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Behavioral Patterns of Drivers under Signalized and Unsignalized Urban Intersections

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Featured Application: The human-like driving model helps improve the interaction between ADSs and conventional vehicles, and personalized human-like driving models enhance the acceptance and safety of ADSs. Deeply studying the driving behaviors at intersections can improve the performance of ADS driving at intersections.

Abstract: Under the general trend of mixed traffic flow, an in-depth understanding of the driving behaviors of traditional vehicles is of great significance for the design of autonomous vehicles and the improvement in the safety and acceptance of autonomous vehicles. This study first obtained microdata on the behaviors of drivers through driving simulation experiments and conducted research in stages. Then, generalized linear mixed-effects models were constructed to study the main effects and interaction effects of driver attributes and traffic conditions on driving behaviors. The data analysis shows that the overall speed of drivers passing through intersections follows a "deceleration acceleration" mode, but the fluctuations are more pronounced at signalized intersections, and the signal control significantly changes the position of the lowest speed when turning left. According to the different signal control and driving tasks, there are significant differences in a driver's acceleration patterns between the entry and exit stages. A driver's heart rate fluctuates greatly during the exit phase, especially during straight tasks. Compared with other indicators, the change in the gaze duration is not significant. In addition, interaction effects were observed between driver attributes and traffic conditions, with participants exhibiting different behavioral patterns based on their different attributes. The research results can provide a basis for the design of driving assistance systems and further improve the interactions between autonomous vehicles and traditional vehicles at intersections.

Keywords: driver behavior; intersection; driver safety; individual difference; driving simulator study

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1. Introduction

Autonomous driving has brought a lot of new opportunities for the automotive industry. The Society of Automotive Engineers (SAE) classifies autonomous vehicles into 6 levels (Level 0–Level 5) [1]. Among them, the advanced driver-assistance system (ADAS) (Level 1 to Level 2) has specific functions, mainly including providing warnings or performing a limited set of lateral and/or longitudinal vehicle motion control actions to help drivers operate the vehicle safer [1,2]. The automated driving system (ADS) (Level 3 to Level 5) can continuously perform complete dynamic driving tasks (DDTs) and reduce and avoid collisions. Nowadays, many people believe that autonomous vehicle technologies (such as ADASs and ADSs) can greatly improve driver safety by eliminating collisions caused by human error, which 94% of road traffic accidents are attributed to [3,4]. However, if the driving behavior of an autonomous vehicle is significantly different from that of a conventional vehicle, not only will the driver's trust and acceptance of autonomous vehicles be weakened [5,6], but it may also lead to unpredictable risks in traffic accidents [7,8]. At the same time, personalized assisted driving can also improve the safety and acceptance of autonomous driving. Therefore, an in-depth understanding of the driving behaviors of conventional vehicles is of great significance for the design of autonomous vehicles and the improvement in the safety and acceptance of autonomous vehicles.

Due to the complexity of the intersection scene, intersection accidents are one of the most common types of urban vehicle accidents for both conventional vehicles and autonomous vehicles [3,7–9]. Intersection areas are shared by drivers from multiple directions, and the diversity of vehicle movements leads to multiple conflict points [10,11]. The convergence of traffic flow and various driving tasks forces drivers to rapidly assimilate information from multiple angles, which can significantly increase the complexity of the situation [12]. Therefore, intersections involve a series of complex information acquisition, reaction judgments, and operational processes. Understanding the driving behaviors of surrounding conventional vehicles and making a human-like driving model based on them is a necessary condition for autonomous vehicle to successfully pass the intersection.

The geometric features and functional design of an intersection significantly affects intersection maneuvers [13], and successful intersection maneuvering requires the ability to perceive all useful information resources and make correct and safe decisions in this dynamic driving environment, whereas the individual differences in drivers similarly affect their operational decisions. Indeed, Dukic and Broberg [14] recorded drivers' visual behaviors at a signalized intersection in real-world traffic and found that younger drivers focus more on dynamic objects, such as other road users, while older drivers pay more attention to static objects, such as road markings. Wu and Xu [15] analyzed the driving behaviors of right-turning drivers at signalized intersections using naturalistic driving research data. They found that drivers exhibit a high acceleration and low observation frequency during right-turn-on-red (RTOR) maneuvers, which can pose potential dangers to other road users. Pathivada and Perumal [16] examined the factors influencing driver behaviors in the dilemma zone at signalized approaches under mixed traffic conditions and found that the approach speed and type of vehicle significantly impacts the probability of stopping. More research has focused on drivers' abilities to perceive information at unsignalized intersections than at signalized intersections. Li et al. [17] conducted a comparative analysis of the differences in driving behaviors between older and younger drivers in unsignalized intersection conflict scenarios and established driving behavior graphs, which found that older drivers were slower in observing and collecting traffic information based on the changes in behavioral nodes. Additionally, research by Yamani et al. [18] indicated that older drivers performed worse in visual search tasks compared to middle-aged drivers and required more steering adjustments. Romoser et al. [19] suggested that when approaching and entering unsignalized intersections, the reason why older drivers are unable to scan for hazards is because some of the difficulties experienced by them in scanning intersections stem from specific attentional deficits that hinder their ability to suppress the primary goal of monitoring the expected path of other vehicles. Werneke and Vollrath [9] conducted a study on the psychological processes of driving behaviors and attention allocation of drivers at unsignalized T-intersections with varying environmental characteristics. The results revealed that drivers' attention allocation and driving behaviors systematically depended on the environmental features of the intersection. Lemonnier et al. [20] investigated the allocation of explicit visual attention at unsignalized intersections with different priority rules under multitasking and dynamic situations. The results showed that visual attention to the intersecting roads varied according to the priority rules and visual attention was influenced by vehicle control subtasks. Subsequently, a field study was conducted to examine the visual attention of intersection drivers [21]. The study found that the effects of priority rules, the expected traffic density, and familiarity were reliable factors in understanding drivers' gaze allocations on the road.

