with customised sensors. The configurations were detailed with great replicability for the future work. Second, our empirical study showed the effects of distraction types, driving scenarios and driving modes on driving behaviours, and their interaction effects. This work extended previous studies on investigating the single-factor effects and laid a foundation for future work in modelling distracted human driving behaviours. Third, our study adopted both software-instrumented measurements and data collected from hardware sensors. While these were commonly agreed to be reliable, we observed some contradictory results and discussed the implications. These findings also provide insights to the future study measurements and evaluation of driving behaviours.

2 Related Work

This section reviews existing literature that are in particular relevant to ours on the development of driving simulation environments, including VR-based simulators, and the influence of multiple factors on driving behaviour data.

2.1 Driving Simulator

Driving simulators are widely employed in autonomous driving research and human-vehicle interaction studies, especially in research involving risky or hazardous driving scenarios. They reduce costs and enhance safety in experimental setups. Several platforms have been developed for research in driving behaviour, autonomous driving algorithms, and automotive system testing. Notable examples include AirSim by Microsoft [35], Carla by the Computer Vision Center at the Autonomous University of Barcelona [9], and the LGSVL Simulator developed by LG AI Research [32]. Each platform offers varying levels of functionality and environmental customisation, catering to different research needs. Both AirSim and Carla are built on the Unreal Engine 4. Similarly, Michalík et al. developed a driving simulator using Unreal Engine 4 for driving behaviour analysis, focusing on technical implementation [24]. However, there was a limitation of its reliance on traditional display interfaces, which somewhat reduces the realism of the driving experience and limits the ability to measure head movement data. DReyeVR, an example that is relevant to our research, is a VR-based driving simulator that can record and analyse drivers' visual behaviour [36]. The system provides a valuable tool for studying human-vehicle interaction and behavioural responses in driving scenarios.

2.2 Driving Behavioural Studies

In this study, we collected both physiological and behavioural human data in driving, including heart rate, skin conductance, head movements, steering wheel and pedal manipulations (e.g. wheel's angular speed and acceleration), and the vehicle status from its operation metrics (e.g. throttle, steering, braking, speed, etc.). Data were analysed in the context of designed driving scenes to explore their

relationships with three designed experimental factors, namely the driving mode, the scene type, and the distraction type.

Previous research has shown that factors like traffic congestion, accidents, road curvature, and slope can significantly elevate driver stress levels. This stress manifests in both physiological indicators and driving behaviour, such as changes in heart rate, speed, and steering wheel control. For example, Ni et al. (2024) conducted a systematic review exploring the complex relationship between traffic conditions, road environment, and driver stress. Their work highlights how these factors impact cognitive load and decision-making processes [26]. Similarly, Sato and Akamatsu (2007) analysed driver behaviour in real-world traffic scenarios, focusing on preparatory actions before making right turns. Their study emphasises the influence of surrounding traffic, including the position of nearby vehicles, on driver decision-making and behaviours [34].

Driving style, such as aggressive or safe driving, also has measurable effects on both driver behaviour and physiological responses. Dillen et al. (2020) explored the impact of different driving styles on passenger comfort and anxiety by collecting data on physiological responses such as skin conductance, heart rate, and eye activity. They concluded that smoother, slower driving styles improve passenger comfort, whereas aggressive driving tends to increase anxiety levels [8]. Furthermore, Su et al. (2023) conducted a systematic review and meta-analysis, finding that aggressive driving significantly increases vehicle speed, thereby affecting safety and control [38].

Driving is essentially an attention and action selection task. In literature, attention mechanisms were usually classified as top-down and bottom-up, referring to attentional guidance by either prior knowledge and current target or stimulus-driven process captures the salient properties in the scenarios [10, 19, 25, 40, 42]. For driving, the distractions have been found to significantly affect driving behaviour and brain activity. Karthaus et al. (2018) demonstrated how distractions alter driving performance, including vehicle speed, lane positioning, steering, and eye movements [17]. Additionally, under similar distraction conditions—whether visual or auditory—the content of the distraction can further influence behaviour. For instance, Horrey et al. (2017) found that engagement with interesting auditory material while driving can delay reaction times to braking events, compared to when drivers are exposed to boring or no auditory material [13]. One of the main purpose of the current study is to test the effects of distractions types for further developing computationally model of the experimental evidence in human driving, following the recent developments in neurobiologically plausible modelling methods for attention and action selection tasks (e.g., see in [6, 22, 27, 37]).

3 Method

3.1 Participants

A total of twenty volunteered participants were recruited for this study (aged 21.95 ± 2.72 , thirteen male and seven female), including eighteen who obtained a driver's license. All twenty participants were right-handed and had normal colour vision. Ten had normal vision and ten were nearsighted with corrected-vision. Specifically, considering the use of VR devices during driving simulations, we required nearsighted participants to wear contact lenses to prevent

any potential effects of myopia on driving performance. In addition, the researchers also screened the participants for motion sickness, especially motion sickness associated with 3D environments, to minimise the risk of dizziness during the VR experience.

This study adhered to the ethical standards outlined in the Declaration of Helsinki. All procedures involving human participants were reviewed and approved by the Ethics Review Panel of the University. Before participation, all participants were provided with detailed information about the study, including its purpose, procedures, potential risks, and benefits. Informed consent was obtained from each participant, ensuring they were fully aware of their right to withdraw from the study at any time without consequence. To protect privacy and confidentiality, all participant data were anonymised throughout the study.

3.2 Apparatus and Software

Considering the high cost and potential danger of conducting driving experiments in real vehicles, we referred to DReyeVR's solution [36] and built a VR-based driving simulation and data acquisition system.

The experimental setup included a VR headset, a driving simulator (including a car seat, a steering wheel, and car pedals), a heart rate monitor, a single-axis rotation angle sensor, a six-axis sensor, and a laptop. The software utilised primarily included Unreal Engine 4 and the AirSim plugin [35]. The roles of these devices and software in the study are detailed below.

3.2.1 VR Headset Based Driving Simulation Environment.

VIVE Pro 2. The VR headset used in this experiment was the VIVE Pro 2 (See [Figure 1 left](#)). This high-end VR headset offers a dual-eye resolution of 4896 x 2448 pixels, providing a 5K resolution for an exceptionally clear visual experience. It features a 120° wide field of view (FOV) that closely matches human visual perception. The headset supports both 90Hz and 120Hz refresh rates and is equipped with Hi-Res certified headphones, ensuring a high level of immersion.

Existing research shows that using a VR headset to visually provide a driving simulation environment can improve attention, engagement, and enjoyment compared to traditional displays [21], and it is desirable to use a VR headset to measure driving performance [28].

This steering wheel (See [Figure 1 right](#)) is equipped with a 3.2 Nm force feedback motor that can simulate the feeling of bumps and collisions, bringing an immersive driving experience to the driver. This feedback has an important impact on the driver's driving behaviour [41], especially lateral control performance. It features built-in high-precision sensors that accurately capture steering inputs, ensuring a quick response for both sharp turns and fine directional adjustments. The adjustable pedals can be customised to the player's preferred height, offering stable foot support and precise control.

Unreal Engine 4. Unreal Engine 4 (UE4) is a powerful game development platform that supports advanced graphics rendering, physical simulation, and blueprint visual scripting systems. It is



Figure 1: The VIVE Pro 2 VR Display (left) and the PXN V99 gaming steering wheel (right) with customised sensors.

used in this experiment to build a car driving environment, including animations of roads and vehicles that interfere with the driver.

AirSim. AirSim is an open source simulator developed by Microsoft based on Unreal Engine, designed for autonomous vehicles such as drones and cars. It provides realistic physics and sensor simulation, and allows programmatic interaction with devices in the simulation environment through APIs. AirSim's initial settings are all stored in the 'settings.json' file. If any settings are missing in the json file, the default values will be used. By modifying 'settings.json', we can adjust many settings, including simulation mode, camera settings, view mode, etc.

In the experiment, we can see the screen of AirSim running in UE4 on the computer (See [Figure 2](#)). In the upper left corner of the screen, we can see some real-time status information of the vehicle during operation, such as throttle, brake, steering, etc. Through the recording function of AirSim, we can get a file named 'airsim_rec.txt' after the experiment, which records the status information of the vehicle during the entire experiment. Therefore, although AirSim is usually used for deep learning research in autonomous driving, it is also suitable as a driving simulator for driving simulation and vehicle data collection in this experiment.



Figure 2: AirSim operation interface

3.2.2 Human Physiological and Behavioural Data Collection.

Angular motion sensors. This experiment utilised a single-axis angular motion sensor for the wheel and a six-axis angular motion sensor for the head movement. The single-axis sensor employs a high-performance microprocessor and a Kalman dynamic filtering algorithm to quickly calculate the sensor’s current real-time motion posture. We attached it to the steering wheel to record its angular velocity and compare the recordings with that from the vehicle operation status; The six-axis posture measurement sensor captures three-axis acceleration and three-axis angular velocity. A Bluetooth 5.0 chip enables wireless connection between the sensor and the computer, ensuring faster data transmission. We attached it on the VR headset to collect the movement of the driver’s head during driving, including acceleration, angle and angular velocity, and compare it with that of the VR recordings. The sensor settings in the experiment are shown in Figure 1.

