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Research Article

A Precrash Scenario Analysis Comparing Safety Performance across Autonomous Vehicle Driving Modes

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Precrash scenario analysis for autonomous vehicles (AVs) is critical for improving the safety of autonomous driving, yet the scenario differences between different driving modes are unexplored. Using the precrash scenario typology of the USDOT, this study classified 484 AV crash reports from the California DMV from 2018 to 2022, revealing the differences in the scenario proportions of the three modes of autonomous driving, driving takeover, and conventional driving in 34 types of scenarios. The results showed that there were significant differences in the proportion of six scenarios such as "Lead AV stopped" and "Lead AV decelerating" among different driving modes ($p < 0.05$). To analyze the relative risk of different driving modes in specific scenarios, an evaluation model of the risk level of AV precrash scenarios was established using the analytic hierarchy process (AHP). The findings indicated that autonomous driving has the highest risk rating and poses the greatest danger in Scenario 1, while conventional driving is associated with Scenario 2b, and driving takeover corresponds to Scenario 3, respectively. In-depth analysis of the crash characteristics and causes of these three typical scenarios was conducted, and suggestions were made from the perspectives of autonomous driving system (ADS) and drivers to reduce the severity of crashes. This study compared precrash scenarios of AV by different driving modes, providing references for the optimization of ADS and the safety of human-machine codriving.

1. Introduction

Autonomous driving technology is a scientific technology that brings creative changes to the future automotive field, which is expected to provide a fundamental transformation for traffic problems and will make transportation safer, smoother, and more convenient [1]. However, due to the limitations of the current technological development, the current perception, recognition, and planning decision-making systems for autonomous vehicles (AVs) are not perfect, and they are unable to effectively deal with the various factors affecting driving safety [2]. Despite continuous progress in autonomous driving technology, even advanced autonomous driving system (ADS) cannot completely eliminate crashes due to vehicle dynamics and traffic constraints [3]. As a result, varying severity of hundreds of crashes have occurred in U.S. states, which have allowed the deployment or testing of AVs [4].

In September 2014, the California Department of Motor Vehicles (DMV) gave permission for AVs to be tested on California's roadways [5]. Companies and manufacturers authorized to conduct autonomous driving tests are required to submit a crash report (OL 316) involving an AV and a disengagement report (OL 311R), which includes a complete description of the crash and other specific and effective information such as the reason, frequency, and mileage of AV disengaged from the system [6–8]. As of December 31st, 2022, the California DMV has approved the public publication of 540 crash reports involving AVs since 2014, along with nearly eight years of disengagement reports.

Between 2015 and 2022, there have been a steady rise in the yearly count of AV crashes tested on California highways [6], as shown in Figure 1, but the sudden drop in the number

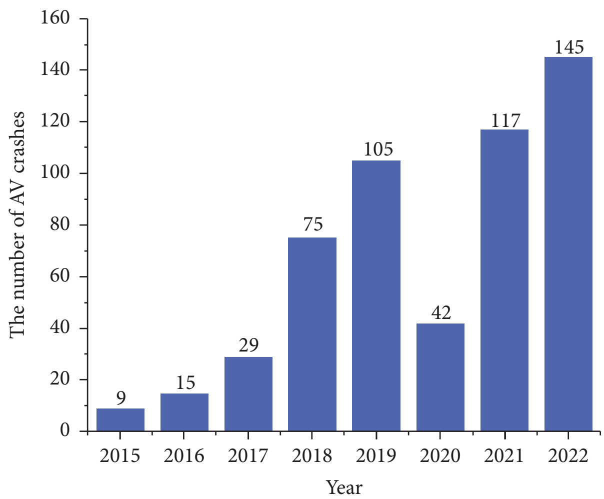


Figure 1: The number of California AV crashes.

of crashes in 2020 is attributed to the COVID-19 epidemic. Meanwhile, the total annual AV miles traveled in California, as reported in the disengagement report OL 311R, has been increasing each year for the last eight years. The average total miles traveled per year account for 2,197,780. Furthermore, AV crash mileage is determined by dividing the total autonomous mileage driven in a year by the number of AV crashes that occurred during that same year. According to the AV crash report OL 316, this calculation gives an annual average crash mileage of 34,590 miles. The description of the total mileage and crash mileage of AV in California in the past eight years is shown in Figure 2. Since the actual test of AV is still in the initial stage, the safety of AV cannot be verified by miles traveled and crash mileage alone. As more AVs are put into use, the safety performance of different driving modes is also to be explored in depth because of the switching of driving modes during driving.

In recent years, there have been many advances in research for the analysis of AV crashes, but there are fewer studies related to the safety of different driving modes. Petrović et al. [9] focused on analyzing the characteristics of AV crashes in California, U.S.A. Meanwhile, a comprehensive examination was conducted to compare and analyze the occurrence of crashes involving conventional vehicles (CVs) at a specific location. The study encompassed various aspects such as crash types, driving maneuvers, and errors made by conventional drivers. The statistical analysis revealed that AVs were more prone to being involved in rear-end crashes at this location, whereas CV crashes primarily stemmed from drivers exceeding the speed limit or failing to maintain control of their vehicles while following others. A comprehensive analysis and review of crashes involving AVs and an in-depth evaluation of DMV crash data by Almaskat et al. [10] showed that AVs are more likely to be involved in rear-end crashes, but in most cases they are not the responsible party for the crashes, further confirming that AVs have the potential to improve road safety. Lee et al. [11] used frequency theory and Bayesian methods to construct a crash analysis framework for AVs. The analysis results showed that in the autonomous driving mode, the probability of rear-end crashes is higher than that in the conventional driving mode. Furthermore, before the crashes, when the AVs are passing CVs, the drivers of the AVs are more likely to manually take over the vehicle.

To drive safely, an AV requires a more optimized ADS capable of automatically adjusting its operation mode according to various conditions, including but not limited to geographic area, driving speed, road type, traffic environment, and prevailing traffic laws. These ranges of conditions constitute the operational design domain (ODD), which is crucial for the ADS to function properly [12]. Hence, the development of an ODD framework heavily relies on the construction of driving scenarios, which is significant importance. In analyzing driving scenarios of AVs, Song et al. [13] defined the analysis of crash sequence and ODD as the crash scenario of AV and constructed a crash mechanism model using Bayesian networks. Their analysis revealed that considering human factors and environmental conditions is advantageous in accurately identifying the distribution of specific types of ODD crash sequences. After utilizing the precrash scenario typology developed by the National Highway Traffic Safety Administration (NHTSA) under the United States Department of Transportation (USDOT), Liu et al. [14] analyzed crash patterns of AVs and CVs. Their comparative analysis of precrash scenarios led them to conclude that substantial dissimilarities exist between these two driving scenario types. However, different driving modes also vary in terms of crash type and severity [15], and comparative analysis of different driving modes using precrash scenarios has greater research significance. Simultaneously, for a considerable period in the future, AVs will be in the stage of human-machine codriving [16], and switching driving modes before a traffic accident occurs can help coordinate the relationship between the driver and the ADS and achieve effective control of the AV by both humans and the system.

In this paper, we have extracted precrash scenarios involving AVs from the California DMV database, analyzed AV precrash scenarios using the classification method of the USDOT, and determined the scenario differences between autonomous driving, driving takeover, and conventional driving. Based on the macro-statistical characteristics of crashes, vehicle damage levels, and personnel injury indicators, the danger level evaluation model of AV precrash scenarios is established. Meanwhile, three precrash scenarios with the highest crash frequency are selected for discussion, which provides a certain reference basis for the optimization and improvement of ADS and the safety of human-machine codriving.

2. Literature Review

2.1. Precrash Scenario Typology. The investigation and dissection of the root causes of a crash heavily rely on precrash scenarios, which include the vehicle movements leading up to the crash, the number of vehicles involved, and other detailed information surrounding the crash [17]. Several scholars have developed standard precrash scenarios by

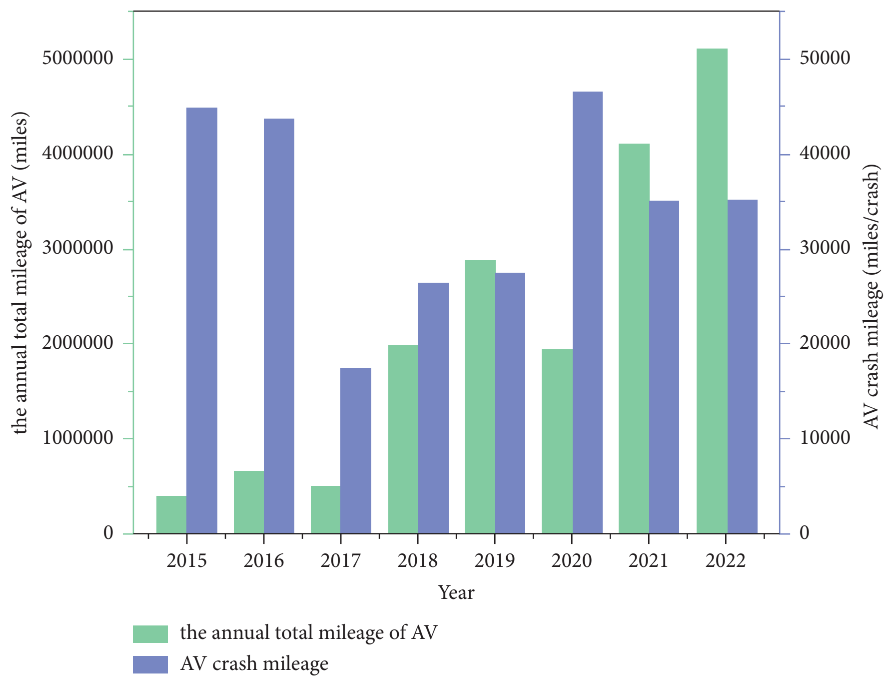


FIGURE 2: Description of total AV miles traveled and crash mileage.