Although previous research has analyzed driver behaviors at intersections, we found only two studies that investigated the differences in driver behaviors between signalized and unsignalized intersections. Specifically, Liu and Ozguner [22] used simulation to analyze driver decision-making and operational responses. Li et al. [23] examined the differences in visual scanning behaviors between signalized and unsignalized intersections using naturalistic driving data. However, these studies only focused on a single aspect of driver behavior and did not provide a comprehensive understanding of the differences, as driving tasks involve perception, cognition, and operation. The type of intersection can influence driver behavior, as drivers adopt different driving strategies at signalized and unsignalized intersections, leading to variations in safety levels. Existing research is not yet sufficient to fully elucidate the performance of drivers under different traffic conditions, and there are even fewer studies in China. Considering potential cultural and regional differences, there may also be differences in the conclusions regarding driving behaviors among different countries. To explore the underlying mechanisms behind this situation, there is a pressing need to determine the existing differences in driver behaviors. Therefore, to fully understand driver behaviors at intersections, it is necessary to study the impacts of external and internal factors on driver behaviors.

Thoroughly studying the driving behaviors at intersections can improve the performance of ADS driving, improve the interaction between ADSs and conventional vehicles, and enhance the acceptance and safety of ADSs. Therefore, the study aims to examine the impact patterns of intersection types on driver behaviors by driving simulation experiments. And the contributions of this article can be summarized as follow:

(1) The type of intersection affects a driver's behavioral performance, but there are fewer studies on the differences in driving behaviors between signalized and unsignalized intersections, and the research in this paper fills the gap that exists in this area.
(2) In this paper, the driver's behavior when crossing an intersection is studied in stages, and the stages of the driving behavior pattern can reflect the different characteristics of the driving process, and this pattern is the inherent behavioral pattern of the driver. Therefore, it can help researchers to deeply understand the driving behaviors at intersections and provide theoretical behavior support for the research and design of safety systems afterwards.
(3) Individual differences in driving behaviors based on intersection characteristics were assessed, i.e., the influence of personal characteristics such as gender and age on drivers' physiological, psychological and operational performances. By addressing the interactive effects of personal characteristics as well as intersection characteristics on a driver's intersection performance, the preferred behavioral patterns of different drivers are investigated. This case study of driving behavior patterns can inform personalized driving behavior modeling as well as vehicle system safety designs.

2. Materials and Methods

2.1. Experimental Equipment

The main equipment for this experiment is shown in Figure 1. The experiment was conducted using the KMRTDS (Kunming University of Science and Technology Driving Simulation System) (Figure 1). It includes 4 graphics computers, 3 projectors, and a 120° horizontal view screen and was supported by the cockpit system, main control computer system, simulation view system, image projection view system, sound system, and car dynamics model. The iView ETG2W eye tracker from German SMI was used to collect eye-movement data. The sampling frequency of the eye tracker was set to 200 Hz/s to ensure the reliability and integrity of the data collection as the driver passed through the intersection. The driver's ECG indices were collected using an ErgoLAB intelligent wearable human factor physiological recorder from KINGFA, Beijing, China.

2.2. Subjects

From the School of Traffic Engineering at Kunming University of Science and Technology and surrounding communities, a total of 39 licensed drivers were recruited for the study. The age range of the participants was between 22 and 70 years, including 13 women (mean = 45.15 ± 18.89 (SD) years).

(**a**) (**b**)

Figure 1. Experimental equipment. (**a**) KMRTDS driving simulation platform. (**b**) Simulated scenario.

