

14 **ABSTRACT**

15 Rear-end collisions constitute a large portion of crashes on the road, and they are closely related
16 to drivers' car-following (CF) behaviors. An increasing number of studies show that drivers would
17 pursue beyond-visual-range (BVR) information in CF events. However, a few studies have
18 investigated the visualization of BVR information to support CF behaviors. Thus, four human-
19 machine interfaces (HMIs) providing different BVR information in CF events were designed,
20 including Brake-HMI showing brake action of indirect leading vehicles, Distance-HMI and
21 Headway-HMI showing the relative distance and time headway between the indirect leading
22 vehicle and direct leading vehicle, respectively, and Video-HMI showing the live-stream video of
23 the indirect leading vehicle from the perspective of the direct leading vehicle. A driving simulator
24 study with 40 participants was conducted to evaluate the impact of BVR-based HMIs on CF
25 performance. We found that BVR information could improve CF safety by enabling quicker brake
26 responses and increasing time headway and time-to-collision in brake events, without overloading
27 drivers and impairing their gaze dispersion. The Brake-HMI yielded the safest performance in
28 chain brake events, whereas Video-HMI increased attentional demands without observable
29 benefits. The Brake-HMI also achieved the highest perceived usability and learnability, and none
30 of the HMIs increased subjective mental workload. This research provides insights into the design
31 of V2V-based BVR information visualization to enhance safety in CF events.

32
33 **Keywords:** human-machine-interface, driver behavior, car-following, V2V communication,
34 Beyond-Visual-Range information.

35

36 1 INTRODUCTION

37 According to a statistical report published by the National Safety Council in the United States,
38 rear-end collisions accounted for approximately 28.85% of all reported road incidents in 2023
39 (National Safety Council, 2023). Such collisions commonly result in injuries, particularly
40 whiplash-associated disorders, as well as significant economic losses and property damage (Avery
41 & Weekes, 2009; Siegmund et al., 2009). To reduce the chance of rear-end collisions, previous
42 research has tried to enhance drivers' perception of surrounding vehicles (e.g., the direct leading
43 vehicle) in car-following (CF) events. This type of information can be ad-hoc, such as forward
44 collision warnings (Adell et al., 2011) that are provided only when a critical event (i.e., small time
45 to collision) occurs. More recent studies have been conducted to explore the possibility of
46 providing drivers with proactive information in the CF events. For example, in a driving simulation
47 experiment, Ali et al. (2020) found that drivers maintained a longer headway to the direct leading
48 vehicle when a tailgate warning was provided. In another on-road study, Adell et al. (2011) found
49 that safe speed and safe distance reminders can also increase headway in CF events. In addition to
50 the basic safety messages (Liu & Khattak, 2016), Zheng et al. (2023) found that the speed
51 information of the direct leading vehicle can reduce the drivers' response time to the speed change,
52 resulting in an increase in the minimum time-to-collision (TTC) when the leading vehicle slowed
53 down.

54 However, the information provided in the above-mentioned studies was all about the road
55 agents within the visual range of the ego driver. In recent years, more and more evidence shows
56 that drivers not only rely on information within the visual range (e.g., states of the nearby or direct
57 leading vehicle), but also actively sought for beyond-visual range (BVR) information to make
58 proactive decisions (He & Donmez, 2022; Stahl et al., 2019). **More specifically, the information**

59 asymmetry and delays in information transmission among road users have been found to contribute
60 to rear-end collisions (Huang et al., 2023; J. Wang et al., 2025) and phantom traffic jams (Chen et
61 al., 2025; Treiber et al., 2000; Wang et al., 2024).

62 The BVR information has been made possible in the transportation system thanks to
63 vehicle-to-vehicle (V2V) communication technologies (Jiang et al., 2025; Sun et al., 2018; Sun et
64 al., 2020; Xiao et al., 2023; Y. Yao et al., 2025; Yogha Bintoro et al., 2024). For example, the
65 perception module in intelligent vehicles can now dynamically identify vehicles and obstacles well
66 ahead of the traffic (Li et al., 2025; Shen et al., 2024; Sun et al., 2025; Y. Wang et al., 2025; Yao
67 et al., 2023; Zou et al., 2023). Also, vehicle positioning data can be transmitted through networks
68 and thus enable perception of congestion in global road networks (Gao et al., 2023; Yang et al.,
69 2025). Similarly, Sun et al. (2019) proposed a parked-vehicle-assistant to support information
70 sharing between vehicles with a high success rate and low time delay. However, to date, most of
71 the V2V information has been used to optimize driving automation systems (e.g., Samarakoon et
72 al., 2020). Given that human-driven vehicles may still dominate the market in the next decades
73 (Guo et al., 2021) and that rear-end collisions accounted for a large portion of collisions among
74 autonomous vehicles or vehicles with driving automation (Liu et al., 2024), it is necessary to
75 explore how to make better use of the V2V technologies to support human drivers before the fully
76 autonomous and connected vehicles saturate the market.

77 Regarding how BVR information may benefit drivers in CF scenarios, the research from
78 the human-automation interaction domain may provide some insights. For example, He et al. (2021)
79 found that providing traffic scenario information (i.e., showing the location of surrounding road
80 agents) based on V2V communication can facilitate drivers' earlier actions to potential traffic
81 hazards in vehicles with driving automation. In recent years, a small number of studies regarding

82 the use of BVR information have been conducted. For example, W. Ren et al. (2025) found that
83 the HMIs providing the sudden brake of the indirect leading vehicle can reduce crash risk on foggy
84 freeways. However, their investigation was limited to specific information visualization under a
85 single emergent scenario. In another study, Li et al. (2017) found that V2V-based warnings that
86 alert drivers of potential hazards in their vicinity can reduce the risk of crashing into the hazards
87 ahead. However, this study focused on the road agents in nearby areas in general instead of traffic
88 in the CF events. Our previous preliminary work also investigated whether providing braking
89 information of indirect leading vehicles (i.e., the vehicle ahead of the direct leading vehicle) can
90 facilitate safer CF behaviors in chain-braking events. Though only a video-based experiment was
91 conducted with five participants, we still observed a larger safety margin (as indicated by a larger
92 TTC and earlier brake responses) when indirect leading vehicle information was provided (Yan et
93 al., 2023), which provides evidence to support the role of the BVR information in CF events.
94 However, a limited number of participants were involved in the study, and we have only
95 investigated two types of information visualization – the symbolic one and the video-streaming
96 one, which provided limited information regarding how to design the V2V HMI to provide CF-
97 related BVR information.

98 As such, a driving simulation experiment was conducted to investigate how BVR
99 information provided through a connected driving environment can be used to support driver
100 behavior in CF events. Given that the perceiving and responding to traffic flow ahead are basic but
101 critical tasks in CF scenarios, and the state of the indirect leading vehicle can provide drivers with
102 imminent upcoming traffic disturbances, in this study, we focused on the BVR information of the
103 indirect leading vehicle. Specifically, on top of Yan et al. (2023), we considered both the normal
104 CF scenarios without emergent brakes (but with slight speed variations) and the chain brake

105 scenarios. This broader range of scenarios allows us to evaluate the BVR information
106 comprehensively in more realistic scenarios, i.e., the BVR information should not just support
107 drivers in critical braking events but should also not impair driving performance in normal driving
108 scenarios. Further, given that the driving task is already mentally demanding (Salmon et al., 2005),
109 this study investigates whether providing additional BVR information would further overload the
110 drivers, and how the indirect leading vehicle-related BVR information can be more effectively
111 presented. To this end, we explored different types of BVR information in the experiment, along
112 with different ways of visualization, including brake actions of the indirect leading vehicle, the
113 distance gap between the direct lead vehicle (direct leading vehicle) and indirect leading vehicle,
114 the collision risk between these vehicles (as materialized by time headway), and the live video
115 stream from the perspective of the direct leading vehicle. Given that the driving experience was
116 associated with crash rates (da Silva et al., 2012; McCartt et al., 2003; Mullin et al., 2000), forty
117 participants with diverse driving experience were recruited.

118 2 METHOD

119 2.1 Participants

120 A total of 40 gender-balanced participants with valid driver's licenses completed the experiment.
121 Participants had an average age of 27 years old (min: 20, max: 44, SD = 5.9). Half of the
122 participants (10 males and 10 females) were classified as experienced drivers, having held their
123 licenses for over 5 years and driven more than 15,000 kilometers in the past year. The remaining
124 participants (10 males and 10 females) were novice drivers who had first obtained their licenses in
125 the past year and had accumulated less than 5,000 kilometers of driving experience since licensure
126 (i.e., in the past year). The study received ethical approval from the Human and Artefacts Research

127 Ethics Committee at the Hong Kong University of Science and Technology (Guangzhou) (protocol
128 number: HREP-2024-0026).

129 **2.2 Apparatus**

130 The experiment was conducted using a fixed-based driving simulator by Info Tech, China (Figure
131 1). Driving scenarios were developed using SILAB 7.1 software (WIVW GmbH, Germany) and
132 projected onto three 43-inch displays, each positioned around one meter away from the driver.
133 Each display had a resolution of 1920*1080, providing a horizontal viewing angle of 150° and a
134 vertical viewing angle of 47°. The driving data was continuously logged at a frequency of 60 Hz
135 within the simulation software. Additionally, during the experiment, participants' eye movement
136 data was recorded at 100 Hz using a remote 4-camera tracking system (Smart Eye Pro) running
137 Smart Eye Pro 10.2. **After each calibration, the inherent validation was performed. Calibration was**
138 **accepted only if the gaze point error was $\leq 0.2^\circ$, which met the system's guideline.** With the
139 calibration, the system could reach 0.5° gaze tracking accuracy, +/-5mm head position tracking
140 accuracy, 1.5° head rotation accuracy (Smart Eye, 2025). As a result, our eye tracking data had an
141 average quality of 0.99 (min: 0.20, max: 1, SD = 0.07, where 1.0 indicates a high confidence and
142 0.0 indicates no confidence) (Smart Eye, 2025). All data streams were synchronized using local
143 timestamps with a millisecond alignment.

