Supporting Car-Following Behaviors for Heterogeneous Drivers with Explicit Information of the Lead Vehicle

Xiaoyu Zhou
Thrust of Intelligent Transportation
Hong Kong University of Science and Technology (Guangzhou)
Guangzhou, China
xzhou174@connect.hkust-gz.edu.cn

Dengbo He*
Thrust of Intelligent Transportation
Hong Kong University of Science and Technology (Guangzhou)
Guangzhou, China
Division of Emerging Interdisciplinary Areas
The Hong Kong University of Science and Technology
Hong Kong, China
dengbohe@ust.hk

Abstract

Rear-end collisions are prevalent and are closely related to car-following (CF) behavior. In this study, we proposed three in-vehicle human-machine interfaces (HMIs) to provide progressively richer information about the lead vehicle (LV), including speed information (HMI-vel), time headway (THW) information on top of HMI-vel (HMI-THW), and coloured risk warnings based on THW thresholds on top of HMI- THW (HMI-alert). Cluster analysis was conducted to identify heterogeneous driver groups in a driving simulator study with 24 participants. Results showed that, in general, enhancing drivers' perception of lead-vehicle states improved the safety margin during car-following segments without intensive braking, but certain HMIs impaired speed stability, with the effects varying across driver groups. Furthermore, the safety benefits of HMIs, reflected by reduced collision risk, differed across driver groups. These findings highlight the importance of considering driver heterogeneity and adaptive HMI designs to support safe car-following behaviors.

CCS Concepts

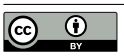
• **Human-centered computing** → **Empirical studies in HCI**; **Field studies**.

Keywords

Human-Machine Interface, Car-Following, Driving Style

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*Corresponding author.



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1 Introduction

With the rapid expansion of urban areas, traffic congestion is increasing, leading to more crashes—predominantly rear-end collisions [5]. Such collisions are closely tied to drivers' car-following (CF) behavior, traditionally guided by perceptual processes based on visual information from the lead vehicles (LVs) [18, 43]. Advances in sensing technologies now enable continuous perception of LV states, raising the question of whether such technologies can improve CF safety.

Drivers typically monitor speed, distance, time-headway (THW), and time to collision (TTC) during CF events. THW reflects temporal safety margins, while TTC indicates remaining time before a potential collision. Thus, various in-vehicle HMIs have been proposed to assist drivers in car-following events, many focusing on providing warning information in case of small TTC or THW. For instance, Zhu et al. [45] developed a pre-collision warning system, and Locken et al. [22] found that TTC-encoded lighting displays can facilitate better CF decisions.

However, warning-based systems have inherent limitations. The reliability of such systems, if not properly calibrated, can produce unintended negative consequences. On one hand, high false alarm rates may trigger the "cry-wolf" effect [9]—drivers gradually lose trust in the system due to frequent false alerts, leading to slower or even absent responses when actual hazards occur. On the other hand, even highly reliable systems can induce over-reliance and the "lumberjack " effect [3]—drivers, accustomed to dependable automation, may become complacent and reduce their active monitoring of the driving environment, resulting in degraded situation awareness. Both effects can potentially delay hazard responses [16, 33], and their negative impacts are particularly pronounced in complex driving environments where cognitive load is already high [19].

To mitigate these issues, continuous information flows have been proposed. He et al. [16] found that continuous information about system capability and traffic conditions facilitates earlier hazard detection. Inspired by this, we investigate whether continuous LV-related information can improve CF performance. Given the cognitive demands of manual driving, excessive information may overload drivers [8, 17, 42]; thus, ecological interface designs [35] that align information presentation with natural perceptual processes have been proposed in our study. Further, previous studies show that drivers with different driving styles may adopt different strategies in CF scenarios [30, 39]. For example, aggressive drivers

maintain shorter THW and show higher acceleration variability, while conservative drivers rely more on TTC [36, 37]. Thus, driver heterogeneity was also considered in our study: understanding the associations among driving style, CF-related information, and CF strategies may facilitate adaptive HMI design.

