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Characterizing Behavioral Differences of Autonomous Vehicles and Human-Driven Vehicles at Signalized Intersections Based on Waymo Open Dataset

Yiyun Wang[1,2,3], Haneen Farah[3], Rongjie Yu[1,2], Shuhan Qiu[1,2], and Bart van Arem[3]

Abstract

Autonomous vehicles (AVs) are being introduced to the traffic system with the promise of improving current traffic status. However, the empirical data also indicate contrary effects with estimated higher crash rate and change of crash patterns. Therefore, it is necessary to investigate the driving behavior of AVs and human-driven vehicles (HDVs) in real mixed traffic. Current studies have analyzed the driving behavior of AVs and HDVs, as well as behavioral adaptations of drivers of HDVs based on empirical data. While they play an important role in traffic systems, signalized intersections have not been studied sufficiently in this context. Therefore, this study aims to utilize the Waymo open dataset to characterize and quantify the behavioral differences of AVs and HDVs at signalized intersections. Five parameters of driving behavior related to signalized intersections were characterized according to five critical maneuver phases, which were identified by wavelet transform and threshold-based method. Statistically significant differences in driving behavior between AVs and HDVs were found, from three categorized situations: vehicle approaching the red light/queue, vehicle responding to the green light (as the first vehicle), and vehicle responding to its preceding vehicle (in the queue). Further, behavioral adaptations of HDV drivers were revealed in that they tended to keep closer to the stopped AVs in a queue and to react more strongly to AV start-up maneuvers when the traffic light turns to green.

Keywords

operations, traffic flow theory and characteristics, automated/autonomous vehicles, traffic flow

Autonomous vehicles (AVs) are being introduced to the traffic system with the promise of improving traffic safety and efficiency (*1*). As AVs are increasingly being tested on public roads, however, the testing results show that the performance of AVs is contrary to expectations. It is estimated that AVs have a crash rate per million miles traveled more than twice that of conventional human-driven vehicles (HDVs) (9.1 versus 4.1) (*2*). The distinctive driving style of AVs also brings about changes in conventional crash pattern distributions. For example, in data on AV-involved crashes from the California Department of Motor Vehicles (CDMV), the rear-end pattern predominates, with a value of 57.5%, compared with 27.9% for HDVs. Moreover, most of the rear-end crashes are AVs being rear-ended by HDVs, a phenomenon caused by complex interactions (*3*). Therefore, it is very important to investigate the behavioral differences of AVs and HDVs, and their interactions in real traffic.

In some recent studies, researchers utilized field experiment data or real-world road-testing data to investigate the driving behavior of AVs and HDVs in mixed traffic (*4*), such as the driving behavior properties (*5*, *6*) and human drivers' behavioral adaptations (*7–9*). However, these studies mainly focus on car-following

[1]Key Laboratory of Road and Traffic Engineering, Ministry of Education, Shanghai, China
[2]College of Transportation Engineering, Tongji University, Shanghai, China
[3]Department of Transport and Planning, Delft University of Technology, Delft, The Netherlands

Corresponding Author:
Yiyun Wang, wangyiyun@tongji.edu.cn

scenarios instead of signalized intersections which play vital roles in traffic safety and efficiency (*10*). It is indicated that signalized intersections contribute to about 36% of traffic crashes (*11*). Despite the importance of signalized intersections in traffic systems, only a few studies, to the best of our knowledge, have characterized and quantified the driving behavior of AVs and HDVs at signalized intersections based on empirical data.

Therefore, this study utilized real-world empirical data to investigate driving behavior of AVs and HDVs at the approaches to signalized intersections. Behaviors were characterized based on different maneuver phases, such as approaching the intersection, responding to traffic light, and starting up. The behavioral differences between AVs and HDVs and the behavioral adaptations of drivers of HDVs were analyzed. The obtained results could provide insights for evaluation of implications of AVs, such as microscopic simulation calibration. The main contributions of this study are summarized as follows:

1. Utilizing real-world empirical dataset to characterize signalized intersection-related driving behaviors of AVs and HDVs.
2. Revealing the behavioral differences between AVs and HDVs based on different maneuver phases.
3. Finding the behavioral adaptations of HDVs when interacting with AVs at the discharge of queue.

Literature Review

This section first reviews the studies that investigate AV and HDV driving behavior in mixed traffic with a real-world dataset, then the key parameters adopted by the literature to quantify signalized intersection-related behaviors are summarized.

Behavior Analyses Based on Real-World Dataset

As AV technology becomes available, studies using field experiments and empirical public road-testing datasets are increasing. For example, Mahdinia et al. (*7*) conducted a field experiment to test human drivers' behavior when following an AV, and analyzed the speed profiles of HDVs and AVs. They quantified the behavioral changes of HDVs that are induced by the presence of AVs, and found that HDVs have lower driving volatility in mixed traffic. Similarly, Rahmati et al. (*8*) designed a three-vehicle platoon scenario to identify the differences between HDV–HDV and HDV–AV interactions in a series of speed profiles determined by another HDV-leading vehicle. They characterized the behavioral changes of HDV based on a data-driven and a model-based approach. The results indicated significant behavioral changes of the HDV when it follows an AV compared with when it follows an HDV. In addition, the HDV driver feels more comfortable following the AV. In similar experiments, Zhao et al. (*9*) experimented with settings with differentiable or indifferentiable appearance of AVs. It was found that with differentiable appearance of AVs, HDVs exhibited behavioral changes, while no significant changes were found in an indifferentiable AV setting. This means that the behavioral changes of HDVs depend on subjective trust in AV technologies rather than their actual driving behavior. Only one study so far has adopted a real-world public road-testing dataset to characterize AV and HDV driving behavior in mixed traffic. Utilizing the Waymo open dataset, Wen et al. (*4*) extracted different vehicle pairs consisting of AV–HDV, HDV–HDV, and AV–HDV to analyze their driving behavior. They applied volatility, time headway, and time-to-collision measures to quantify the driving behavior, and employed cluster method to categorize HDV–AV following driving styles. It was found that HDVs exhibit less volatility in velocity and acceleration/deceleration.

The above studies mainly investigated behavioral adaptation or car-following styles of human drivers when encountering AVs. There are also some studies that directly investigated driving behavior of the adaptive cruise control (ACC) system when interacting with HDVs. For instance, Raju et al. (*6*) tested the real performance of a commercial ACC system under different desired speeds in a car-following situation, and found that the system response times were not instantaneous but were rather comparable to human response times. Li et al. (*5*) characterized car-following behavior of ACC vehicles based on empirical experiments, and explained the behaviors underlying mechanisms, such as factors influencing the response time, oscillation growth, and overshoot.

