Does the Small Blue Light Matter? Naturalistic Evidence on the Influence of External ADAS Status Signals on Car-Following Behavior

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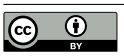
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Abstract

As Advanced Driver Assistance Systems (ADAS) become increasingly common in production vehicles, surrounding drivers may increasingly encounter vehicles whose behavior is partly controlled by automation. In China, some ADAS-supported vehicles use an externally visible indicator, commonly referred to as the "small blue light," to signal that ADAS is active. However, limited naturalistic evidence is available on whether such external ADAS status visibility influences surrounding drivers. This study investigated following drivers' car-following behavior in naturalistic traffic when the lead vehicle operated with ADAS activated and the small blue light was on or off. Results showed speed-dependent changes under the blue-light-on condition. In particular, following drivers maintained larger time headway when the lead vehicle traveled at higher speeds with the light on. By providing naturalistic evidence from ADAS-supported production vehicles, this study contributes to understanding how external ADAS status visibility may shape following drivers' longitudinal driving behaviors in real traffic.

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AutomotiveUI Adjunct '26, Gothenburg, Sweden

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ACM ISBN 979-8-4007-2815-0/26/09
https://doi.org/10.1145/3828158.3838224

CCS Concepts

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

Keywords

Advanced driver assistance systems, external ADAS status signal, car-following behavior, naturalistic driving, mixed traffic

ACM Reference Format:
Yue Hong, Fangning Zhang, Xiangyu Li, Yonglin Weng, Ke Ma, and Dengbo He. 2026. Does the Small Blue Light Matter? Naturalistic Evidence on the Influence of External ADAS Status Signals on Car-Following Behavior. In *18th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI Adjunct '26), September 20–23, 2026, Gothenburg, Sweden.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3828158.3838224

1 Introduction

The market share of Advanced Driver Assistance Systems (ADAS) has been increasing in recent years. These systems can support steering, acceleration, and braking under certain conditions and can be categorized as Level 2 automation according to SAE J3016 [13]. However, SAE Level 2 automation still requires a human driver to continuously supervise the driving task and take over or respond when necessary. In other words, when ADAS is activated, the vehicle's behavior is regulated by the ADAS, and it may behave

differently compared to human drivers, which may elicit different interacting behaviors of its surrounding vehicles [19].

At the same time, in China, some production vehicles equipped with ADAS have begun to use external blue indicators, commonly referred to as the "small blue light," to indicate the engagement of the ADAS. These lights are turned on when ADAS is engaged, as shown in Figures 1a and 1b. It should be noted that although blue lights for automated-driving operation are required in some regulatory contexts for highly automated vehicles such as robotaxis (typically categorized as SAE Level 4 or higher) in China [12], they are not required for SAE Level 2 vehicles. Therefore, the use of such an external human-machine interface (eHMI) for SAE Level 2 vehicles remains controversial.

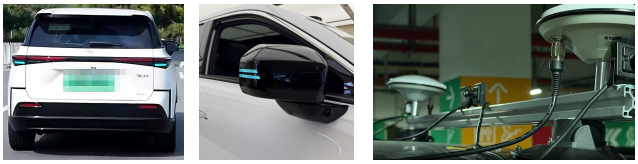
Previous research on the interaction between human-driven vehicles (HDVs) and autonomous vehicles (AVs) may provide some insights. At the operational level, previous studies have found that human drivers may exhibit different driving behaviors when interacting with AVs, including different car-following (CF) distances, speed variations, and lateral distances when overtaking AVs [5, 19]. At the tactical level, on one hand, drivers may interact with AVs "more cautiously" if they are aware that the vehicle is automated [10]. On the other hand, some drivers have been found to bully AVs or take advantage of their conservative and rule-based behaviors [9]. Automation identity may also elicit negative social responses, such as driving anger, honking, or uncivil interactions [4]. Together, these behavioral adaptations may impair traffic safety or efficiency in mixed traffic.

