TRB Annual Meeting

EHMI on the Rear of Leading Vehicle – Supporting Safety and Efficiency of Car-following Behaviors

--Manuscript Draft--

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Order of Authors:	Feiqi Gu
	Yufan Chen
	Zhenyu Wang
	Zhixiong Wang
	Jiahui Li
	Hongling Sheng
	Dengbo He

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Feiqi Gu
Thrust of Robotics and Autonomous Systems, Systems Hub, The Hong Kong University of Science and Technology (Guangzhou), Guangzhou, China, 511453
Email: fgu519@connect.hkust-gz.edu.cn

Yufan Chen
Thrust of Intelligent Transportation, Systems Hub, The Hong Kong University of Science and Technology (Guangzhou), Guangzhou, China, 511453
Email: intsquirrel@gmail.com

Zhenyu Wang
Thrust of Intelligent Transportation, Systems Hub, The Hong Kong University of Science and Technology (Guangzhou), Guangzhou, China, 511453
Email: zwang209@connect.hkust-gz.edu.cn

Zhixiong Wang
Thrust of Robotics and Autonomous Systems, Systems Hub, The Hong Kong University of Science and Technology (Guangzhou), Guangzhou, China, 511453
Email: zwang477@connect.hkust-gz.edu.cn

Jiahui Li
Shanghai AgiBot Innovation Technology Co., Ltd., 201315
Email: jiahuili_2050@outlook.com

Hongling Sheng
Thrust of Robotics and Autonomous Systems, Systems Hub, The Hong Kong University of Science and Technology (Guangzhou), Guangzhou, China, 511453
Email: hsheng598@connect.hkust-gz.edu.cn

Dengbo He*
Thrust of Intelligent Transportation, Systems Hub, The Hong Kong University of Science and Technology (Guangzhou), Guangzhou, China, 511453
Email: dengbohe@hkust-gz.edu.cn

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*Corresponding Author

ABSTRACT

Rear-end collisions constituted a large portion of crashes on the road, despite efforts to mitigate rear-end collisions, such as forward collision warnings. The chance of rear-end collisions is closely related to drivers' car-following (CF) behaviors in the traffic flow. Given that drivers may rely on more than the information of the direct lead vehicle (DLV) when making CF decisions, expanding drivers' perceptual range by providing beyond-visual-range (BVR) information based on vehicle-to-vehicle (V2V) communication may enhance CF safety. Thus, four external different human-machine interfaces (eHMIs) providing various types of BVR information in CF events were designed, including Brake-eHMI showing only brake action of indirect lead vehicle (ILV), Dis-eHMI and THW-EHMI showing the relative distance and time headway between the ILV and DLV, respectively, and Video-eHMI showing the live-stream video of ILV from the perspective of DLV. A field experiment with 30 participants was conducted to evaluate the impact of BVR-based HMI on driving safety and efficiency in CF events. We found that, in general, BVR information could improve CF safety without overloading drivers but Video-eHMI compromised visual attention allocation strategies, by enabling quicker brake responses. The Brake-eHMI and Dis-eHMI yielded the safest performance, whereas Video-eHMI increased attentional demands. This research provides insights into enabling drivers' BVR perception based on single smart vehicle capability to enhance driving safety and efficiency in CF scenarios.

Keywords: External human machine interface, Car-following behavior, Field study

INTRODUCTION

The car-following (CF) behaviors are closely related to rear-end collisions, which are one of the most common types of road crashes [1]. Thus, a lot of efforts have been made to understand CF behaviors, with the goal of regulating drivers' CF behaviors [2, 3]. To date, most of the research has assumed the CF behaviors to depend on the information of the directly leading vehicle (DLV) alone. However, an increasing amount of evidence has either demonstrated the benefits of seeing beyond the DLV or suggested that experienced drivers consider more than DLV information when following lead vehicles (LVs). For example, D. He et al. [4] found that when provided with the beyond-visual range (BVR) information regarding obstacles on the road, drivers were better able to predict the slowdown of traffic flow before the direct LV brakes, significantly increasing the safety margin. Experienced drivers would actively seek the BVR information to make earlier preparations for potential events in CF scenarios. Thus, explicitly informing drivers of the BVR information may support safer and more efficient driving behaviors in CF events.

Despite advancements in vehicle and road technologies, communication between road users remains reliant on explicit signals - primarily visual (e.g., headlights, brake lights, hazard lights, and turn signals) and auditory (e.g., horns) - with occasional support from implicit cues such as vehicle kinematics and driver gestures [5]. These vehicle-to-vehicle interactions are based on legacy systems developed over a century ago (e.g., brake lights in 1915, turn signals in 1909) and convey only basic, operational-level information regarding the immediate actions of the DLV. As has been pointed out by Yan, Huang [6], BVR information can enhance safety margin in CF scenarios.