2 Literature Review

Forward collision warning (FCW) systems have shown positive effects in CF scenarios in both simulator and on-road studies. [7] found that the FCW can yield more accurate headway estimation and safer CF distances. [26] found that early auditory alerts led to faster accelerator release times, fewer crashes, and less severe crashes than late-warning or no-warning conditions. [6] observed that an integrated crash warning system helped heavy-truck drivers maintain longer THWs in dense traffic and reduced brake reaction time, mitigating 15% of forward conflicts. However, [12] reported mixed driver acceptance of the FCW due to false alarms. Moreover, FCW systems are typically event-triggered and only activate when collision risk becomes imminent, making them insufficient for continuously regulating CF behavior in dynamic traffic.

To overcome FCW limitations, several HMIs have been proposed to support continuous LV situation awareness. [14] demonstrated that kinesthetic-tactile displays of headway and relative velocity could compensate for perceptual limitations and improve CF performance. [11] found that salient visual headway information increased THW by up to 0.5 s, whereas auditory warnings improved reaction times during LV deceleration but were less effective in promoting safer headways. [34] used rear-window displays to show the ego vehicle's acceleration and THW (between the ego vehicle and the following vehicle), improving CF performance of following drivers. [13] found that infrastructure-to-vehicle cooperative systems providing early information about accidents, congestion, weather, roadwork, and speed limits effectively harmonized and smoothed CF behavior, enhancing traffic flow safety.

Driving style and experience can also influence CF behavior. [2] found that drivers with higher self-reported aggression scores exhibited shorter THWs, faster speed recovery, and more abrupt deceleration than non-aggressive drivers, which improved response speed but reduced safety margins during braking. Similarly, [41, 44] found that different driving styles are associated with distinct responses to rear-end collision risk, including differences in braking response time, maximum deceleration, and jerk. [40] found that experienced drivers are not necessarily safer; their behavioral patterns reflect different risk-response strategies that may increase hazard exposure under specific scenarios.

In summary, CF-related information and driving style were both found to affect CF strategies; however, it is yet unknown how to match the richness of CF-related information to driving styles. A study that considers both the presentation of CF-related information and driving styles is needed to answer this question.

3 Method

3.1 Participants

A total of 24 valid drivers (12 male and 12 female, age range: 24–45) were recruited via posters in nearby residential areas and online forums. All participants held a valid driver's license for over 3 years and reported annual driving mileage of at least 3,000 km in the past year, ensuring they had sufficient driving experience. Before the experiment, participants filled out a multidimensional driving style inventory (MDSI) questionnaire [37], which measures driving style on four dimensions: Careful, Risky, Angry, and Anxious.

3.2 Apparatus

The experiment used a fixed-base driving simulator (Info Tech, China; Fig. 1) with automatic transmission, allowing control via steering wheel, accelerator, and brake pedal. Visuals were displayed on three 43-inch screens (front and sides), offering a 150° horizontal and 47° vertical field of view. CF-related HMIs appeared at the bottom of the front screen, simulating a head-up display (HUD) position.

Scenarios were built in SiLAB 7.1 (WIVW GmbH), enabling high-fidelity simulation and real-time data logging at 100 Hz. Recorded data included ego-vehicle and LV distances, speeds, accelerations, and pedal states (0 = no input, 1 = fully engaged).



Figure 1: The driving simulator.

3.3 Scenario Design and Driving Task

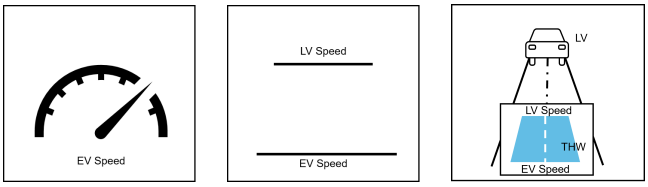
Participants drove on an 18.6 km, 6-lane bidirectional highway (clear weather, straight and curved sections, 3.75 m lane width, 120 km/h speed limit). They were instructed to follow an LV at a self-determined safe distance. The LV varied speed from 60 to 120 km/h with acceleration between -1.5 and 1.5 m/s^2, simulating diverse driving patterns. Participants stayed in lane and adjusted speed to the LV's acceleration, cruising, and deceleration, as if following a friend's vehicle to an unknown destination.