However, previous research mostly targeted SAE Level 4 or higher automation. Explicit SAE Level 2 ADAS states may have different effects, given the inferior performance of an SAE Level 2 system and the presence of fallback drivers [15]. Therefore, findings from existing studies cannot directly answer whether external ADAS status signals, i.e., the small blue light, are associated with surrounding drivers' behavioral adaptation. To address this research gap, we collected naturalistic driving data on roads. In this preliminary study, we specifically focused on CF behaviors, as it is a basic driving task [18], highly associated with the rear-end collision risk [11, 16], and traffic efficiency [17] and stability [2]. In the study, we analyzed ADAS-on CF segments in which the small blue light was either on or off. We aim to provide naturalistic evidence on how the visibility of the ADAS states can affect following drivers' CF behaviors in traffic.

2 Method

2.1 Data Collection

The data used in this study were collected from a naturalistic on-road experiment in real urban traffic in Guangzhou, China. The experimental vehicle was a Toyota bZ3X driven by research staff on urban roads. The small blue lights were externally visible and were located at the rear of the vehicle (Figure 1a) and on the side mirrors (Figure 1b). In the CF analysis, the experimental vehicle was treated as the lead vehicle (LV), and the rear vehicle following it was treated as the following vehicle (FV). The LV was equipped with RTK positioning and a rear-view monocular camera system. The RTK data were used to obtain the LV trajectory, speed, motion state, and time alignment with the video stream. The rear-view video was



(a) Rear-mounted small blue light **(b) Side-mirror small blue light** **(c) Rear-view sensing setup**

Figure 1: Experimental vehicle setup, including the externally visible small blue lights and the rear-view sensing system.

captured by a roof-mounted rear-facing 30-degree telephoto monocular camera (Jeriweitong, Figure 1c). The original video stream was recorded at 1920 × 1080 and 10 Hz. In the following sections, the blue-light-on and blue-light-off conditions refer to ADAS-on segments in which the small blue light was on or off, respectively. The blue-light-off videos ranged from January 28, 2026 to May 18, 2026, and the blue-light-on videos ranged from April 1, 2026 to May 14, 2026.

2.2 Data Preprocessing

Rear-view videos were processed to extract rear-vehicle position information. Vehicle segmentation was performed using SAM 3.1 [3]. SAM 3.1 was run at 10 Hz and produced vehicle masks, bounding boxes, and track IDs for rear-view vehicles. Monocular depth estimation was performed using ViPE [6], also at 10 Hz. The SAM 3.1 vehicle masks and tracking outputs were then fused with the ViPE depth maps to obtain a depth summary for each tracked vehicle region. These fused outputs provided the basis for estimating the longitudinal gap between the LV and candidate FV. After video integrity screening and exclusion of ADAS-off segments, the dataset entering the CF event extraction pipeline totaled 18.37 h and 751.88 km, including 12.05 h and 507.75 km from videos in which the small blue light was off and 6.32 h and 244.13 km from videos in which the small blue light was on.

2.3 Extraction of CF Events

Car-following events. In the dataset, if one vehicle followed another vehicle in the same lane for over 15 seconds [14] and the behaviors of the two vehicles satisfied all the criteria listed below, then the event was extracted as a CF event.

- None of the two vehicles made lane changes or turns [1].
- The estimated speed of the FV was greater than 10 km/h [20].
- The estimated longitudinal gap between the FV and the LV was less than 85 m [7].

Same-lane FV candidates were first identified using rear-view geometry, lateral position thresholds, and event continuity. The lateral position of each detected rear vehicle was approximated from its bounding-box center, camera intrinsics, and the depth summary within the corresponding vehicle mask. Vehicles within a predefined rear-centerline corridor were treated as same-lane candidates. When multiple valid candidates were present, the nearest one was selected as the primary FV.