2.3. Experimental Steps

Before the experiment began, the participants completed informed consent forms and demographic questionnaires. Then, the participants completed a practice exercise on intersection scenes (left and right turns). The subjects were instructed to navigate through a series of intersections like they would in a natural environment while complying with traffic rules. After completing the experimental block, each participant was paid a reward of RMB 100.

2.4. Experimental Scenarios

In the driving scenario, there were oncoming vehicles as the driver approached the intersection. And these vehicles had an average speed of 50 km/h. As independent variables, the situation at the intersection differed in two environmental factors: (1) signal control and (2) driving task. For a description of the scenario, refer to Table 1.

Table 1. Descriptions of experimental scenarios.

	Scenario		**Traffic Description**
	Signal Control	**Driving Task**	
NSS SS	No signal control Signal control	Straight	Vehicles turned left from the opposite lane into the intersection at 50 km/h
NSL SL	No signal control Signal control	Left turn	Vehicles drove straight ahead from the opposite lane into the intersection at 50 km/h
NSR SR	No signal control Signal control	Right turn	Vehicles turned right from the opposite lane into the intersection at 50 km/h

2.5. Analytical Methods

2.5.1. Generalized Linear Mixed Models (GLMM)

Generalized linear mixed models (GLMM) based on the generalized linear model [24], which introduces random-effect parameters, can handle a variety of research designs and data types, and can fit data with a non-normal distribution and complex correlation structures. The general expression for the generalized linear mixed-effects model is

$$\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{Zu} + \boldsymbol{\varepsilon} \tag{1}$$

where $\boldsymbol{X}$ is the matrix constructed with known fixed-effect variables; $\boldsymbol{Z}$ is the design matrix constructed by random-effect variables, and its construction method is the same as that of $\boldsymbol{X}$; $\boldsymbol{\beta}$ is a vector composed of unknown regression coefficients, called a fixed effect; $\boldsymbol{u}$ is the random-effect parameter vector; and $\boldsymbol{\varepsilon}$ is a random error vector.

With n samples y_i (i = 1, 2, . . ., n), the generalized linear mixed model family can be defined using the exponential family-type probability–density function, that is, the density function of y_i is

$$f(y_i|a) = \exp\left\{\frac{ya - b(a)}{a(\phi)} + c(y, \phi)\right\} \tag{2}$$

where a is a natural parameter; ϕ is the divergence parameter; and $a(\cdot)$, $b(\cdot)$, and $c(\cdot)$ are all known functions.

Assuming the given random effect $\boldsymbol{u}$, the distribution pattern of y_i, the $\boldsymbol{\eta}$ being determined, and the $\boldsymbol{u}$ being associated with $\boldsymbol{\eta}$ by associating with $g(\boldsymbol{u})$, then there is

$$g(\boldsymbol{u}) = \boldsymbol{\eta} = \boldsymbol{x}^T\boldsymbol{\beta} + \boldsymbol{z}^T\boldsymbol{u} \tag{3}$$

where $\boldsymbol{x}$ and $\boldsymbol{z}$ are known vectors, $\boldsymbol{\beta}$ is an unknown regression coefficient vector, and $\boldsymbol{u}$ a random-effect parameter.

Therefore, given the random effect $\boldsymbol{u}_i$, the density function of y_i is simplified as

$$f(y_i|\beta, u_i, \phi) = \exp\left\{\frac{y_i\eta - b(\eta)}{a(\phi)} + c(y_i, \phi)\right\} \tag{4}$$

2.5.2. Indicator Selection

- Speed: Research [25] has shown a positive correlation between the average speed and accident occurrence within the speed limit range. Therefore, a comparison of the average speeds of drivers at different types of intersections can be conducted to evaluate their driving safety.
- Acceleration: Acceleration values are directly related to driving comfort. Generally, a lower acceleration indicates lower levels of driver psychological stress and increased driving comfort. A comparison of the acceleration levels can be made between drivers at signalized and unsignalized intersections to understand the differences in driving comfort and driving stability.
- Heart rate: The heart rate and heart rate increase are indicators of driver psychological stress [26,27]. By monitoring changes in driver heart rates, we can infer the impact of different types of intersections on their psychological states.
- Gaze duration: The average gaze durations of drivers are closely related to the visual load and driving task difficulty [28,29]. By comparing the gaze durations of drivers at signalized and unsignalized intersections, we can gain insights into their attention allocations at different intersection types.

