SHARING THE ROAD: HOW HUMAN DRIVERS INTERACT WITH AUTONOMOUS VEHICLES ON HIGHWAYS

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With more autonomous vehicles (AVs) being tested or deployed on public roads, human-driven vehicles (HVs) have to share the road with AVs. However, human drivers may not interact AVs the same way as they interact with HVs. Very few studies have investigated drivers' behaviors when sharing the road with AVs. Based on a real-world dataset, our study explored drivers' interactions with AVs in two types of events on highway, i.e., car-following event and car-passing event. The results show that, compared to interacting with HVs, drivers tended to keep a larger safety margin (i.e., larger gap distance and time gap) at high speed in both types of events when interacting with AVs. At the same time, drivers seemed to have difficulty anticipating AVs' speed changes at high speed, as indicated by a larger standard deviation of the HVs' speed and a smaller time to collision when following AVs versus following HVs.

INTRODUCTION

With the advancements of sensor and computation technologies, autonomous vehicle (AVs) services, such as Waymo in the U.S. (Waymo, 2021) and Baidu in China (Baidu Apollo, 2021), are being tested and deployed on public roads. As no lanes are designated for the implementation of AVs, inevitably, there will be a transition period in the foreseeable future, in which human-driven vehicles (HVs) and AVs share the road. This may bring challenges to traffic safety, especially with the increasing percentage of AVs on the road – not just because AVs need to perceive and understand human drivers' behaviors, but also because human drivers may take different strategies to interact with AVs.

When sharing the road with other HVs, drivers can safely assume that most HVs will follow commonly accepted "rules" and their behaviors will be "predictable" to some extent. Thus, drivers may have developed their own strategies to interact with HVs. For example, drivers may keep a gap time that they feel safe when following lead vehicles (LVs) (Saifuzzaman & Zheng, 2014), assuming the lead vehicles will follow the speed of traffic when there is no emergency. Drivers may also keep a comfortable lateral distance (LD) when passing other HVs through adjacent lanes, assuming other drivers will not change lanes before checking blind spots. However, AVs are new to most drivers, and drivers may not have developed appropriate expectations of AVs' behaviors. Thus, human drivers may take different strategies when interacting with AVs, which may or may not lead to unsafe situations.

Although research based on traffic simulation has discussed the safety implications of mixing AVs and HVs in traffic network (e.g., Sinha et al., 2020), the outcomes of these studies were susceptible to the choice of human drivers' behavioral model. Most of these previous traffic simulations adopted arbitrary parameters when modeling drivers' behaviors in the mixed traffic (Papadoulis et al., 2019; Sinha et al., 2020; Virdi et al., 2019), which brings concerns on the validity of the simulation results. To address this issue, a few studies have investigated how human drivers react to AVs on road. In a field study, Mahdinia et al (2021) found that when following AVs, drivers exhibited lower speed volatility and lower acceleration volatility and increased time to collision (TTC) compared to that when following HVs. In another field study, Zhao et al (2020) found that the impact of AVs on human drivers' car-following behaviors are subject to drivers' subjective trusts toward AVs. However, it should be noted that the speed of lead vehicles was less than 40 km/h in Mahdinia et al (2021) and less than 60 km/h in Zhao et al (2020), and thus they may not reveal drivers' behaviors on highway. Further, both of them were conducted in controlled environments and only car-following events were investigated, which may limit the generality of the results. To evaluate the impact of sharing road with AVs on human drivers' behaviors, further research based on real-world data is needed.

Thus, our study explored the influence of AVs on human drivers' behaviors using a real-world dataset, the Waymo Open Dataset (Waymo LLC, 2020), which is a public dataset released by Waymo LLC. The dataset records the movements of other road agents surrounding the AVs. As AVs are expected to be first deployed on highway, in this study, we mainly focused on the influence of AVs on human drivers' behaviors on highway. Two types of events were analyzed in this study, i.e., the car-following events in which HV follows an AV or HV, and the car-passing events in which HV passes an AV or HV. Four safety-relevant metrics were extracted from the car-following events, i.e., the time gap, gap distance, time to collision (TTC), and the standard deviation of the following vehicle speed (SD-FVspeed); while for car-passing events, we focused on the lateral distance (LD) between the passing vehicle (PV) and vehicle being passed (BPV).

METHOD

Data Description

The data used in this study was extracted from the Waymo Open Dataset, which contains the road test data from several AVs that can be categorized as SAE Level 4 or Level 5 automation (SAE On-Road Automated Vehicle Standards Committee, 2021). Waymo has conducted over 32 million kilometers test of these AVs on public roads in selected U.S. cities, such as Phoenix, Mountain View and San Francisco. In the dataset, the AVs' trajectories and surrounding traffic environment were captured at 10-Hz frequency through sensors mounted on the AVs (e.g., lidars and cameras).

