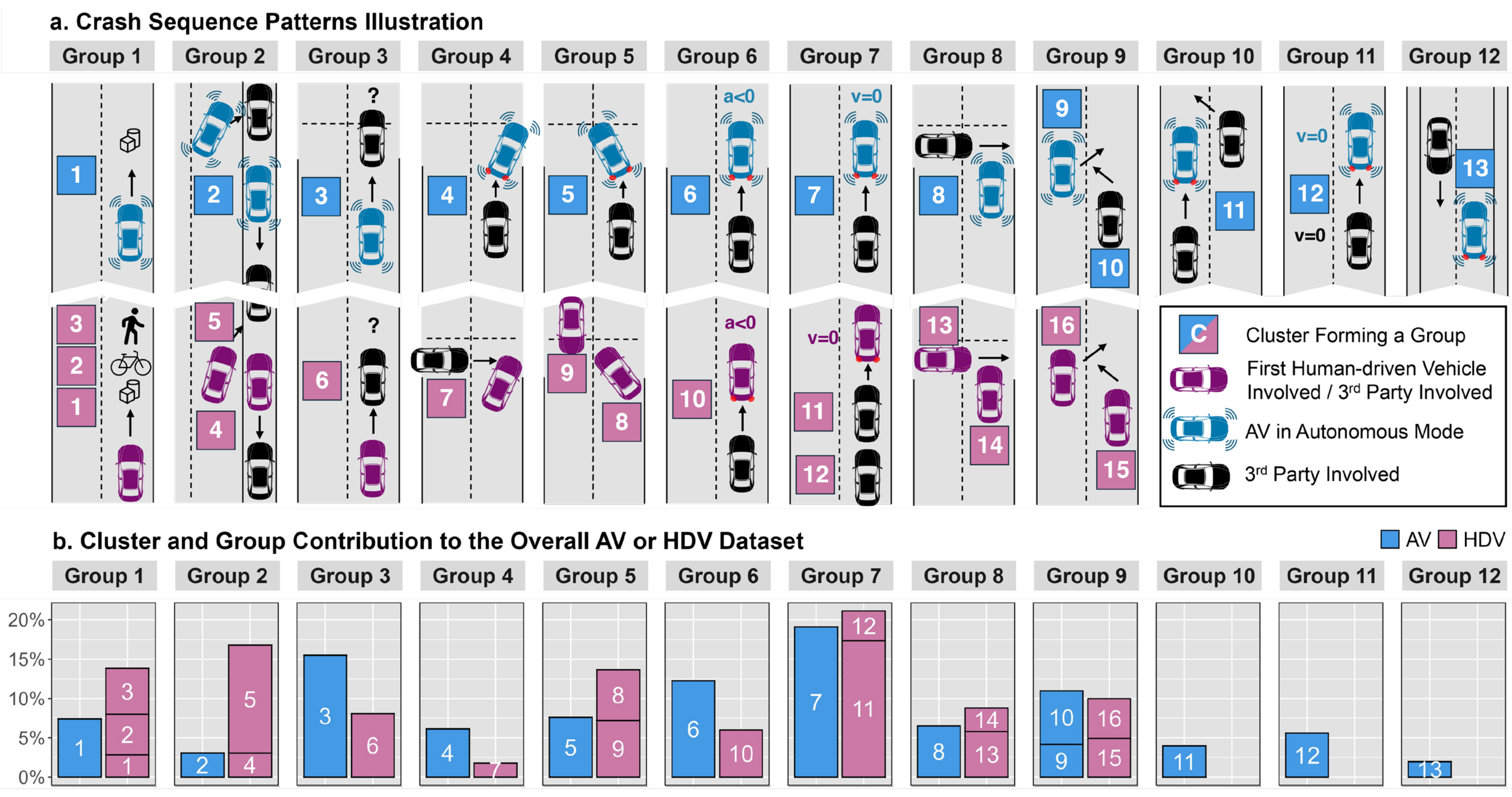
CENTER FOR CONNECTED AND AUTOMATED TRANSPORTATION

Final Report 119
August 2026



Road User-Automated Vehicle Expectancies, Interactions, and Safety

Cesar Andriola
Madhav V. Chitturi
David A. Noyce
Sikai Chen
Soyoung (Sue) Ahn

WISCONSIN
UNIVERSITY OF WISCONSIN–MADISON

CENTER FOR CONNECTED AND AUTOMATED TRANSPORTATION

Report No. 119
Project Start Date: 09/01/2024
Project End Date: 05/31/2026

August 2026

Road User-Automated Vehicle Expectancies, Interactions, and Safety

Cesar Andriola
Graduate Researcher

Madhav V. Chitturi
Scientist

David A. Noyce
Professor

Sikai Chen
Assistant Professor

Soyoung (Sue) Ahn
Professor

University of Wisconsin-Madison

DISCLAIMER

Funding for this research was provided by the Center for Connected and Automated Transportation under Grant No. 69A3552348305 of the U.S. Department of Transportation, Office of the Assistant Secretary for Research and Technology (OST-R), University Transportation Centers Program. The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the Department of Transportation, University Transportation Centers Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

Suggested APA Format Citation:

Andriola, C., Chitturi, M.V., Noyce, D.A., Chen, S., Ahn, S. (2026). Road User-Automated Vehicle Expectancies, Interactions, and Safety. CCAT Report #119, The Center for Connected and Automated Transportation, University of Michigan,

Contacts

For more information:

David A. Noyce
2620 Engineering Hall
1415 Engineering Drive
Madison, WI 53706
Phone: 608 265 1882
Email: danoyce@wisc.edu

CCAT
University of Michigan Transportation Research Institute
2901 Baxter Road
Ann Arbor, MI 48152
umtri-ccat@umich.edu
(734) 763-2498

CENTER FOR CONNECTED AND AUTOMATED TRANSPORTATION

Technical Report Documentation Page

1. Report No. Final Report #119	**2. Government Accession No.**	**3. Recipient's Catalog No.**
4. Title and Subtitle Road User-Automated Vehicle Expectancies, Interactions, and Safety		**5. Report Date** August, 2026 **6. Performing Organization Code** N/A
7. Author(s) Cesar L. Andriola, https://orcid.org/0000-0002-1555-6568 Madhav V. Chitturi https://orcid.org/0000-0003-0580-3454 David A. Noyce https://orcid.org/0000-0001-5887-8391 Sikai Chen https://orcid.org/0000-0002-5931-5619 Soyoung (Sue) Ahn https://orcid.org/ 0000-0001-8038-4806		**8. Performing Organization Report No.** **N/A**
9. Performing Organization Name and Address Center for Connected and Automated Transportation University of Michigan Transportation Research Institute 2901 Baxter Road Ann Arbor, MI 48109 University of Wisconsin-Madison 1415 Engineering Dr, Madison, WI 53706		**10. Work Unit No.** **11. Contract or Grant No.** Contract No. 69A3552348305
12. Sponsoring Agency Name and Address U.S. Department of Transportation Office of the Assistant Secretary for Research and Technology 1200 New Jersey Avenue, SE Washington, DC 20590		**13. Type of Report and Period Covered** Final Report (September 2024 – May 2026) **14. Sponsoring Agency Code** OST-R
15. Supplementary Notes Conducted under the U.S. DOT Office of the Assistant Secretary for Research and Technology's (OST-R) University Transportation Centers (UTC) program.		