Heart Rate Sensor. The Polar H10¹ is a high-precision wireless heart rate monitor that supports Bluetooth and ANT+ connections, providing comprehensive heart rate monitoring and training data synchronization. In this experiment, the Polar H10 was used to record the subjects’ heart rate changes during driving.

3.3 Simulated Driving Scenarios

In Unreal Engine 4 (UE4), we developed three distinct traffic scenarios, namely a crossroads, a T-junction, and a roundabout, adapted from [2]. For each scenario, participants were required to execute a left-turn operation, with the roundabout scenario specifically requiring the vehicle to make a 3/4 circuit around the roundabout before exiting via the left-hand opening. Figures 3 to 5 show three scenarios and the vehicle’s driving path in each scenario. The paths represent the trajectory of the vehicle’s center of gravity, and all trajectories are successful examples.

Here we will explain the coordinate system, units and starting point in the scene. According to the description of the Coordinate System on the AirSim official website, the NED coordinate system is used in all AirSim APIs, that is, +X represents north, +Y represents east, and +Z represents down. All units are in SI system. This is different from the coordinate system used in Unreal Engine. In Unreal Engine, +Z represents up, and the length unit is centimeters instead of meters in AirSim. The AirSim API converts the coordinate system in Unreal Engine to the coordinate system in AirSim. The spawn point of the vehicle in Unreal Engine is the position of the Player Start component. For AirSim, the starting point of the vehicle is always (0,0,0) in the NED coordinate system. Therefore, the Unreal Engine coordinate system needs to be converted to the NED coordinate system. We first need to subtract the starting offset, and then scale by 100 to convert centimeters to meters. Finally, there is a setting called ‘OriginGeopoint’ in ‘settings.json’, which is used to assign geographic longitude, longitude and altitude to the Player Start component.

To replicate realistic driving conditions, animated car movements were incorporated into each scenario. At the intersection, vehicles traveled back and forth in a direction parallel to the test subject’s vehicle. At the T-junction, vehicles moved perpendicularly to the

test subject’s vehicle. In the roundabout scenario, vehicles circulated around the roundabout.

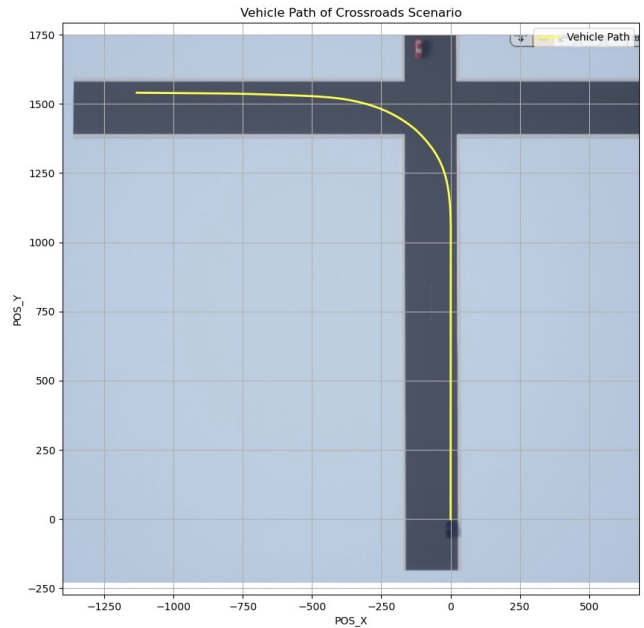


Figure 3: The Vehicle Path of Crossroads Scenario

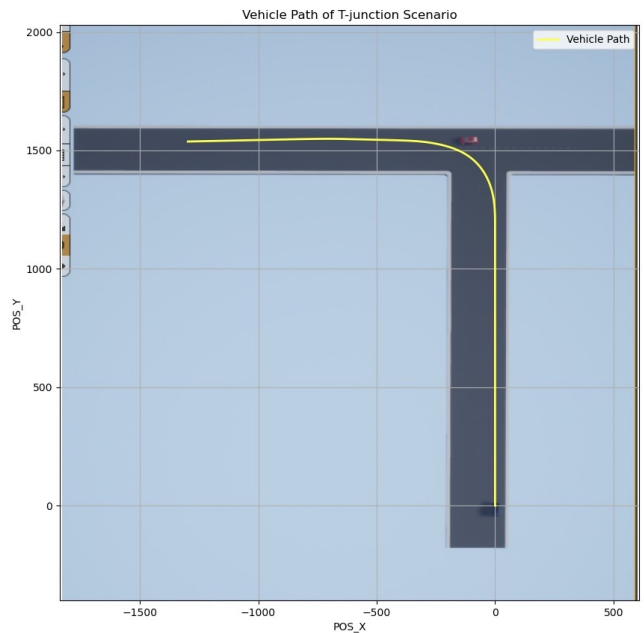


Figure 4: The Vehicle Path of T-junction Scenario

¹<https://www.polar.com/sensors/h10-heart-rate-sensor>

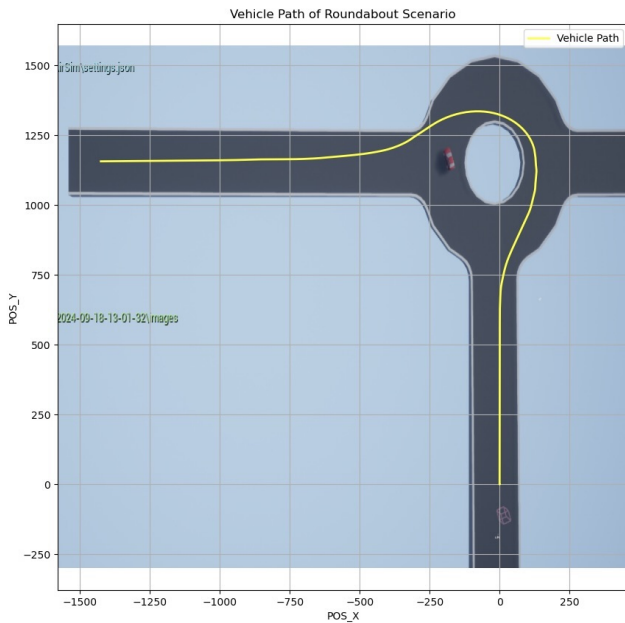


Figure 5: The Vehicle Path of Roundabout Scenario

3.4 Experimental Design

This experiment employed a mixed design with three main independent variables. The first independent variable, which is a between-subjects factor, was the driving mode: safe driving versus aggressive driving. Prosocial Driving is defined as a safe driving mode that is associated with fewer traffic accidents and violations, including obeying traffic rules, paying attention to others, and maintaining good driving habits. In contrast, Aggressive Driving is associated with more traffic accidents and violations [11]. Therefore, in this experiment, our definition and requirements for safe driving are to obey traffic rules (keep to the right), avoid traffic accidents (avoid moving vehicles and do not collide with them), and ensure the safety of your own vehicle (do not run off the designated road). Conversely, we do not make the above requirements for aggressive driving. Research has found that different driving modes significantly affect passenger comfort and anxiety, thereby affecting human physiological responses, including but not limited to galvanic skin response, heart rate and eye movement patterns [8]. In addition, there are behavioural differences between different driving modes [38].

Similarly, different types of curves [12] and traffic conditions [26] will affect driving comfort and stress, leading to different physiological reactions and driving behaviours. Therefore, we set three different scenarios for the second independent variable, which included crossroads, T-junction, and roundabout. We set up interfering vehicles with different driving paths in each scenario, and we require drivers to make left turns at intersections.

The third independent variable was the distraction conditions. Different types of distraction (visual, audio, action, and cognitive) have different effects on driving [17]. The five distraction types tested in the experiment are listed below:

- **No distraction:** Participants completed the driving task without any distraction.
- **Audio × Cognitive:** Participants will hear an audio clip asking them to solve a multiplication arithmetic problem.
- **Audio × Action:** Participants will hear an audio instruction asking them to do an action, which may be to touch their face, touch their knees, or remove a sticker. We will put stickers on the side of the seat (See Figure 6) and ask participants to tear them off while driving to simulate the scene of picking up objects while driving.
- **Visual × Cognitive:** Participants will see a sign with a number on the side of the road, and we will ask participants to remember the number and tell me what the number is when they turn left (See Figure 7).
- **Visual × Action:** The participant will see a sign with instructions on the roadside, and then he needs to perform the corresponding action. The instructions are the same as in the ‘Audio × Action’ task (See Figure 8).



Figure 6: The experiment setup and an example of the stickers on the car seat for the action tasks.