The Waymo Open Dataset is constituted of two parts: the perception and motion parts. The perception part of the Waymo dataset was first released in August 2019, which includes 1,000 segments of 20-second data, consisting of high-resolution lidar and camera raw data (Sun et al., 2020). The motion part was first released in March 2021, which contains 103,354 segments of high-quality 3D environmental data (including the size and location of other road agents) and high-resolution map data (Ettinger et al., 2021); each segment was also 20 seconds long. Both parts of the dataset were used for the extraction of car-following events and car-passing events in this study.

Extraction of Events

Car-following events. In any 20-second segment, if one vehicle followed another vehicle in the same lane for over 15 seconds (Shangguan et al., 2021) and the behaviors of the two vehicles satisfied all the criteria listed below, then the event was extracted as a car-following event.

- None of the two vehicles made lane changes or turns (Bao et al., 2020);
- The speed of following vehicle (FV) was greater than 10 km/h (Zhu & Zhang, 2018);
- The gap distance (from the front bumper of the FV to the rear bumper of the LV) was less than 85 m (Hammit et al., 2018);

Based on these criteria, 229 HV-following-AV events and 1,246 HV-following-HV events on highway were extracted through customized python codes.

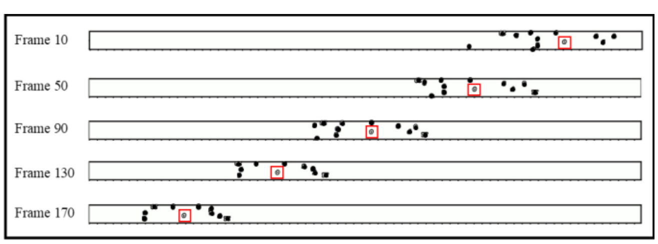

Figure 1. An example of five frames from a car-passing video. In the video, AV is highlighted as red box and the surrounding HVs are marked as black dots.

Car-passing events. To extract the car-passing events, each 20-second segment was visualized as a short video that shows the motion of the AV and the motion of the surrounding vehicles detected by the AV (Figure 1). A car-passing event was extracted if one vehicle passed another vehicle through adjacent lanes (i.e., either left or right lane). By manually inspecting the videos, 37 HV-pass-AV events, and 26 HV-pass-HV events on highways were extracted.

Dependent Variables

For car-following events, four metrics were extracted as dependent variables: i.e., gap distance, time gap, the reciprocal of TTC (reTTC), and the standard deviation of the following vehicle speed (SD-FVspeed). The time gap was defined as the gap distance divided by the speed of the following vehicle. The TTC was defined as the gap distance divided by the speed difference between the following vehicle and the lead vehicle. The reTTC, instead of TTC, was used so that infinite or negative TTC can be avoided: when the lead vehicle was equal or faster than the following vehicle, the reTTC was set to 0. All these four metrics were found to be associated with crash risk (Kamrani et al., 2018; Liu & Selpi, 2020; Minderhoud & Bovy, 2001; Vogel, 2003). The gap distance, time gap, and the TTC were extracted every 1 second in a car-following event, while the SD-FVspeed was calculated based on the speed of FV throughout a whole car-following event.

For car-passing events, we selected LD as the dependent variable. Following previous research (Dozza et al., 2016), the LD was defined as the lateral distance between the geometric centers of two vehicles in a car-passing event at the moment the PV and BPV were the closest.

Statistical Analysis

For the metrics in car-following events, the car-following type (i.e., HV-follow-HV versus HV-follow-AV), the speed of the LV (LVspeed), and their interactions were used as independent variables. The LVspeed was the mean speed of the LV in the data extraction period of the metrics (i.e., 1 second for gap distance, time gap and reTTC, and the duration of the car-following events for SD-FVspeed). Further, for gap distance, time gap and reTTC, the car-following event was included as a random effect. For LD, the car-passing type (i.e., HV-pass-HV versus HV-pass-AV), the speed of the BPV (BPVspeed), and their interaction were used as independent variables. Specifically, the BPVspeed was the speed of the BPV when the PV and BPV were closest in a passing event.

For models including random effects, mixed models were built using the *lmer* function within the *lme4* package in *R* 3.6.1 (R Development Core Team, 2019), while other models were built using the *glm* function within the *stat* package. To satisfy the assumptions of the mixed model, the square root transformation (sqrt) was applied to the reTTC.