The above studies have mostly focused on car-following behaviors of AVs and HDVs, while limited research was conducted on signalized intersection behaviors based on a real-world dataset. Şentürk Berktaş and Tanyel (*12*) utilized data on signalized intersections from a field study, and analyzed HDV behavior characteristics. For AVs, they applied driving characteristic parameters from the literature. They suggested a passenger car equivalent value to define the effect of AVs at a signalized intersection without communication. The results showed that AVs may significantly decrease intersection capacity.

To conclude, although there are studies utilizing field experiments or empirical datasets to investigate scenarios involving ACC vehicles and AVs, we can conclude that most of them focused on car-following behavior and few studies have focused on signalized intersections-related behavior. Besides, these studies mainly investigated HDV behavior, without analyzing AVs' real behavior.

Signalized Intersection-Related Behaviors

Different from the car-following scenario, more parameters could be extracted to characterize signalized intersection-related behavior in the presence of traffic lights. In the literature, starting response time (to traffic green light), acceleration and deceleration, headway, distance gap were usually analyzed.

Starting response time is defined as the time gap between the start of the green light phase and the start of the leading vehicle moving. For HDVs in Turkey, Çalişkanelli and Tanyel (*13*) found a time gap of 1.48 s. The values found in other studies include: 1.35 s (*14*), 1.0 to 2.5 s (*15*), 1 s (*16*), 0.9 s (*17*), and 1.76 s and 1.42 s for through and left turning respectively (*18*). It is expected that the response time of AVs could be reduced and thus enhance the safety and efficiency of intersections. However, AVs without communication with traffic signal infrastructure or other vehicles cannot achieve a short response time (*12*). In the literature, the response time for AVs was suggested to be around 0.6 s (*19*), and the smallest default value in the AIMSUN program is 0.75 s (*13*). Abraham (*20*) employed 0 s of response time for AVs and 0.8 s for HDVs.

Deceleration of vehicles approaching the intersection characterizes how vehicles respond to the red light. Early studies suggested the acceptable deceleration rate of 3.04 m/s^2 (*21*), with similar values of 2.95 m/s^2 and 2.9 m/s^2 (*22*), and 3.27 m/s^2 (*23*). In the literature, the upper and lower values of deceleration rate of AVs are assumed to be 3.50 m/s^2 and 1.80 m/s^2 (*12*). In the AIMSUN program (*12*), the average value of the deceleration is 1.55 m/s^2.

Acceleration of vehicles from the stop line or the queue after the green light appears is important for determining the capacity of an intersection. For human drivers, 1.5 m/s^2 (*24*), 1.45 m/s^2 (*25*), and 0.83 to 1.43 m/s^2 (*26*) were suggested in the literature. Niels et al. (*19*) assumed the maximum acceleration rate for an AV to be 3.0 m/s^2. Şentürk Berktaş and Tanyel (*12*) applied the upper and lower acceleration values for AV as 1.40 m/s^2 and 0.75 m/s^2. The average value of acceleration adopted in the AIMSUN program (*12*) is 1.62 m/s^2.

Headway between vehicles at the discharge of a queue was also calibrated. As is well known, the first vehicle in the queue is always expected to respond the quickest since it directly receives the traffic light signal. There will be an increase in headway for the second vehicle and decrease for the following vehicles. However, Çalişkanelli (*27*) found that, in contrast with previous research, headway values did not decrease for the vehicles after the second queueing position. Similarly, Çalişkanelli and Tanyel (*13*) found the average headway values of queued vehicles except the first one to be around 2.3 s. Niroumand et al. (*28*) calibrated HDV headway time at 0.9 s under three levels of driving aggressiveness (aggressive, normal, and cautious) for connected vehicles and AVs to be 0.6 s, 0.9 s, and 1.5 s respectively. Parameters such as distance of the vehicles when stationary were also analyzed. Le Vine et al. (*29*) assumed a vehicle-to-vehicle (V2V) communication environment and set the distance gap of vehicles in the queue to 1.83 m.

To conclude, studies have mainly conducted simulations to evaluate the impacts of AVs on traffic at signalized intersections, in which they usually adopt key parameters referred from the literature or based on a simple assumption. The selected values were inconsistent through different studies, because of the lack of empirical analyses for signalized intersections.

Therefore, to fill the above gaps, this study aims to characterize AV and HDV behavior at a signalized intersection based on an empirical road-testing dataset. The remainder of this paper is organized as follows: the research questions are presented in the following section. In the Methodology section, the processing procedures of Waymo open dataset, the methods to classify the critical maneuver phases, characterize signalized intersection driving behaviors and quantify key parameters are exhibited. In the Results section, the behavioral analysis results of AVs and HDVs are presented by three categorized situations. In the Discussion section, comparison with literature, future work outlook, and limitations are provided. Finally, the conclusions are summarized in the Conclusion section.

Research Questions

Following the above literature review and the identified research gaps, the main research questions were defined as follows:

RQ1: How do AV and HDV driving behaviors differ when approaching signalized intersections with red light on: (RQ1.1) as the first vehicle in the queue, and (RQ1.2) as a vehicle in the queue?

RQ2: Are the AVs' response times to the green light comparable to those of HDVs?

RQ3: Will HDV drivers adapt their driving behavior when they interact with AVs at signalized intersections in comparison with how they interact with HDVs?

Methodology

This section illustrates the methods used to process the data and quantify driving behaviors of vehicles at signalized intersections.

The Waymo Dataset

The data utilized in this study were processed from the Waymo perception open dataset collected by Waymo AVs in three cities in the U.S. (i.e., San Francisco and Mountain View, CA, and Phoenix, AZ) and released in 2019 (*30*). The dataset contains 1,000 scenarios, with 10 HZ data collection frequency and about 20 s duration for each scenario. The dataset includes high-resolution lidar and camera data, recording vehicles' type, size (i.e., length, width, and height), position (i.e., latitudinal and longitudinal), and movement (i.e., velocity). Note that the AVs do not have any communication with the infrastructure and there is no possibility for driver take-over or disengagement events (*31*, *32*). More information can be found at https://waymo.com/open/data/.

This study is based on the processed dataset conducted by Hu et al. (*33*). In that work, the original dataset was re-structured and transformed to tabular format trajectory data, therefore, it is more user-friendly. The outliers have also been removed, so the processed dataset has higher data quality. The dataset and processing codes can be downloaded from https://data.mendeley.com/datasets/wfn2c3437n/2. The processed dataset contains 25 attributes, which are listed in table 2 of Hu et al. (*33*).