144



145

146

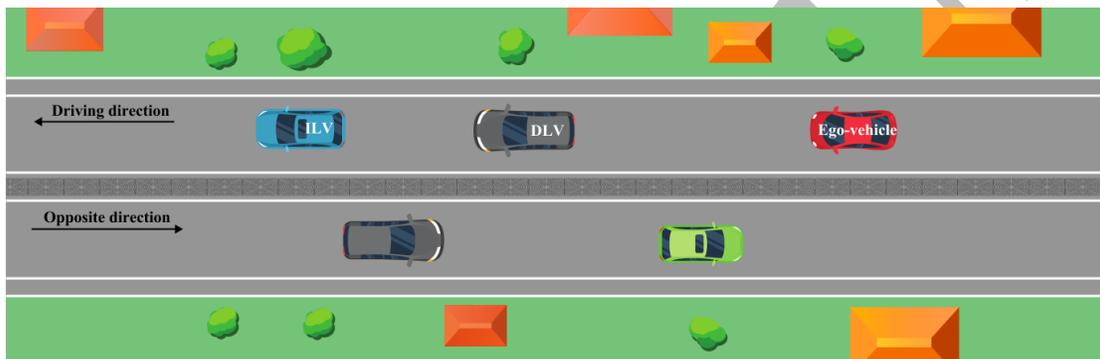
Figure 1. The apparatus used in this study.

147 2.3 HMI Design for BVR Information

148 In this study, we mainly considered the BVR information regarding the relationships between the
149 direct leading vehicle and the indirect leading vehicle, as illustrated in Figure 2. In total, four
150 different types of BVR information were presented to the drivers: (1) the braking behavior of the
151 indirect leading vehicle, (2) the bumper-to-bumper distance between the direct leading vehicle and
152 indirect leading vehicle, (3) the risk of rear-end collision, as represented by the time headway
153 between the direct leading vehicle and the indirect leading vehicle, (4) the live-stream video
154 captured from the perspective of direct leading vehicle. We visualized the information following
155 Jakob Nielsen's 10 general principles (Nielsen, 1994). All HMI was presented on the bottom of
156 the windshield, simulating the location of the head-up display (HUD).

157 We hypothesized that the BVR information would improve CF safety in general, as
158 reflected by minimum time-to-collision (minTTC) and minimum time headway (minTHW).
159 Specifically, the Brake-HMI was expected to reduce response time by enabling earlier detection

160 of the brake of the indirect leading vehicle. The **Distance-HMI** was expected to support safer CF
161 behaviors by improving drivers' perception of inter-vehicle spacing. The **Headway-HMI** was
162 designed to communicate rear-end collision risk and was expected to help drivers avoid critically
163 short headways, as well as maintain safer headways during normal conditions (i.e., CF without
164 braking events). The **Video-HMI** was expected to enhance situational awareness of upstream
165 traffic conditions and thereby mitigate abrupt or delayed responses. The details of the four design
166 concepts are as follows (see Table 1):
167



168
169 Figure 2. CF event in the experiment.

170
171 **Brake-HMI:** The brake of the indirect leading vehicle was represented by brake light icons. Once
172 the indirect leading vehicle brakes, the circles become red.

173 **Distance-HMI:** To represent the bumper-to-bumper distance between the direct leading vehicle
174 and indirect leading vehicle, two vehicle icons were used, with the space between them
175 representing the actual distance between the direct leading vehicle and indirect leading vehicle. As
176 the distance increased, the distance between the icons increased, and vice versa. Similarly, the
177 circle on the tail of the indirect leading vehicle icon would represent the indirect leading vehicle
178 braking states.

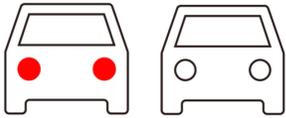
179 **Headway-HMI:** The risk of a rear-end collision between the direct leading vehicle and indirect
180 leading vehicle was quantified using time headway. When the time headway increased, the vehicle
181 icon would become larger and vice versa. Further, a dashed-line circle indicated the 2-second time
182 headway threshold, which has been widely recommended for safe CF behaviors (Lewis-Evans et
183 al., 2010). If the vehicle icon exceeded the circle, it signified a high-risk situation, and vice versa.
184 Similar to the Brake-HMI and the Distance-HMI, when the indirect leading vehicle braked, the
185 brake light icons would become red, informing brake of the indirect leading vehicle.

186 **Video-HMI:** The live video stream of the indirect leading vehicle shows the real-time video
187 captured from the perspective of the direct leading vehicle.

188 The BVR information presented in the above HMIs can be enabled by V2V communication
189 technologies and the perception capability of driving automation. Specifically, brake information
190 of the indirect leading vehicle can be obtained from the brake sensor and transmitted to the
191 following vehicle via V2V communication. The Distance-HMI and Headway-HMI can be realized
192 through GPS information of the two leading vehicles or through the perception module of the
193 driving automation. The Video-HMI can be realized through a front-view camera installed on the
194 direct leading vehicle, providing real-time video of the indirect leading vehicle.

195
196

197 Table 1. Four HMI concepts.

Type of HMI	HMI Visualization	HMI displayed in the simulator	Parameters
Brake-HMI			Angular size: 7.0°× 5.6° Color: #EC1010, #000000 Position (px): (836, 699)
Distance-HMI			Angular size: 17.2°× 4.8°; Color: #EC1010, #000000 Position (px): (750, 702)
Headway-HMI			Angular size: 7.1°× 6.0°; Color: #EC1010, #000000, #008CFF Position (px): (844, 704)
Video-HMI			Angular size: 14.0°× 4.6° Color: N/A Position (px): (729, 723)

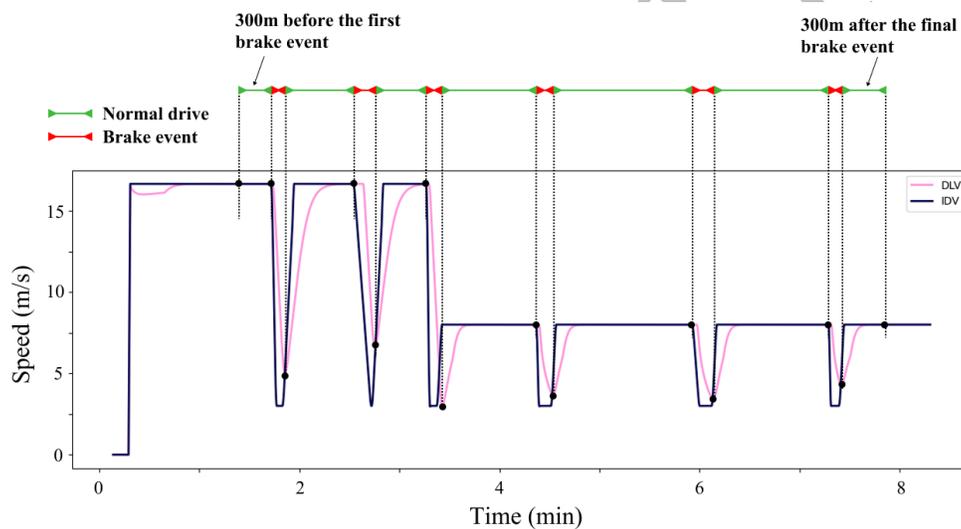
198 *Note:* Angular size was expressed as horizontal × vertical visual angle (degrees); pixel coordinates were given as (x,
199 y) and referred to the top-left corner of the icon, with the origin located at the top-left corner of the central display,
200 which was with the size 0.496 mm/px; N/A indicated that the parameter was not independently manipulated.

201

202 2.4 Driving Tasks

203 In the experiment, drivers were required to follow the traffic on a two-lane suburban road on a
204 sunny day, with a speed limit of 60km/h. The ego vehicle followed a direct leading vehicle, which
205 further followed the indirect leading vehicle in the scenario. At the start of the drive, the two

206 leading vehicles drove at the same speed. In each drive, indirect leading vehicle braked six times,
 207 with three different rates of deceleration (-1.3m/s^2 , -5m/s^2 and -9.6m/s^2) and two initial speeds
 208 before brakes (16m/s and 8m/s). In each brake event, the indirect leading vehicle decelerated to
 209 3m/s and kept driving at the speed for 5 to 20 seconds, then accelerated to its initial speed at 2m/s^2 .
 210 Figure 3 illustrates the speed profiles of the indirect leading vehicle and direct leading vehicle
 211 throughout an example drive. The behavior of the direct leading vehicle followed the Intelligent
 212 Driver Model (IDM, (Treiber et al., 2000)). During the experiment, participants were instructed to
 213 drive safely, adhere to traffic regulations, and avoid rear-end collisions, similar to the scenario
 214 when they follow a friend's car to an unknown destination (Zhao et al., 2024).



215
 216 Figure 3. Speed profile of the indirect leading vehicle and direct leading vehicle in an example
 217 drive with periods of interest marked. Note that the order of the speed and the intensity of the
 218 braking action was shuffled in the actual experiment.

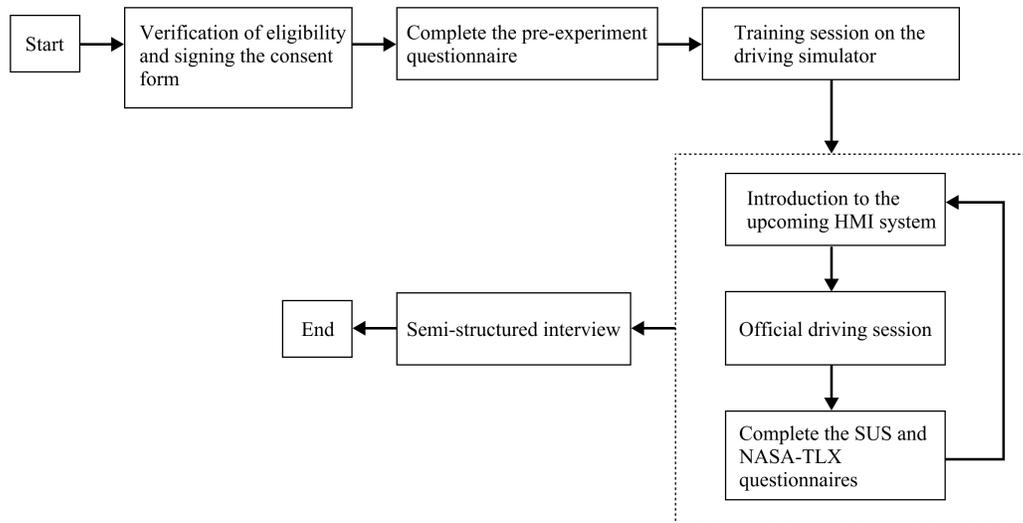
219 2.5 Experiment Design

220 A mixed experiment design was used in this study. The within-subject factors included the HMI
 221 design (i.e., a baseline and four HMIs), the initial speed of indirect leading vehicle (8m/s and

222 16m/s), chosen to represent typical congested and normal urban driving speeds (Ahmed et al.,
223 2025), and deceleration rate of the indirect leading vehicle (-1.3m/s^2 , -5m/s^2 and -9.6m/s^2), chosen
224 to reflect mild, moderate, and intensive braking, in consistent with Ali et al. (2020). The between-
225 subject factor was driving experience (novice vs. experienced drivers). The order of the HMI
226 design was counterbalanced across the 40 participants in a Latin Square design. Each participant
227 completed five drives, four with the HMI designs and one baseline drive. The baseline drive was
228 a normal drive without any HMI in the HUD area (where the BVR information was provided in
229 other experimental conditions). The order of speed and deceleration rate was shuffled across the
230 five drives, leading to five distinct drives in terms of the speed profile of the indirect leading
231 vehicle to reduce the learning effect. Each participant experienced the same five drives with the
232 same order of speed profiles but with different HMI designs. We collected data from 200 drives
233 (40 participants * 5 conditions) and 1200 braking events in total.