3. Results

3.1. Descriptive Statistics for Variables

A preliminary analysis of the dataset was conducted, and the summarized descriptive statistics are presented in Table 2. The independent variables included in the initial model included the age, gender, driving experience, presence of a signal control, and driving task. The initial model also included second-order interactions between the type of signal control and personal characteristics, the driving task and personal characteristics, and the type of signal control and driving task, as well as third-order interactions between the type of signal control, driving task, and personal characteristics. Participants were also included in the model as random effects. The dependent variables included the driving performance and physiological and psychological characteristics. We inputted the processed data into a generalized linear mixed-effects model and selected the optimal covariance structure based on the principle of the Akaike information criterion (AIC) and Bayesian information criterion (BIC) values being as small as possible. Due to the introduction of multiple fixed-effect factors into the model, some factors and their interactions have no statistical significance on the response variables, resulting in data redundancies in the table. Therefore, the data with $p < 0.05$ selected from GLMM are put into the fixed-effect solution model for analysis.

Table 2. Summary of descriptive statistics of variables.

	Element	Level	Mean	SD
Intersection	Signal control (SC)	No (N) Yes (Y)		
	Driving task (DT)	Straight (S) Left turn (LT) Right turn (RT)		
Driver attribute	Gender	Male driver (M) Female driver (F)		
	Age (year)	Young (Y), 18–35 Middle (M), 35–60 Older (O), over 60	23.64 43.22 65.06	0.633 8.54 2.86
	Driving experience level (DE, year)	Low (L), 2–5 Moderate (M), 5–20 High (H), over 20	3 10.93 26.15	0.77 4.58 8.44

3.2. Speed

The speed variations for the entry and exit sections are shown in Figure 2. When crossing intersections, drivers generally exhibit a pattern of decreasing and then increasing their speeds. At both signalized and non-signalized intersections, the minimum speed for the straight task occurs 20–30 m in front of the intersection center, and the minimum speed for right turns occurs at the intersection center. In the case of a left turn, the lowest speed at an unsignalized intersection occurs 40–60 m behind the center of the intersection, while the lowest speed at a signalized intersection occurs 10–20 m before the center of the intersection. The signal control has the most obvious effect on speed control in the left-turn task. The speeds at unsignalized intersections are higher than those at signalized intersections.

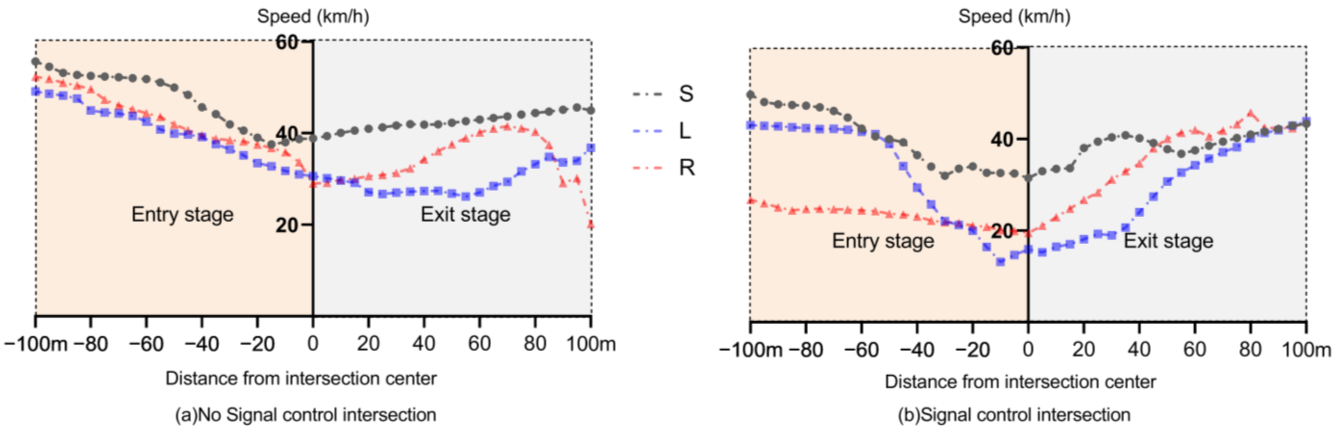

Figure 2. Speed change. S represents straight ahead, L represents left turn, and R represents right turn.

According to the speed model in Table 3, the main effects of steering tasks are significant. The speed of straight-driving tasks is 7.664 km/h higher than that of right-turning tasks. When using signalized intersections as the reference, unsignalized intersections have higher speeds for straight-driving tasks. There is a significant interaction effect between the signal control and age on the speed, where the speed decreases with an increasing age. The signal control, driving task and driver age, and gender and driver age all had interaction effects. At unsignalized intersections, male drivers had lower speeds in the left-turn task and drivers with a moderate level of driving experience had higher speeds in the straight task. At signalized intersections, younger drivers had lower speeds in the left-turn task.

Table 3. Generalized linear mixed model of speed.