CENTER FOR CONNECTED AND AUTOMATED TRANSPORTATION

16. Abstract			
Trust in the Automated Vehicles (AVs) is predicated on their ability to conform to expectancies of the road users and community. Rapid advancement and adoption of AVs raises the important question of how well AVs can respect road users' expectancies and coexist in harmony. The objective of this research is to identify patterns in AV and HDV crashes as well as the role of expectancy violations in AV crashes using sequences of events. Data from 555 AV crashes and 39,270 HDV crashes were used. Overall data analysis shows that intersections are much more challenging to AVs than to HDVs. Other interesting observations are the higher proportion of rear end crashes and the much lower severity for AV crashes. The first observable result is the presence of clusters representing pedestrian and bicyclist crashes only in the HDV data. A second trend is the difference in crash patterns between AVs and HDVs during right and left turns. For these movements, while rear end is the most common crash type for AV, angle is the most common for HDV crashes. Another relevant observation is the greater presence of crashes involving red light/stop sign violations by a second vehicle involved in AV crashes. Finally, the results show three groups with contexts particular to AV crashes. Narratives of AV Crashes representing Turning Movements and Vehicle Crossings indicate expectancy violation played a role in these crashes. AVs violated expectancy of HDVs with hesitation/caution in permissive turning movements and not yielding to emergency vehicles. HDVs violated expectancy of AVs by running stop signs or red lights at intersections. Systematic human-in-the-loop (HIL) experiments simulating AV-HDV-Pedestrian and AV-HDV interactions should be conducted to probe expectancy violations and safety impacts in future research.			
17. Key Words Automated vehicle, safety, road users, interactions, expectancies		**18. Distribution Statement** No restrictions.	
19. Security Classif. (of this report) Unclassified	**20. Security Classif. (of this page)** Unclassified	**21. No. of Pages** 32	**22. Price**

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

Table of Contents

List of Figures

List of Tables

CHAPTER 1. Introduction

Automated vehicles (AVs) have the potential to enable a safe, efficient, equitable, healthy, and sustainable transportation system and communities. However, broad public adoption of AVs is predicated on the AVs' ability to engage in safe and efficient interactions with other road users: conventional human-driven vehicles (HDVs), pedestrians, and bicyclists, in our current infrastructure and traffic systems. Human road users have certain *expectancies* for how other road users behave and interact accordingly. While humans can anticipate and handle a range of other road users' behaviors, unexpected behaviors that fall outside or in tail end of the range, i.e., *expectancy violations*, can incite improper responses that could have ramifications for traffic safety and operations.

In the context of interactions with an AV, trust is closely tied to 'expectancy,' which is primed over many experiences. Trust in the AV is predicated on its ability to conform to *expectancies* of the road users and community. Rapid advancement and adoption of AVs raises the important question of how well AVs can respect road users' expectancies and coexist in harmony. Expectancy violations can incite improper responses, which can cause traffic instability, conflicts, and in extreme cases, crashes, and erode trust in the AVs. A survey study found that 41% of the 11,827 respondents would feel uncomfortable driving alongside an AV (Tennant, et al., 2017). Many respondents worried that AVs would lack common sense and could not have the same understanding of the roads as human drivers, and 34% of the respondents did not like the idea of mixing HDVs and AVs. These concerns are not unwarranted, as there is mounting evidence that AVs on the road behave against our expectancy, at times even in "ordinary" circumstances. Independent testing of Tesla's Full Self-Driving Capability suite found glaring abnormalities including: slowing to a stop at a green signal, driving through stop signs, stopping at every leg of a roundabout, etc. (Monticello, n.d.). For the vast majority of AV-involved crashes (over 80%), where the other party, not the AV, was determined to be at fault, the underlying cause was the AV behaved differently from what they expected (Dixit, et al., 2016). An AV crash sequence analysis found hesitation of AVs at intersections (represented by a sequence of events: AV stops, proceeds, and stops again) as one of the crash patterns (Song, et al., 2021). The objective of this research is to identify patterns in AV and HDV crashes as well as the role of expectancy violations in AV crashes using sequences of events. The goal is to lay the foundation for a future study to examine interactions between human-driven vehicles, pedestrians, and automated vehicles to elucidate potential expectancy violations and consequent impact on safety.

CHAPTER 2. Methodology

Crash sequence analysis was used to identify patterns in AV crashes. Event information from crash data is input to Crash sequence analysis and clusters based on the sequence of events are the output (Song et al., 2023), as shown in Figure 1. The steps described in detail below were implemented using the libraries "TraMineR" (Gabadinho et al., 2010) in R and "Scikit-learn" (Pedregosa et al., 2012) in Python.

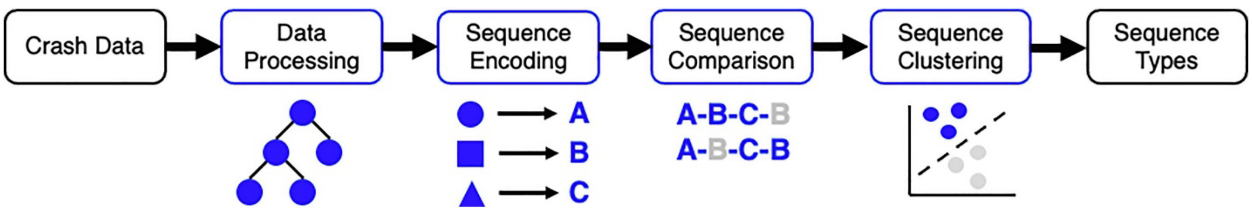


Figure 1. Crash Sequence Analysis Methodology.

Crash Data and Data Processing

California's automated vehicle collision reports and NHTSA's Standing General Order on Crash Reporting data were used for AV crashes, and the NHTSA Crash Report Sampling System (CRSS) data were used for HDV crashes. California's automated vehicle collision reports derive from the state's mandatory reporting of any collisions that lead to property damage, bodily harm, or death within a 10-day timeframe following the incident (California DMV, 2023). NHTSA's General Order was issued in 2021 to require manufacturers and operators to report property damage or injury crashes involving vehicles equipped with an automated driving system that was in use within 30 seconds of the crash (NHTSA, 2023). California's reports from 2014 to 2023, NHTSA's General Order data from 2021 to 2023 were used in the study to address the data size limitation, representing all the available data at the time. Data from California's reports and NHTSA's General Order were combined to generate a bigger sample size. Duplicated crashes and crashes that occurred during Manual operation were excluded. Furthermore, to minimize the bias caused by different narrative styles and operational characteristics used by different manufacturers, only crashes from Cruise and Waymo, the manufacturers with the most crashes, were considered.