employing crash data and natural driving data and utilizing various mining algorithms. Char and Serre [18] created a risk scenario database involving cycling by utilizing natural driving data, and the objective of this database was to provide theoretical support for developing advanced driver assistance systems. Rui Zhou et al. [19] identified typical precrash scenarios of AVs and powered-two-wheelers (PTWs) based on a scenario construction method with real-world dynamic crash features and provided more detailed scenario descriptions. Bangert et al. [20] used an unsupervised decision tree model to group crash scenarios with similar key features at intersections to derive 44 functional intersection crash patterns, which provide a theoretical basis for the design of advanced assisted driving systems at intersections. Precrash scenario studies have primarily focused on analyzing the behaviors and characteristics of vulnerable road users, examining conflict points and patterns at intersections, and studying the dynamics and interactions among various vehicles [14].

The technique of precrash scenario typology involves the identification and classification of crash scenarios based on various contributing factors, such as the driving environment, driver characteristics, and vehicle conditions. This method allows for a comprehensive understanding of the different types of scenarios that lead to crashes. The NHTSA established and statistically described a typology of precrash scenarios for lightweight vehicles that includes 37 precrash scenarios, summarizing previous experiences in 2007 [21]. These scenarios depict the condition of vehicle motion and dynamics, along with significant incidents preceding at least one light vehicle crash. The novel typology facilitates an understanding of all prevalent precrash scenarios and exposes the crash triggers and specific circumstances in each case.

Encompassing both public and private organizations, the establishment of this new precrash scenario serves to create a collaborative research foundation for vehicle safety. This initiative aims to help researchers in identifying key areas for traffic safety research and developing effective crash avoidance systems [22]. In accordance with the Crash Avoidance Research Precrash Scenario Typology, Table 1 precisely outlines the specific 37 precrash scenarios.

2.2. Analysis of the Causes of AV Crashes. Based on the AV crash data (OL 316) released by the California DMV, the safety of AVs has sparked prolonged and widespread concerns. In analyzing the causes and safety ramifications of these crashes, numerous scholars have highlighted the contributing factors that determine their severity. Zhu and Meng [23] constructed a cost-sensitive classification and regression tree (CART) model by developing a classification tree of crash severity for AVs and concluded that the main influencing factors affecting the severity of AV crashes are vehicle manufacturer, facility type, precrash motion, crash type, lighting conditions, and year. Chen et al. [24] analyzed the crash characteristics of AVs, and, by combining POI data, they concluded, based on the XGBoost model, that the main characteristics that determine the severity of accidents are weather, vehicle damage, crash location, and crash type. Zhang and Xu [25] used association rule analysis to conclude that downhill, nighttime, and high-density traffic flow increase the likelihood of crash severity for AVs.

On the other hand, the analysis of the causes of crashes in AVs will focus on road intersections. Liu et al. [26] conducted an in-depth mining based on the crash causality analysis of precrash scenarios using an association rule algorithm for the crash characteristics and causes of AVs

Table 1: 37 Specific descriptions of precrash scenarios [22].

No.	Scenarios description
1	Vehicle failure
2	Control loss with prior vehicle action
3	Control loss without prior vehicle action
4	Running red light
5	Running stop sign
6	Road edge departure with prior vehicle maneuver
7	Road edge departure without prior vehicle maneuver
8	Road edge departure while backing up
9	Animal crash with prior vehicle maneuver
10	Animal crash without prior vehicle maneuver
11	Pedestrian crash with prior vehicle maneuver
12	Pedestrian crash without prior vehicle maneuver
13	Pedalcyclist crash with prior vehicle maneuver
14	Pedalcyclist crash without prior vehicle maneuver
15	Backing up into another vehicle
16	Vehicle(s) turning-same direction
17	Vehicle(s) parking-same direction
18	Vehicle(s) changing lanes-same direction
19	Vehicle(s) drifting-same direction
20	Vehicle(s) making a maneuver-opposite direction
21	Vehicle(s) not making a maneuver-opposite direction
22	Following vehicle making a maneuver
23	Lead vehicle accelerating
24	Lead vehicle moving at lower constant speed
25	Lead vehicle decelerating
26	Lead vehicle stopped
27	Left turn across path from opposite directions at signalized junctions
28	Vehicle turning right at signalized junctions
29	Left turn across path from opposite directions at nonsignalized junctions
30	Straight crossing paths at nonsignalized junctions
31	Vehicle(s) turning at nonsignalized junctions
32	Evasive action with prior vehicle maneuver
33	Evasive action without prior vehicle maneuver
34	Noncollision incident
35	Object crash with prior vehicle maneuver
36	Object crash without prior vehicle maneuver
37	Other

Note. Vehicle action refers to a range of maneuvers performed by a vehicle in response to a preceding critical event, including deceleration, acceleration, starting, overtaking, parking, turning, reversing, lane changing, merging, and successful corrective actions. Vehicle maneuver includes braking, acceleration, take-off, passing, parking, turning, reversing, lane change, merging, and successful recovery from a previous vehicle critical event.

located at intersections. The analysis findings indicate that for rear-end scenarios involving AVs, key factors include being located outside the intersection, traffic signal control, autonomous driving mode, mixed-use or public land, and weekdays, whereas the main factors for the lane-change scenario are on-street parking and the time of day at 8 a.m. The main factors for the lane-change scenario are on-street parking and 8 a.m. time of day. The combination of these factors plays a crucial role in contributing to AV crashes that occur at intersections. Song et al. [13] used the data collected by the NHTSA Crash Report Sampling System (CRSS) pertaining to two-vehicle crashes that occurred at intersections. They recoded the initial positions and trajectories of the vehicles involved, generated crash sequences, and categorized two-vehicle crashes at intersections into 55 distinct types. To further analyze the data, Bayesian networks were employed as a statistical modeling technique to uncover the relationships between crash sequence types, crash outcomes, human factors, and environmental conditions. This analytical approach not only enhances our understanding of the underlying mechanisms of crash occurrence but also offers more targeted recommendations for crash prevention and reduction.

In addition to focusing on AV crashes that occur at intersections, some scholars have studied whether disengagement of the ADS leads to crashes, which is related to the safety analysis of the driving mode. Liu et al. [27] used the XGBoost algorithm to predict in real time the crash risk of an AV on different sections of a motorway, while considering whether the ADS is disengaged or not. When the ADS fails or the sensors malfunction, the driver can choose to take over the vehicle and control the speed difference with the vehicle in front to minimize the accident risk and optimize the outcome. This predictive approach helps to improve the safety and reliability of AVs. Khattak et al. [28] analyzed three different ADS disengagement scenarios and concluded that factors related to the ADS and other road participants increase the tendency for the system to disengage without a crash. It is necessary to analyze the situation where the system disengages and then performs a driving takeover and a crash occurs, using crash data from AVs.

3. Methodology

3.1. Data Collection. From 1st January 2018 to 31st December 2022, the California DMV collected a total number of 484 crash reports involving AVs, as submitted by manufacturers, for use in this paper. The crash information recorded in the OL 316 report can be viewed in Figure 3.

Based on the standardized information provided in the OL 316 report, specific information on the people, vehicles, roads, and environment where the crash occurred can be extracted. Statistical data regarding the crash encompass details such as the precise time and location of the crash, the prevailing weather and lighting conditions at the time, the type of the crash, and the number of vehicles involved, as well as the behavior of the vehicles immediately preceding the crash, the severity of the crash, and the driving mode employed. Based on the accident narrative detailed in Part V of the crash report, additional crash variables can be extracted, as illustrated in Figure 4. In the accident narrative, the terms "autonomous mode" and "took manual control" are mentioned, indicating that the AV transitioned from autonomous driving mode to manual control, i.e., the driver took over the vehicle before the crash occurred. Additionally, the phrase "making a right turn" implies that the vehicle was in the process of turning right, presumably at an intersection, at the time of the crash. Although similar terminology is frequently encountered in accident narratives, it is not consistently recorded in a standardized format. Therefore, statistical analyses were conducted to identify characteristic variables that impact the occurrence of crashes involving AVs. The specific crash characterization variables are shown in Table 2.