3.4 CF-Related HMI Design and Visualization

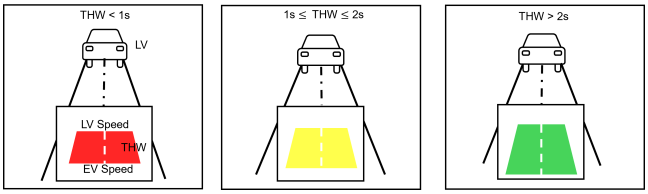
To evaluate the impact of information presentation on driving behavior, drawing on relevant research findings [27, 31, 38], we designed three HMIs (as shown in Fig 2), incrementally enhancing the information richness:

Baseline: Traditional instrument cluster, no additional CF information, assessing experience-based distance/speed control (Fig 2a).

HMI-vel: Adds a dynamic icon showing real-time speeds of both LV and ego-vehicle, enhancing perception of LV speed changes (Fig 2b).



(a) Baseline (b) HMI-vel (c) HMI-THW



(d) HMI-alert

Figure 2: The baseline and the LV-related HMIs.

HMI-THW: Adds the THW metric to speed info, providing intuitive time-headway feedback. This helps drivers assess following distance without mental calculation, enabling proactive adjustments and improved decision-making (Fig 2c).

HMI-alert: Builds on HMI-THW with color-coded THW alerts: red (THW $\leq$ 1 s), yellow (1 $\leq$ THW $\leq$ 2 s), green (THW $\geq$ 2 s). This reduces cognitive load, facilitates rapid risk identification, and supports faster responses, especially in complex/urgent scenarios (Fig 2d).

All HMIs were integrated into SiLAB 7.1, with real-time speed and distance data collection and visualization.

3.5 Experiment Design

A within-subject design was used, with HMI type (baseline, HMI-vel, HMI-THW, HMI-alert) as the sole controlled factor. Each participant completed four drives, one per HMI, with order counterbalanced via a Latin-square design. Four distinct LV speed profiles were randomly generated for each experiment, with LV speed ranging from 60 to 120 km/h and acceleration from -1.5 to 1.5 m/s^2, covering constant speed, acceleration, deceleration, and emergency braking. Note that the mean acceleration of the lead vehicle across all speed profiles was zero, meaning that the acceleration and deceleration phases were approximately balanced. A total of 24 participants were recruited, enabling detection of an effect size of $\eta^2 \geq 0.106$ (Cohen's f = 0.345) at power 0.8 and $\alpha = 0.05$.

3.6 Evaluation Metrics

We specifically focused on the CF-related metrics from two types of segments during the drive:

Braking segment, which was defined as the period from when the LV's deceleration $\geq$ 1.3 m/s^2 [28] to when the LV's acceleration $\geq$ 0 m/s^2. This segment captured drivers' responses to LV braking events using the following metrics from the braking segments:

- Response time (RT), which refers to the time interval between the onset of the LV's deceleration and the initiation of the ego-vehicle driver's braking response. It reflects the driver's speed of perceptual and cognitive response and has been found to be associated with crash risk in previous studies [10]. The longer the RT in a braking event, the higher the crash risk.
- TTC, which is calculated as TTC $= \frac{D_{\text{follow}}}{v_{\text{rel}}}$, where v_{rel} denotes the relative speed between the ego-vehicle and the LV. In this study, we focused on the maximum inverse of TTC (MaxInvTTC), as it is a commonly used surrogate metric of driving safety [4]. The larger the MaxInvTTC, the higher the crash risk.