In recent years, the broad adoption of perception sensors in smart vehicles, such as LiDAR and cameras, has made BVR information potentially available for surrounding road agents[7, 8]. However, in most of the previous studies, the perception capabilities of the road agents were assumed for AVs [9], or based on the vehicle-to-vehicle (V2V) communication technologies [10], which are still far from wide-range real-world applications, though they have shown the potential of allowing drivers to see beyond the DLV. Given that the market penetration rates of smart vehicles has been progressively increasing (estimated to reach between 24% and 87% by 2045, [11]), at this stage, making better use of the perception capabilities of the smart vehicles to benefit drivers in the traffic has become an urgent need.

The research in AV-pedestrian interactions may provide some insights, where the external HMIs (eHMIs) were widely explored. The eHMIs are displays or other types of interfaces that can provide surrounding vehicles with specific information. In pedestrian-AV interaction scenarios, the eHMIs are usually used to convey the intention or the states of the AVs [12, 13]. However, eHMIs also have the potential to show what the subject-vehicle (SV) perceives (e.g., the BVR information) in the CF scenarios, which can be a technically feasible and low-cost solution to make full use of sensors in the smart vehicles and satisfy drivers' needs in CF scenarios.

As such, an on-road study was conducted to investigate how the BVR information perceived by the LV, when conveyed through a rear-facing eHMI can support following drivers' CF behaviors. Considering the driving task is already mentally demanding [14], in the experiment, we evaluated how to provide BVR information more effectively without overloading the following drivers by systematically manipulating the richness of BVR information through different visualizations on the eHMI mounted at the back of the LV.

METHODS

Participants

A total of 30 participants (15 males and 15 females) with valid driver's licenses completed the experiment. Participants had an average age of 31 years (min: 23, max: 45, SD = 5.23). All participants were required to be experienced drivers in order to ensure the safety of the on-road study. Thus, they were required to have held their driver's licenses for over 2 years and driven more than 10,000 kilometers in the past year. The study received ethical approval from the Human and Artefacts Research Ethics Committee at the HKUST(GZ)- HSP- 2024- 0085.

Apparatus

We conducted an on-road study to explore how following drivers would react to leading vehicle with additional BVR information provided through eHMI. The field study was conducted on a 2.6 km straight suburban road with a speed limit of 60km/h (**Figure 1**). Three vehicles were involved mocking up the CF platoon: the indirect leading vehicle (ILV), the direct leading vehicle (DLV), and the subject vehicle (SV) (**Figure 2(a)**). The ILV and SV were hatchback and DLV was a SUV whose size is large enough to block the front view of SV. An outdoor display (dimensions: 64 cm × 32 cm; brightness: 5000 nits) was installed on the rear of the DLV to present the eHMI, also shown in **Figure 2(a)**. The first two vehicles were driven by the same two experimenters through the whole experiment. The speed of ILV was pre-decided and followed by the driver to simulate rich CF scenarios which would be elaborate in the following paragraph. The driving data of the three vehicles was continuously logged at a frequency of 20 Hz within the Real-Time Kinematic (RTK) equipment with an accuracy of 10 mm (**Figure 2 (b)**). The RTK equipment were installed on the middle top of the vehicles. Additionally, Vehicle dynamics were recorded using an Inertial Measurement Unit (IMU) mounted at a fixed position on the left armrest of the right-side seat (**Figure 2(c)**). The IMUs looged acceleration at 20 Hz with an accuracy of 0.01 G. According to ISO8855 (2011), the z-, x-, and y-axes corresponded to the upward (vertical), forward (longitudinal), and rightward (lateral) directions of the vehicle, respectively. Pressure Sensor was installed in the brake pedal of ILV to record and transmit the time when the driver stepped the brake pedal (**Figure 2(d)**). A camera (Logitech 1080P, 30 fps) was installed in SV to shoot the foot action of participant. Participants' eye movement data were recorded at 100 Hz using a remote 4-camera tracking system (Smart Eye Pro) running Smart Eye Pro 10.2 (**Figure 2(e)**).