3.2. AV Precrash Scenario Mapping. There is a limited amount of research available on precrash scenarios specifically focused on AVs. Liu et al. [14] screened AV crash variables, excluded AV crashes in conventional driving mode, selected crashes involving only two vehicles, and finally defined 15 precrash scenarios of AV. Meanwhile, its research team, based on previous studies, screened and organized crash data of AVs located at intersections, revealing a total of 30 precrash scenarios of AV [26].

In this paper, we will comprehensively screen the characteristic variables of OL 316 to refine and supplement the AV precrash scenario in all aspects. Identifying the traffic scenarios that require priority testing and development of crash avoidance systems is the main objective of the implementation of the precrash scenario typology. Therefore, in order to develop different crash scenarios as precrash mapping for AVs, it is necessary to analyze the number of vehicles involved in the crash, the movement of the vehicles, the significant events leading up to the crash, and the cause of the crash.

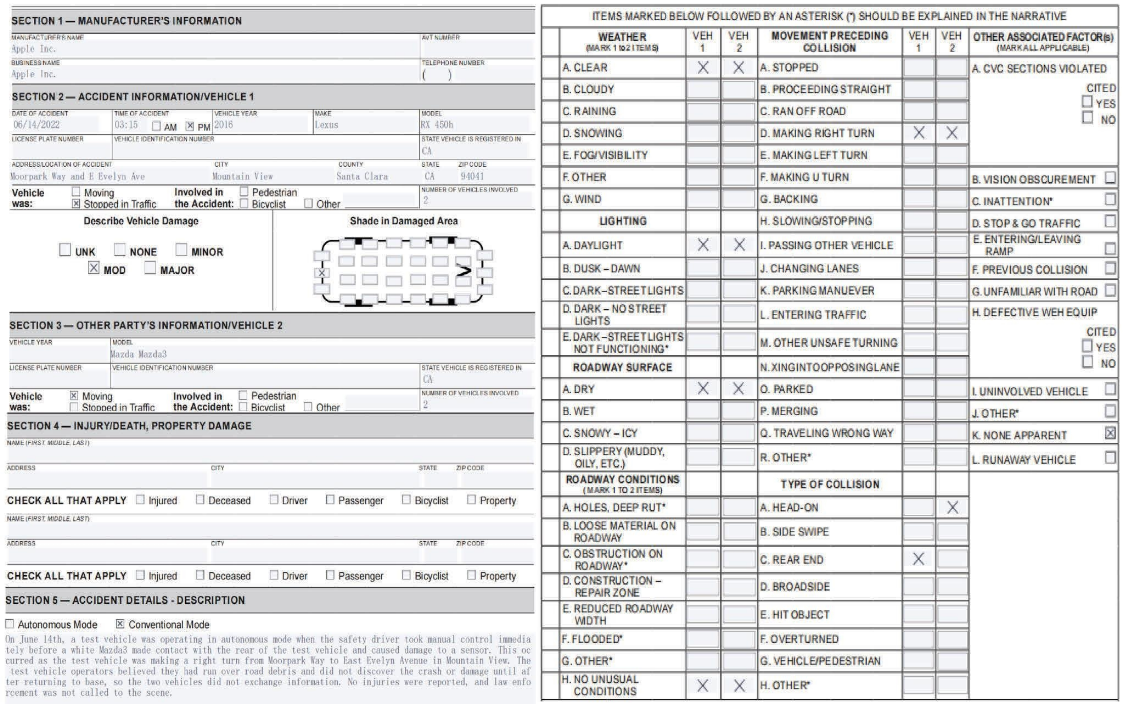
First, determine the number of vehicles involved in the crash in the OL 316 report; when the number of vehicles is 1, check whether the crash with the AV is with a pedestrian, or any other object. Additionally, it is necessary to determine if the vehicle exhibited any motorized behaviors and then classify the crash type by referring to the detailed description of the crash chapter. Subsequently, the relationship between the crash and the precrash scenario can be established. If two vehicles are involved in a crash, first check if the AV has stopped. Then, determine the relative position of the AV and CV based on the detailed description of the crash. After that step, examine the precrash behavior of both vehicles. Finally, establish the relationship between the crash and the precrash scenario by taking into account the crash type. If more than two vehicles are involved in a crash, determine whether the process is basically the same as when there are two vehicles. The precrash scenario mapping flowchart is shown in Figure 5.

By analyzing and mapping the precrash scenarios of AVs, along with considering the driving modes of the AVs, we can determine the quantity, types, and proportions of precrash scenarios in various driving conditions such as autonomous driving, driving takeover, and conventional driving, as shown in Table 3, where the proportions in the table are the percentages of each driving mode in all the scenarios, and the proportions of the compared driving modes in a single scenario show which driving mode is more likely to cause crashes in that scenario. The precrash scenarios of AV are categorized by creating a list in descending order of occurrence frequency and deriving subcategories (such as scenarios 2, 4, 6, 7, 8, 10, 12, 13, 15, and 22) based on the different relative positions of the AV to the CV. A total of 34 types of such scenarios have been identified, although the AV scenarios do not include the 37 types in the crash scenario typology due to the limitations of the number of AV crashes.

To provide a visual representation of precrash scenarios involving AV in Table 3 and display the relative positions of the AV and the CV, Figure 6 illustrates the 34 precrash scenarios that were reconstructed visually.

3.3. Comparison of AV Precrash Scenario for Different Driving Modes. From Table 3, it can be concluded that among the 34 precrash scenarios of AV, different driving modes differ in the types of scenarios, for example, in the autonomous driving mode, there are no precrash scenarios such as 12a, 13a, and 16, and in the driving takeover mode, there are no precrash scenarios such as 7b, 10a, and 12b, whereas in the conventional driving mode, there are no precrash scenarios such as 15b, 22b, and 23. Where the same precrash scenarios existed in all three driving modes, they also differed in their proportions.

To compare the proportions between the three driving modes in AV precrash scenarios, we merged similar scenarios listed in Table 3 (e.g., scenarios 2a and 2b) resulting in 24 categories, instead of the original 34 categories. To



SECTION 1 — MANUFACTURER'S INFORMATION

MANUFACTURER'S NAME: Apple Inc.

BUSINESS NAME: Apple Inc.

TELEPHONE NUMBER: ( )

SECTION 2 — ACCIDENT INFORMATION/VEHICLE 1

DATE OF ACCIDENT: 06/14/2022 | TIME OF ACCIDENT: 03:15 ☐ AM ☒ PM | VEHICLE YEAR: 2016 | MAKE: Lexus | MODEL: RX 450h

LICENSE PLATE NUMBER | VEHICLE IDENTIFICATION NUMBER | STATE VEHICLE IS REGISTERED IN: CA

ADDRESS/LOCATION OF ACCIDENT: Moorpark Way and E Evelyn Ave | CITY: Mountain View | COUNTY: Santa Clara | STATE: CA | ZIP CODE: 94041

Vehicle was: ☐ Moving ☒ Stopped in Traffic | Involved in the Accident: ☐ Pedestrian ☐ Bicyclist ☐ Other | NUMBER OF VEHICLES INVOLVED: 2

Describe Vehicle Damage: ☐ UNK ☐ NONE ☐ MINOR ☒ MOD ☐ MAJOR | Shade in Damaged Area

SECTION 3 — OTHER PARTY'S INFORMATION/VEHICLE 2

VEHICLE YEAR | MODEL: Mazda Mazda3

LICENSE PLATE NUMBER | VEHICLE IDENTIFICATION NUMBER | STATE VEHICLE IS REGISTERED IN: CA

Vehicle was: ☒ Moving ☐ Stopped in Traffic | Involved in the Accident: ☐ Pedestrian ☐ Bicyclist ☐ Other | NUMBER OF VEHICLES INVOLVED: 2

SECTION 4 — INJURY/DEATH, PROPERTY DAMAGE

NAME (FIRST, MIDDLE, LAST) | ADDRESS | CITY | STATE | ZIP CODE

CHECK ALL THAT APPLY ☐ Injured ☐ Deceased ☐ Driver ☐ Passenger ☐ Bicyclist ☐ Property

NAME (FIRST, MIDDLE, LAST) | ADDRESS | CITY | STATE | ZIP CODE

CHECK ALL THAT APPLY ☐ Injured ☐ Deceased ☐ Driver ☐ Passenger ☐ Bicyclist ☐ Property

SECTION 5 — ACCIDENT DETAILS - DESCRIPTION

☐ Autonomous Mode ☒ Conventional Mode

On June 14th, a test vehicle was operating in autonomous mode when the safety driver took manual control immedia tely before a white Mazda3 made contact with the rear of the test vehicle and caused damage to a sensor. This oc curred as the test vehicle was making a right turn from Moorpark Way to East Evelyn Avenue in Mountain View. The test vehicle operators believed they had run over road debris and did not discover the crash or damage until af ter returning to base, so the two vehicles did not exchange information. No injuries were reported, and law enfo rcement was not called to the scene.