Normal driving segment, which was defined as all continuous CF episodes excluding braking segments. These segments represented typical CF behavior under non-braking conditions. We focused on the following metrics from the normal driving segments:

- THW, which is defined as THW $= \frac{D_{\text{follow}}}{v_{\text{ego}}}$, where D_{follow} represents the following distance and v_{ego} is the speed of the ego-vehicle. We focused on the average THW (MeanTHW), as it is related to crash risks [38]. The larger the MeanTHW, the higher the crash risk.
- Speed variance (SV), which is expressed as $\sigma_v^2 = \frac{1}{n}\sum_{i=1}^{n}(v_i - \bar{v})^2$. It characterizes the dispersion of instantaneous speeds v_i relative to the average speed $\bar{v}$ across n data points, serving as an indicator of driving smoothness [15]. The larger the SV, the less smooth the driving smoothness.

It should be noted that the driving data were logged continuously at 100 Hz throughout each drive. In normal driving segments, MeanTHW and SV were aggregated at the segment level (averaged over segments) for each participant and HMI condition. In braking segments, each braking event was treated as a separate observation, and metrics including RT and MaxInvTTC were extracted per event.

3.7 Data Analysis

To account for driving style heterogeneity, hierarchical clustering was conducted using four MDSI features and two sociodemographic indicators (*Driving Experience* and *Annual Mileage*) to identify natural groupings of driving styles.

Mixed-effects models [29] were then fitted to examine the effects of driving style and HMI type on the extracted metrics. Driving style cluster, HMI type, and their two-way interactions were included as fixed effects, with participant as a random effect to account for repeated measures. Tukey post-hoc analyses [1] were conducted for significant effects ($p < .05$). All models were built in **R**. Comparisons across driving styles are not reported, as we focus on how CF-related information affects CF behaviors instead of the driving style itself.

4 Result

4.1 Cluster of Drivers Based on Driving Style

Before clustering, all variables were standardized using z-score normalization. Hierarchical clustering was performed using Euclidean distance and Ward's linkage method. The optimal number of clusters was determined based on the Calinski–Harabasz index

and silhouette coefficient, with three clusters providing the best separation.

As shown in Table 1, Group 0 scored higher on *Careful Style* and *Risky Style*, with lower *Driving Experience*, *Annual Mileage*, and *Angry Style*. Thus, it is labeled as **Conservative**. Group 1 showed higher *Angry Style*, *Driving Experience*, and *Annual Mileage*, with lower *Careful Style*, and thus it is labeled as **Aggressive**. Group 2 exhibited moderately high *Anxious Style* and *Annual Mileage*, with intermediate *Careful Style* and *Angry Style*, and thus it is labeled as **Moderate**.

4.2 Behavior in the Normal Driving Segments

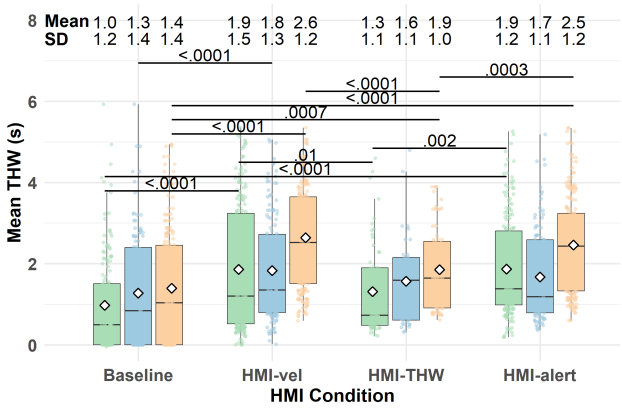


Figure 3: Boxplot of MeanTHW (s) in normal driving segments. In this figure and the following figures, the boxplot shows the 1st and 3rd quantiles and the median. The group means are indicated by white squares. Significant post-hoc comparisons ($p < .05$) are marked with the p−value and connecting lines. SD denotes the standard deviation.

