Rear Vehicle Matters: How Tailgaters Influence the Car-Following Behaviors of the Ego-Vehicle

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Rear-end collisions account for a significant proportion of traffic accidents, highlighting the importance of analyzing drivers' car-following (CF) behavior for traffic safety research. Previous studies, whether based on modeling or data analysis, have primarily focused on the influence of the lead vehicle's (LV) state on a driver's CF behavior. However, in real-world driving, the information perceived by drivers is not limited to the LV; drivers also receive information about the following vehicle (FV), and their behavior may be influenced accordingly. Thus, this paper investigates the influence of FV states on the CF behavior of the ego-vehicle, specifically the impact of tailgating (where the time headway between the FV and the ego-vehicle is less than 2 seconds) on the behavior of the ego-vehicle. The results indicate that when being tailgated, ego-vehicles tend to keep a smaller time headway to their LVs, confirming the nudging effects of the FV in CF events.

INTRODUCTION

Rear-end collision accounts for a large proportion of traffic accidents among both non-automated and autonomous vehicles (Almutairi et al., 2023; Huang et al., 2024), which is highly related to the car-following (CF) behavior of the vehicles (Almutairi et al., 2023; Bella & Russo, 2011; Huang et al., 2024). Thus, the CF behaviors have been widely modeled in previous research, from both driver behavior modeling (Ahmed et al., 2021) and traffic controller design (Poudel & Li, 2023) perspectives of view. By modeling CF behaviors, more efficient, energy-saving, and comfortable driving control models can be designed, and the influential factors of driving CF strategies can be identified.

Existing CF models mostly assume that the CF behaviors depend on the interaction between the lead vehicle (LV) and the ego-vehicle (Zhu et al., 2018). However, the relationship between the ego-vehicle and the LV may not fully explain the variations in CF performance. For example, in a video-based study, Yan et al. (2023) found that drivers with traffic flow information ahead of the LV behaved more safely in critical events.

At the same time, drivers may also consider the rear information when following LVs, given that a large portion of drivers self-reported to have used tailgating to nudge the LVs (Stephens et al., 2023) and that the optical and video rearview mirrors can affect drivers' perceived distance of rear hazards (Flannagan, 2005), indicating that drivers do look back in CF events. However, to the best of our knowledge, no research has quantified the effect of following vehicles (FVs) on the CF behaviors of the ego-vehicle. Though several CF models have considered the behaviors of FV when designing CF models to stabilize traffic flow (Ma et al., 2023; Wang et al., 2022), they mostly simplified the mutual interactions between the FV and ego-vehicle by only considering the influence of ego-vehicle on the FV, without quantifying the effects of the FV on ego-vehicle.

Thus, in this study, we aim to understand how drivers' CF strategies can be affected by the FVs. Specifically, CF event segments from naturalistic driving datasets were extracted to analyze the influence of tailgaters on the CF behaviors of the leading ego-vehicle.

APPROACH

Extraction of CF Segments

This study extracts CF segments from the highD dataset based on the following criteria (Wen et al., 2022): 1) the CF duration should be over 15 seconds; 2) the following distance should be less than 100 meters; 3) no lane changes occur in the segment; and 4) the vehicle's minimum speed should be over 10 m/s to avoid creeping traffic.

Further, as shown in Figure 1, we defined two types of CF events, i.e., the tailgated CF events, where the FV kept a time headway less than 2 seconds (Agency, 2014), and the normal CF event, where the time headway of the FV was always over 2 seconds. In total, 2,999 tailgated CF events and 1,679 normal CF events were extracted.

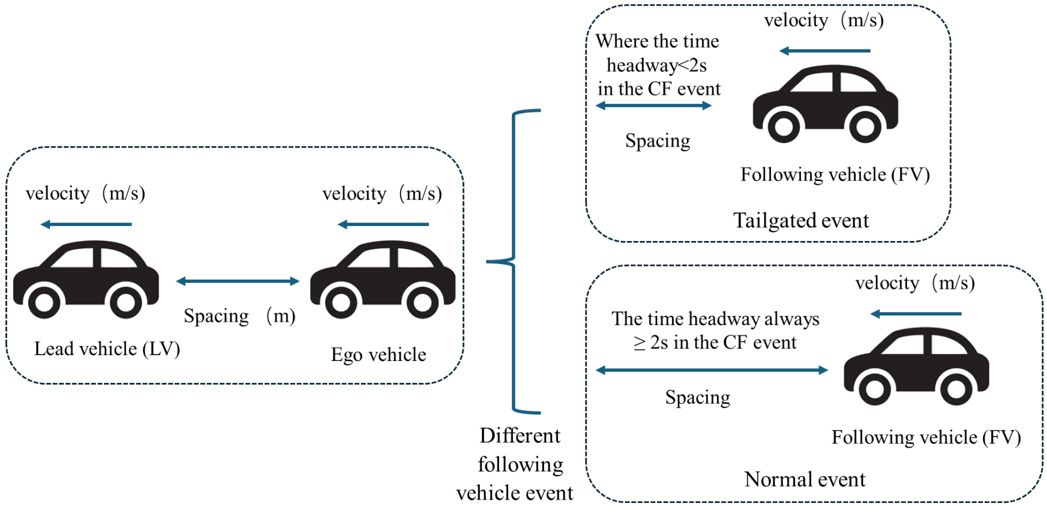

Figure 1. Different car-following events.