CRSS is a United States crash database with data extracted from nationally sampled crash reports, containing four levels of data: crash level, vehicle level, person level, and event level, linked through case, vehicle, and person identification numbers (NHTSA, 2022). California's reports from 2014 to 2023, NHTSA's General Order data from 2021 to 2023 were used in the study to address the data size limitation, representing all the available data at the time. Regarding HDV crashes, CRSS data from 2016 to 2021 were used in this study, also representing all the available data at the time. Although different time periods were used, the crash pattern groups in the CRSS dataset remained consistent throughout the years, thereby minimizing compatibility issues.

In the case of HDV crashes, the CRSS dataset was filtered to obtain a subset of crashes that closely matched the AV dataset in terms of geography and land use. To this end, the filters URBANICITY = 1 (urban areas) and REGION = 4 (West: MT, ID, WA, OR, CA, NV, NM, AZ, UT, CO, WY, AK, and HI) were used. These filters were applied because other sources of HDV crash data with available location, which would support more precise geographical matching, do not provide readily available sequence data in line with the CRSS format. The resulting dataset was comprised of 39,270 data points in the CRSS data, representing 4,675,600 crashes in the real world, considering the weights associated with each data point. Considering the SAE levels of automation, the CRSS dataset has included related information since 2019. However, this information was not used here, as it is absent in most data points.

Sequence Encoding

Sequence encoding refers to converting the text narratives of pre-crash and crash events into a series of event labels ordered by time (Song, 2021). The AV crash datasets do not explicitly contain elements representing sequence of events. However, the datasets present crash narratives, which allow us to build events and the derived sequences. The AV data encoding used the codes of Song et al (2021), supplemented by eight additional events that were present in more recent crashes: "v1 pass v2 on left", "v1 pass v2 on right", "v1 contact v3", "v1 (v2/v3) change lanes", "v1 hit parked vehicle", "v1 go straight", "v1 (v2) leave roadway", and "v1 (v2) encroach opposite lane" resulting in a total of 52 possible types of events.

The CRSS dataset, on the other hand, already contains information about events leading up to and during a crash. Pre-crash information is available in the VEHICLE data file, which includes the variables PCRASH1 (pre-crash movement), PCRASH2 (the main event before the crash), and PCRASH3 (attempts to avoid the crash). Regarding events during the crash, the CEVENT data file records harmful and non-harmful events chronologically through the SOE (sequence of events) variable. Each SOE event is associated with a vehicle, which allows for determining the order of vehicle involvement in the crash. In this study, we combined the PCRASH1~3 variables with the SOE variable to create a sequence of events for each crash, following the procedure described in Song et al. (Song et al., 2023), which generates a set of 123 types of events.

Sequence Comparison

The Sequence Comparison step compares every crash based on its sequence of chronologically encoded events (described in the previous step). The present study uses the Optimal Matching (OM) dissimilarity measure associated with the Levenshtein distance, since the existing literature suggests this combination as a suitable choice for crash sequence analysis (Ye et al., 2021; Song, 2021). The OM generates a dissimilarity matrix by calculating the smallest transformation cost needed to transform one sequence into another, using operations such as substitutions, insertions/deletions (or indels), compression and expansions, and transpositions (or swaps) (Song, 2021). The Levenshtein distance adds to the metric by specifying the value of two for substitution cost and one for indel cost. The mathematical expression of OM-based dissimilarity between a pair of sequences, x and y, is given below:

$$d_{OM}(x, y) = min_j \sum_{i=i}^{Ij} Y\left(T_i^j\right) \quad (1)$$

Where l_j denotes the transformations needed to turn sequence x into y, and $y(T_i^j)$ is the cost of each elementary transformation T_i^j (e.g., indel or substituition).

Sequence Clustering

Sequence clustering uses the dissimilarity matrix to cluster the crashes into groups of similar characteristics. The most fundamental variant of cluster analysis is partitioning, a technique that categorizes the elements within a set into distinct, non-overlapping partitions or clusters. Most applications adopt the k-means or k-medoids methods. In the context of this analysis, the k-medoids approach was selected due to its ability to accommodate dissimilarity matrices as input and its enhanced resilience against outliers (Jin & Han, n.d.). The k-medoids algorithm partitions a dataset into k clusters by iteratively selecting representative data points (medoids) for each cluster, minimizing the sum of dissimilarities between data points and their corresponding medoids, as shown below:

$$E = \sum_{i=i}^{k} \sum_{p \in C_i} dist\left(p, o_i\right) \tag{2}$$

Where E is the sum of the absolute error for all objects p in the data set, and o_i is the representative object of C_i.

As the previous equation shows, an important step in the clustering process is selecting the number of clusters (k). For this task, the present study deploys the Silhouette method (Rousseeuw, 1987), which describes how well a data point lies within its own cluster when compared to other clusters, as shown in Equation 3. The Average Silhouette Width (ASW), considering all points in the dataset, ranges from -1 to 1, with higher values representing a better separation of clusters.

$$S_i = \frac{b_i - a_i}{max(a_1,\ b_i)} \tag{3}$$

Where S_i is the silhouette width of object i, a_i is the average dissimilarity of object i to all the other objects of the same cluster, and b_i is the average distance from i to all clusters to which i does not belong.

Sequence Types

The last step of the Crash Sequence Analysis methodology uses domain knowledge to interpret the results of the clustering process. This interpretation is facilitated by examining the events and sequences within each cluster. Furthermore, crash, vehicle, and environmental factors such as collision types, intersection-relation, lightening conditions, weather conditions, alcohol involvement, and driver age were considered to aid this interpretation. Given that these factors were not directly utilized in the clustering process, the emergent trends can illuminate the underlying characteristics linking the crashes within each cluster.

CHAPTER 3. Findings

The general trends from the combined AV and CRSS datasets are presented first. Then, the results of the crash sequence analysis are presented in order to delve deeper into the differences or similarities in AV and HDV crash patterns. Finally, expectancy violations identified in AV crashes are presented.

General Trends

Figure 2 presents a general comparison between the 555 AV crashes and 39,270 HDV crashes used in this study, with the latter being the result of a filtering process aimed at matching the geography and characteristics of AV driving domain, minimizing bias. The figure shows the distribution of crashes for the variables crash location (a), number of vehicles involved (b), collision types (c), traffic control (d), pre-crash movement (e), weather (f), and lighting (g), which were chosen based on their availability in both the AV and HDV datasets. The variables pre-crash movement and collision types have values that differ between datasets, making a direct comparison challenging. In those cases, the different values are presented individually to allow for a better understanding of the variable.