MeanTHW: As shown in Table 2 and Figure 3, the linear mixed-effects model revealed a significant interaction effect between the HMI and the driving style. Specifically, for conservative drivers (Group 0), the HMI-vel and HMI-alert both led to a larger MeanTHW than the baseline (HMI-vel vs. baseline: estimated difference [Δ] = 0.82, 95% confidence interval [95% CI]: [0.60, 1.04], $t(1564) = 7.33$, $p < .0001$; HMI-alert vs. baseline: $\Delta = 0.91$, 95% CI [0.70, 1.13], $t(1564) = 8.12$, $p < .0001$). Within-group comparisons further showed HMI-vel yielded a larger MeanTHW than HMI-THW ($\Delta = 0.45$, 95% CI [0.16, 0.73], $t(1564) = 3.06$, $p = .01$), and HMI-THW yielded a smaller MeanTHW than HMI-alert ($\Delta = -0.53$, 95% CI [-0.82, -0.25], $t(1564) = -3.65$, $p = .002$).

Aggressive drivers (Group 1) showed a similar pattern but with a greater effect. The HMI-vel, HMI-THW, and HMI-alert all led to larger MeanTHW than the baseline (HMI-vel vs. baseline: $\Delta = 1.35$, 95% CI [1.15, 1.55], $t(1564) = 13.24$, $p < .0001$; HMI-THW vs. baseline: $\Delta = 0.54$, 95% CI [0.26, 0.81], $t(1565) = 3.86$, $p = .0007$; HMI-alert vs. baseline: $\Delta = 1.10$, 95% CI [0.90, 1.30], $t(1564) = 10.92$, $p < .0001$). Pairwise contrasts further indicated that HMI-vel led to a larger MeanTHW than the HMI-THW ($\Delta = 0.81$, 95% CI [0.54, 1.09], $t(1564) = 5.83$, $p < .0001$) and HMI-THW led to a smaller MeanTHW than HMI-alert ($\Delta = -0.56$, 95% CI [-0.83, -0.30], $t(1564) = -4.07$, $p = .0003$). Finally, for moderate drivers (Group 2), only HMI-vel led to a larger MeanTHW than the baseline ($\Delta = 0.59$, 95% CI [0.34, 0.84], $t(1564) = 4.68$, $p < .0001$); all other pairwise differences against baseline and among HMIs were nonsignificant (all $p \geq .05$).

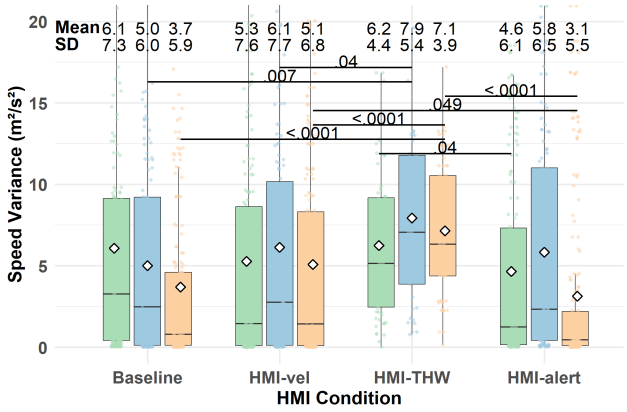


Figure 4: Boxplot of Speed Variance $(m/s)^2$ in normal driving segments.

SV: As shown in Table 2 and Figure 4, the mixed-effects model revealed a significant interaction effect between the HMI and the driver group. Specifically, for conservative drivers (Group 0), only the HMI-THW led to a significantly larger SV than the HMI-alert ($\Delta = 1.95$, 95% CI [0.51, 3.40], $t(1566) = 2.65$, $p = .04$). No other pairwise differences reached significance (all $p > .05$).

For aggressive drivers (Group 1), again, the most pronounced effects were observed. The HMI-THW led to a larger SV than the baseline ($\Delta = 4.04$, 95% CI [2.67, 5.42], $t(1568) = 5.78$, $p < .0001$), HMI-vel ($\Delta = 3.44$, 95% CI [2.08, 4.80], $t(1567) = 4.90$, $p < .0001$), and HMI-alert ($\Delta = 4.75$, 95% CI [3.37, 6.13], $t(1567) = 6.82$, $p < .0001$). Additionally, HMI-vel yielded higher a SV than HMI-alert ($\Delta = 1.32$, 95% CI [0.01, 2.63], $t(1566) = 2.58$, $p = .049$). Finally, for moderate drivers (Group 2), the HMI-THW again led to a larger SV than both the baseline ($\Delta = 2.93$, 95% CI [0.65, 5.21], $t(1564) = 3.22$, $p = .007$) and HMI-vel ($\Delta = 2.39$, 95% CI [0.16, 4.62], $t(1565) = 2.68$, $p = .04$).