Data Processing

This subsection explains the process of selection of target intersections. First, intersections were recognized as locations where there are turning AVs or HDVs. To judge if a vehicle is turning, the angle between the beginning and the end of its headings was calculated, and if it was found to be larger than $0.9 \cdot \frac{\pi}{2}$, the vehicle was recognized as turning. The identified locations were then checked manually through real-world camera video in case some curve segments were misclassified as intersections. Signalized intersections were then selected from all the identified intersections. Finally, scenarios in which AVs just pass during the green light without starting or stopping maneuvers (i.e., green light phase) were excluded. Furthermore, to obtain the time stamps of traffic lights turning green, real-world camera videos were converted into still images, and the frame in which the signal light changed its color was identified.

Behavior Characterizing and Quantifying Method

Identification of critical maneuver phases. To characterize the driving behavior, it is necessary to identify the time stamps of critical maneuvers and classify maneuver phases. Sharma et al. (*34*) identified six critical phases for calibration in a general car-following model: acceleration, deceleration, following, free acceleration, cruising without a leader, and standstill. In this study we

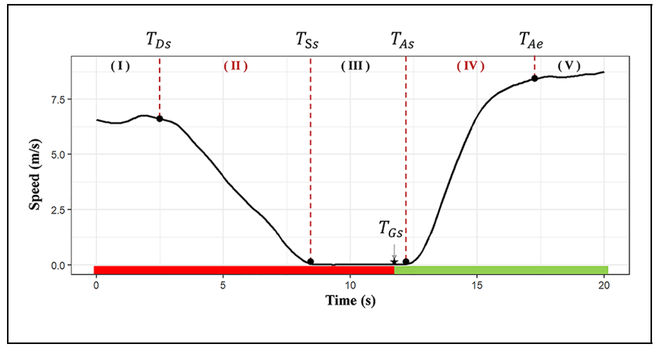

Figure 1. Illustration of critical maneuver times.

identified five critical maneuver phases for the signalized intersection. A typical speed profile is shown in Figure 1. It consists of five phases:

I. Approaching the signalized intersection with a stable speed (traffic signal is red and the driver might yet have not decided to decelerate);
II. Decelerating to respond the traffic light or the queue at the intersection (traffic signal is red);
III. Remain at a standstill at the stop line or within the queue (traffic signal is red);
IV. Accelerating to leave the intersection (traffic signal turns to green);
V. Leaving the intersection with stable speed.

Based on these phases, five critical time stamps were also identified: deceleration start time T_{Ds}, standstill start time T_{Ss}, acceleration start time T_{As}, acceleration end time T_{Ae}, and green light start time T_{Gs}.

To identify critical maneuver time stamps, the wavelet transform (WT) algorithm and the threshold-based method were adopted together (*5*, *35*).

WT is a time-frequency decomposition tool and could capture the local changes of the time-series data by identifying the points with highest average wavelet energy (*36*). Zheng et al. (*37*) utilized WT to identify the location of bottlenecks, transient traffic, and traffic oscillations, and Li et al. (*35*) applied it to recognize the critical maneuver times of the oscillation speed profile. The Mexican hat wavelet was found to be the most efficient (*37*), which is adopted in this study. The formulation of the WT output of the continuous signal (i.e., speed over time) $v(t)$ is:

$$T(a,b) = \omega(a)\int_{-\infty}^{\infty} v(t)\psi\left(\frac{t-b}{a}\right)dt \tag{1}$$

$$\psi\left(\frac{t-b}{a}\right) = \left[1-\left(\frac{t-b}{a}\right)^2\right]e^{-\left(\frac{t-b}{2a}\right)^2} \tag{2}$$

where a is the scale parameter which controls the dilation and contraction of the wavelet, b determines the

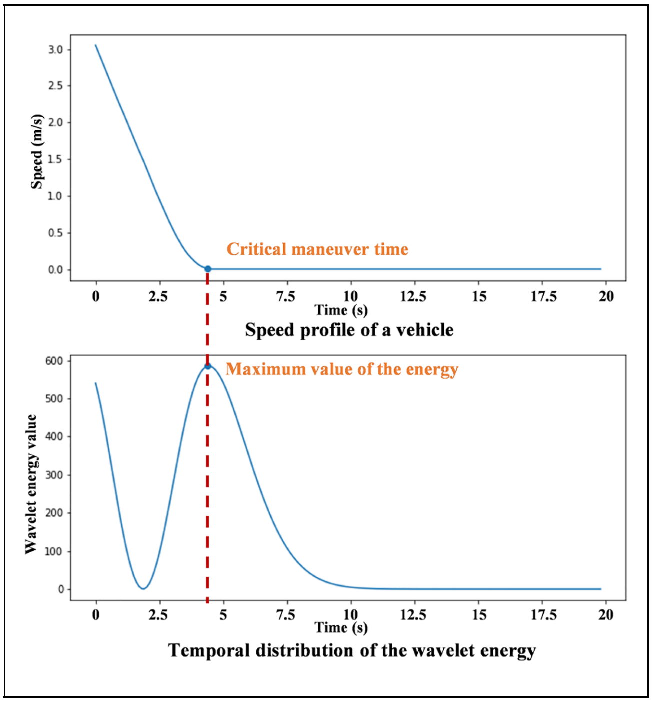

Figure 2. Illustration of wavelet transform algorithm.

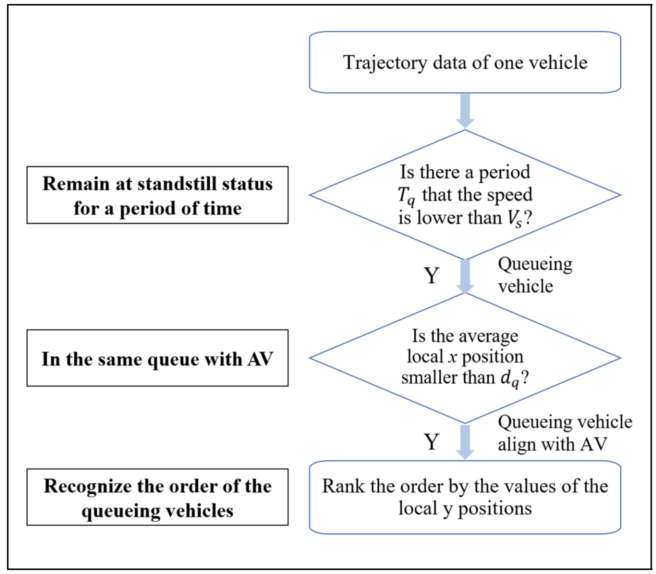

Figure 3. Illustration of queue recognition algorithm.

movement of the wavelet along the time. When $a = 1$ and $e = 0$, $\psi(t)$ is the mother wavelet, and is the second derivative of the Gaussian distribution function $e^{-\frac{t^2}{2}}$. $\omega(a)$ is the weighting function which is typically set to $\frac{1}{\sqrt{a}}$ to ensure that wavelets at all scales have the same energy. Therefore, the final formulation of the WT coefficient is:

$$T(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} v(t) \left[1 - \left(\frac{t-b}{a}\right)^2\right] e^{-\left(\frac{t-b}{2a}\right)^2} dt \qquad (3)$$

The average wavelet-based energy at b is calculated as:

$$E_b = \frac{1}{max(a)} \int_0^{\infty} |T(a,b)|^2 da \qquad (4)$$

An abrupt speed change over time will generate a sharp increase in the temporal distribution of the energy (*35*). Therefore, the significant speed alterations could be identified by exploiting the energy distribution. Figure 2 gives an example of how the WT recognizes the abrupt change of a speed profile.