ITEMS MARKED BELOW FOLLOWED BY AN ASTERISK (*) SHOULD BE EXPLAINED IN THE NARRATIVE

WEATHER (MARK 1 to 2 ITEMS)	VEH 1	VEH 2	MOVEMENT PRECEDING COLLISION	VEH 1	VEH 2	OTHER ASSOCIATED FACTOR(s) (MARK ALL APPLICABLE)
A. CLEAR	X	X	A. STOPPED			A. CVC SECTIONS VIOLATED CITED ☐ YES ☐ NO
B. CLOUDY			B. PROCEEDING STRAIGHT			
C. RAINING			C. RAN OFF ROAD			
D. SNOWING			D. MAKING RIGHT TURN	X	X	
E. FOG/VISIBILITY			E. MAKING LEFT TURN			
F. OTHER			F. MAKING U TURN			B. VISION OBSCUREMENT ☐
G. WIND			G. BACKING			C. INATTENTION* ☐
LIGHTING			H. SLOWING/STOPPING			D. STOP & GO TRAFFIC ☐
A. DAYLIGHT	X	X	I. PASSING OTHER VEHICLE			E. ENTERING/LEAVING RAMP ☐
B. DUSK – DAWN			J. CHANGING LANES			F. PREVIOUS COLLISION ☐
C. DARK – STREET LIGHTS			K. PARKING MANUEVER			G. UNFAMILIAR WITH ROAD ☐
D. DARK – NO STREET LIGHTS			L. ENTERING TRAFFIC			H. DEFECTIVE WEH EQUIP CITED ☐ YES ☐ NO
E. DARK – STREET LIGHTS NOT FUNCTIONING*			M. OTHER UNSAFE TURNING			
ROADWAY SURFACE			N. XING INTO OPPOSING LANE			
A. DRY	X	X	O. PARKED			I. UNINVOLVED VEHICLE ☐
B. WET			P. MERGING			J. OTHER* ☐
C. SNOWY – ICY			Q. TRAVELING WRONG WAY			K. NONE APPARENT ☒
D. SLIPPERY (MUDDY, OILY, ETC.)			R. OTHER*			L. RUNAWAY VEHICLE ☐
ROADWAY CONDITIONS (MARK 1 TO 2 ITEMS)			TYPE OF COLLISION			
A. HOLES, DEEP RUT*			A. HEAD-ON		X	
B. LOOSE MATERIAL ON ROADWAY			B. SIDE SWIPE			
C. OBSTRUCTION ON ROADWAY*			C. REAR END	X		
D. CONSTRUCTION – REPAIR ZONE			D. BROADSIDE			
E. REDUCED ROADWAY WIDTH			E. HIT OBJECT			
F. FLOODED*			F. OVERTURNED			
G. OTHER*			G. VEHICLE/PEDESTRIAN			
H. NO UNUSUAL CONDITIONS	X	X	H. OTHER*			

Figure 3: AV crash report in OL 316 form.

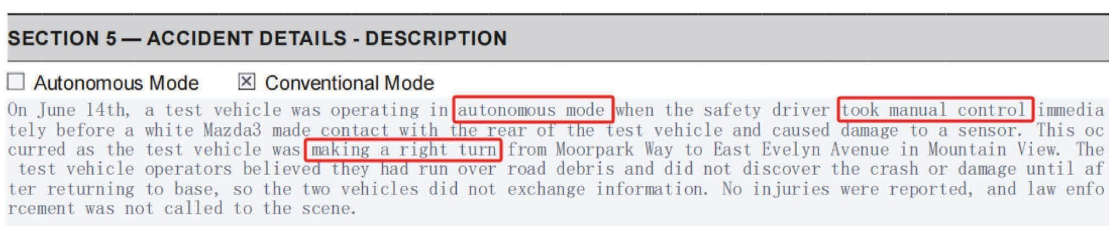


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Figure 4: Section 5 of the AV crash report with a specific description.

determine if there were significant differences in the proportions of driving patterns within the 24 precrash scenarios, a one-way analysis of variance (ANOVA) was conducted using SPSS software. Additionally, a nonparametric (NPar) test was performed on different driving modes within each scenario to assess if there were any significant variations. The findings of the investigation are displayed in Table 4, where the value of the F-test in the ANOVA is 4.338 and the p value $\leq 0.001 < 0.05$, which shows that the different precrash scenario types present significant differences for the three driving modes in general. Meanwhile, the results of the NPar test show that the p values of scenarios 1, 3, 5, 6, 7, and 9 are all less than 0.05, which concludes that there is a significant difference between the three driving modes of AVs in the above six scenarios.

Table 4 presents the analysis results, allowing for a descriptive examination of the precrash scenarios that exhibit variability. For example, in Scenario 1 (Lead AV Stopped), the percentage of possible crashes in autonomous driving mode is 43.16%, which is approximately seven times higher than that in the driver takeover mode and twice as high as in the conventional driving. In Scenario 3 (Lead AV Decelerating), the percentage of possible crashes in driving takeover mode is 14.63%, which is approximately 1.5 times higher than that in autonomous driving mode and 3 times higher than that in conventional driving mode. In Scenario 5 (Pedalcyclist Crash with Prior Vehicle Maneuver), the driving takeover mode is significantly different from both the autonomous driving mode and the conventional driving mode, with the percentage of possible crashes being about 4 times higher than the latter, a difference of roughly 13.60%. In Scenario 6 (Vehicle Turning at Nonsignalized Junctions), the percentage of possible crashes is similar between autonomous driving mode and conventional driving mode but differs significantly from the percentage of driving takeover mode, with a difference of approximately 5.91%. In Scenario 7 (Vehicle Parking-Same Direction), the proportion of possible crashes for the conventional driving mode is about 5 times higher than that for the autonomous driving mode and 3.5 times higher than that for the driving takeover mode, which is a large difference from the autonomous driving mode. In Scenario 9 (Road Edge Departure with Prior Vehicle Maneuver), the proportion of possible crashes in conventional driving mode is about 5.6 times higher than

Table 2: Descriptive statistics of California AV crash dataset (sample size = 484).

Variable	Frequency	Percentage (%)
Someone injured		
Yes	73	15.08
No	411	84.92
Vehicle damage		
None	38	7.85
Minor	368	76.03
Moderate	71	14.67
Major	7	1.45
Vehicle manufacturer		
Waymo LLC	193	39.88
Cruise LLC	176	36.36
Other	115	23.76
Production year of the AV		
2016	71	14.67
2017	117	24.17
2018	7	1.45
2019	81	16.74
2020	71	14.67
2021	124	25.62
2022	13	2.69
Number of vehicles involved		
1	77	15.91
2	402	83.06
3	5	1.03
Movement preceding crash		
Stopped	188	38.84
Proceeding straight	199	41.12
Making left turn	41	8.47
Making right turn	35	7.23
Backing	21	4.34
Type of crash		
Head-on	87	17.98
Rear-end	230	47.52
Left crash	85	17.56
Right crash	82	16.94
AV driving mode		
Autonomous driving	234	48.35
Conventional driving	168	34.71
Driving takeover	82	16.94
Facility type		
Intersection	238	49.17
Road segment	231	47.73
Parking lot	15	3.10
Time of the crash		
Morning peak 7:00–9:00	47	9.71
Daytime 9:00–17:00	273	56.40
Evening peak 17:00–19:00	42	8.68
Night 19:00–7:00	122	25.21
Weather		
Clear	432	89.26
Rainy	14	2.89
Cloudy	33	6.82
Fog/visibility	5	1.03
Light		
Daylight	357	73.76
Dark with street lights	122	25.21
Dark without streetlights	5	1.03

that in autonomous driving mode and not much different from the driving takeover mode, which is only 1.3 times higher.

In the five precrash scenarios (Scenarios 1, 3, 13b, 17, and 21), the AV encountered a CV rear-end crash, which accounted for 56.83% in the autonomous driving mode, about 2.7 times that of the driving takeover mode, and about twice that of the conventional driving mode. In contrast, the driving takeover mode and the conventional driving mode accounted for only 20.73% and 27.99% in these five scenarios. In the lane changing of AV or CV in the same direction (Scenario 2), AV encountered lane changing crash, which accounts for 15.85% in the driving takeover mode, while 13.24% and 11.91% in the autonomous driving mode and conventional driving mode, respectively. The data suggest that lane changing crashes are more prone to happen during the driving takeover mode. In the crash between AV and Pedalcyclist (Scenarios 5 and 11), the proportion of driving takeover mode is significantly higher than that of autonomous driving mode and conventional driving mode, up to 20.73%, while for the other two modes, the proportion is 5.98% and 8.33%, respectively. In the case of crashes (scenarios 6, 10, and 15) in which AV or CV turns, the proportion of autonomous driving mode and conventional driving mode is similar, 7.70% and 7.75%, respectively, while the proportion of driving takeover mode is relatively high, 12.20%.