4.3 Behaviors in Braking Segments

MaxInvTTC: As shown in Table 3 and Fig 5, we observed a significant interaction effect between HMI and Style on MaxInvTTC. Specifically, for Group 0 (conservative drivers), MaxInvTTC under baseline was significantly higher than under HMI-alert ($\Delta = 0.38$, 95% CI [0.23, 0.53], $t(1252) = 5.07$, $p = .0001$), but lower than HMI-vel ($\Delta = 0.34$, 95% CI [0.18, 0.50], $t(1250) = 4.35$, $p = .0001$) and HMI-THW ($\Delta = 0.36$, 95% CI [0.1, 0.57], $t(1254) = 3.49$, $p = .003$). No significant differences were observed among HMIs for Group 1 (aggressive drivers) or Group 2 (moderate drivers) ($p > .05$).

RT: As shown in Table 3 and Fig 6, the mixed-effects model revealed a significant main effect of HMI on RT ($F(3, 156.79) = 10.52$, $p < .0001$). Specifically, as shown in Fig 6, the RT under baseline was significantly higher than under HMI-vel ($\Delta = 0.88$,

Table 1: Demographic Summary of Participants by Driving Style Group.

Group	N	Male	Female	Age (Mean ± SD)	Driving Exp. (Mean ± SD)	Annual Mileage (Mean ± SD)
0: Conservative	8	4	4	25.0 ± 0.7	4.5 ± 0.4	8,731 ± 3,662
1: Aggressive	6	5	1	34.5 ± 5.9	11.5 ± 4.3	19,990 ± 5,253
2: Moderate	10	4	6	31.0 ± 8.4	8.8 ± 4.3	15,725 ± 6,646

Table 2: Statistical results of the mixed-effects models in normal driving segments.

Dependent	Independent	F (NumDF, DenDF)	p-value
MeanTHW	HMI	$F(3, 1564.5) = 75.43$	$< .0001$
	Style	$F(2, 21.2) = 1.38$	.3
	HMI × Style	$F(6, 1564.4) = 5.99$	$< .0001$
SV	HMI	$F(3, 1567.3) = 15.11$	$< .0001$
	Style	$F(2, 22.6) = 3.64$	.04
	HMI × Style	$F(6, 1567.1) = 2.36$	.03

Table 3: Statistical results of the mixed-effects models in braking segments.

Dependent	Independent	F (NumDF, DenDF)	p-value
MaxInvTTC	HMI	$F(3, 1260.11) = 4.39$	.004
	Style	$F(2, 24.14) = 3.29$	.054
	HMI × Style	$F(6, 1257.30) = 2.85$	.009
RT	HMI	$F(3, 156.79) = 10.52$	$< .0001$
	Style	$F(2, 156.65) = 1.68$	.2
	HMI × Style	$F(6, 156.39) = 0.21$	.9

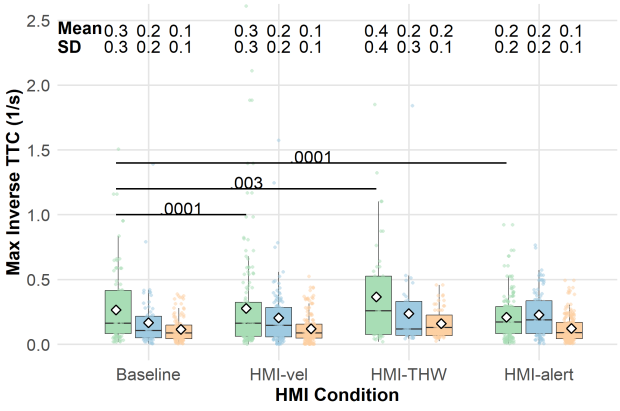


Figure 5: Boxplot of Max Inverse TTC (s^{-1}) in braking segments.