Figure 7: An example of the Scene of the Visual x Cognitive Task

With randomised allocations, each participant was explicitly instructed to drive in either the driving mode of safe driving or



Figure 8: An example of the scene of the Visual x Action Task

aggressive driving. Each combination of scenario and distraction condition was repeated three times, with the five distraction conditions across the three driving scenarios, resulting a total of forty-five trials, with each trial lasting 30 to 60 seconds. The entire experiment was designed to be completed within 1 hour. This design allows for a systematic analysis of how various factors affect driving behaviour, providing a foundation for the improvement of future driver monitoring systems.

3.5 Procedure

Before the experiment, participants were asked to read the Participant Information Sheet and complete the Screening Questionnaire after signing the Consent Form. They also filled out a form for demographics. Participants were then equipped with the heart rate belt and the VR headset. Basic operating instructions were provided, and participants were allowed to practice for about five minutes to familiarise themselves with the road conditions, steering wheel sensitivity, and response times for the accelerator and brake. Practice sessions involved non-distraction scenarios to prevent participants from anticipating the experimental tasks, which could affect cognitive task performance.

After the practice session, the formal experimental process and potential scenarios were explained to the participants. Participants were then asked to take their hands off the steering wheel, sit upright, and allow the sensors to be zeroed and calibrated. Before the experiment officially began, we would first turn on the heart rate belt, the steering wheel and head sensors, and finally start running AirSim.

Each participant experienced 45 trials (3 road conditions \times 5 distraction conditions \times 3 repetitions). The trial order was randomly shuffled before the experiment began. In UE4, fifteen levels were set up as corresponding to fifteen different key presses on the keyboard. After the experiment started, we manually switched levels according to the shuffled order. The experimenter would sit next to the participants to observe the participants' driving performance on an external screen and recorded the executions of the action or cognitive tasks. For cognitive tasks, we instructed the participants to tell us the results when they turned left. For action tasks, we instructed the participants to make corresponding actions after receiving instructions. A trial was considered to be finished when the participant's feet was no longer stepping on the pedals. We would then instruct the participants to recover the initial

sitting state (hands off the steering wheel, sit upright) and reset the sensors, to minimise the errors. After the experiment, AirSim will be stopped first, and then the data collection of the heart rate belt and sensor will be turned off. In this way, when we process data, the AirSim timestamp could be used as the starting point of the data to calibrate the time across different devices.

Additionally, breaks were offered after every 10 trials to minimise discomfort for those who may experience dizziness.

3.6 Data Collection

We implemented two approaches for the data collection, i.e. via the hardware equipment collection and software recording. Below section will explain the data collection methods and data types for different dependent variables with technical details.

AirSim Records. The vehicle status information is recorded by AirSim's Recorder. Every time the AirSim is executed, 'Record' will automatically start and end when you finish running, and generate a 'airsim_rec.txt' file. Some of the data recorded in the file are shown in Table 1. The first column is the timestamp. The timestamp here is UNIX time. Standard UNIX time refers to the number of seconds calculated from January 1, 1970 (Greenwich Mean Time). This time point is called the Epoch. UNIX time is the total number of seconds measured in seconds starting from this time point. However, in AirSim, the timestamp is in milliseconds, which is more accurate than the standard UNIX time. POS_X, Y, Z are the position coordinates of the center of gravity of the vehicle, in meters. The last seven columns of data represent the vehicle's throttle, steering, brake, party committee, handbrake, speed and speed. The range of the throttle and brake values is 0 to 1. The range of Steering is -1 to 1, with negative numbers representing left turns and positive numbers representing right turns. In addition, by comparing the steering wheel rotation angle recorded by the single-axis sensor on the steering wheel, we found that the AirSim Steering value of -1 is -130 degrees and +1 is 130 degrees, but it does not change linearly. When the steering wheel rotation angle exceeds 130 degrees, the vehicle's steering degree will not increase, and the Steering value will remain at -1 or 1. The range of the gear value is 0 to 5. The handbrake value is always 0. RPM stands for Revolutions Per Minute, which is the engine's speed per minute. The unit of speed value is m/s.

Heart rate. When it comes to collecting heart rate data, wearable devices are a good choice considering cost and convenience. We have evaluated both the Apple Watch Series 7 and the Polar H10 for this purpose. Preliminary testing has revealed that the Apple Watch's heart rate data collection frequency is not consistently stable, whereas the Polar H10 reliably provides a heart rate value every second. Furthermore, research has demonstrated a high association and good to excellent agreement between ECG measurements and the Polar H10. Although there is a good to excellent agreement between the Apple Watch and ECG as well, the accuracy of the Apple Watch tends to decline with increasing exercise intensity [33]. Consequently, we have chosen to utilise the Polar H10 for heart rate data collection in this study. The final collected heart rate data is saved as a CSV file, which contains a column of time and a column of heart rate.

Table 1: Example of the vehicle status raw data records

TimeStamp	POS_X	POS_Y	POS_Z	Throttle	Steering	Brake	Gear	Handbrake	RPM	Speed
1725615633317	0.0388158	-161.79	-4.94724	1	0	0	2	0	4072.62	8.40016
1725615633367	0.0404608	-165.867	-4.94229	1	0	0	2	0	4069.28	8.61648
1725615633417	0.0404608	-165.867	-4.94229	1	0	0	2	0	4069.28	8.61648
1725615633467	0.042288	-170.089	-4.9462	1	0	0	2	0	4078.48	8.5471
1725615633517	0.0440965	-174.234	-4.94042	1	0	0	2	0	4075.47	8.81063
1725615633567	0.045982	-178.557	-4.9459	1	0	0	2	0	4089.4	8.83071

Steering wheel rotation angular and angular velocity. The single-axis sensor on the steering wheel can collect the steering wheel rotation angle and angular velocity. After the data recording is completed, a csv file will be generated, which contains time (%H:%M:%S.%f), angular velocity (°/s) and angle (°). Both angular velocity and angle are accurate to three decimal places.

Head position and posture data. We initially aimed to use the VIVE Pro 2’s Lighthouse base station system[39], which tracks the headset’s position and orientation using infrared lasers and sensors. The system calculates the headset’s 3D position through triangulation, providing a position and orientation matrix. However, we encountered issues running both the headset tracking and the UE4 VR scene simultaneously, as SteamVR and OpenVR use the same API to communicate with the headset, preventing concurrent access. As a second approach, we considered extracting the driver’s camera posture directly from UE4, but since we could not modify AirSim assets (including the vehicle’s camera), this method was also not feasible. Finally, we chose to put a six-axis attitude sensor on the VR headset. The recorded data is saved as a txt file. The data recorded by some sensors are shown in Table 2, you can see what data is recorded and the units of the data. In Results section, we present driver’s head yaw (z-axis) rotation results as it represents the head movements of looking left and right.

4 Results

In this study, we aimed to explore the impact of different distraction conditions, different Scenario Types and different driving modes on the driver’s physiological and behavioural data. To achieve this purpose, we used a three-factor Analysis of Variance (ANOVA). We mainly explored the impact of independent variables on the following dependent variables:

- **Physiological data:** Heart rate.
- **Behavioural data:** AirSim Records(Throttle, Acceleration, Steering, Break, RPM, Speed), steering wheel rotation angle and angular velocity, driver’s head Z-axis rotation angle and angular velocity.

Independent variables include:

- **Distraction Type:** No distraction, Audio × Cognitive, Audio × Action, Visual × Cognitive, Visual × Action.
- **Scene Type:** Crossroads, T-junction, Roundabout.
- **Driving Mode:** aggressive driving, safe driving.

In the following sections, we report the results of ANOVA in detail, including main effects, interaction effects, and corresponding p

values. In addition, after conducting analysis of variance, for those factors or interactions that show significant effects (i.e., p value is less than 0.05), we use Tukey HSD test to conduct post hoc tests to determine which groups have significant differences. This approach allows us to more precisely understand the specific impact of different combinations of conditions on driver performance, providing deeper insights into the study of driving behaviour.

4.1 AirSim Records

We performed ANOVA on the five dependent variables (Throttle, Steering, Break, RPM, Speed) recorded by AirSim to evaluate the effects of distraction type, Scenario Type, and driving mode on these variables.

Throttle. For Throttle, the ANOVA results show that driving mode has a significant effect on Throttle ($F(1, 570) = 11.20, p < 0.001$). The effects of distraction type and Scenario Type are not significant, $F(4, 570) = 0.71, p = 0.584$ and $F(2, 570) = 0.045, p = 0.956$, respectively. The Tukey HSD post hoc test results on driving mode show that there is a significant difference between aggressive driving and safe driving (Mean Difference $-0.0181, p < 0.001$). From Figure 9, the average throttle usage during aggressive driving was significantly greater than that during safe driving.

Acceleration. The results of three-way analysis of variance (ANOVA) showed that driving mode had a significant effect on acceleration ($F(1, 270) = 23.51, p < 0.001$), while the effects of Distraction Type and Scenario Type did not reach a significant level ($p = 0.067$) and ($p = 0.108$). Further analysis by post hoc test (Tukey HSD) showed that no significant difference was found between distraction types, but there was a significant difference between aggressive driving and safe driving (Mean Difference $0.387, p < 0.001$), indicating that aggressive driving was associated with significantly lower acceleration values. Figure 10 shows the average acceleration of the vehicle in different situations.