234 **2.6 Procedures**

235 As shown in Figure 4, upon arrival, participants' eligibility was verified based on years of licensure
236 and driving mileage over the past year, and written informed consent was obtained. Then, they
237 completed a pre-experiment questionnaire, collecting their demographic information. Participants
238 then underwent training with the driving simulator. They first received verbal instructions,
239 followed by a practice drive without the HUD to familiarize themselves with the simulator
240 environment. The elements of the driving scenario in the training session (including the road type
241 and the traffic conditions) were the same as those in the experimental drives, but without leading
242 vehicle. After finishing the training drive, the experimenter conducted the eye tracker calibration,
243 following the procedures provided by the Smart Eye (Smart Eye, 2025).



A total of 5 drives including four HMI-assisted drives and one baseline drive; in the baseline drive, the introduction and SUS questionnaire were skipped.

244

245

Figure 4. Flow diagram of experiment procedure.

246

247

248

249

250

251

252

253

254

Then, the formal experiment started, which included five experimental drives. Before each drive with the designed HMIs, the HMI design was explained to the participants verbally with a pre-recorded 30-second video showing the animation of the HMI. After the explanation, the experimenter asked the participants to explain the HMI design back to the experimenter to make sure they had fully understood it. After each experimental drive, a post-experiment questionnaire was administered, measuring participants' workload in the previous drive (measured by NASA-Task Load Index (Hart & Staveland, 1988)) and perceived usability of the HMI (measured by System Usability Scale (SUS) (Brooke, 1996)). Finally, at the end of the experiment, we asked an open question seeking any comments regarding the HMI designs in the experiment.

255

3 DATA ANALYSIS

256

257

We first focused on driving performance data to evaluate the effect of HMI on drivers' CF behaviors. Further, we evaluated drivers' eye-tracking data given that HMIs may affect drivers'

258 attention allocation strategies. Finally, to evaluate the usability of the HMI designs, we compared
 259 drivers' workload and perceived usability of the HMI designs when using different HMIs.

260 At the same time, as shown in Figure 3, to comprehensively evaluate the impact of HMI
 261 on drivers' behaviors, we focused on two periods of interest in the experiment, i.e., the brake events
 262 (from indirect leading vehicle brake onset to the direct leading vehicle stopping braking) and the
 263 normal drive (drive sections outside of brake sections). All driving performance metrics were
 264 extracted from one or both sections, as detailed in Table 2.

265 3.1 Driving Performance Data

266 In this study, as shown in Table 2, we adopted four driving-performance-related metrics. It should
 267 be noted that, for the response time, a total of 14 response times smaller than 0.1 s or larger than 5
 268 s were discarded from the data analysis, as such response time was considered irrelevant to the
 269 stimuli (i.e., the brake of the indirect leading vehicle) (Zheng et al., 2023).

270
 271 Table 2. Driving performance metrics, their definitions and data extraction sections.

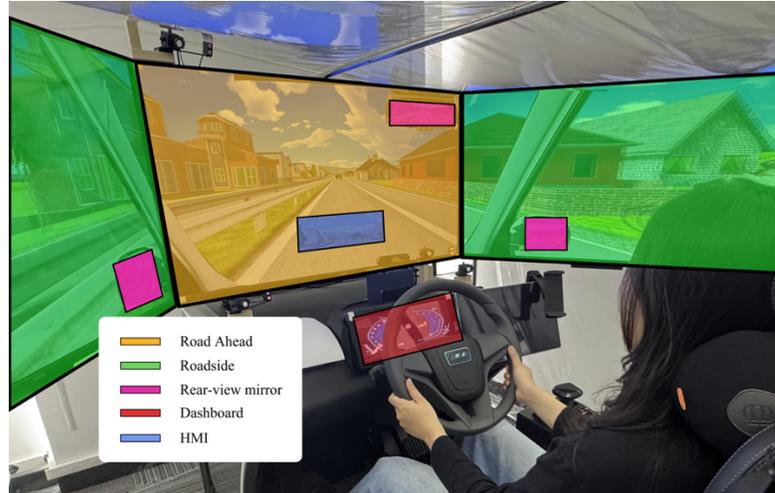
Metric (Abbreviation)	Definitions (Unit)	Periods of interest
Response time	The brake time difference between indirect leading vehicle and the ego-vehicle (ms).	Brake event
Minimum time headway (MinTHW)	The minimum elapsed time during braking events between the front of the direct leading vehicle and the front of the ego-vehicle passing the same fixed point on the roadway (s).	Brake event
Minimum time-to-collision (MinTTC)	The time required for ego-vehicle to collide with direct leading vehicle if they continue at their current speeds and on the same path in the current lane (s).	Brake event

Average time headway (MeanTHW)	The mean elapsed time during braking events between the front of the direct leading vehicle and the front of the ego-vehicle passing the same fixed point on the roadway (s).	Normal drive
Maximum deceleration rate	The maximum deceleration rate of ego-vehicle in brake events (m ² /s).	Brake event
Root mean square jerk (RMS jerk)	RMS jerk of the ego-vehicle in braking events (m/s ³), where a is the acceleration of the ego-vehicle, t is the time and n is the number of samples.	Brake event

$$RMS\ jerk = \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\frac{da}{dt}\right)_i^2}$$

272 3.2 Eye-Tracking Metrics

273 The eye-tracking data was recorded using Smart Eye Pro 10.2. In this study, eye movement data
 274 was analyzed during the normal drive in order to understand the impact of the additional
 275 information provided by the HMI on drivers' visual attention allocation. Inspired by Ezzati Amini
 276 et al. (2023), as shown in Figure 5, we defined five areas of interest (AOI) for the analysis of eye-
 277 tracking metrics, including road ahead (excluding the HMI area), roadside, rear-view mirror,
 278 dashboard and HMI.



279

280

Figure 5. Demonstration of AOIs.

281

282

283

284

285

286

287

288

289

290

291

292

293

294

295

For the eye-tracking measures, we followed the ISO 15007–1:2013(E) standard to process and extract the corresponding metrics. Specifically, each glance was defined as the moment the gaze shifted toward an AOI until it started to move away from it. For the glances towards the HMI area in the baseline drive, we calculated glances toward the same area of interest where the BVR information was provided in other experimental drives, even though no HMI was present in the baseline, to enable a direct comparison of visual attention patterns between the baseline and the drives with HMIs. Following Crundall and Underwood (2011), glances smaller than 100ms were excluded from analysis. Based on the data collected by the eye tracker, we calculated the percent of time looking at the specific AOI during normal drive sections to understand the distribution of visual attention across different AOIs when different HMIs were provided. The mean glance durations on the HMI areas were also analyzed in order to evaluate the potential distracting effect of HMIs, as long off-road glances can increase the crash risks (Horrey & Wickens, 2007). Besides, we also extracted gaze-related metrics, including the vertical and horizontal gaze dispersion, to compare the ranges of visual attention when different HMIs were provided (Huang et al., 2024; Pillai et al., 2022).

296 3.3 Subjective Metrics

297 We followed the standard approach (Hart & Staveland, 1988) to calculate the weighted overall
298 workload of drivers throughout each drive, leading to 200 data points (40 participants * 5 drives).
299 As for the perceived usability of the HMIs, we followed the standard approach (Brooke, 1996) to
300 calculate the SUS score for each HMI, again, leading to 160 data points (40 participants * 4 drives
301 with HMI).

302 3.4 Independent Variables and Statistical Models

303 Two independent variables and their interaction effect were included in the model, i.e., driving
304 experience and HMI design. Different models were built to investigate whether the HMIs were
305 effective in different traffic conditions. Mixed-effects linear models were fitted using the *lme4*
306 version 1.1.35 (Bates et al., 2015) in RStudio. Post-hoc comparisons were conducted for
307 significant main effects or interaction effects ($p < 0.05$), using Tukey's method to control for
308 multiple comparisons. When the residuals of the models violated the normality assumption
309 (including minTHW, minTTC, meanTHW, maximum deceleration rate, RMS jerk, percentage of
310 glance duration on HMI area, and mean glance duration on HMI area), robust mixed models were
311 built with the package *robustlmm* version 3.3.3 (Koller, 2016). As the package *robustlmm* does
312 not produce p -values for fixed effects, we used Wald χ^2 tests derived from the robust variance-
313 covariance matrix to obtain p -values for the fixed effects. Cohen's d was also reported as the effect
314 size, with $|d|$ values of 0.2, 0.5, and 0.8 as thresholds of small, medium, and large effect sizes,
315 respectively (Cohen, 1988).

316 **4 RESULTS**

317 **4.1 Driving Performance Metrics**

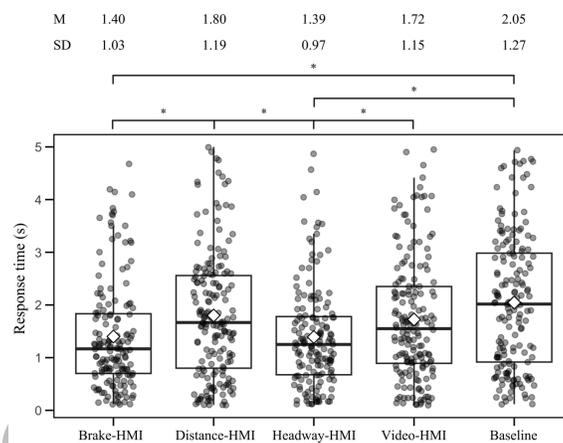
318 Table 3 summarizes the results regarding the influence of HMIs on the driving performance
 319 metrics.