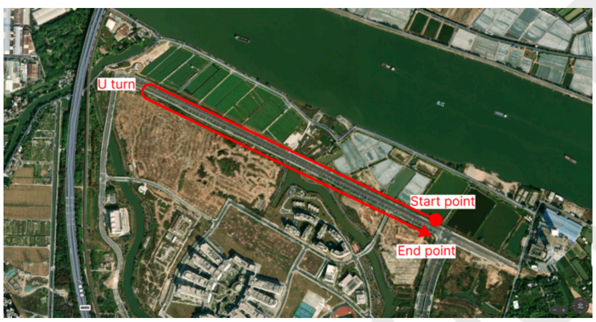
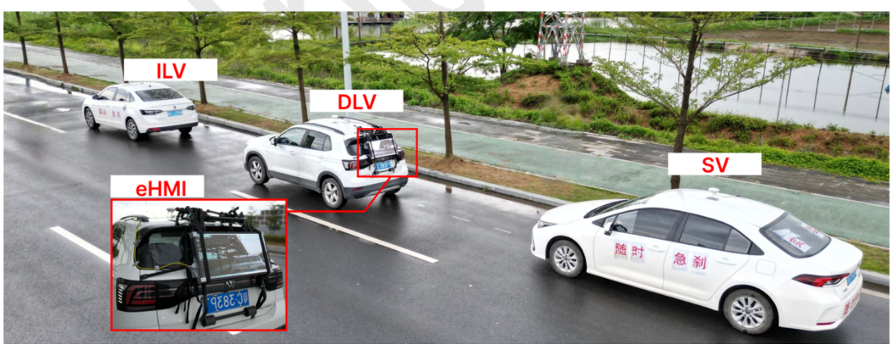
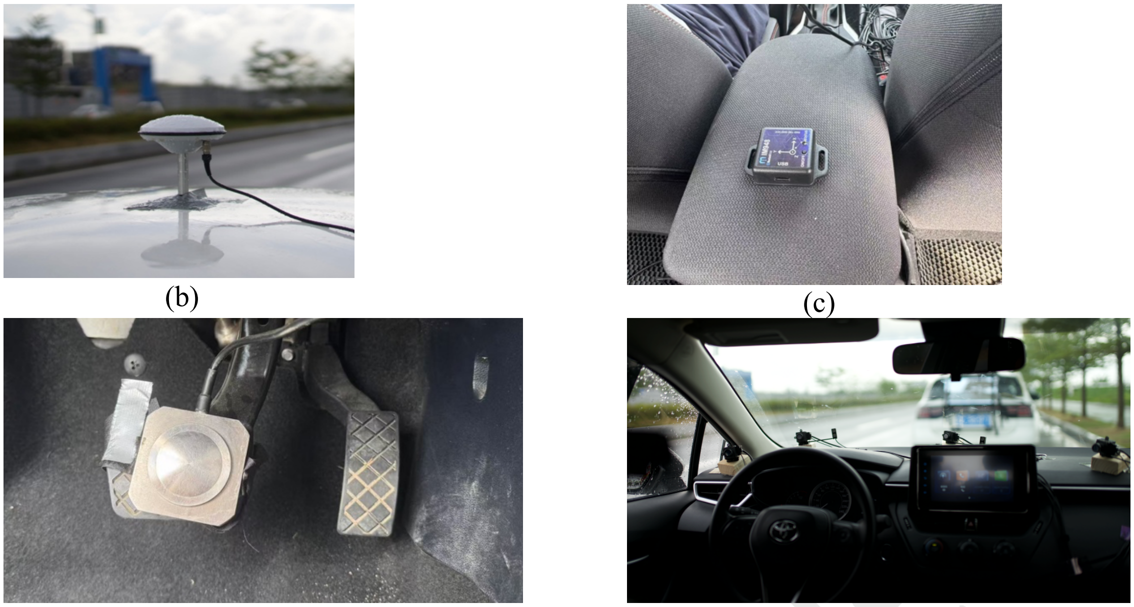


Figure 1 Experiment field



(a)



(b) (c) (d) (e)

Figure 2 The apparatus used in this study (a) CF platoon of the three vehicles used in the experiment; (b) antenna of RTK; (c) IMU; (d) pressure sensor; (e) four cameras of Smart Eye Pro.

eHMI Design for BVR Information

In this study, we mainly considered the BVR information regarding the relationships between the DLV and the ILV. In total, four different types of BVR information were presented to the drivers: (1) the braking behavior of the ILV, (2) the bumper-to-bumper distance between the DLV and ILV, (3) the risk of rear-end collision, as represented by the THW between the DLV and the ILV, (4) the live-stream video captured from the perspective of DLV. All eHMI was displayed on the rear of DLV. The details of the four design concepts are as follows (**Table 1**):

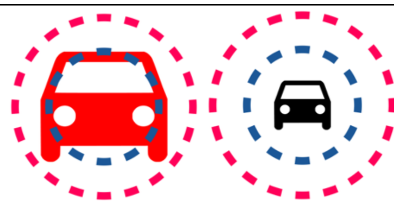
Brake-eHMI: The brake of the ILV was indicated with a vehicle icon that turned red whenever the brakes were applied. Brake actions were recorded and transmitted to the host via the pressure pedal installed in the ILV. The brake signal in following eHMI were the same.

Dis-eHMI: Three triangles visualized the bumper-to-bumper space among the three vehicles (SV, DLV, ILV). The leftmost triangle remained fixed representing SV, the center triangle represented the DLV, and the rightmost triangle represented the ILV. As the inter-vehicle distances grew or shrunk, the horizontal gaps between the triangles widened or contracted accordingly. If the distance exceeds 85 meters, the ILV triangle would be on the rightmost side of the screen. Additionally, the ILV triangle turned red when the ILV is braking, providing an immediate visual cue of its braks action. The distance was calculated by the signal of the two RTK equipment.

THW-eHMI: The risk of a rear-end collision between the DLV and ILV was quantified using THW. When the THW increased, the vehicle icon would become larger and vice versa. Further, a dashed-line circle indicated the 2-second (the blue one) and 1-second (the red one) headway threshold , which has been widely recommended for safe CF behaviors [15]. If the vehicle icon exceeded the circle, it signified a high-risk situation, and vice versa. IF the THW was larger than 10s, the icon would keep a smallest state – around 0.4 times of the blue circle in length. Similar to the Brake-eHMI and the Dis-eHMI, when the ILV braked, the vehicle icon would become red, informing brake of the ILV. Still the THW was calculated by the RTK.