RESULTS

Table 1 summarizes the statistical results for all the metrics in both car-following events and car-passing events.

Car-following Events

Gap distance. A significant interaction effect of car-following type and LVspeed has been observed for the gap distance (Table 1 and Figure 2). In general, the gap distance increased with the increase of the LVspeed but to different extents in two types of events. For each 1 km/h increase in LVspeed, the gap distance increased 0.45 m in HV-follow-AV events, with 95% a confidence interval (CI) of 0.44 to 0.46; while in HV-follow-HV events, a 0.41 m (95%CI: 0.38, 0.44) increase in gap distance was observed for each 1 km/h increase in LVspeed. When comparisons were made across car-following types, it was found that compared to that in HV-follow-HV events, in HV-follow-AV events, the gap distance was smaller when the LVspeed was less than 42 km/h, and larger when the LVspeed was over 103 km/h. No significant difference was observed between two types of car-following events when the LVspeed was between 42 km/h to 103 km/h.

Table 1. Statistical results for the metrics

Metrics	***IVs***	***Estimate (SE)***	***t value***	***p-value***
Gap distance	Intercept	-0.71 (0.61)	-1.17	.3
	CFT	2.75 (0.66)	4.18	<.0001
	LVspeed	0.45 (0.008)	58.11	< .0001
	CFT * LVspeed	-0.04 (0.008)	-4.869	< .0001
Time gap	Intercept	1.44 (0.06)	23.85	< .0001
	CFT	0.35 (0.07)	5.32	< .0001
	LVspeed	0.006 (0.00)	7.73	< .0001
	CFT* LVspeed	-0.0055 (0.00)	-6.46	< .0001
Sqrt of reTTC	Intercept	0.18 (0.008)	21.10	< .0001
	CFT	0.029 (0.009)	3.17	.0009
	LVspeed	-0.002 (0.000)	-11.06	< .0001
	CFT * LVspeed	-0.001 (0.0001)	-6.207	< .0001
SD-FVspeed	Intercept	1.61 (0.11)	13.81	< .0001
	CFT	-0.25 (0.13)	-1.95	.052
	LVspeed	-0.017 (0.0077)	-2.16	.03
	CFT * LVspeed	0.032 (0.009)	3.54	.0004
LD	Intercept	5.2 (0.75)	6.94	< .0001
	CPT	-2.6 (1.0)	-2.49	.016
	BPVspeed	0.0003 (0.04)	0.01	.99
	CPT * BPVspeed	0.10 (0.06)	1.83	.072

Note: IV stands for independent variables; SE stands for standard error; CFT stands for car-following type; CPT stands for car-passing type. The baseline types for CFT and CPT are the HV-follow-HV and the HV-pass-HV, respectively.

Time gap. A significant interaction effect of car-following type and LVspeed has been observed for the time gap. As shown in Figure 3, in both HV-following-HV and HV-following-AV events, the time gap decreased with the increase of the LVspeed, but to different extents in two types of events. For each 1 km/h increase in LVspeed, the time gap increased 0.006 s (95%CI: 0.0045, 0.0076) in HV-follow-AV events but did not change in HV-follow-HV events. This indicates that although drivers tended to increase the gap distance with increasing speed, they may not be able to fully compensate the effect of speed, especially when they were following the AVs. When comparisons were made across car-following types, it was found that compared to that in HV-follow-HV events, in HV-follow-AV events, the time gap was smaller when the LVspeed was less than 45 km/h, and larger when the LVspeed was over 85 km/h. No significant difference was observed between two types of car-following events when the LVspeed was between 45 km/h to 85 km/h.

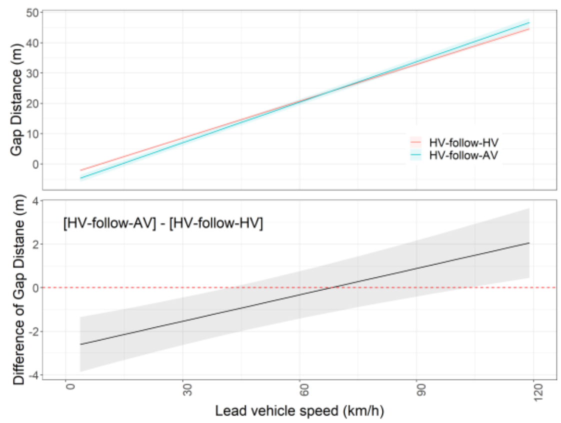

Figure 2. The results of the gap distance model. In this figure and the following figures, the shadow represents 95% confidence interval (CI) of the estimated differences between the two types of car-following events.