Here, we applied WT to identify T_{Ds} and T_{Ae}, as they are characterized by significant speed changes (*37*). a is set to be 32 which was usually applied when the frequency of the original signal is 0.1 s. b is set to be when the speed profile has the lowest value (*35*, *37*). Most speed profiles of the vehicles' trajectories do not have complete stages, as shown in Figure 1, therefore, T_{Ds} and T_{Ae} are further judged by the acceleration and the duration.

During the experiment, we found that if phase II, phase III, and phase IV co-exist in one speed profile, then the time interval between T_{Ss} and T_{As} could be too short and the wavelet energy only has one extreme maximum value in phase III. Therefore, we identify them via threshold-based algorithm. T_{Ss} and T_{As} are recognized between T_{Ds} and T_{Ae}. Further, T_{Ss}/T_{As} satisfies both: (i) speed threshold: the afterwards/beforehand speed is less than 0.1 m/s and continues for more than 1.5 s; and (ii) the deceleration/acceleration rate beforehand/afterwards threshold: the absolute value is over 0.25 m/s^2. Several other values were tested and results best capturing the T_{Ss} /T_{As} were obtained according to manual checks to ensure the accuracy.

Queue Recognition Based on Trajectory Data. Since we want to characterize the driving behavior of AVs and HDVs, especially when they have interactions with each other, only the queues that contained AVs were extracted. The algorithm can be seen in Figure 3. T_q is the period when the vehicle remains stationary, V_s is the speed threshold to recognize T_q in case some vehicles do not absolutely stop but maintain a very low speed. Here the value of T_q is 2.5 s and V_s is 0.1 m/s. d_q is the distance threshold of average local x (latitudinal) to judge whether the vehicle is within the same queue as AV is; d_q = 1 m is adopted.

Driving Behavior at Signalized Intersections

After applying WT and threshold-based method to detect critical maneuver time stamps, and recognizing the queue, five parameters were defined and calculated, as further explained below.

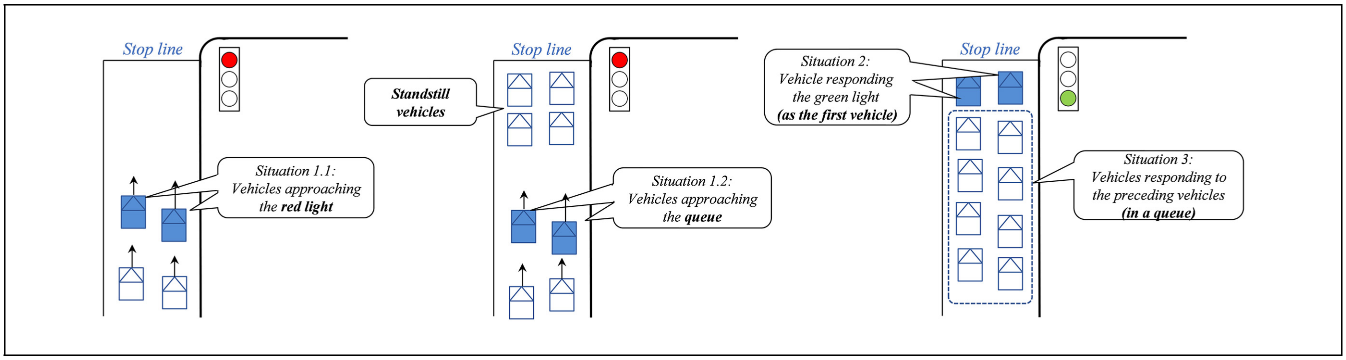

Figure 4. Illustration of different situations.

- Deceleration approaching the red light/the queue: The deceleration is calculated based on phase II (Figure 1) from T_{Ds} to T_{Ss}. Two deceleration parameters are calculated: maximum deceleration and average deceleration.
- Distance gap to the preceding vehicle (standstill distance): This parameter refers to the distance gap between two vehicles within the queue, during phase III. It is the distance gap between the rear end of the leading vehicle and the head of the following vehicle.
- Starting response time to the green light: This parameter refers to the time gap between the start of the green light T_{Gs} and the moment the vehicle starts to accelerate T_{As}.
- Acceleration from the stop line: The acceleration is defined based on phase IV, from T_{As} to T_{Ae}. Two acceleration parameters were calculated: maximum acceleration and average acceleration.
- Reaction time to the preceding vehicle: Distinguished from the response time, reaction time is the time gap in which the ego vehicle reacts to the preceding vehicle's movement (*38*). Here it refers to the time gap between two consecutive vehicles starting to accelerate, that is, ${T_{As}}^F - {T_{As}}^L$, ${T_{As}}^F$ is the acceleration start time of the following vehicle and ${T_{As}}^L$ is that of the leading vehicle.

Table 1. Data Sample Size for Test Situations

	Vehicle type		
Situation	AV	HDV	
Situation 1.1	53	73	
Situation 1.2	51	75	
Situation 2	40	450	
	Vehicle pair		
Situation 3	AV–HDV	HDV–AV	HDV–HDV
For distance gap	113	142	150
For reaction time	45	56	80

Note: AV = autonomous vehicle; HDV = human-driven vehicle.

Results

Of the 1,000 scenarios in this study, 73.2% are intersection scenarios (732), and 66.12% of these intersections are signalized (484). Within the signalized intersections, 301 are interesting scenarios, in which an AV has a stopping or a starting maneuver. The results of the analyses were categorized into three situations, the illustration of each situation is presented in Figure 4, and the description of sample size is summarized in Table 1. For reaction time in Situation 3, since the first vehicles were excluded, the sample size is smaller than that for distance gap.

> Situation 1: vehicle approaching the red light (Situation 1.1); vehicle approaching the queue (Situation 1.2);
> Situation 2: vehicle responding to the green light as the first vehicle;
> Situation 3: vehicle responding to its preceding vehicle in a queue when the queue is dissipating.