Pairing of the LV Speed Profiles

To eliminate the impact of different traffic flow speeds on the analysis, we used the Dynamic Time Warping (DTW) (Müller, 2007) algorithm to identify matched ego-vehicle trajectories under different types of CF events (i.e., tailgated and normal). DTW is an algorithm commonly used to compare the similarity between time series. Specifically, the DTW can non-linearly align two time series to find the optimal match.

The specific implementation of DTW is as follows: given two time series sequences $X = (x_1, x_2, \dots, x_n)$ and $Y = (y_1, y_2, \dots, y_m)$, where m and n represent the lengths of the two sequences, a matrix D of size m×n was constructed. The element $D(i, j)$ represents the minimum cumulative distance between the subsequence x_1 to x_i and y_1 to y_j. The recursive relationship for the matrix is defined as follows:

$$D(i,j) = d(x_i, y_j) + \min[D(i-1,j), D(i,j-1), D(i-1,j-1)] \tag{1}$$

where $d(x_i, y_j)$ represents the Euclidean distance between x_i and y_j in two sequences. The lower-right element $D(n, m)$ of the matrix D is the DTW distance between the two sequences - the smaller the distance, the higher similarity between the sequences. With the DTW algorithm, we identified 477 pairs of tailgater and normal CF events.

Metrics Evaluating the CF Behaviors

To assess the influence of tailgaters on drivers' CF behaviors, we compared ego-vehicles' speed fluctuation and driving safety metrics across two types of paired CF events with paired t-tests. Specifically, the speed fluctuations were measured by the following metrics:

Standard Deviation (Vsd) (Lee et al., 2015), which can be calculated following Equation (2):

$$V_{sd} = \sqrt{\frac{\sum_{i=1}^{n}(v_i - \bar{v})^2}{n-1}} \tag{2}$$

where, v_i is the sample point of speed in a dataset; $\bar{v}$ is the mean value of speed samples; and n is the sample size in the dataset.

Mean Absolute Deviation (Dmean) (Konno & Koshizuka, 2005), which can be calculated with Equation (3):

$$D_{mean} = \frac{\sum_{i=1}^{n}|v_i - \bar{v}|}{n} \tag{3}$$

Coefficient of Variation (Cv) (Abdi, 2010), which can be expressed as follows:

$$C_v = \frac{V_{sd}}{|\bar{v}|} \times 100\% \tag{4}$$

where, $\bar{v}$ is the mean speed in a CF segment.

Time-Varying Stochastic Volatility (Vf) (Nakajima, 2011), which can be calculated following Equation (5):

$$V_f = \sqrt{\frac{\sum_{i=1}^{n}(r_i - \bar{r})^2}{n-1}} \quad (5)$$

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

The safety of the ego-vehicle's CF behavior was measured by the following metrics:

Mean time headway (meanHDW) (Swaroop & Rajagopal, 2001), which can be calculated as follows:

$$meanHDW(t) = mean\left(\frac{X_L(t) - X_E(t)}{V_E(t)}\right) \quad (6)$$

where, $X_L(t)$ and $X_E(t)$ are the positions of lead vehicle and ego-vehicle at time t. $V_E(t)$ is the speed of ego-vehicle at time t

Maximum reciprocal time-to-collision (maxreTTC) (Alonso-Mora et al., 2012), which can be calculated as follows:

$$maxreTTC(t) = \max\left(\frac{V_E(t) - V_L(t)}{X_L(t) - X_E(t) - L}\right) \quad (7)$$

OUTCOMES

The statistical results are shown in Table 1.