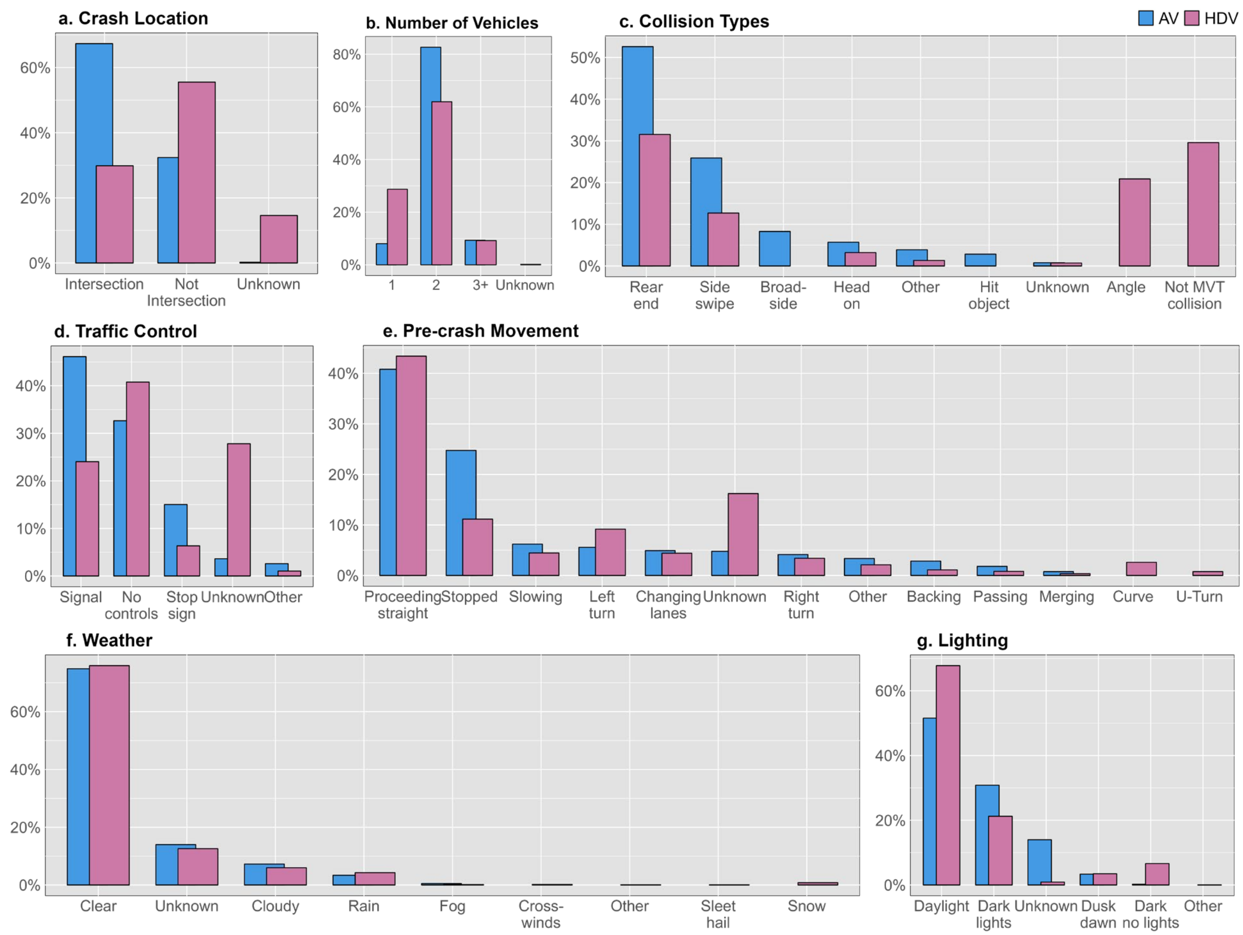


Figure 2. Overall Data Description for the AV and HDV datasets.

The first variable presented in Figure 2 is the crash location (Figure 2a), suggesting that intersections are more challenging to AVs than to HDVs. Over two-thirds (68.5%) of AV crashes occurred at intersections while about one-third (34.9%) of HDV crashes occurred at intersections. However, this difference does not translate to a significant difference in the type of traffic control, as seen in Figure 2d. The distribution of traffic control (signal control, stop control, and other) at intersections is similar for both AVs and HDVs, which suggests that intersections are challenging to AVs rather than the type of control at intersections. Another significant difference can be seen in the number of vehicles involved in the crash (Figure 2b). While both AV and HDV crashes present as most common the involvement of 2 vehicles (84.1% and 62.1%, respectively), the proportion of crashes involving only one vehicle is higher for HDV crashes (28.7% against 6.6% in the AV dataset). Considering the latter group, while the majority of HDV crashes involve running of the road (71.1%), the majority AV crashes involve the collision with “objects” on the road (60.8%), such as debris, downed power cables, or the curb.

Another variable presented in Figure 2 is the type of collision (Figure 2c), which shows differences in the values present in the AV and HDV datasets, such as the “broadside” and “hit object” values in the AV dataset and the “not a collision with a Motor Vehicle in Transport (MVT)” and “angle” values in the HDV dataset. However, the comparison between datasets still presents some relevant observations, such as a higher proportion of “rear end” and “side swipe” crashes in the AV dataset. The data shows a higher proportion of HDV crashes where the collision does not involve a second MVT, which aligns with the number of vehicles involved in the crash, as discussed above. Furthermore, the previous observation is associated with the involvement of pedalcyclists and pedestrians in HDV crashes, which is less present in AV crashes.

The data also suggests differences in terms of pre-crash movement (Figure 2e), a variable constructed to address the differences in encoding between the AV and HDV datasets. While the AV dataset considers the AV as the first vehicle, the HDV dataset does not explicitly define a vehicle order for the pre-crash events. To address this limitation, the pre-crash events of all vehicles involved in the crashes were combined into an overall pre-crash movement variable that can be compared between datasets. With this new variable, we can observe a higher proportion of AV crashes where one of the vehicles involved was stopped prior to the crash (26.3% against 13.3% in the HDV dataset), with the stopped vehicle being the AV in most of the cases (93.8%). Although the crash narratives do not provide information regarding the AV's hesitation or the human response to the AV, this result differs from HDV dataset, which sees a higher proportion of crashes involving a vehicle proceeding straight prior to the crash (51.8% against 42.7% in the AV dataset) or turning left (10.9% against 5.5% in the AV dataset).