Situation 1. Vehicle Approaching the Red Light and Approaching the Queue

The analyses of this situation adopted data of vehicles' dynamics from phase II (Figure 1). This situation describes when and how a vehicle decelerates in response to the red light or the queue present at the approach to an intersection. The behavior is quantified from deceleration approaching the red light/the queue using two

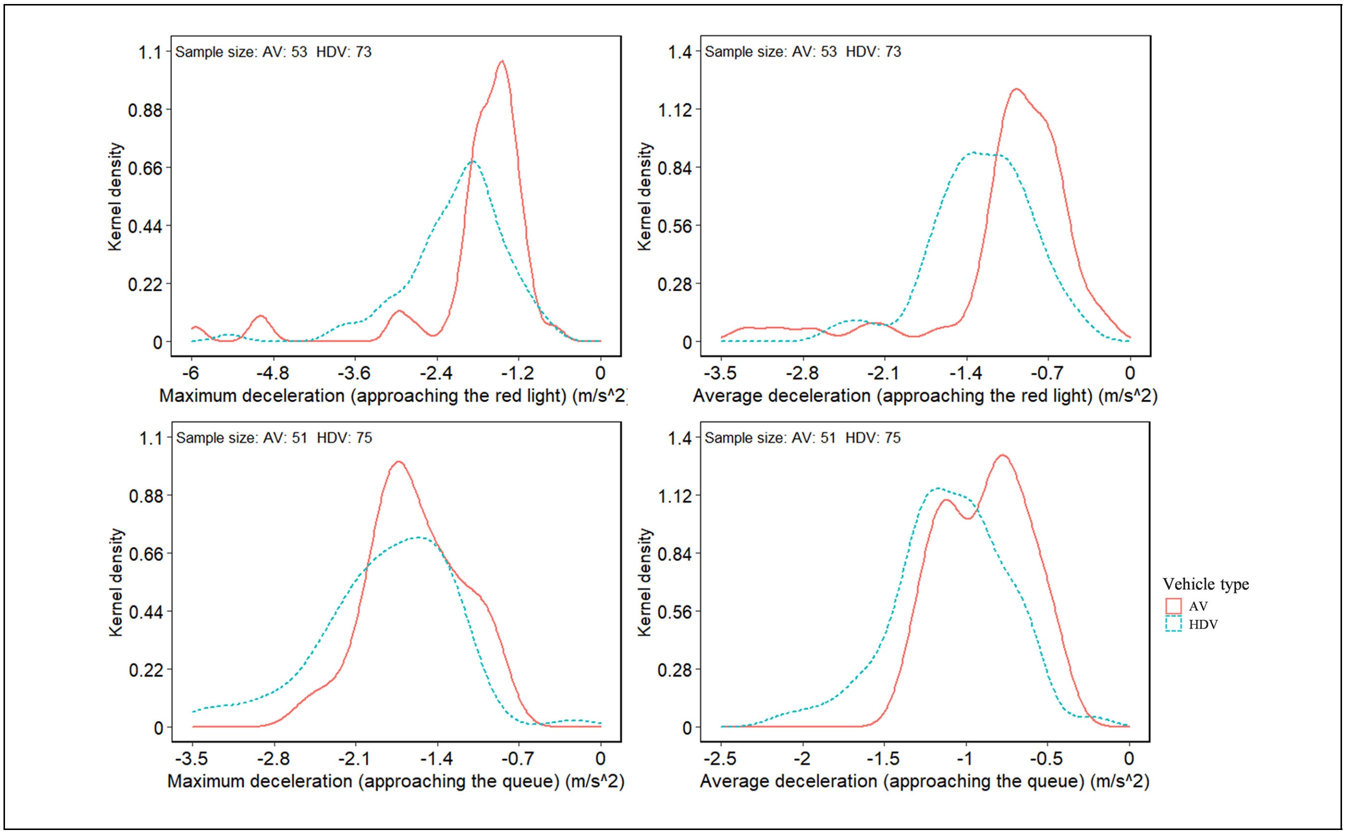

Figure 5. Distributions of deceleration driving behavior when approaching the red light (Situation 1.1) and the queue (Situation 1.2).

Table 2. Descriptive Statistics of Deceleration when Approaching Red Light (Situation 1.1) and Queue (Situation 1.2)

	Vehicle type	Mean	SD	*P* value for Kolmogorov–Smirnov test
Situation 1.1				
Maximum deceleration (m/s^2)	AV	−1.82	0.97	0.00013
	HDV	−2.09	0.80	
Average deceleration (m/s^2)	AV	−1.04	0.61	1.539e-05
	HDV	−1.27	0.43	
Situation 1.2				
Maximum deceleration (m/s^2)	AV	−1.59	0.40	0.01567
	HDV	−1.84	0.57	
Average deceleration (m/s^2)	AV	−0.88	0.26	0.00208
	HDV	−1.10	0.34	

Note: AV = autonomous vehicle; HDV = human-driven vehicle; SD = standard deviation.

parameters: maximum deceleration and average deceleration. The kernel density curves (Figure 5) of these two parameters were plotted by R using the density function of the ggplot2 package. The descriptive statistics and the Kolmogorov-Smirnov (K-S) test results of behavioral differences between AVs and HDVs are shown in Table 2.

K-S test results indicate that there are significant differences in the approaching behavior of AVs and HDVs, regardless of whether approaching the red light or the queue. For approaching the red light (Situation 1.1), the absolute mean values of maximum deceleration and average deceleration for AVs ($1.82\,m/s^2$ and $1.04\,m/s^2$) are slightly smaller than those for HDVs ($2.09\,m/s^2$ and $1.27\,m/s^2$). The standard deviations (SD) of these two parameters are larger for AVs than for HDVs. For the situation when vehicles are approaching the queue (Situation 1.2), the absolute mean values of maximum deceleration and average deceleration for AVs are $1.59\,m/s^2$ and $0.88\,m/s^2$ respectively, which are also slightly smaller than those for HDVs ($1.84\,m/s^2$ and

Table 3. Kolmogorov–Smirnov Test Results for Deceleration Between Approaching the Red Light (Situation 1.1) and Approaching the Queue (Situation 1.2)

Vehicle type	Deceleration behavior	*P* value for Kolmogorov–Smirnov test
Autonomous vehicle	Maximum deceleration (m/s^2)	0.5631
	Average deceleration (m/s^2)	0.2282
Human-driven vehicle	Maximum deceleration (m/s^2)	0.0379
	Average deceleration (m/s^2)	0.0116