Video-eHMI: The live video stream of the ILV showed the real-time video captured from the perspective of the DLV. Like the previous design, when the ILV braked, a red vehicle icon would appear on the top of the display, informing brake of the ILV.

TABLE 1 Four eHMI concepts

Type of eHMI	eHMI Visualization	eHMIs in the simulated scenario
Brake-eHMI		
Dis-eHMI		
THW-eHMI		
Video-eHMI		

Driving Tasks

In the experiment scenario, the SV followed the DLV, which further followed the ILV. In each drive, four driving regimes for trajectory completeness, as illustrated by [16], were designed, namely acceleration, following, deceleration, and standstill. Considering experiment safety, standstill was replaced by following in a low speed (less than 2 m/s). Two different deceleration rates ($-1.5m/s^2$, and $-4.5m/s^2$) and two initial speeds before brakes (16m/s and 8m/s) was shuffled for the four trajectory in one drive. Because these maneuvers were performed by human drivers, the realized deceleration and speed in each drive exhibited modest variability around the nominal values. **Figure 3** illustrated the speed profiles of the ILV and DLV throughout an example drive with four trajectories.

Experiment Design

A within experiment design was used in this study, with the eHMI design (i.e., a baseline and four eHMIs), the initial speed of ILV (8m/s and 16m/s) and deceleration rate of the ILV ($-1.5m/s^2$, and $-4.5m/s^2$) as within-subject factors. The order of the eHMI design was counterbalanced across the 30 participants in a Latin Square design. Each participant completed five drives, four with the eHMI designs and one baseline drive. The order of speed and deceleration rate was shuffled across the five drives, leading to five distinct drives in terms of the speed profile of the ILV to reduce the learning effect. Each participant experienced the same five drives with the same order of speed profiles but with different eHMI designs. We collected data from 150 drives (30 participants * 5 eHMI conditions).

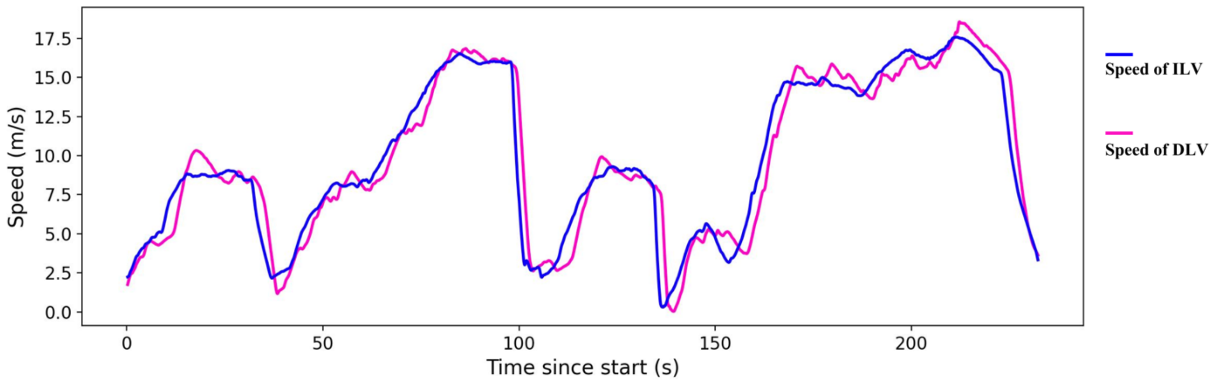


Figure 3 Speed profile of the IDV and DLV in an example drive

Procedures

As shown in **Figure 4**, upon arrival, participants' eligibility was verified based on years of licensure and driving mileage over the past year, and written informed consent was obtained. Then, they completed a pre-experiment questionnaire, collecting their demographic information. Participants then underwent test driving to familiarize themselves with the experiment field and vehicle. After finishing the test drive, the experimenter conducted the eye tracker calibration.

Then, the formal experiment started, which included five experimental drives. Before each drive with the designed eHMIs, design was explained to the participants verbally. After the explanation, the experimenter asked the participants to explain the eHMI design back to the experimenter to make sure they indeed understood the eHMI. After each experimental drive, a post-experiment questionnaire was administered, measuring participants' workload in the previous drive (measured by NASA-Task Load Index [17] and perceived usability of the eHMI (measured by System Usability Scale (SUS) [18]. Finally, at the end of the experiment, we asked an open question seeking any comments regarding the eHMI designs in the experiment.