Dependent Variable	Effect	Coefficient	p
Speed	Intercept	19.164	0.000 ***
	DT = S	7.664	0.045 **
	DT = RT	0	
	SC = N * DT = S	10.445	0.049 **
	SC = N * DT = RT	0	
	SC = Y * DT = S	0	
	SC = Y * DT * LT	0	
	SC = Y * DT * RT	0	
	SC = N * Age = Y	17.296	0.000 ***
	SC = N * Age = M	7.862	0.039 **
	SC = N * Age = O	0	
	SC = Y * Age = Y	11.971	0.020 **
	SC = Y * Age = O	0	
	SC = N * DT = LT * Gender = M	−4.928	0.038 **
	SC = N * DT = LT * Gender = F	0	
	SC = N * DT = RT * Gender = M	0	
	SC = N * DT = RT * Gender = F	0	
	SC = Y * DT = LT * Age = Y	−10.639	0.022 **
	SC = Y * DT = LT * Age = O	0	
	SC = Y * DT = RT * Age = Y	0	
	SC = Y * DT = RT * Age = M	0	
	SC = Y * DT = RT * Age = O	0	
	SC = N * DT = S * DE = M	8.265	0.047 **
	SC = N * DT = S * DE = H	0	
	SC = N * DT = RT * DE = L	0	
	SC = N * DT = RT * DE = M	0	
	SC = N * DT = RT * DE = H	0	

AIC is 1516.661; BIC is 1523.176. **, represent significance levels of 0.05; ***, represent significance levels of 0.05.

3.3. Acceleration

Since each participant participated in all scenarios, a one-way repeated measures ANOVA (RM ANOVA) was used to analyze the differences between different scenarios. The results of the RM ANOVA on acceleration indicate that there are statistically significant differences in acceleration during the entering and exiting stages at various intersections (entering stage: F = 2.979, $p = 0.013 < 0.05$; exiting stage: F = 3.571, $p = 0.004 < 0.05$), Therefore, post-hoc tests with a Bonferroni adjustment were conducted for each stage at different intersections (Figure 3). During the entering stage, left turns exhibited the fastest deceleration, and there were statistically significant differences in the acceleration for right turns with and without a signal control ($p = 0.004 < 0.05$). During the exiting stage, right turns exhibited the fastest acceleration, and there were statistically significant differences in the acceleration for left turns with and without a signal control ($p = 0.028 < 0.05$). At unsignalized intersections, there were statistically significant differences in the acceleration for straight driving and right turns during the exiting stage ($p = 0.002 < 0.05$). At signalized intersections, there were statistically significant differences in the acceleration for straight driving and left turns during the entering stage ($p = 0.003 < 0.05$), as well as for left turns and right turns during the exiting stage ($p = 0.003 < 0.05$).

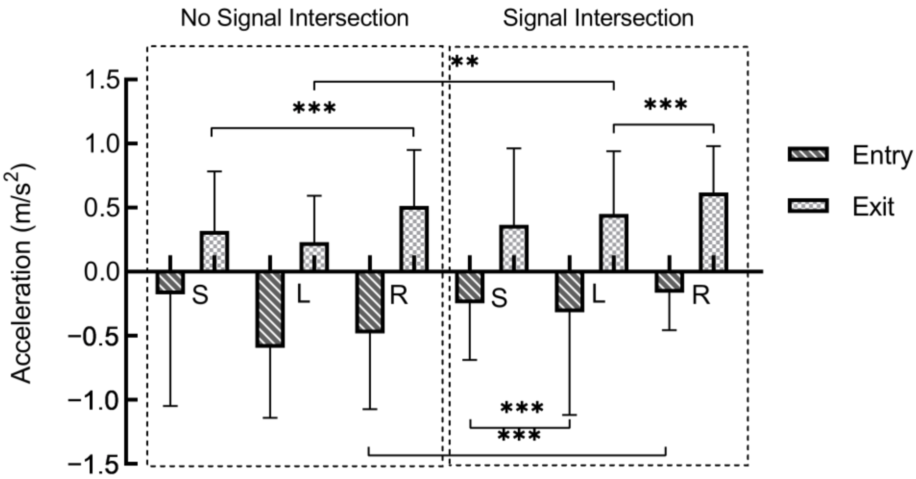

Figure 3. Acceleration change. ***, ** represent significance levels of 0.01, 0.05 respectively.

According to the acceleration standard deviation model in Table 4, significant main effects were found for both the signal control and driving tasks. The acceleration standard deviation for the unsignalized straight task is 1.388 m/s^2 lower than for the right-turn task. In signalized intersections, the acceleration standard deviation is higher for inexperienced drivers, and in particular, middle-aged drivers performing the straight task have lower acceleration standard deviations than elderly drivers. At unsignalized intersections, middle-aged drivers have lower acceleration standard deviations for left turns than older drivers, and moderately experienced drivers have higher acceleration standard deviations for left turns than experienced drivers.

Table 4. Generalized linear mixed model of acceleration standard deviation.