Table 1. The comparison of CF behaviors between tailgated and normal CF events

Metrics	Tailgated Events				Normal Events					
	Max	Min	Mean	SD	Max	Min	Mean	SD	Δ (%)	*p*-value
					Speed Fluctuation					
V_{sd} (m/s)	6.02	0.06	1.42	1.00	5.54	0.08	1.45	1.02	-2.11	.7
D_{mean}(m/s)	5.25	0.05	1.21	0.87	5.03	0.06	1.24	0.89	-2.48	.5
C_v	42.68	0.28	12.45	10.78	44.64	0.52	12.78	11.24	-2.65	.7
V_f(m/s)	0.79	0.02	0.10	0.10	0.75	0.02	0.11	0.10	-10.00	.9
					Safety					
meanHDW (s)	7.02	0.22	2.38	1.15	12.78	0.20	2.62	1.33	-10.08	.003*
maxreTTC (s)	121.87	0.0003	0.64	7.36	76.10	0.0003	0.46	4.83	28.13	.6

*Note: In the table, * marks significant results (p < .05), Δ is the percentage difference between two types of CF events, and SD stands for standard deviation.*

Speed Fluctuation

In this study, although there are minor differences in the descriptive statistics (Vsd, Dmean, Cv, and Vf), none of them were significant ($p > .05$). This indicates that our DTW algorithm has selected CF events with similar speed profiles. However, it should be noted that, descriptively, more extreme speed fluctuations have occurred in the tailgated CF events, as indicated by the percentage differences of the mean values of the metrics.

Safety

As shown in Figure 2, the meanHDW in the tailgated CF event was 10.8% lower in the normal CF event. Given that the speed profiles were similar across the event pairs, the smaller meanHDW in the tailgated CF event as compared to that in the normal CF event indicates that the ego-vehicle drove closer and more aggressively to the LV in the tailgated CF events. The lack of significant differences in the reTTC may because the drivers got increasingly more cautious and thus more sensitive to the LV speed changes when following LV at a closer distance, as indicated by the smaller meanHDW.

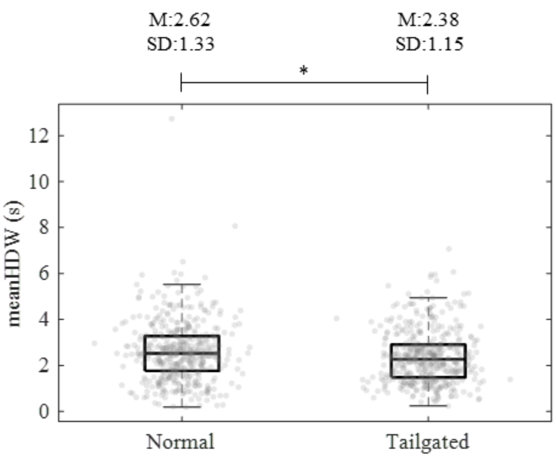

Figure 2. Comparisons of meanHDW in different CF conditions, M stands for mean value, SD stands for standard deviation, and significant comparisons ($p < .05$) are marked using “*”. In the figure, each box represents the interquartile range (IQR) of the data: the bottom and top edges of the box correspond to the first (Q1) and third quartiles (Q3), respectively, while the bold line inside the box indicates the median. The whiskers extend to the minimum and maximum values within 1.5 times the IQR from the quartiles.

DISCUSSION

In this study, CF events with and without tailgaters were extracted from an on-road dataset, the highD dataset. Then, the DTW method successfully identified CF pairs with similar speed profiles as indicated by non-significant ($p > .05$) differences in speed fluctuation metrics across these two types of CF events.

As a result, for the first time, we observed the nudge effects (Zadka-Peer & Rosenbloom, 2024) of the FV on drivers’ CF behaviors in a naturalistic environment. Specifically, we found that with a tailgater, drivers kept a shorter time headway to the LV. This result provides evidence that drivers consider more than LV information in CF events (Gunawan, 2012; Jiang et al., 2001; Treiber et al., 2000) – the peer pressure from behind can also shape drivers’ CF strategies. Further, drivers may have driven more cautiously when they kept a shorter time headway to the LV, as indicated by the larger, though statistically non-significant difference in remaxTTC. This result indicates that drivers could still adapt their driving behaviors based on the complexity of the traffic, even with the peer pressure from behind.

However, it should be noted that due to the nature of the on-road observation dataset, we could not explore drivers' subjective thoughts on being tailgated and their decision-making process. Further research with recruited participants could provide further information on these topics. Further, our results were based on a single dataset. Future research should validate our findings on other datasets. Nevertheless, our research indicates that future driver behavior models in the traffic simulation should take the impact of the FV into consideration. As a next step, additional research should be conducted to quantitatively model drivers’ CF behaviors in different conditions, potentially using data-driven methods, such as inversed reinforcement learning (Wen et al., 2023), to recover drivers' strategies in different situations

CONFLICT OF INTEREST

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

AKNOWLEDGEMENTS

This work was supported by the Scientific Research Projects for the Higher-educational Institutions of Guangzhou (No. 2024312135), and in part by the Guangzhou Municipal Science and Technology Project (No. 2023A03J0011), and Guangdong Provincial Key Lab of Integrated Communication, Sensing and Computation for Ubiquitous Internet of Things (No. 2023B1212010007).

REFERENCES

Abdi, H. (2010). Coefficient of variation. Encyclopedia of Research Design, N. Salkind, Ed. *Sage, https://doi. org/10.4135/9781412961288.10, 4135*, 9781412961288.

