Optimizing Followers' Car-Following Behaviors using Rear-Facing eHMIs

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ABSTRACT

Rear-end collisions are closely related to car-following (CF) behaviors and account for a large proportion of road crashes. Existing countermeasures mainly enhance drivers' perception of the direct leading vehicle; however, growing evidence suggests that CF decisions rely on information beyond the direct leading vehicle. Thus, expanding drivers' perceptual range by providing information of the indirect leading vehicle (i.e., vehicle ahead of the direct leading vehicle) may enhance CF safety. Unlike in-vehicle human-machine interfaces (HMIs) that rely on vehicle-to-vehicle (V2V) communications, external HMIs (eHMIs) without relying on V2V technologies are more feasible at this stage. However, no research has explored whether eHMIs can improve CF safety. Thus, four rear-facing eHMIs providing information regarding the indirect leading vehicle in CF events were designed, including Brake-eHMI showing only brake action of the indirect leading vehicle, Distance-eHMI and Headway-eHMI showing the relative distance and time headway between the indirect leading vehicle and direct leading vehicle, and Video-eHMI showing the live-stream video ahead of the direct leading vehicle. A field experiment with 30 participants was conducted to evaluate the impact of eHMIs on driving safety and efficiency in CF events. We found that, in general, indirect leading vehicle information could improve CF safety in chain-braking events by enabling quicker brake responses and increasing minimum time-to-collision, without overloading drivers in CF events. This research provides insights into the design of innovative vehicle systems that leverage smart vehicles' perception capabilities to enhance driving safety.

Keywords: Human-Machine Interface; Driver Behavior; Car-Following; Beyond-Visual-Range Information; External Human-Machine Interface.

1 INTRODUCTION

Car-following (CF) behavior is closely associated with rear-end collisions, which accounted for 28.8% of road crashes in the United States (National Safety Council, 2023). Thus, considerable effort has been made to understand CF behavior (Kerwin & Bushman, 2020; Nicolls et al., 2022). Traditionally, previous studies largely attribute drivers' CF behavior to the kinematic information (e.g., relative speed and distance) of the direct leading vehicle, i.e., the vehicle immediately ahead of the ego-vehicle (Boer, 1999; Gipps, 1981; Louw et al., 2021; Markkula et al., 2016; Svärd et al., 2017; Treiber et al., 2000; Zhang et al., 2025). However, an increasing amount of evidence has demonstrated that drivers may also consider the information of indirect leading vehicles (i.e., vehicles located further upstream in the traffic flow, ahead of the direct leading vehicle, that can be visually occluded by the direct leading vehicle) (Cui et al., 2023; Ren et al., 2025; Yan et al., 2023) when following the traffic flow. For example, in a driving simulator study, Stahl et al. (2019) found that experienced drivers were better at perceiving information regarding a slow tractor ahead and thus achieved longer minimum gap times during chain-braking events than novice drivers. Such information of the indirect leading vehicle is a kind of beyond-visual-range information (i.e., information that is not directly perceivable by drivers through their natural field of view, typically due to visual occlusion by the environment or surrounding vehicles). It has the potential to support Level 3 situation awareness (Endsley, 1995) by enabling the projection of future traffic flow in CF events. Thus, explicitly informing drivers of the kinematic state of the indirect leading vehicle, in addition to that of the direct leading vehicle, may support safer and more efficient CF behavior.

However, despite advancements in vehicle and traffic infrastructure technologies, beyond vehicle kinematics information (such as relative speed and position), explicit communication between road users in CF events remains reliant on signals of adjacent vehicles - primarily visual (e.g., headlights, brake lights, hazard lights, and turn signals) and auditory (e.g., horns) signals (Moore & Rumar, 1999). These legacy systems were developed over a century ago (e.g., brake lights in 1915, turn signals in 1909) and convey only basic, operational-level information about the immediate actions of the direct leading vehicle. Thus, previous research has begun to explore the transmission of beyond-visual-range information in traffic flow.

For example, in a driving simulator study, researchers found that V2V-enabled information from the indirect leading vehicle, transmitted via V2V communication, can reduce crash risk in foggy conditions (Ren et al., 2025).

Although modern vehicles are equipped with sensors that can perceive the states of leading vehicles (e.g., through LiDAR of adaptive cruise control systems) (Muhammad et al., 2022), transmitting the perceived information through V2V communication technology is still practically infeasible, given its relatively low penetration rate for now. Thus, another solution to convey the beyond-visual-range information to the following vehicles should be explored. The research on autonomous vehicle (AV)-pedestrian interactions may provide some insights, where the external human-machine interfaces (eHMIs) were widely explored. The eHMIs provide surrounding road agents with specific information. In AV-pedestrian interaction scenarios, eHMIs are usually used to convey the intentions or the states of the AVs (Dey et al., 2020; Wilbrink et al., 2021). Thus, eHMIs also have the potential to show what the ego-vehicle perceives (e.g., the beyond-visual-range information) in CF events, which can be a technically feasible and low-cost solution to make full use of sensors, given that the market penetration rates of smart vehicles have been progressively increasing (estimated to reach between 24% and 87% by 2045, Rahman & Abdel-Aty, 2018; Talebpour & Mahmassani, 2016) and that the eHMIs do not have specific requirements for the information receiver (in contrast, V2V communication requires the receiver devices on the surrounding vehicles).

However, it remains unclear how the beyond-visual-range information of the indirect leading vehicle conveyed through a rear-facing eHMI affects CF behavior. Especially, given that driving is already a demanding task (Salmon et al., 2005), it is necessary to evaluate what and how to provide beyond-visual-range information to drivers. As such, an on-road study was conducted to evaluate how to provide the information of the indirect leading vehicle more effectively without overloading the following drivers. In the experiment, we systematically manipulated the richness of beyond-visual-range information by varying the visualizations displayed on a rear-facing eHMI mounted on the rear window of a direct leading vehicle.

The rest of the paper will be organized as follows. In Section 2, we further provide a detailed review of relevant literature. In Section 3, we describe the experiment design and the approaches for data analysis. In Section 4, we present the results. In Section 5, we discuss the implications and theoretical explanations of the findings, identify limitations, and outline potential future work. Finally, in Section 6, we summarize the major takeaways of our study.

2 LITERATURE REVIEW

2.1 Supplemental information to improve CF behaviors

Numerous studies have examined the role of supplemental information in influencing CF behavior. These studies, in general, focused on two different CF events: (1) steady-state CF, focusing on metrics such as headway maintenance and speed regulation, and (2) emergent braking events, focusing on collision avoidance and brake reaction performance. For the former, researchers found that providing drivers with real-time headway feedback (warning thresholds at 2s and 1.5s) via an in-vehicle display can increase mean headway and mitigate tailgating in an on-road study (Birrell et al., 2014). For the latter, forward-collision warning (FCW) systems have demonstrated effectiveness in reducing rear-end collision risk. For example, in real-world crash data analysis, vehicles equipped with FCW systems experienced 27% fewer police-reported rear-end collisions than those without such systems (Cicchino, 2017). Similar benefits were observed in a driving simulator experiment, in which FCW systems significantly reduced serious traffic conflicts (Olufowobi et al., 2025). In addition to providing warnings, a simulator experiment by Zheng et al. (2023) found that providing the vehicle kinematic states of the direct leading vehicle (i.e., decelerating, accelerating, or steadily cruising) can increase the minimum time-to-collision when the leading vehicle decelerates.

Although substantial research has proposed and validated various types of information to avoid rear-end collisions, the role of beyond-visual-range information remains underexplored. Thus, Yan et al. (2023) proposed two types of in-vehicle human-machine interfaces (HMIs) to convey the states of the indirect leading vehicle to the following drivers, and found that such information, regardless of the presentation format, significantly reduced the collision risk in chain-braking events. D. He et al. (2021)

introduced a bird-view display to present upcoming traffic information to drivers and found that such an in-vehicle HMI could improve drivers' capability to anticipate chain-braking events. However, though different in-vehicle HMIs were explored and some of them were found to be effective, most of them have been assumed to be based on the V2V communication technology and can hardly be implemented before such technologies reach high saturation, and the communication protocol has been standardized (El et al., 2020; Gyawali et al., 2021).