320 Table 3. Results of driving performance metrics.

Dependent variables	Independent variables	F-value / Wald χ^2	p-value
Response time	HMI	F (4, 752) = 10.97	<.0001
	Driving experience	F (1, 37) = 0.09	.7
	HMI* Driving experience	F (4, 752) = 0.71	.6
MinTHW ^R	HMI	$\chi^2(4) = 15.79$.003
	Driving experience	$\chi^2(1) = 6.67$.009
	HMI* Driving experience	$\chi^2(4) = 8.04$.09
MinTTC ^R	HMI	$\chi^2(4) = 12.52$.01
	Driving experience	$\chi^2(1) = 4.21$.04
	HMI* Driving experience	$\chi^2(4) = 0.29$.9
MeanTHW ^R	HMI	$\chi^2(4) = 2.08$.7
	Driving experience	$\chi^2(1) = 4.80$.03
	HMI* Driving experience	$\chi^2(4) = 2.17$.7
Maximum deceleration rate ^R	HMI	$\chi^2(4) = 6.73$.2
	Driving experience	$\chi^2(1) = 1.39$.2
	HMI* Driving experience	$\chi^2(4) = 4.62$.3
RMS jerk ^R	HMI	$\chi^2(4) = 2.71$.6
	Driving experience	$\chi^2(1) = 0.72$.4
	HMI* Driving experience	$\chi^2(4) = 6.75$.1

321 *Note:* In this table and the following tables, the significant main or interaction effects are bolded in the table; in this
 322 and the following tables, the superscript R indicates that a robust mixed model was built for the dependent variable.

323 **Response time:** As shown in Table 3 and Figure 6, HMIs were found to have a significant effect
 324 on response time. The Brake-HMI led to a smaller response time compared to the baseline, with
 325 an estimated difference (Δ) of -0.65 seconds (s), 95% confidence interval (95%CI) of [-0.99, -
 326 0.31], $t(793) = -5.25, p < .0001, d = -0.83$. At the same time, Headway-HMI led to a 0.66s shorter
 327 response time compared to the baseline (95%CI: [0.33, 1.00], $t(789) = 5.38, p < .0001, d = 0.85$),
 328 a 0.42s shorter response time compared to the Distance-HMI (95%CI: [0.08, 0.75], $t(787) = 3.42,$
 329 $p = .006, d = 0.54$) and a 0.34s shorter response time compared to the Video-HMI (95%CI: [0.004,
 330 0.67], $t(787) = 2.77, p = .046, d = 0.44$). Finally, the Brake-HMI yielded a 0.41s shorter response
 331 time than the Distance-HMI (95%CI: [0.07, 0.74], $t(788) = 3.31, p = .009, d = 0.52$).



332
 333 Figure 6. Post hoc comparisons of the effects of HMIs on response time. In this figure and the
 334 following figures, significant post-hoc comparisons ($p < 0.05$) are marked with “*”; the boxplot
 335 represents the 1st quantile, median, and 3rd quantile; the white squares are the mean of the
 336 group; M stands for mean, and SD stands for standard deviation.

337
 338 **MinTHW:** As shown in Figure 7(a), in brake events, we observed significant effects of the HMI
 339 and the driving experience on minTHW. When provided with the Brake-HMI and Headway-HMI,
 340 the minTHW was 0.75s (95%CI: [0.18, 1.33], $z = 3.558, p = .003, d = 0.78$), and 0.50s (95%CI:

341 [0.11, 0.88], $z = 3.54$, $p = .004$, $d = 0.52$) higher than baseline, respectively. At the same time,
342 when provided with the Distance-HMI and Video-HMI, the minTHW was 0.39s (95%CI: [0.07,
343 0.71], $z = 3.32$, $p = .008$, $d = 0.40$), and 0.72s (95%CI: [0.25, 1.19], $z = 4.14$, $p = .0003$, $d = 0.75$)
344 lower than Brake-HMI, respectively. Finally, Video-HMI yielded a 0.46s (95%CI: [0.15, 0.78], z
345 = 4.02, $p = .0006$, $d = 0.49$) lower minTHW than Headway-HMI. There was no significant
346 difference between novice drivers and experienced drivers.

347
348 **MinTTC:** As shown in Figure 7(b), in brake events, when provided with Brake-HMI, Distance-
349 HMI, and THW-HMI, the minTTC was 3.07s (95%CI: [1.19, 4.94], $z = 4.45$, $p < .0001$, $d = 0.59$),
350 2.48s (95%CI: [0.75, 4.21], $z = 3.91$, $p = .0001$, $d = 0.48$), and 2.19s (95%CI: [0.57, 3.81], $z =$
351 3.68 , $p = .002$, $d = 0.42$) higher than that of baseline, respectively. At the same time, when provided
352 with Brake -HMI and Distance-HMI, minTTC was 2.42s (95%CI: [0.70, 4.15], $z = 3.83$, $p = .001$,
353 $d = 0.47$) and 1.84s (95%CI: [0.23, 3.45], $z = 3.11$, $p = .02$, $d = 0.35$) higher than that of Video-
354 HMI, respectively. As shown in Figure 7(c), the minTTC of novice driver was 2.52s ((95% CI:
355 [0.28, 4.76], $z = 2.21$, $p = .03$, $d = 0.49$)) lower than experienced driver.

356

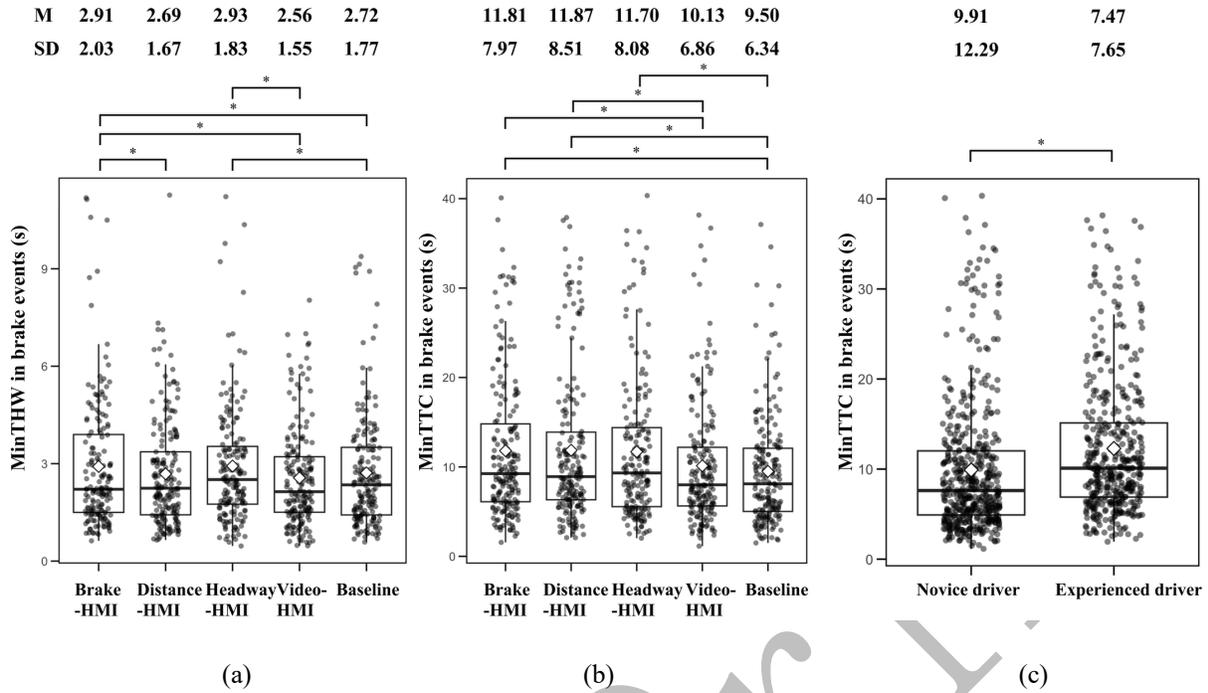
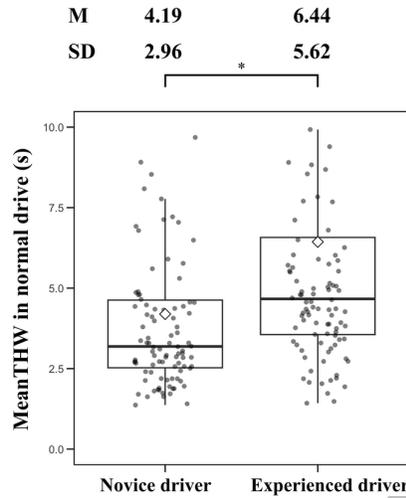


Figure 7. Post hoc comparisons: (a) the effect of HMI on minTHW; (b) the effect of HMI on minTTC; (c) the effect of driving experience on minTTC.

MeanTHW: As shown in Figure 8 and Table 3, in normal drive sections, only a significant driving experience effect was observed. For novice drivers, meanTHW was 1.21s (95%CI: [0.06, 2.37], $z = 2.06, p = .04, d = 1.21$) lower than that of experienced drivers.



366

367 Figure 8. Post hoc comparison of the effect of driving experience on meanTHW in normal drive.

368

369 **Maximum deceleration rate and Jerk: No significant results were observed ($p > .05$) for**

370 **maximum deceleration rate and RMS jerk.**

371 4.2 Eye-Tracking Metrics during Normal Drive Sections

372 Table 4 summarizes the results for the influence of HMIs on drivers' visual attention allocation
373 during normal drive sections.