Finally, environmental conditions like lighting during crashes indicate that AVs struggle more in dark conditions with typical urban lightings (30.8% against 21.2% in the HDV dataset), and that AV crashes hardly occur in dark areas without lightings (Figure 2f). Weather differences were minimal, aside from regional weather events affecting HDVs (Figure 2g). Finally, a severity comparison enhances the overall understanding, with no fatal crashes in the AV dataset (compared to 0.6% in the HDV dataset) and a significantly lower proportion of injury crashes (11.6% versus 36% in the HDV dataset).

Observed differences in Figure 2 do not give information on AVs' safety level when directly compared with HDVs. Nevertheless, the differences show how the challenges currently faced by these types of vehicles differ, as described above. These differences in crash trends can largely be attributed to the technical capabilities and/or limitations of AVs, the behavioral patterns of HDV drivers, and the specific conditions under which AVs are tested. Additionally, this comparison is limited by the HDV dataset filtering process, which might not have fully captured the AV crash contexts. To address these limitations, crash progression and contributing factors is used to create the context-specific results presented below.

Context-specific Trends

As described previously, the first step of the clustering process is choosing the number of clusters. The upper part of Figure 3 shows that thirteen ($\mathrm{k}_{\mathrm{AV}} = 13$) and sixteen ($\mathrm{k}_{\mathrm{HDV}} = 16$) are the ideal choice for the number of clusters for the AV (left) and HDV (right) datasets, respectively, since they deliver the best ASW score in each case. The lower part of Figure 3 shows the Silhouette Coefficient for each crash in the defined clusters, showing that Cluster 8 for the AV dataset (AV8) and Cluster 11 for the HDV dataset (HDV11) are the most well-defined clusters. In contrast, Cluster 3 for the AV dataset and Cluster 6 for the HDV datasets are the least well-defined clusters.

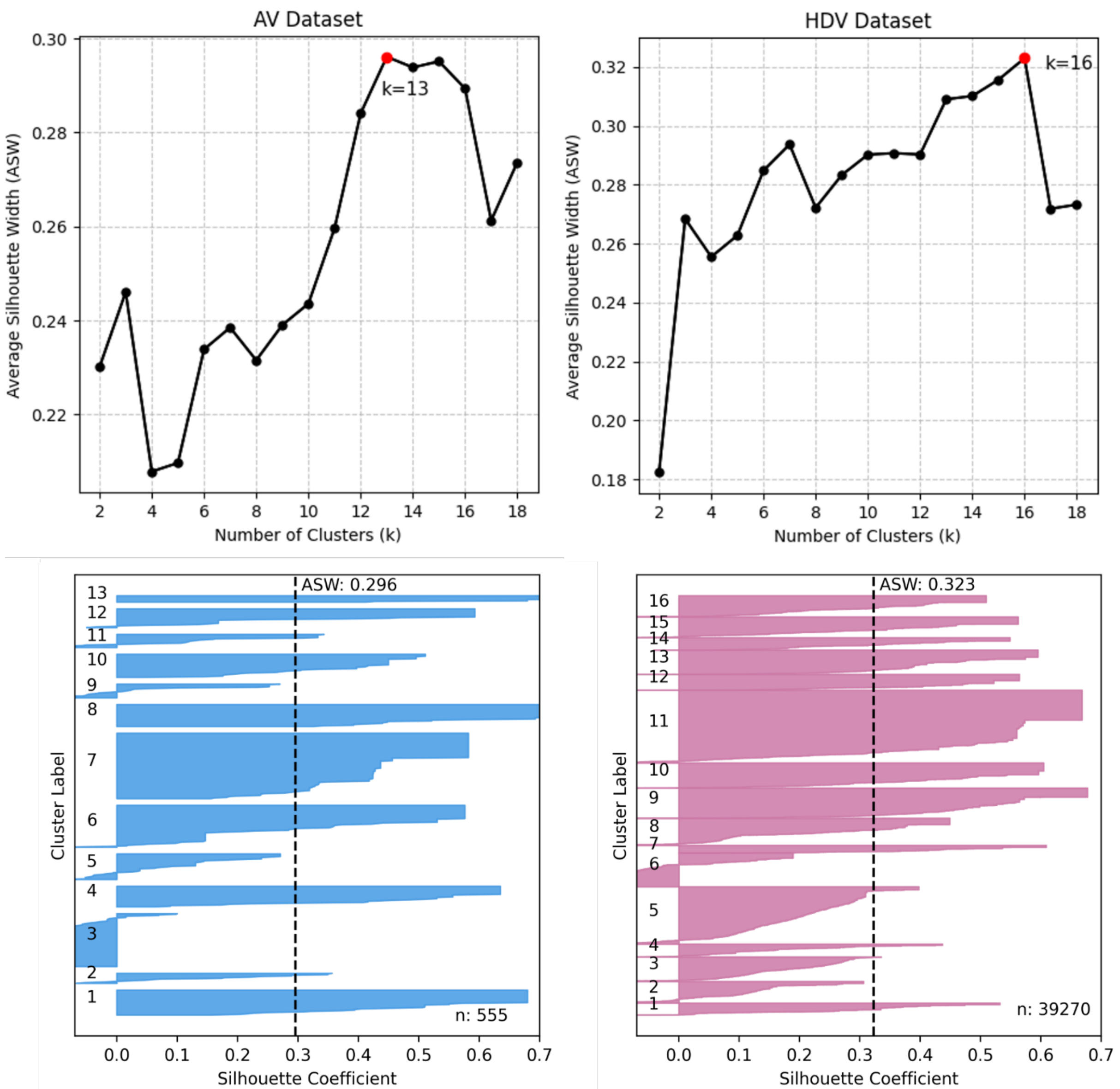


Figure 3. Clusters performance for the AV and HDV datasets.

After defining the number of clusters, the data points were assigned to each cluster using the k-medoids method described in section 2. Table 1 and Table 2 show each cluster's most frequent sequences of events, with the difference in events resulting from the different encodings used in the HDV and AV datasets. The columns of the tables display the count and percentage of each specific sequence of events within its cluster, along with the distribution by manufacturer (Cruise or Waymo) and their respective groups.