2.2 eHMI development

In addition to the design of in-vehicle HMIs, eHMIs have attracted increasing research interest in recent years, particularly for facilitating interaction between AVs and human road users (e.g., Dey et al., 2024; Eisma et al., 2021; Z. He et al., 2021; Song et al., 2023). For instance, in a driving simulator study, Yang et al. (2025) found that a 360° external band with cyan light on yielding AV can facilitate participants' passing decisions and improve perceived safety and trust. Similarly, a controlled field study conducted by İppoliti et al. (2023) found that an LED matrix display conveying the acceleration and deceleration intentions of AV can improve the interaction efficiency in a bottleneck scenario (where only one vehicle can pass a narrow road section). In another study by Gwak et al. (2025), a cyan-colored dashed-line LED band was introduced to the sides of the Level 4 truck, which blinked continuously in an AV merging scenario. It was found that such an LED band can support surrounding human drivers' speed choices and reduce the risk of collisions with the AV. However, to the best of our knowledge, no prior studies have explored using eHMIs to provide beyond-visual-range information to following human drivers during CF events; as a result, little is known about how to design rear-facing eHMIs on the direct leading vehicle to support safer CF behavior.

2.3 Cognitive process in CF events and the role of beyond-visual-range information

A substantial body of research has examined the cognitive processes underlying CF behavior, consistently suggesting that CF is not a purely reactive control task but a cognitively mediated regulation process. For example, Gipps (1981) conceptualized CF as a safety-driven process in which drivers maintain a gap that is sufficient to avoid a collision, based on estimated reaction times and braking capabilities. This formulation implicitly assumes that drivers engage in mental simulation of future stopping scenarios, with their own and others' braking capabilities estimated. In contrast, the Intelligent Driver Model (Treiber et al., 2000) adopted a physics-inspired view, with its parameters (e.g., desired time headway, comfortable deceleration) calibrated to reproduce empirical traffic dynamics. Such parameters are often interpreted (though not explicitly modeled) as reflecting aggregate driver characteristics such as risk tolerance. Further, Wiedemann (1974) argued that driver behavior is governed by perceptual thresholds, highlighting that driver responses are not continuous reactions to physical variables but are mediated by heterogeneous cognitive thresholds.

Beyond these behaviorally inspired formulations, several theoretical frameworks have explicitly framed CF as a cognitive regulation task. For example, the Adaptive Control of Thought-Rational based CF framework (Salvucci, 2006) explicitly modeled CF behaviors with three cognitive components, including perception, cognition, and action. Similarly, according to Kikuchi and Chakroborty (1992), drivers used imprecise (fuzzy) rules to make CF decisions, such as "*if the gap is small and closing fast, brake gently.*" More recently, CF decision-making models (Chen et al., 2024; Ratcliff & Strayer, 2014) have been adopted to conceptualize CF as a belief-updating process under uncertainty. Within this framework, drivers maintain and continuously update beliefs about the states and intentions of leading vehicles based on noisy sensory input. Once the accumulated belief exceeds a specified threshold, a decision (e.g., acceleration or deceleration) is generated.

In general, CF behavior depends on how drivers perceive, interpret, and predict the behavior of leading vehicles. As drivers rely on internal models, heuristics, and belief updating to make CF decisions, supplementing the beyond-visual-range information has the potential to reduce uncertainty, support more accurate mental simulations, and facilitate earlier and more appropriate control responses in CF events.

2.4 Research gaps and current study

The synthesis of the literature reveals that (i) early efforts focused on providing supplemental CF-related information based on sensors of ego-vehicle; (ii) more recent studies have shifted toward providing beyond-visual-range information via in-vehicle HMIs, disseminated through V2V communication technology; (iii) yet no research has explored the feasibility of using eHMI as a medium for conveying beyond-visual-range information in CF events. The eHMIs are a technically feasible way to transfer information compared to in-vehicle HMIs based on V2V communication technology, and it has the potential to optimize CF decisions according to cognitive models of CF behaviors. However, it remains unclear how beyond-visual-range information delivered through eHMI influences CF safety, and what information content and presentation methods are most effective. Addressing this gap is critical for innovating existing eHMIs on top of brake lights and turning lights on vehicles.

Specifically, we evaluated the influence of eHMIs from three perspectives. From a safety perspective, we expect that all eHMIs displaying beyond-visual-range information can improve safety-related metrics, as they provide information to anticipate future situations and thus facilitate Level 3 situation awareness (Endsley & Garland, 2000). However, we expect that certain eHMIs (especially those with increasing amounts of information) may narrow drivers' attention allocation, given that additional information may overload drivers to some extent, leading to attention tunneling effects (Wickens & Alexander, 2009). Second, from the perspectives of traffic efficiency and speed variance, we expect that all eHMIs improve traffic efficiency and stabilize traffic flow, as beyond-visual-range information enables more proactive responses to variations in the leading traffic flow (Yan et al., 2023). Finally, from a user-experience perspective, we expect that the proposed eHMIs will reduce stress and workload, as beyond-visual-range information can make drivers more aware of upcoming variations in traffic flow.

3 METHOD

3.1 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, standard deviation (SD) = 5.23). All participants were required to be experienced drivers in order to ensure the safety of the on-road study. Specifically, they had held their driver's licenses for over 3 years and had 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 [**placeholder for double-blinded review**].

3.2 Apparatus

Three vehicles were used to form a CF platoon: the indirect leading vehicle, the direct leading vehicle, and the ego-vehicle (Figure 1(a)). The indirect leading vehicle and the ego-vehicle were hatchbacks, and the direct leading vehicle was an SUV whose size was large enough to obstruct the ego-vehicle's forward view. An outdoor LED display (dimensions: 64 cm × 32 cm; brightness: 5000 nits) was installed on the rear of the direct leading vehicle to serve as a rear-facing eHMI, as shown in Figure 1(a). The first two vehicles were driven by the same two experimenters throughout the whole experiment.

The trajectory data of the three vehicles were continuously logged at 20 Hz using Real-Time Kinematic (RTK) equipment mounted on the roof of each vehicle, with an accuracy of 10 mm (Figure 1(b)). Additionally, vehicle dynamics of each vehicle were recorded using Inertial Measurement Units (IMUs) mounted on the left armrest of the right-front seat (Figure 1(c)), recording acceleration at 20 Hz with an accuracy of 0.01 G. According to International Organization for Standardization (2011), the z-, x-, and y-axes corresponded to the upward (vertical), forward (longitudinal), and leftward (lateral) directions of the vehicle, respectively. A pressure sensor was installed on the brake pedal of the indirect leading vehicle to record and transmit the time when the experimenter pressed the brake pedal (Figure 1(d)). A camera (Logitech 1080p, 30 fps) was mounted in the ego-vehicle to record the participants' foot action. 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 1(e)).