95% CI [0.46, 1.30], $t(156) = 4.15$, $p = .0003$). Additionally, HMI-alert led to a significantly longer RT than both HMI-THW ($\Delta = 0.48$, 95% CI [0.06, 0.90], $t(141) = 2.14$, $p = .04$) and HMI-vel ($\Delta = 0.97$, 95% CI [0.65, 1.30], $t(156) = 5.26$, $p < .0001$). No other pairwise contrasts were statistically significant ($p > .05$).

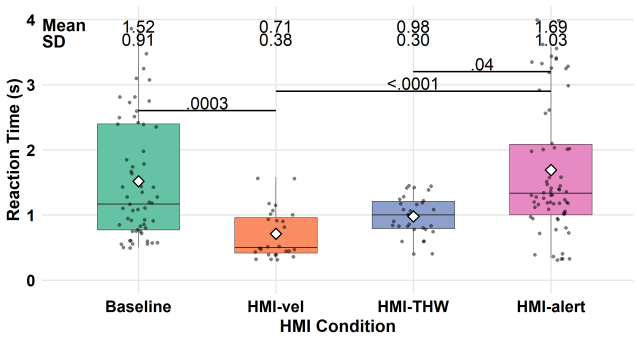


Figure 6: Boxplot of RT (s) in braking segments.

5 Discussion

In-vehicle HMIs that enhance drivers' perception of LVs have been proposed and validated in a simulator experiment, aiming to improve driving safety in CF events among drivers with different driving styles. Drivers' performance was evaluated in both normal driving segments without intensive braking events and normal driving segments with intensive braking events.

5.1 Behavior in Normal Driving Segments

First, we found that enhancing drivers' perception of LV states can, in general, improve the safety margin in normal CF segments without intensive braking events, as indicated by a larger MeanTHW. However, certain HMIs (including HMI-vel and HMI-THW) can worsen traffic stability, as indicated by greater speed variance.

Although some comparisons were non-significant, the overall benefits of HMIs for MeanTHW relative to the baseline are expected, as observed in previous studies that also provided LV-related information (e.g., [11, 14, 34]). When drivers are provided with explicit information about the LV's states, they can more quickly acquire the LV's states without waiting for the "looming effects" [25] to take effect. Specifically, with only looming effects, drivers can be aware of relative speed changes only when the change in visual angle exceeds 0.0275 rad/s [24], whereas HMIs can provide instant cues to such speed changes.

However, our research finds that how drivers use such cues is driver-dependent and the effects vary across drivers. All HMIs led to greater time headway for aggressive drivers (See Figure 3), with HMI-vel being the most prominent and HMI-THW the least effective. Similarly, the HMI-THW failed to increase the THW for conservative drivers, while the other two LV-related HMIs did. Finally, only the HMI-vel increased the THW compared to the baseline. The different effects of the HMI-alert are surprising but explainable. It is possible that the alerts in the HMI have corrected

the aggressive drivers' original close-following habits by explicitly informing them of the risk levels, whereas the conservative drivers were already aware of the close-following headway, even without the alerts. Finally, it is also interesting that, although the HMI-THW yielded a larger THW than the baseline, it yielded the smallest THW among the three HMIs, statistically for both conservative and aggressive drivers and descriptively for moderate drivers. It is possible that drivers could estimate THW based on the speed difference in the HMI or the front view; thus, HMI-THW may not have provided additional valuable information to drivers, but it further loaded drivers compared to HMI-vel.

In addition to their effects on THW, HMIs also affected SV differently across driver groups. Specifically, HMI-THW significantly increased the variation in speed among aggressive and moderate drivers. In contrast, HMI-alert resulted in relatively lower SV. The increase in SV under the HMI-THW condition may be attributed to continuous feedback, which likely encouraged frequent corrective adjustments. Drivers may have attempted to maintain a specific headway value, leading to repeated minor accelerations and decelerations. In contrast, the event-based nature of HMI-alert provided intermittent warnings only when necessary, reducing unnecessary control corrections and resulting in lower speed variability. However, such an effect is not evident among conservative drivers, as they may drive less aggressively when following the LV even without additional supports [23].

