Beyond-Line-of-Sight Traffic Information HMIs Shape Car-Following and Visual Behaviors

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***Abstract*—A lack of upstream traffic information in car-following (CF) scenarios can increase the risk of rear-end collisions and degrade traffic stability. Beyond-line-of-sight (BLOS) human-machine interfaces (HMIs) can extend drivers' perceptual range. Yet it remains unknown how different BLOS distance ranges influence drivers' control strategies and visual attention in the CF scenario. In a driving simulator with 24 novice drivers, we examined drivers' CF and visual behaviors under three BLOS HMI conditions: No HMI, Indirect Leading Vehicle HMI (ILV HMI), and Upstream Traffic Flow HMI (UTF HMI). The CF control strategies were quantified using calibrated parameters from the Intelligent Driver Model (IDM), and visual attention was assessed using eye-tracking metrics, including horizontal and vertical fixation dispersion in non-braking segments and HMI-related fixation measures in braking events. We found that BLOS HMIs across different ranges had distinct effects on drivers' CF strategies during gradual and emergency braking events. Eye-tracking results showed no significant HMI effects on fixation count rate or fixation dispersion, whereas UTF HMI produced longer fixation duration on the HMI area than ILV HMI during emergency braking events. These findings explain how the BLOS information range affects CF control strategies and show that richer upstream information takes longer to process during emergency events. Information range should therefore be considered as a key design factor when developing HMIs to support CF strategies.**

***Index Terms*—Car following, V2V communication, driver behavior, HMI design**

I. Introduction

Car-following (CF) is a core longitudinal control task in which drivers continuously regulate speed and spacing in response to preceding traffic [1], [2]. Though the CF decision is mainly regulated by the relative distance and speed between the direct lead vehicle (DLV) and the ego vehicle [3]–[5], advanced driving decisions (such as hazard perception) also rely on the perception of traffic states well ahead of the direct LV [6], [7]. In everyday traffic, however, it is often difficult for drivers to perceive upstream traffic conditions, especially when their forward view is partially or fully occluded by large lead vehicles. Limited perception of the upstream traffic can lead to reactive braking and thus destabilize headway regulation [8], as reduced preview time has been shown to impair CF stability and increase collision risk [9]. Thus, it is necessary to extend the drivers' perceptual horizon if possible.

Thanks to the connected-vehicle and vehicle-to-vehicle (V2V) communication technologies, it is now possible to enable the perception of beyond-line-of-sight (BLOS) information in the traffic stream [10], [11]. However, driving is a demanding task, and more information does not necessarily lead to better performance due to the risk of information overload [12]. Thus, it is necessary to understand what BLOS information should be conveyed in a CF task. In recent years, research on BLOS and V2V-based human-machine interfaces (HMIs) has examined how different contents and formats of upstream traffic information can support CF behaviors. For example, in a video simulation study, V2V-based HMIs that show the braking of the indirect lead vehicle (ILV, i.e., the vehicle in front of the DLV) have been found to facilitate earlier, smoother responses to sudden decelerations during a chain braking event, and drivers preferred a simpler ILV braking message over a live stream of the ILV [13]. Building upon previous studies, [14] also explored the effects of various encodings of V2V-based BLOS braking information (e.g., braking state of the ILV, time headway between the DLV and the ILV, video of the ILV) on CF behaviors in a

driving simulation study. They observed varying levels of CF performance improvements across visualizations, with simpler icons receiving higher user acceptance.

Although different information encodings were explored, both [13] and [14] examined only the influence of ILV information, without considering the range of BLOS information, even though previous research has found that experienced drivers could use traffic information ahead of the ILV in the traffic flow [7]. Thus, in a driving simulation study, [15] explored whether information about the upcoming traffic flow (e.g., from tens to hundreds of meters away) can improve CF performance on top of ILV information. Additional benefits (e.g., earlier responses to chain-braking events) were observed when drivers were provided with information about the upstream traffic disturbance via an in-vehicle HMI.

Despite previous endeavors, two important gaps remain. First, although previous research on ILV information has observed a shift in attention allocation strategies when ILV states are informed [14], the effects of different BLOS ranges on drivers' attention allocation strategies remain unknown. Given the importance of visual perception in the driving task, it is necessary to further evaluate BLOS information from an attentional-allocation perspective. Second, prior studies on the effect of BLOS information on CF behaviors mostly report event-level performance metrics (e.g., headway, reaction time, braking profiles) without linking them to the underlying CF strategies that govern traffic stability and safety margins [16]. Without understanding the influence of the BLOS information from a behavioral perspective, the analysis of BLOS impact at a traffic flow level would be limited.