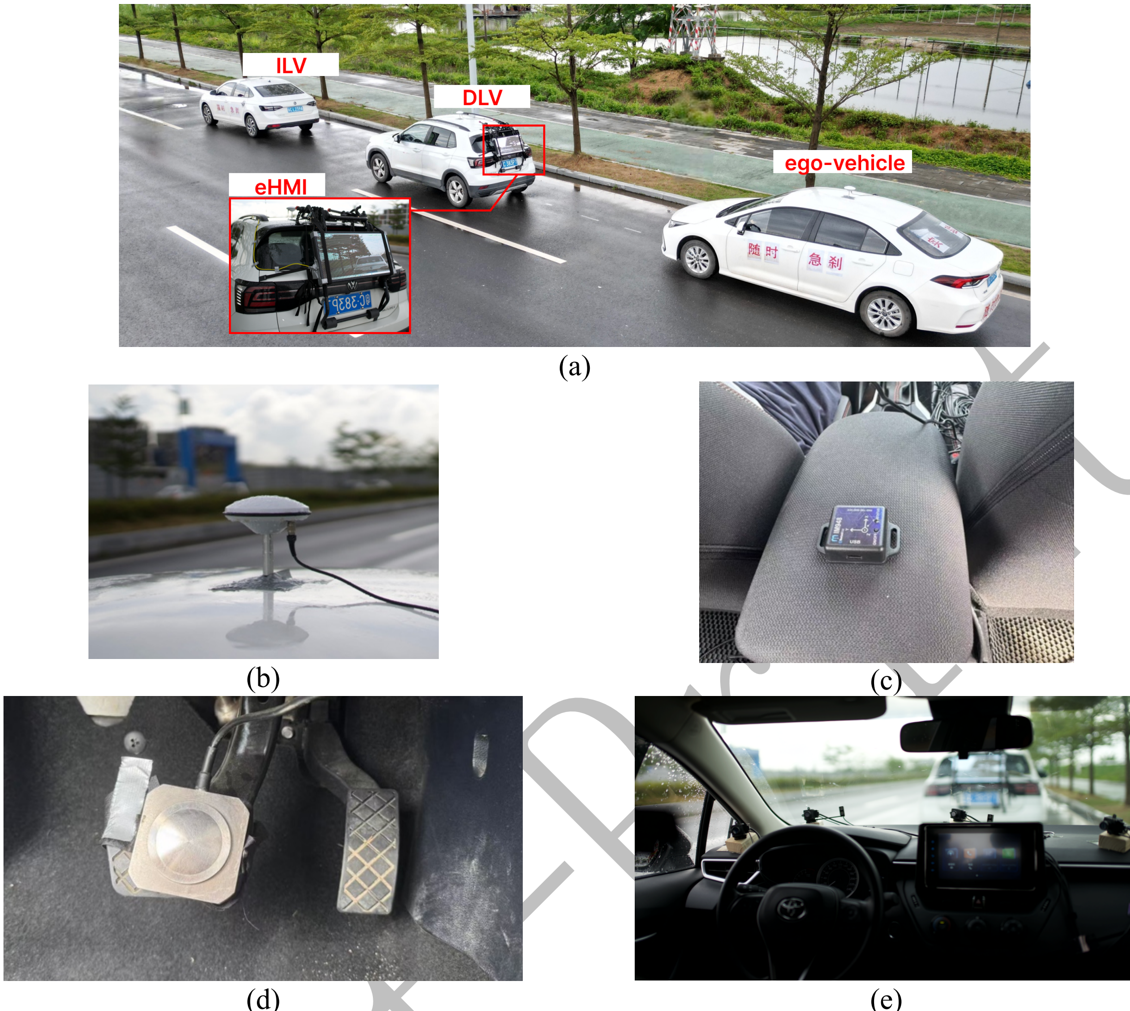


Figure 1. The apparatus: (a) platoon of the three vehicles in the experiment; (b) antenna of RTK; (c) IMU; (d) pressure sensor; (e) four cameras of Smart Eye Pro. In this figure, ILV denotes the indirect leading vehicle, and DLV denotes the direct leading vehicle.

3.3 eHMI design for beyond-visual-range Information

In this study, we focused on the beyond-visual-range information regarding the relationships between the direct leading vehicle and the indirect leading vehicle. In total, four different types of beyond-visual-range information were presented to the drivers: (1) the braking behavior of the indirect leading vehicle, (2) the bumper-to-bumper distance between the direct leading vehicle and the indirect leading vehicle, (3) the risk of rear-end collision, as represented by the time headway between the direct leading vehicle and the indirect leading vehicle, (4) the live-stream video captured from the perspective of direct leading vehicle. All eHMIs were displayed on the rear-facing LED screen of the direct leading vehicle. In the baseline condition, no information was presented, although the same LED screen was mounted on the rear of the vehicle to ensure a consistent vehicle appearance across all experimental conditions. The four eHMIs were designed as follows (see Table 1):

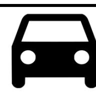
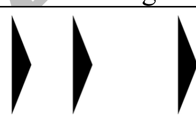
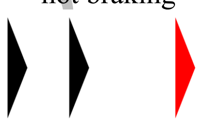
Brake-eHMI: The brake of the indirect leading vehicle was indicated with a vehicle icon that turned red when the brake was applied. Brake actions were recorded by the pressure sensor on the brake pedal of the indirect leading vehicle (see Figure 1d).

Distance-eHMI: Three triangles visualized the bumper-to-bumper spaces among the three vehicles (ego-vehicle, direct leading vehicle, indirect leading vehicle), as calculated based on the RTK-recorded location information. The leftmost triangle remained fixed, representing the ego-vehicle, the center triangle represented the direct leading vehicle, and the rightmost triangle represented the indirect leading vehicle. As the inter-vehicle distances increased or decreased, the gaps between the triangles widened or contracted accordingly. The distance between the leftmost and rightmost points on the screen corresponded to 100 meters on the road, a commonly accepted threshold for CF event extraction (Xing & Liu, 2022). Additionally, when the indirect leading vehicle braked, the triangle indicator would turn red, similar to the Brake-eHMI.

Headway-eHMI: The rear-end collision risk between the direct leading vehicle and indirect leading vehicle was quantified using time headway. We abandoned the time-to-collision metric because it can be highly sensitive to minor speed fluctuations, which may distract following drivers. Instead, the size of the vehicle icon was proportional to the time headway between the indirect and direct leading vehicles, with a larger icon indicating a smaller time headway. Furthermore, dashed circles indicated the 2-second (blue) and 1-second (red) headway thresholds, which have been widely recommended for safe CF behavior (Lewis-Evans et al., 2010). If the vehicle icon exceeded the circle, it indicated that the risk exceeded a specified threshold; conversely, a smaller icon indicated a lower risk. If the time headway exceeded 10s, the vehicle icon would remain at its smallest size (approximately 0.4 times the size of the blue circle) and no longer change size. As with the Brake-eHMI, when the indirect leading vehicle braked, the vehicle icon turned red.

Video-eHMI: The Video-eHMI displayed real-time video captured from the perspective of the direct leading vehicle, using a webcam mounted on the windshield of the direct leading vehicle. The video was zoomed to mimic the focal length of 50mm, approximating the field of view of an average human observer (Persichetti et al., 2007). As in the previous design, when the indirect leading vehicle braked, the vehicle icon would also turn red.

Table 1. Four eHMI concepts.

Type of eHMI	eHMI Visualization	eHMIs in the experiment, viewed from the ego-vehicle
Brake-eHMI	 State 1: Indirect leading vehicle not braking  State 2: Indirect leading vehicle braking	
Distance-eHMI	 State 1: Indirect leading vehicle not braking  State 2: Indirect leading vehicle braking	

Headway-eHMI	 State 1: Indirect leading vehicle not braking  State 2: Indirect leading vehicle braking	
Video-eHMI	NA	

Note: In the table, the eHMI visualization presents the key frame of the design (i.e., the brake state of the indirect leading vehicle); for Video-eHMI, the visualization is unavailable because it is a real-time video captured from the perspective of the direct leading vehicle.

3.4 Driving tasks

As shown in Figure 2, the experiment was conducted on a newly paved public road approximately 2.6 km long, with low traffic and a speed limit of 60 km/h. In the experiment, the ego-vehicle followed a direct leading vehicle, which further followed an indirect leading vehicle. In each drive, following Sharma et al. (2018), four driving regimes were included: acceleration, following, deceleration, and standstill. For safety considerations, in the standstill regime, the minimum speed was approximately 2 m/s rather than a full stop. For the deceleration regime, two deceleration rates (-1.5m/s^2 and -4.5m/s^2) and two initial speeds before brakes (16m/s and 8m/s) were shuffled in a drive, leading to five different orders to mitigate learning effects when participants experienced five eHMI conditions. Figure 3 illustrates the speed profiles of the indirect leading vehicle and the direct leading vehicle throughout an example drive.