5.2 Behavior in Braking Segments

To further evaluate the safety impact of the HMIs, we evaluated the safety-related metrics during the braking events. We found that HMI-vel significantly reduced RT compared to baseline and other HMIs, while HMI-THW and HMI-alert failed to reduce RT relative to the baseline. It is likely that directly showing LV speed variation can make drivers more aware of LV deceleration and thus facilitate quicker responses. In contrast, the HMI-alert yielded the slowest RT among all HMIs, yet still led to the least crash risk (as indicated by the smallest MaxInvTTC). A similar phenomenon has been observed in research targeting TORs in vehicles with ADAS. For example, [16] found that when TORs were provided, drivers exhibited a slower takeover action compared to the conditions where the TORs were absent. It is possible that drivers would wait until an action becomes very necessary (i.e., the red icon appears in the HMI-alert condition in our experiment). However, it should be noted that a faster RT does not necessarily mean better performance, as frequent but unnecessary brake actions may increase the chance of being rear-ended [21] and negatively affect traffic efficiency [32].

At the same time, we found that the HMIs had different effects on TTC in different user groups. Only conservative drivers showed safety improvements (as indicated by a smaller MaxInvTTC) with the HMI-alert compared to baseline. However, no significant safety benefits were observed for moderate or aggressive drivers. It is possible that moderate and aggressive drivers in our experiment were more experienced (as indicated by larger annual mileage and longer driving experience) and thus were better at perceiving the LV states even without the support from the additional HMI [20]. Therefore, additional HMI information may provide limited incremental safety benefits for these drivers. Among the conservative drivers, the HMI-Vel and HMI-THW even increased the crash risk relative to the baseline. It is possible that the additional information allowed drivers to notice the LV speed reduction earlier (as indicated by smaller RTs compared to the HMI-alert or baseline), yet failed to prompt appropriate actions. This is especially the case for the conservative drivers, given their relatively less experience compared to the moderate and aggressive drivers.

Limitations

This study has several limitations. First, although driving simulators provide effective experimental control, future studies should validate the findings using naturalistic driving data or field experiments. Second, the participant demographics may not fully represent the broader driver population, limiting generalizability. Third, this study only considered clear weather and highway scenarios; future work should examine more complex conditions, such as adverse weather and urban environments. Finally, the effects of different HMI presentation methods (e.g., visual encoding and auditory cues) remain unexplored.

6 Conclusions

This study investigated the effects of progressive LV information on CF behavior of drivers with different driving styles. The results indicate that HMI effectiveness can be moderated by both information richness and driver characteristics.

First, safety benefits of HMIs during emergencies were driver-dependent. For example, conservative (less experienced) drivers gained safety improvements only with HMI-alert, while HMI-vel and HMI-THW might increase their crash risk by triggering early but potentially inappropriate braking; more experienced (moderate/aggressive) drivers derived little added benefit, likely due to existing perceptual competence.

Second, enhanced perception of LV states via HMIs generally improved THW (safety margin) in normal CF segments, but effects varied by driving style. For example, aggressive drivers benefited most from velocity-based HMIs (HMI-vel) and conservative drivers showed limited response to THW-based displays (HMI-THW). Thus, personalization of LV perception enhancement is necessary.

Finally, certain HMIs can negatively impact traffic stability by increasing SV. Particularly, HMI-THW led to frequent speed adjustments among aggressive and moderate drivers; in contrast, event-based alerts (HMI-alert) reduced unnecessary control actions and yielded lower speed variance. Thus, the impact of the LV perception enhancement HMIs on traffic stability should also be evaluated in future research.

Overall, the study highlights that HMI design should consider driver heterogeneity, and adaptive, style-aware LV-related in-vehicle interaction systems should be evaluated from both safety and traffic flow stability perspectives.

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