4. Evaluation System for Precrash Scenarios of AV

4.1. Selection of Evaluation Indicators and Establishment of Models. To analyze the degree of danger in precrash scenarios of AV, according to the crash characteristic variables collected in this paper, the analytical method is used to refine the evaluation indexes layer by layer into quantifiable indexes, and the evaluation elements are set to be the macro-statistical characteristics of crashes, vehicle damage levels, and personnel injury indicators. The specific evaluation indexes include the number of vehicles involved in the crash, the frequency of crashes, whether the vehicle is severely, moderately, or slightly damaged, or undamaged, and whether there are injuries to personnel or no injuries. The specific indicators constructed are shown in Figure 7.

The indicators describing the macro-statistical characteristics of crashes include the number of vehicles involved in the crash and the frequency of crashes, with the evaluation function shown as follows:

$$C = w_1 C_1 + w_2 C_2, \tag{1}$$

wherein w_1 and w_2 represent the weights of the number of vehicles involved in the crash and the frequency of crashes, respectively, $w_1 + w_2 = 1$, and C_1 and C_2 represent the evaluation values of the number of vehicles involved in the crash and the frequency of crashes, respectively, which are taken according to the average value of crash characteristics in a certain scenario.

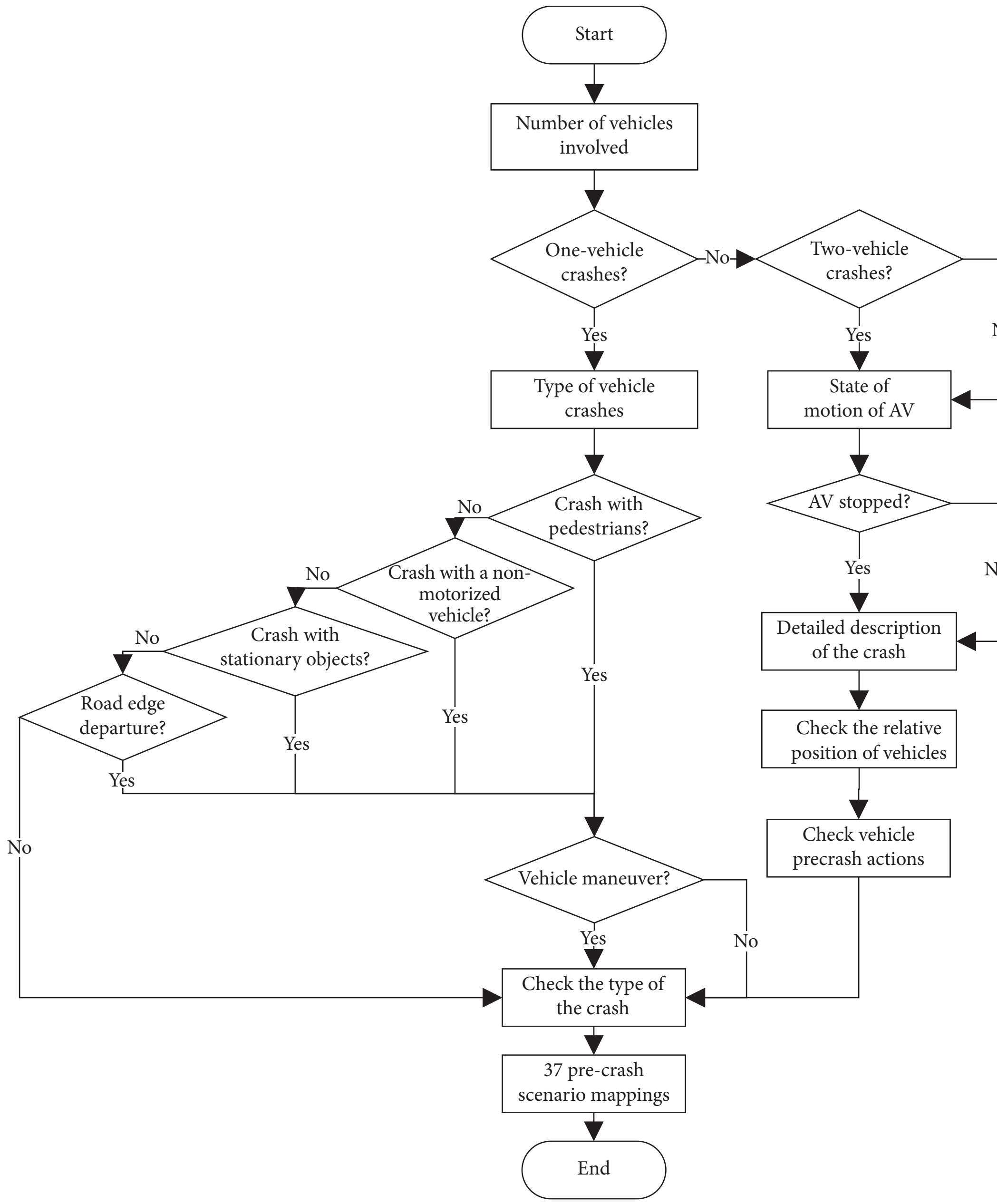

Figure 5: Flowchart for mapping precrash scenarios.

The indicators describing the vehicle damage levels include major, moderate, minor, and undamaged, with the evaluation function shown as follows:

$$D = y_1 D_1 + y_2 D_2 + y_3 D_3 + y_4 D_4, \tag{2}$$

wherein y_1, y_2, y_3, y_4 represent the weights of major, moderate, minor, and no damage to the vehicle, respectively, and the sum of the four is 1. D_1, D_2, D_3, D_4 represent the evaluation values of the damage level of the vehicle, which are taken according to the proportion of the damage level of the vehicle in a certain scenario.

The indicators describing personnel injury indicators include injuries to personnel or no injuries, with the evaluation function shown as follows:

$$E = z_1 E_1 + z_2 E_2, \tag{3}$$

wherein z_1 and z_2 represent the weights of injuries to personnel or no injuries, $z_1 + z_2 = 1$, and E_1 and E_2 represent the evaluation values of injuries to personnel or no injuries, according to the proportion of personnel with or without injuries in a certain scenario, respectively, to take the value.

Combining the above factors, the danger level evaluation model of AV precrash scenario is

$$P = n_1 C + n_2 D + n_3 E, \tag{4}$$

where n_1, n_2, n_3 are the weight values of indicators C, D, E, respectively, and $n_1 + n_2 + n_3 = 1$.

Table 3: AV precrash scenario types for different driving modes.

Precrash scenario types	Autonomous driving		Driving takeover		Conventional driving		Total	%
	N	%	N	%	N	%		
(1) Lead vehicle (AV) stopped	101	43.16	5	6.10	36	21.43	142	29.34
(2a) AV changing lanes-same direction	2	0.85	2	2.44	5	2.98	64	13.22
(2b) CV changing lanes-same direction	29	12.39	11	13.41	15	8.93		
(3) Lead vehicle (AV) decelerating	22	9.40	12	14.63	8	4.76	42	8.68
(4a) AV backing up into another vehicle	1	0.43	5	6.10	9	5.36	37	7.64
(4b) CV backing up into AV	11	4.70	3	3.66	8	4.76		
(5) Pedalcyclist crash with prior vehicle maneuver	11	4.70	15	18.29	8	4.76	34	7.02
(6a) CV turning at nonsignalized junction	7	2.99	2	2.44	3	1.79	24	4.96
(6b) AV turning and CV going straight across path at nonsignalized junction	1	0.43	4	4.88	3	1.79		
(6c) CV turning and AV going straight across path at nonsignalized junction	1	0.43	2	2.44	1	0.60		
(7a) AV parking-same direction	1	0.43	2	2.44	6	3.57	20	4.13
(7b) CV parking-same direction	3	1.28	0	0.00	8	4.76		
(8a) AV making a maneuver-opposite direction	1	0.43	1	1.22	3	1.79	18	3.72
(8b) CV making a maneuver-opposite direction	7	2.99	3	3.66	3	1.79		
(9) Road edge departure with prior vehicle maneuver	2	0.85	3	3.66	8	4.76	13	2.69
(10a) AV turning-same direction	1	0.43	0	0.00	2	1.19	12	2.48
(10b) CV turning-same direction	5	2.14	2	2.44	2	1.19		
(11) Pedalcyclist crash without prior vehicle maneuver	3	1.28	2	2.44	6	3.57	11	2.27
(12a) AV drifting-same direction	0	0.00	2	2.44	6	3.57	11	2.27
(12b) CV drifting-same direction	2	0.85	0	0.00	1	0.60		
(13a) Following AV making a maneuver	0	0.00	0	0.00	3	1.79	9	1.86
(13b) Following CV making a maneuver	5	2.14	0	0.00	1	0.60		
(14) Object crash without prior vehicle maneuver	2	0.85	0	0.00	5	2.98	7	1.45
(15a) AV left turn across path from opposite directions at signalized junctions	1	0.43	0	0.00	2	1.19	5	1.03
(15b) CV left turn across path from opposite directions at signalized junctions	2	0.85	0	0.00	0	0.00		
(16) CV running red light	0	0.00	3	3.66	2	1.19	5	1.03
(17) Lead vehicle (AV) accelerating	3	1.28	0	0.00	1	0.60	4	0.83
(18) CV running stop sign	2	0.85	1	1.22	1	0.60	4	0.83
(19) Object crash with prior vehicle maneuver	0	0.00	0	0.00	4	2.38	4	0.83
(20) Pedestrian crash without prior vehicle maneuver	2	0.85	0	0.00	1	0.60	3	0.62
(21) Lead vehicle (AV) moving at lower constant speed	2	0.85	0	0.00	1	0.60	3	0.62
(22a) AV straight crossing paths at nonsignalized junctions	0	0.00	0	0.00	1	0.60	3	0.62
(22b) CV straight crossing paths at nonsignalized junctions	1	0.43	1	1.22	0	0.00		
(23) Pedestrian crash with prior vehicle maneuver	0	0.00	1	1.22	0	0.00	1	0.21
(24) Other (such as ADS failure and scrape when opening the door)	3	1.28	0	0.00	5	2.98	8	1.65

