In-Vehicle Trajectory Guidance System Considering Road Emergency Events

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ABSTRACT
Connected and automated vehicles (CAVs) can enhance traffic flow characteristics through the implementation of advanced control algorithms and real-time coordination mechanisms. In the near future when fully autonomy cannot be achieved, it is expected that human-driven vehicles (HDVs) can be indirectly controlled in a manner similar to CAVs through an in-vehicle information system, which has the potential to further stabilize traffic flow and foster cooperation in mixed traffic. This paper contributes to this area of research by designing an in-vehicle longitudinal trajectory guidance system for human drivers and evaluate its impact on driving performance and driver behavior. Given a pre-defined longitudinal vehicle trajectory, the system displays the real-time guidance information through a virtual block. The system was tested through driving simulator experiments with a total of 35 subjects. Two different traffic scenarios, open road and dedicated road, with random disturbances were considered. The experimental results indicate that the proposed trajectory guidance system can effectively promote efficiency and reduce environmental impact. Side effects regarding driver behavior are limited and the overall compliance with the system is satisfactory. Under unexpected pedestrian crossing settings, drivers are able to recognize road safety hazards and perform braking in time to ensure safety with trajectory guidance. It takes 3.63 seconds on average for guided drivers to regain a position in virtual block after an emergency. The findings in this paper can support the realization of some trajectory-based traffic control methods in mixed traffic considering random road safety hazards.

KEYWORDS
Connected vehicle; Trajectory guidance system; Driving simulator; Driver behavior; Road emergency event

1. Introduction

The real-time control of connected and automated vehicles (CAVs) at intersections can lead to improvements in traffic efficiency (Bifulco et al., 2022; X. Chen et al., 2021; Han et al., 2020), enhancement of traffic safety (Bifulco et al., 2022), and mitigation of environmental impact (Z. Du et al., 2018; Han et al., 2020), by utilizing vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. However, in the near future, it is widely acknowledged that CAV will operate in traffic scenarios together with human-driven vehicles (HDVs) (Cheng et al., 2023). In mixed traffic, if HDVs

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can be driven in a way similar to the movements of CAVs, it is expected that more desired mixed traffic characteristics can be fulfilled.

To this end, rather than being directly manipulated, HDVs can be indirectly controlled or guided when human drivers are provided with speed recommendation or trajectory reference through in-vehicle information systems. The effectiveness of the guidance not only depends on the in-vehicle information system design, but is also profoundly related to the behavioral characteristic of human drivers (Sharma et al., 2018). There is substantial evidence in the literature of detrimental effects of in-vehicle information systems on driver behavior, including lateral control (Vashitz et al., 2008), brake reaction time (A. H. Jamson & Merat, 2005), visual attention (Caird, Chisholm, et al., 2008; Y. Wang et al., 2010), workload (S. L. Jamson et al., 2015), etc.

In this paper, we refer to the concept of offering pre-defined longitudinal trajectory suggestions to human drivers as trajectory guidance. The difference between trajectory guidance and other forms of in-vehicle guidance (e.g., speed suggestion, green light countdown, etc) mainly lies in the way information is presented and how drivers understand and process the information. Thus, it is of high need to design a trajectory guidance system and to study the change of driving performance and driver behavior under this new way of individual in-vehicle guidance.

Moreover, one critical aspect affecting the performance of trajectory guidance is random road hazards. In response to a road emergency event, human drivers necessitate proactive measures to ensure safety, which may lead to a deviation from the intended trajectory. It remains unknown how drivers react when they face road safety hazards and receive trajectory guidance information at the same time.

To fill the void, an in-vehicle trajectory guidance system is designed and evaluated in this study. The main contribution is summarized as follows:

(1) Development of an in-vehicle trajectory guidance system in a connected environment, including the design of a trajectory guidance method and an in-vehicle guidance interface.
(2) Conducting driving simulator experiments to examine the impact of trajectory guidance on driving performance and various aspects of driver behavior, including driver distractions, workload, compliance and learning effect.
(3) Examining in-vehicle trajectory guidance system-related driving safety problems. Focusing on driver behavior under the coupling effect of trajectory guidance system and random road emergency events.

The remainder of this article is organized as follows: Section 2 reviews the related work. Section 3 discusses the algorithm development and human machine interface (HMI) design of the trajectory guidance system. The performance measures and hypotheses of the study are also included. Then, settings of the driving simulator experiments are introduced in Section 4. Furthermore, in Section 5, the detailed results of the experiments are given, including the effects of the proposed trajectory guidance system on driving performance and driver behavior. Driver behavior in emergency situations when using the trajectory guidance system is also evaluated. Finally, Section 6 discusses the experimental results and concludes our work.

2. Literature Review

In this section, we first review the related study that discusses the impact of in-vehicle guidance systems on driver behavior, mainly focusing on the potential negative impact like visual distraction, mental workload, etc. Then, an investigation into the study concerning driver's acquisition of knowledge and their level of conformity with the system's functionalities is conduct, which is, driver compliance and learning effect. By approaching the study from these dual perspectives, we aim to provide a holistic understanding of the intricate interaction between the system and the drivers. Additionally, we review the impact of in-vehicle guidance systems on driver behavior in emergency situation, which contributes to a more comprehensive understanding of the system's implications in safety-critical scenarios.

2.1. Impact of in-vehicle guidance systems on driver behavior

In a series of experiments within a national project on the cooperative optimization of traffic signal control (KOLIBRI) in Germany, five HMIs based on a traffic light assistance system (TLAS) were evaluated using drivers' gaze behavior (glance duration both to the display and off the forward roadway) and standardized subjective ratings (Krause & Bengler, 2012; Krause et al., 2012). A TLAS provides a speed range recommendation derived by a simple division of distance to next traffic light by remaining time to help drivers pass through signalized intersections. The driving simulator experiment results supported the selection of a "carpet" HMI out of five candidates because it had the lowest distraction and mental workload on drivers while ensuring high vehicle efficiency. In a subsequent field experiment (Krause et al., 2013), NASA-TLX (Hart & Staveland, 1988) was additionally adopted to subjectively evaluate drivers' workload.

Giving speed advice to a driver approaching a traffic light is also believed to introduce environmental benefits by lowering CO_2 emissions and fuel consumption (Tielert et al., 2010), in addition to promoting driving efficiency. To this end, numerous studies have investigated driver behavior under in-vehicle eco-driving systems. An eco-driving system was evaluated using driving simulator experiments (Staubach et al., 2014). Time to green and pedal force recommendations were given to drivers through a visual display. A reduction in average fuel consumption of 15.9% in urban scenarios and 18.4% in rural scenarios was observed, and no negative effect was found considering the time to collision (TTC). An eye tracking experiment was conducted to evaluate the visual distraction of an eco-driving guidance system (Beloufa et al., 2019), and no significant effect on safety was found by analyzing the mean fixation duration, number of gazes at the dashboard and time spent with eyes off the road. Furthermore, Li et al. (2020) confirmed that drivers have a higher mental workload when they receive and process additional eco-safe information in advice and feedback conditions.

Instead of giving speed recommendations, the in-vehicle intelligent speed adaptation (ISA) system mainly releases speed limit information in real time. Reagan and Bliss (2013) investigated drivers' trust, acceptance, and mental workload of an advisory level ISA system through field tests. Each scale of NASA-TLX was evaluated, and an increase in frustration, effort and mental demand was observed when using the system. A discussion of monetary incentives was also included. Trust and acceptance were generally positive, as indicated by a subjective rate scale. Through a driving simulator experiment, informative, warning, and intervening ISA systems were evaluated (Spyropoulou et al., 2014). It was concluded that in-vehicle informative and warning ISA systems have an impact on driver speed behavior but that this effect is influenced by the posted speed limit and can vary greatly between individuals. Drivers may misuse ISA systems, potentially resulting in negative road safety effects. Additional research endeavors (Starkey et al., 2020) have provided further evidence to support the conclusion that speed warnings provided by smartphone applications influence drivers' speed behaviors. In addition, no adverse distraction effect of this system was found considering drivers' lane keeping ability.

In this subsection, the impact of in-vehicle guidance systems on driver behavior is reviewed by system type, i.e., traffic light assistance systems, eco-driving systems and intelligent speed adaptation systems. In this research area, the in-vehicle guidance information is often given in the form of speed range or speed limit. It is rare that the impact of spatial-temporal position-based trajectory guidance on driver behavior has been thoroughly investigated.