To address these gaps, a driving simulation study was conducted to evaluate three ranges of in-vehicle V2V-based BLOS information in a CF scenario. Drivers' CF control strategies were quantified using calibrated Intelligent Driver Model (IDM) parameters [1], and visual behaviors were assessed using eye-tracking data, aiming to clarify the trade-offs across different BLOS ranges from CF and visual allocation perspectives. In this study, we focused specifically on novice drivers, given that they are less likely to exhibit anticipatory actions in CF events [17] and more vulnerable to additional information load [18], [19] than experienced drivers.

II. Methods

A. Participants

The sample comprised 24 novice drivers (12 males and 12 females). To be eligible, participants must have obtained their driver's license within the past year and accumulated less than 5,000 km of driving experience during that period. Participants had a mean age of 20.83 years (SD = 1.95). Ethical approval was obtained from the Hong Kong University of Science and Technology (Guangzhou) (Protocol number: HREP-2024-0026), and written informed consent was obtained from all participants before the experiment.

B. Apparatus

As illustrated in Fig. 1, the experiment was implemented in a high-fidelity fixed-base driving simulator. Traffic conditions and speed dynamics were systematically manipulated to create control demands that closely match realistic longitudinal control in a typical CF scenario. The simulator used SILAB 7.1 software to simulate highway driving conditions, including both free-flowing and congested traffic scenarios. The software recorded all relevant data at 60 Hz, including vehicle speed, headway, and acceleration. Eye-tracking data was collected using Smart Eye Pro. The HMI area of interest (AOI) was defined as the fixed screen region where HMI information was displayed. The same screen region was used across all conditions (including the baseline without BLOS information).



Fig. 1: Driving simulator apparatus with integrated eye-tracking system and the in-vehicle display used to present BLOS information.

C. Scenario Design

The driving scenario was designed to replicate a bidirectional four-lane highway with straight road segments. The overall roadway configuration is shown in Fig. 2.

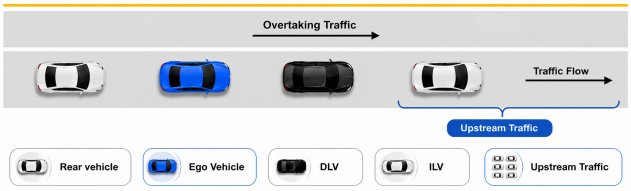


Fig. 2: Highway scenario used in the simulator.

The experiment included two distinct traffic conditions, based on the state of the virtual upstream traffic:

- **Congested Traffic**: Under this condition, the DLV moved at approximately 16.67 m/s (60 km/h), representing a dense traffic situation characterized by reduced speeds and shortened headways in the traffic flow.
- **Free-flowing Traffic**: Under this condition, the DLV traveled steadily at 27.78 m/s (about 100 km/h), reflecting a low-density traffic state with comparatively larger spacing between vehicles in the traffic flow.

The experiment also included chain-braking events to simulate situations in which the DLV (driven by the simulation system) must suddenly adjust its speed due to potential hazards or changes in upstream traffic. These braking events were introduced in both free-flow and congested traffic

scenarios to simulate real-world conditions. There were two distinct types of braking events (shown in Fig. 3), which varied in intensity:

- **Gradual Braking (GB)**: Due to the speed adjustment of the upstream traffic, the DLV decelerated at a rate of -1.5 m/s^2 over a 3-second period [20]. After this, the vehicle would continue coasting at the current speed for 2 seconds before gradually recovering to the original speed at an acceleration of 1 m/s². This recovery phase was followed by smooth driving until the next braking event occurred. This scenario mimicked the gentle speed adjustments commonly made in real-world situations, such as proactive speed control in response to road conditions or slight changes in traffic flow.
- **Emergency Braking (EB)**: In this scenario, the DLV decelerated at a more intense rate of -5.5 m/s^2 for 3 seconds due to the abrupt traffic variations in the upcoming traffic, simulating an abrupt deceleration triggered by a sudden obstacle or hazard, such as an unexpected vehicle in the road or an obstacle ahead [21]. After this, the DLV would again coast at the current speed for 2 seconds, followed by a recovery phase at 1 m/s² to return to the original speed. This event simulated DLV's emergency braking in response to an imminent collision risk.