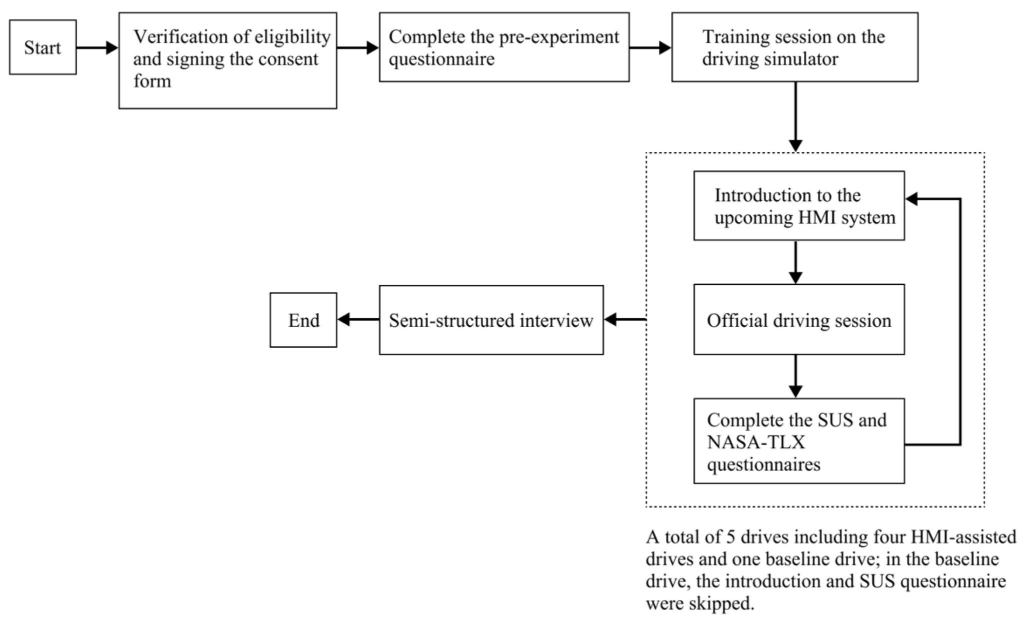


Figure 4 Flow diagram of experiment procedure

DATA ANALYSIS

We first focused on driving performance data to evaluate the effect of eHMI on drivers' CF behaviors. Further, to evaluate the usability of the eHMI designs, we compared drivers' workload and perceived usability of the eHMI designs when using different eHMIs. Finally, we evaluated the attention allocation through the gaze data.

Driving Performance Data

In this study, as shown in **Table 2**, we adopted three driving-performance-related metrics. It should be noted that, for the response time. A total of 18 response times (RTs) smaller than 0.1s or larger than 5s were discarded from the data analysis, as such RTs were considered irrelevant to the stimuli (i.e., the brake of the ILV) [8].

TABLE 2 Driving performance metrics and their definitions

Metric (Abbreviation)	Definitions (Unit)
Response time (RT)	The brake time difference between ILV and the subject-vehicle (ms).
Minimum time-to-collision (MinTTC)	The time required for subject-vehicle to collide with DLV if they continue at their current speeds and on the same path in the current lane (s)
Average time headway (MeanTHW)	The mean elapsed time during braking events between the front of the DLV and the front of the subject-vehicle passing the same fixed point on the roadway (s)

Subjective Metrics

We followed the standard approach [17] to calculate the weighted overall workload of drivers throughout each drive, leading to 150 data points (30 participants * 5 drives). As for the perceived usability of the eHMIs, we followed the standard approach [18] to calculate the SUS score for each eHMI, again, leading to 120 data points.

Eye-Tracking Metrics

The eye-tracking data was recorded using Smart Eye Pro 10.2. In this study, we followed the ISO 15007–1:2013(E) standard to process and extract the corresponding metrics. We extracted gaze-related metrics, including the vertical and horizontal gaze dispersion, to compare the ranges of visual attention when different eHMIs were provided [19, 20].

Independent Variables and Statistical Models

One independent variable was included in the model, i.e., driving experience and eHMI design. Different models were built to investigate whether the eHMIs were effective in different traffic conditions. Mixed-effects linear models were fitted using the lme4 package in R. Post-hoc comparisons were conducted for significant main effects or interaction effects ($p < 0.05$), using the Turkey adjustment method to control for multiple comparisons. Logarithmic transformation was applied to the dependent variables when the residuals of the model violated the normality assumption (including minTTC, and meanTHW).

RESULTS

Driving Performance Metrics

TABLE 3 Results of driving performance metrics

Dependent variables	Independent variables	F-value	p-value
RT	**eHMI**	**F (4, 208) = 4.94**	**.0008**
MinTTC	**eHMI**	**F (4, 130) = 4.86**	**.001**
MeanTHW	**eHMI**	**F (4, 130) = 7.35**	**<.0001**

RT: As shown in **Table 3** and **Figure 5**, eHMIs were found to have significant effect on RT. Compared with baseline, Brake-eHMI, Dis-eHMI and Video-eHMI reduced RT (Brake-eHMI VS. Baseline: difference (Δ) = 0.61 sec, 95% confidence interval (95%CI): [0.13, 1.07], t (242) = -2.56, p = .004; Dis-eHMI VS. Baseline: Δ = - 0.61 sec, 95% CI: [0.15, 1.07], t (194) = -3.65, p = .003; Video-eHMI VS. Baseline: (Δ = 0.65 sec, 95% CI: [0.17, 1.12], t (241) = -3.72, p = .002).