For each depth frame, the raw estimated gap was calculated as the median depth within the selected FV depth summary after subtracting 2.12 m, which was the longitudinal distance from the rear-view camera to the rear bumper of the LV. The gap samples were smoothed within each event using local linear smoothing with a 5-second window. After automatic extraction, manual quality control was performed to remove or trim invalid events caused by wrong vehicle selection, non-following cases, or poor visual quality. The final dataset included 203 CF events from 90 daytime videos, including 142 events in the blue-light-off condition and 61 events in the blue-light-on condition. These events contributed 5452 s of ADAS-on observations, including 3980 s in the blue-light-off condition and 1472 s in the blue-light-on condition.

2.4 Dependent Variables

Four dependent variables were extracted from the CF events: gap distance, time gap, the reciprocal of time-to-collision (reTTC), and the standard deviation of following-vehicle speed (SD-FVspeed). These metrics have been used in previous studies to describe CF behavior and traffic safety risk [11, 16].

Gap distance was defined as the estimated bumper-to-bumper gap between the FV and the LV. For each CF event, gap distance was first estimated at 10 Hz from the vehicle-level depth summaries. Time gap and reTTC were then calculated at the same 10-Hz frame level. Finally, these frame-level measures were averaged within each event-second to generate the 1-Hz observations used in the statistical models. This averaging was intended to increase the robustness of vision-based distance estimation, as averaging samples within one second is expected to cancel out random estimation noise. The time gap was defined as the gap distance divided by the FV speed. Because FV speed was not directly measured from the video, it was estimated from the LV speed and the temporal change in the gap distance. Let $g(t)$ denote the estimated longitudinal gap and $\dot{g}(t)$ denote its time derivative. The FV speed was calculated as:

$$v_{\mathrm{FV}}(t) = v_{\mathrm{LV}}(t) - \dot{g}(t). \tag{1}$$

With this definition, a decreasing gap indicates that the FV is moving faster than the LV.

Time to collision (TTC) was defined as the gap distance divided by the difference in speed between the FV and the LV. The reciprocal of TTC was used instead of TTC to avoid infinite or negative TTC values. When the LV speed was greater than or equal to the FV speed, reTTC was set to 0. Finally, the SD-FVspeed was calculated from FV speed over an entire CF event and used as an event-level metric.

2.5 Statistical Analysis

For the metrics in CF events, the blue-light condition, LV speed, and their two-way interaction were used as independent variables. The blue-light-off condition served as the reference group, and LV speed was the mean speed of a CF event. The interaction term tested whether the difference between blue-light-on and blue-light-off conditions changed as LV speed changed. For second-level analyses, including gap distance, time gap, and reTTC, multiple observations came from the same CF event. Therefore, event random-intercept mixed models were used, with CF event included as a random effect. To satisfy model assumptions, the square-root transformation (sqrt) was applied to reTTC before modeling. Mixed models were built using the *lmer* function in the *lme4* package in *R* 4.6.0. For the event-level analysis for SD-FVspeed, a linear model without random effects was used, with video-cluster robust standard errors to account for multiple CF events from the same video clip.

3 Results

Table 1 summarizes the statistical results. The model-predicted curves are shown in Figure 2, and the corresponding estimated LVspeed slopes and slope differences are summarized in Figure 3.

3.1 Gap distance

A significant interaction effect of blue-light condition and LVspeed was observed for gap distance (Table 1). As shown in Figures 3, in the blue-light-off condition, gap distance increased by 0.764 m for each 10 km/h increase in LVspeed, with a 95% confidence interval (95% CI) between [0.600, 0.927], t(5423) = 9.16, p < .0001. The estimated slope in the blue-light-on condition was approximately 1.596 m per 10 km/h increase in LVspeed (95% CI: [1.326, 1.866], t(5446) = 11.59, p< .0001). Further, the estimated difference (Δ) of the slope between the blue-light-on and blue-light-off conditions was 0.833 m per 10 km/h, 95% CI: [0.517, 1.148], t(5442) = 5.17, p < .0001. These results indicate that gap distance increased more steeply with LVspeed when the blue light was on.