2.2. Driver compliance and learning effect

The above subsection mainly discusses the impact of in-vehicle trajectory-guidance-like displays on driving performance and driver behavior. However, when interacting with an in-vehicle guidance device, a driver can adapt his or her behavior and become familiar with the guidance display over time. Thus, drivers' compliance and learning behavior can be studied.

The percentage of time within the recommended speed range (Krause & Bengler, 2012) and average difference between the recommended speed and actual speed of ego vehicle (Niu & Sun, 2013) are two commonly used driver compliance indicators. Matowicki and Pribyl (2022) adopted a binary compliance indicator when evaluating drivers' speed compliance with respect to a variable speed limit (VSL) system. The analysis of driving simulator experimental results revealed that drivers' understanding of the VSL system and education level were two factors that have a significant positive impact on speed compliance.

Considering the learning effect, 19 participants completed experimental sessions on iPod interactions for six successive weeks in a driving simulator study (Chisholm et al., 2008). The results indicated that drivers' slow responses to critical events were reduced through practice, but the decrement was relative to the baseline condition. By conducting experiments with the same participants on two consecutive days, evidence of practice and learning effects was also found in the literature (Rouzikhah et al., 2013). While engaged in critical maneuvers, drivers were able to detect significantly more dangerous events on the second day in an eco-driving scenario. A learning effect to reduce visual distraction was confirmed in eco-driving research (Staubach et al., 2014). A negative correlation was observed between HMI glance duration and the duration of the trial.

2.3. Driver behavior in emergency situations

Most of the aforementioned studies assume that ego vehicles are in a rather simple and safe road condition. However, human drivers often encounter complicated and random traffic conditions in daily life, such as unexpected pedestrian crossing and leading vehicle braking. When drivers focus more on the vehicle itself (including in-vehicle devices), the chance of missing critical external events increases, therefore producing high potentials for collisions (Green, 2007; Klauer et al., 2006).

Previous studies have consistently considered the impact of cell phone or smart device interactions on drivers when facing unexpected events. It can be concluded that different types of smart device usage, including conversation, sending messages, turning off devices and playing music, could have decremental effects on hazard detection and subsequently increase the possibility of safety critical events (Caird, Willness, et al., 2008; Choudhary et al., 2022; Choudhary & Velaga, 2018; Hosking et al., 2009). In a driving simulator study, 19 young drivers were recruited to evaluate driver behavior during critical events while interacting with an iPod (Chisholm et al., 2008). The safety critical events include a pedestrian entering the roadway, vehicle pullout, and lead vehicle braking. Visual distraction and slowed responses to driving hazards were detected through measures of hazard response, vehicle control and eye movements. Additional research examined the effects of phone and music player usage on reaction times and accident probabilities (Choudhary & Velaga, 2018). The results showed reaction time increases for the pedestrian crossing event by 42%, 113%, and 62% due to the presence of conversation, texting, and music player operations.

Beloufa et al. (2019) evaluated the contribution of instructional videos and interactive guidance systems on eco-driving behavior while considering unexpected events such as pedestrian crossing, construction and vehicle pullout. One-factor ANOVA indicated no significant side effect on vehicle lateral control and car following behavior. Moreover, the results proved that the learned eco-driving behaviors had no negative effect on participants' safe driving behavior during emergency events.

3. Trajectory guidance system development

In this study, we develop a virtual block-based trajectory guidance system. In connected vehicle environment, the guidance system can obtain the ego vehicle's location and signal light status, and provide guidance information in the form of a virtual block. The detailed guidance method and HMI design is introduced in the following subsections.

3.1. Trajectory guidance method

A virtual block is a virtually moving area covering a certain longitudinal distance of road segment, inspired by the concept of virtual container in literature (X. Chen et al., 2021; Lin et al., 2021). It is programmed to arrive at the intersection stop line when the green light starts and fully passes the stop line when the green light ends, following the preset trajectory. Vehicles that stay within the virtual block are able to pass through signalized intersections without stopping.

Given the vehicle's distance to the intersection, signal timing information and predefined trajectory, the optimal virtual block position can be calculated using algorithm 1. When the explicit expression of $F(q)$ is approachable (e.g., a pre-defined trajectory with uniform acceleration or constant velocity motion), the virtual block positions can be calculated by the inverse function of $F(q)$ (see Appendix A for a detailed explanation). While for other cases, $d_{\mathrm{vb,i}}^{\mathrm{start}}$ and $d_{\mathrm{vb,i}}^{\mathrm{end}}$ can be determined analytically. Multiple candidate virtual blocks might exist at the same time depending on the signal timing status at the upcoming intersection. Thus, the distances between the ego vehicle and the midpoints of multiple candidate virtual blocks are calculated to select the closest one as the final output.

Algorithm 1: Virtual block position calculation.

Input:

1) Longitudinal distance between ego vehicle and intersection stop line d_{ego}

2) The i^{th} start and end time of the green light for next n cycles at the upcoming intersection $[t^{\text{start}}_{\text{green,i}}, t^{\text{end}}_{\text{green,i}}]$, i = 1, 2, . . . , n

3) Pre-defined trajectory (speed profile) of virtual block $v(x)$, where x is the distance to the intersection

Output:

Virtual block position $[d^{\text{start}}_{\text{vb}}, d^{\text{end}}_{\text{vb}}]$

```
1 Let F(q) = ∫_0^q 1/v(x) dx
2 for i ← 1 to n do
3     d^start_vb,i = F^{-1}(t^start_green,i)
4     d^end_vb,i = F^{-1}(t^end_green,i)
5 end
6 k = arg min_i |d_ego − (d^start_vb,i + d^end_vb,i)/2|
7 [d^start_vb, d^end_vb] = [d^start_vb,k, d^end_vb,k]
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3.2. Trajectory guidance interface

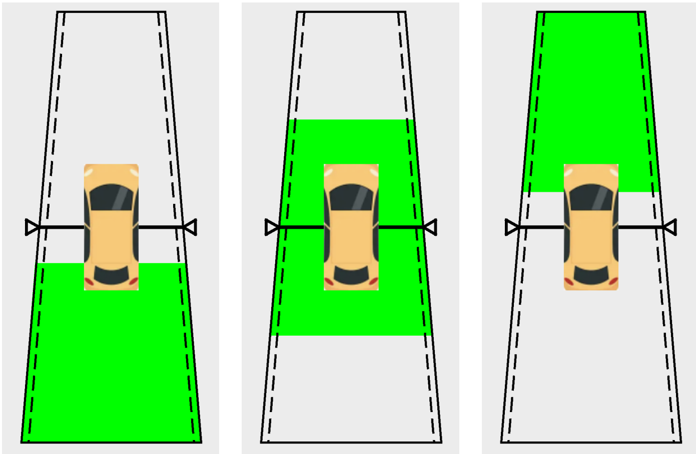
The proposed virtual block-based trajectory guidance system is designed to have a visual in-car display. The corresponding human-machine interface is shown in Figure 1. The vehicle in the interface travels ahead, while the road has a dynamic effect of rolling backward. The thick solid line and the vehicle icon indicate the position of the vehicle, which remain static. The green area is the virtual block that moves up and down according to the output of Algorithm 1. While the vehicle icon stays in this area, the real ego vehicle is able to pass through the upcoming intersection without stopping.

This HMI design is similar to the ”carpet” style HMI in the literature (Krause & Bengler, 2012; Krause et al., 2012; Krause et al., 2013; Krause et al., 2014), which displays the recommended speed range for drivers. However, the biggest difference between the two HMIs lies in that, instead of directly giving specific speed suggestions, the proposed trajectory guidance HMI only advises drivers to speed up or slow down based on the relative position between the ego vehicle and virtual block. For example, Figure 1b indicates that the vehicle is within the virtual block and the driver only needs to maintain its current speed to pass through the signalized intersection. Figure 1a and Figure 1c illustrate situations where the vehicle is outside of the virtual block. In this case, the vehicle needs to slow down or speed up to reach the virtual block. Therefore, spatio-temporal information is fully utilized and expressed in our HMI.

3.3. Performance measures

Table 1 displays the performance measures adopted in the study.

(1) **Vehicle control**. The average speed and intersection waiting time are selected as basic measures for vehicle longitudinal control performance. Furthermore, driving speed fluctuation is used to assess driving stability, which is calculated by the standard deviation of the vehicle longitudinal speed. Moreover, the standard



(a) Position ahead. (b) Position in. (c) Position behind.

Figure 1. Trajectory guidance HMI with virtual block.

Table 1. Performance measures.

Evaluation category	Performance indicators
Vehicle control	- Average speed - Intersection waiting time - Speed fluctuation - Lane position deviation
Environment	- Emissions - Fuel consumption
Eye movement	- Eye fixation duration - Eye fixation time percentage
Workload	- NASA-TLX
Compliance	- In-block rate
Emergency response	- Brake reaction time - Deceleration rate - Distance loss - Recovery time

deviation of lane position (SDLP) is selected to measure drivers' lateral control ability.

(2) **Environment**. A VSP-based model is adopted to estimate driving performance on environmental aspects, including fuel consumption and emissions. For a typical light-duty vehicle, the VSP (kW/metric ton) can be calculated as:

$$VSP = \frac{0.156461v + 0.00200193v^2 + 0.000492646v^3 + 1.4788va}{1.4788} \tag{1}$$

where v is the vehicle longitudinal speed (m/s) and a is the longitudinal acceleration (m/s^2). The instantaneous emission rate (ER, g/s) of CO_2, CO, HC and NO_x is gained through the corresponding relationship between discrete VSP values and emission rates based on VSP bins (see Appendix B (X. Zhao et al., 2015)). The total emission of one test drive is then calculated by summing the emission rates since the data collected from the driving simulator is discrete.

The fuel consumption rate (FC, mL/s) is calculated through the following equation, which is derived using the carbon balance method.

$$FC = (0.866ER_{\mathrm{HC}} + 0.4286ER_{\mathrm{CO}} + 0.2727ER_{\mathrm{CO_2}}) \times 1.545 \qquad (2)$$

where ER_{HC}, ER_{CO} and $ER_{\mathrm{CO_2}}$ are the emission rates (g/s) of HC, CO and CO_2, respectively.

(3) **Eye movement**. Eye fixation duration and eye fixation time on areas of interest (AOIs) are calculated based on the eye movement results. The percentage of eye fixation time is then calculated by dividing total eye fixation time by total driving time.

(4) **Workload**. Mental workload is measured by paper and pencil administration of NASA-TLX (Hart & Staveland, 1988). An average score measuring each dimension of mental demand, physical demand, temporal demand, performance, effort, and frustration, and a weighted global NASA-TLX score are calculated.

(5) **Compliance**. Drivers' compliance with trajectory guidance is measured by the percentage of time that the vehicle remains in the virtual block, which is referred to as in-block rate.

(6) **Emergency response**. Brake reaction time (BRT) is selected to measure drivers' reaction under emergency events and is defined by the interval between the instant that a driver recognizes a hazard in the roadway and the instant that the driver brakes. In our study, we measure BRT from the instant that a hazard is triggered, a similar approach to that by Yan et al. (2015). Deceleration is calculated by the change rate of longitudinal speed for a certain time span before an emergency. Distance loss measures the loss of relative distance to the virtual block due to an emergency event. Recovery time measures the time needed to catch up with the virtual block after an emergency.

3.4. Hypotheses

Given the design of the guidance system and the performance measures, we formulate four hypotheses to investigate the interaction between the system and the drivers.

- H1: The proposed trajectory guidance system will improve driving performance, more specifically:
  - H1.1: The system will enhance driving efficiency by reducing intersection stopping delay and increasing the average travel speed.
  - H1.2: The system will improve longitudinal driving stability.
  - H1.3: The system will reduce emissions and fuel consumption.
- H2: The proposed trajectory guidance system will impose extra information that needs processing such that:
  - H2.1: The drivers will have more glances at the HMI and fewer glances at the main road.
  - H2.2: The lateral control ability of drivers will deteriorate, resulting in higher SDLP.
  - H2.2: The drivers will report higher ratings of perceived mental workload when engaged with the system.
- H3: The drivers will have a overall high trust and acceptance to the guidance system such that:
  - H3.1: The drivers will have higher in-block rate when engaged with the system.

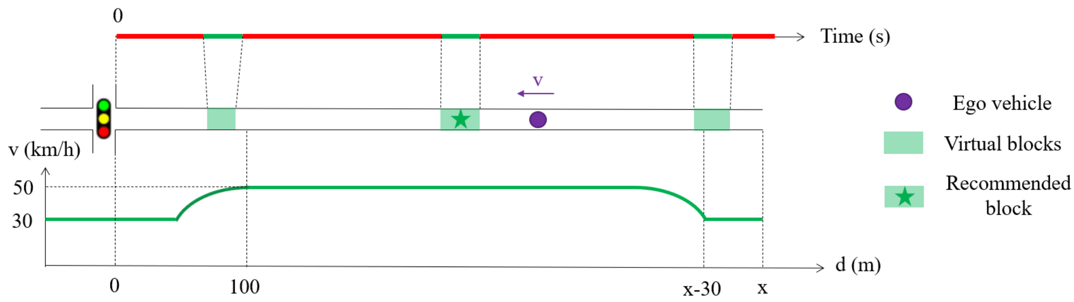


Figure 2. Pre-defined trajectory of virtual block.

  - H3.2: The drivers will learn about the guidance system through repeated trials.
- H4: The proposed trajectory guidance will not affect drivers' awareness of hazardous situations, more specifically:
  - H4.1: The system will not postpone the time for braking when emergency events happen.
  - H4.2: The drivers will be able to make sufficient deceleration to emergency events when engaged with the system.

3.5. Statistical analysis procedure

We apply analysis of variance (ANOVA) to examine whether the observed differences in the independent variables are significant different. The independent variables include:

- Driving condition (two levels: with trajectory guidance and without trajectory guidance)
- Experimental scenario (two levels: open road and dedicated road, will be introduced in Section 4.3)
- Number of trials (three levels: the first, the second and the third trial with trajectory guidance)
- Compliance type (three levels: high compliance, low compliance and others, will be introduced in Section 5.2.3)

4. Experimental design

4.1. Pre-defined vehicle trajectory

The preset trajectory of the virtual block in the experiment is illustrated in Figure 2. The longitudinal speed of the virtual block moving along the road is 50 km/h, and the speed decreases to 30 km/h when the virtual block approaches intersections to ensure safety. The virtual block maintains a constant acceleration and deceleration rate of 2 m/s^2 during the change in speed. Deceleration initiates when the virtual block is 100 meters away from an intersection, and acceleration commences when the virtual block is 30 meters past an intersection.

(a) Driving simulator. (b) Trajectory guidance device.

