Characteristics of Rear-End Collisions: A Comparison between ADS-Involved Crashes and ADAS-Involved Crashes

Chunxi Huang
Robotics and Autonomous Systems, Division of Emerging Interdisciplinary Areas (EMIA) under Interdisciplinary Programs Office (IPO), The Hong Kong University of Science and Technology, Hong Kong SAR, China, 999077
Email: tracy.huang@connect.ust.hk

Xiao Wen
Intelligent Transportation, Division of Emerging Interdisciplinary Areas (EMIA) under Interdisciplinary Programs Office (IPO), The Hong Kong University of Science and Technology, Hong Kong SAR, China, 999077
Email: xiao.wen@connect.ust.hk

Dengbo He, Corresponding Author
Intelligent Transportation Thrust, Systems Hub, The Hong Kong University of Science and Technology (Guangzhou), Guangdong, China, 511400
HKUST Shenzhen-Hong Kong Collaborative Innovation Research Institute, Futian, Shenzhen
Department of Civil and Environmental Engineering, The Hong Kong University of Science and Technology, Hong Kong SAR, China, 999077
Email: dengbohe@hkust-gz.edu.cn

Keywords: ADS, ADAS, crashes, rear-end collisions

Funding Statement: This research was funded by the National Natural Science Foundation of China (Grant No. 52202425) and partially by the Guangzhou Municipal Science and Technology Project (No. 2023A03J0011), the Guangzhou Science and Technology Program City-University Joint Funding Project (No. 2023A03J0001), and Project of Hetao Shenzhen-Hong Kong Science and Technology Innovation Cooperation Zone (HZQB-KCZYB-2020083).

Data accessibility: Raw data was downloaded from an open dataset provided by National Highway Traffic Safety Administration (NHTSA). Processed data can be provided upon request.

ABSTRACT

With the increasing number of vehicles equipped with Automated Driving System (ADS) being tested on the public road and the expanding market share of vehicles equipped with Advanced Driving Assistance System (ADAS), the number of ADS- or ADAS-involved crashes increases. Thus, it is necessary to investigate the distribution of ADS- and ADAS-involved crashes and the factors leading to them. The rear-end collision has been found to dominate among ADS-involved crashes. However, no research has explored the conditions when ADS-involved rear-end collisions are more likely to happen and no research has investigated ADAS-involved rear-end crashes. Based on 130 ADS-involved crashes and 84 ADAS-involved crashes extracted from a dataset collected by National Highway Traffic Safety Administration (NHTSA) between July 2021 and May 2022, this study explored the crash patterns, especially rear-end crashes of ADS- and ADAS-controlled vehicles. Results show that the rear-end collisions dominate both the ADS- and ADAS-involved crashes and this is especially the case for ADAS-involved crashes. The type of ADS-involved and ADAS-involved crashes were both affected by the speed of the ego-vehicle relative to the posted speed limit. Further, the type of ADS-involved crash was affected by the pre-crash movement of the crash partner; while the type of ADAS-involved crash was further associated with the road type. The findings can provide insights into the design of ADAS and ADS control algorithms, the external human-machine interface design of the vehicles with ADS or ADAS, and the training program of human road users to improve traffic safety in mixed traffic.

Keywords: ADS, ADAS, crashes, rear-end collisions

INTRODUCTION

Over 90 percent of vehicle crashes can be attributed to human errors (*1*). Thus, introducing driving automation is expected to improve driving safety. In the past decades, with the development of both sensors (e.g., lidars) and artificial intelligence, SAE Level 2 driving automation (*2*) has become a reality, with over one-third of new cars sold with advanced driving assistance systems (ADAS) in major markets such as Mainland China, Europe, Japan, and the US in 2021 (*3*). Although still not being available to consumers, higher level of driving automation (i.e., SAE Level 3 to 5), for example, automated driving system (ADS), has been widely tested on open roads in some states in the U.S. (e.g., Waymo in California and Uber in Arizona). The co-existing of vehicles driven by human drivers, vehicles controlled by ADAS, and vehicles driven by ADS makes it possible to explore the safety benefits of introducing different levels of driving automation.

Previous studies have compared the safety performance of ADS-controlled vehicles to human-driven vehicles. It was found that the ADS being tested on road at the current stage generally exhibited worse safety record compared to human drivers (*4–7*). Specifically, research found that the rear-end crashes dominate the ADS-involved crashes (*5*, *8–10*), potentially due to the reduced behavioral predictability of ADS-controlled vehicles (*11*, *12*). The crash pattern of ADAS-controlled vehicles, however, has been under-investigated, potentially due to the lack of data. The ADAS-controlled vehicles, with human drivers in the control loop, may exhibit different behaviors compared to ADS-controlled vehicles. On one hand, the perception capability of ADAS is in general weaker than that of ADS and thus the behavior of ADAS-driven vehicles should be even less predictable; on the other hand, with SAE Level 2 automation, drivers are still actively monitoring the road and may step in proactively to avoid emergencies (*13*). This anticipation capability may even be enhanced in ADAS-control vehicles, as drivers should have more spare attentional recourses to perceive the environment (*14*). But it should be noted, the drivers may adapt to new technologies. In extremely cases, drivers may even give up their role when ADAS is controlling the vehicle (*15*). All these factors may influence the crash patterns of ADAS-controlled vehicles.

Although a large number of studies have investigated the safety implications of ADAS in closed tracks or driving simulators (*16–20*), to the best of our knowledge, no studies have compared the crash patterns between ADAS-controlled and ADS-controlled vehicles. A scrutiny of the crash patterns, as well as an exploration of the potential factors influencing the crash patterns in ADAS-controlled and ADS-controlled vehicles, can reveal how the advancement of technologies impacts road safety and guide the optimization of ADS and ADAS control algorithm. From human road users' perspective of view, the analyses of crash patterns with ADS- and ADAS-controlled vehicles can also guide the behaviors of human road users in mixed traffic. Thus, in our study, we compared the crash patterns, especially rear-end collision patterns between ADS-controlled and ADAS-controlled vehicles and explored the factors leading to the rear-end collisions. Given the fast evolution of driving automation technologies (*10*), we adopted a newly released crash report dataset by the National Highway Traffic Safety Administration (NHTSA dataset), which includes the ADS- and ADAS-involved crashes from July 2021 to May 2022.