3.2 Time gap

A significant interaction effect of blue-light condition and LVspeed was observed for time gap (Table 1. As shown in Figure 3, in the blue-light-off condition, time gap decreased by 0.217 s for each 10 km/h increase in LVspeed, 95% CI: [-0.235, -0.198], t(4663) = -22.86, p < .0001. The estimated slope in the blue-light-on condition was approximately -0.105 s per 10 km/h increase in LVspeed, 95% CI: [-0.135, -0.074], t(4929) = -6.64, p < .0001. Further, the Δ of the slope between the blue-light-on and blue-light-off conditions was 0.112 s per 10 km/h, 95% CI: [0.076, 0.148], t(4861) = 6.10, p < .0001. These results indicate that the reduction in time gap with increasing LVspeed was attenuated when the blue light was on.

3.3 Square-root-transformed reciprocal TTC

A significant interaction effect of blue-light condition and LVspeed was observed for sqrt(reTTC) (Table 1). As shown in Figure 3, in the blue-light-off condition, sqrt(reTTC) decreased by 0.0041 for each 10 km/h increase in LVspeed, 95% CI: [-0.0073, -0.0010], t(889) = -2.55, p = .0109. The estimated slope in the blue-light-on condition was approximately -0.0147 per 10 km/h increase in LVspeed, 95% CI: [-0.0202, -0.0093], t(1064) = -5.32, p < .0001. Further, the Δ of the slope between the blue-light-on and blue-light-off conditions was -0.0106 per 10 km/h, 95% CI: [-0.0169, -0.0043], t(1015) = -3.30, p = .0010. These results indicate that sqrt(reTTC) decreased more steeply with LVspeed when the blue light was on.

3.4 Standard deviation of FVspeed

No significant interaction effect of blue-light condition and LVspeed was observed for SD-FVspeed (Table 1 and Figure 3). Only a significant effect of LVspeed was observed: for each 10 km/h increase

Table 1: Statistical Results for the Metrics

Metrics	IVs	Estimate (SE)	t value	p-value
Gap distance	Intercept	13.015 (.783)	16.616	< .0001
	BLS	-1.477 (1.429)	-1.033	.3027
	LVspeed	.076 (.008)	9.160	< .0001
	BLS × LVspeed	.083 (.016)	5.171	< .0001
Time gap	Intercept	1.107 (.060)	18.604	< .0001
	BLS	-.117 (.109)	-1.078	.2823
	LVspeed	-.022 (.001)	-22.856	< .0001
	BLS × LVspeed	.011 (.002)	6.097	< .0001
Sqrt of reTTC	Intercept	.083 (.005)	16.154	< .0001
	BLS	-.025 (.009)	-2.669	.0083
	LVspeed	-.000 (.000)	-2.552	.0109
	BLS × LVspeed	-.001 (.000)	-3.299	.0010
SD-FVspeed	Intercept	1.740 (.136)	12.806	< .0001
	BLS	-.274 (.183)	-1.492	.1372
	LVspeed	-.009 (.004)	-2.007	.0461
	BLS × LVspeed	-.004 (.008)	-.518	.6053

Note. IV stands for independent variable; SE stands for standard error; BLS stands for blue-light state. The reference condition for BLS is blue light off. Therefore, the BLS main-effect estimates represent blue light on minus blue light off at the mean LVspeed.