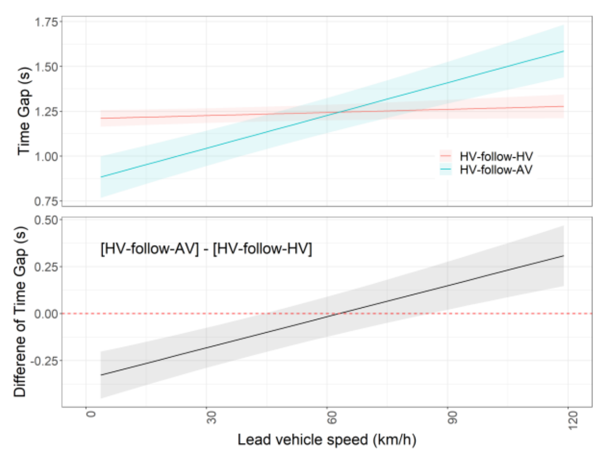

Figure 3. The results of the time gap model.

Reciprocal of TTC. A significant interaction effect of car-following type and LVspeed has been observed for the reTTC. As shown in Figure 4, in both HV-following-HV and HV-following-AV events, the reTTC decreased with the increase of the LVspeed, indicating that drivers tended to keep a larger time margin with increasing speed. Further, in HV-follow-AV event, the drivers seemed to be less responsive to the change of speed in terms of reTTC, compared to that in HV-follow-HV events: for each 1km/h increase in speed, the sqrt of reTTC in HV-follow-AV events decreased 0.0016 (95%CI: 0.0013, 0.0019); while in HV-follow-HV events, the sqrt of reTTC decreased 0.0026 (95%CI: 0.0021, 0.0031). When comparisons were made across car-following types, it was found that compared to that in HV-follow-HV events, when the LVspeed was less than 15 km/h, the reTTC was smaller in HV-follow-AV events; while when the LVspeed was over 38 km/h, the reTTC was larger in HV-follow-AV events. No significant difference was observed when the LVspeed was between 15 km/h and 38 km/h.

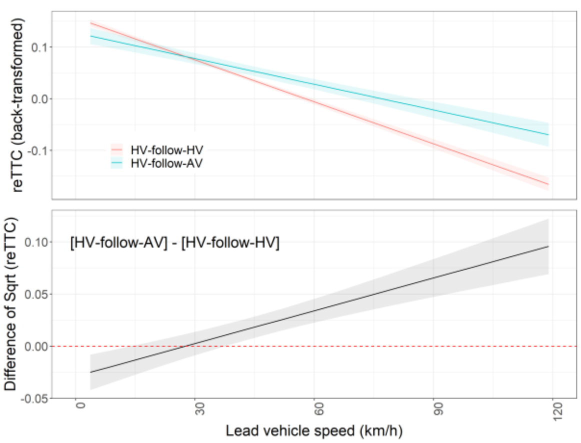

Figure 4. The results of the reTTC model.

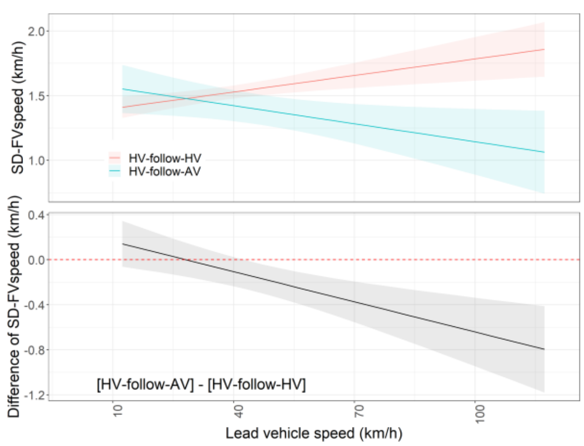

Figure 5. The results of the SD-LVspeed model.

Standard Deviation of FVspeed. A significant interaction effect of car-following type and LVspeed has been observed for the SD-FVspeed. As shown in Figure 5, with each 1 km/h increase in LVspeed, the SD-FVspeed decreased 0.02 km/h (95%CI: 0.01, 0.03) in HV-follow-AV events, while no significant trend was observed in HV-follow-HV events. When comparisons were made across car-following types, it was found that only when the LVspeed was over 43 km/h, the SD-FVspeed in HV-follow-AV events was smaller compared to that in HV-follow-HV events. No significant difference was observed when the LVspeed was less than 43 km/h.

Car-Passing Events

In car-passing events, only a significant effect of the car-passing event type has been observed for the LD (Table 1 and Figure 6). It was found that the LD in HV-pass-AV events was 0.78 m (95%CI: [0.70, 0.86]) larger than that in HV-overtake-HV events.