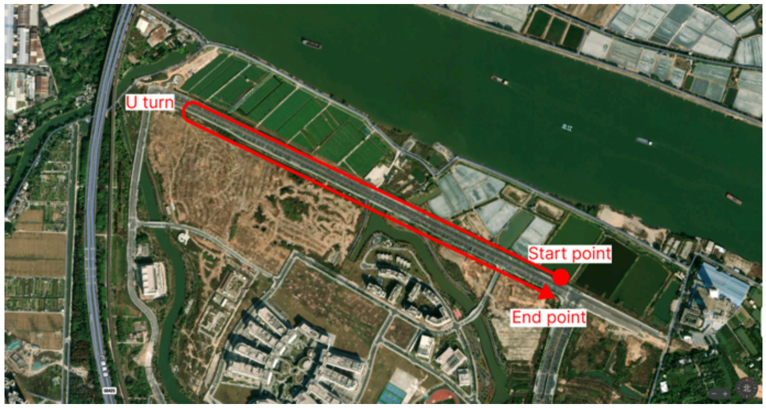


Figure 2. Experiment field (Base image © 2012–2022 Apple Inc).

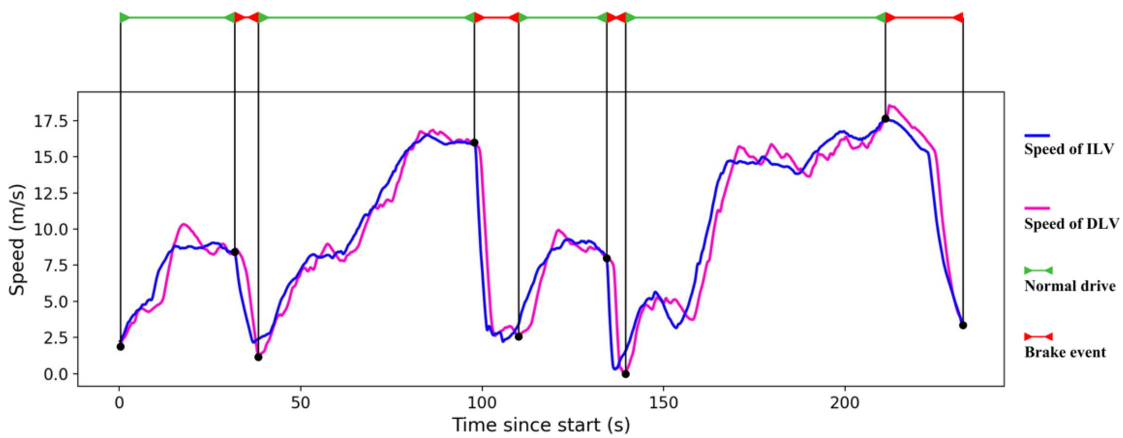


Figure 3. Speed profile of the indirect leading vehicle and direct leading vehicle in an example drive.

3.5 Experiment design

A within-experiment design was adopted, with the eHMI conditions (i.e., a baseline and four eHMIs) as the within-subject factors. Each participant completed five drives, four with the eHMIs and one baseline drive, which was counterbalanced using a Latin Square design. Each participant experienced the five drives in the same order of speed profiles, but with different eHMIs. Thus, each combination of the eHMI condition and speed profile appeared the same number of times throughout the whole experiment. In total, we collected data from 150 drives (30 participants * 5 eHMI conditions) and 600 braking events (4 braking events * 150 drives). To ensure consistency across participants and trials, the first two leading vehicles in the platoon were driven by the same two experimenters, both of whom had more than three years of driving experience. The experimenter driving the indirect leading vehicle was trained to apply the brake at certain deceleration rates. During training, deceleration rates were measured by an IMU (Figure 1(c)), enabling the experimenter to calibrate braking force accordingly. After the experiment, we conducted ANOVA for the braking events with different designed deceleration rates, and did not find significant differences ($p > .05$) in the maximum deceleration rate across the five eHMI conditions (shown in Table 2).

Table 2. Results of the maximum deceleration rate in the braking events.

Dependent variables	**Independent variables**	**F-value**	***p*-value**
Maximum deceleration rate ($-1.5 m/s^2$)	eHMI	$F(4,91) = 1.15$	.3
Maximum deceleration rate ($-4.5 m/s^2$)	eHMI	$F(4,90) = 1.33$	.3

3.6 Procedures

As shown in Figure 4, upon arriving at the experiment field, 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 to collect their demographic information, including gender, driving experience, and age. Participants then completed a 2.6 km practice drive on the experiment field to familiarize themselves with the field and vehicle. The indirect leading vehicle and the direct leading vehicle did not participate in this practice drive. After finishing the practice drive, the experimenter calibrated the eye tracker for the participant.

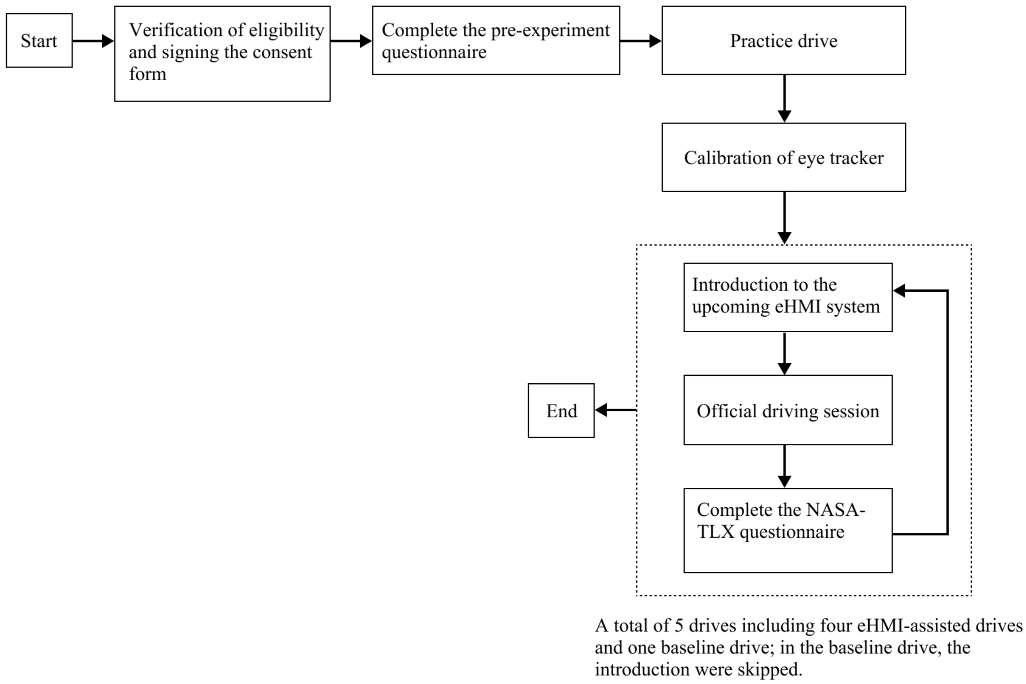


Figure 4. Flow diagram of experiment procedure.

Then the formal experiment began, comprising five experimental drives. Before each drive involving eHMIs, the corresponding eHMI was verbally explained to participants. After the explanation, the experimenter asked the participants to explain the eHMI back to the experimenter to confirm understanding. After each experimental drive, a post-experiment questionnaire was administered, measuring participants' workload in the previous drive, using NASA-Task Load Index (NASA-TLX) (Hart & Staveland, 1988).

3.7 Dependent variables

To evaluate the effects of the eHMIs on CF behaviors, we focused on two key periods of interest: (i) sections of braking event (from brake onset of the indirect leading vehicle to the resumption of acceleration by the direct leading vehicle) and (ii) normal driving sections (drive sections outside of braking event sections and the U-turn sections, see Figure 2).

The braking event was selected because it is highly relevant to the rear-end collision. Hence, we extracted drivers' response time and the minimum time-to-collision as two safety metrics. The response time was calculated as the time difference between the brake onset of the indirect leading vehicle (recorded by a pressure sensor installed on the brake pedal) and the brake onset of the ego-vehicle (i.e., the press of the brake pedal, as recorded by the foot camera). According to previous studies (Chouhan et al., 2025; Dingus et al., 2011), longer response times were associated with higher crash risk. The minimum time-to-collision was the minimum time required for the ego-vehicle to collide with the direct leading vehicle, if the ego-vehicle and the direct leading vehicle maintained their current speeds and directions at any moment during a braking event. A lower minimum time-to-collision has been found to be associated with a higher crash risk (Yi & Wei, 2024).