Figure 3. Experimental apparatus.

4.2. Apparatus

Human-in-the-loop driving simulator experiments were conduct to evaluate the performance and usability of the trajectory guidance system. The experiments took place in the Lab of Intelligent and Connected Vehicles, School of Vehicle and Mobility of Tsinghua University. The simulator used in the experiments was a one-person compact simulator with three degrees of freedom (Figure 3a), and the simulation was generated by SCANeR Studio (That & Casas, 2011). ASee mobile eye tracking glasses were used to collect data related to the eye movement of drivers. Vehicle data were recorded at a frequency of 100 Hz, and eye tracking data were recorded at a frequency of 60 Hz. Trajectory guidance information was given to the driver via an 8-inch in-vehicle screen located in the center console to the right of the driver (Figure 3b).

4.3. Driving scenario

The driving scenario implemented in the driving simulator was based on Beijing BRT Line 1, which operates in Fengtai District, Beijing. Participants were required to drive straight along the test route (Figure 4) and pass through 2 four-leg intersections and 2 three-leg intersections. The road was 4.38 kilometers long with 3 lanes in one way, and the width of each lane was 3.5 m. The speed limit was 60 km/h. The signal cycle length of each intersection was 72 s, and the green time for through traffic was 20 s. The signals were not coordinated or optimized. Buildings, vertical signs, markings and all the features of a typical urban environment were reproduced in the simulation scenario to give drivers a real sense of driving.

Two scenarios, namely, an open road scenario and a dedicated road scenario, were further designed. In the open road scenario (Figure 5a), the ego vehicle was allowed to change lanes freely in the right two lanes and interact with other surrounding vehicles. In the dedicated road scenario (Figure 5b), the ego vehicle must stay in the left-most lane of the road and was not interrupted by other vehicles. The purpose of this driving scenario design is to evaluate driver behavior and driving performance in scenarios with different levels of complication, where the dedicated road indicates a simple traffic environment and the open road indicates a complicated traffic environment with vehicle interaction.

Pedestrian crossing configurations were randomly simulated in both scenarios to

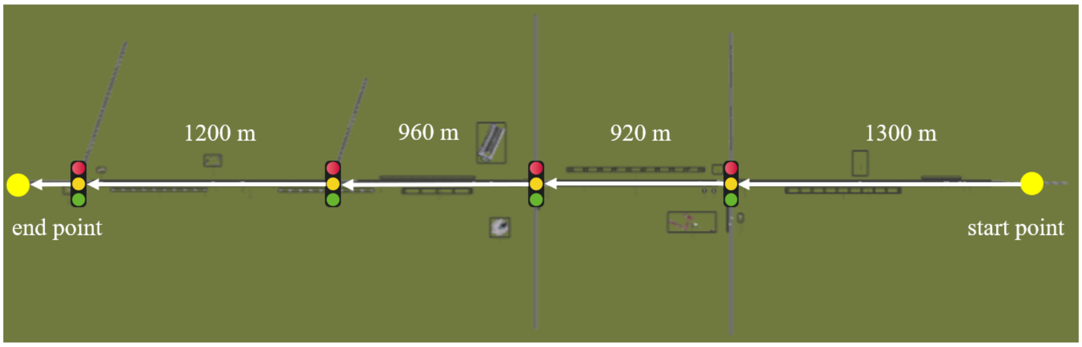


Figure 4. Test route.

(a) Open road.

(b) Dedicated road.

Figure 5. Experimental scenarios.

evaluate the response of drivers to emergency events under the influence of trajectory guidance HMI. Pedestrian movement is activated when a driver is at a longitudinal distance of d_{veh} to the pedestrian, as shown in Figure 6. d_{veh} is calculated as follows:

$$d_{\text{veh}} = \frac{v_{\text{veh}}}{v_{\text{ped}}} d_{\text{ped}} \tag{3}$$

where v_{veh} is the longitudinal speed (assuming 50 km/h) of the ego vehicle, v_{ped} is the running speed (10 km/h) of the pedestrian, and d_{ped} is the lateral distance from the pedestrian to the vehicle centerline. In the above setting, it is assumed that the ego vehicle maintains its original speed after the pedestrian is noticed, which produces a high risk of collision. Drivers are supposed to decelerate in time to ensure safety. In each drive of the formal test, pedestrian crossing events occurred randomly no more than 3 times and no less than 1 time. The occurrence time and location of each pedestrian crossing event were random to avoid anticipatory behavior.

4.4. Participants

Overall, 35 participants (21 males and 14 females) were recruited for the experiment, balanced for gender, age and driving experience (Table 2). All participants had held a full driving license for at least one year, with an average of 3.49 years and a standard deviation (SD) of 2.91 years. Participants were randomly assigned into 2 groups: open road and dedicated road. No participants were reported to have experience with trajectory guidance systems or in-vehicle speed advisory systems. We ensured that participants were free from fatigue and the influence of alcohol and were aware of the

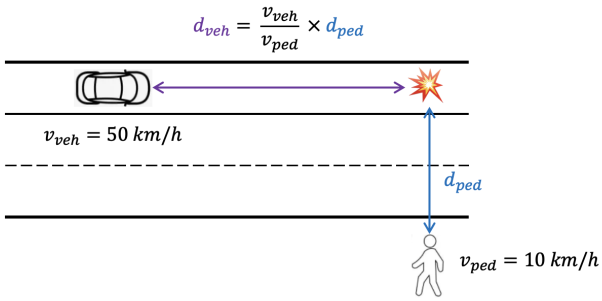


Figure 6. Illustration of the unexpected pedestrian crossing setting.

Table 2. Participant characteristics.

	Open road (n=17)	Dedicated road (n=18)
Age (year)	23.88 (3.77)	23.61 (3.74)
Driving experience (year)	4.00 (3.57)	3.00 (2.11)
Male percentage (%)	64.71	55.56

purpose of the experiment. All participants successfully completed the driving session, and a total of 80 CNY was offered to thank each participant.

4.5. Experimental procedure

The experimental procedure is shown in Figure 7. First, participants were asked to complete a questionnaire with information considering their age, gender, time since they obtained driving license, and number of kilometers driven per year. Their knowledge and experience with trajectory guidance systems was also investigated.

After completing the questionnaire, participants were formally introduced to the experimental purpose, basic procedure and trajectory guidance system. The researchers stated that trajectory guidance was not compulsory. However, participants were informed that instruction given by the system would help them pass through the intersections without stopping. Furthermore, researchers advised all participants to drive safely and obey the speed limit of the road (60 km/h).

Before the formal experiment, participants first wore eye tracking glasses. Then, they were allowed to familiarize themselves with the driving simulator during a 5-minute driving practice. No pedestrian crossing events appeared in the driving practice stage, and participants were able to experience both the open road scenario and dedicated road scenario. During the formal trial, each participant was asked to complete the experiment sessions four times, including one test with no trajectory guidance (NG) system and three tests with the trajectory guidance system (G1, G2, and G3). The last three tests were identical in content to evaluate drivers' adaptation process to the trajectory guidance interface.

Each drive lasted approximately 7 minutes. Between each trial drive, participants had a 10-minute rest to reduce the possibility of simulator sickness (Cobb et al., 1999). During the rest time, the participants were asked to complete the NASA-TLX to obtain an estimate of the mental workload associated with the use of the trajectory guidance system.

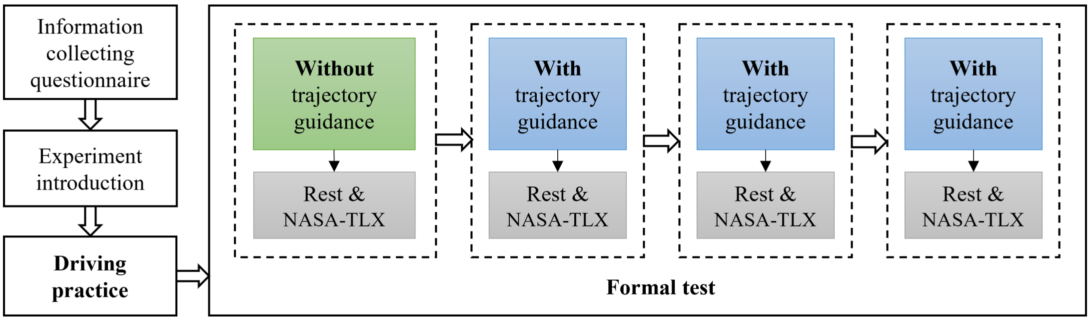


Figure 7. Experimental procedure.

Table 3. Mean values of performance indicators on vehicle control and environmental impact for different scenarios and driving conditions.

	Open road				Dedicated road			
	NG	G1	G2	G3	NG	G1	G2	G3
Average speed (km/h)	44.18	45.69	44.52	46.67	42.98	44.25	45.73	45.99
Intersection waiting time (s)	16.86	15.97	15.85	9.22	29.84	19.65	21.79	16.42
Speed standard deviation (km/h)	18.66	15.92	16.85	15.01	17.98	15.20	14.36	13.99
SDLP (m)	0.28	0.28	0.30	0.33	0.18	0.21	0.20	0.20
Emissions (g)	1050.78	1009.59	987.25	981.95	1003.63	970.21	951.08	942.86
Fuel assumption (mL)	443.29	425.90	416.46	414.25	423.39	409.28	401.21	397.75

5. Results

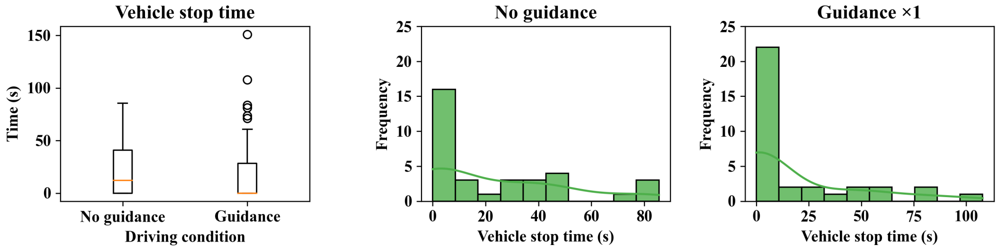
A total of 140 samples (35 participants × 4 trials) were collected from the driving simulator experiment. Due to equipment failure, four samples collected from the driving simulator and eight samples collected from the eye tracking glasses were missing. The remaining data were used for analysis.

5.1. Driving performance

The observed mean values of driving performance indicators for different scenarios and driving conditions are presented in Table 3.

5.1.1. Driving efficiency

The recommendations of the trajectory guidance system led to higher driving efficiency, supported by higher average speed [$F(1,134)=3.98$, $p<0.05$]. The vehicle waiting time at intersections also decreased (without guidance: 23.35 s on average, with guidance: 16.58 s on average) with the help of trajectory guidance. However, ANOVA indicated no significant main effect of driving condition on intersection waiting time [$F(1,134)=1.55$, $p=0.22$]. The major reason may lie in the outliers that appeared in the guidance group, as shown in Figure 8a. Nevertheless, a shift of distribution toward zero waiting time was observed in the guidance group compared to the NG group (Figure 8b, G1 vs. NG is used as an example). Moreover, intersection waiting time had a tendency to decrease during repeated drives with trajectory guidance according to Table 3, which indicated a learning effect on trajectory guidance HMI to help drivers improve vehicle efficiency. In particular, trial G3 exhibited a significantly smaller waiting time than that of NG in both scenarios [$F(1,67)=4.49$, $p<0.05$].