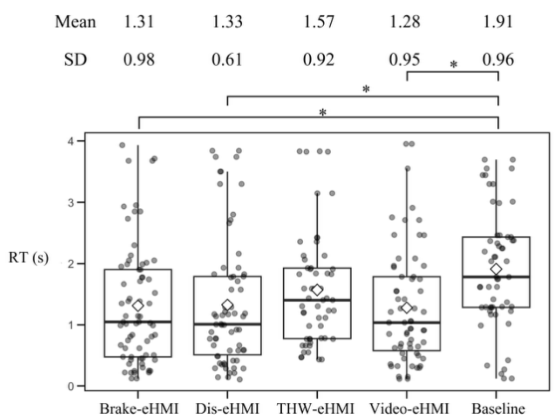


Figure 5. Post hoc comparisons of the effects of eHMIs on RT. In this figure and the following figures, significant post-hoc comparisons (p < 0.05) are marked with "*"; the boxplot represents the 1st quantile, median, and 3rd quantile; the white squares are the mean of the group.

MinTTC: As shown in **Figure 6**, Brake-eHMI led to a larger minTTC than baseline (Δ = 0.44, 95%CI: [0.14, 0.74], t (130) = 4.00, p = .0001). At the same time, Dis-eHMI had a larger minTTC than baseline (Δ = 0.36, 95%CI: [0.06, 0.67], t (130) = 3.31, p = .01).

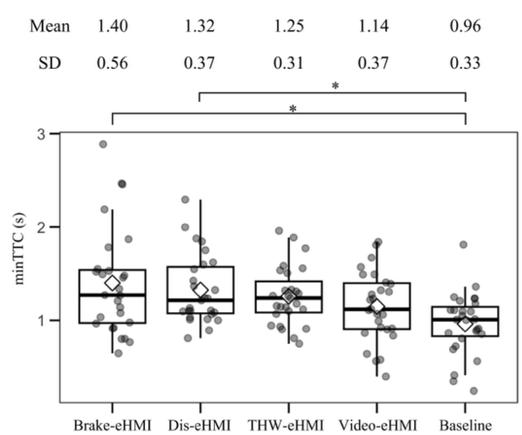


Figure 6. Post hoc comparisons of the effect of eHMIs on minTTC.

MeanTHW: As shown in **Figure 7**, Brake-eHMI led to a smaller meanTHW than THW-eHMI(Δ = 1.00, 95%CI: [0.42, 1.57], t (130) = 4.82, p < .0001). At the same time, Dis-eHMI had a smaller meanTHW than THW-eHMI ($\Delta = 0.83$, 95%CI: [0.06, 0.67], $t(130) = 4.03$, $p = .0009$). At the same time, Video-eHMI had a smaller meanTHW than THW-eHMI ($\Delta = 0.81$, 95%CI: [0.23, 1.38], $t(130) = 3.92$, $p = .001$).

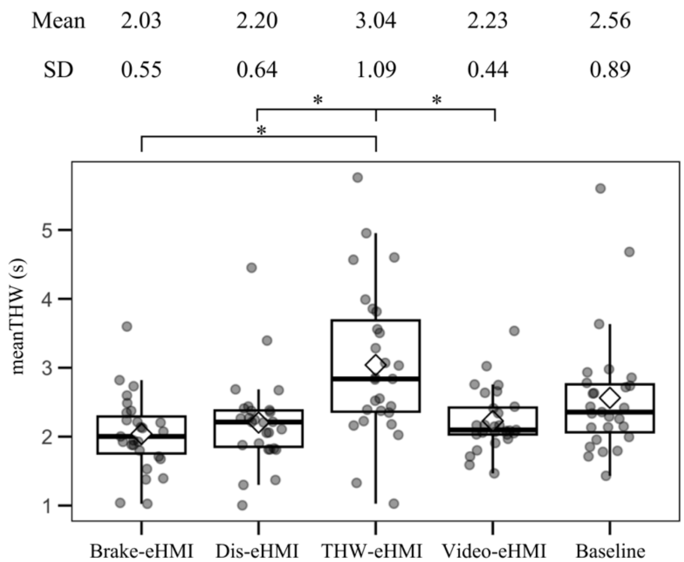


Figure 7. Post hoc comparisons of the effect of eHMIs on meanTHW.