For the normal driving section, as mentioned, we focused on metrics related to traffic efficiency and speed variation. Specifically, the mean time headway was adopted as a measure of road capacity and traffic efficiency (Schakel & Arem, 2014). It was calculated as the mean elapsed time between the front of the direct leading vehicle and the front of the ego-vehicle, as both vehicles passed the same fixed point on the roadway. At the same time, the speed variance of the ego-vehicle was represented by the SD, coefficient of variation, and time-varying stochastic volatility of speed (Yang et al., 2022), which can impact the stability of traffic flow (Li et al., 2015; Zhao et al., 2024). Specifically, the SD of speed was calculated as follows:

$$SD\ of\ speed = \sqrt{\frac{\sum_{i=1}^{n}(v_i - \bar{v})^2}{n-1}}$$

Where v_i is the sample point of speed in a normal driving section, $\bar{v}$ is the average speed in a normal driving section, and n is the sample size. At the same time, the coefficient of variation measures the relative speed variability in a normal driving section, which can be calculated as follows:

$$Coefficient\ of\ variation\ of\ speed = \frac{Std}{|\bar{v}|} \times 100\%$$

Where $\bar{v}$ is the mean speed in the normal driving section. Finally, the time-varying stochastic volatility measures the fluctuation of the speed sample by computing the changes in the proportion of observations, as shown below:

$$Time - varying\ stochastic\ volatility\ of\ speed\ = \sqrt{\frac{\sum_{i=1}^{n}(r_i - \bar{r})^2}{n-1}}$$

where $r_i = \ln(\frac{v_i}{v_{i-1}}) \times 100\%$; v_i and, v_{i-1} are the observed speed samples i and $i - 1$ in the normal driving section; $\bar{r}$ is the mean value of r; and n is the sample size.

To investigate whether the eHMIs altered the pattern of attention allocation during normal driving, we calculated gaze dispersion in normal driving sections. Gaze dispersion was quantified as the SD of horizontal and vertical gaze locations within a normal driving section. A larger variation in gaze locations indicates a broader scanning area, which can bring safety benefits (Huang et al., 2024; Pillai et al., 2022). Previous research further found that a larger variance in gaze locations can be associated with higher levels of driving experience (Lehtonen et al., 2014; Robbins & Chapman, 2019; Underwood et al., 2003).

At the same time, pupil diameter was adopted as an objective indicator of workload and stress during normal driving sections. Inspired by Goodridge et al. (2025), Radhakrishnan et al. (2023), and Louw et al. (2021), we calculated the average pupil diameter in the normal driving section as a measure of workload. In addition, we adopted the coefficient of variation of pupil diameter as a measure of stress:

$$Coefficient\ of\ variation\ of\ pupil\ diameter = \frac{SD\ of\ pupil\ diameter}{Mean\ pupil\ diameter} \times 100\%$$

According to Pedrotti et al. (2014), a higher coefficient of variation of pupil diameter suggested increased physiological arousal, indicating a stronger sense of stress experienced by the participant during the interaction.

Finally, to investigate whether the beyond-visual-range information imposed additional cognitive load on following drivers in general, we calculated NASA-TLX scores following the standard procedure outlined by Hart and Staveland (1988) under each eHMI condition, leading to 150 samples (30 participants * 5 drives).

3.8 Statistical models

For braking event metrics, we included the eHMI condition (five levels, including baseline and the four eHMIs), the speed of the indirect leading vehicle when the indirect leading vehicle started braking, and their two-way interaction as independent variables. The speed of the indirect leading vehicle was included to account for uncontrolled variations in traffic flow, as previous research has observed its association with drivers' responses in braking events (Zhuodan et al., 2025). For normal driving metrics, we included eHMI condition, the mean speed of the indirect leading vehicle, and their two-way interaction effect as independent variables. The mean speed of the indirect leading vehicle was included to account for uncontrolled speed variation, based on the association between mean speed, traffic efficiency, and speed variations observed in previous studies (Geroliminis & Daganzo, 2008; Keyvan-Ekbatani et al., 2012). For the models of workload, stress, and gaze dispersion, the eHMI condition was included as the independent variable.

Multicollinearity among the independent variables was assessed using the Variance Inflation Factor (VIF), with a threshold of 10 (Belsley et al., 2005). In all models, the participant was included as a random effect to account for the repeated measures. Mixed-effects linear models were fitted using the lme4 package in *R*. Post-hoc comparisons were conducted for significant main effects or interaction effects ($p < .05$), using the Tukey adjustment method to control for multiple comparisons. A logarithmic transformation was applied to the dependent variable when the model residuals violated the normality assumption (specifically, for the minimum time-to-collision). With the transformation, the normality assumption was met.

4 RESULTS

4.1 Driver performance in the braking events

Table 3 shows the descriptive analysis for the metrics. For the response time, a total of 63 response times shorter than 0.1 s or longer than 5 s were excluded from the data analysis, as such response times were considered irrelevant to the stimuli (i.e., the brake of the indirect leading vehicle) (Zheng et al., 2023). Due to occasional failures of the data collection device and the RTK, data from 564 (of 600) braking events and 578 (of 600) normal driving sections were retained for analysis.

Table 3. Descriptive results for driver behavior indicators in braking events.

Dependent variables	Sample size	Mean	SD
Response time	537	2.00	1.31
MinTTC	564	1.91	0.97

Table 4. Statistical results of driving performance metrics in braking events.

Dependent variables	Independent variables	F-value	p-value	*Model diagnostic*
Response time	**eHMI**	**F (4, 521) = 4.37**	**.002**	-2 Res Log Likelihood = 1773.6; AIC = 1777.6
	speed of ILV	F (1, 521) = 0.61	.4	
	eHMI * speed of ILV	F (4, 523) = 0.89	.5	
Minimum time-to-collision	**eHMI**	**F (4, 438) = 3.39**	**.009**	-2 Res Log Likelihood = 1245.4; AIC = 1249.4
	speed of ILV	F (1, 442) = 0.05	.8	
	eHMI * speed of ILV	F (4, 438) = 2.26	.06	

Note: In this table and the following tables, the significant ($p < .05$) effects are bolded; ILV represents indirect leading vehicle; AIC stands for Akaike information criterion.

Response time: As shown in Table 4 and Figure 5, eHMI significantly affected response time. Compared with baseline, Brake-eHMI, Distance-eHMI and Video-eHMI significantly reduced response time (Brake-eHMI vs. baseline: difference (Δ) = -1.27 sec (s), 95% confidence interval (95%CI): [-1.73, -0.82], t (502) = -7.75, $p < .0001$; Distance-eHMI vs. baseline: Δ = -0.70s, 95% CI: [-1.15, -0.25], t (501) = -4.26, $p = .0002$; Video-eHMI vs. baseline: Δ = -0.70s, 95% CI: [-1.15, -0.25], t (501) = -4.27, $p = .002$). At the same time, Brake-eHMI led to a smaller response time than Distance-eHMI, Headway-eHMI, and Video-eHMI (Brake-eHMI vs. Distance-eHMI: Δ = -0.58s, 95% CI: [-1.03, -0.13], t (502) = -3.56, $p = .004$; Brake-eHMI vs. Headway-eHMI: Δ = -1.06s, 95% CI: [-1.51, -0.61], t (502) = -6.41, $p < .0001$; Brake-eHMI vs. Video-eHMI: Δ = -0.58s, 95% CI: [-1.03, -0.13], t (497) = -3.48, p = .0005). Finally, Distance-eHMI led to a smaller response time than Headway-eHMI (Δ = -0.48s, 95% CI: [-0.92, -0.03], t (501) = -2.91, p = .03).