Table 1. AV Dataset: Most Frequent Sequence of Events by Cluster

Group	***Manuf*[1]**	***Cluster***	***Count*[2]**	**%[3]**	***Sequence of Events***
1	71/29	1	21	51.2	v1 go straight - v1 hit object
2	65/35	2	2	11.8	v1 back up - v1 disengage - v1 back up - v1 hit parked vehicle
3	21/79	3	7	8.1	v1 go straight - v2 contact v1
4	82/18	4	14	41.2	v1 make right turn - v1 stop - v1 yield - v2 contact v1
5	71/29	5	6	14.3	v1 merge left - v1 stop - v1 yield - v2 contact v1
6	51/49	6	22	32.4	v1 decelerate - v2 contact v1
7	67/33	7	40	37.7	v1 stop - v2 contact v1
8	19/81	8	21	58.3	v1 go straight - v2 run stop sign/red light - v2 contact v1
9	28/72	9	4	17.4	v1 go straight - v1 change lanes - v1 contact v2
		10	10	26.3	v1 go straight - v2 change lanes - v2 contact v1
10	41/59	11	5	22.7	v1 go straight - v2 change lanes - v1 decelerate - v3 contact v1
11	84/16	12	14	45.2	v1 stop - v2 stop - v2 accelerate/proceed - v2 contact v1
12	82/18	13	6	54.5	v1 go straight - v2 from opposing - v1 stop - v1 yield - v2 pass v1 on left - v2 contact v1

[1]*Percentage of Cruise and Waymo vehicles in the group*
[2]*Number of times the presented sequence repeats within the cluster*
[3]*Percentage contribution of the sequence to the cluster*

Table 2. HDV Dataset: Most Frequent Sequence of Events by Cluster

Group	Cluster	Count[2]	%[3]	Sequence of Events
1	1	17173	12.9	v1 go straight - v1 pedalcyclist in road - v1 unknown - v1 hit pedalcyclist
	2	21047	8.7	v1 go straight - v1 pedestrian in road - v1 unknown - v1 hit pedestrian
	3	6500	2.4	v1 go straight - v1 off the edge on left - v1 unknown - v1 ran off left - v1 hit barrier
2	4	15625	10.9	v1 back up - v1 back up - v1 unknown - v2 stop - v2 other veh: back up - v2 no avoidance - v1 contact MVT
	5	47854	7.5	v1 go straight - v1 over lane on right - v1 unknown - v1 ran off right - v1 hit parked vehicle
3	6	57171	15.2	v1 go straight - v1 other veh: slower - v1 unknown - v2 go straight - v2 other veh: faster - v2 unknown - v1 contact MVT
4	7	20261	24.1	v1 make right turn - v1 turn right - v1 unknown - v2 go straight - v2 other veh: from crossing into same direction - v2 unknown - v1 contact MVT
5	8	68551	22.7	v2 go straight - v2 other veh: from oposing left - v2 unknown - v1 make left turn - v1 turn left - v1 unknown - v2 contact MVT
	9	99577	29.6	v1 make left turn - v1 turn left - v1 unknown - v2 go straight - v2 other veh: from oposing left - v2 unknown - v1 contact MVT
6	10	89063	31.8	v1 go straight - v1 other veh: decelerate - v1 unknown - v2 decelerate - v2 other veh: faster - v2 unknown - v1 contact MVT
7	11	332925	41	v1 go straight - v1 other veh stop - v1 unknown - v2 stop - v2 other veh: faster - v2 no avoidance - v1 contact MVT
	12	69464	39.4	v1 go straight - v1 other veh stop - v1 unknown - v2 stop - v2 other veh: faster - v2 no avoidance - v3 stop - v3 other veh: faster - v3 no avoidance - v1 contact MVT - v2 contact MVT
8	13	77293	28.5	v1 go straight - v1 cross junction - v1 unknown - v2 go straight - v2 other veh: from crossing across path - v2 unknown - v1 contact MVT
	14	37195	26.8	v2 go straight - v2 other veh: from crossing across path - v2 unknown - v1 go straight - v1 cross junction - v1 unknown - v2 contact MVT
9	15	78556	34.1	v1 change lanes - v1 over lane on right - v1 unknown - v2 go straight - v2 other veh: from left adjacent - v2 unknown - v1 contact MVT
	16	73061	30.8	v1 change lanes - v1 over lane on left - v1 unknown - v2 go straight - v2 other veh: from right adjacent - v2 unknown - v1 contact MVT

Figure 4 presents the results from the Crash Sequence of Events methodology, which shows the presence of 13 clusters for AV crashes and 16 clusters for HDV crashes. Figure 4a shows the crash sequence patterns illustration, with each group representing a specific crash context for both AVs (top) or HDVs (bottom), including: collisions involving pedestrian and pedalcyclists (Group 1), parked vehicles (Group 2), unknown or diverse type of vehicle contact (Group 3), turning movements (Groups 4 and 5), stopping movements (Groups 6 and 7), vehicle crossings (Group 8), lane changes (Group 9), a lane change in front of the AV (Group 10), both vehicles initially stopped (Group 11), and side swipe crashes on narrow streets (Group 12). The numbers in the Figure represent the original clusters produced by the methodology for each dataset. Figure 4b shows the percent contribution of each group to the overall AV or HDV datasets, including the contribution of each cluster to its specific group. Finally, Figure 4c shows the severity by group and by dataset, with the left and right columns of each group representing the AV and HDV datasets, respectively.

Domain knowledge and other crash variables were used to interpret the observed results. From this interpretation, AV and HDV clusters were grouped based on the crash context, as shown in Figure 4a, with the top portion of each group representing AV crashes and the bottom portion representing HDV crashes. The figure also shows that each AV group usually corresponds with more than one HDV cluster in a similar context, which can be explained by the difference in encoding and the number of crashes. Furthermore, as exemplified in Groups 4 and 5, different characteristics for AV and HDV crashes can be observed, even if they are part of the same context (right and left turns, respectively). Finally, Figure 4a also shows three AV clusters/groups that do not directly correspond to HDV clusters. This indicates that, although crashes within these contexts happen in the HDV dataset, the smaller proportion and characteristics of these crashes do not lead to individual HDV clusters.