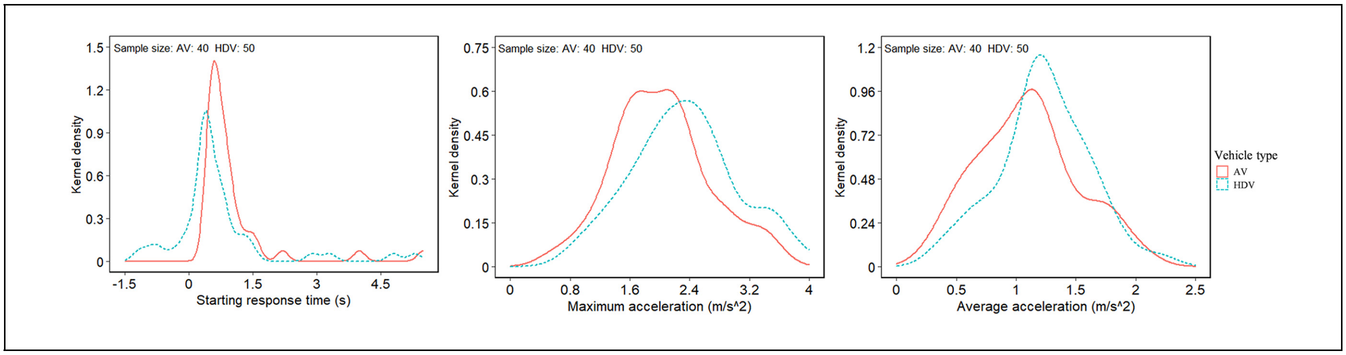

Figure 6. Distributions of driving behavior when responding to the green light as the first vehicle (Situation 2).

Table 4. Descriptive Statistics of Driving Behavior When Responding to the Green Light as the First Vehicle (Situation 2)

Situation 2	Vehicle type	Mean (s)	SD (s)	*P* value for Kolmogorov–Smirnov test
Starting response time (s)	AV	1.01	0.96	3.729e-5
	HDV	0.70	1.18	
Maximum acceleration (m/s^2)	AV	2.02	0.65	0.0738
	HDV	2.33	0.71	
Average acceleration (m/s^2)	AV	1.09	0.43	0.11
	HDV	1.23	0.38	

Note: AV = autonomous vehicle; HDV = human-driven vehicle; SD = standard deviation.

1.1 m/s^2). However, different from Situation 1.1, the results for AVs have smaller SD than HDVs on the two parameters.

K-S tests for the same type of vehicle under Situation 1.1 and Situation 1.2 were conducted, as shown in Table 3. The results indicate that whether AVs are approaching the red light or the queue, the maximum and average deceleration show no difference, while for HDVs the approaching behaviors are significantly different between these two situations.

Situation 2. Vehicle Responding to the Green Light (as the First Vehicle)

This situation describes when a vehicle in the first place in a queue, that is, stationary at the stop line, will respond to the traffic light changing from red to green, and how it accelerates from the stop line (i.e., phase IV). The parameters employed for this situation are: (i) response time to the green light, (ii) acceleration from the stop line (maximum acceleration and average acceleration). The distributions and descriptive statistics of the three parameters can be seen in Figure 6 and Table 4. The maximum and average accelerations of AVs and HDVs do not show significant differences, with values around 2.2 m/s^2 and 1.1 m/s^2. The starting response time to the green light has significant differences among the AVs and HDVs, however, as indicated by the K-S test results. The mean starting response time of AVs is about 1 s, which is longer than HDVs with 0.70 s. The SD of the starting response time of AVs (0.96 m/s^2) is less than that of HDVs (1.18 m/s^2).

Situation 3. Vehicle Responding to Preceding Vehicle (in the Queue)

This situation happens when the traffic light changes from red to green and the vehicle is in the queue (i.e., not

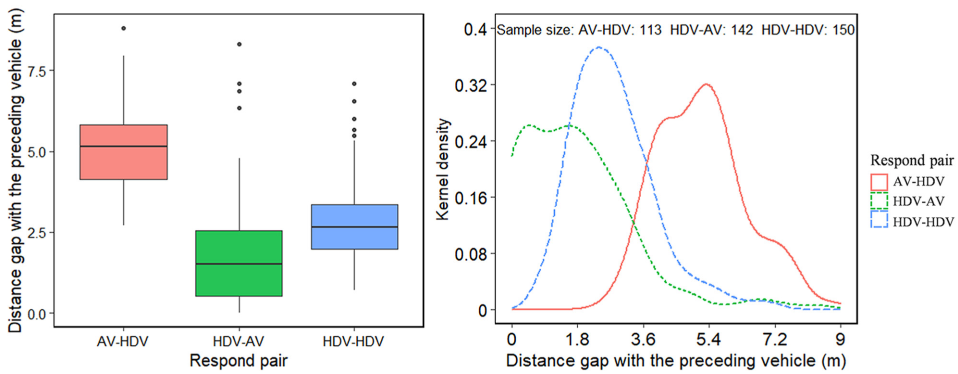

Figure 7. Distributions of distance gap for different response pairs (Situation 3).

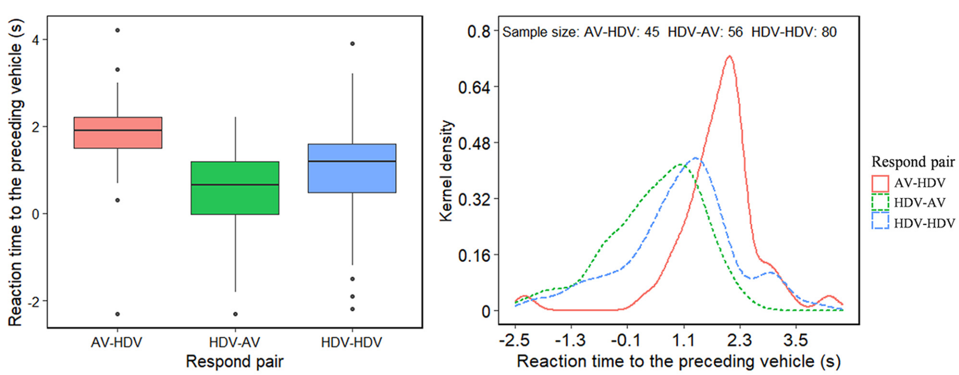

Figure 8. Distributions of reaction time for different response pairs (Situation 3).

Table 5. Descriptive Statistics of Driving Behavior when Responding to the Preceding Vehicle (Situation 3)

Situation 3	Vehicle type	Mean	SD	*P* value for Kolmogorov–Smirnov test
Distance gap to preceding vehicle (m)	AV–HDV	5.20	1.21	AV–HDV HDV–HDV: ¡2.2e-16
	HDV–AV	1.73	1.52	HDV–HDV HDV–AV: 1.17e-11
	HDV–HDV	2.77	1.14	AV–HDV HDV–AV: ¡2.2e-16
Reaction time to preceding vehicle (s)	AV–HDV	1.82	0.93	AV–HDV HDV–HDV: 1.262e-5
	HDV–AV	0.49	0.99	HDV–HDV HDV–AV: 0.01
	HDV–HDV	1.04	1.19	AV–HDV HDV–AV: 3.712e-10

Note: AV = autonomous vehicle; HDV = human-driven vehicle; SD = standard deviation.

the first vehicle in the queue). In this situation we analyze how the vehicle responds to the queue-discharging start of its preceding vehicle. The parameters applied in this situation are: (i) distance gap to the preceding vehicle (standstill distance) (Figure 7) and (ii) reaction time to preceding vehicle when green light appears (Figure 8). The descriptive statistics can be seen in Table 5.