LITERATURE REVIEW

Safety Performance of ADS-controlled vehicles

Using the open data, previous research found that compared to human-driven vehicles, the ADS-controlled vehicles being tested on road at the current stage exhibited worse safety record regardless of the metrics being adopted. For example, based on the California Department of Motor Vehicles (DMV) dataset, Favarò et al. (*5*) found that the mean mileage before a human-driven vehicle involving a crash was 500,000 miles, as compared to 42,017 miles before ADS-controlled vehicles (SAE Level 3 or above) involving a crash. From the injury perspective of view, researchers found that among ADS-involved crashes in the DMV dataset, 70.83% of the injuries were in ADS-controlled vehicles; while only 29.17% of injuries were in human-driven vehicles (*4*). Similarly, based on a different dataset collected in California (i.e., publicly disclosed on-road data from Google, Delphi, and Audi), Schoettle & Sivak (*6*) found that the number of crashes among ADS-controlled vehicles was 9.1 per million miles traveled, which was much higher compared to that of conventional human-driven vehicles (1.9). In addition, a more recent naturalistic driving study revealed that ADS-controlled vehicles were 4.8 times more likely to be rear-ended by following vehicles compared to that of human-driven vehicles (*7*).

Patterns of ADS-related crashes

TABLE 1 Summary of literatures about patterns of ADS-related crashes

Study	Data source (data extraction period)	Number of crashes	Main findings
Dixit et al. (*21*)	DMV dataset (Sep. 2014 - Nov. 2015)	12	For autonomous vehicles, the number of crashes was highly correlated with the miles travelled.
Favarò et al. (5)	DMV dataset (Sep. 2014 - Mar. 2017)	26	Being rear-ended by a conventional vehicle is the most frequent type of ADS-involved collisions.
Petrović et al. (9)	DMV dataset (Jan. 2015 – Dec. 2017)	53	- Rear-end collisions occurred the most often among ADS-involved collisions (64.2%). - Collisions related with "pedestrian" (none) and "broadside" (5.7%) were the two least types of collisions in ADS-involved collisions.
Boggs et al. (*8*)	DMV dataset (Sep. 2014 – Nov. 2018)	113	- The most frequent ADS-involved crash type was rear-end collisions (61.1%; N = 69). - When the ADS was engaged, the likelihood of involving a rear-end crash was substantially higher.
Liu et al. (*10*)	DMV dataset (Oct. 2014 – Jun. 2020)	122	- The most frequent ADS-involved pre-crash scenarios were rear-end collisions (52.46%). - Three dominating causes of ADS-involved crashes were: larger perception-reaction time, inappropriate path planning before emergencies, and inaccurate identification of lane-changing intentions of other vehicles
Song et al. (*11*)	DMV dataset (2015 – 2019)	168	- The most representative pattern of AV-involved crashes was "collision following AV stop". - ADS disengagement had a transition probability of 68% to an immediate collision.

To understand why ADS exhibited a worse safety record compared to human drivers, previous research explored the patterns of ADS-related crashes, as summarized in **Table 1**. It was found that compared to human-driven vehicles, the ADS-controlled vehicles were more likely to be rear-ended by following vehicles (*5*, *8–10*, *21*). Specifically, from the start of the DMV program (2014) to Nov. 2018, rear-end collision takes up to 61.1% of all ADS-involved crashes in DMV dataset (*8*). Similarly, research based on Waymo open dataset (*22*) also revealed that compared to human driven vehicles, ADS-driven vehicles lead to smaller time to collisions of following vehicles (*12*). The research by Song et al. (*11*) provided further details regarding ADS-involved rear-end crashes - it was found that the most representative temporal pattern of ADS-involved crashes was "collision following autonomous vehicle stopping". Another research by Liu et al. (*10*) further found that compared to human drivers, ADS led to a larger perception-reaction time, inappropriate path planning before emergencies, and inaccurate identification of lane-changing intentions of other vehicles. As a result, compared to that when the lead vehicle was controlled by a human driver, it is in general more difficult for the following vehicle drivers to anticipate the motion of ADS-controlled lead vehicles and thus brake proactively. However, it should be noted that these previous studies were mostly based on the DMV dataset collected crash between 2014 to 2019, which may not reveal the most up-to-date ADS behaviors. Further, the DMV dataset did not include ADAS-involved crashes. Thus, these previous studies only focused on the comparisons between

ADS-controlled and human-driven vehicles. A research based on newly collected dataset should be conducted to better understand the impact of technology revolution on safety record of driving automation (including ADS and ADAS).

METHODS

Dataset Description

On June 29, 2021, the National Highway Traffic Safety Administration (NHTSA) issued a Standing General Order requiring relevant entities (e.g., vehicle manufacturers, operators) to report certain crashes involving vehicles equipped with SAE Level 2 ADAS or SAE Level 3-5 ADS (*23*). This General Order requires manufacturers and operators to report certain crashes when ADS or ADAS is engaged or immediately after the ADS or ADAS is disengaged, and to provide sufficient information for NHTSA to identify crashes warranting further follow-up. Specifically, for any ADS-involved and ADAS--involved crashes, the automation (i.e., ADS or ADAS) should be in use at the time of the collision or disengaged within 30 seconds prior to the crash and the crash resulted in property damage or injury.

As of May 15, 2022, there are 392 ADAS-involved crashes reported by 12 reporting entities and 130 ADS-involved crashes reported by 25 reporting entities in the NHTSA dataset. Reporting entities submitted crash reports in electronic format using the web-based incident report form. The crash report includes subject vehicle (SV) information (e.g., make, model, model year, mileage), incident information (e.g., date, time), incident scene (e.g., location, city, roadway type, surface condition, speed limit, weather, lighting), crash description (e.g., crash partner, pre-crash movement of SV, pre-crash speed of SV, the crash contact area of SV and crash partner, highest injury severity), post-crash information (e.g., whether investigated by a law enforcement agency or not), and the narrative (e.g., written description of other information). NHTSA released the summarized crash report data in the format of .csv files, with 122 variables containing all information covered in the incident report form.

Data Preprocessing and Variable Extraction

The raw data of the NHTSA dataset was first pre-processed to remove repeating and invalid records, following the guidance from NHTSA. In total, 392 ADAS-involved crashes and 130 ADS-involved crashes were extracted using customized R codes, which are in line with the number of crashes presented in NHTSA's report (*24*, *25*). Next, due to the data accessibility issues, the information on the selected variables was missing in some ADAS-involved crashes. Hence, we filtered out the ADAS-involved crashes where data was missing in three variables, i.e., the contact area of crash partner (CP), the contact area of SV, and the pre-crash movement of CP – as we were not able to extract the collision type of the crash without these three variables. As a result, 84 of 392 ADAS-equipped vehicle crashes were kept for further analysis. The data of all ADS-involved crashes were complete, and all 130 crashes were kept for further analysis. It should be noted that not all 122 variables in NHTSA are related to crash patterns. Thus, following previous research, 9 variables that might be related to crash patterns in ADS- and ADAS-involved crashes were selected, as described below. Among the selected variables, 5 categorical variables that include data aggregation are summarized in **Figure 1**.