(a) Intersection waiting time under different driving condition.

(b) Distribution of intersection waiting time under different driving condition.

Figure 8. Intersection waiting time.

No significant impact of driving scenario was found on average speed [$F(1,134)=0.38$, $p=0.54$] or intersection stopping time [$F(1,134)=2.48$, $p=0.12$].

5.1.2. Driving stability

The standard deviation of longitudinal speed was found to be significantly smaller with the aid of trajectory guidance [$F(1,134)=13.50$, $p<0.001$]. A 17.24% decrease in speed deviation after the use of trajectory guidance was observed, which indicates a transition to a smooth and steady driving style with fewer longitudinal deceleration or acceleration maneuvers. One-factor ANOVA also revealed a main effect of number of trials on longitudinal speed deviation [$F(3,132)=4.90$, $p<0.01$]. A post hoc test indicated that there was no significant difference in speed deviation between the first trial with trajectory guidance (G1) and the control group (NG) [$p=0.06$]. However, a significant decrease in speed deviation compared to that of NG [$p<0.05$] was revealed for the last two trials (G2 ad G3). This result suggests that there was improvement in longitudinal driving stability over time. The main effect of scenario did not reach statistical significance [$F(1,134)=2.69$, $p=0.10$], indicating that the scenario made no difference in drivers' longitudinal driving ability.

Regarding the SDLP, no significant main effect of driving condition was revealed [$F(1,134)=1.78$, $p=0.28$], which proves that the trajectory guidance system did not lead to side effects on drivers' lateral control ability.

5.1.3. Emissions and fuel consumption

The experimental results confirmed that trajectory guidance was able to reduce emissions and fuel consumption by 5.31% on average, as shown in Table 3. A significant main effect of driving condition on both emissions and fuel consumption was found [$F(1,134)=10.96$, $p<0.01$]. An identical significance test result was obtained since emissions and fuel consumption had a near linear relation, according to Equation (2).

A significant impact of scenario was revealed [$F(1,134)=8.20$, $p<0.01$]. There was significantly lower (-4.12%) fuel consumption and emissions on the dedicated road than on the open road.

Table 4. Mean values of eye movement indicators for different AOIs, scenarios and driving conditions.

		Open road				Dedicated road			
		NG	G1	G2	G3	NG	G1	G2	G3
Percentage of fixation time (%)	Road	61.76	60.69	60.89	55.38	66.71	56.48	59.79	60.01
	Dashboard	12.74	7.12	6.64	7.94	7.11	8.32	8.93	8.72
	HMI	0.03	2.64	1.42	1.21	0.25	3.61	2.17	1.51
Mean fixation duration (s)	Road	0.24	0.28	0.25	0.22	0.28	0.24	0.26	0.26
	Dashboard	0.24	0.18	0.15	0.15	0.18	0.18	0.19	0.17
	HMI	0.02	0.11	0.10	0.08	0.05	0.12	0.10	0.10

5.2. *Overall driver behavior*

5.2.1. Eye movement

Measures of eye movement include mean fixation duration and percentage of fixation time spent on different AOIs (i.e., main road, dashboard and trajectory guidance HMI). We present the mean value of eye movement indicators in Table 4.

The results of eye fixation analysis revealed a certain level of distraction caused by the guidance HMI. A significant main effect of driving condition on percentage of fixation time on HMI was found [$F(1,130)=19.74$, $p<0.001$]. When engaged with the guidance system, the drivers looked away from the road and toward the HMI for 2.64% (open road) and 3.61% (dedicated road) of total driving time at G1 compared to NG. Over the repeated trials with trajectory guidance, a clear drop in mean values of percentage of fixation time on HMI was observed. Compared to that of G1, the percentage of fixation time on HMI of G3 decreased by 56.82% from 3.14% to 1.36%. However, this learning effect did not receive statistic support [$F(2,94)=2.97$, $p=0.06$]. No main effect of driving condition on percentage of fixation time on the main road [$F(1,130)=2.67$, $p=0.10$] or dashboard [$F(1,130)=0.89$, $p=0.35$] was found.

The mean fixation duration on HMI and dashboard was 0.10 s and 0.17 s, respectively. Significantly shorter dashboard fixation duration [$F(1,130)=3.97$, $p<0.05$] and longer HMI fixation duration [$F(1,130)=19.74$, $p<0.001$] were found. This result indicates that, as more visual search on HMI was conduct, less visual processing on the dashboard was need when engaged with the guidance system. By contrast, there was no significant difference in the mean fixation duration on the main road between the guidance group and the control group [$F(1,130)=0.40$, $p=0.53$].

In the further analysis of driver distraction in different road scenarios, we found no evidence that the scenario had a significant main effect on mean fixation duration or percentage of fixation time spent on the three AOIs. Only considering drivers in dedicated road scenario, a significant decrease in percentage of fixation time on the road was revealed [$F(1,64)=5.29$, $p<0.05$].

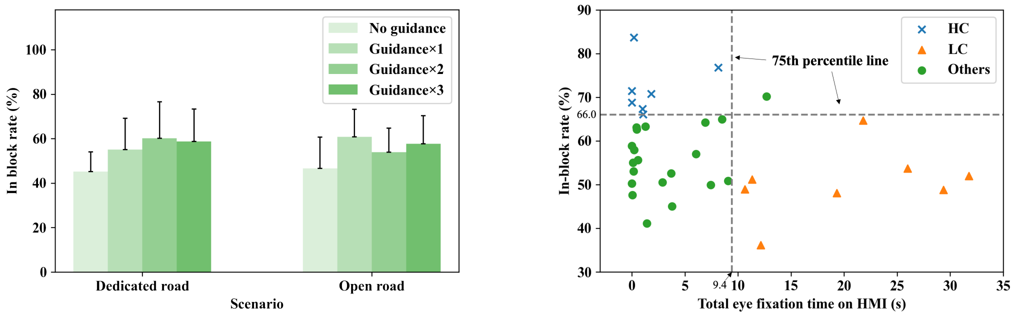
5.2.2. Workload

We present the mean (SD) ratings of NASA-TLX workload scores in Table 5. With regard to the global score, we found that although an initial increase for both scenarios was observed (dedicated road: 11.74%, open road: 32.68%), the use of the trajectory guidance system did not produce a significantly higher workload statistically speaking [$F(1,138)=1.59$, $p=0.21$]. Meanwhile, we did not find a significant main effect of scenario on the global score [$F(1,138)=0.68$, $p=0.41$].

Considering NASA-TLX score for each dimension, ”effort” received the highest score (3.66), while ”frustration” received the lowest score (2.36). Moreover, we found that the

Table 5. Mean (SD) ratings for NASA-TLX workload, encompassing six dimensions as well as the overall global score.

	Open road				Dedicated road			
	NG	G1	G2	G3	NG	G1	G2	G3
Mental demand	2.8 (1.6)	3.4 (2.1)	3.2 (2.1)	3.1 (2.0)	3.2 (2.2)	3.5 (1.7)	3.1 (1.9)	2.9 (1.7)
Physical demand	2.1 (1.3)	2.9 (1.7)	3.1 (2.0)	3.0 (2.0)	2.2 (1.5)	2.9 (1.4)	3.1 (1.8)	3.0 (1.8)
Temporal demand	2.7 (1.4)	3.5 (1.6)	3.2 (1.6)	3.2 (1.7)	3.7 (1.8)	4.0 (1.8)	3.7 (1.9)	3.7 (2.2)
Performance	2.5 (2.0)	3.6 (3.2)	3.2 (2.4)	2.7 (2.5)	2.8 (2.6)	2.3 (1.8)	2.7 (2.2)	3.0 (2.9)
Effort	3.4 (1.5)	3.5 (2.0)	3.4 (1.8)	3.1 (1.8)	3.8 (1.9)	4.5 (1.5)	3.7 (2.0)	4.0 (2.2)
Frustration	1.7 (1.2)	2.7 (1.9)	2.4 (1.7)	2.2 (1.7)	2.6 (2.3)	2.8 (1.6)	2.4 (1.8)	2.1 (1.6)
Global score	2.6 (1.0)	3.2 (1.9)	3.1 (1.5)	3.0 (1.6)	3.0 (1.6)	3.3 (1.3)	3.2 (1.5)	3.1 (1.6)



(a) Compliance to trajectory guidance by driving condition and scenario (error bar means SD over subjects).

(b) Scatter plot of eye fixation on HMI and in-block rate.

Figure 9. Driver compliance characteristic.

use of the trajectory guidance system led to higher physical demand [F(1,138)=7.00, p<0.01]. In the comparison of the two different road scenarios, a significant main effect on temporal demand [F(1,138)=4.22, p<0.05] and effort [F(1,138)=4.74, p<0.05] was found. Drivers on the dedicated road perceived higher temporal demand and effort (3.76 and 3.99, respectively) than those on the open road (3.16 and 3.31, respectively).

5.2.3. Compliance

The in-block rate, defined as the percentage of time that the vehicle stayed in the virtual block, was calculated to evaluate driver compliance, as presented in Figure 9a. Overall, high obedience to trajectory guidance among open road and dedicated road drivers was observed, supported by the significant main effect of driving condition on the in-block rate [F(1,134)=20.77, p<0.001]. These results matched the initial assumption that most drivers would take the system output as a reliable reference for real-time trajectory. No significant impact of scenario was found on driver compliance [F(1,134)=0.01, p=0.92].

Surprisingly, a weak negative correlation was found between each driver's average in-block rate and eye fixation time on the HMI when driving with trajectory guidance, according to the Pearson correlation coefficient [r=-0.26, p=0.018]. The results indicated that although the trajectory guidance system led to a certain level of distraction, a higher eye fixation time on the HMI did not inherently produce a higher in-block rate. To this end, we classified all participants into three categories: high compliance (HC), low compliance (LC) and others. The total number of participants in each cate-