With regard to the distance gap with the preceding vehicle when stopped at the intersection, significant differences were found among the three vehicle pairs: AV–HDV, HDV–HDV, and HDV–AV (where the former object is the following vehicle, i.e., Follower–Leader). The results indicate that AVs maintain the largest distance gap from the vehicle in front, with a mean of

5.20 m and standard deviation of 1.21 m. HDVs exhibit different behaviors according to the type of leader vehicle. HDVs maintained a smaller distance gap with an AV (with a mean of 1.73 m and SD of 1.52 m) compared with a HDV (with a mean of 2.77 m and SD of 1.14 m).

As for the reaction time to the preceding vehicle starting to move, HDVs also react differently depending on whether the preceding vehicle is an AV or HDV. HDVs react to an AV with a mean of 0.49 s, which is about half that for another HDV at 1.04 s. The reaction times of AVs are the longest at 1.82 s.

Discussion

According to the analysis results for AV and HDV driving behavior parameters in three situations (vehicle approaching the red light/queue, vehicle responding to the green light as the first vehicle, and vehicle responding to the preceding vehicle in a queue), the quantified values are compared with relevant findings from the literature. Further, insightful findings are inferred in this section:

(i) The mean maximum deceleration of AVs when approaching the red light and the queue was found to be 1.82 m/s^2 and 1.59 m/s^2 respectively, which matches, and is slightly smaller than, those reported in the literature, which suggested a value of 1.80 m/s^2 (*12*). For HDVs, the mean maximum deceleration values are 2.09 m/s^2 and 1.84 m/s^2, which is higher than the suggested value. It is noticeable that the mean maximum deceleration of HDVs when approaching the queue is significantly less than when approaching the red light, meaning they are more cautious in case they collide with the preceding vehicle.

To better understand the deceleration process, the two-dimensional kernel density distributions were plotted as shown in Figure 9. The deceleration, speed, and distance to the stop position during the deceleration stage are extracted from each vehicle trajectory with 1 s intervals. Several findings were obtained: (i) AVs begin deceleration from a longer distance compared to HDVs, indicating that AVs tend to start the deceleration maneuver earlier, when they are farther away from the intersection than HDVs. This phenomenon can sometimes be observed in human drivers too, when they aim to avoid coming to a complete stop at an intersection. (ii) AVs enhibit lower deceleration at a short distance from the stop position compared to HDVs. This means that when the vehicle is close to the red light/queue, an AV can maintain a relatively stable and lower deceleration. Compared to AVs' mild driving strategy, HDVs exhibit higher deceleration when close

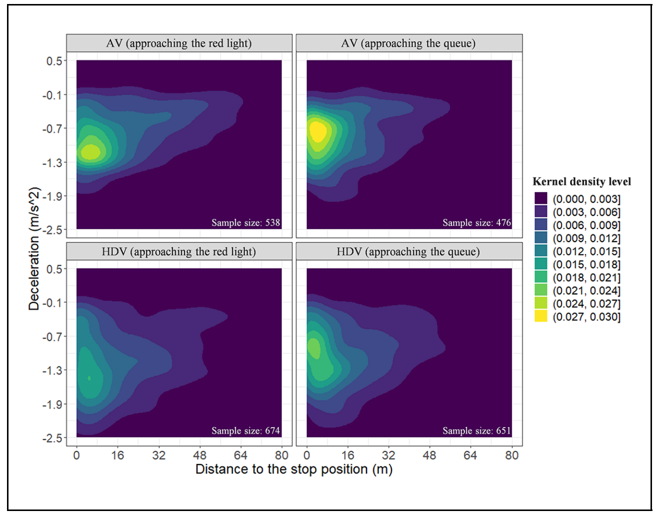

Figure 9. Deceleration and distance to the stop position two-dimensional (2D) kernel density distributions.

to the position where the vehicle is about to stop. AVs' mild strategy may be considering safety (*39*), comfort (*40*), and fuel consumption reduction (*41*). It might also benefit from the accurate judgment on the stopping distance and the speed detected from AV's high-resolution lidar and camera sensors. (iii) Furthermore, the distributions of HDVs are more dispersed compared to AVs, indicating greater heterogeneity among HDVs. For example, the drivers of HDVs might have different driving styles, with some being more cautious and others being more risk-taking.

(ii) During the acceleration phase (phase IV), the average acceleration for AVs is around 1.09 m/s^2, which is within the range specified in the literature (*26*). The maximum acceleration is about 2.02 m/s^2, which is lower than the value assumed for AVs in Niels et al. (*19*) (3.0 m/s^2), but higher than the upper acceleration for AV in Şentürk Berktaş and Tanyel (*12*) (1.4 m/s^2). The starting response time to green light of HDVs is 0.70 s, which is slightly shorter than Clement et al. (*17*) and Abraham (*20*), which reported values between 0.8 and 0.9 s. Contrary to the much shorter response time expected in the literature (*19*, *13*, *20*), it is 1.01 s for AVs which is comparable to or slightly longer than HDVs (*6*). In addition, some HDVs have a response time that is shorter than 0 s, meaning that they anticipate the green light and tend to react before the light turns green. This is not the case for AVs.

In addition, the 2D kernel density distributions were plotted in Figure 10 to better understand the acceleration process. The samples were extracted in the same way as

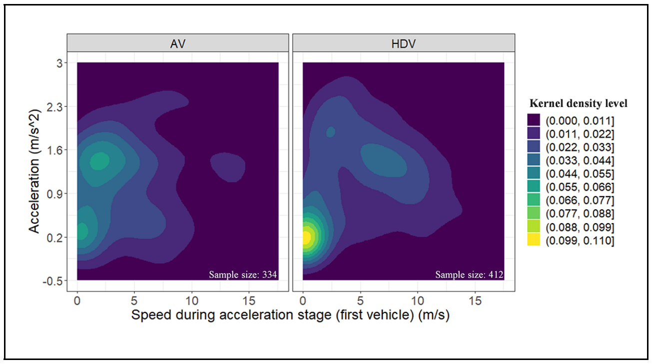

Figure 10. Acceleration speed two-dimensional kernel density distributions.

for deceleration. It is worth mentioning that possible disturbances were excluded, including situations where the vehicle is waiting for a gap to turn, or is influenced by merging vehicles from the other approaches. Several findings are inferred from Figure 10: (i) AVs have higher acceleration at lower speeds, when the vehicles begin to accelerate from stationary. This indicates that HDVs can accelerate smoothly at the beginning, while for AVs, higher acceleration occurs at lower speeds. AVs' abrupt and unstable acceleration at the start might lead to discomfort for passengers. (ii) Furthermore, the speed distribution of HDVs extends further to the right than that of AVs, meaning that within the maximum frame of each accelerating scenario, HDVs can driver farther than AVs. This could be explained by the higher acceleration of HDVs afterwards.