Steering. For Steering, the ANOVA results show that Scenario Type has a significant effect on Steering ($F(2, 570) = 111.47, p < 0.001$), while the effect of distraction type is not significant ($F(4, 570) = 0.84, p = 0.501$). For driving mode, the results also show a significant effect ($F(1, 570) = 23.81, p < 0.001$). The Tukey HSD test results show that there is a significant difference between aggressive driving and safe driving (Mean Difference $-0.012, p < 0.001$). In the Tukey HSD results of Scenario Type, the comparison between T-junction and roundabout showed significant difference (Mean Difference $0.039, p < 0.001$), while the difference between

Table 2: Example of the Raw Data Recorded from the sensors

Time	Accel X (g)	Accel Y (g)	Accel Z (g)	Gyro X (°/s)	Gyro Y (°/s)	Gyro Z (°/s)	Angle X (°)	Angle Y (°)	Angle Z (°)
13:41:38:364	0.024	0.081	0.984	0	0	0	-0.18	-0.15	-0.01
13:41:38:474	0.025	0.081	0.987	0	0	0	-0.19	-0.15	-0.01
13:41:38:586	0.025	0.078	0.982	0	0	0	-0.20	-0.16	-0.02
13:41:38:696	0.028	0.078	0.984	0	0	0	-0.21	-0.17	-0.02
13:41:38:754	0.029	0.078	0.985	0	0	0	-0.23	-0.18	-0.02
13:41:38:888	0.024	0.078	0.981	0	0	0	-0.24	-0.19	-0.02

Table 3: Summary of the main effects found in ANOVA. Note that the Crossroads, T-junction, the Roundabout are represented by S1, S2, and S3, respectively.

Variable	Factor	Significant Effect	<i>p</i> Value
Throttle	Driving Mode	Safe (0.549 ± 0.004) < Aggressive (0.567 ± 0.004)	<i>p</i> < 0.001
Acceleration	Driving Mode	Safe (0.199 ± 0.049) > Aggressive (−0.189 ± 0.061)	<i>p</i> < 0.001
Steering	Driving Mode	Safe (0.097 ± 0.002) < Aggressive (0.109 ± 0.002)	<i>p</i> < 0.001
Steering	Scenario Type	S1 = 0.089 ± 0.002, S2 = 0.091 ± 0.002, S3 = 0.130 ± 0.003	<i>p</i> < 0.001
Brake	Driving Mode	Safe (0.096 ± 0.002) < Aggressive (0.104 ± 0.003)	<i>p</i> = 0.01
Brake	Scenario Type	S1 = 0.104 ± 0.003, S2 = 0.103 ± 0.003, S3 = 0.093 ± 0.003	<i>p</i> = 0.019
Speed	Driving Mode	Safe (7.437 ± 0.073) < Aggressive (7.742 ± 0.072)	<i>p</i> = 0.004
Heart rate	Distraction Type	visual action (0.357 ± 0.010) < audio cognitive (0.407 ± 0.010)	<i>p</i> = 0.015
Steering Angle	Driving Mode	Aggressive Driving (25.469 ± 1.441) < Safe Driving (30.084 ± 1.682)	<i>p</i> = 0.042
Head Angular Velocity	Driving Mode	Aggressive Driving(3.343 ± 0.261) < Safe Driving(4.563 ± 0.318)	<i>p</i> = 0.003
Head Angle	Driving Mode	Aggressive Driving(13.661 ± 0.773) < Safe Driving(20.587 ± 1.352)	<i>p</i> < 0.001

intersection and roundabout was also significant (Mean Difference 0.040, $p < 0.001$) As can be seen from Figure 11, the turning range in roundabouts is significantly greater than that in crossroads and T-junctions. And in all cases, the steering amplitude is greater when driving aggressively than when driving safely.

Brake. The ANOVA results showed that Scenario Type had a significant effect on Brake ($F(2, 570) = 4.00, p = 0.019$), while the effects of distraction type and driving mode were not significant, respectively ($F(4, 570) = 0.50, p = 0.738$) and ($F(1, 570) = 6.59, p = 0.0105$). The Tukey HSD test results show that the mean difference between aggressive driving and safe driving is significant (Mean Difference $-0.009, p = 0.010$).

Figure 12 shows the average amount of brake usage in different situations. It is obvious that the amount of brake usage in roundabouts is significantly less than that in crossroads and T-junctions. The amount of brake usage in aggressive driving is also greater than that in safe driving

RPM. For RPM, the ANOVA results show that the influence of each factor on RPM is not significant(See Figure 13), and the p values of distraction type, Scenario Type and driving mode are 0.615, 0.470 and 0.206 respectively.

Speed. For Speed, the ANOVA results show that the driving mode has a significant effect on Speed ($F(1, 570) = 8.55, p = 0.0036$), while the influence of Distraction Type and Scenario Type is not significant, with p values of 0.978 and 0.259 respectively. The Tukey HSD test results show that the mean difference between aggressive driving and safe driving is significant (Mean Difference $-0.305, p =$

0.003). It can also be seen from Figure 14 that the average speed during aggressive driving is greater than that during safe driving.

4.2 Heartrate

Figure 15 shows the mean heart rate under different driving conditions. Based on the ANOVA results, distraction type has a significant effect on the average heart rate ($F(4, 870) = 3.08, p = 0.015$), whereas Scenario Type ($F(2, 870) = 0.41, p = 0.667$) and Driving Mode ($F(1, 870) = 1.88, p = 0.171$) do not show significant effects. Additionally, the interaction effects among the variables are not significant. The Tukey HSD post hoc test for Distraction Type reveals that the difference in average heart rate between audio_cognitive and visual_action is significant ($p = 0.006$), indicating that visual_action causes a significantly higher average heart rate compared to audio_cognitive. No significant differences are observed among the other distraction conditions. In summary, Distraction Type is a key factor affecting heart rate, with visual_action having a notably higher impact than audio_cognitive. Scenario Type and driving mode, on the other hand, do not have significant effects on heart rate.

4.3 Steering angular velocity and angle data recorded by the sensor

For the ANOVA results of steering angular velocity, the analysis indicates that "Distraction Type," "Scenario Type," "Driving Mode," and the interactions between these factors do not significantly impact steering angular velocity (all p -values are greater than 0.05). Specifically, the F-value for Distraction Type is 1.37 ($p = 0.244$),

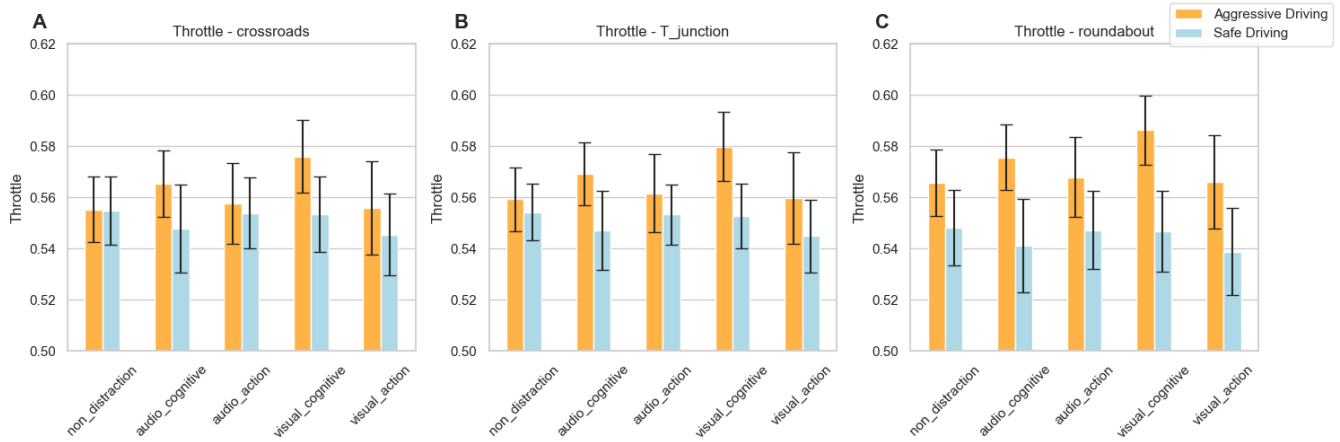


Figure 9: The averaged throttle level (0-1), per driving mode (aggressive driving as in orange colour and safe driving as in cyan colour), per distraction type (as labelled on the x-axis), and per driving scene (A: the crossroads, B: the T-junction, and C: the roundabout). Error bars represent ± 1 SEM.