Dependent Variable	Effect	Coefficient	p
ACSD	Intercept	1.298	0.000 ***
	SC = N	0.397	0.020 **
	SC = Y	0	
	DT = S	0.958	0.002 ***
	DT = RT	0	
	SC = N * DT = S	−1.388	0.000 ***
	SC = N * DT = RT	0	
	SC = Y * DT = S	0	
	SC = Y * DT = LT	0	
	SC = Y * DT = RT	0	
	SC = Y * DE = L	0.843	0.041 **
	SC = Y *DE = H	0	
	SC = N * DT = LT * Age = M	−0.632	0.019 **
	SC = N * DT = LT * Age = O	0	
	SC = N * DT = RT * Age = Y	0	
	SC = N * DT = RT * Age = M	0	
	SC = N * DT = RT * Age = O	0	
	SC = Y * DT = S * Age = M	−0.983	0.010 **
	SC = Y * DT = S * Age = O	0	
	SC = N * DT = LT * DE = M	0.554	0.050 **
	SC = N * DT = LT * DE = H	0	
	SC = N * DT = RT * DE = L	0	
	SC = N * DT = RT * DE = M	0	
	SC = N * DT = RT * DE = H	0	

AIC is 420.319; BIC is 426.813. **, represent significance levels of 0.05; ***, represent significance levels of 0.01.

3.4. Heart Rate

The mean heart rate change curves for each section are shown in Figure 4. During the entering stage at intersections, drivers' heart rates fluctuated within a small range, mainly ranging from 80–100 bpm. The heart rate fluctuations are slightly greater at signalized intersections compared to unsignalized intersections. During the exiting stage at intersections, the drivers' heart rates showed more significant fluctuations, especially at signalized intersections.

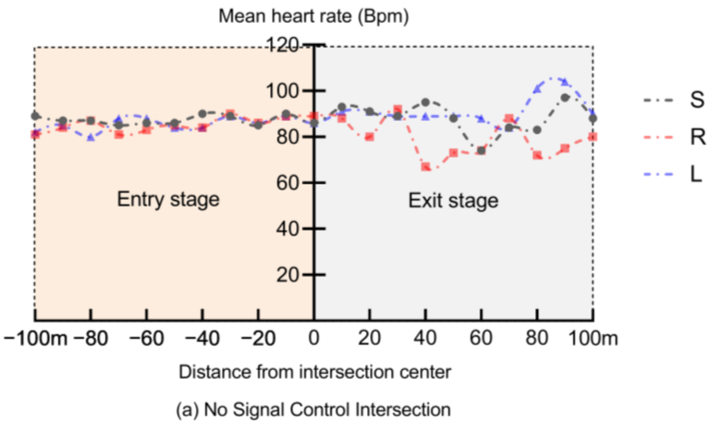

Figure 4. Heart rate changes.

According to the heart rate model in Table 5, there was a significant main effect from the steering task, as well as significant interaction effects of the signal control with both the age and driving experience. The heart rate was 13.594 bpm higher in a straight task than in a right turn, indicating that drivers are more nervous during straight driving. In signalized intersections, the heart rates of young drivers are lower than those of older drivers, and the heart rates of drivers with a low level of driving experience are higher than those of drivers with a high level of driving experience. In unsignalized intersections, male drivers have lower heart rates during straight-driving tasks, while older drivers have the highest heart rates during left-turning tasks. In signal-controlled intersections, compared to older drivers, young drivers have higher heart rates during straight-driving tasks, and middle-aged drivers have lower heart rates.

3.5. Gaze Duration

The average gaze durations during crossing intersections for different intersection scenarios are shown in Figure 5. Overall, at unsignalized intersections, the gaze duration was longest when turning left. And at signalized intersections, the gaze duration was longer when going straight. In general, when compared to unsignalized intersections, the drivers tend to have longer gaze durations at signalized intersections. However, the results of the RM ANOVA on the gaze duration did not show statistically significant results ($F = 0.845$, $p = 0.520$).

According to the gaze duration model in Table 6, for the gaze duration, there were no significant main effects for any of the variables, and the interaction effect was only present at unsignalized intersections. Compared to the reference task of unsignalized right turns, older individuals have longer gaze durations when performing unsignalized left turns, while younger and middle-aged individuals have shorter gaze durations. Similarly, when using unsignalized right turns as the reference task, individuals with lower and moderate levels of driving experience exhibit longer gaze durations during unsignalized left turns compared to those with a higher level of driving experience.

Table 5. Generalized linear mixed model of heart rate.