374

375 Table 4. Results of eye-tracking metrics.

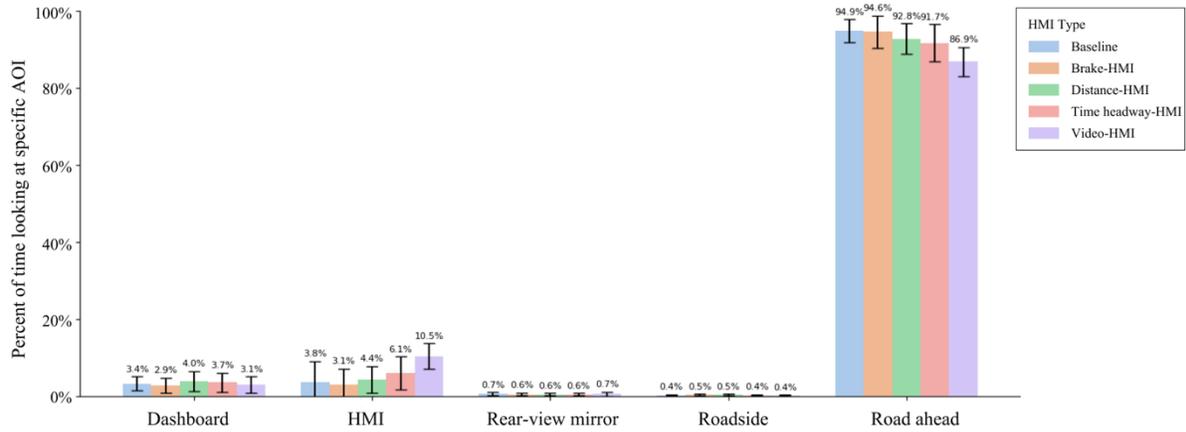
Dependent variables	Independent variables	F-value / Wald χ^2	p-value
Percent of time	HMI	$\chi^2(4) = 157.60$	<.0001
looking at HMI area ^R	Driving experience	$\chi^2(1) = 0.002$.9
	HMI* Driving experience	$\chi^2(4) = 2.30$.7
Percent of time	HMI	F (4, 180) = 0.91	.9
looking at dashboard	Driving experience	F (1, 25) = 1.25	.3
	HMI* Driving experience	F (4, 80) = 0.9	.9

Dependent variables	Independent variables	F-value / Wald χ^2	p-value
Percent of time	HMI	F (4, 143) = 4.72	.001
looking at road ahead	Driving experience	F (1, 37) = 0.02	.8
	HMI* Driving experience	F (4, 143) = 0.87	.4
Percent of time	HMI	F (4, 86) = 0.47	.8
looking at roadside	Driving experience	F (1, 28) = 1.20	.3
	HMI* Driving experience	F (4, 86) = 1.85	.1
Percent of time	HMI	F (4, 80) = 1.56	.2
looking at rear-view	Driving experience	F (1, 28) = 1.37	.2
mirrors	HMI* Driving experience	F (4, 80) = 0.84	.5
Mean duration of	HMI	$\chi^2(4) = 31.57$	<.0001
looking at HMI area ^R	Driving experience	$\chi^2(1) = 0.60$.4
	HMI* Driving experience	$\chi^2(4) = 7.88$.09
SD of horizontal gaze	HMI	F (4, 143) = 1.65	.2
	Driving experience	F (1, 37) = 0.66	.4
	HMI* Driving experience	F (4, 143) = 0.71	.6
SD of vertical gaze	HMI	F (4, 142) = 1.91	.1
	Driving experience	F (1, 37) = 3.79	.06
	HMI* Driving experience	F (4, 142) = 0.81	.5

376

377 **Percent of Time Looking at Different AOIs:** The HMI type significantly influenced the percent
378 of time looking at HMIs. Specifically, as shown in Figure 9, Figure 10, and Table 5, with Distance-
379 HMI, Headway-HMI, and Video-HMI, drivers spent a significantly larger percent of time looking
380 at the HMI area than the baseline, with the Video-HMI attracting most of the visual attention. No
381 significant difference in the time looking at HMIs between Brake-HMI and baseline.

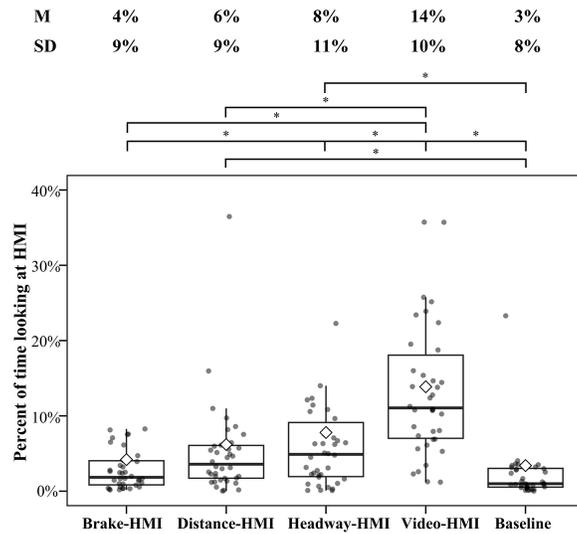
382



383

384

Figure 9. Percent of time looking at specific AOIs under different HMI conditions.



385

386

Figure 10. Post hoc comparison of the effect of HMI on percent of time looking at HMI area.

387

388

Table 5. Significant pairwise comparisons for the percent of time looking at the HMI area.

HMI condition	Δ (95%CI)	z-value	p-value	d
Brake-HMI over Headway-HMI	-3% (-4%, 1%)	z = -4.11	.0004	-0.97
Brake-HMI over Video-HMI	-8% (-7%, -10%)	z = -13.49	<.0001	-3.18
Distance-HMI over Video-HMI	-7% (-9%, -5%)	z = -11.11	<.0001	-2.63
Distance-HMI over Baseline	3% (1%, 3%)	z = -4.26	.0002	-1.03

HMI condition	Δ (95%CI)	z-value	p-value	d
Headway-HMI over Video-HMI	-6% (-8%, -4%)	z = -9.39	<.0001	-2.21
Headway-HMI over Baseline	4% (2%, 6%)	z = -6.04	<.0001	-1.45
Video-HMI over Baseline	10% (8%, 11%)	z = -15.28	<.0001	-3.66

389

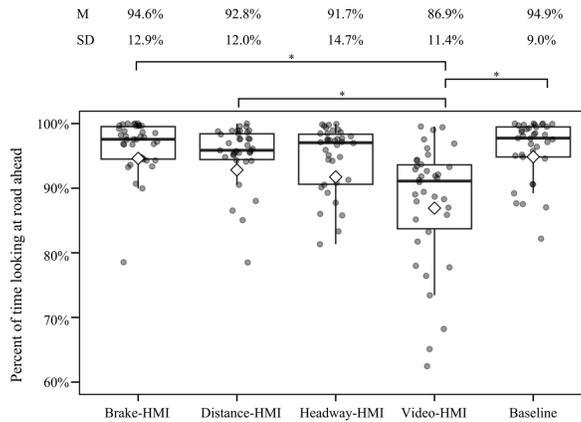
390

As shown in Figure 10 and Figure 11, Video-HMI led to a lower percent of time looking at the road ahead area compared to that of Brake-HMI ($\Delta = -9\%$, 95%CI: [-14%, -3%], $t(177) = -4.32$, $p = .0003$, $d = -0.68$), Distance-HMI ($\Delta = -7\%$, 95%CI: [-12%, -2%], $t(164) = -3.96$, $p = .001$, $d = -0.63$) and baseline ($\Delta = -9\%$, 95%CI: [-12%, -6%], $t(141) = -6.89$, $p < .001$, $d = -1.09$).

391

392

393



394

395

Figure 11. Post hoc comparison regarding the effect of HMI on the percent of time looking at road ahead area.

396

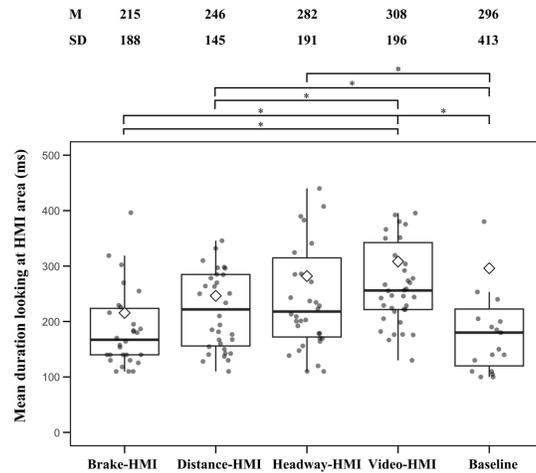
397

Mean Duration Looking at HMI: As shown in Figure 12 and Table 6, Video-HMI led to significantly longer mean duration looking at the HMI area than other HMIs and baseline.

398

399

Headway-HMI led to a longer mean duration than baseline.



400

401 Figure 12. Post hoc comparisons of the effect of HMI on mean duration looking at HMI area.

402

403 Table 6. Significant pairwise comparisons for mean duration looking at HMI area.

HMI condition	Δ (95%CI)	z-value	p-value	d
Brake-HMI over Headway-HMI	-48.32 (-95.85, -0.80)	$z = -2.77$.04	-0.73
Brake-HMI over Video-HMI	-80.53 (-127.56, -33.50)	$z = -4.67$	<.0001	-1.22
Distance-HMI over Video-HMI	-50.33 (-95.17, -5.49)	$z = -3.06$.02	-0.76
Distance-HMI over Baseline	62.44 (3.68, 121.20)	$z = 2.90$.03	0.95
Headway-HMI over Baseline	80.56 (22.74, 138.38)	$z = 3.80$.001	1.22
Video-HMI over Baseline	112.77 (56.68, 168.85)	$z = 5.48$	<.0001	1.71

404

405 **SD of Horizontal and Vertical Gaze:** No significant association was observed between HMI and
 406 SD of vertical and horizontal eye movements ($p > .05$).

407 **4.3 Mental Workload and Perceived Usability**

408 Table 7 summarizes the results of drivers' perceived usability, learnability of the HMIs and the
 409 corresponding workload.

410

411 Table 7. Statistical analysis results.

Dependent variables	Independent variables	F-value	p-value
Perceived usability	HMI	F (3, 114) = 3.44	.02
	Driving experience	F (1, 38) = 0.01	.9
	HMI* Driving experience	F (3, 114) = 1.01	.4
Perceived learnability	HMI	F (3, 114) = 4.09	.008
	Driving experience	F (1, 38) = 0.68	.4
	HMI* Driving experience	F (3, 114) = 10.31	.8
Mental workload	HMI	F (3, 158) = 0.51	.5
	Driving experience	F (1, 63) = 0.58	.8
	HMI* Driving experience	F (3, 158) = 0.73	.4

412

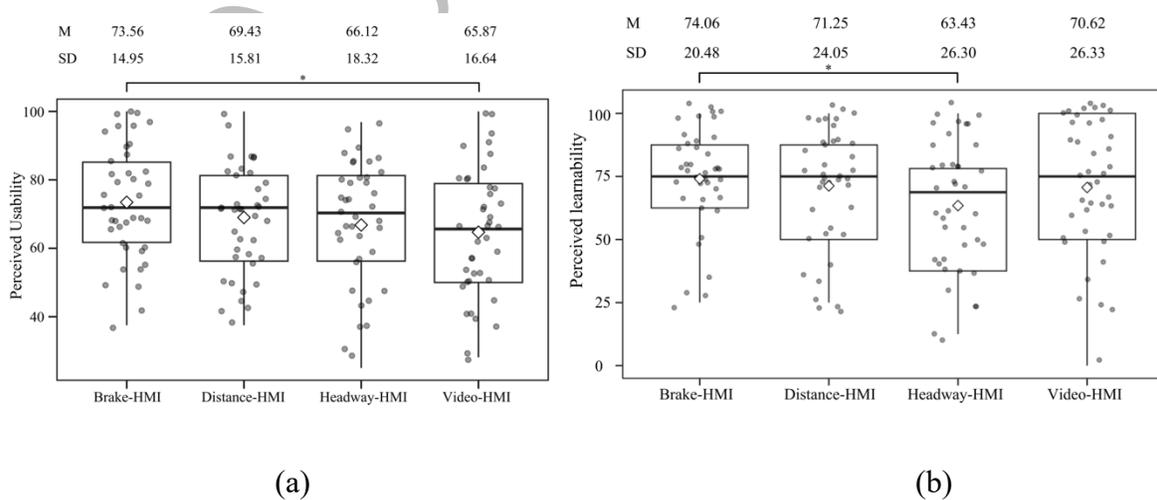
413 As shown in Table 7, neither HMI type nor driving experience affected mental workload ($p > .05$).