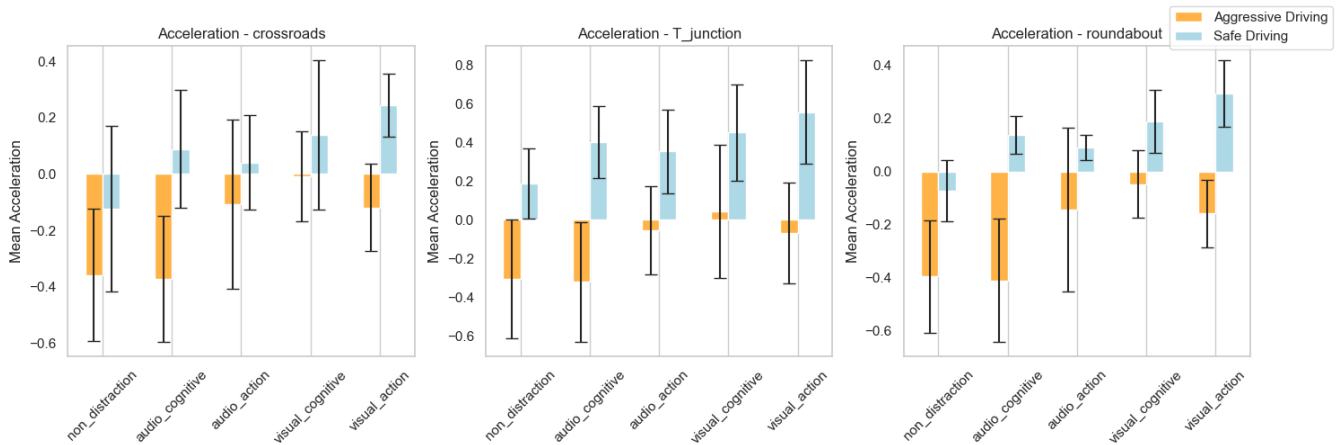


Figure 10: The averaged acceleration (m/s^2), per driving mode (aggressive driving as in orange colour and safe driving as in cyan colour), per distraction type (as labelled on the x-axis), and per driving scene (A: the crossroads, B: the T-junction, and C: the roundabout). Error bars represent ± 1 SEM.

for Scenario Type is 0.60 ($p = 0.550$), and for Driving Mode is 0.01 ($p = 0.916$). These results suggest that steering angular velocity remains relatively stable and is not significantly influenced by these external factors or their interactions. For the ANOVA results of steering angle, Driving Mode has a significant effect on steering angle ($F = 8.78, p = 0.003$), indicating a notable difference between aggressive and safe driving modes. This significance implies that different driving styles affect vehicle control behaviors. On the other hand, Distraction Type ($F = 0.92, p = 0.454$) and Scenario Type ($F = 0.06, p = 0.939$), along with their interactions, did not show significant effects, suggesting limited influence on steering angle. Additionally, the Tukey HSD post-hoc test reveals that the steering angle in safe driving is significantly higher than in aggressive driving ($meandifference = 6.69, p = 0.0029$), highlighting a meaningful impact of driving style on vehicle control.

4.4 Driver's head yaw

The ANOVA results for head velocity show that the driving mode has a significant effect ($F(1, 869) = 8.68, p < 0.001$), indicating that head velocity differs between safe driving and aggressive driving conditions. However, the distraction type and Scenario Type do not significantly affect head velocity, as their p-values are greater than 0.05 (distraction type: $p = 0.717$, Scenario Type: $p = 0.579$). Additionally, there are no significant interactions between distraction type, Scenario Type, and driving mode (all p values > 0.05), suggesting that these factors do not interact to influence head velocity. For head angle, the results show that driving mode again has a significant effect ($F(1, 869) = 19.40, p < 0.001$), with aggressive driving leading to a larger head angle compared to safe driving. In contrast, neither distraction type ($p = 0.622$) nor Scenario Type ($p = 0.377$) has a significant impact on head angle. Similar to head

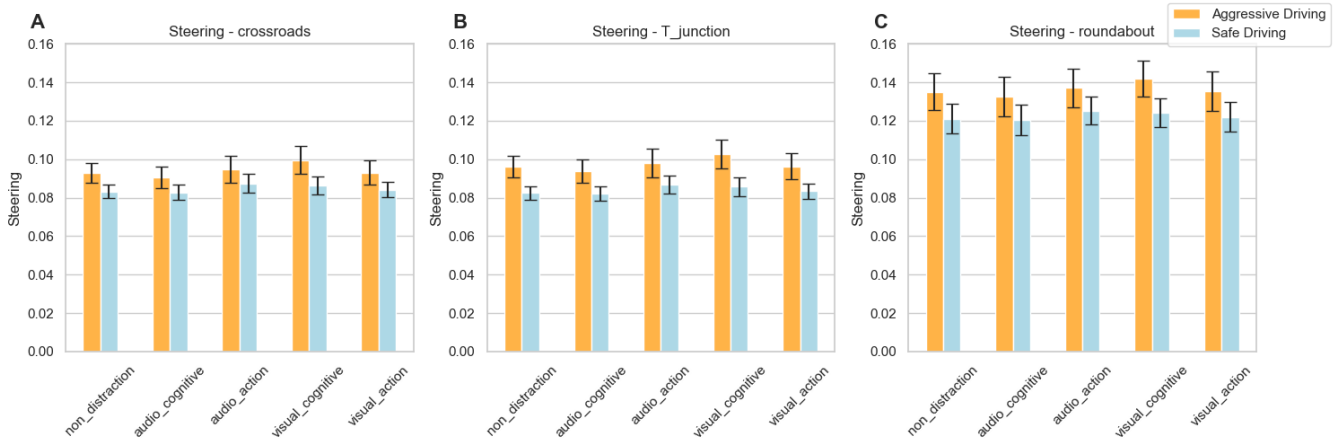


Figure 11: The averaged absolute value of the standardised steering angle (-1 to 1), per driving mode (aggressive driving as in orange colour and safe driving as in cyan colour), per distraction type (as labelled on the x-axis), and per driving scene (A: the crossroads, B: the T-junction, and C: the roundabout). Error bars represent ± 1 SEM.

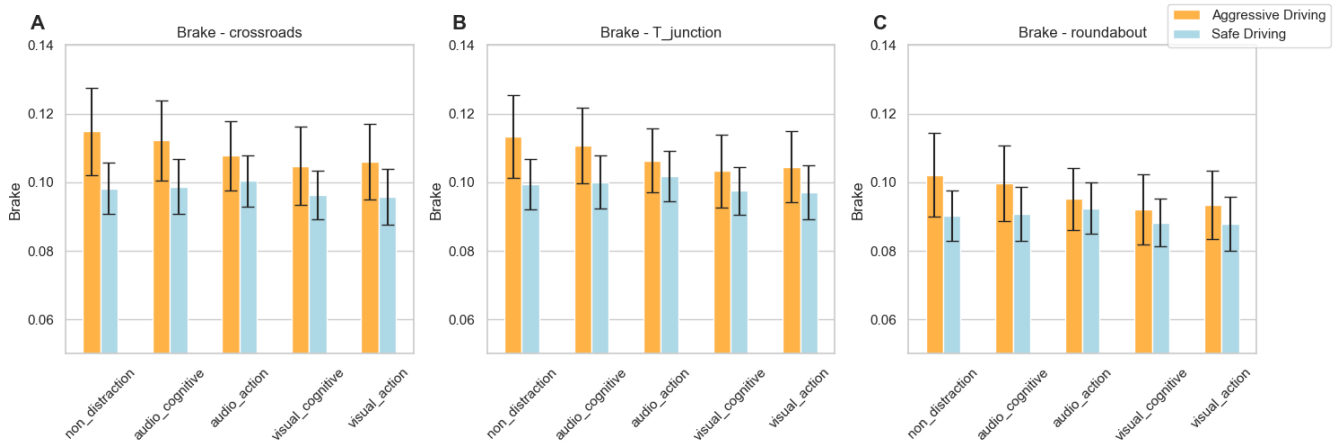


Figure 12: The averaged normalised brake uses (0-1), per driving mode (aggressive driving as in orange colour and safe driving as in cyan colour), per distraction type (as labelled on the x-axis), and per driving scene (A: the crossroads, B: the T-junction, and C: the roundabout). Error bars represent ± 1 SEM. Note that most of the time participants did not brake, i.e. brake = 0, and thus on average it was around 0.1, without significant difference found between conditions.

velocity, no significant interactions are found between distraction type, Scenario Type, and driving mode (all p values > 0.05), implying that these factors do not influence head angle together. The Tukey HSD tests further confirm that safe driving results in significantly higher head angular velocity and head angle compared to aggressive driving, with p -values of 0.0031 and 0.0, respectively.

Figures 18 and 19 show the average values of the Z-axis rotation angle and angular velocity of the driver’s head under different conditions during driving.

5 Discussion

Overall, Distraction type had a significant effect on drivers’ heart rate. Driving mode had a significant effect on most dependent variables, including throttle, acceleration, steering, brake, speed,

steering angle (recorded by sensor), head rotation angular velocity and angle. Scenario Type also had an effect on both steering and brake. Specifically, steering amplitude was greater in the roundabout than in the other two scenarios, while braking usage was significantly less in the roundabout than in the other two scenarios.