[Insert Figure 1 Here]

Figure 1 The aggregation of selected categorical variables in the NHTSA dataset. The numbers in brackets are the numbers and percentages of instances under each category.

Collision Type (CT)

As we mainly focus on rear-end collisions, by manually inspecting the information about the contact area of CP, the contact area of SV, and the narrative, we labeled the collision type of all ADS and ADAS crashes as two types: rear-end collision and others. In rear-end collision, the contact area of the SV should be rear left, rear right, or rear; the contact area of the CP should be front left, front right, or front.

In other words, in this study, we only considered rear-end crashes that ADS- or ADAS-controlled vehicles were rear-ended by other vehicles (i.e., ADS- or ADAS-controlled vehicles as SVs). In case of unclear contact areas, the collision type was labeled based on the written description in the narrative. In total, 52 (40% out of 130) of ADS-equipped vehicle crashes and 44 (52.4% out of 84) of ADAS-equipped vehicle crashes were rear-end collisions.

Vehicle Type (VT)

The vehicle type was defined as the type of vehicle involved in the crashes, which includes two categories: ADS and ADAS.

Speed Gap Ratio (SGR)

The speed of the involving road agents was found to be associated with the ADS-involved crashes in previous research (*5*, *26*). To quantify the influence of the speed on ADS- or ADAS-involved crashes, a new variable, the speed gap ratio (SGR), was generated (**Equation 1**):

$$SGR = \frac{PSL - SVPCS}{PSL} \qquad (1)$$

where, PSL is the posted speed limit (in mph) on the roadway where the incident occurred; SVPCS, as defined in the NHTSA dataset, is the speed (in mph) of the SV (i.e., ADS- or ADAS-equipped vehicles) at the time of the incident.

When the SVPCS is lower than the PSL, the SGR is a positive number between 0 and 1. In this case, the smaller the SGR, the closer the speed of the SV is closer to the posted speed limit. When the SV-pre crash speed is over the posted speed limit, the speed gap ratio would be negative.

Incident Time (IT)

The time of day was found to be associated with the risk of ADS-involved crashes (*27*) and conventional human-driven vehicle crashes (*28*). The incident time (IT) was recorded as the time of a day (e.g., 21:20) in the NHTSA dataset. To facilitate the analysis, following the previous practice of the National Safety Council (NSC) (*29*), we categorized the incident time into three time slots: morning-noon (4:00 – 12:00, 53 cases), noon-night (12:00 – 20:00, 90 cases), and night (20:00 – 4:00, 71 cases).

Roadway Type (RT)

The roadway type (RT) was defined as the type of road on which the collision happened and the crash risk of ADS on different RT was found to be different (*8*, *30*). The RT recorded in the NHTSA dataset includes street, intersection, highway/freeway, parking lot, traffic circle, rural road, unpaved road, and unknown. As there were differences in roadway type distributions between ADS- and ADAS-involved crashes, two categorization strategies were adopted. Three categories of RT were generated for ADS-involved crashes, i.e., street, intersection/traffic circle, and others; while for ADAS-involved crashes, the three categories of RT were highway/freeway/rural road, street, and intersection.

Roadway Surface (RS)

As another potential contributing factor to the crash risk of ADS-controlled vehicles (*27*), the roadway surface was defined as the roadway surface (RS) conditions at the time of the incident. The RS in NHTSA includes dry, wet, snow/slush/ice, others, and unknown. Due to the small number of instances of some RS types, after inspecting the roadway surface distribution of all ADS and ADAS crashes, we divided the roadway surface of all crashes into two categories: dry and others.

Lighting (LT)

The performance of ADS and ADAS might differ under different lighting conditions (*31*). In the original data, the lighting (LT) was defined as the lighting conditions at the time and location of the incident. The LT in NHTSA includes daylight, dawn/dusk, dark - lighted, dark - not lighted, dark -

unknown lighting, unknown, and others. To facilitate statistical analyses, we aggregated the LT with small number of instances and generated two levels for LT, i.e., daylight and others.

Crash-With (CW)

The crash-with (CW) was referred to as the object with which the subject vehicle came into contact in the incident. The CW in NHTSA dataset includes passenger car, SUV, Van, heavy truck, pickup truck, van, etc. To facilitate statistical analyses, we aggregated the CW with small number of instances and categorized the CW into three categories: passenger car, SUV, and others.

Pre-crash Movement of Crash Partner (PMCP)

The pre-crash movement of the crash partner (PMCP) was defined as the pre-crash movement of the other agents involved in the crash and was found to be a predictor of ADS-involved crashes in previous research (*27*). Possible values of PMCP in the NHTSA dataset include stopped, proceeding straight, lane/road departure, making a right turn, making a left turn, making a U-turn, changing lanes, backing, etc. After inspecting the data, we categorized the PMCP into three categories according to the direction of the movement, i.e., proceeding straight, changing lanes/taking turns, and others.

Statistical Analysis

Three statistical models were built to: 1) compare the chance of rear-end collisions between the ADS-involved and ADAS-involved crashes (Model 1); 2) investigate the factors affecting the collision types in ADS-involved (Model 2) and ADAS-involved crashes (Model 3).

In all models, the CT (rear-end vs. others) was used as the dependent variable and the binomial logistic regression was used. Specifically, in Model 1, the independent variables of the full model include the IT (morning-noon vs. noon-night vs. night), RS (dry vs. others), LT (daylight vs. others), CW (passenger car vs. SUV vs. others), PMCP (proceeding straight vs. changing lanes/taking turns vs. others), SGR, and VT (ADS vs. ADAS). The two-way interactions between VT and other independent variables were also included in the model. In Model 2 and Model 3, the independent variables of the full model include IT, RT, RS, LT, CW, PMCP, SGR, and their two-way interactions. The model equations for the fitted models are presented as follows. For Model 1:

$$ln\left(\frac{p(CT = rear - end)}{p(CT = others)}\right) = \beta_0 + \beta_1 * IT + \beta_2 * RS + \beta_3 * LT + \beta_4 * CW + \beta_5 * PMCP + \beta_6 * SGR + \beta_7 * VT + \sum \beta_{VT|X} * (VT|X) \qquad (2)$$

where, $X \in \{\mathrm{IT, RS, LT, CW, PMCP, SGR}\}$, while $(VT|X)$ stands for the two-way interaction effect between VT and factor X (e.g., $VT|IT$, $VT|RS$).