414 At the same time, as shown in Figure 13, Brake-HMI yielded higher perceived usability than

415 Video-HMI ($\Delta = 8.61$, 95%CI: [0.92, 16.31], $t(115) = 2.92$, $p = .02$, $d = 0.46$) and higher perceived

416 learnability than Headway-HMI ($\Delta = 10.62$, 95%CI: [4.40, 16.84], $t(114) = 3.38$, $p = .005$, $d =$

417 0.53). No other significant results were observed ($p > .05$).



418

419

420 Figure 13. Post hoc comparison of the perceived a) usability and b) learnability of HMIs.

421 **5 DISCUSSION**

422 A driving simulator study was conducted to explore the effect of BVR information on drivers'
423 performance in CF events. We evaluated participants' driving behavior, visual behavior, and
424 subjective attitudes when provided with different BVR-related HMIs.

425 **5.1 Effect of BVR Information on Driving Performance**

426 First, we did not observe the influence of HMI condition on the meanTHW in the drive sections
427 without braking events, which indicated that drivers' CF strategies may still be primarily based on
428 the relative motion between the ego-vehicle and the direct leading vehicle in normal driving.

429 However, we found that drivers in general exhibited safer driving behaviors without compromised
430 driving smoothness (as indicated by the maximum deceleration and jerk) in response to leading
431 vehicle chain braking events when supported by BVR information. Specifically, the Brake-HMI
432 and Headway-HMI led to a shorter response time than baseline, which was consistent with the idea
433 that making the indirect leading vehicle's braking perceivable can prompt earlier reactions. These

434 results echo the findings in Yan et al. (2023) who also found indirect leading vehicle braking
435 information can facilitate quicker responses to the brake of leading vehicles, providing further
436 empirical evidence that drivers would consider the surrounding information when following
437 leading vehicles, other than relative distance to the direct leading vehicle (Han et al., 2022).

438 However, neither Distance-HMI nor Video-HMI yielded shorter response times than the baseline.

439 It is possible that both Brake-HMI and Headway-HMI contained obvious information about the
440 brake signal of indirect leading vehicles (the red circles on the top of the vehicle icon), while the
441 indirect leading vehicle brake signals in Distance-HMI and Video-HMI were less obvious in the

442 HMI. Thus, future HMI design may need to explicitly convey BVR information with high salience
443 to support drivers' reactions. It should also be noted that such a shorter response time was also
444 associated with improved safety performance in the brake events. With quicker response time,
445 Brake-HMI and Headway-HMI led to a larger MinTHW in the braking events compared to the
446 baseline, and all HMIs except Video-HMI increased the MinTTC in the braking event.

447 Further, we did not observe the effects of Distance-HMI on the response time and minTHW,
448 but still observed a significant effect of Distance-HMI on minTTC. It is possible that the Distance-
449 HMI was intuitive and provided drivers with easy-to-perceive information regarding the relative
450 distance and speed between the indirect leading vehicle and the direct leading vehicle. Thus,
451 drivers might tend to brake until the distance or headway was short enough instead of braking once
452 the brake light of the indirect leading vehicle turned on, which facilitated a more appropriate time
453 of braking and thus led to improved minTTC, though without affecting response time and
454 minTHW. This may have also explained why only the Brake-HMI led to shorter minTTC
455 compared to Distance-HMI – drivers tended to brake anyway once they noticed the indirect leading
456 vehicle braking, if they did not have additional information to help them judge the level of
457 emergency in the event (as has been provided in Distance-HMI and Headway-HMI). However, it
458 should be noted that such a simple response to indirect leading vehicle braking may not always be
459 good, as it may potentially worsen the stability of the traffic flow and increase the fuel consumption
460 (Horn, 2013) if the braking is unnecessary (e.g., when the indirect leading vehicle is far away from
461 the direct leading vehicle). Therefore, future HMI designs for BVR information should be carefully
462 evaluated from more than safety-perspective of view.

463 Finally, it should be noted that the Video-HMI failed to exhibit any effects on the safety
464 metrics. It is possible that the drivers had difficulty judging the relative distance between the

465 indirect leading vehicle and the direct leading vehicle based on the visual angle of the direct leading
466 vehicle alone, especially when the direct leading vehicle was far away (Flannagan et al., 1997). It
467 is also possible that the Video-HMI is visually complex, even though it was potentially the most
468 informative among the four HMIs. Such complexity may have introduced visual clutter and
469 increased the cognitive effort required to extract task-relevant cues (e.g., the brake of the indirect
470 leading vehicle) from the continuous video stream (Edquist, 2008). In contrast, the other three
471 HMIs have explicitly visualized the relative distance or time headway between the indirect leading
472 vehicle and the direct leading vehicle. Thus, given that driving is already an attentionally
473 demanding task (Salmon et al., 2005), explicitly visualizing implicit information may reduce
474 drivers' workload and support better driver decisions, especially in emergent events.

475 **5.2 Effect of BVR Information on Drivers' Attention Allocation**

476 To better explain the difference in driving performance when different types of HMIs were used,
477 we compared drivers' visual attention allocation across the HMI conditions. We found that the
478 amount of visual attention attracted by the HMIs was roughly proportional to the amount of
479 information in the HMIs. Specifically, echoing the results of driving performance metrics, though
480 not all pairwise comparisons were significant, in general, out of all HMIs, Video-HMI attracted
481 the most visual attention among all HMIs and the Brake-HMI attracted the least amount of visual
482 attention, as indicated by the percent of time spent on the HMI area, the percent of time on the
483 road ahead and the mean glance duration on the HMI area. This supports our previous assumptions
484 that perceiving the relative distance and motion between the direct leading vehicle and the indirect
485 leading vehicle based on video alone can be attentionally demanding. Such results also aligned
486 with participants' subjective ratings of the HMIs, with the Video-HMI being rated as having a
487 relatively low level of usability, which also agrees with the conclusions from (Yan et al., 2023).

488 These results underscore the importance of balancing informativeness and usability in HMI
489 design. In other words, the Video-HMI contained the richest information among all HMIs (as the
490 indirect leading vehicle braking, time headway, and distance can all be perceived from the live
491 video captured from the perspective of the direct leading vehicle), but providing more information
492 in an HMI without appropriate information extraction and visualization may not always be good,
493 especially during an already attention-demanding task such as driving. As suggested by the
494 multiple-source theory (Wickens, 1981), the competing visual demands of reading the Video-HMI
495 and other driving-related visual tasks may have cancelled out the benefits of rich information in
496 the Video-HMI, highlighting the importance of balancing conciseness and the informativeness of
497 the BVR HMIs in vehicles.

498 Finally, the lack of difference in the perceived workload (NASA-TLX) among all HMIs
499 implies that the additional BVR information provided by these HMIs did not significantly overload
500 the drivers. Further, none of the HMIs yielded different gaze dispersion than baseline. Given that
501 the increased variance of fixation locations, as indicated by broader scanning areas (Robbins &
502 Chapman, 2019), was associated with the increased driving experience and thus lower crash risk
503 (Lehtonen et al., 2014; Underwood et al., 2003), all our HMI designs might not have compromised
504 driving safety from the visual attention allocation perspective. However, it should be noted that,
505 as limited by the scenario design, we were not able to extract more driving safety-related visual
506 metrics, such as glances to cues in hazardous scenarios and responses to hazards (He et al., 2023;
507 He & Donmez, 2022). Thus, future research should further evaluate the influence of BVR
508 information on driving safety in more complex scenarios.

509 5.3 Limitation

510 In this study, we only considered the influence of driving experience, and we did not observe
511 different effects of BVR information on drivers with different levels of experience. Instead, we
512 only observed that experienced drivers seemed to have exhibited safer CF behaviors in both normal
513 drive (as indicated by a larger meanTHW) and braking event (as indicated by a larger minTTC)
514 than novice drivers. This is partly in line with previous research, where it was found that without
515 a forward collision warning, novice drivers tended to exhibit a shorter minTTC than experienced
516 drivers during near-collision events (Navarro et al., 2023). This indicates that the BVR HMI design
517 we proposed had homogeneous effects on CF behaviors regardless of the users' driving experience.
518 However, other driving styles may also affect the CF strategies (Liu et al., 2021; Song et al., 2025),
519 and drivers may perceive the HMIs differently, which should be carefully evaluated if any of the
520 HMIs are to be deployed in the real world.

521 Second, we only evaluated the HMIs from the safety perspective. Future research should
522 evaluate the impact of the HMIs on the traffic flow stability and the environmental impact
523 perspectives of view. Next, the experiment was conducted in a driving simulator, which may have
524 nullified the influence of crash risk on drivers' behaviors and may have biased drivers' perception
525 of relative speed and motion between the ego-vehicle and the leading vehicle. Future research
526 should validate our HMIs in on-road studies. Further, we only presented the BVR information on
527 a simulated HUD. It is necessary to explore the optimal locations to show the BVR information
528 (e.g., the dashboard or the infotainment system) in future research.

529 Finally, similar to the behavioral adaptation observed following the introduction of anti-
530 lock braking systems in vehicles (Sagberg et al., 1997), drivers may exhibit riskier CF behaviors
531 when provided with BVR information, as they tend to maintain what they perceive as an acceptable

532 level of risk (Summala, 1988). At the same time, the heterogeneity of the participants (e.g.,
533 different thresholds of risk and sensitivity to risk variation) may also influence the effect of the
534 HMIs. Therefore, future research should carefully examine the long-term safety implications of
535 HMI implementation in real-world conditions and consider the heterogeneity of drivers when
536 designing the BVR-related HMIs (Song et al., 2024). Future research could also consider
537 improving driving safety by supporting drivers with enhanced driving automation modules, such
538 as obstacle avoidance systems (Liang et al., 2025; Luan et al., 2025; Luo et al., 2022; Y. Ren et
539 al., 2025; Xu et al., 2023; Yang et al., 2024; S. Yao et al., 2025).