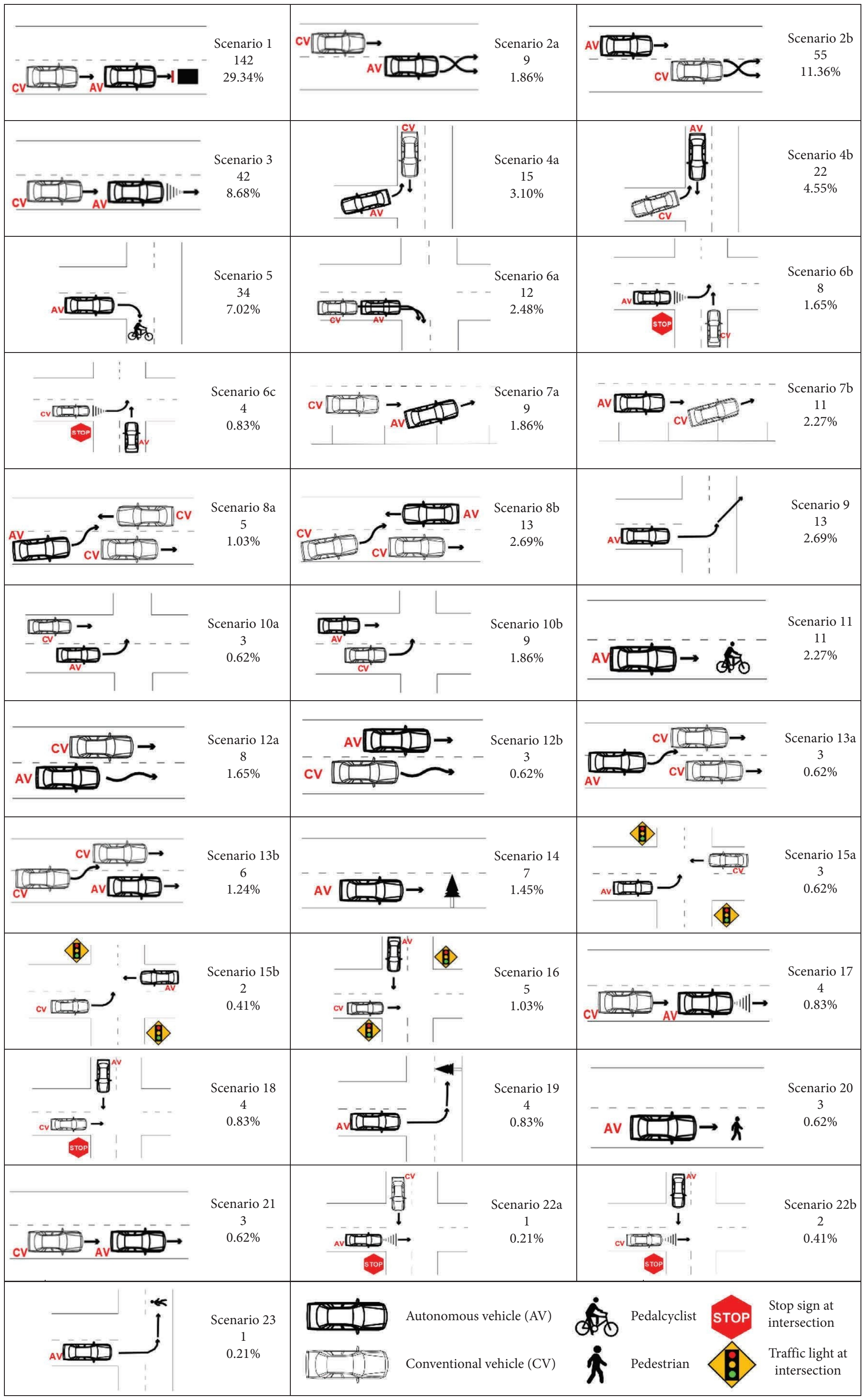

Figure 6: Reconstructing precrash scenarios for AVs through visual means.

Table 4: Results of one-way ANOVA and NPar test of precrash scenarios with different driving modes.

Precrash scenarios	Autonomous driving		Driving takeover		Conventional driving		ANOVA (mean ± standard deviation)	NPar test	
	N	%	N	%	N	%		Chi-square value	p value
1	101	43.16	5	6.10	36	21.43	0.236 ± 0.186	69.491	**≤0.001***
2	31	13.25	13	15.85	20	11.90	0.137 ± 0.020	1.313	0.519
3	22	9.40	12	14.63	8	4.76	0.096 ± 0.049	11.851	**0.003***
4	12	5.13	8	9.76	17	10.12	0.083 ± 0.028	4.508	0.105
5	11	4.70	15	18.29	8	4.76	0.093 ± 0.078	31.508	**≤0.001***
6	9	3.85	8	9.76	7	4.17	0.059 ± 0.033	8.714	**0.013***
7	4	1.71	2	2.44	14	8.33	0.042 ± 0.036	15.200	**0.001***
8	8	3.42	4	4.88	6	3.57	0.040 ± 0.008	0.667	0.717
9	2	0.85	3	3.66	8	4.76	0.031 ± 0.020	6.091	**0.048***
10	6	2.56	2	2.44	4	2.38	0.025 ± 0.001	0.000	1.000
11	3	1.28	2	2.44	6	3.57	0.024 ± 0.011	2.235	0.327
12	2	0.85	2	2.44	7	4.17	0.025 ± 0.017	5.333	0.069
13	5	2.14	0	0.00	4	2.38	0.015 ± 0.013	0.091	0.763
14	2	0.85	0	0.00	5	2.98	0.013 ± 0.015	2.778	0.096
15	3	1.28	0	0.00	2	1.19	0.008 ± 0.007	0.000	1.000
16	0	0.00	3	3.66	2	1.19	0.016 ± 0.019	3.000	0.083
17	2	0.85	1	1.22	1	0.60	0.009 ± 0.003	1.000	0.607
18	3	1.28	0	0.00	1	0.60	0.006 ± 0.006	1.000	0.317
19	0	0.00	0	0.00	4	2.38	0.008 ± 0.014	—	—
20	2	0.85	0	0.00	1	0.60	0.005 ± 0.004	0.333	0.564
21	2	0.85	0	0.00	1	0.60	0.005 ± 0.004	0.333	0.564
22	1	0.43	1	1.22	1	0.60	0.007 ± 0.004	1.600	0.449
23	0	0.00	1	1.22	0	0.00	0.004 ± 0.007	—	—
24	3	1.28	0	0.00	5	2.98	0.014 ± 0.015	1.600	0.206
$F = 4.338$		$p \leq 0.001^*$							

Note. *Reject the null hypothesis at the 5% level. The significance of the bold values is that the p value of the NPar test results is less than 5%, which indicates that the null hypothesis is rejected at the 5% level, and that the proportions of the different precrash scenario types show significant differences for the three driving modes overall.

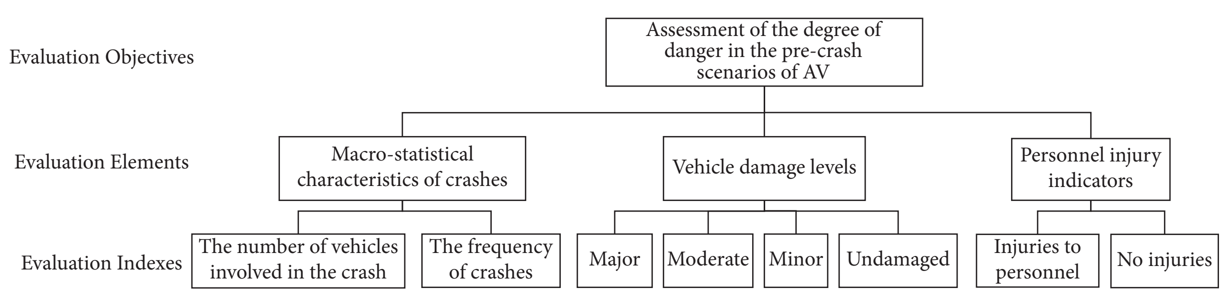

Figure 7: Establishment process of precrash scenario evaluation system for AV.