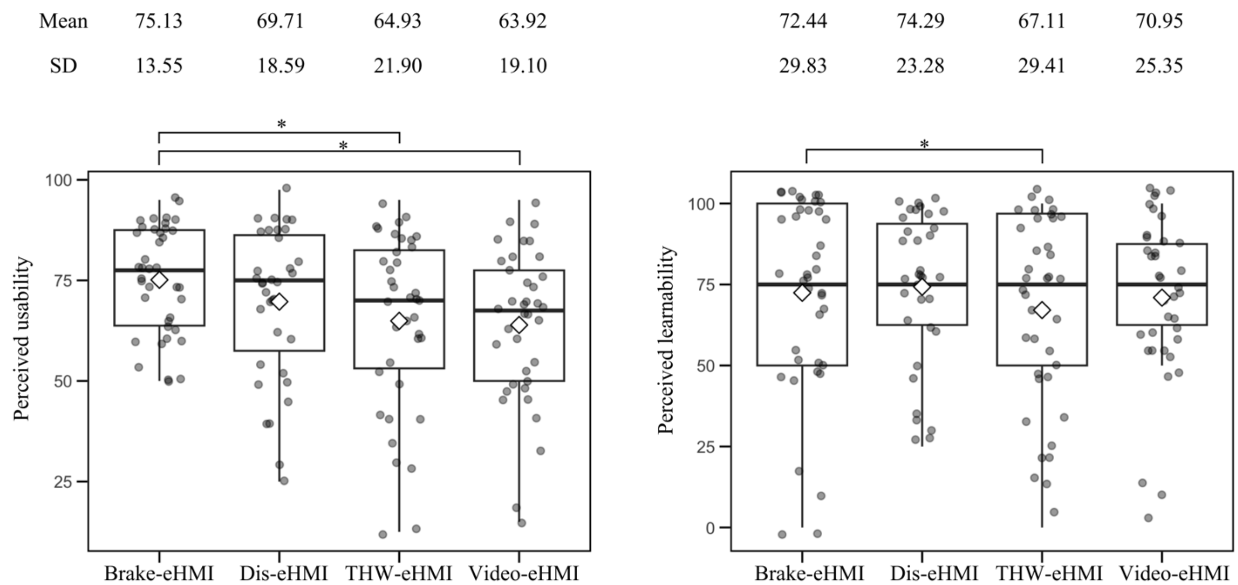
Mental Workload and Perceived Usability

Table 4 summarized the results of drivers' perceived usability, learnability of the HMIs and the corresponding workload.

TABLE 4 Statistical analysis results

Dependent variables	**Independent variables**	**F-value**	**p-value**
Perceived usability	**eHMI**	**F (3, 103) = 6.38**	**.0005**
Perceived learnability	**eHMI**	**F (3, 103) = 4.19**	**.008**
Mental workload	eHMI	F (3, 137) = 1.67	.2

As shown in **Table 4**, eHMI type does not affected mental workload ($p > .05$). At the same time, as shown in **Figure 8**, Brake-eHMI yielded higher perceived usability than THW-EHMI ($\Delta = 13.04$, 95%CI: [4.96, 21.13], $t(110) = 4.21$, $p = .0003$) and higher perceived learnability than Video-eHMI ($\Delta = 10.76$, 95%CI: [2.22, 19.29], $t(114) = 3.29$, $p = .007$). Brake-eHMI yielded higher perceived learnability than THW-eHMI ($\Delta = 9.56$, 95%CI: [0.47, 18.64], $t(102) = 2.75$, $p = .04$). No other significant results were observed ($p > .05$).



(a) (b)

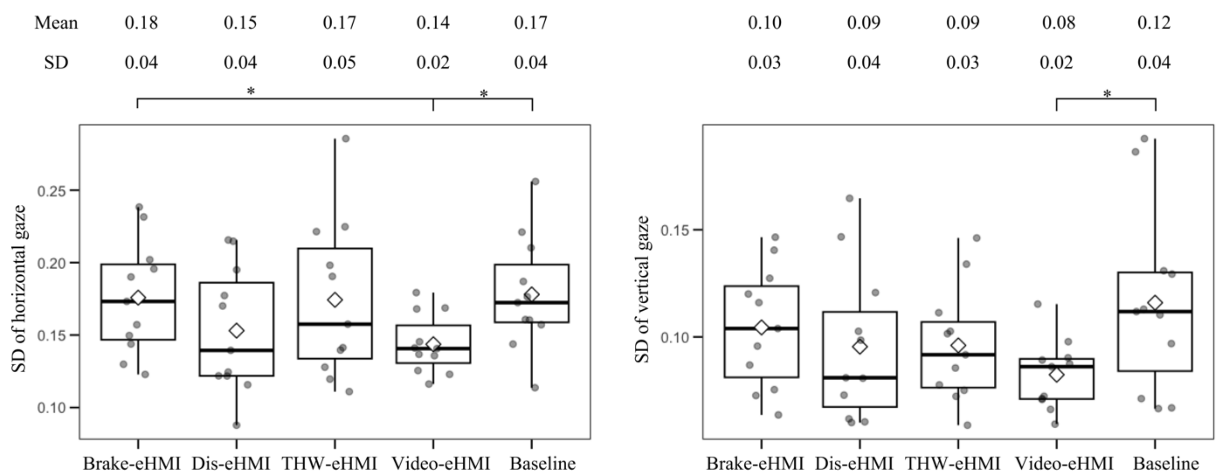
Figure 8. Post hoc comparison of the effect of eHMIs on perceived a) usability and b) learnability of eHMIs.

Attention Allocation

TABLE 5 Results of attention dispersion metrics

Dependent variables	Independent variables	F-value	p-value
Standard deviation of horizontal gaze	**eHMI**	**F (4, 40) = 2.64**	**.04**
Standard deviation of vertical gaze	**eHMI**	**F (4, 40) = 3.91**	**.0009**

As shown in **Figure 9** and **Table 5,** Video-eHMI yielded lower SD of horizontal gaze than baseline and Brake-eHMI (Video-eHMI vs. baseline: Δ = 0.03, 95%CI: [0.002, 0.07], t (40) = 3.08, p = .03; Video-eHMI vs. Brake-eHMI: Δ = 0.03, 95%CI: [0.0003, 0.06], t (40) = 2.88 p = .046;). Video-eHMI yielded lower SD of vertical gaze than baseline (Δ = 0.03, 95%CI: [0.002, 0.06], t (40) = 3.11, p = .03). No other significant results were observed (p > .05).