(iii) AVs tend to keep a relatively large distance gap to the preceding vehicle when stationary. This could be explained by the conservative driving strategy applied by AVs. It is also found that HDVs maintained a smaller distance gap with an AV than with another HDV. Similar results were indicated in the literature (*4*, *7*, *8*). One possible reason might be AVs' early and long-distance deceleration, making HDV drivers feel safer when following an AV and thus reducing the standstill distance gap from the AV. On the other hand, it could be explained by the psychological factors of human drivers. As the appearance of Waymo cars is obviously different from ordinary vehicles, when approaching an AV, human drivers can recognize it and are curious about it. Thus, they tend to stay closer to the stopped AVs for better observation (*42*). This indicates a potential negative behavioral adaptation.

(iv) Compared with the reaction times to the front vehicle's movement at the discharge of the queue (Figure 8), the starting response time to the green light (Figure 6) was found to be smaller for both HDVs and AVs. It might be that drivers/vehicles respond more quickly and directly when they observe the traffic light color change stimulus than when they need to comprehensively judge the movement of vehicles in front.

(v) The reaction time of AVs is the longest, as expected. This could be explained by AVs' driving strategy that requires the AV to keep certain distance from the preceding vehicle (*39*), therefore, it is likely to respond more slowly on purpose. HDVs react differently to AVs and HDVs. The reaction time of human drivers is shortened to half when they respond to AVs compared with HDVs. This might be because the delayed response of AVs arouses the impatience emotion of human drivers, especially when they are observing vehicles already moving in other adjacent queues. This matches the AV-involved crash pattern of the CDMV data, where most of the crashes were AVs being rear-ended when starting to move at an intersection (*3*).

Furthermore, the analyses from AV crash and disengagement reports (such as CDMV reported crashes in which often Waymo AVs are involved) from the other literature can be linked to the findings of this study. Some findings are concluded. (i) Most AV-involved crashes occur at intersections, and rear-end crashes are the predominant collision type, accounting for 57.5% of AV-involved crashes. The percentages of rear-end and side-swipe patterns are obviously higher compared with normal (HDV) crashes (*3*). (ii) From the speed information preceding the occurrence of AV-involved crashes, in the majority of these crashes the AV is stationary or traveling at low speed (*3*, *43*). (iii) Similar ratios of rear-end crashes occur right after the AV starts moving (21%) or decelerating (19%) (*44*).

These findings indicate that most AV-involved crashes that happened at an intersection were caused by the complex interactions between AVs and the following vehicles (*3*). When related to the micro-driving behaviors observed from this study, AV behaviors during the decelerating and accelerating process could be concerned. (i) Observing the red light or queueing vehicles in front of it, an AV decelerates earlier and from a longer distance than the average HDV to maintain a safe distance from its preceding vehicles. The following vehicles might not expect the early deceleration of the front vehicle, however. (ii) When the traffic light suddenly turns from green to yellow, or when the leading vehicles suddenly brake, AVs tend to brake much harder to maintain the safe distance gap, which may not give the following vehicles enough time to take appropriate actions. (iii) AVs usually have a longer reaction time to the preceding vehicle within the queue starting to move. When the surrounding vehicles start to move, the AV remains still, which might cause impatience and overtaking attempts by the human drivers of following vehicles. It is worth indicating that there could be a possible linkage but there is no evidence of a causal or correlated relationship between them.

Conclusion

With the increase of AVs in the current transportation system, potential risks have been revealed by road-testing reports. Most studies have estimated that AVs have a crash rate per million miles traveled much higher than that of the conventional HDVs, and with different crash pattern distributions. Therefore, it is very important to evaluate the real implication of AVs on the traffic system. Current studies which utilized real-world empirical data mainly investigated the driving behavior of AVs and HDVs in car-following scenarios. While having a vital role in traffic systems which influences both the safety and efficiency of traffic, signalized intersections have obtained less attention.

Therefore, this study utilized the real-world empirical Waymo open dataset to characterize and quantify the behavior of AVs and HDVs at the approaches to signalized intersections. Five critical maneuver phases and corresponding critical maneuver time stamps were identified by WT and threshold-based method. The queues in front of the intersection were also recognized. Five parameters were applied to quantify the signalized intersection-related behavior, and the analysis results were presented in three situations: vehicle approaching red light or queue, vehicle responding to green light (as the first vehicle), and vehicle responding to its preceding vehicle (in the queue). The results indicate statistically significant differences in driving behavior between AVs and HDVs at signalized intersections, as well as behavioral adaptations of HDVs when interacting with AVs.

These findings can provide insights for improving AV's control algorithm, and also aid in the evaluation of AVs' impacts. For instance, the driving behavior models of AVs and HDVs in the simulation platform concerning the signalized intersection should be calibrated to overcome the contradictory evaluation results obtained by the literature based on different assumptions. Along with the insightful analysis results of this study, there are several limitations and outlook for future work. The sample size of the applied dataset is small. We expect more data to be available in the future, and more precise analyses can be conducted. For example, analyzing reaction time according to vehicles with different queue orders, classifying the scenarios by different road infrastructure, weather, and volume level. Besides, alterations of driving behavior in a V2X environment, that is, with connectivity to other vehicles and infrastructure, could be investigated and compared. In addition, future research could adopt datasets from different countries and compare the varying driving behavior of different AVs and HDVs among different cultures or traffic regulations. Furthermore, our future work will apply and implement the analysis results of this study to calibrate simulation models, and evaluate the impacts of AVs on traffic safety and efficiency.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Y. Wang, H. Farah, R.Yu, B. van Arem; data collection: Y. Wang, S. Qiu; methodology: Y. Wang, S. Qiu; analysis and interpretation of results: Y. Wang, H. Farah, R. Yu; draft manuscript preparation: Y. Wang, H. Farah, R. Yu, S. Qiu. All authors reviewed the results and approved the final version of the manuscript.

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ORCID iDs

Yiyun Wang https://orcid.org/0000-0002-7361-5386
Haneen Farah https://orcid.org/0000-0002-2919-0253
Shuhan Qiu https://orcid.org/0000-0003-2331-1496
Bart van Arem https://orcid.org/0000-0001-8316-7794

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