Agency, D. a. V. S. (2014). *Highways Agency warns tailgaters that 'only a fool breaks the 2-second rule'*. Retrieved February 5 from https://www.gov.uk/government/news/highways-agency-warns-tailgaters-that-only-a-fool-breaks-the-two-second-rule

Ahmed, H. U., Huang, Y., & Lu, P. (2021). A review of car-following models and modeling tools for human and autonomous-ready driving behaviors in micro-simulation. *Smart Cities*, *4*(1), 314-335.

Almutairi, M. S., Almutairi, K., & Chiroma, H. (2023). Hybrid of deep recurrent network and long short term memory for rear-end collision detection in fog based internet of vehicles. *Expert Systems with Applications*, *213*, 119033.

Alonso-Mora, J., Breitenmoser, A., Beardsley, P., & Siegwart, R. (2012). Reciprocal collision avoidance for multiple car-like robots. *2012 IEEE International Conference on Robotics and Automation*,

Bella, F., & Russo, R. (2011). A collision warning system for rear-end collision: a driving simulator study. *Procedia-Social and Behavioral Sciences*, *20*, 676-686.

Flannagan, M. J. (2005). *Distance Perception with a Camera-Based Rear Vision System in Actual Driving* (UMTRI-2005-38). University of Michigan, Ann Arbor, Transportation Research Institute.

Gunawan, F. E. (2012). Two-vehicle dynamics of the car-following models on realistic driving condition. *Journal of Transportation Systems Engineering and Information Technology*, *12*(2), 67-75.

Huang, C., Wen, X., & He, D. (2024). Characteristics of rear-end collisions: a comparison between automated driving system-involved crashes and advanced driving assistance system-involved crashes. *Transportation Research Record*, *2678*(7), 771-782.

Jiang, R., Wu, Q., & Zhu, Z. (2001). Full velocity difference model for a car-following theory. *Physical Review E*, *64*(1), 017101.

Konno, H., & Koshizuka, T. (2005). Mean-absolute deviation model. *Iie Transactions*, *37*(10), 893-900.

Lee, D. K., In, J., & Lee, S. (2015). Standard deviation and standard error of the mean. *Korean Journal of Anesthesiology*, *68*(3), 220-223.

Ma, M., Wang, W., Liang, S., Xiao, J., & Wu, C. (2023). Improved car-following model for connected vehicles considering backward-looking effect and motion information of multiple vehicles. *Journal of Transportation Engineering, Part A: Systems*, *149*(2), 04022148.

Müller, M. (2007). Dynamic time warping. *Information Retrieval for Music and Motion*, 69-84. Springer, Berlin, Heidelberg.

Nakajima, J. (2011). Time-varying parameter VAR model with stochastic volatility: An overview of methodology and empirical applications. *Monetary and Economic Studies*, 2011, vol. 29, 107-142

Poudel, B., & Li, W. (2023). Beyond simulated drivers: Evaluating the impact of real-world car-following in mixed traffic control. *arXiv Preprint arXiv:2311.12261*.

Stephens, A., Stephan, K., Crotty, R., O'Hern, S., & Björklund, G. (2023). Too close for comfort: A mixed methods study to understand self-reported tailgating using the theory of planned behaviour. *Transportation Research Part F: Traffic Psychology and Behaviour*, *93*, 11-22.

Swaroop, D., & Rajagopal, K. (2001). A review of constant time headway policy for automatic vehicle following. *ITSC 2001. 2001 IEEE Intelligent Transportation Systems. Proceedings (Cat. No. 01TH8585)*, 65-69.

Treiber, M., Hennecke, A., & Helbing, D. (2000). Congested traffic states in empirical observations and microscopic simulations. *Physical Review E*, *62*(2), 1805.

Wang, Z., Huang, H., Tang, J., Meng, X., & Hu, L. (2022). Velocity control in car-following behavior with autonomous vehicles using reinforcement learning. *Accident Analysis & Prevention*, *174*, 106729.

Wen, X., Cui, Z., & Jian, S. (2022). Characterizing car-following behaviors of human drivers when following automated vehicles using the real-world dataset. *Accident Analysis & Prevention*, *172*, 106689.

Wen, X., Jian, S., & He, D. (2023). Modeling the effects of autonomous vehicles on human driver car-following behaviors using inverse reinforcement learning. *IEEE Transactions on Intelligent Transportation Systems*.

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

Zadka-Peer, S., & Rosenbloom, T. (2024). Targeted nudging for speeding behavior: The influence of interpersonal characteristics on responses to in-vehicle road nudges. *Accident Analysis & Prevention*, *204*, 107638.

Zhu, M., Wang, X., & Wang, Y. (2018). Human-like autonomous car-following model with deep reinforcement learning. *Transportation Research Part C: Emerging Technologies*, *97*, 348-368.