5.1 Interpretation of Results

AirSim Records (Throttle). The results showed that the use of the accelerator in aggressive driving mode is significantly greater than that in safe driving. Combined with the result that the heart rate is significantly higher in aggressive driving than in safe driving, we believe that this is because the driver will step on the accelerator more frequently or harder in aggressive driving mode, which leads

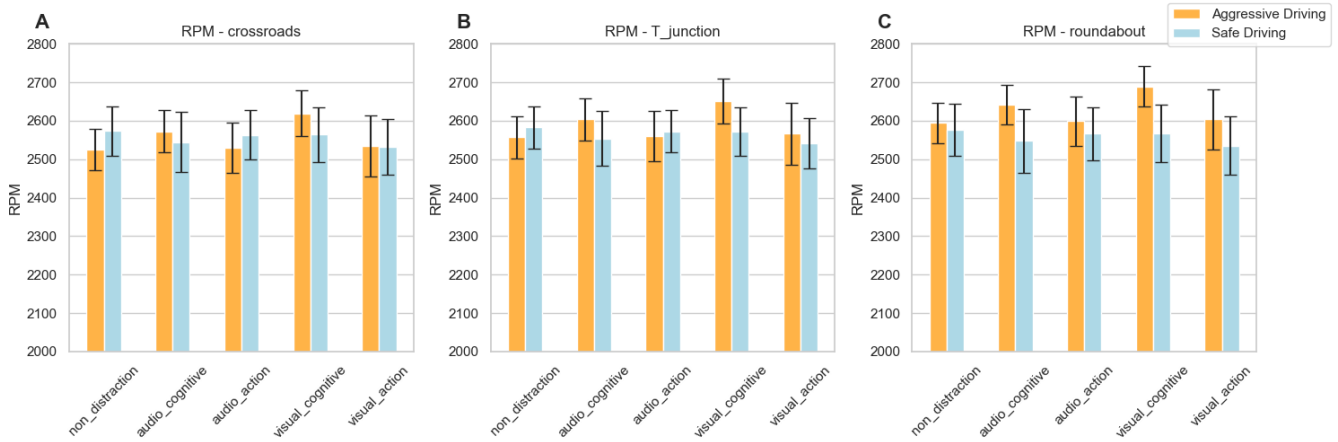


Figure 13: The average engine Revolutions Per Minute (RPM), per driving mode (aggressive driving as in orange colour and safe driving as in cyan colour), per distraction type (as labelled on the x-axis), and per driving scene (A: the crossroads, B: the T-junction, and C: the roundabout). Error bars represent ± 1 SEM.

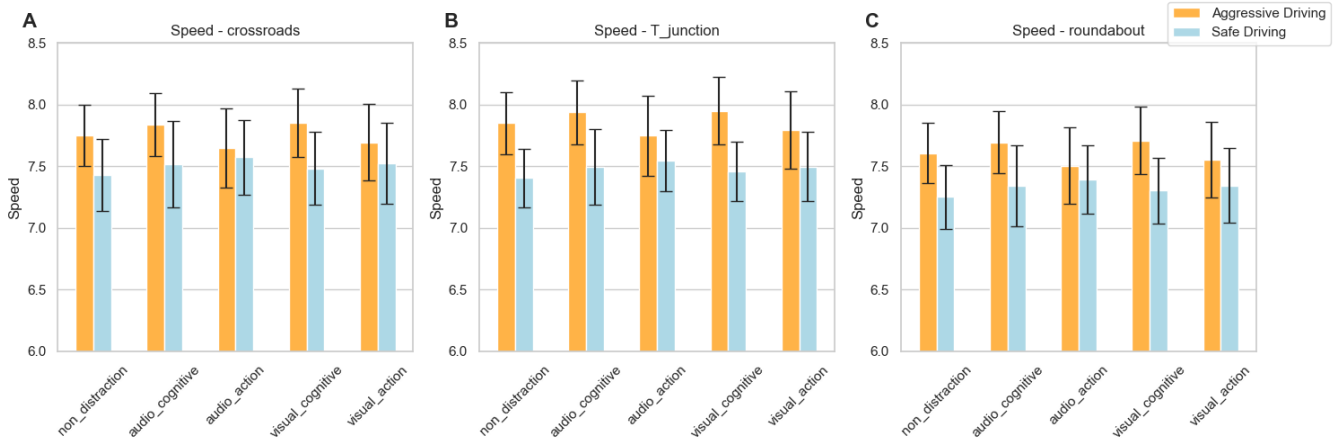


Figure 14: The averaged car speed (m/s), per driving mode (aggressive driving as in orange colour and safe driving as in cyan colour), per distraction type (as labelled on the x-axis), and per driving scene (A: the crossroads, B: the T-junction, and C: the roundabout). Error bars represent ± 1 SEM.

to higher acceleration of the vehicle and thus higher stress. On the contrary, stress has a positive effect on acceleration behaviours [30]. This is also the reason why the driver’s heart rate is higher in aggressive mode.

AirSim Records (Acceleration). The analysis results show that the driving mode has a significant effect on acceleration ($F(1, 270) = 23.51, p < 0.0001$). From the Figure 10, we can see that in the aggressive driving mode, the average acceleration is almost always negative, which means that there are very frequent sudden deceleration operations during aggressive driving, which leads to negative average acceleration. This driving mode is usually accompanied by more intense driving behaviors, such as sharp turns and sudden braking when turning, which may have a negative impact on the stability and safety of the vehicle.

AirSim Records (Steering). Based on the analysis of steering data recorded by Airsim, we found that the steering range of the vehicle in the roundabout is greater than that in the other two scenarios. We believe that this result is in line with our expectations and has certain significance in actual driving. The road in the roundabout is more curved, and the driver needs to steer more to ensure the normal driving of the vehicle. In addition, we also found that the steering range in aggressive driving is greater than that in safe driving in any case, which means that in more aggressive driving situations, the driver needs to use a larger steering range to ensure that the vehicle passes the curve normally [29].

Break. The results of the analysis of Break show that driving mode and road environment have a significant impact on braking behaviour. In aggressive driving mode, drivers may use the brakes

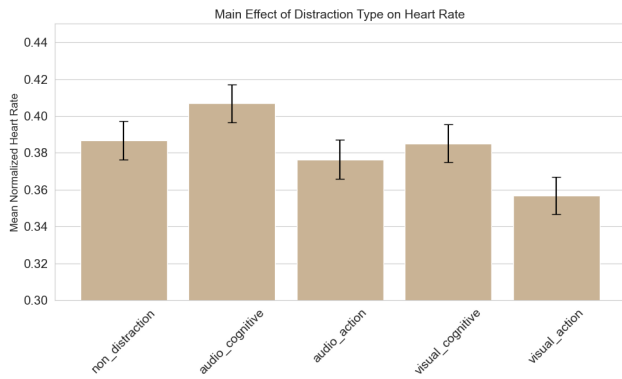


Figure 15: The averaged heartrate, per driving mode (aggressive driving as in orange colour and safe driving as in cyan colour), per distraction type (as labelled on the x-axis), and per driving scene (A: the crossroads, B: the T-junction, and C: the roundabout). Error bars represent ± 1 SEM.

more frequently, which may be due to more frequent acceleration and deceleration, or braking harder when a quick reaction is required[7].

In addition, the use of brakes in the roundabout is significantly lower than in the other two scenarios. This shows that drivers will adjust their braking behaviour according to the degree of danger of the conflict [14]. From our experimental design, at intersections and T-junctions, the interference vehicles we set up are more likely to collide with the driver’s vehicle, while it is difficult to collide in the roundabout, so the use of brakes in these two scenarios is significantly higher than that in the roundabout.

Speed. From the data analysis results, the average speed in the aggressive driving mode is higher than that in the safe driving mode. This shows that when drivers take more aggressive driving actions, they tend to drive at a higher speed. This is in line with our expectations.

Heart rate. Judging from the results of the heart rate data, the average heart rate of ‘audio cognitive’ is the highest, which is in line with our expectations. In the experiment, we set the task of ‘audio cognitive’ to calculate multiplication, and only 3 participants calculated the result while completing the driving task. 13 participants made at least 2 calculation errors. The increase in heart rate may reflect the driver’s nervousness or high stress level[45], which shows that more complex cognitive tasks will cause certain psychological pressure on people and cause emotional tension. From the perspective of driving safety, higher pressure will increase the driver’s physiological load, which may cause fatigue, anxiety and other problems, thereby increasing the risk of traffic accidents[4]. However, we found that the heart rate in the ‘visual action’ condition was the lowest, even lower than in the non-distraction condition. This result is not intuitive and further investigation is needed in the future.