4.2. Calculating the Weight of Each Evaluation Index Using the Analytic Hierarchy Process. In this section, the weights of each evaluation indicator will be calculated using the analytic hierarchy process (AHP) methodology. The basic idea of the AHP is to first establish a hierarchical structure that describes the functions and characteristics of the system and then compare the relative relationships between evaluation factors by pairwise comparison. Through the calculation, sorting, and inspection of the judgment matrix, the weights of each indicator are obtained, and the analysis results are obtained. The specific steps are as follows [29].

4.2.1. Constructing a Judgment Matrix. Based on the reference values of the evaluation indicators and the relative importance between two or two evaluation indicators, the judgment matrix is constructed as

$$S = \left[a_{ij}\right]_{n\times n} \quad (\mathrm{i, j} = 1, 2, \ldots, \mathrm{n}), \tag{5}$$

wherein $a_{ij} = f(x_i, x_j)$, $a_{ij} > 0$, $a_{ii} = 1$.

The significance of the two evaluation indicators is reflected by the judgment matrix value, which ranges from 1 to 9. Table 5 provides a breakdown of the meaning behind each value.

Taking the degree of damage to the vehicle as an example, according to the reference values of the evaluation indexes in Table 5, the corresponding judgment matrix of evaluation indexes is drawn, as shown in Table 6.

Table 6 displays the judgment matrix as follows:

Table 5: Reference values for evaluation indicators using the AHP [30].

Factor x_i compared to factor x_j	$f(x_i, x_j)$	$f(x_j, x_i)$
Equal importance	1	1
Moderate importance	3	1/3
Strong importance	5	1/5
Very strong importance	7	1/7
Extreme importance	9	1/9
Between two adjacent judgments	2, 4, 6, 8	1/2, 1/4, 1/6, 1/8

Table 6: Importance relationship of evaluation indicators for vehicle damage degree.

	Evaluation indexes			
	Major damage	Moderate damage	Minor damage	Undamaged
Major damage	1	3	5	7
Moderate damage	1/3	1	3	5
Minor damage	1/5	1/3	1	3
Undamaged	1/7	1/5	1/3	1

$$S = \begin{bmatrix} 1 & 3 & 5 & 7 \\ \frac{1}{3} & 1 & 3 & 5 \\ \frac{1}{5} & \frac{1}{3} & 1 & 3 \\ \frac{1}{7} & \frac{1}{5} & \frac{1}{3} & 1 \end{bmatrix}. \tag{6}$$

4.2.2. Calculation of Evaluation Indicator Weights. Once the judgment matrix S is constructed, the next step involves calculating the weights of the n evaluation indicators $x_1, x_2, \ldots, x_n$ within the evaluation system and checking the consistency of the judgment matrix. CR is used for this purpose, and if CR <0.1, it indicates that the judgment matrix satisfies the consistency requirements. RI is the average random consistency index, with values shown in Table 7, where n is the number of indicators.

The steps for calculating the evaluation index weights and checking the consistency of the judgment matrix are as follows:

(a) Normalize the judgment matrix by column
(b) Add up the rows to obtain the sum vector
(c) Normalize the sum vector to obtain the weight vector
(d) Calculate the largest eigenvalue of the judgment matrix S
(e) Calculate the consistency index of the judgment matrix S

Take the vehicle damage degree $D = y_1 D_1 + y_2 D_2 + y_3 D_3 + y_4 D_4$ as an example to calculate the weight of each of its indicators. Sum the judgment matrix S by row to get the vector, and normalize the sum vector to get the weight vector as

Table 7: Random index (RI).

n	2	3	4	5	6	7	8	9	10
RI	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

$$W_1 = \begin{bmatrix} 0.558 \\ 0.263 \\ 0.122 \\ 0.057 \end{bmatrix}. \tag{7}$$

The maximum characteristic root of judgment matrix S is $\lambda_{\max} = 4.117$, $\mathrm{CI} = (\lambda_{\max} - n)/(\mathrm{n} - 1)$; when $n = 4$, according to Table 7, RI = 0.90, CR=CI/RI = 0.039 < 0.1, and the judgment matrix meets the consistency requirements. Therefore, the weights of vehicle damage degree index $y_1, y_2\, y_3, y_4$ are 0.558, 0.263, 0.122, 0.057, respectively.

The same method was used to calculate the metrics of the hazard level evaluation model for the AV precrash scenarios, and the results of the calculations were counted in the comprehensive evaluation table of the hazard level of individual AV precrash scenarios, as shown in Table 8.

4.3. Evaluation Results of Different Driving Modes for Precrash Scenario. After calculating the weights of each evaluation index, this paper assigns scores to the danger level of different precrash scenarios and their driving modes, with higher scores representing their corresponding higher danger level. However, the scoring method is solely intended for comparing different driving modes within a specific scenario. Since scenario 1, scenario 2b, and scenario 3 have a higher proportion of precrash scenarios with AV and more crashes have occurred compared to other scenarios, which

Table 8: Comprehensive evaluation of the hazard level of a single AV precrash scenario.

Evaluation elements	Weights	Evaluation indexes	Weights
C (macro-statistical characteristics of crashes)	0.137	C1 (the number of vehicles involved in the crash)	0.333
		C2 (the frequency of crashes)	0.667
D (vehicle damage levels)	0.239	D1 (major)	0.558
		D2 (moderate)	0.263
		D3 (minor)	0.122
		D4 (undamaged)	0.057
E (personnel injury indicators)	0.623	E1 (injuries to personnel)	0.75
		E2 (no injuries)	0.25

can provide a more adequate source of data, these three scenarios with different driving modes are selected for evaluation.

According to equations (1)–(4) and the evaluation model indicators in Table 8, the scores for each indicator in this scenario were calculated. The number of vehicles involved in the crash was taken as the average value at the time of the crash, and the crash frequency, vehicle damage levels, and personal injury indicators were taken as the proportion of a certain driving mode. The calculation results are shown in Table 9.

According to the above results, in scenario 1, the danger level scoring value: autonomous driving > conventional driving > driving takeover; it can be known that the danger level of the autonomous driving mode is the highest while the danger level of the driving takeover mode is the lowest in this scenario. In scenario 2b, the danger level scoring value: conventional driving > autonomous driving > driving takeover; it can be known that the danger level of the conventional driving mode is the highest while the driving takeover mode has the highest degree of danger, while the driving takeover mode has the lowest degree of danger. In scenario 3, the danger degree score value: driving takeover > autonomous driving > conventional driving; it can be known that the driving takeover mode has the highest degree of danger, while the driving takeover mode has the lowest degree of danger in this scenario. According to the scoring and comparative analysis of different driving modes in the precrash scenario, it is concluded that a certain driving mode in a specific precrash scenario will have better performance and higher safety than other driving modes, which is conducive to reducing the probability of crashes and the severity of crashes and provides a certain theoretical basis for the improvement of the ADS and the driver's perception of risk.

5. Discussion of AV Precrash Scenarios for Different Driving Modes

5.1. Rear-End: Leading AV Stopped. In Scenario 1, the rear vehicle is close to a complete stop of the AV. According to the scoring results in Table 9, this scenario has the highest rating value of 0.384 for the level of danger of autonomous driving and the lowest rating value of 0.288 for driving takeover. It can be seen that in this scenario, the autonomous driving mode is more likely to cause dangerous rear-end crashes, which is due to the fact that the braking time of the ADS is shorter when it stops, and the following CV driver cannot react to the brakes in time, which leads to the occurrence of rear-end crashes.

Typical Scenario. In daylight and clear weather conditions, a CV is traveling straight on an urban roadway, heading towards an area associated with an intersection, and approaching a leading and stopped AV. This scenario usually occurs when there is a traffic signal or when the leading AV stops and prepares to turn.

Specifically, since the Perception-Reaction Time (PRT) of the ADS differs from that of human drivers [31], the average PRT of human drivers is 1.1 seconds and the 95th percentile is 2.0 seconds, whereas the PRT of AVs is slightly lower than that of human drivers, with PRT values ranging from 0.5 to 1.0 seconds, often calibrated to 0.5 seconds [32]. Therefore, due to the nearly 1-second difference in PRT between human drivers and AVs, it increases the possibility of rear-end crashes between AVs and CVs in emergency situations, such as when pedestrians or pedalcyclists suddenly cross the road in front of them or when they have to stop and wait before an intersection. When the ADS detects the danger, it will take emergency braking, and the driver of the CV behind cannot take effective braking in time to avoid rear-end of the AV in front.

Suggestions. (1) For ADS, due to the significant differences between the operation of AVs and CVs, it is difficult for human drivers to adapt to the operation of AVs in mixed traffic flows [33], and it is recommended that automobile manufacturers improve the emergency braking interventions of ADS to reduce the risk factor of rear-end crashes in mixed traffic flows. (2) For human drivers, when approaching a pedestrian crossing or intersection while driving and there is a following vehicle behind, they should pay attention to the surrounding road conditions in a timely manner, and if an emergency situation requires stopping while in autonomous driving mode, the driver should concentrate, take over the vehicle in a timely manner, apply effective braking, and give the following vehicle enough reaction time to avoid rear-end crashes.