Table 6. Statistical comparison of driver behavior and driving performance measures between different driver compliance categories.

Performance measures	Driver compliance category			F-Stat.	p-value	Post hoc comparison
	LC	HC	Others			
Intersection waiting time (s)	28.74 (40.79)	0.07 (0.32)	17.95 (23.76)	6.54	<0.01	(LC, HC)** (HC, Others)*
Speed deviation (km/h)	16.25 (3.80)	11.44 (1.96)	16.43 (4.69)	12.21	<0.001	(LC, HC)*** (HC, Others)***
Emissions (g)	991.98 (89.33)	918.04 (34.41)	991.13 (81.32)	7.65	<0.001	(LC, HC)*** (HC, Others)***
Fuel consumption (mL)	418.45 (37.68)	387.26 (14.51)	418.12 (34.34)	7.65	<0.001	(LC, HC)*** (HC, Others)***
Fixation duration (s)						
Road	0.21 (0.04)	0.26 (0.11)	0.27 (0.10)	3.24	<0.05	(LC, Others)*
Dashboard	0.22 (0.07)	0.14 (0.07)	0.16 (0.07)	7.67	<0.001	(LC, HC)*** (LC, Others)***
HMI	0.18 (0.05)	0.05 (0.05)	0.08 (0.06)	30.48	<0.001	(LC, HC)*** (LC, Others)***
Fixation time percentage (%)						
Road	50.88 (8.51)	57.24 (16.00)	64.14 (17.89)	5.71	<0.01	(LC, Others)*
Dashboard	9.68 (4.44)	9.40 (7.18)	6.05 (7.84)	2.87	0.06	-
HMI	5.84 (4.05)	1.04 (1.74)	0.86 (1.26)	38.43	<0.001	(LC, HC)*** (LC, Others)***
Mental workload	3.35 (0.95)	4.30 (1.55)	2.87 (1.46)	7.94	<0.001	(HC, Others)*

gory was 7, 8, and 20, respectively. This classification was based on the third quartile of mean in-block rate and mean eye fixation time on HMI, as shown in Figure 9b. Each data point in the figure represents the mean values of these parameters for one participant. Drivers in HC group had high eye fixation on HMI and low in-block rate, while drivers in LC group had low eye fixation on HMI and high in-block rate. Only trials with trajectory guidance (G1, G2 and G3) were used for calculation.

Table 6 demonstrates a comparison of driving performance and driver behavior indicators among different driver compliance groups. One-factor ANOVA revealed a significant main effect of driver compliance categories on intersection waiting time [$F(2,91)=6.54$, $p<0.01$], speed deviation [$F(2,91)=12.21$, $p<0.001$], emissions [$F(2,91)=7.65$, $p<0.001$] and fuel consumption [$F(2,91)=7.65$, $p<0.001$]. It was further confirmed from the post hoc comparisons that HC drivers exhibited lower intersection waiting time, smaller speed deviation, lower emissions and fuel consumption than those of LC drivers and others. Drivers in the HC group perceived higher mental demand [$F(2,91)=7.94$, $p<0.001$]. Considering eye movement indicators, LC drivers had a significantly higher fixation time percentage on the HMI [$F(2,91)=38.43$, $p<0.001$] and lower fixation time percentage on the main road [$F(2,91)=5.71$, $p<0.01$] than that of HC drivers and others. Moreover, LC drivers showed a significantly higher eye fixation duration on the HMI [$F(2,91)=30.48$, $p<0.001$] and dashboard [$F(2,91)=7.67$, $p<0.001$] than those of HC drivers and others.

5.3. Driver behavior in emergency situations

Overall, 3 crashes with pedestrians occurred. The crash occurrence rate is 1.07%. One crash occurred in the dedicated road scenario without trajectory guidance. The other two crashes occurred in the open road and dedicated road scenarios respectively with trajectory guidance. Since there were three times as many trials with guidance than without guidance, we can draw the conclusion that trajectory guidance did not raise the crash rate. After each crash, participants continued to finish the trial.

Table 7. Mean (SD) values of driving performance measures in emergency situations within different categories of factors.

Condition	BRT (s)	Deceleration (m/s^2)	Distance loss (m)	Recovery time (s)
Scenario				
Dedicated road	1.42 (0.70)	4.01 (1.31)	19.83 (9.32)	3.91 (7.90)
Open road	1.01 (0.55)	3.33 (1.43)	12.13 (8.83)	3.39 (7.70)
Driving condition				
without guidance	1.38 (0.76)	3.68 (1.60)	18.44 (9.59)	3.79 (7.27)
with guidance	1.18 (0.62)	3.71 (1.33)	15.54 (9.87)	3.63 (8.00)

Table 8. Statistical comparison of driving performance measures in emergency situations between different driver compliance categories.

Performance measure	Driver compliance category			F-Stat.	p-value	Post hoc comparison
	LC	HC	Others			
BRT (s)	1.42 (0.58)	1.25 (0.65)	1.15 (0.65)	1.94	0.15	-
Deceleration (m/s^2)	4.30 (1.21)	3.38 (1.55)	3.64 (1.20)	4.27	<0.05	(LC, HC)*** (LC, Others)***
Distance loss (m)	19.29 (8.45)	14.08 (12.24)	15.90 (9.10)	2.27	0.11	-
Recovery time (s)	3.84 (6.98)	2.50 (5.77)	4.10 (8.84)	0.44	0.65	-

A significant main effect of the number of emergency events on the vehicle speed standard deviation was discovered [$F(2,133)=3.22$, $p<0.05$]. No significant main effect was found for the number of emergency events on other driving performance or driver behavior indicators.

In the following subsections, four indicators including the brake reaction time (BRT), deceleration rate, distance loss and recovery time were used to analyze the impact of trajectory guidance on driver behavior before and after emergency events. The mean value and standard deviation of these indicators under different scenarios and driving conditions are listed in Table 7. We present a statistical comparison of these indicators among different driver compliance groups, as shown in Table 8.

5.3.1. Reaction to emergency

The brake reaction time (BRT) is measured from the time at which a test vehicle arrives at a certain distance to a pedestrian, with the pedestrian crossing event being triggered at the same time, to the time at which the driver of the test vehicle depresses the brake pedal. Deceleration is calculated as the change rate of vehicle longitudinal speed during the period of first braking to the largest braking when facing emergency events. A hard braking was further recognized if deceleration was higher than 3.5 m/s^2, following the definition in (Staubach et al., 2014).

The average BRT was 1.23 s. No significant main effect of driving condition on BRT was revealed [$F(1,127)$, $p=0.13$], which proves that the trajectory guidance system did not postpone the timing for braking. One-factor ANOVA indicated a significant main effect of scenario [$F(1,127)=13.50$, $p<0.001$]. The BRT on open road was 28.87% shorter than that on dedicated road. For different driver compliance categories, no main effect on the BRT was revealed [$F(2,126)=1.94$, $p=0.15$].

No statistically significant difference in deceleration was observed between trials with and without guidance [$F(1,127)=0.01$, $p=0.90$]. Drivers were able to decelerate in a timely manner to avoid collisions, although with the equipment of the trajectory guidance device. Moreover, participants performed hard braking for 64.51% of emergency events when driving without guidance and 59.57% when driving with guidance.

A significant effect of the scenario on the deceleration rate was found [$F(1,127)=6.79$, $p<0.05$]. 20.42% higher deceleration rate before an emergency was found on dedicated road than on open road. However, the observation of hard braking did not support this finding [$F(1,127)=1.46$, $p=0.23$]. Moreover, we found a main effect of driver compliance type on deceleration [$F(2,132)=3.53$, $p<0.05$]. Post hoc comparisons revealed that LC drivers had a significantly higher deceleration rate in emergency situations than that of HC drivers and others.

5.3.2. Driver behavior after emergency

Distance loss is calculated as the change of relative distance to the virtual block from the time the driver depresses the the brake pedal to an emergency event to the time the driver starts to accelerate after an emergency. Virtual block recovery time is measured from the time at which the driver begins to accelerate after an emergency to the time the ego vehicle catches up the virtual block.

On average, an unexpected pedestrian crossing event resulted in a distance loss of 16.31 meters to the virtual block. When driving with trajectory guidance, this number is 15.54 m. However, no significant main effect of driving condition on distance loss was observed [$F(1,127)=2.19$, $p=0.14$]. Considering the impact of scenario, we found significantly less distance loss in open road scenario [$F(1,127)=22.94$, $p<0.001$]. No main effect of driver compliance type was revealed [$F(2,126)=2.27$, $p=0.11$].