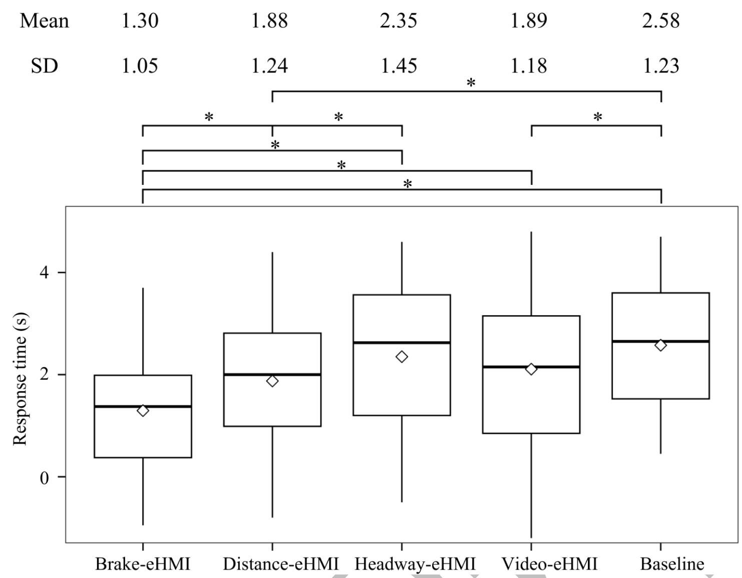


Figure 5. Post hoc comparisons of the effects of eHMIs on response time. In this figure and the following figures, significant post-hoc comparisons (p < 0.05) are marked with "*"; the boxplot represents the 1st quantile, median, and 3rd quantile; the white squares are the means of groups.

Minimum time-to-collision: In addition to the response time of the ego-vehicle, we analyzed the effects of eHMIs on the minimum time-to-collision. As mentioned previously, a logarithmic transformation was applied to the dependent variables because the model residuals violated the normality assumption. As shown in Figure 6, the minimum time-to-collision during Brake-eHMI, Distance-eHMI, Headway-eHMI, and Video-eHMI was 1.61 (95%CI: [1.38, 1.92], t(427) = 7.93, p < .0001), 1.23 (95%CI: [1.04, 1.46], t(424) = 3.44, p = .006), 1.37 (95%CI: [1.16, 1.63], t(424) = 5.17, p < .0001) and 1.36 (95%CI: [1.15, 1.61], t (424) = 4.99, p < .0001) times of that in the baseline, respectively. At the same time, Brake-eHMI led to a 1.30 (95%CI: [1.11, 1.55], t(427) = 4.44, p = .0001), 1.19 (95%CI: [1, 1.39], t(427) = 4.44, p = .049) and 1.20 (95%CI: [1.01, 1.40], t(426) = 2.91, p = .03) times of minimum time-to-collision than that of Distance-eHMI, Headway-eHMI, and Video-eHMI, respectively.

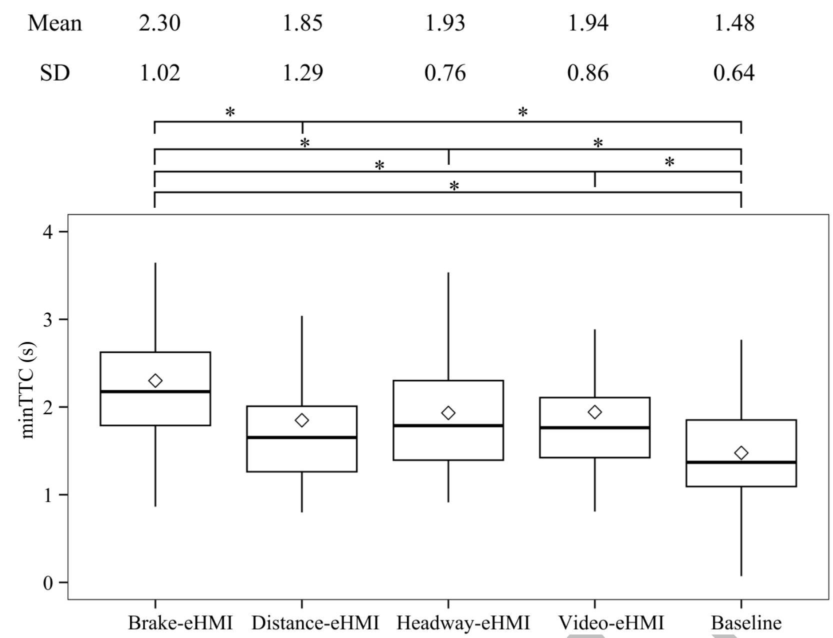


Figure 6. Post hoc comparisons for the effects of eHMIs on minimum time-to-collision (minTTC).

4.2 Driver performance in the normal driving sections

Table 5. Descriptive results for driver behavior indicators in normal driving sections.

Dependent variables	**Sample size**	**Mean**	**SD**
Mean time headway	578	2.20	0.64
SD of speed	578	11.66	3.96
Coefficient of variation of speed	578	43.67	12.49
Time-varying stochastics volatility of speed	578	2.09	1.86

Table 6. Statistical results for driver behavior indicators in normal driving sections.

Dependent variables	**Independent variables**	**F-value**	***p*-value**	***Model diagnostic***
Mean time headway	eHMI	F (4, 567) = .24	.9	-2 Res Log Likelihood = 796.9; AIC = 800.9
	mean speed of ILV	**F (1, 567) = 162.06**	**<.0001**	
	eHMI * mean speed of ILV	F (4, 567) = 0.04	.9	
SD of speed	eHMI	F (4, 567) = 1.06	.4	-2 Res Log Likelihood = 3229.9; AIC = 3233.9
	mean speed of ILV	**F (1, 567) = 576.18**	**<.0001**	
	eHMI*mean speed of ILV	F (4, 567) = 1.19	.3	
Coefficient of variation of speed	eHMI	F (4, 548) = 0.56	.7	-2 Res Log Likelihood = 4448.0; AIC = 4452.0
	mean speed of ILV	**F (1, 553) = 103.63**	**<.0001**	
	eHMI*mean speed of ILV	F (4, 548) = 0.65	.6	
Time-varying stochastic volatility of speed	eHMI	F (4, 550) = 0.26	.9	-2 Res Log Likelihood = 2349.0; AIC = 2353.0
	mean speed of ILV	**F (1, 558) = 42.24**	**<.0001**	
	eHMI*mean speed of ILV	F (4, 550) = 0.29	.9	

Mean time headway: As shown in Table 6, eHMI was not found to affect the mean time headway; while a significant effect of mean speed was found: for every 1 m/s increase in mean speed, the mean time headway decreased by 0.022 seconds, 95%CI: [-0.026, -0.020], t(546) = -5.64, $p < .0001$.

Speed variance of ego-vehicle: Further, eHMI did not affect any metrics of speed variance of ego-vehicle, while a significant effect of mean speed of indirect leading vehicle was observed for all metrics (SD of speed: estimated slope (ES) = 0.25, 95%CI: [0.23, 0.27], t(559) = 24.09, *p* < .0001; coefficient of variation of speed: ES = -0.45, 95%CI: [-0.53, -0.36], t(560) = -10.36, *p* <.0001; time-varying stochastic volatility of speed: ES = -0.044, 95%CI: [-0.058, -0.031], t(558) = -6.50, p <.0001).

4.3 Driver workload and stress

Table 7. Descriptive results for driver workload and stress indicators.

Dependent variables	**Sample size**	**Mean**	**SD**
Subjective workload	150	7.98	3.32
Mean of pupil diameter	142	0.19	0.032
Coefficient of variation of pupil diameter	142	2.16	1.46

Table 8. Statistical results for driver workload and stress indicators.