Steering Wheel Rotation Angle and Angular Velocity. Our analysis of the steering wheel selection angle data is inconsistent with the

analysis of the steering data recorded by AirSim. Specifically, the analysis of the steering data in AirSim shows that both the Scenario Type and the driving mode have an impact on the steering amplitude, and the steering amplitude of aggressive driving is greater than that of safe driving. However, the steering data recorded by the sensor only shows that the driving mode has an impact on the steering amplitude, and the steering amplitude of safe driving is greater than that of aggressive driving. The two results are contradictory. There are several reasons for this. First, AirSim’s steering data has a specific range (-1 to 1) and is a normalized value relative to the steering wheel rotation. ± 1 represents a steering wheel rotation angle of approximately ± 130 degrees, while the sensor data recording range is ± 180 degrees. When the steering wheel exceeds 130 degrees, the steering data is still recorded as ± 1 , resulting in it not being able to reflect a larger rotation range. Through data statistics, we found that the data recorded by the sensor on the steering wheel with a rotation angle greater than 130 degrees or less than -130 degrees, safe driving has 55.86% more data points than aggressive driving. These data cannot be reflected in the steering data recorded by AirSim. This may lead to the opposite results of the two data recording methods in the analysis of the impact of driving mode on steering. In addition, there is no linear relationship between the steering value and the actual steering wheel rotation angle. For example, we found that when the steering value is 0.5, the steering wheel rotation angle is not 65 degrees. When the driver steers, the steering wheel deflection reflected in the AirSim steering value may be a large value, which leads to the AirSim data analysis results that the scene type has a significant effect on steering. From the perspective of human-computer interaction, the nonlinear scenarioing between the steering wheel angle and the actual steering of the vehicle may be different in driver perception and control. The angular velocity of the steering wheel is an important indicator of vehicle control stability [1]. Although all factors have no statistically significant effect on the steering angular velocity, but in actual driving, these factors may still have a certain impact on the driver’s steering behavior. For example, visual distraction may temporarily distract the driver’s attention, resulting in delayed or inaccurate steering operations[18]. From the analysis of steering, we found that different data recording methods may produce different analysis results, or even completely opposite results. This is worth our further study.

Driver’s head Z-axis rotation angle and rotation angle velocity. We found that driving mode affects the angular velocity and angle of the driver’s head rotation. The angular velocity and angle of head rotation during safe driving are greater than those during aggressive driving. In actual driving, head movement is an important way for drivers to obtain information about the surrounding environment[44]. Compared with safe drivers, unsafe drivers have less head movement, especially small head turns. This head movement pattern can be used to distinguish safe and unsafe driving behaviors[20, 43]. Therefore, we believe that in this experiment, the driver turned his head more and faster to ensure driving safety.

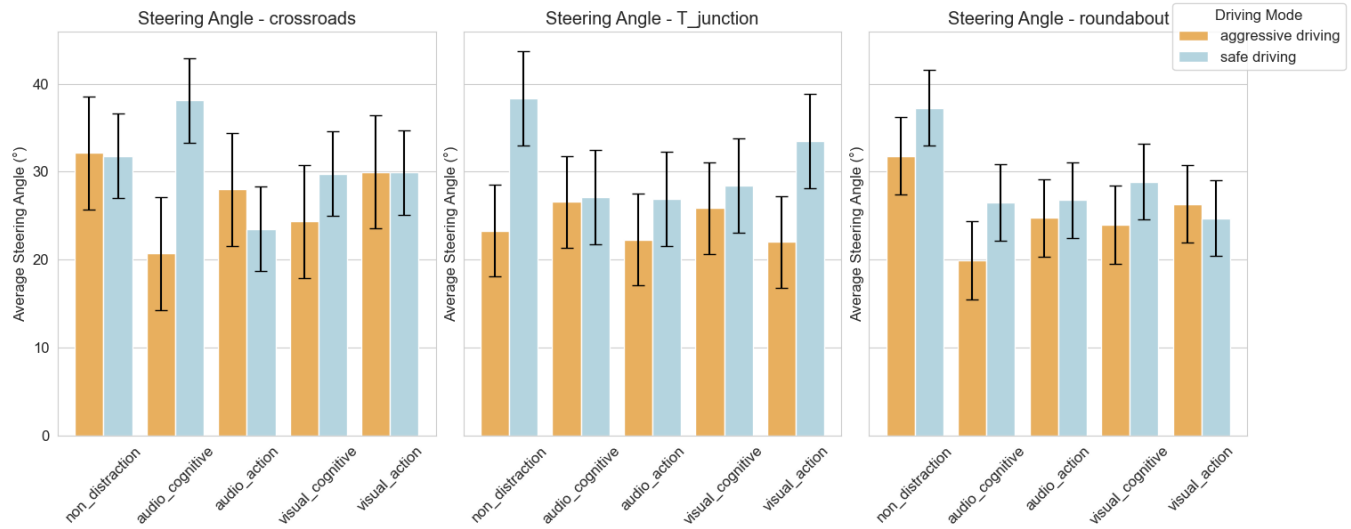


Figure 16: The averaged steering wheel rotation angle ($^{\circ}$), per driving mode (aggressive driving as in orange colour and safe driving as in cyan colour), per distraction type (as labelled on the x-axis), and per driving scene (A: the crossroads, B: the T-junction, and C: the roundabout). Error bars represent ± 1 SEM.

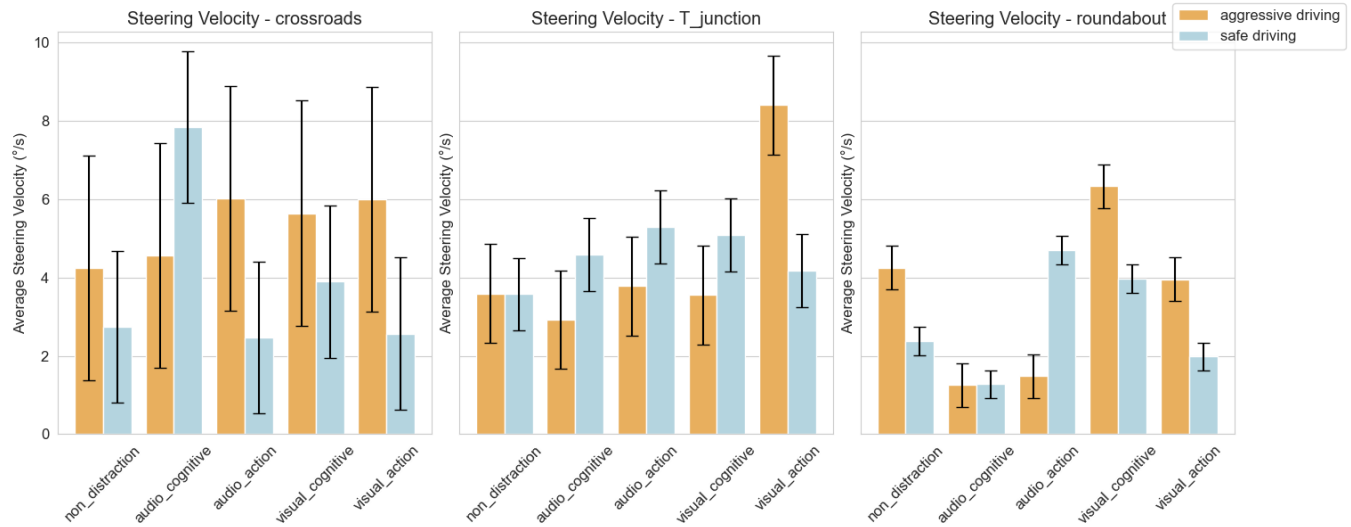


Figure 17: The averaged steering wheel rotation angular velocity ($^{\circ}/s$), per driving mode (aggressive driving as in orange colour and safe driving as in cyan colour), per distraction type (as labelled on the x-axis), and per driving scene (A: the crossroads, B: the T-junction, and C: the roundabout). Error bars represent ± 1 SEM.

5.2 Implications of the results for autonomous driving system design

The impact of driving mode on control behavior. From the experimental results, the biggest feature is that driving mode has an impact on many dependent variables, including throttle, vehicle acceleration, steering, braking, vehicle speed, head rotation, etc. This shows that by analyzing the vehicle's throttle, braking, steering, acceleration, and driver's head rotation data, we can understand the driver's driving tendency, learn the driver's driving habits[5],

and dynamically adjust the vehicle's control strategy according to different driving styles.

The impact of Scenario Type on driving behavior. Steering and braking responses vary in different Scenario Types. Therefore, when designing an autonomous driving system, it is necessary to consider the impact of different scenarios on driving behavior in order to understand the driver's decision-making intentions in certain specific scenarios.