After an emergency, it took 3.63 ± 8.00 s to get back in the virtual block, due to the distance loss caused by the emergency event. Among all emergency events, vehicle was still inside the virtual block when it began to accelerate in 85.14% of cases, and the recovery time of which were 0. No main effect of driving condition [$F(1,127)=2.19$, $p=0.14$] or scenario [$F(1,127)=0.14$, $p=0.70$] on recovery time was observed. For different driver compliance groups, HC drivers achieved the lowest recovery time (2.50 s), but the result did not reach statistical significance [$F(2,126)=0.44$, $p=0.65$].

6. Discussion and conclusions

In this study, an in-vehicle longitudinal trajectory guidance system was proposed in connected environment. The impact of the trajectory guidance system on driving performance and driver behavior was explored through driving simulator experiments. Two road scenarios, namely, open road and dedicated road, were compared and evaluated. Overall, the developed system was verified to be a useful and acceptable tool to provide real-time guidance information on vehicle trajectories.

6.1. Effectiveness of trajectory guidance

The first hypotheses we formulated in this study examines the potential benefits of the proposed trajectory guidance system. The analysis of driving performance confirms H1.1 and H1.2. Compared with baseline condition, the experimental results indicated that the guidance information can effectively increase longitudinal speed by 4.38% and reduce intersection waiting time by 28.99%, which is in line with most of the related research (P. Chen et al., 2018; Staubach et al., 2014; W. Wu et al., 2015) using either driving simulator experiments or traffic simulation experiments. In addition, when provided with trajectory guidance, drivers were able to drive in a smooth and steady style with 17.25% less speed deviation on average, which indicates a transition toward a more stable driving maneuver with trajectory guidance. Considering the environmental impact, the proposed trajectory guidance system was verified to be able to reduce emissions and fuel consumption by 5.31%, which confirms H1.3. The environmental performance of the system reaches those of some existing eco-driving systems (P. Chen et al., 2018; Staubach et al., 2014; X. Zhao et al., 2015), although it is not designed for eco-driving purpose.

6.2. Potential negative effects of trajectory guidance

The second hypotheses stated that the proposed system would provide extra information that needed processing such that more glances at the HMI (H2.1), higher SDLP (H2.2) and higher mental workload (H2.3) would be observed. The analysis of eye movement behavior indicated that the presence of the guidance display produced certain negative effects on drivers. H2.1 was confirmed since higher glances at the HMI was initially found when most of the drivers looked away from the road and the dashboard, which is a common effect for drivers using in-vehicle guidance systems (Erke et al., 2007; S. L. Jamson et al., 2015). However, a weak evidence of learning effect that helped with reducing the initial distraction was indicated by the statistic test. The average glance duration on the trajectory guidance HMI was 0.10 s, which meets the 1 second limit recommended by Stevens et al., 2002. This result demonstrates that drivers were capable of assimilating visual information with a few glances. In this respect, the designed trajectory guidance HMI is clear and brief enough not to adversely cause distraction. Moreover, the change in glance duration on HMI and dashboard indicated that the guidance system may serve as a substitute for the dashboard (i.e., speedometer) when drivers acquire real-time speed information, which might also be the case in (Schewe & Vollrath, 2019).

Visual distraction has been demonstrated to increase the deviation of lane position from previous researchers (e.g. Engström et al., 2005, Santos et al., 2005). In our study, the attention to the HMI did not lead to higher vehicle lateral deviation, thus rejecting H2.2. This means that the scale of eye distraction caused by the system did not reach a level that influences vehicle lateral control and driving performance, thereby proving the usability of the proposed system.

H2.3 was rejected by the experimental results as well. No significant increase in perceived mental workload was revealed when considering the TLX global score. After analyzing each dimension of the NASA-TLX score, we found an increase in physical demand with the use of trajectory guidance. This could be explained by the frequent transition of eye fixation points between the main road, dashboard and HMI.

6.3. Driver compliance and learning effect

The third hypotheses stated that the drivers would have a overall high trust and acceptance to the guidance system. Driver compliance, referring to the extent to which drivers follow the instructions provided by a trajectory guidance system, is directly related to the usefulness of the guidance information. Feedback that has little use to drivers will inevitably annoy them and prevent them from following the system well (S. L. Jamson et al., 2015). In our study, H3.1 was confirmed since high obedience to trajectory guidance was observed overall measured by the in-block rate, which indicates that participants had a clear understanding of the driving task and were satisfied with the guidance system. Furthermore, we classified all participants into three driver compliance categories: LC, HC and others. The results of the differentiation analysis among these drivers provided valuable insights into the relationship between driver compliance and other driver behavior characteristics.

We can create basic driver personas for LC and HC drivers. HC drivers, with high compliance and low eye fixation time on the HMI, achieved higher driving efficiency and better eco-performance than LC drivers. In addition, HC drivers had considerably lower fixation time on the HMI. The fixation duration on the dashboard and HMI were also shorter. In other words, under the guidance system, HC drivers were able to drive efficiently with fewer and shorter glances. Y. Du et al., 2022 reported that the change on a driver's information collection method from long fixation to multi-frequency can potentially improve the driving performance. The experimental results obtained here confirm this finding. By contrast, since LC drivers put much visual attention on the HMI, a lower fixation time on the road was observed. Considering eye fixation duration, LC drivers had a shorter fixation duration on the road but a longer duration on the dashboard and HMI. This indicates that LC drivers had both a higher level of interest and a deeper cognitive process for the trajectory guidance HMI but relatively less interest on the main road. Correspondingly, some safety-related issues were raised. For example, LC drivers were more likely to perform hard braking than HC drivers when they observed emergency events, hence creating a larger deceleration rate. However, we did not observe significantly different BRTs for LC and HC drivers, which indicates that different levels of compliance did not impact drivers' perception of road hazards. Furthermore, HC drivers perceived higher mental workload when driving, which may reflect the stress caused by the urgency to follow the virtual block.

H3.2, related to the drivers' adaptation process to the system, was also verified by the analysis results. A learning effect on intersection waiting time and longitudinal driving stability was confirmed, and a weak evidence of learning effect on HMI fixation time was observed. We can conclude that drivers familiarized themselves with the guidance system through repeated trials and, as a result, exhibited better performance.

6.4. Emergency response

In the experiments, we set different numbers of emergency events in all trials, regardless of driving condition or scenario. The purpose of setting emergency events was to evaluate driver behavior where a safety–critical event happens in the driver's forward view while the driver interacts with the trajectory guidance display.

The experimental results confirmed H4.1 and H4.2. The trajectory guidance did not disturb drivers' awareness of impending accidents or postpone the timings for braking, according to BRT analysis results. Previous studies have put much effort into characterizing drivers' reactions to road emergency events through BRT. Table 9 summarizes the mean BRT or BRT range in some related driving simulator studies that involve road emergency events. In our study, the mean BRT to emergencies when driving with trajectory guidance was 1.18 ± 0.62 s, which is in a reasonable BRT range compared with that of most related research. Hence, the proposed trajectory guidance system is confirmed to be safe and reliable for drivers against road hazards. Meanwhile, drivers were able to reduce their speed sufficiently to avoid collision with the trajectory guidance equipment. The average deceleration with trajectory guidance was 3.71 m/s^2, which meets the threshold of 5.2 m/s^2 discriminating near-misses and collisions, as recommended by Y. Zhao et al. (2021).