For Model 2 (ADS-involved crashes) and Model 3 (ADAS-involved crashes):

$$ln\left(\frac{p(CT = rear - end)}{p(CT = others)}\right) = \beta_0 + \beta_1 * IT + \beta_2 * RT + \beta_3 * RS + \beta_4 * LT + \beta_5 * CW + \beta_6 * PMCP + \beta_7 * SGR + \sum \beta_{M|N} * (M|N) \qquad (3)$$

where, $M, N \in \{\mathrm{IT, RT, RS, LT, CW, PMCP, SGR}\}$, while $(M|N)$ stands for the two-way interaction effect between factor M and factor N (e.g., $IT|RT$, $RT|RS$).

It should be noted that different categories were used for RT in Model 2 and Model 3 (RT of Model 2 for ADS: intersection/traffic circle, street, and others; RT of Model 3 for ADAS: highway/freeway/rural road, intersection, and street). We applied the backward stepwise selection method based on Bayesian Information Criterion (BIC) (*32*) for model selection. All models were built using the *GENMOD* procedure in SAS OnDemand for Academics.

RESULTS

We report all significant effects ($p<.05$) and marginally significant effects ($.05<p<.1$) in the fitted models after model selection. The post-hoc contrasts were conducted if the main or interaction effects were significant or marginally significant. It should be noted that in the model selection process, all dropped variables were not significant ($p>.1$). For Model 1, we only report the post-hoc effects of VT and its interactions with other independent variables. **Table 2** summarizes the model results.

TABLE 2 Wald statistics of type 3 analysis for models

IV	Model 1 (ADS & ADAS)		Model 2 (ADS)		Model 3 (ADAS)	
	χ^2-value	*p*	χ^2-value	*p*	χ^2-value	*p*
VT	$\chi^2(1) = 13.57$	.0002**	*N.A.*	*N.A.*	*N.A.*	*N.A.*
SGR	$\chi^2(1) = 17.27$	<.0001**	$\chi^2(1) = 6.74$	.0094**	$\chi^2(1) = 5.36$	.02**
PMCP	$\chi^2(2) = 8.97$	.01**	$\chi^2(2) = 27.78$	<.0001**	$\chi^2(2) = 3.74$	.15
RT	*N.A.*	*N.A.*	$\chi^2(2) = 6.68$	.04**	$\chi^2(2) = 14.97$	.0006**
IT	-	-	-	-	$\chi^2(2) = 3.78$	.15
PMCP*VT	$\chi^2(2) = 25.45$	<.0001**	-	-	-	-
SGR*VT	$\chi^2(1) = 5.32$	.02**	-	-	-	-
SGR*RT	-	-	$\chi^2(2) = 4.96$	.08*	-	-

Note: in this table and the following tables, * marks marginal significant effect, ** marks significant effects. IV stands for independent variable; N.A. standards for not applicable; - means that the variable was removed during the model selection process.

Comparison of ADS and ADAS Crashes

As shown in **Table 2**, it was found that Vehicle Type (VT), Speed Gap Ratio (SGR), and Pre-crash Movement of Crash Partner (PMCP) were significant predictors of the collision types. Further, significant interaction effects between PMCP and VT, and between SGR and VT were also observed for crash type. **Table 3** presents the parameter estimation of the model. Post-hoc comparisons show that, when an ADS-involved crash happened, it is less likely to be a rear-end collision compared to that when an ADAS-involved crash happened, but to different extents when there was different PMCP (*Proceeding Straight*: OR=0.03, 95%CI: [0.002, 0.766]; *Changing Lanes/Taking Turns*: OR=0.005, 95%CI: [0.0002, 0.1149]; *Others*: OR=0.0002, 95%CI: [0.0001, 0.0057]).

TABLE 3 Analysis of Maximum Likelihood Parameter Estimates for Model 1

Parameter	Estimate	S.E.	95% CL		*p*
Intercept	-0.70	0.54	-1.76	0.36	.2
PMCP (changing lanes/taking turns)	0.02	0.59	-1.14	1.19	.97
PMCP (others)	1.27	0.65	-0.02	2.56	.055*
VT (ADS)	-3.37	1.58	-6.47	-0.27	.03**
PMCP (changing lanes/taking turns)*VT (ADS)	-1.97	0.80	-3.54	-0.40	.01**
PMCP (others)*VT (ADS)	-5.35	1.06	-7.43	-3.27	<.0001**
SGR	1.68	0.78	0.16	3.20	.03**
SGR*VT (ADS)	4.19	1.82	0.63	7.75	.02**

Note: in this table and the following tables, S.E. stands for standard error; CL standards for Wald confidence limits.

Rear-End Collisions in ADS-Involved Crashes

As shown in **Table 2**, the Pre-crash Movement of Crash Partner (PMCP), Speed Gap Ratio (SGR), and Road Type (RT) were found to significantly affect the collision type of ADS-involved crashes. Further, a marginally significant interaction effect between SGR and RT was observed.

TABLE 4 Analysis of Maximum Likelihood Parameter Estimates for Model 2

Parameter	Estimate	S.E.	95% CL		*p*
Intercept	1.21	1.70	-2.13	4.54	.48
PMCP (changing lanes/taking turns)	-2.22	0.60	-3.41	-1.04	.0002**
PMCP (others)	-4.68	0.95	-6.54	-2.81	<.0001**
SGR	1.00	2.62	-4.13	6.12	.7
RT (intersection/traffic circle)	-5.20	2.67	-10.43	0.02	.051*
RT (street)	-21.69	10.83	-42.92	-0.46	.04**
SGR* RT (intersection/traffic circle)	5.02	3.47	-1.78	11.82	.15
SGR* RT (street)	21.99	11.23	-0.02	44.00	.0502*

Table 4 presents the analysis of maximum likelihood parameter estimates of the model. The likelihood of an ADS-involved crash being a rear-end crash was the highest when the PMCP was *Proceeding Straight*, followed by *Changing Lanes/Taking Turns*, and then followed by *Others* (*Changing Lanes/Taking Turns* vs. *Proceeding Straight*: OR=0.11, 95%CI: [0.03, 0.35]; *Changing Lanes/Taking Turns* vs. *Others*: OR=11.58, 95%CI: [1.98, 67.84]; *Proceeding Straight* vs. *Others*: OR=107.38, 95%CI: [16.67, 691.54]).