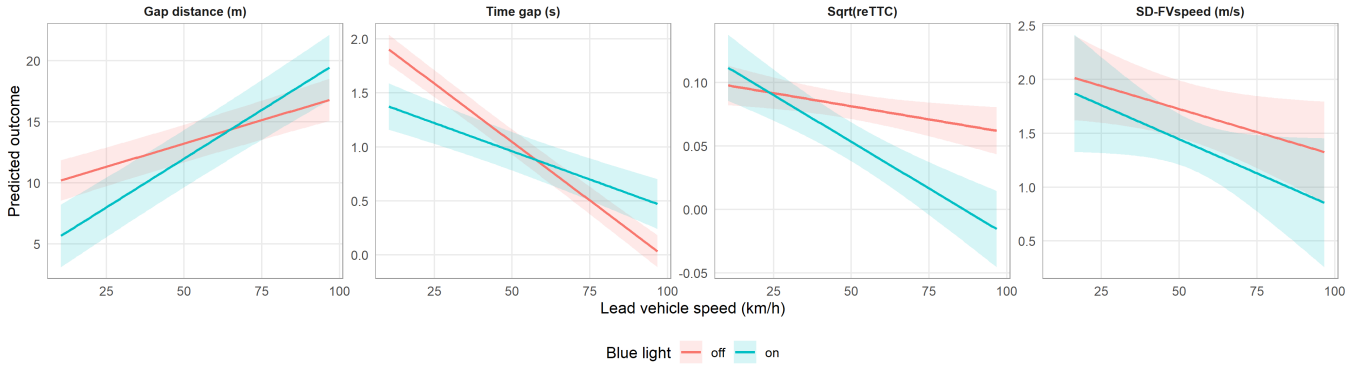


Figure 2: Model-predicted outcome curves across LVspeed for the blue-light-off and blue-light-on conditions. Lines represent model-predicted means, and shaded bands represent 95% confidence intervals.

in LVspeed, the SD-FVspeed decreased by 0.085 m/s, 95% CI: [0.02, 0.169].

4 Discussion

Using naturalistic driving data collected on public roads, this study investigated whether the visibility of an external ADAS-active status can affect following drivers' CF behavior in real traffic. The results showed that the blue-light-on condition did not make following drivers consistently follow closer or farther and did not affect the standard deviation of LV's speed. Instead, drivers' behavior was speed-dependent: as LV speed increased, following drivers adjusted their longitudinal safety margins differently in the blue-light-on and blue-light-off conditions.

First, the time gap and gap distance results provide evidence for this speed-dependent spacing adjustment. Time gap decreased with LV speed in both conditions, but this decrease was weaker in the blue-light-on condition. Similarly, gap distance showed a consistent pattern, increasing more steeply with LV speed when the blue light was on. The trends and magnitudes of our findings are consistent with previous studies regarding automated vehicle–human-driven vehicle interactions [5], which also showed speed-dependent results. Importantly, the present study extends this discussion from highly automated vehicles to vehicles with an SAE Level 2 ADAS system, indicating that even with a driver as a fallback in vehicles with ADAS, drivers may still have concerns about the safety of sharing the road with the ADAS-controlled vehicles.

The sqrt(reTTC) result, at the same time, provides additional evidence to interpret the speed-dependent blue-light-on effects. In general, such cautious behavior has brought a potential safety benefit: the sqrt(reTTC) decreased more steeply with increasing LV speed in the blue-light-on condition. A smaller reTTC can be interpreted as a lower rear-end collision risk [11, 16]. For example, Li et