540 6 CONCLUSIONS

541 In a driving simulator experiment, we evaluated four types of BVR HMIs in CF events. The results
542 showed that:

- 543 ● The BVR information can potentially improve CF safety, regardless of the experience of
544 drivers.
- 545 ● Simple and intuitive Brake-HMI showing the indirect leading vehicle brake actions can
546 facilitate faster brake response time and increase time headway and TTC in brake events.
- 547 ● In contrast, complex displays with the richest information, i.e., the Video-HMI providing
548 video streams, increased attentional demands but without yielding obvious performance
549 gain.
- 550 ● Though BVR HMIs attracted drivers' visual attention, they did not impair drivers' gaze
551 dispersion and did not seem to overload drivers in CF events.
- 552 ● This study indicated the potential for the deployment of BVR HMIs in real-world settings
553 based on V2V technologies.

554 Overall, the BVR information has the potential to enhance driving safety if well-designed
555 to balance informativeness, complexity, and intuitiveness. Future research should systematically
556 examine optimal information density and visual complexity in BVR HMIs, compare visualization
557 modalities (e.g., argument reality HUD), and explore how adaptive systems can tailor these
558 designs to driver needs (e.g., simplifying information if drivers are detected to be overloaded) to
559 support safer and more efficient driving in connected vehicle environments.

560 ACKNOWLEDGMENT

561 This work was supported by the National Natural Science Foundation of China (No. 52202425),
562 and in part by the Nansha District Key Area S&T Scheme, Science and Technology Bureau of
563 Nansha District (No. 2023ZD006).

564

565
566
567
568
569
570
571
572
573
574
575
576
577
578
579
580
581
582
583
584
585
586
587
588
589
590
591
592
593
594
595
596
597
598
599
600
601
602
603
604
605
606
607

REFERENCES

- Adell, E., Várhelyi, A., & Fontana, M. d. (2011). *The effects of a driver assistance system for safe speed and safe distance – A real-life field study*. *Transportation Research Part C: Emerging Technologies*, 19(1), 145-155.
- Ahmed, M. A., Shariff, A. R. M., & Abubakar, S. (2025). *Long Term Traffic Congestion Detection Method Based on Speed-Threshold*. *Proceedings of the Internet of Things – ICIOT 2024*, Cham, 15427, 25-39.
- Ali, Y., Sharma, A., Haque, M. M., Zheng, Z., & Saifuzzaman, M. (2020). *The impact of the connected environment on driving behavior and safety: A driving simulator study*. *Accident Analysis & Prevention*, 144, 105643.
- Avery, M., & Weekes, A. (2009). *Autonomous braking systems and their potential effect on whiplash injury reduction*. *Proceedings of the International Technical Conference on Enhanced safety of vehicles, Germany*, 15-18.
- Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). *Fitting Linear Mixed-Effects Models Using lme4*. *Journal of Statistical Software*, 67(1), 1 - 48.
- Brooke, J. (1996). *SUS-A quick and dirty usability scale*. *Usability evaluation in industry*, 189(194), 4-7.
- Chen, J., Zhang, S., & Xu, W. (2025). *Scalable prediction of heterogeneous traffic flow with enhanced non-periodic feature modeling*. *Expert Systems with Applications*, 294, 128847.
- Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences*. Routledge.
- Crundall, D., & Underwood, G. (2011). *Visual attention while driving*. In B. E. Porter (Ed.), *Handbook of traffic psychology* (pp. 137–148). Elsevier Academic Press.
- da Silva, D. W., de Andrade, S. M., Soares, D. F., Mathias, T. A., Matsuo, T., & de Souza, R. K. (2012). *Factors associated with road accidents among Brazilian motorcycle couriers*. *ScientificWorldJournal*, 2012, 605480.
- Edquist, J. (2008). *The effects of visual clutter on driving performance* (Publication Number 01138121) [Doctoral dissertation, Monash University].
- Ezzati Amini, R., Al Haddad, C., Batabyal, D., Gkena, I., De Vos, B., Cuenen, A., Brijs, T., & Antoniou, C. (2023). *Driver distraction and in-vehicle interventions: A driving simulator study on visual attention and driving performance*. *Accident Analysis & Prevention*, 191, 107195.
- Flannagan, M. J., Sivak, M., Schumann, J., Kojima, S., & Traube, E. C. (1997). *Distance perception in driver-side and passenger-side convex rearview mirrors: Objects in mirror are more complicated than they appear*. <https://trid.trb.org/View/471872>
- Gao, X., Liao, C., Chen, C., & Li, R. (2023). *Visual Exploration of Cycling Semantics with GPS Trajectory Data*. *Applied Sciences*, 13(4), 2748.
- Guo, Q., Ban, X., & Aziz, H. M. A. (2021). *Mixed traffic flow of human driven vehicles and automated vehicles on dynamic transportation networks*. *Transportation Research Part C: Emerging Technologies*, 128, 103159.
- Han, J., Wang, X., & Wang, G. (2022). *Modeling the Car-Following Behavior with Consideration of Driver, Vehicle, and Environment Factors: A Historical Review*. *Sustainability*, 14(13), 8179.

- 608 Hart, S. G., & Staveland, L. E. (1988). *Development of NASA-TLX (Task Load Index): Results of*
609 *Empirical and Theoretical Research*. *Advances in Psychology*, 52, 139-183.
- 610 He, D., DeGuzman, C. A., & Donmez, B. (2023). *Anticipatory Driving in Automated Vehicles: The*
611 *Effects of Driving Experience and Distraction*. *Human Factors*, 65(4), 663-663.
- 612 He, D., & Donmez, B. (2022). *The Influence of Visual-Manual Distractions on Anticipatory*
613 *Driving*. *Human Factors*, 64(2), 401-417.
- 614 He, D., Kanaan, D., & Donmez, B. (2021). *In-vehicle displays to support driver anticipation of*
615 *traffic conflicts in automated vehicles*. *Accident Analysis & Prevention*, 149, 105842.
- 616 Horn, B. K. P. (2013). *Suppressing traffic flow instabilities*. *Proceedings of the 16th International*
617 *IEEE Conference on Intelligent Transportation Systems*, Netherlands, 13-20.
- 618 Horrey, W., & Wickens, C. (2007). *In-Vehicle Glance Duration: Distributions, Tails, and Model of*
619 *Crash Risk*. *Transportation Research Record*, 1, 22-28.
- 620 Huang, C., Wang, Z., & He, D. (2024). *The effect of dual training on the hazard response and*
621 *attention allocation of novice drivers when driving with advanced driver assistance*
622 *system*. *Accident Analysis & Prevention*, 208, 107802.
- 623 Huang, C., Wen, X., & He, D. (2023). *Characteristics of Rear-End Collisions: A Comparison*
624 *between Automated Driving System-Involved Crashes and Advanced Driving Assistance*
625 *System-Involved Crashes*. *Transportation Research Record*, 2678(7), 771-782.
- 626 Jiang, H., Cai, J., Xiao, Z., Yang, K., Chen, H., & Liu, J. (2025). *Vehicle-Assisted Service Caching*
627 *for Task Offloading in Vehicular Edge Computing*. *IEEE Transactions on Mobile*
628 *Computing*, 24(7), 6688-6700.
- 629 Koller, M. (2016). *robustlmm: An R Package for Robust Estimation of Linear Mixed-Effects*
630 *Models*. *Journal of Statistical Software*, 75(6), 1 - 24.
- 631 Lehtonen, E., Lappi, O., Koirikivi, I., & Summala, H. (2014). *Effect of driving experience on*
632 *anticipatory look-ahead fixations in real curve driving*. *Accident Analysis & Prevention*,
633 70, 195-208.
- 634 Lewis-Evans, B., De Waard, D., & Brookhuis, K. A. (2010). *That's close enough—A threshold*
635 *effect of time headway on the experience of risk, task difficulty, effort, and comfort*.
636 *Accident Analysis & Prevention*, 42(6), 1926-1933.
- 637 Li, R., Wang, Y., Sun, S., Zhang, Y., Ding, F., & Gao, H. (2025). *UE-Extractor: A Grid-to-Point*
638 *Ground Extraction Framework for Unstructured Environments Using Adaptive Grid*
639 *Projection*. *IEEE Robotics and Automation Letters*, 10(6), 5991-5998.
- 640 Li, W., Wu, G., Boriboonsomsin, K., Barth, M. J., Rajab, S., Bai, S., & Zhang, Y. (2017).
641 *Development and Evaluation of High-Speed Differential Warning Application Using*
642 *Vehicle-to-Vehicle Communication*. *Transportation Research Record*, 2621(1), 81-91.
- 643 Liang, J., Tan, C., Yan, L., Zhou, J., Yin, G., & Yang, K. (2025). *Interaction-Aware Trajectory*
644 *Prediction for Safe Motion Planning in Autonomous Driving: A Transformer-Transfer*
645 *Learning Approach*. *IEEE Transactions on Intelligent Transportation Systems*, PP, 1-16.
- 646 Liu, J., & Khattak, A. J. (2016). *Delivering improved alerts, warnings, and control assistance*
647 *using basic safety messages transmitted between connected vehicles*. *Transportation*
648 *Research Part C: Emerging Technologies*, 68, 83-100.
- 649 Liu, Q., Wang, X., Liu, S., Yu, C., & Glaser, Y. (2024). *Analysis of pre-crash scenarios and*
650 *contributing factors for autonomous vehicle crashes at intersections*. *Accident Analysis &*
651 *Prevention*, 195, 107383.

652 Liu, X., Wang, Y., Zhou, Z., Nam, K., Wei, C., & Yin, C. (2021). *Trajectory Prediction of*
653 *Preceding Target Vehicles Based on Lane Crossing and Final Points Generation Model*
654 *Considering Driving Styles*. IEEE Transactions on Vehicular Technology, 70(9), 8720-
655 8730.

656 Luan, Z., Xu, K., Zhao, W., & Wang, C. (2025). *An Event-Triggered Steering Angle Collaborative*
657 *Control Strategy for the Four-Wheel Independent Steering System*. IEEE Transactions on
658 Vehicular Technology, 74, 7468-7482.

659 Luo, J., Wang, G., Li, G., & Pesce, G. (2022). *Transport infrastructure connectivity and conflict*
660 *resolution: a machine learning analysis*. Neural Computing and Applications, 34(9), 6585-
661 6601.

662 McCartt, A. T., Shabanova, V. I., & Leaf, W. A. (2003). *Driving experience, crashes and traffic*
663 *citations of teenage beginning drivers*. Accident Analysis & Prevention, 35(3), 311-320.

664 Mullin, B., Jackson, R., Langley, J., & Norton, R. (2000). *Increasing age and experience: are both*
665 *protective against motorcycle injury? A case-control study*. Injury Prevention, 6, 32-35.