When the RT was *Street*, every 10% increase of the SGR (i.e., percent of speed gap out of the posted speed) leads to a 9.96 (95%CI: [1.35, 235.09]) multiplicative increase in the odds of an ADS-involved crash to be a rear-end collision. However, the effect of SGR was not observed when the RT was *Intersection/Traffic Circle* or *Others*.

Rear-End Collisions in ADAS-Involved Crashes

As shown in **Table 2**, it was found that the Speed Gap Ratio (SGR) and Road Type (RT) were significant predictors of the likelihood of collision types in ADAS-involved crashes. As shown in **Table 5**, an ADAS-involved crash was more likely to be a rear-end crash on *Highway/Freeway/Rural Road* compared to that when the crash happened on *Street* (OR=7.67, 95%CI: [1.96, 29.95]) or in *Intersection* (OR=15.58, 95%CI: [2.80, 86.66]); no significant difference was observed between *Street* and *Intersection*. Further, every 10% increase of the SGR (i.e., percent of speed gap out of the posted speed) leads to a 1.27 (95%CI: [1.05,1.57]) multiplicative increase in the odds of an ADAS-involved crash being a rear-end collision.

TABLE 5 Analysis of Maximum Likelihood Parameter Estimates of Model 3

Parameter	**Estimate**	**S.E.**	**95% CL**		***p***
Intercept	-2.85	1.09	-4.99	-0.70	.009**
PMCP (changing lanes/taking turns)	0.51	0.72	-0.91	1.92	.5
PMCP (other)	1.52	0.82	-0.08	3.13	.06*
SGR	2.36	1.02	0.36	4.35	.02**
IT (afternoon-night)	0.12	0.77	-1.38	1.62	.9
IT (night)	1.19	0.70	-0.18	2.57	.09*
RT (highway/freeway/rural road)	2.04	0.70	0.68	3.40	.003**
RT (intersection)	-0.71	0.98	-2.64	1.22	.5

DISCUSSIONS

Through a recently released ADAS/ADS crash dataset by NHTSA, this study investigated the patterns of rear-end collisions among ADS- and ADAS-involved crashes. Previous research has found that ADS-equipped vehicles were more likely to involve in rear-end collisions compared to conventional human-driven vehicles (*8*). Our results show that the rear-end collisions also dominate the ADAS-involved crashes: a larger portion of the rear-end collisions has been observed in ADAS-involved crashes even compared to that in ADS-involved crashes. The drivers are expected to be in the control loop in vehicles with SAE Level 2 ADAS and should be able to step in promptly before the ADAS can detect and respond to emergencies, given that drivers are better at anticipating the evolving situations on road compared to ADAS (*33*). However, as has been observed in previous research, drivers may shift their attention away from driving-related tasks in ADAS-equipped vehicles (*34*). Thus, drivers may not be able to take back control of the vehicle in time (*35*), or they may not be able to control the vehicle well even after stepping in (*36*).As ADAS was less capable of foreseeing the development of the situation compared to ADS, the lack of human-intervention may explain the even larger portion of rear-end collisions in ADAS-involved collisions compared to that in ADS-involved collisions. However, the readers should be aware that we were not comparing the ADS- and ADAS-involved crashes under the same conditions. ADS and ADAS were designed for different types of roads – ADS has been tested mostly on city roads, while ADAS is suggested to be used on highways or freeways only. It would be practically infeasible to compare the crash patterns of ADS- and ADAS-controlled vehicles on the same types of roads that one of them is not designed for.

To further illustrate the crash patterns in conditions where ADS and ADAS were designed for, two additional models were built for ADS-involved and ADAS-involved crashes, respectively. For ADAS-involved crashes, as expected, with the increase of the SGR, the likelihood of an ADAS-involved crash being a rear-end collision increases, regardless of the type of road the ADAS-involved crashes happened. At the same time, we noticed that on highway/freeway/rural road, a larger portion of rear-end collisions in ADAS-involved crashes has been observed compared to that in urban areas (i.e., street or intersections). It is likely that drivers have over-relied on ADAS on highway/freeway/rural road where most ADASs were designed for and thus they tended not to take control of the vehicle until the situations become critical. This may can lead to unexpected hard braking of the ADAS-controlled vehicles and increase the likelihood of being rear-ended. Similar phenomenon has been observed when new technologies are implemented in vehicles. For example, based on the results of a naturalistic driving study in China, the forward collision system with a headway monitoring function led to shorter headway of the ego-vehicle as drivers may adapt to the system (*37*). Further, the portion of rear-end collisions did not differ across PMCP conditions for ADAS-controlled vehicles. In other words, regardless of the pre-crash movement of another involving crash partner, the likelihood of an ADAS-involved crash being a rear-end crash remained the same, potentially because of the already high likelihood of rear-end collisions in ADAS-involved crashes under all conditions.

While for ADS-involved crashes, it was found that when the pre-crash movement of the crash partner (PMCP) was proceeding straight, the portion of rear-end collisions was the largest. It seems that when proceeding straight, human drivers were less capable to anticipate the motion of an ADS-controlled vehicle compared to when there was lateral movement of human-driven vehicles. Previous research has observed a smaller TTC when human drivers were following an ADS-controlled vehicle in mixed traffic compared to that when following a human-driven vehicle (*12*). It might be possible that when proceeding straight, the front view of the following driver is more likely to be “blocked” by the lead vehicle; if the ADS-controlled vehicle is not pre-active to the incidents ahead, the time budget left for the following vehicle to respond will be limited. While when there was lateral movement of the following human-driven vehicles (e.g., changing lanes or making turns), the human drivers’ view is less likely to be “blocked” by the lead vehicles, and thus they are more capable of anticipating an intensive slowdown of the ADS-controlled vehicle ahead and avoid colliding into it. Further, the effect of SGR (i.e., percent of speed gap out of the posted speed) was only observed when the ADS-involved rear-end crashes happened on straight city road (i.e., *Street*) but not in other scenarios such as at intersections, indicating that the following vehicle had difficulty in responding to the slowdown of an ADS-controlled lead vehicle. The external human-machine interfaces (eHMIs) may support the decisions of human drivers surrounding the ADS-controlled vehicles (*38–40*) and thus reduce the risk of crashes with ADS-equipped vehicles.

It should be noted that the incident time, roadway surface, lighting condition, and the types of the crash partner did not affect the likelihood of rear-end collision for both ADS-controlled and ADAS-controlled vehicles. It seems that the types of the ADS- or ADAS-involved crashes are more related to the motion-related factors (i.e., relative movement of the road agents or the factors that can affect the movement of the road agents) in the scenarios rather than the environment-related factors (i.e., lighting, surface condition, time of the day and type of the crash partner). However, given the limited sample size in this study, further study should further explore the effects of these factors.