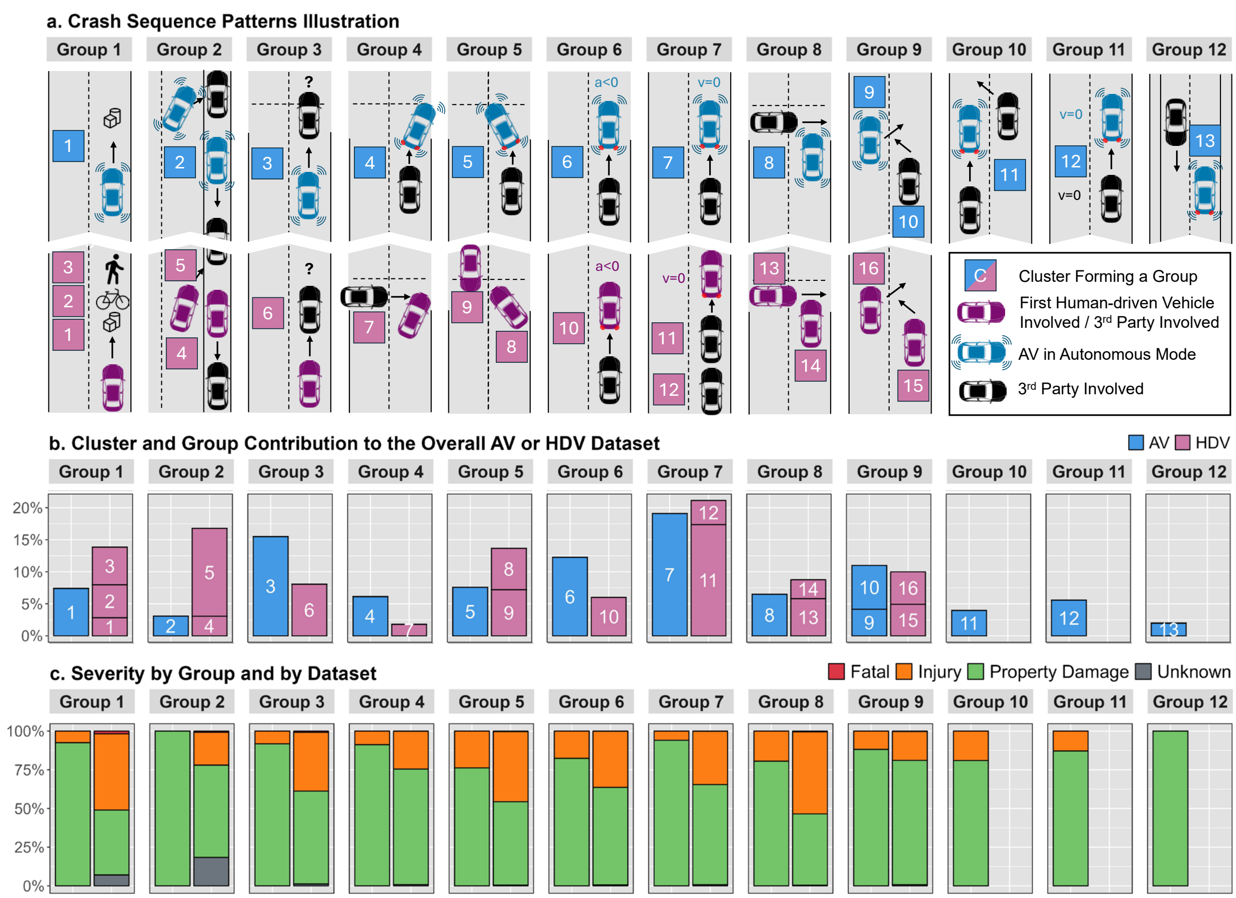


Figure 4. Crash Patterns Characteristics for the AV and HDV datasets.

Figure 4b shows that the proportion of HDV crashes for Groups 1 (collision with objects and vulnerable road users), 2 (collision with a parked vehicle), and 5 (left-turns) are larger than the proportions of these groups in AV crashes. The opposite trend is observed for Groups 3 (unknown or diverse vehicle contact), 4 (right-turns), 6 (rear end crashes following the deceleration of the vehicle in front), 10 (rear end crashes following a lane change of the vehicle in front), 11 (rear end crashes following the stopping of both vehicles involved), and 12 (collision in a narrow road), with the last three groups only representing only AV crashes. The remaining groups (7: rear end crashes following the stopping of the vehicle in front, 8: running a red light/stop sign, and 9: lane change) show similar proportions for both datasets.

Figure 4c shows that AV crashes are significantly less severe than HDV crashes, despite occurring in similar contexts. This result is further evidenced by the overall severity of the datasets, with no fatal crashes in the AV dataset (compared to 0.6% in the HDV dataset) and a substantially lower proportion of injury crashes (14.5% compared to 36.0% in the HDV dataset). Considering group-specific results, every group shows the proportion of AV injury crashes as a fraction of those in HDV crashes. This is particularly relevant considering Group 1, which involves collisions with objects, pedestrians, and bicyclists, and the fact that AVs are being tested in urban areas with a considerable presence of vulnerable road users such as bicyclists and pedestrians.

The following subsections expand on the differences and similarities observed in different Groups by considering the sequences of events and traditional crash variables presented in the datasets.

Pedestrian and Pedalcyclist Involvement

Group 1 represents predominantly crashes involving an object in contact with a Motor Vehicle in Transport (MVT), as seen by the events "v1 hit object" (AV crashes) and "v1 hit barrier " (HDV crashes) in the group's most common sequence of events (Tables 1 and 2). The similarities between AV and HDV crashes can also be observed with "hit object" (52.6% in AV crashes) and "not MVT collision" (94.9% in HDV crashes) being the most common values for the variables "Collision Types" and "no" (84.2% in AV crashes and 70.2 in HDV crashes) being the most common value for the variable "Intersection". The main difference between the group's AV and HDV data is the presence of a considerable proportion of crashes involving pedalcyclists and pedestrians in the HDV dataset (and consequently higher severity), which is uncommon in the AV dataset (18 crashes or 3.2%). This difference produces two additional HDV clusters (Clusters 2 and 3), with similar sequence of events but distinct characteristics from the AV cluster (Cluster 1), as seen by the many crashes during daylight, which is particularly common for pedalcyclists and pedestrians.

The above results might indicate additional caution from AVs regarding these populations, as discussed by Patel et al. (2023), Petrovic et al. (2020), and Ye et al. (2021). Additionally, while the AV crashes in this group are usually associated with objects on the road (e.g., potholes/manholes and road debris), HDV crashes are usually associated with running off the road. Although this can indicate the underreporting of such crashes in the HDV dataset, it also suggests that humans might be better at detecting objects on the road and/or worse at staying in the roadway, which is supported by a higher proportion of alcohol involvement in this group when compared to the overall HDV data.

Collision with a Parked Vehicle

Group 2 represents predominantly crashes involving a collision with a parked vehicle, as seen by the event "v1 hit parked vehicle" (AV2 and HDV4-5) in Tables 1 and 2. The similarities between AV and HDV crashes can also be observed in similar trends in the variables "Intersection" and "Lighting", with the majority of crashes occurring off intersections and during daylight. The main difference between the Group's AV and HDV data is the presence of individual HDV clusters for the two types of movements observed in Figure 4. Given the smaller number of crashes in the AV dataset, both types of movements are part of only one cluster. Another difference is observed in the variable "Collision Types", with "side swipe" being the most common value in the AV dataset (63.6%) and "not MVT collision" being the most common value in the HDV dataset (93.9%). This difference arises from the different encoding used, with "sideswipe" considered in the AV dataset even if the second vehicle is not an MVT. Additional variables also add to the understanding of AV crashes, such as a higher proportion of the event "v1 disengage" (21% against 4.9% overall), and crashes during cloudy weather (19.7% against 8.4% overall). Considering HDV crashes, a higher proportion of crashes during dark lighting (32.2% against 21.4% overall) was observed.