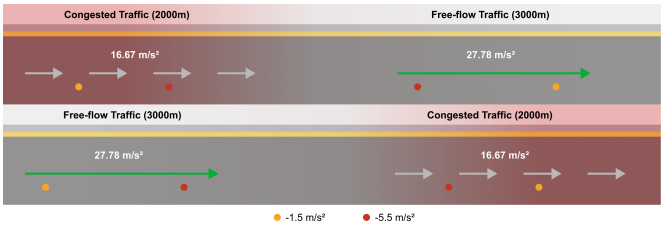


Fig. 3: Traffic states and braking events.

In the experiment, participants were asked to follow the DLV as if following another car (i.e., the DLV) toward an unfamiliar location. Their objective was to adopt longitudinal control strategies to drive safely throughout the drive while avoiding excessive gaps to the DLV.

D. HMI Design

Two V2V-based HMIs with different BLOS ranges were designed, along with a baseline without any BLOS information:

1) No HMI Condition (baseline): In the No HMI condition, participants received no additional BLOS traffic information. This condition served as the baseline, in which participants relied solely on their direct visual information about the DLV ahead and environmental cues to make CF decisions.

2) ILV HMI: As shown in Fig. 4, the indirect-lead-vehicle HMI (ILV HMI) condition provided participants with information about the braking state of the ILV. The ILV HMI used yellow to indicate GB and red to indicate EB.

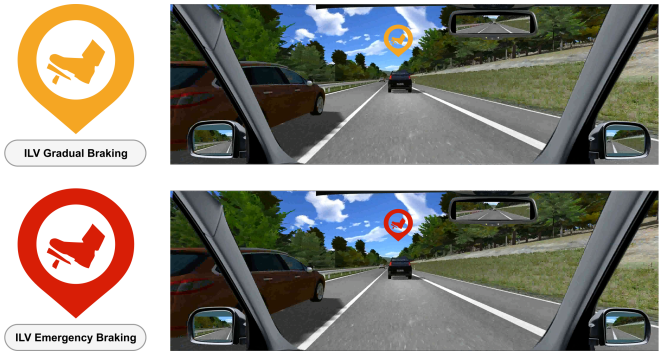


Fig. 4: ILV HMI visualization.

3) UTF HMI: As shown in Fig. 5, the upstream-traffic-flow HMI (UTF HMI) provided a broader view of the upstream traffic flow ahead of the DLV by dividing it into three distance ranges: near-field traffic within 0–100 m, mid-field traffic within 100–200 m, and far-field traffic within 200–300 m ahead of the DLV. These ranges corresponded to the bottom, middle, and top arrows in the icon, respectively. Green arrows indicated free-flowing traffic, yellow arrows indicated slow traffic, and red arrows indicated vehicles braking within the corresponding upstream distance range. An example of the UTF interface during dynamic driving is shown in Fig. 6.

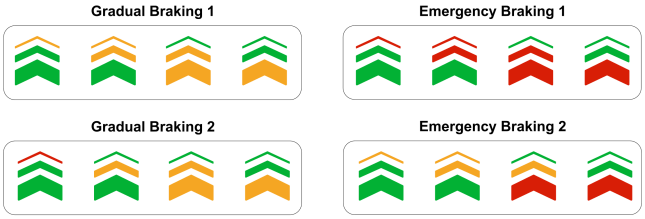


Fig. 5: UTF HMI design overview.

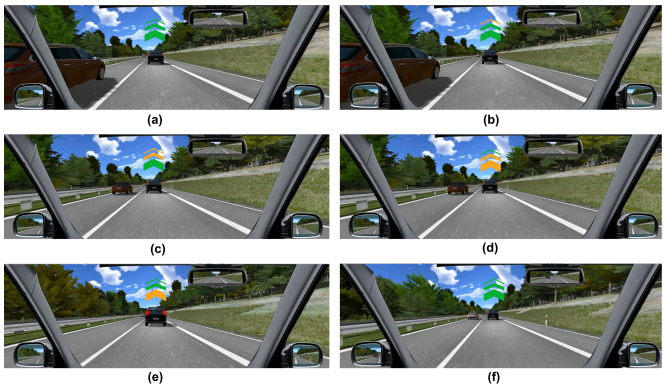


Fig. 6: Example of UTF HMI during dynamic driving, illustrating how upstream traffic cues evolve with changing upstream traffic conditions.