In summary, the findings from our study may help improve the safety of mixed traffic from different stakeholders’ perspective of view. Specifically, for vehicle manufacturers, a comparison between ADS- and ADAS-involved crashes can guide the design of ADAS and ADS control algorithms, for example, in which scenarios the control algorithms need further improvement and whether the more advanced driving automation technologies can significantly benefit the traffic safety. For government/policy makers, the analyses of ADS- and ADAS-involved crashes can help design regulations for ADS- and ADAS-controlled vehicles. For example, we found that the high risk of rear-end collisions among ADS-controlled vehicles might be partially attributed to the block of front view. Thus, the law makers may consider making the external human machine interface mandatory to support better human-ADS coordination. From the perspective of driver education, our study may provide insights on how to support drivers to better coordinate with ADS- or ADAS-controlled vehicles. For example, improving drivers’ awareness of the limitations of ADAS and ADS may help drivers take more appropriate strategies when interacting with ADS- and ADAS-controlled vehicles (e.g., keep a large headway distance to the ADAS- or ADS-controlled lead vehicles to better prepare for sudden brake of them).

CONCLUSIONS

In this study, using NHTSA dataset, we explored the crash patterns of ADS- and ADAS-controlled vehicles by extracting the data from the most up-to-date crash reports at the time of the paper submission (between July 2021 and May 2022). The major findings from this study are summarized as follows:

- There were higher portion of rear-end collisions in ADAS-involved crashes compared to that in ADS-involved crashes.
- Regardless of vehicle type (i.e., ADS-controlled or ADAS-controlled), the type of driving-automation-involved crashes are more related to motion-related factors (i.e., relative movement of the road agents or the factors that can affect the movement of the road agents) compared to

environment-related factors (i.e., lighting, surface condition, time of the day and type of the crash partner) in scenarios.

- The likelihood of an ADAS-involved crash being a rear-end collision would: (1) increase with the increase of the speed gap ratio (SGR); (2) be higher on highway/freeway/rural road compared to that in urban areas (i.e., street and intersections).
- The likelihood of an ADS-involved crash being a rear-end collision would: (1) be the highest when the pre-crash movement of the crash partner was proceeding straight; (2) increase with the increase of SGR when the crash happened on straight city road (i.e., street).

Several limitations of this study should also be noted. First, due to the data accessibility, only a small part (around 22%) of ADAS-equipped vehicle crash data was included in this study. Secondly, it should be also noted that the NHTSA dataset did not provide the status of crash partners or subject vehicles before a collision. Thus, we were not able to fully recover the dynamic scenarios leading to a crash. Future research with more comprehensive data is needed to further explore the leading factors of the rear-end collisions of ADS-controlled vehicles. Besides, we only considered cases that ADS- or ADAS controlled vehicles were rear-ended by other vehicles. However, different factors might be associated with the cases when the ADS- or ADAS rear-ended other vehicles (e.g., the ADS-controlled vehicles might rear-end other vehicles when they have difficulty predicting the behaviors of other road agents; while they are more likely to be rear-ended when their own behaviors are less predictable). Future research should take this into consideration when more data becomes available. In addition, we only adopted the binomial logistic regression in this study for data analyses, which was not able to account for potential unobserved factors. Future research can consider more sophisticated models (e.g., random parameters logit models) to capture potential unobserved heterogeneity in the data. Finally, it should be further noted that the ADS-controlled vehicle crashes are occurring in the test stage on public roads, so their crash pattern might be different after they are fully commercialized. Future research may investigate how the development of ADS-related and ADAS-related technologies can impact mixed traffic safety by comparing the crash patterns years apart.

ACKNOWLEDGMENTS

This research was funded by the National Natural Science Foundation of China (Grant No. 52202425) and partially by the Guangzhou Municipal Science and Technology Project (No. 2023A03J0011), the Guangzhou Science and Technology Program City-University Joint Funding Project (No. 2023A03J0001), and Project of Hetao Shenzhen-Hong Kong Science and Technology Innovation Cooperation Zone (HZQB-KCZYB-2020083). The authors would like to thank the Transportation Behavioral Psychology and Safety (TBPS) Lab at the Hong Kong University of Science and Technology (Guangzhou). The authors would also express their most sincere thanks to the National Highway Traffic Safety Administration (NHTSA) for their efforts in collecting and releasing the raw data used in this study.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: C.H., D.H.; data processing: C.H.; analysis and interpretation of results: C.H., X.W., D.H.; draft manuscript preparation: C.H., X.W., D.H. All authors reviewed the results and approved the final version of the manuscript.

CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

REFERENCES

1. Singh, S. *Critical Reasons for Crashes Investigated in the National Motor Vehicle Crash Causation Survey (DOT HS 812 115)*. 2015.
2. SAE International. Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles (J3016_202104). https://www.sae.org/standards/content/j3016_202104/. Accessed Feb. 17, 2022.
3. Canalys. Huge Opportunity as Only 10% of the 1 Billion Cars in Use Have ADAS Features. https://canalys.com/newsroom/huge-opportunity-as-only-10-of-the-1-billion-cars-in-use-have-adas-features. Accessed Jul. 21, 2022.
4. Ye, W., C. Wang, F. Chen, S. Yan, and L. Li. Approaching Autonomous Driving with Cautious Optimism: Analysis of Road Traffic Injuries Involving Autonomous Vehicles Based on Field Test Data. *Injury prevention : journal of the International Society for Child and Adolescent Injury Prevention*, Vol. 27, No. 1, 2021, pp. 42–47. https://doi.org/10.1136/injuryprev-2019-043402.
5. Favarò, F. M., N. Nader, S. O. Eurich, M. Tripp, and N. Varadaraju. Examining Accident Reports Involving Autonomous Vehicles in California. *PLOS ONE*, Vol. 12, No. 9, 2017, p. e0184952. https://doi.org/10.1371/journal.pone.0184952.
6. Schoettle, B., and M. Sivak. A Preliminary Analysis of Real-World Crashes Involving Self-Driving Vehicles. *University of Michigan Transportation Research Institute*, 2015.
7. Goodall, N. J. Comparison of Automated Vehicle Struck-from-behind Crash Rates with National Rates Using Naturalistic Data. *Accident Analysis & Prevention*, Vol. 154, 2021, p. 106056. https://doi.org/10.1016/j.aap.2021.106056.
8. Boggs, A. M., B. Wali, and A. J. Khattak. Exploratory Analysis of Automated Vehicle Crashes in California: A Text Analytics & Hierarchical Bayesian Heterogeneity-Based Approach. *Accident Analysis & Prevention*, Vol. 135, 2020, p. 105354. https://doi.org/10.1016/j.aap.2019.105354.
9. Petrović, Đ., R. Mijailović, and D. Pešić. Traffic Accidents with Autonomous Vehicles: Type of Collisions, Manoeuvres and Errors of Conventional Vehicles' Drivers. *Transportation Research Procedia*, Vol. 45, 2020, pp. 161–168. https://doi.org/10.1016/j.trpro.2020.03.003.
10. Liu, Q., X. Wang, X. Wu, Y. Glaser, and L. He. Crash Comparison of Autonomous and Conventional Vehicles Using Pre-Crash Scenario Typology. *Accident Analysis & Prevention*, Vol. 159, 2021, p. 106281. https://doi.org/10.1016/j.aap.2021.106281.
11. Song, Y., M. V. Chitturi, and D. A. Noyce. Automated Vehicle Crash Sequences: Patterns and Potential Uses in Safety Testing. *Accident Analysis & Prevention*, Vol. 153, 2021, p. 106017. https://doi.org/10.1016/j.aap.2021.106017.
12. Huang, C., X. Wen, D. He, and S. Jian. Sharing the Road: How Human Drivers Interact with Autonomous Vehicles on Highways. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, Vol. 66, No. 1, 2022, pp. 1437–1441. https://doi.org/10.1177/1071181322661165.
13. He, D., C. A. DeGuzman, and B. Donmez. Anticipatory Driving in Automated Vehicles: The Effects of Driving Experience and Distraction. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 2021, p. 001872082110261. https://doi.org/10.1177/00187208211026133.
14. de Winter, J. C. F., R. Happee, M. H. Martens, and N. A. Stanton. Effects of Adaptive Cruise Control and Highly Automated Driving on Workload and Situation Awareness: A Review of the Empirical Evidence. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 27, 2014, pp. 196–217. https://doi.org/10.1016/j.trf.2014.06.016.
15. He, D., and B. Donmez. Influence of Driving Experience on Distraction Engagement in Automated Vehicles. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2673, No. 9, 2019, pp. 142–151. https://doi.org/10.1177/0361198119843476.
16. Mahdinia, I., R. Arvin, A. J. Khattak, and A. Ghiasi. Safety, Energy, and Emissions Impacts of Adaptive Cruise Control and Cooperative Adaptive Cruise Control. *Transportation Research*

Record: Journal of the Transportation Research Board, Vol. 2674, No. 6, 2020, pp. 253–267. https://doi.org/10.1177/0361198120918572.

17. Tu, Y., W. Wang, Y. Li, C. Xu, T. Xu, and X. Li. Longitudinal Safety Impacts of Cooperative Adaptive Cruise Control Vehicle's Degradation. *Journal of Safety Research*, Vol. 69, 2019, pp. 177–192. https://doi.org/10.1016/j.jsr.2019.03.002.
18. Monfort, S. S., I. J. Reagan, J. B. Cicchino, W. Hu, P. Gershon, B. Mehler, and B. Reimer. Speeding Behavior While Using Adaptive Cruise Control and Lane Centering in Free Flow Traffic. *Traffic Injury Prevention*, Vol. 23, No. 2, 2022, pp. 85–90. https://doi.org/10.1080/15389588.2021.2013476.
19. Lyu, N., Z. Duan, C. Ma, and C. Wu. Safety Margins – a Novel Approach from Risk Homeostasis Theory for Evaluating the Impact of Advanced Driver Assistance Systems on Driving Behavior in near-Crash Events. *Journal of Intelligent Transportation Systems*, Vol. 25, No. 1, 2021, pp. 93–106. https://doi.org/10.1080/15472450.2020.1795846.
20. Dumitru, A. I., T. Girbacia, R. G. Boboc, C.-C. Postelnicu, and G.-L. Mogan. Effects of Smartphone Based Advanced Driver Assistance System on Distracted Driving Behavior: A Simulator Study. *Computers in Human Behavior*, Vol. 83, 2018, pp. 1–7. https://doi.org/10.1016/j.chb.2018.01.011.
21. Dixit, V. V., S. Chand, and D. J. Nair. Autonomous Vehicles: Disengagements, Accidents and Reaction Times. *PLOS ONE*, Vol. 11, No. 12, 2016, p. e0168054. https://doi.org/10.1371/journal.pone.0168054.
22. Waymo LLC. Waymo Open Dataset. waymo.com/open/. Accessed Feb. 17, 2022.
23. National Highway Traffic Safety Administration. Standing General Order on Crash Reporting for Incidents Involving ADS and Level 2 ADAS. https://www.nhtsa.gov/laws-regulations/standing-general-order-crash-reporting. Accessed Jul. 21, 2022.
24. National Highway Traffic Safety Administration. *Summary Report: Standing General Order on Crash Reporting for Automated Driving Systems*. 2022.
25. National Highway Traffic Safety Administration. *Summary Report: Standing General Order on Crash Reporting for Level 2 Advanced Driver Assistance Systems*. 2022.
26. Banerjee, S. S., S. Jha, J. Cyriac, Z. T. Kalbarczyk, and R. K. Iyer. Hands Off the Wheel in Autonomous Vehicles?: A Systems Perspective on over a Million Miles of Field Data. 2018.
27. Dadvar, S., and M. M. Ahmed. *California Autonomous Vehicle Crashes: Explanatory Data Analysis and Classification Tree*. 2021.
28. Chance Scott, M., S. Sen Roy, and S. Prasad. Spatial Patterns of Off-the-System Traffic Crashes in Miami–Dade County, Florida, during 2005–2010. *Traffic Injury Prevention*, Vol. 17, No. 7, 2016, pp. 729–735. https://doi.org/10.1080/15389588.2016.1144878.
29. National Safety Council. Car Crashes by Time of Day and Day of Week. https://injuryfacts.nsc.org/motor-vehicle/overview/crashes-by-time-of-day-and-day-of-week/. Accessed Jul. 21, 2022.
30. Xu, C., Z. Ding, C. Wang, and Z. Li. Statistical Analysis of the Patterns and Characteristics of Connected and Autonomous Vehicle Involved Crashes. *Journal of Safety Research*, Vol. 71, 2019, pp. 41–47. https://doi.org/10.1016/j.jsr.2019.09.001.
31. Bullough, J. D., E. T. Donnell, and M. S. Rea. To Illuminate or Not to Illuminate: Roadway Lighting as It Affects Traffic Safety at Intersections. *Accident Analysis & Prevention*, Vol. 53, 2013, pp. 65–77. https://doi.org/10.1016/j.aap.2012.12.029.
32. Burnham, K. P., and D. R. Anderson. Multimodel Inference. *Sociological Methods & Research*, Vol. 33, No. 2, 2004, pp. 261–304. https://doi.org/10.1177/0049124104268644.
33. He, D., D. Kanaan, and B. Donmez. In-Vehicle Displays to Support Driver Anticipation of Traffic Conflicts in Automated Vehicles. *Accident Analysis & Prevention*, Vol. 149, 2021, p. 105842. https://doi.org/10.1016/j.aap.2020.105842.