Table 9: Calculation results of the danger level of different driving modes in the AV precrash scenario.

Scenario	Driving mode	C1 (*N*)	C2 (%)	D1 (%)	D2 (%)	D3 (%)	D4 (%)	E1 (%)	E2 (%)	Rating value
1	Autonomous driving	2.01	43.16	0.99	10.89	81.19	6.93	20.79	79.21	0.384
	Driving takeover	2	6.10	0.00	20.00	80.00	0.00	0.00	100.00	0.288
	Conventional driving	2	21.43	2.78	16.67	66.67	13.89	16.67	83.33	0.354
2b	Autonomous driving	2	12.39	0.00	17.24	75.86	6.90	10.34	89.66	0.324
	Driving takeover	2	13.41	0.00	27.27	72.73	0.00	0.00	100.00	0.298
	Conventional driving	2.2	8.93	6.67	26.67	60.00	6.67	6.67	93.33	0.329
3	Autonomous driving	2	9.40	4.55	13.64	81.82	0.00	13.64	86.36	0.337
	Driving takeover	2	14.63	8.33	25.00	58.33	8.33	50.00	50.00	0.461
	Conventional driving	2	4.76	0.00	0.00	100.00	0.00	12.50	87.50	0.319

5.2. Lane-Change: CV Traveling in the Same Direction. In Scenario 2b, a CV changes lanes and collides with an AV traveling in the same direction. According to the scoring results in Table 9, this scenario has the highest rating value of 0.329 for the level of danger of conventional driving, while the autonomous driving and conventional driving have similar scoring values, with a difference of 0.005. The driving takeover has the lowest scoring value of 0.298. It can be seen that in this scenario, autonomous driving is more prone to lane-changing crashes, and the degree of danger is similar to that of the conventional driving, which is due to the inaccurate recognition of the lane-changing intention of the other vehicle by the ADS, which leads to lane-changing crashes.

Typical Scenario. In daytime and clear weather conditions, a CV changing lanes on a nonintersection urban road encroaches on an AV traveling in the same direction. This scenario usually occurs when a CV overtakes a vehicle or when vehicles merge.

Specifically, although the ADS can sense the instantaneous position and speed of CVs changing lanes, it is difficult to determine the intention and trajectory of CVs changing lanes [34], and the AV cannot reasonably control the traveling speed when overtaking or merging with CVs, while the real-time potential risk of CVs changing lanes is difficult to predict [35], and the following distance is too close, and the LIDAR of the AVs is not sensitive enough to react, which leads to the insufficient path planning of the ADS and then a lane-change crash.

Suggestions. (1) For ADS, the development and application of obstacle detection and avoidance systems are beneficial for drivers to safely avoid obstacles and prevent crashes caused by lane changing of CV [36]. It is recommended that automobile manufacturers optimize various sensors for obstacle detection to improve the obstacle avoidance performance of ADS. (2) For human drivers, when the AV is faced with an impending lane change by a CV in front of it, the drivers need to concentrate, take over the vehicle manually in time, and control the speed reasonably to maintain the distance between the front and rear vehicles, so as to reduce the risk of lane change crashes.

5.3. Rear-End: Leading AV Decelerating. In Scenario 3, the rear vehicle approaches and rear-ends a slowing AV. Scenario 3 differs from Scenario 1 because the AV in front was in the middle of slowing down and had not yet fully stopped at the moment of the crash. According to the scoring results in Table 9, this scenario has the highest rating value of 0.461 for the level of danger of driving takeover and the lowest rating value of 0.319 for conventional driving. It can be seen that in this scenario, both the autonomous driving and driving takeover are more likely to have rear-end crashes, which is due to the fact that in the mixed road traffic flow, when there are pedestrians, pedalcyclists, or a sudden deceleration of the front vehicle in front of them, the ADS will slow down accordingly, but the driver will overreact to the emergency situation in order to take over the vehicle and slow it down, which will lead to rear-end crashes of the rear vehicle.

Typical Scenario. In daylight and clear weather conditions, a CV is traveling straight ahead on an urban roadway, approaching an area associated with an intersection and approaching an AV that is leading and decelerating. This scenario usually occurs with traffic signals or in complex mixed traffic flow environments.

Specifically, the difference between the PRT of the ADS and the human driver obviously leads to the occurrence of crashes in this scenario, where the AV suddenly slows down and the driver of the vehicle behind cannot brake in time. Moreover, the crash avoidance system of AVs in complex road environments is not perfect enough [37], and more complex situations will occur in mixed traffic flows near intersections, where the sensing, planning, decision making, and control of the ADS are not yet able to cope with complex road environments well, and drivers taking over the vehicle in emergencies may also produce overaggressive braking, which results in rear-end crashes where the rear-end vehicle is unable to react in a timely manner. The driver may also produce aggressive braking when taking over the vehicle in an emergency, resulting in rear-end crashes when the vehicle cannot react in time.

Suggestions. (1) For ADS, an important cause of crash is the excessive braking due to encountering complex situations. The automatic preventive braking (APB) is to avoid rear-end crashes without affecting driving comfort and traffic efficiency by applying lighter braking earlier [38]. It is recommended that automobile manufacturers develop more efficient APB systems to improve the safety of AVs when braking is required. (2) For human drivers, in the complex road environment with following vehicles, they should predict the movement trajectory of the pedestrians or pedalcyclists, and in the case of the need to decelerate to avoid a crash, the drivers should focus on taking over and manually driving the vehicle in advance, braking and decelerating smoothly, so as to avoid overly hasty braking by the ADS or the driver generating a stress reaction, thus avoiding the rear-end crashes.

6. Conclusion

In order to understand the developmental testing of three driving modes of AVs in different scenarios and the safety of human-machine codriving, this study compares and analyzes the precrash scenarios of the three driving modes. The precrash scenario typology defined by the USDOT in 2007 is used to map 34 precrash scenarios of AVs. Through statistics and comparative analysis of crash data, it is verified that different precrash scenarios show significant differences in the proportion of autonomous driving, driving takeover, and conventional driving modes overall. Meanwhile, there are significant differences between autonomous driving, driving takeover, and conventional driving modes in six scenarios such as “Lead AV stopped” and “Lead AV decelerating.”

In order to analyze the relative degree of danger of different driving modes in the precrash scenario of AV, a comprehensive evaluation was conducted using the analytic hierarchy process (AHP) on indicators such as macro-statistical characteristics of crashes, vehicle damage levels, and personal injury conditions. A risk assessment model for precrash scenarios for AV was established, and three precrash scenarios with the highest frequency of crashes were selected for analysis. The results show that in the scenario of “Lead AV stopped,” the autonomous driving mode has the highest rating, which means that the scenario has the greatest degree of danger. In the scenario of “CV changing lanes in the same direction,” the conventional driving mode has the highest rating. And in the scenario of “Lead AV decelerating,” the driving takeover mode was rated the highest.

The crash characteristics and causes of three typical scenarios are analyzed from the perspective of the ADS and human driver. Improvements to emergency braking interventions and APB systems for AVs, as well as the development of a reliable decision-making algorithm to determine when the ADS should stop or slow down [39], can reduce the risk of rear-end crashes in mixed traffic. Additionally, enhancing sensors for obstacle detection and refining the lane-changing algorithm of the ADS can improve the system’s obstacle avoidance capabilities and allow for earlier and more accurate identification of lane-changing intentions of CVs in mixed traffic flows [40]. For drivers in complex environments requiring stopping or decelerating, early switch to conventional driving could prevent tailgating from excessive braking. For imminent front vehicle lane-changes, taking over the vehicle manually can reduce the risk of lane change crashes. Scenario comparisons by different driving modes inform the testing of ADS and the safety of human-machine codriving.

There are certain limitations in this study, namely, that the assessment of precrash scenarios of AVs is largely contingent on the precision of California DMV crash reports. These reports do furnish an ample amount of information for precrash scenarios analysis, but details such as prior vehicle motion parameters and traffic flow are unattainable. In the future, a more extensive range of AV crash data can offer further verification of the study’s outcomes. Meanwhile, AVs are still in a testing state, and driving behavior in mixed traffic flows is still conservative. With the maturity of the ADS and the full-scale input of AVs, different precrash scenarios and driving modes need to be reevaluated and analyzed.

Data Availability

Autonomous driving crash report data can be found on the following website: https://www.dmv.ca.gov/portal/vehicle-industry-services/autonomous-vehicles/autonomous-vehicle-collision-reports/.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Authors’ Contributions

Tao Wang and Juncong Chen were responsible for study conception and design. Juncong Chen and Jun Chen were responsible for data collection. Tao Wang, Juncong Chen, and Wenyong Li were responsible for analysis and interpretation of results. Tao Wang, Juncong Chen, and Xiaofei Ye were responsible for original draft preparation. All authors reviewed the results and approved the final version of the manuscript.

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