Dependent Variable	Effect	Coefficient	p
Heart rate	Intercept	86.293	0.000 ***
	DT = S	13.594	0.006 ***
	DT = RT	0	
	SC = Y * Age = Y	−8.707	0.041 **
	SC = Y * Age =O	0	
	SC = Y * DE = L	12.483	0.017 **
	SC = Y * DE = H	0	
	SC = N * DT = S * Gender = M	−11.108	0.004 ***
	SC = N * DT = S * Gender = F	0	
	SC = N *DT = LT * Age = Y	−3.715	0.022 **
	SC = N * DT = LT * Age = M	−5.143	0.002 ***
	SC = N * DT = LT * Age = O	0	
	SC = N * DT = RT * Age = Y	0	
	SC = N * DT = RT * Age = M	0	
	SC = N * DT = RT * Age = O	0	
	SC = Y * DT = S * Age = Y	12.780	0.049 **
	SC = Y * DT = S * Age = M	−10.762	0.020 **
	SC = Y * DT = S * Age = O	0	

AIC is 1217.945; BIC is 1224.133. **, represent significance levels of 0.05; ***, represent significance levels of 0.01.

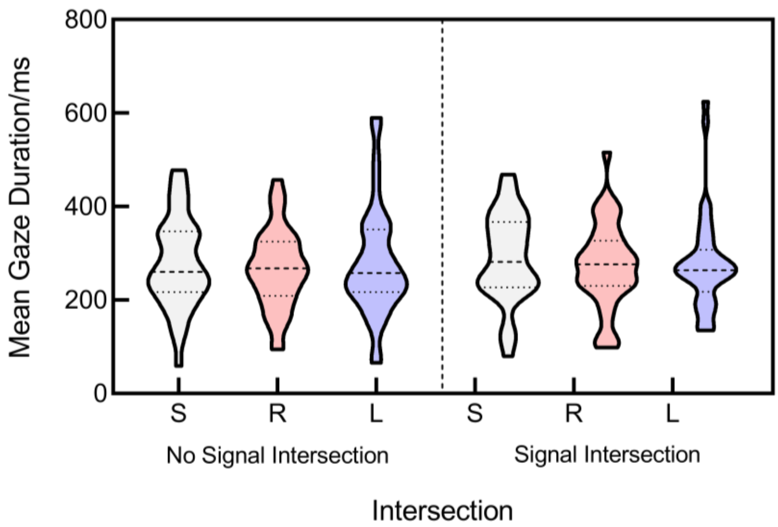

Figure 5. Mean gaze duration distribution.

Table 6. Generalized linear mixed model of gaze duration.

Dependent Variable	Effect	Coefficient	p
Gaze duration	Intercept	244.077	0.000 ***
	SC = N * DT = LT * Age = Y	−135.497	0.000 ***
	SC = N * DT = LT * Age = M	−48.512	0.043 **
	SC = N * DT = LT * Age = O	0	
	SC = N * DT = RT * Age = Y	0	
	SC = N * DT = RT * Age =M	0	
	SC = N * DT = RT * Age = O	0	
	SC = N * DT = LT * DE = L	138.521	0.000 ***
	SC = N * DT = LT * DE = M	73.074	0.005 ***
	SC = N * DT = LT * DE = H	0	
	SC = N * DT =RT * DE = L	0	
	SC = N * DT = RT * DE = M	0	
	SC = N * DT = RT * DE = H	0	

AIC is 2209.080; BIC is 2215.499. **, represent significance levels of 0.05; ***, represent significance levels of 0.01.

4. Discussion

The study results showed that, compared to the physiological and psychological characteristics, the differences in the driving performances were more pronounced at intersections. From the changes observed throughout the entire process, depicted in Figures 2 and 3, it is evident that speeds steadily decreased at unsignalized intersections, while the deceleration effect was more noticeable at signal-controlled intersections. This indicates that drivers tended to maintain a more consistent speed when crossing unsignalized intersections, without coming to a complete stop. This behavior may be attributed to the prevalent culture of risky driving practices in Chinese traffic conditions [30]. Furthermore, the results of the acceleration indicators also revealed that under unsignalized conditions, the acceleration during the right-turn task while entering the intersection was significantly higher compared to signal-controlled intersections. Conversely, the acceleration during the left-turn task while exiting the intersection was significantly lower at unsignalized intersections. These findings are related to the driving rules in China, which require drivers to drive on the right side of the road, resulting in a higher demand for left-turn maneuvers at unsignalized intersections compared to right-turn and straight-through tasks, particularly during the exit stage. Drivers making a left turn must pay more attention to opposing traffic and the surrounding traffic environment to safely navigate the intersection without conflicts with other vehicles [9,31]. Therefore, when drivers make a left turn at unsignalized intersections, they tend not to manipulate their speed significantly for safety. However, at signal-controlled intersections, where traffic lights organize orderly vehicle movements during the green phase, it is a subconscious reaction of most drivers to slow down and pass through instinctively. The variations in the physiological and psychological characteristics also demonstrated significant differences in the heart rates between the entering and exiting stages (Figure 4). The fluctuations and noticeable peak in the heart rate values during the exiting stage indicated that drivers were more tense, experienced higher mental workload, and were more prone to be involved in traffic accidents during this stage. Meanwhile, the results regarding the gaze duration indicated that drivers tended to have slightly longer gaze durations at signal-controlled intersections compared to unsignalized intersections, although the difference was not significant (Figure 5). TAY et al. [32] suggested that the higher collision risk at signal-controlled intersections could be attributed to differences in scanning behaviors between signalized and unsignalized intersections.