E. Experiment Procedures

Upon arrival, participants were provided with consent forms. Then, an eye-tracker calibration was conducted before the experiment to ensure accurate gaze recording. Participants received a brief explanation of the driving task and the meaning of each BLOS HMI. A short practice drive without any BLOS HMI was provided to familiarize participants with the simulator. No data were recorded during the practice. The formal experiment consisted of three driving blocks corresponding to the three HMI conditions. The order of conditions was counterbalanced using a Latin square design. Each block included both GB and EB events under congested and free-flow traffic contexts. Participants were given short breaks between blocks. After completing all blocks, they were debriefed and compensated.

F. Data Analysis

1) Calibration of the Intelligent Driver Model: The Intelligent Driver Model (IDM) was adopted to characterize drivers' CF behavior. The objective of IDM parameter calibration was to compress raw time-series CF measurements into a compact set of behaviorally interpretable parameters, thereby enabling quantitative and explainable descriptions of longitudinal control strategies [22]. In IDM, the longitudinal acceleration of the ego vehicle is jointly governed by desired speed and desired spacing to the DLV, as formulated in Eq. (1):

$$\dot{v}(t) = a\left[1 - \left(\frac{v(t)}{v_0}\right)^{\delta} - \left(\frac{s^*(t)}{s(t)}\right)^2\right] \tag{1}$$

where a denotes maximum acceleration, $v(t)$ is the ego vehicle speed at time t, v_0 is the desired speed, $s(t)$ is the spacing between the ego and the DLV, and δ is the acceleration exponent (typically fixed at 4) [23].

The desired spacing $s^*(t)$ is defined as:

$$s^*(t) = s_0 + v(t)T + \frac{v(t)\Delta v(t)}{2\sqrt{ab}} \tag{2}$$

where s_0 is the minimum gap at standstill, T is the desired time headway, $\Delta v(t)$ represents relative speed between the ego vehicle and the DLV, and b denotes comfortable deceleration.

IDM parameters were calibrated using bounded nonlinear least-squares optimization, given that IDM is a nonlinear dynamical model with no analytic linear mapping between parameters and observations. Calibration was performed on each braking event, specifically, from 10 s preceding the DLV braking onset to 8 seconds after the DLV resumed to its original speed. Specifically, parameters were estimated by minimizing the squared error between the observed and simulated trajectories of speed and spacing. Goodness-of-fit was assessed using the root mean square error (RMSE) over the analyzed segment; all segments converged under parameter bounds set to ensure physical plausibility and improve numerical stability.

2) Visual Allocation Metrics: To understand how the BLOS HMI affects drivers' visual attention allocation, we first evaluated the standard deviation (SD) of horizontal and vertical fixation locations within the drive, excluding the braking events (i.e., excluding the window from the onset of the DLV braking event to the moment the DLV resumed to its original speed). Previous research has found that the decrease in the SD of horizontal and vertical fixation locations was associated with increased cognitive load [24] and worse hazard perception performance [25]. Furthermore, to evaluate visual engagement with HMI information during time-critical responses, fixation count and fixation duration were computed for fixations directed to the HMI AOI within the window from DLV brake onset to the driver's own brake onset.

3) Statistical Models: Linear mixed models (LMMs) were used to model IDM parameters, SDs of horizontal and vertical fixation locations, and log-transformed fixation duration (due to violations of the normality assumption), with the participant as a random intercept. Fixation count was analyzed using a negative binomial generalized linear mixed model (GLMM) with participant-specific random intercepts and an offset of $\log$ data extraction window.

SDs of horizontal and vertical fixation locations were analyzed regardless of the braking intensity (as we excluded the braking events while extracting the metrics), with the HMI (No HMI, vs. ILV HMI vs. UTF HMI) as the only independent variable; whereas IDM parameters, fixation count and fixation duration were analyzed separately for different types of braking events, again, with the HMI as the only independent variables. Traffic state (free-flow vs. congested) was introduced to enrich the ecological realism of the driving context and was not treated as an independent factor in the statistical models. Holm-adjusted contrasts were used for pairwise comparisons when the main effect was significant. All analyses were performed in *R*.