666 National Safety Council. (2023). *Injury Facts*. [https://injuryfacts.nsc.org/motor-](https://injuryfacts.nsc.org/motor-vehicle/overview/type-of-crash/)
667 [vehicle/overview/type-of-crash/](https://injuryfacts.nsc.org/motor-vehicle/overview/type-of-crash/)

668 Navarro, J., Reynaud, E., Ouimet, M. C., & Schnebelen, D. (2023). *Comparison of Experienced*
669 *and Novice Drivers' Visual and Driving Behaviors during Warned or Unwarned Near-*
670 *Forward Collisions*. Sensors, 23(19), 8150.

671 Nielsen, J. (1994). *10 Usability Heuristics for User Interface Design*.
672 <https://www.nngroup.com/articles/ten-usability-heuristics/>

673 Pillai, P., Balasingam, B., Kim, Y. H., Lee, C., & Biondi, F. (2022). *Eye-Gaze Metrics for*
674 *Cognitive Load Detection on a Driving Simulator*. IEEE/ASME Transactions on
675 Mechatronics, 27(4), 2134-2141.

676 Ren, W., Zhao, X., Yao, Y., Chen, C., Fu, Q., & Zhang, Y. (2025). *Does connected vehicle*
677 *information reduce beyond-visual-range crash risk in foggy freeway conditions? A study*
678 *based on extreme value theory*. Accident Analysis & Prevention, 217, 108060.

679 Ren, Y., Wang, L., Li, M., Jiang, H., Cui, Z., Yang, M., Yu, H., & Yang, D. (2025). *R M 2 Occ:*
680 *Re-Projection Multi-Task Multi-Sensor Fusion for Autonomous Driving 3D Object*
681 *Detection and Occupancy Perception*. IEEE Transactions on Intelligent Transportation
682 Systems, PP, 1-18.

683 Robbins, C., & Chapman, P. (2019). *How does drivers' visual search change as a function of*
684 *experience? A systematic review and meta-analysis*. Accident Analysis & Prevention, 132,
685 105266.

686 Sagberg, F., Fosser, S., & Sætermo, I.-A. F. (1997). *An investigation of behavioural adaptation to*
687 *airbags and antilock brakes among taxi drivers*. Accident Analysis & Prevention, 29(3),
688 293-302.

689 Salmon, P. M., Regan, M., & Johnston, I. (2005). *Human error in road transport: Phase 1-*
690 *Literature review. Monash University Accident Research Report Volume 256*. Monash
691 university.

692 Samarakoon, S., Bennis, M., Saad, W., & Debbah, M. (2020). *Distributed Federated Learning for*
693 *Ultra-Reliable Low-Latency Vehicular Communications*. IEEE Transactions on
694 Communications, 68(2), 1146-1159.

- 695 Shen, Z., He, Y., Du, X., Yu, J., Wang, H., & Wang, Y. (2024). *YCANet: Target Detection for*
696 *Complex Traffic Scenes Based on Camera-LiDAR Fusion*. *IEEE Sensors Journal*, 24(6),
697 8379-8389.
- 698 Siegmund, G. P., Winkelstein, B. A., Ivancic, P. C., Svensson, M. Y., & Vasavada, A. (2009). *The*
699 *anatomy and biomechanics of acute and chronic whiplash injury*. *Traffic Injury*
700 *Prevention*, 10(2), 101-112.
- 701 Smart Eye. (2025). *Smart Eye Pro - remote eye tracking system*. [https://www.smarteye.se/smart-](https://www.smarteye.se/smart-eye-pro/)
702 [eye-pro/](https://www.smarteye.se/smart-eye-pro/)
- 703 Song, D., Zhao, J., Zhu, B., Han, J., & Jia, S. (2024). *Subjective Driving Risk Prediction Based on*
704 *Spatiotemporal Distribution Features of Human Driver's Cognitive Risk*. *IEEE*
705 *Transactions on Intelligent Transportation Systems*, 25(11), 16687-16703.
- 706 Song, D., Zhu, B., Zhao, J., & Han, J. (2025). *Modeling lane-changing spatiotemporal features*
707 *based on the driving behavior generation mechanism of human drivers*. *Expert Systems*
708 *with Applications*, 284, 127974.
- 709 Stahl, P., Donmez, B., & Jamieson, G. A. (2019). *Eye glances towards conflict-relevant cues: the*
710 *roles of anticipatory competence and driver experience*. *Accident Analysis & Prevention*,
711 132, 105255.
- 712 Summala, H. (1988). *Risk control is not risk adjustment: The zero-risk theory of driver behaviour*
713 *and its implications*. *Ergonomics*, 31(4), 491-506.
- 714 Sun, G., Song, L., Yu, H., Chang, V., Du, X., & Guizani, M. (2019). *V2V Routing in a VANET*
715 *Based on the Autoregressive Integrated Moving Average Model*. *IEEE Transactions on*
716 *Vehicular Technology*, 68(1), 908-922.
- 717 Sun, G., Zhang, Y., Liao, D., Yu, H., Du, X., & Guizani, M. (2018). *Bus-Trajectory-Based Street-*
718 *Centric Routing for Message Delivery in Urban Vehicular Ad Hoc Networks*. *IEEE*
719 *Transactions on Vehicular Technology*, 67(8), 7550-7563.
- 720 Sun, G., Zhang, Y., Yu, H., Du, X., & Guizani, M. (2020). *Intersection Fog-Based Distributed*
721 *Routing for V2V Communication in Urban Vehicular Ad Hoc Networks*. *IEEE*
722 *Transactions on Intelligent Transportation Systems*, 21(6), 2409-2426.
- 723 Sun, T., Guo, R., Chen, G., Wang, H., Li, E., & Zhang, W. (2025). *RID-LIO: robust and accurate*
724 *intensity-assisted LiDAR-based SLAM for degenerated environments*. *Measurement*
725 *Science and Technology*, 36(3), 036313.
- 726 Treiber, M., Hennecke, A., & Helbing, D. (2000). *Congested traffic states in empirical*
727 *observations and microscopic simulations*. *Physical Review E*, 62(2), 1805-1824.
- 728 Underwood, G., Chapman, P., Brocklehurst, N., Underwood, J., & Crundall, D. (2003). *Visual*
729 *attention while driving: sequences of eye fixations made by experienced and novice*
730 *drivers*. *Ergonomics*, 46(6), 629-646.
- 731 Wang, J., Wang, H., Song, J., Chen, X., Guo, J., Li, K., Li, X., & Huang, B. (2025). *Knowledge-*
732 *guided self-learning control strategy for mixed vehicle platoons with delays*. *Nature*
733 *communications*, 16(1), 7705.
- 734 Wang, Q., Chen, J., Song, Y., Li, X., & Xu, W. (2024). *Fusing Visual Quantified Features for*
735 *Heterogeneous Traffic Flow Prediction*. *Promet - Traffic&Transportation*, 36(6), 1068-
736 1077.

737 Wang, Y., Sun, R., Jiang, L., Chen, H., Mao, Y., & Ochieng, W. Y. (2025). *Multipath Inflation*
738 *Factor for Robust GNSS/IMU/VO Fusion-Based Navigation in Urban Areas*. IEEE
739 *Internet of Things Journal*, 12(11), 16256-16265.

740 Wickens, C. D. (1981). *The Structure of Attentional Resources*. Psychology Press.

741 Xiao, Z., Shu, J., Jiang, H., Min, G., Chen, H., & Han, Z. (2023). *Overcoming Occlusions:*
742 *Perception Task-Oriented Information Sharing in Connected and Autonomous Vehicles*.
743 *IEEE Network: The Magazine of Global Internetworking*, 37(4).

744 Xu, G. J. W., Guo, K., Park, S. H., Sun, P. Z. H., & Song, A. (2023). *Bio-inspired vision mimetics*
745 *toward next-generation collision-avoidance automation*. *Innovation (Camb)*, 4(1), 100368.

746 Yan, S., Huang, C., Xie, W., & He, D. (2023). *HMI Design for Chain-Braking Event Based on*
747 *V2V Communication*. *Adjunct Proceedings of the 15th International Conference on*
748 *Automotive User Interfaces and Interactive Vehicular Applications*, German, 105-110.

749 Yang, J., Zang, X., Chen, W., Luo, Q., Wang, R., & Liu, Y. (2024). *Improved social force model*
750 *based on pedestrian collision avoidance behavior in counterflow*. *Physica A: Statistical*
751 *Mechanics and its Applications*, 642, 129762.

752 Yang, X., Zhang, H., Zhuang, Y., Wang, Y., Shi, M., & Xu, Y. (2025). *uLiDR: An inertial-assisted*
753 *unmodulated visible light positioning system for smartphone-based pedestrian navigation*.
754 *Information Fusion*, 113, 102579.

755 Yao, S., Guan, R., Peng, Z., Xu, C., Shi, Y., Ding, W., Lim, E. G., Yue, Y., Seo, H., Man, K. L.,
756 Ma, J., Zhu, X., & Yue, Y. (2025). *Exploring Radar Data Representations in Autonomous*
757 *Driving: A Comprehensive Review*. *IEEE Transactions on Intelligent Transportation*
758 *Systems*, 26(6), 7401-7425.

759 Yao, Y., Shu, F., Cheng, X., Liu, H., Miao, P., & Wu, L. (2023). *Automotive Radar Optimization*
760 *Design in a Spectrally Crowded V2I Communication Environment*. *IEEE Transactions on*
761 *Intelligent Transportation Systems*, 24(8), 8253–8263.

762 Yao, Y., Xiao, W., Miao, P., Chen, G., Yang, H., Chae, C.-B., & Wong, k.-k. (2025). *UAV-Relay-*
763 *Aided Secure Maritime Networks Coexisting with Satellite Networks: Robust Beamforming*
764 *and Trajectory Optimization*. *IEEE Transactions on Wireless Communications*.

765 Yogha Bintoro, K. B., Permana, S. D. H., Ade, S., Yaddarabullah, & Budi, A. (2024). *V2V*
766 *Communication in Smart Traffic Systems: Current status, challenges and future*
767 *perspectives*. *Jurnal PROCESSOR*, 19(1).

768 Zheng, J., Ma, L., & Zhang, W. (2023). *Promotion of driver compliance with V2V information in*
769 *car-following tasks via multimodal display*. *Transportation Research Part F: Traffic*
770 *Psychology and Behaviour*, 94, 243-253.

771 Zou, F., Xia, C., Guo, F., Cai, X., Cai, Q., Luo, G., & Ye, T. (2023). *Dynamic Identification*
772 *Method for Potential Threat Vehicles beyond Line of Sight in Expressway Scenarios*.
773 *Applied Sciences*, 13(23).

774