In addition, the driving tasks also had a significant impact on the behaviors of drivers at intersections. The left-turn task exhibited the most noticeable decrease in speed while crossing the intersection, and during both the exiting and entering stages, the acceleration during the straight-through task was significantly lower than that of the left-turn and right-turn tasks. This can be attributed to the higher operational demands and workloads associated with turning tasks, especially during left turns. For safety reasons, drivers need to exhibit more noticeable speed changes during turning tasks compared to tasks with lower requirements, such as going straight. Regarding the physiological and psychological characteristics, the heart rate showed a declining trend throughout the entire stage of crossing the intersection for the right-turn task, and the gaze duration was also the lowest. This indicates that drivers experienced the lowest driving workload when performing the right-turn task.

Furthermore, the driver characteristics were also considered as influential factors in this study. And the results indicated that the age, gender, and driving experience had significant influences on intersection driving behaviors, albeit with some differences across different scenarios. Overall, middle-aged drivers were relatively the safest group. And for elderly drivers, the impact of age on driving was negative. The speed decreased with age, and elderly drivers had higher heart rates at signal-controlled intersections, as well as longer gaze durations during left turns at unsignalized intersections and the highest heart rates overall. This suggests that elderly drivers experienced higher levels of anxiety while crossing intersections, particularly during tasks that required higher demands. To ensure safe crossing, compensatory strategies such as reducing the speed, maintaining larger following distances, avoiding specific traffic conditions, or shortening driving distances are often adopted [33,34]. On the other hand, for young drivers, at signal-controlled intersections, they exhibited lower speeds during left-turn tasks and higher heart rates during straight-through tasks. This may be attributed to a lack of confidence resulting from their limited experience, making young drivers more nervous and inclined to maintain lower speeds. Feng et al. [35] demonstrated that as information and task demands increased, the differences between different age groups became more apparent. Regarding driving experience, it was found that driving behaviors also followed certain patterns among different levels of driving experience. Drivers with little experience showed a "nervous" type of behavior, those with a moderate level of experience exhibited an "impulsive" type, and those with a high level experience showed a "steady" type, with the latter being the safest group. This is because drivers with little experience had higher heart rates, longer gaze durations during left turns at unsignalized intersections, and larger acceleration standard deviations at signalized intersections. This indicates that drivers with little experience experienced higher levels of anxiety and workload while crossing intersections, particularly during tasks with higher demands, and exhibited less stable driving behaviors. Drivers with a moderate level of experience, due to their self-perceived rich driving experience, became less cautious when performing critical driving tasks, such as lane changes or turning. They exhibited higher speeds during straight-through tasks at unsignalized intersections and larger acceleration standard deviations during left-turn tasks, potentially showing unstable and unsafe driving tendencies. Drivers with a high level of driving experience not only possessed proficient vehicle control but were also capable of handling various situations with ease. They exhibited a more relaxed and calm driving behavior throughout the driving process, as indicated by their lowest gaze durations during left turns at unsignalized intersections. Nabatilan et al. [36] also found that experienced drivers had lower error rates compared to inexperienced drivers. In terms of gender, male drivers exhibited lower speeds during left turns at unsignalized intersections and lower heart rates during straight-through tasks. This suggests that male drivers, compared to female drivers, demonstrated more confidence and stability while driving. This finding is consistent with reports indicating a higher involvement of women in crashes involving injury and higher rates of all reported accidents by the police [37].

5. Conclusions

This study not only examined the differences in driver behaviors between signalized and unsignalized intersections but also investigated their correlations with driver factors, providing a comprehensive understanding of the characteristics of driver behaviors at intersections. We found that both the intersection type and driver factors have an impact on a driver's behavior. These findings suggest that future developments in advanced driver assistance systems and intersection design should take into account the behavioral characteristics and needs of different drivers at different intersections, in order to provide better services for drivers.

Traffic environments at intersections are diverse and complex, and this study only introduces the signal control and driving task variables, with a limited sample size. Further research should include more factors (such as road geometry, car following behavior, and the presence of other traffic participants) as well as more critical situations (such as dilemma zones and yellow lights). This will help to increase the understanding of driving behaviors at intersections. Considering the design, evaluation, and implementation of future autonomous vehicles, it is also necessary to model and predict the driving behaviors at intersections.

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