(a) (b)

Figure 9. Post hoc comparison of the (a) SD of horizontal gaze and (b) SD of vertical gaze.

DISCUSSION

A field study was conducted to explore the effect of BVR information on drivers' performance in CF events. We evaluated participants' driving behavior, subjective attitudes and attention allocation with different BVR information in CF events.

First, we found that drivers in general exhibited safer driving behaviors in response to lead vehicle chain braking events when supported by BVR information. Specifically, the Brake-eHMI, Dis-eHMI and Video-eHMI led to a shorter RT than baseline, possibly by reminding the drivers of the brake of ILV in advance. These results echo the findings in [6] who also found ILV braking information can facilitate quicker responses to the brake of lead vehicles, providing further empirical evidence that drivers would consider the surrounding information when following lead vehicles, other than relative distance to the DLV [21]. However, THW-eHMI did not yielded shorter RTs. It is possible that Brake-eHMI, THW-eHMI and Video-eHMI contained obvious information about the brake signal of ILVs (the big red icons on the display), while the size of brake indicator in THW-eHMI changed with the real-time THW. Hence, it is hard to capture the brake signal. Another possibility is that when the THW is large, the size of ILV brake signal is small which is hard to recognize especially when the following distance is long. Thus, future eHMI design may need to explicitly convey BVR information with high salience and keep the key information in a steady state.

Such a difference in RT also led to improved safety performance. Specifically, Brake-eHMI and Dis-eHMI led to larger minTTC. Although the Video-eHMI decreased RT, it did not lead to larger minTTC. It is possible that the information in the Video-eHMI is rich, the other information in the video might influence driver behavior. It should be noted that the explicit brake information can help CF safety.

Further, we observed the THW-eHMI led to larger meanTHW than Brake-eHMI, Dis-eHMI and Video-eHMI. However, all additional BVR information did not significantly influence the meanTHW compared to the baseline drive. It is possible that the THW-eHMI may instruct the following driver to keep a larger THW but sacrificed the efficiency. In contrast, the other information explicitly provides brake information which had a good influence in safety critical scenario. This result also aligns with the relatively high learnability and usability of the brake-eHMI – it is straightforward for the drivers to perceive, understand and respond directly. However, it should be noted that such a simple response to ILV braking may not always be good, as it may potentially worsen the stability of the traffic flow and increase the fuel consumption [22] if the braking is unnecessary (e.g., when the ILV is far away from the DLV).

Given that driving is already an attentionally demanding task [14], explicitly visualizing implicit information may reduce drivers' workload and support better driver decisions, especially in emergent events. The lack of difference in the perceived workload (NASA-TLX) among all eHMIs implies that the additional BVR information provided by these eHMIs did not significantly overload the drivers. Further, Video-eHMI yielded lower gaze dispersion than baseline. Given that the increased variance of fixation locations, as indicated by broader scanning areas [23], was associated with the increased driving experience and thus lower crash risk [24, 25], Video-eHMI may have compromised driving safety.

LIMITATION

In this study, we only considered experienced drivers as participants. However, the driving experience may also affect the CF strategies [26] and they may perceive the eHMIs differently, which should be carefully evaluated if any of the eHMIs are to be deployed in the real world. Second, we only evaluated the eHMIs from micro driving behavior; future research should evaluate the impact of the eHMIs on the traffic flow stability and the environmental impact of the eHMIs. Finally, all participants were explicitly informed of the meaning of the eHMIs, assuming that the eHMIs can be standardized in the future. However, future research should evaluate whether such eHMIs can be understood when the drivers were not informed of the meaning of the eHMIs, assuming these eHMIs are deployed in mass-production vehicles directly.

CONCLUSIONS

In a real road experiment, we evaluated four types of BVR in CF scenarios. The results showed that:

- The rear-mounted BVR information can improve CF safety.
- Simple and intuitive Brake-eHMI showing the ILV brake action can significantly facilitate faster brake response time and increase minTTC.
- Direct guide of THW can influence driving behavior but should carefully consider the necessity.
- By adding the eHMIs at the rear of vehicle, they did not overload drivers in CF scenarios.
- Complicated BVR information might restrict attention allocation and decreased driving safety.

Overall, the BVR information has the potential to enhance driving safety if well-designed to balance informativeness, complexity and intuitiveness. Future research should explore adaptive systems that tailor BVR displays to driver experience and context, supporting safer and more efficient driving with the increasing penetration of smart vehicles.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: Feiqi Gu, Yufan Chen; data collection: Feiqi Gu, Zhenyu Wang, Zhixiong Wang, Jiahui Li, Hongling Sheng; analysis and interpretation of results: Feiqi Gu, Dengbo He; draft manuscript preparation: Feiqi Gu. All authors reviewed the results and approved the final version of the manuscript.

DECLARATION OF CONFLICTING INTERESTS

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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