III. Results

A. IDM Parameters

1) EB Condition: For EB events, the HMI condition had no significant effect on the desired speed v_0 or maximum acceleration a. However, HMI significantly affected comfortable deceleration b ($F(2, 116.47) = 9.15, p < .001$)(Fig. 7a). Both ILV HMI ($t(120.01) = -4.08, p < .001, \Delta = -1.480$, 95% CI: [-2.361, -0.599]) and UTF HMI ($t(120.01) = -3.21, p = .003, \Delta = -1.166$, 95% CI: [-2.047, -0.285]) led to a lower b than No HMI. For minimum standstill gap s_0, HMI condition was also significant ($F(2, 113.92) = 6.61, p = .002$)(Fig. 7b): ILV HMI led to a higher s_0 than No HMI ($t(117.33) = 3.37, p = .003, \Delta = 2.340$, 95% CI: [0.654, 4.027]), while UTF HMI led to a lower s_0 than ILV HMI ($t(114.02) = -2.69, p = .02, \Delta = -1.734$, 95% CI: [-3.301, -0.167]).

HMI also affected desired time headway T ($F(2, 113.11) = 5.02, p = .008$)(Fig. 7c). Pairwise comparisons showed that UTF HMI led to a higher T than No HMI ($t(115.86) = 2.71, p = .02$), with a estimated

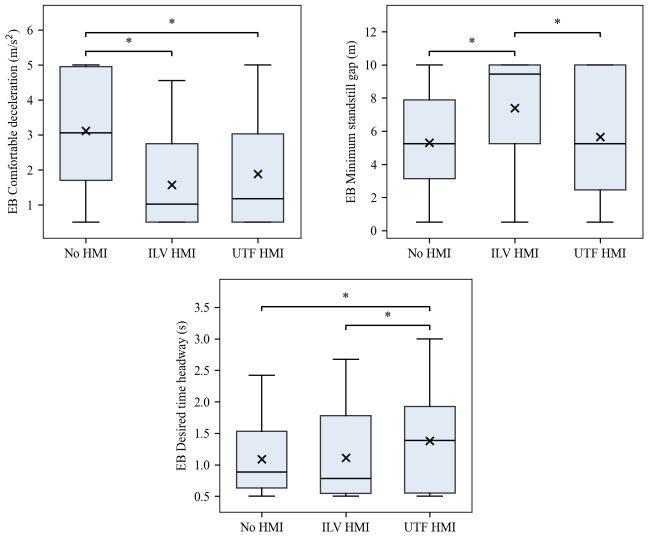


Fig. 7: Distributions of IDM parameters in the EB condition across HMI conditions: (a) comfortable deceleration b; (b) minimum standstill gap s_0; (c)desired time headway T.

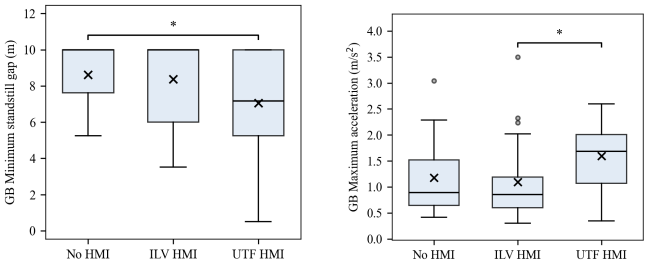


Fig. 8: Distributions of IDM parameters in the GB condition across HMI conditions: (a) minimum standstill gap s_0 and (b) maximum acceleration a.

difference (Δ) of 0.297, and 95% confidence interval of ($95\%CI$) between [0.031, 0.563]. UTF also led to a higher T than ILV HMI ($t(114.02) = 2.66, p = .02, \Delta = 0.270$, 95% CI: [0.023, 0.516]).

2) GB Condition: For GB events, the HMI condition had no significant effect on the desired speed v_0, the desired time headway T, or the comfortable deceleration b. However, HMI affected the minimum standstill gap s_0 ($F(2, 116.67) = 3.51, p = .03$)(Fig. 8a). Pairwise comparisons showed that UTF HMI led to a lower s_0 than No HMI ($t(121.35) = -2.44, p = .048, \Delta = -1.746$, 95% CI: [-3.482, -0.010]). HMI also affected maximum acceleration a ($F(2, 117.21) = 3.97, p = .02$) (Fig. 8b), with UTF HMI yielding a higher a than ILV HMI ($t(114.17) = 2.63, p = .03, \Delta = 0.500$, 95% CI: [0.039, 0.960]).