34. Matthews, G., C. Neubauer, D. J. Saxby, R. W. Wohleber, and J. Lin. Dangerous Intersections? A Review of Studies of Fatigue and Distraction in the Automated Vehicle. *Accident Analysis & Prevention*, Vol. 126, 2019, pp. 85–94.
35. Gold, C., D. Damböck, L. Lorenz, and K. Bengler. "Take over!" How Long Does It Take to Get the Driver Back into the Loop? *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, Vol. 57, No. 1, 2013, pp. 1938–1942. https://doi.org/10.1177/1541931213571433.
36. Vogelpohl, T., M. Kühn, T. Hummel, T. Gehlert, and M. Vollrath. Transitioning to Manual Driving Requires Additional Time after Automation Deactivation. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 55, 2018, pp. 464–482. https://doi.org/10.1016/j.trf.2018.03.019.
37. Zhu, M., X. Wang, and J. Hu. Impact on Car Following Behavior of a Forward Collision Warning System with Headway Monitoring. *Transportation Research Part C: Emerging Technologies*, Vol. 111, 2020, pp. 226–244. https://doi.org/10.1016/j.trc.2019.12.015.
38. Hensch, A.-C., I. Neumann, M. Beggiato, J. Halama, and J. F. Krems. Effects of a Light-Based Communication Approach as an External HMI for Automated Vehicles--a Wizard-of-Oz Study. *Transactions on Transport Sciences*, Vol. 10, No. 2, 2019.
39. Papakostopoulos, V., D. Nathanael, E. Portouli, and A. Amditis. Effect of External HMI for Automated Vehicles (AVs) on Drivers' Ability to Infer the AV Motion Intention: A Field Experiment. *Transportation research part F: traffic psychology and behaviour*, Vol. 82, 2021, pp. 32–42.
40. Schieben, A., M. Wilbrink, C. Kettwich, J. Dodiya, F. Weber, L. Sorokin, Y.-M. Lee, R. Madigan, G. Markkula, and N. Merat. Testing External HMI Designs for Automated Vehicles–An Overview on User Study Results from the EU Project InterACT. *9. Tagung Automatisiertes Fahren*, 2019.

Figure

ADS-equipped vehicle crashes (n = 130)	
Original Data	**After aggregation (frequency, percentage)**
Crash-With (CW)	
Passenger Car (61)	Passenger Car (n = 61, 46.9%)
SUV (27)	SUV (n = 27, 20.8%)
Heavy Truck (3)	Others (n = 42, 32.3%)
Motorcycle (2)	
Non-Motorist: Cyclist (7)	
Non-Motorist: Other (2)	
Other Fixed Object (6)	
Other, see Narrative (7)	
Pickup Truck (10)	
Van (5)	
Roadway Type (RT)	
Intersection (65)	Intersection/Traffic Circle (n = 67, 51.5%)
Traffic Circle (2)	
Highway / Freeway (5)	Others (n = 13, 10%)
Rural Road (1)	
Parking Lot (6)	
Unknown (1)	
Street (50)	Street (n = 50, 38.5%)
Roadway Surface (RS)	
Dry (120)	Dry (n = 120, 92.3%)
Snow/Slush/Ice (1)	Others (n = 10, 7.7%)
Wet (7)	
Unknown (2)	
Lighting (LT)	
Daylight (84)	Daylight (n = 84, 64.6%)
Dark - Lighted (38)	Others (n = 46, 35.4%)
Dark - Not Lighted (2)	
Dark - Unknown Lighting (1)	
Dawn/Dusk (4)	
Unknown (1)	
Pre-crash Movement of Crash Partner (PMCP)	
Proceeding Straight (54)	Proceeding Straight (n = 54, 41.6%)
Changing Lanes (9)	Changing Lanes/Taking Turns (n = 38, 29.2%)
Crossing into Opposing Lane (4)	
Entering Traffic (1)	
Lane / Road Departure (1)	
Making Left Turn (10)	
Making Right Turn (11)	
Making U-Turn (1)	
Merging (1)	
Backing (13)	Others (n = 38, 29.2%)
Other, see Narrative (12)	
Parked (4)	
Passing (4)	
Stopped (3)	
Traveling Wrong Way (2)	

ADAS-equipped vehicle crashes (n = 84)	
Original Data	**After aggregation (frequency, percentage)**
Crash-With (CW)	
Passenger Car (43)	Passenger Car (n = 43, 51.2%)
SUV (17)	SUV (n = 17, 20.2%)
Heavy Truck (8)	Others (n = 24, 28.6%)
Pickup Truck (8)	
Van (5)	
Other, see narative (3)	
Roadway Type (RT)	
Highway/Freeway (50)	Highway/Freeway/Rural Road (n = 53, 63.1%)
Rural Road (3)	
Intersection (16)	Intersection (n = 16, 19.0%)
Street (15)	Street (n = 15, 17.9%)
Roadway Surface (RS)	
Dry (77)	Dry (n = 77, 91.7%)
Snow/Slush/Ice (2)	Others (n = 7, 8.3%)
Wet (5)	
Lighting (LT)	
Daylight (44)	Daylight (n = 44, 52.4%)
Dark - Lighted (20)	Others (n = 40, 47.6%)
Dark - Not Lighted (12)	
Dawn/Dusk (8)	
Pre-crash Movement of Crash Partner (PMCP)	
Proceeding Straight (27)	Proceeding Straight (n = 27, 32.1%)
Changing Lanes (10)	Changing Lanes/Taking Turns (n = 33, 39.3%)
Crossing into Opposing Lane (2)	
Entering Traffic (2)	
Lane/Road Departure (5)	
Making Left Turn (13)	
Merging (1)	
Backing (1)	Others (n = 24, 28.6%)
Other, see narrative (5)	
Stopped (18)	