After an emergency, a lag in relative distance to virtual block was observed. The

Table 9. Summary of drivers' brake reaction times during road emergency events.

Study	Road scenario	Emergency type	BRT (s)
Yan et al., 2015	Urban intersection	Red light running vehicle	2.16 - 4.19
Duan et al., 2017	Urban road and intersection	Cyclist crossing	0.75 - 1.01
Hang et al., 2022	Urban road with fog	Leading vehicle hard brake	1.55
Mollu et al., 2018	Urban road	Pedestrian crossing	1.09 - 1.62
Our study	Urban road (open and dedicated)	Pedestrian crossing	1.18

average distance loss was 15.54 m with trajectory guidance. One factor ANOVA indicated a main effect of scenario on distance loss. This is probably related to the short reaction time in open road scenario, which makes the total braking time shorter. Furthermore, it took 3.63 s on average to catch up with the moving virtual block with the help of trajectory guidance. We did not observe a significant main effect of driving condition, scenario or driver compliance type on recovery time. Nevertheless, the mean values and standard deviations of distance loss and recovery time provide valuable references for future implementation of trajectory guidance in mixed traffic scenarios.

6.5. Discussion of scenario discrepancies

In this study, we assumed that the open road scenario presents a more complicated traffic environment, potentially posing challenges for the application of trajectory guidance systems. Conversely, the dedicated road scenario features a simpler environment, which aligns with some real-life traffic scenarios such as bus rapid transit lanes, mining areas and logistic parks, where drivers encounter considerably fewer disturbances from other vehicles. This may explain the low fuel consumption and emissions on the dedicated road, where less frequent acceleration or deceleration was required. No main effect of scenario was found on vehicle driving efficiency and driving stability. This certifies trajectory guidance as a strong help even in complicated road environments.

Furthermore, in the dedicated road scenario, the duration of eye fixation time on the main road decreased significantly with the use of trajectory guidance. However, such a trend was not observed in the open road scenario. One possible explanation is that since drivers on the dedicated road were not disturbed by other vehicles, little attention to the main road was needed to perform basic driving maneuvers. Consequently, more attention was drawn to the dashboard and trajectory guidance HMI, thus resulting in certain level of visual distraction. Perhaps for the same reason, drivers on the dedicated road perceived higher temporal demand and effort than those on the open road.

Considering driver behavior in emergency situations, drivers in the dedicated road scenario had higher BRTs and accordingly higher deceleration rates. The aforementioned difference in scenario on drivers' emergency reaction may be due to the geometric position of the dedicated road and open road. Since dedicated road was located in the left-most lane, a longer lateral distance was needed for pedestrians to cross the road and reach the conflict point compared to that of the open road scenario. Thus, it was easier for drivers to notice pedestrians beforehand, thus creating a less urgent situation. Previous studies have confirmed that drivers' perception reaction time is strongly correlated with urgency, and lower urgency produces higher perception reaction time (X. Wang et al., 2016; K.-F. Wu & Lin, 2019). This conclusion can be applied to our case where drivers' emergency reactions were measured by the brake reaction time, thus explaining our findings.

6.6. Conclusions

In conclusion, the experiment results confirmed that the proposed system is a useful and reliable tool for providing real-time trajectory guidance information to human drivers. The trajectory guidance system is able to improve driving efficiency, enhance driving comfort and achieve environmental benefits, while maintaining manageable levels of distraction and mental workload for users. Moreover, we find that the system is more beneficial to the drivers if they have higher compliance. In emergency situations, drivers interacting with the guidance system are capable of identifying the hazards and performing appropriate driving maneuvers to ensure safety. A limited period of time is required to regain a position within the virtual block after an emergency. The findings gained here have the potential to support the implementation of trajectory-based traffic control methods (X. Chen et al., 2021; Lin et al., 2021) in mixed traffic considering random road safety hazards.

A further study can assess the proposed trajectory guidance system in more complicated scenarios such as extreme weather, curved roads, sharp turns, etc. In addition, trajectory guidance systems with monetary incentives can be developed in the future to further encourage high compliance and hopefully improve driving performance of a broader demographic.

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Disclosure statement

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Notes on contributors

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Appendix A. Calculation of virtual block positions

This appendix derives the equation $d_{\mathrm{vb,i}}^{\mathrm{start}} = F^{-1}(t_{\mathrm{green,i}}^{\mathrm{start}})$ and $d_{\mathrm{vb,i}}^{\mathrm{end}} = F^{-1}(t_{\mathrm{green,i}}^{\mathrm{end}})$ in Algorithm 1.

Let $v(t)$ denotes the longitudinal speed at time t. Let $x(t)$ denotes the distance to the upcoming intersection at time t. Here we assume $x(0) = 0$. Given a pre-defined trajectory (speed profile) of virtual block $v(x)$, where x is the distance to the upcoming intersection, we have $v(x(t)) = \frac{\mathrm{d}x(t)}{\mathrm{d}t}$, and further $\mathrm{d}t = \frac{\mathrm{d}x}{\mathrm{d}t}$, which can be solved by:

$$
\begin{aligned}
t &= \int_{x(0)}^{x(t)} \frac{1}{v(y)}\mathrm{d}y \\
&= \int_{0}^{x(t)} \frac{1}{v(y)}\mathrm{d}y
\end{aligned}
$$

where $x(t) \geq 0$ and $v(y) \geq 0$. Define

$$
F(q) = \int_{o}^{q} \frac{1}{v(y)}\mathrm{d}y
$$

then for every $t \geq 0$, we have

$$
t = F(x(t))
$$

hence,

$$
\begin{aligned}
x(t) &= F^{-1}(t) \\
d_{\mathrm{vb,i}}^{\mathrm{start}} &= F^{-1}(t_{\mathrm{green,i}}^{\mathrm{start}}) \\
d_{\mathrm{vb,i}}^{\mathrm{end}} &= F^{-1}(t_{\mathrm{green,i}}^{\mathrm{end}})
\end{aligned}
$$

Appendix B. Base emission rate in VSP bins

Table B1. Base emission rate in VSP bins (g/s).

VSP bins	CO_2	CO	HC	NO_x
<0	1.632545455	0.002176150	0.000438919	0.000073716
0	0.568829787	0.001100170	0.000135847	0.000007291
(0,1]	1.255982829	0.003240577	0.000254022	0.000125920
(1,2]	1.849368682	0.003378486	0.000299352	0.000183509
(2,3]	2.306617803	0.003476258	0.000352772	0.000181848
(3,4]	2.384342143	0.003559317	0.000415724	0.000174986
(4,5]	2.416571296	0.003653089	0.000489910	0.000165734
(5,6]	3.501662832	0.003782998	0.000577334	0.000188866
(6,7]	3.491228867	0.003974470	0.000680359	0.000227813
(7,8]	4.543236125	0.004252930	0.000801769	0.000298345
(8,9]	4.678231939	0.004643802	0.000944845	0.000476234
(9,10]	5.053493392	0.005172511	0.001113453	0.000537252
(10,11]	4.339905443	0.005864483	0.001312148	0.000587170
(11,12]	4.781969110	0.006745142	0.001421257	0.000686759
(12,13]	5.810918100	0.007839914	0.001444166	0.000896791
(13,14]	5.232738100	0.010074223	0.001504755	0.001158038
(14,15]	5.414972500	0.010773495	0.001561731	0.001201270
(15,16]	6.245907800	0.013563155	0.001615094	0.001417259
(16,17]	6.041760800	0.014868627	0.001672916	0.001446777
(17,18]	6.379312600	0.017415336	0.001770980	0.001620595
(18,19]	6.207211500	0.020328708	0.001783503	0.001909484
(19,20]	6.868176200	0.023634167	0.002024126	0.001924216
(20,21]	7.317505200	0.027357139	0.001870938	0.002265563
(21,22]	7.616578900	0.031523048	0.002093930	0.002334295
(22,23]	7.823473100	0.034657320	0.002074634	0.002431184
(23,24]	8.001660900	0.038285380	0.002211921	0.002857002
>24	8.343031300	0.040932652	0.002232765	0.002712520