B. Visual Attention Metrics

1) Fixation Dispersion: No significant differences were observed in SD of horizontal fixations ($p = .4$) or vertical fixations ($p = .4$) across HMI conditions.

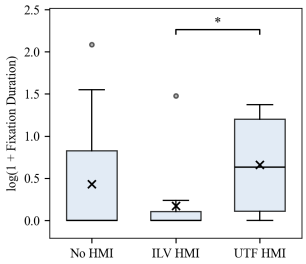


Fig. 9: Log-transformed fixation duration on the HMI AOI across HMI conditions in EB events.

2) Fixation Count: The HMI fixation count rate did not significantly differ across HMI conditions in either EB ($\chi^2(2) = 1.09, p = .6$) or GB ($\chi^2(2) = 0.88, p = .6$) events.

3) Fixation Duration: As shown in Fig. 9, in EB events, log-transformed fixation duration differed significantly across HMI conditions ($F(2, 31.85) = 3.51, p = .042$). Pairwise comparisons showed that UTF HMI yielded longer fixation durations than ILV HMI ($t(67.82) = 2.76, p = .02, \Delta_{\log} = 0.447$), corresponding to a ratio of 1.56 (95% CI: [1.05, 2.33]). No other pairwise comparisons were significant. In GB events, the HMI did not affect fixation durations ($p = .052$).

IV. Discussion

This study shows that the distance range of the BLOS information can affect drivers' CF strategies and visual behaviors. Under EB, ILV HMI increased s_0 and reduced b, whereas UTF HMI reduced b and increased T. These changes suggest that BLOS information made emergency braking less abrupt from the driver's perspective, as reflected by reduced comfortable deceleration. However, the two HMI ranges appeared to support different safety-regulation strategies: ILV HMI mainly promoted a larger spatial safety margin, whereas UTF HMI promoted a larger temporal buffer. These findings are consistent with prior BLOS HMI studies showing that upstream or ILV information can support safer or earlier CF responses [6], [14], [15]. The present IDM-based analysis extends previous event-level findings by showing that information range affects safety by shaping underlying CF control parameters rather than only changing event-level performance.

In contrast, in less urgent GB, UTF HMI increased a and reduced s_0, indicating a smaller safety buffer (i.e., smaller s_0) and faster speed recovery (i.e., larger maximum a) following mild upstream disturbances, likely due to driver's awareness of the mild speed variation instead of emergent braking. In contrast, ILV HMI showed limited effects under GB, implying that localized braking-state cues may be less useful for drivers to anticipate gradual speed adjustments of the leading traffic and make corresponding adjustments.

The eye-tracking results suggest that BLOS information had limited impact on global visual scanning, with fixation dispersion during non-braking segments and fixation count rate during the braking segments being non-associated with

HMI conditions. These non-significant fixation dispersion indicates that the BLOS HMI may not have overloaded drivers in normal CF segments [26]. However, during EB events, UTF HMI increased fixation duration on the HMI AOI relative to ILV HMI, whereas the corresponding effect did not reach significance in GB events. This pattern suggests that broader upstream traffic-flow information may require more sustained visual processing during time-critical braking situations, possibly because UTF HMI requires integration of traffic states across near-, mid-, and far-field regions.

Finally, several limitations remain. Specifically, the simulator setting may not fully capture real-world driving, traffic state was not modeled as an independent factor, and the sample included only novice drivers. Future research may need to further investigate the impact of BLOS HMIs on drivers' hazard perception skills and seek to reduce drivers' attentional load by optimizing HMI design. A validation of the HMIs with a more diverse driver population in on-road studies is also needed.

V. Conclusion

In a driving simulator study with novice drivers, we provide empirical evidence on how the range of BLOS information can modulate novice drivers' CF strategies. We found that drivers adopted different CF strategies with support from BLOS information across different distance ranges. This provides supplementary information to explain the effects of the BLOS HMIs in previous studies. Further, the eye-tracking results showed that BLOS HMIs did not significantly alter fixation dispersion or fixation count rate, although broader UTF information required longer HMI-directed fixation during EB events. These findings suggest that HMIs displaying BLOS information can support safer and more adaptive CF strategies, but richer upstream information should be designed for rapid interpretation in time-critical situations.

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