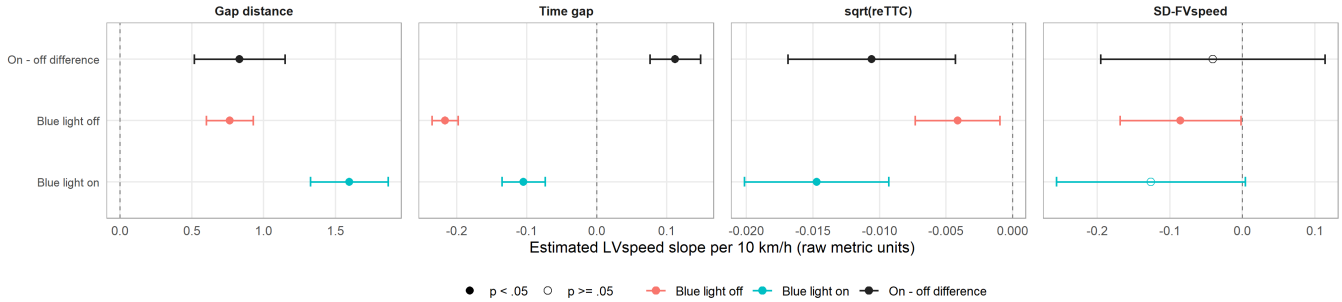


Figure 3: Estimated LVspeed slopes and slope differences for the four CF metrics. For each metric, the blue-light-off and blue-light-on rows show the estimated slope per 10 km/h increase in LVspeed, and the on-off difference row shows the estimated difference in slopes between the two conditions. Points represent estimates and error bars represent 95% confidence intervals. Filled dots indicate p < .05; hollow dots indicate p >= .05.

al. reported a descriptive difference of approximately -0.038 on the sqrt(reTTC) scale between the hand-held-phone and no-phone conditions [8], which is similar in magnitude to the differences across blue-light state conditions observed in the present study. However, our reTTC result should be interpreted cautiously because reTTC is highly sensitive to the relative speed of the LV and the FV, and the FV speed in this study was estimated from LV speed, which could be skewed. Therefore, this result should be considered exploratory and requires further validation with directly measured FV trajectories. Overall, the results suggest that the "bullying" behaviors towards the ADAS-controlled vehicles, as observed in previous studies [9], are less likely to happen at higher speeds, where the crash outcomes would be more severe. Nevertheless, further observational studies with larger sample sizes or survey studies would be needed to better reveal the potential heterogeneity of drivers' responses to ADAS.

These findings highlight the importance of external communication on ADAS-supported production vehicles, which allowed drivers to adjust their behaviors accordingly in different driving contexts. However, several limitations should be noted. First, because this study was based on a relatively small number of observations in a naturalistic driving study and not a fully controlled experiment, the observed differences should be interpreted with caution. Future work should more explicitly control the driving context or consider more potential confounders when modeling the drivers' behaviors. Second, again, due to the naturalistic nature of the study, we cannot tell whether following drivers have noticed or correctly interpreted the small blue light. Therefore, the observed associations may not be solely attributed to the behavioral adaptation. Further, the blue-light-on and blue-light-off conditions were collected during partially overlapping but different time periods. Therefore, variations in traffic conditions, route characteristics, or other environmental factors cannot be fully excluded. At the same time, the current sample was imbalanced, with fewer CF events in the blue-light-on condition. A larger and more balanced dataset would allow more robust estimation across different speed ranges and road contexts. Finally, FV speed and derived safety-related metrics were estimated from rear-view monocular video and LV RTK data rather than directly measured from the FV. For the same reason, the present analysis focused on daytime data to allow more accurate estimation of the following distance. Future work should examine whether lighting conditions could have an effect, especially since the small blue light may be more visually salient at night. Future work should also estimate FV's motion more accurately to quantify relative-speed-based metrics, such as reTTC, more reliably.

5 Conclusion

This study provides naturalistic evidence that small blue light may be associated with following drivers' CF behavior. In particular, the blue-light-on condition was mainly related to larger temporal following margins at higher LV speeds. These findings highlight the role of external ADAS status visibility as a potential influential factor of human drivers' longitudinal vehicle control behaviors when interacting with ADAS-controlled vehicles in real traffic. The results provide preliminary evidence supporting the benefits of the "small blue lights," though further validation with a larger sample size in a longitudinal study is needed to better quantify the effects in the long run.

Acknowledgments

This work was supported by the Nansha District Key Area S&T Scheme, Science and Technology Bureau of Nansha District (No. 2023ZD006).

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