Dependent variables	**Independent variables**	**F-value**	***p*-value**	***Model diagnostic***
Subjective workload	eHMI	F (3, 137) = 1.67	.2	-2 Res Log Likelihood = 808.6; AIC = 812.6
Mean of pupil diameter	eHMI	F (4, 105) = 0.67	.6	-2 Res Log Likelihood = -1370.1; AIC = -1368.1
Coefficient of variation of pupil diameter	**eHMI**	**F (4, 105) = 4.24**	**.003**	-2 Res Log Likelihood = 358.2; AIC = 362.2

As shown in Table 8, eHMI did not affect subjective workload or mean pupil diameter (*p* > .05). Thus, the eHMIs we provided may not have overloaded drivers in our experiment. Further, as shown in

Table 8 and Figure 7, eHMI had a significant effect on the coefficient of variation of drivers' pupil diameter. Specifically, drivers exhibited a lower coefficient of variation of pupil diameter when assisted by Headway-eHMI (Δ = 1.10, 95%CI: [0.21, 1.99], t (84) = 3.45, *p* = .0009) and Video-eHMI (Δ = 1.39, 95%CI: [0.49, 2.27], t (84) = 4.35, p = .0004), compared with baseline. Further, Brake-eHMI led to a higher coefficient of variation of pupil diameter than Video-eHMI (Δ = 0.92, 95%CI: [0.03, 1.81], t (84) = 2.90, p = .03).

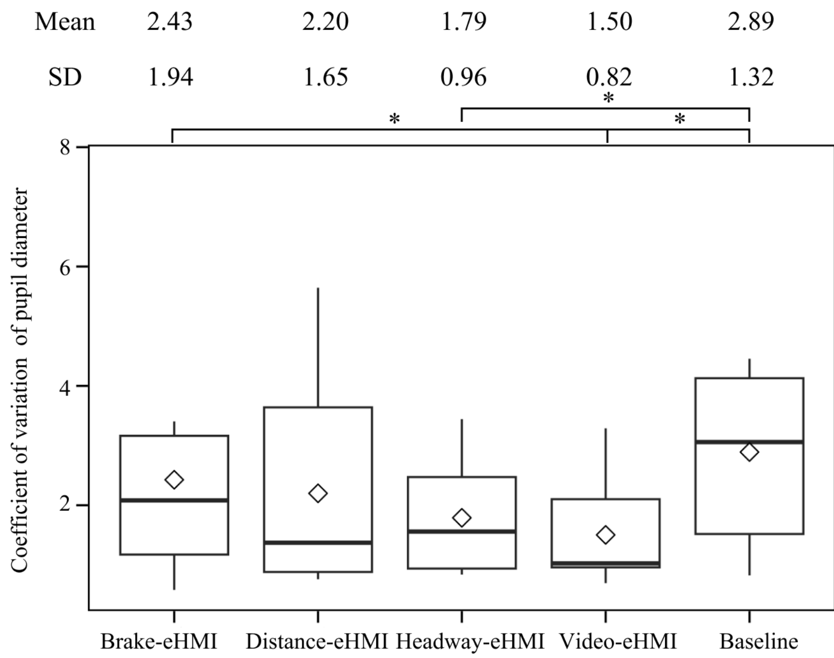


Figure 7. Post hoc comparisons for the effect of eHMI on the coefficient of variation of pupil diameter.

4.4 Gaze dispersion

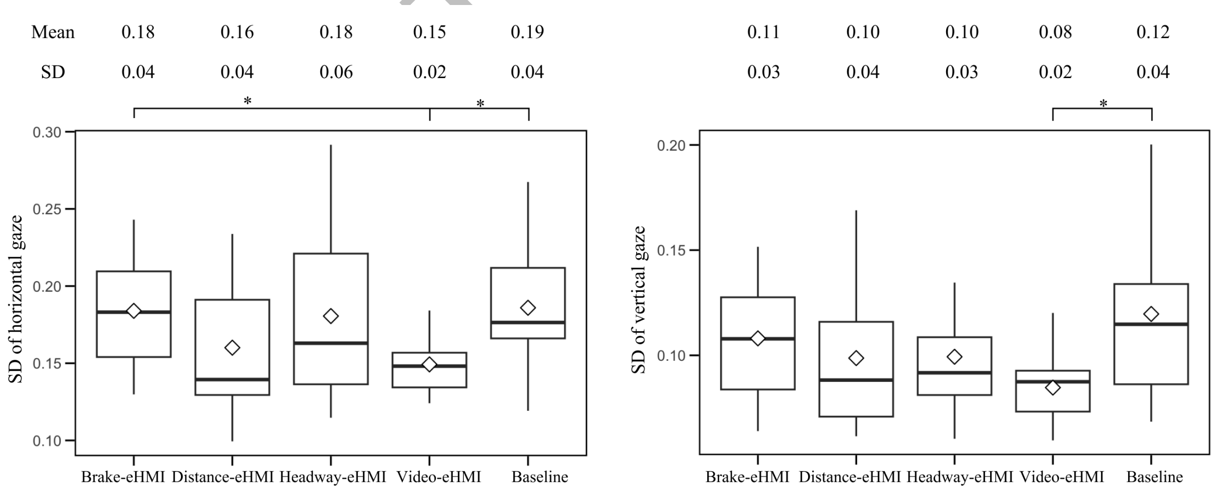
Table 9. Descriptive results for gaze dispersion indicators.

Dependent variables	Sample size	Mean	SD
SD of horizontal gaze locations	142	0.17	0.04
SD of vertical gaze locations	142	0.10	0.03

Table 10. Statistical results for gaze dispersion indicators.

Dependent variables	**Independent variables**	**F-value**	**p-value**	**Model diagnostic**
SD of horizontal gaze locations	**eHMI**	**F (4, 40) = 4.07**	**.007**	-2 Res Log Likelihood = -186.9; AIC = -182.9
SD of vertical gaze locations	**eHMI**	**F (4, 40) = 2.73**	**.04**	-2 Res Log Likelihood = -198.2; AIC = -194.2

As shown in Figure 8 and Table 10, Video-eHMI yielded a lower SD of horizontal gaze locations than baseline and Brake-eHMI (Video-eHMI vs. baseline: Δ = -0.04, 95%CI: [-0.07, -0.003], t (40) = -3.20, *p* = .03; Video-eHMI vs. Brake-eHMI: Δ = -0.03, 95%CI: [-0.07, -0.0002], t (40) = -3.02, *p* = .03). Video-eHMI yielded lower SD of vertical gaze locations than baseline (Δ = -0.04, 95%CI: [-0.07, -0.003], t (40) = -3.17, *p* = .02). No other significant results were observed (*p* > .05).



(a) (b)

Figure 8. Post hoc comparison of the (a) SD of horizontal gaze locations and (b) SD of vertical gaze locations.

5 DISCUSSION

This study is the first to examine the feasibility of conveying indirect leading vehicle information to following drivers via novel rear-facing eHMIs in an on-road field experiment. The study was conducted using an instrumented vehicle equipped with a prototype rear-facing eHMI, with CF behavior, mental workload, stress, and gaze dispersion evaluated.

5.1 The impact of eHMIs in braking events

First, we found that drivers generally exhibited safer driving behavior in response to chain-braking events (i.e., direct leading vehicle brake following indirect leading vehicle brake) when supported by information of the indirect leading vehicle. Specifically, as shown in Figure 5 and 6, based on the post hoc comparisons, the Brake-eHMI, Distance-eHMI, and Video-eHMI led to a shorter response time and a larger minimum time-to-collision than baseline, possibly by reminding the drivers of the brake of the indirect leading vehicle in advance. These results were consistent with prior research, in which the information of indirect leading vehicle provided via a V2V-supported in-vehicle HMI facilitated faster brake responses of ego-vehicle drivers (Yan et al., 2023). However, on top of Yan et al. (2023), our research indicates that a technologically ready solution, the rear-facing eHMI, can also be as effective as the in-vehicle HMI solution in terms of facilitating earlier preparation in chain-braking events (see post hoc comparisons in Figure 5). The benefit of beyond-visual-range information can be explained by theoretical cognitive CF models, which describe CF decisions as arising from continuous belief updating under uncertainty (Chen et al., 2024; Ratcliff & Strayer, 2014). Without our eHMIs, drivers can only infer upstream traffic flow disturbances indirectly from the motion of the direct leading vehicle, resulting in delayed and noisy evidence accumulation. In contrast, the eHMIs can reduce perceptual uncertainty and support predictions of upcoming variations in traffic flow, which can accelerate belief updating and allow the accumulated evidence to reach the decision threshold earlier, leading to shorter response times observed in our experiment.