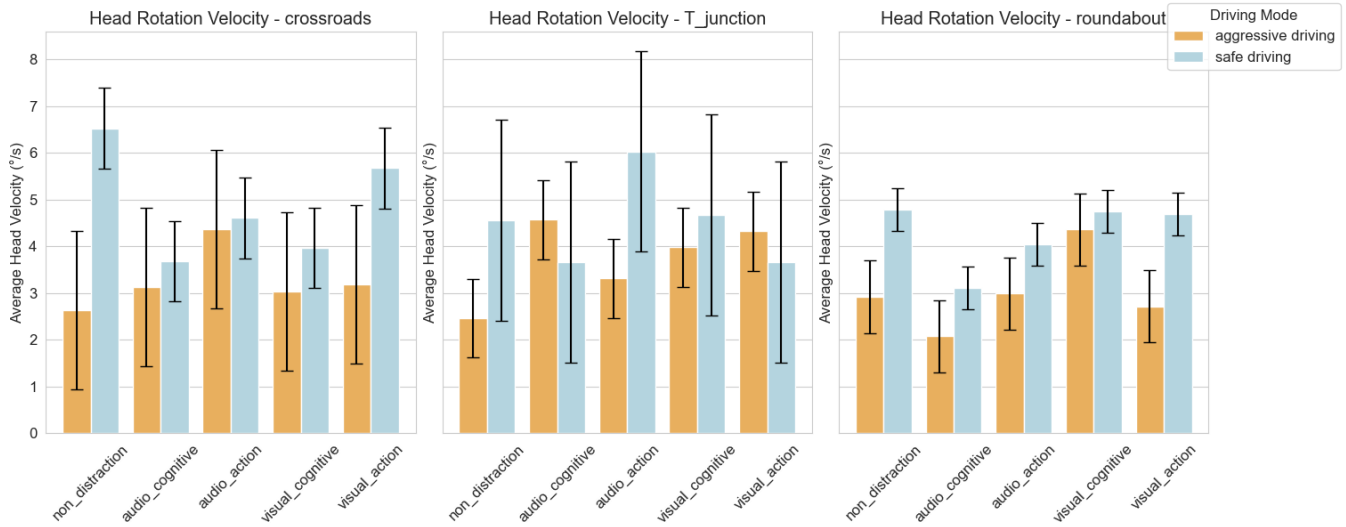


Figure 18: The averaged head rotation angular velocity ($^{\circ}/s$), per driving mode (aggressive driving as in orange colour and safe driving as in cyan colour), per distraction type (as labelled on the x-axis), and per driving scene (A: the crossroads, B: the T-junction, and C: the roundabout). Error bars represent ± 1 SEM.

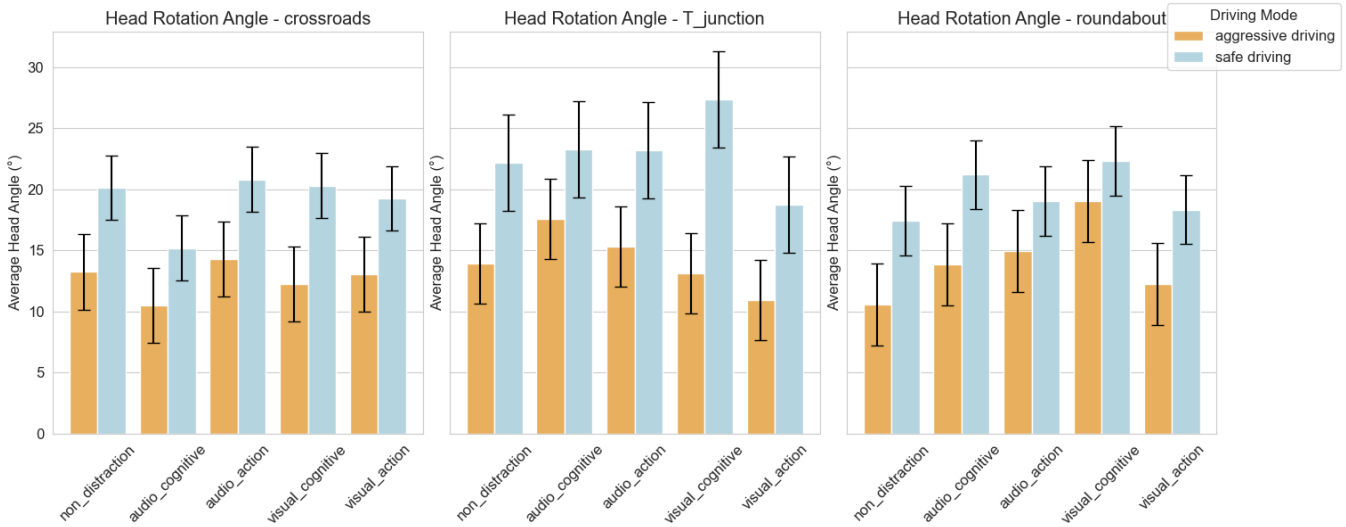


Figure 19: The averaged head rotation angle ($^{\circ}$), per driving mode (aggressive driving as in orange colour and safe driving as in cyan colour), per distraction type (as labelled on the x-axis), and per driving scene (A: the crossroads, B: the T-junction, and C: the roundabout). Error bars represent ± 1 SEM.

Effects of distraction types on physiology and driving behavior. Understanding the impact of disturbance types on driver physiology and behavior can help design autonomous driving systems, especially in terms of driver monitoring and response adjustment. For autonomous driving systems, being able to identify the driver’s state (such as changes in physiological responses) and adjust the autonomous driving strategy based on the type of disturbance can improve safety. For example, when the driver’s heart rate changes or increased cognitive load are identified, the system can automatically

slow down the vehicle or provide more assisted driving support. In addition, although our experiments did not find a correlation between head rotation and distraction factors, the driver’s head movement can be used to detect whether the driver is distracted and fatigued to a certain extent[15, 16]. By monitoring the driver’s head movement characteristics, the autonomous driving system can more accurately identify driving behavior, such as whether the driver turns his head to observe the road conditions or because of

distraction, and adjust the control strategy accordingly to improve overall driving safety.

The meaning of heart rate data. The only physiological data in this experiment is heart rate. By monitoring the heart rate, the autonomous driving system can assess the driver's psychological stress level, which can help evaluate the performance of the autonomous driving system in actual scenarios[31]. In addition, physiological indicators such as blood pressure and skin conductivity[23] can also reflect a person's stress level and can be added to this experiment in the future.

5.3 Limitations of the study

Sample Size. In this study, the average age of the participants was around 22 years old, a relatively young group with various driving experiences. Future research could consider expanding the sample size, including expanding the range of participant age and driving experience, to improve the representativeness and applicability of the study, or to study individual differences in driving behavior. And we found that the analysis results of some data are close to significant effects, such as the impact of scene type on steering angular speed ($p = 0.082$). The results may also change after expanding the sample size.

Driving Scenarios. Although the driving scenarios used in the study (crossroads, T-junctions, and roundabout) cover some common traffic situations, they may not reflect the complexity of all real driving environments. Different types of roads (such as highways or urban streets) and different traffic densities and weather conditions may have a significant impact on driving behaviour. For example, drastic traffic changes or complex environmental factors may cause drivers to respond differently, thus affecting the validity of the study. The lack of diverse scenarios may limit the wide applicability of the results, so future studies should consider testing in a wider variety of driving scenarios.

Data Collection and Analysis. On the technical side, we customised the setup that included the VR display and a driving simulator with multiple sensors attached. Data collection required the experimenter to constantly reset the devices for calibrations, which may lead to error accumulations, posed risks of errors or data loss. The complex reactions in real driving may not be fully recorded. For example, when participants turn their heads quickly multiple times in a short period of time, the picture may drop frames, which will affect the driver's operation. Therefore, the current setup may need to be further improved for the accuracy and completeness of data collection as one of the focus in future research. In terms of data analysis, the analysis relied only on basic ANOVA tests and did not explore more complex analytical methods such as temporal patterns or serial effects.

6 Conclusion

This study aims to investigate whether driving mode, distraction type, and different road scenarios have significant effects on drivers' physiology and driving behaviour by using a simulated driving task in a VR environment combined with multiple sensors. Our main findings show that driving mode significantly affects the control behavior of the vehicle. For example, the aggressive driving

mode has higher throttle, acceleration and vehicle speed, while the safe driving mode is smoother and the driver turns his head more frequently. In addition, scene type and distraction conditions also have an impact on driving behavior and physiological responses, especially in terms of steering angle and heart rate. Overall, drivers in safe driving mode show higher control accuracy and stability, while aggressive driving mode shows stronger reactivity and greater vehicle control.

Our work highlights the importance of considering the impact of multiple factors on the driver's physiology and behaviour when designing autonomous driving systems and driver monitoring systems. Although this study provides some understanding of the changes in human physiological and behavioural responses during driving, there are still certain limitations, including small sample size, limited driving scenarios, convenience and accuracy of data collection, etc. Therefore, in the future, we will expand the sample size and scenario richness, and improve the integration of the data collection system to improve the efficiency of data collection. In addition, we will try to simulate human decision-making in driving tasks and integrate human decision-making models into the planning and control development of autonomous vehicles. Ultimately, we aim to develop explainable autonomous driving artificial intelligence to achieve truly fully autonomous driving. This will further help the public increase their trust in autonomous driving technology and reduce concerns about autonomous driving safety issues.

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