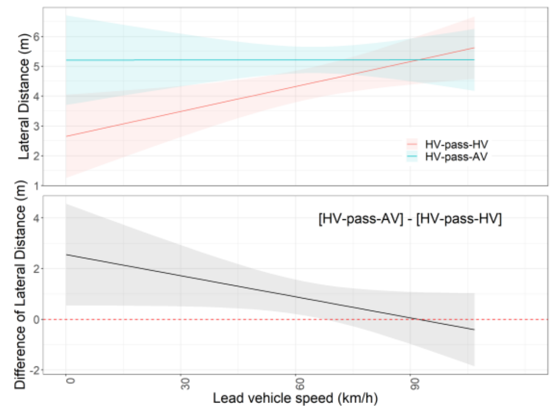

Figure 6. The results of the LD model.

DISCUSSION

Through a dataset collected on open public roads, this study investigated how human drivers respond differently to AVs versus HVs on highway. As expected, we found that drivers tended to keep a larger safety margin with increasing speed regardless of the types of vehicles (i.e., either AV or HV) they interacted with, by keeping a larger gap distance, and a larger TTC (i.e., smaller reTTC) to the lead vehicle in car-following events. At the same time, it is interesting to notice that although the gap distance increased with increasing lead vehicle speed in HV-follow-HV events, the time gap did not change with the speed, indicating that drivers did not fully compensate the effect of vehicle speed increase on highway when following HVs. It is also alerting that drivers kept a less than 2 seconds time gap at most speed regardless the types of car-following events, although 2-second time gap was recommended for the consideration of driving safety (New York State Department of Motor Vehicles, 2020). The speed had no impact on LD in car-passing events, potentially because the vehicles had less freedom to adjust their distance to vehicles being passed, as their lateral positions were restricted by the width of lanes.

Being different from the findings in Mahdinia et al (2021), which observed smaller speed volatility when drivers were following AVs versus following HVs, in our study, we found that the drivers showed smaller speed volatility (as indicated by the SD of FVspeed) when following AVs (versus following HVs) only when the speed of the lead vehicle was over 43 km/h; and there was no difference between car-following types when the lead vehicle speed was less than 43 km/h. Further, the TTC also showed a trend that is different from the findings in Mahdinia et al (2021). Compared to that in HV-follow-HV events, a larger TTC (i.e., smaller reTTC) was only observed in HV-follow-AV events when the lead vehicle speed was less than 15 km/h in our study; while when the lead vehicle speed was over 38 km/h, the TTC in HV-follow-AV events was smaller than that in HV-follow-HV events. This conflicting result as compared to Mahdinia et al (2021) at high speed may be attributed to different scenario complexities in test fields and on public roads. The smaller TTC observed in our study indicates that at high speed, drivers seemed to be less reactive to the speed variations of a leading AV than to a leading HV. It is possible that AVs behaves differently at high speed as compared to human drivers, and thus drivers following a leading AV are less capable of anticipating the speed changes of the AV.

At the same time, drivers seemed to keep a larger safety margin when interacting with AVs compared to interacting with HVs, especially at high speed. In car following events, we observed larger gap distance and time gap in HV-follow-AV events compared to that in HV-follow-HV events when the leading vehicle speed was over 103 km/h and 85 km/h, respectively. In car-passing events, drivers also kept a larger LD regardless of the lead vehicle speed. This indicates that drivers may still trust less in AVs than HVs (Zhao et al., 2020). However, it is interesting to notice that drivers tended to follow a leading AV at a closer gap distance and smaller gap time as compared to following a HV when the speed of the lead vehicle was relatively small. This trend might be explained as drivers having perceived different levels of risk or behavioral control (Ajzen, 1991) at different speed range: drivers might be curious about AVs and regard tailgating an AV as a more controllable behavior when the speed was low.

In summary, our results show that drivers may interact with AVs differently as compared to interacting with HVs and to different extents at different speed. These results indicate the necessity of external human machine interface (eHMI) of AVs that can increase the transparency of AVs. The results may also provide insights on the design of AV control algorithms that take the behaviors of surrounding HVs into consideration. It should be noted that different AV control algorithms may lead to different behaviors of AVs, which can affect human drivers' responses to them (Zhao et al., 2020). Unfortunately, we have no information whether Waymo has updated the control algorithms during the data collection period, which may have introduced a covariate that we cannot quantify in our analysis. Further, we were not able to collect human drivers' subjective ratings and thus we cannot analyze the underlying reasons for the change of behaviors when interacting with AVs. Future research may address these issues through questionnaires and controlled experiments on open roads or test fields.

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