It should be noted that the Headway-eHMI did not yield shorter response time but still yielded a larger minimum time-to-collision in braking events (as shown in Figure 5 and Figure 6, based on the post hoc comparisons). The Headway-eHMI display was the only one that provided clear safety-related thresholds (i.e., the 1-sec and 2-sec thresholds) among all eHMI designs evaluated in this study. Thus, drivers may have realized the brake of the indirect leading vehicle but still chose to wait until critical thresholds were exceeded, even though they were cognitively or physically prepared for the upcoming brake of the direct leading vehicle. Such reliance on the warning message has frequently been observed in previous human-automation interaction studies (D. He et al., 2021), in which warning-based takeover requests delayed responses to events that may require driver intervention when no additional information about automation states was provided. Thus, further research may need to be careful when integrating the warning message into the eHMI design, to avoid behavioral adaptations of drivers (Rudin-Brown & Parker, 2004).

Furthermore, we found that the type of information also affected drivers' responses to chain-braking events. Specifically, the Brake-eHMI led to the potentially safest responses, in terms of the shortest response time and the largest minimum time-to-collision (as shown in Figure 5 and Figure 6, based on the post hoc comparisons). This is not surprising, as the simplified warning message may facilitate prompt action without requiring further information processing, which could otherwise delay action. Such a finding is consistent with Hick-Hyman Law (Hick, 1952; Hyman, 1953) and the design principle of "recognition rather than recall" (Nielsen, 1994). However, it should be noted that such a direct response to indirect leading vehicle braking may not always be beneficial, as unnecessary braking (e.g., when the indirect leading vehicle is still far from the direct leading vehicle) could potentially destabilize traffic flow and increase fuel consumption (Horn, 2013). Thus, future research should more thoroughly evaluate the influence of the eHMI design, not just in chain-braking events, but also in free-flow traffic, by modeling drivers' CF decisions and assessing their impact on traffic efficiency and emissions.

5.2 The impact of eHMIs in normal driving

We did not observe an effect of the rear-facing eHMIs on the mean time headway or speed variance of the ego-vehicle in normal driving sections (as shown in Table 6, based on the non-significant main effects). In other words, the rear-facing eHMI with the beyond-visual-range information might not alter the following drivers' steady CF behavior. Unlike what has been observed when anti-lock braking systems were equipped in vehicles (Sagberg et al., 1997) and what has been suggested by the risk homeostasis theory (Wilde, 1982), drivers did not exhibit riskier CF behavior when they had beyond-visual-range information. There are two possible explanations. First, it is possible that the rear-facing eHMI may not be readable enough in normal driving sessions, when the direct leading vehicle is relatively far away. Thus, the kinematic information as transmitted by the looming effect (Markkula et al., 2016) dominates drivers' CF decisions. Future research may need to explore more intuitive and perceivable HMI designs. Second, it is also possible that the risk homeostasis theory (Wilde, 1982) relied on self-adjusted risk levels in specific scenarios. The relatively short duration of our experiment may not allow drivers to re-evaluate the risk associated with the new eHMI. Thus, further study may still be necessary to assess the long-term effects of the rear-facing eHMI if such technology were to be widely adopted.

5.3 The impact of eHMIs on workload, stress, and gaze dispersion

Considering driving is already an attentionally demanding task (Salmon et al., 2005), we evaluated whether additional information provided by the eHMI would increase drivers' workload. In general, we did not observe differences in perceived workload (NASA-TLX) or in the objective workload metric (i.e., pupil diameter) across all experimental conditions (as shown in Table 8, based on the non-significant main effects). It implies that the beyond-visual-range information provided by the eHMIs did not further overload the drivers. At the same time, according to Figure 7 and post hoc comparisons, the Headway-eHMI and Video-eHMI reduced the coefficient of variation of pupil diameter, implying lower stress levels than the baseline (Tang et al., 2025). It is likely that the Headway-eHMI and Video-eHMI, directly and indirectly, provided the safety threshold via beyond-visual-range information. With such information, drivers can be more relaxed, provided the situation remains within the safety range, thereby reducing stress.

At the same time, most eHMIs in our study did not affect drivers' gaze dispersion during CF events relative to baseline (as shown in Table 10, based on the non-significant main effects). However, Video-eHMI yielded lower horizontal and vertical gaze dispersion than baseline (as shown in Figure 8, based on the post hoc comparisons). It is possible that the rich information in the Video-eHMI has drawn excessive attention from the drivers. The relatively small display area of the rear-facing eHMI might have further exaggerated this effect. Though it is possible that the drivers could obtain the beyond-visual-range information other than the states of the indirect leading vehicle in the Video-eHMI (e.g., whether there is an obstacle ahead of the direct leading vehicle), the smaller visual scanning area is usually associated with lower driving experience, reduced ability to anticipate and detect emerging traffic conflicts, and higher crash risk (Lehtonen et al., 2014; Underwood et al., 2003). Thus, the potential adverse effects of Video-eHMI on driving safety warrant further assessment.

5.4 Future application

Our results show that the beyond-visual-range information displayed on eHMI has the potential to reduce rear-end collisions. In particular, all information used in this study can be readily obtained using existing sensors in vehicles equipped with adaptive cruise control or more advanced driving automation systems. Given that some vehicle models have already adopted rear-facing LED strips (Valdes-Dapena, 2023), rear-facing eHMIs may be technically feasible in existing models. However, for future deployment, eHMI designs should further balance information richness and conciseness, given the limited marginal benefit of providing more information and the potential negative effects of overloading drivers. Further, this experiment is only a demo of providing simple beyond-visual-range information in a relatively simple scenario; future eHMI designs may consider conveying more advanced information adaptively in more complex scenarios. For example, by leveraging the perception capabilities of advanced driving automation, the ego-vehicle may even inform its own planned trajectory to surrounding vehicles to facilitate better cooperation. However, again, the usability of such eHMI-based interaction should be carefully evaluated before deployment.

5.5 Limitation

In this study, we only considered experienced drivers as participants for safety considerations. However, the driving experience and other characteristics of drivers, such as driving style, can affect CF strategies (Wei et al., 2025). Thus, future research should evaluate the eHMIs on a more diverse range of driver populations before deployment in real-world settings. Second, this study only evaluated the eHMIs from the perspective of micro driving behavior; future research should examine their broader effects on traffic flow stability and environmental impacts. Furthermore, we considered only objective performance measures and omitted the subjective evaluation of the eHMIs, which may differ from our objective assessments. Future research may evaluate users' perceptions of beyond-visual-range information using other qualitative approaches, such as questionnaires on iconography and information comprehension (Richman et al., 2002). Finally, all participants were explicitly informed of the meaning of the eHMIs, based on the assumption that such interfaces may be standardized in the future. However, future research should examine whether drivers can interpret these eHMIs without prior instruction, reflecting scenarios in which they are directly deployed in mass-production vehicles.

6 CONCLUSIONS

In an on-road field experiment with 30 participants, we evaluated four rear-facing eHMIs to display the information of the indirect leading vehicle during CF events. We found that:

- Certain beyond-visual-range information of the indirect leading vehicle can potentially improve CF safety, especially in chain-braking events, without clear evidence of overloading drivers, as indicated by non-significant effects on the mean of pupil diameter and subjective workload.
- The simplest and most intuitive Brake-eHMI, which showed brake actions of the indirect leading vehicle, was associated with the fastest brake responses and the largest minimum time-to-collision among all eHMIs we evaluated.
- Richer information about the indirect leading vehicle may not necessarily lead to quicker responses to potential rear-end collisions.

Overall, the findings from this exploratory study indicate that a rear-facing eHMI with information about the indirect leading vehicle may enhance CF safety when carefully designed to balance informativeness, complexity, and intuitiveness. Future research should further evaluate the effectiveness of eHMI designs in naturalistic driving studies and explore adaptive systems that tailor information about the indirect leading vehicle to the driver's experience and the traffic context.

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