The first observable difference in the results presented above is the existence of two HDV clusters in the group, which arises from the high number of crashes in the HDV dataset, making the two types of movement observed in this crash context ("back up" and "ran off right") more dissimilar in the clustering process. The main difference, however, is the higher occurrence of disengagements in the group's AV cluster when compared to the overall AV data, a finding also presented by Kutela et al. (2023). This observation incorporates the human behavioral involvement into AV crashes, making the crash events of both AV and HDV crashes more similar. However, since disengagement happens when AV requests assistance or the operator perceives danger, there might not have been enough time for the operator to take corrective action. Also, the events preceding the disengagement in the AV cluster indicate that the vehicles might find the parking maneuver involving a backing-up movement challenging. Unfortunately, the narratives for these crashes do not present additional information that would provide insight into the issue.

Unknown or Diverse Type of Vehicle Contact

Group 3 represents predominantly crashes with an unknown or diverse type of vehicle contact, as seen in Tables 1 and 2 by the diversity of sequence of events in cluster AV3 and by the events "v1 unknown" and "v2 unknown" in cluster HDV6. The similarities between AV and HDV crashes can also be observed in a diversity of values for the variable "Collision Types" in both datasets. Another similarity is a better match of the Group's variables with the overall data, which indicates a "generic" group of AV and HDV crashes. Another important difference is a higher proportion of AV crashes during dark lighting (53.7%) and at intersections (66.6%), against a higher proportion of HDV crashes during daylight (66.4%) and away from intersections (64.9%). An additional variable that also contributes to the understanding of HDV crashes is the higher proportion of the pre-crash movement "proceeding straight" (77.45% against 51.31% overall). Other variables for both AV and HDV presented similar distributions as the overall data.

The above results show that Group 3 incorporates the two clusters with the lowest performance, considering the Silhouette Coefficient presented in Figure 3. The diversity of crashes in both AV and HDV datasets explains the observed low values. Despite this diversity, both the clusters in the group represent mainly collisions between two motor vehicles, with the first vehicle going straight. This group can also be considered a "generic" group of AV and HDV crashes, given the good match of the group's variables with the overall data, which shows a higher proportion of AV crashes at intersections and during dark lighting.

Turning Movements

Groups 4 and 5 represent predominantly crashes during right and left turn movements, as seen by the events "v1 make right turn" (AV crashes in Group 4), "v1 turn right" (HDV crashes in Group 4), "v1 merge left" (AV crashes in Group 5), and "v1 turn left" (HDV crashes in Group 5) in the group's most common sequence of events (Tables 1 and 2). The similarities between AV and HDV crashes can be observed in the variables "Lighting" and "Intersection", with crashes mainly occurring during daylight (76.9% and 75.6% for AV crashes in Groups 4 and 5, and 78.1% and 72.4% HDV crashes in Groups 4 and 5, respectively) and at intersections (100% and 91.7% for AV crashes in Groups 4 and 5, and 64.9% and 60.1% HDV crashes in Groups 4 and 5, respectively). Despite the similarity in context between AV and HDV datasets, there are important differences in crash progression and behavior, as seen by their sequence of events and crash types. The former is seen by the events "v1 stop" and "v1 yield" in the AV dataset and the events "v2 other veh: from crossing into same direction", "v2 other veh: from driveway into same direction", "v2 other veh: from opposing left" and "v2 other veh: from crossing into opposing direction" in the HDV dataset. The latter is seen by the variable "Collision Type", with "rear end" (88.9% and 83.3% for Groups 4 and 5, respectively) being the most common value for the AV dataset, as opposed to "angle" (60.7% and 68.9% for Groups 4 and 5, respectively) for the HDV dataset.

The above results indicate additional caution from AVs during turns (especially left turns), as observed by the lower percentage contribution of Group 5 to the overall AV dataset (7.5%) when compared to HDV data (13.7%). This behavior, which can lead to rear end crashes, is supported by the discussions of Boggs et al.(2020a) and Wang & Li (2019), and might be associated with several factors, such as the misjudgment from the AVs regarding the conflicts on the road (Boggs, et al., 2020b; Junghans et al., 2021), the misjudgment from the following vehicles regarding the braking behavior of AVs (Boggs, et al., 2020b; Liu et al., 2021; Novat et al., 2023, difference between yielding behavior of AVs and HDVs (Liu et al., 2024), and HDV errors such as unsafe speed, limited safe distance, and distraction (Liu et al., 2024; Petrovic et al., 2020). HDVs, on the other hand, show less hesitation during the turns, as indicated by the absence of events such as "v1 stop" and "v1 decelerate" and by the fact that the collision was usually with a vehicle arriving from another direction. The absence of fatal AV crashes, combined with the typical type of AV crash in the group, suggests that while AVs are still involved in crashes in this context, these tend to be less severe.

Stopping Movements

Groups 6 and 7 represent predominantly rear end crashes following a stopping or stopped vehicle in front, as seen in the group's most common sequence of events by the events "v1 decelerate" and "v2 contact v1" (AV crashes in Group 6), the events "v1 stop" and "v2 contact v1" (AV crashes in Group 7), the event "v1 other veh: decelerate" (HDV crashes in Group 6), and the events "v2 stop" and "v1 contact MVT (HDV crashes in Group 7). The similarities between AV and HDV crashes can be observed in the most common collision type being "rear end" (69.1% and 58.3% for AV crashes in Groups 6 and 7, and 95.9% and 91.1% HDV crashes in Groups 6 and 7, respectively), and with similar trends in terms of lighting, with "daylight" being the most common (62.9% and 50.5% for AV crashes in Groups 6 and 7, and 79% and 79.6% HDV crashes in Groups 6 and 7, respectively). The main difference between the group's AV and HDV data is the location of the crash, with AV crashes being mainly at intersections (76.9% and 72.2% for Groups 6 and 7, respectively), as opposed to HDV crashes, which are mainly away from intersections (84.8% and 58.4% for Groups 6 and 7, respectively). Other observable differences are the higher presence of AV crashes at stop-controlled intersections (25% for Group 6) when compared to the overall data (10.5%) and to the HDV data (0.3% for Group 6), and the higher presence of AV crashes in dark with lighting (42.3% for Group 7) when compared to HDV data (17.9% for Group 7).

The results presented above show the challenges faced by AVs during the stopping movement, as seen by the percentage contribution of Groups 6 and 7 to the overall AV dataset (31.4%), which aligns to the findings of Liu et al. (2024) and Wang et al. (2024). AV crashes happen mainly at intersections, indicating the need for improvement in the manufacturers' algorithms. This result also aligns with the observations from the overall AV data (high proportion of rear end crashes) and explains the presence of other types of crashes, such as side swipe, broadside, and head on (intersection crashes). Also, the results show a higher than overall presence of crashes at stop signs and with disengagements in Group 6, with similar results presented by Liu et al. (2021), indicating that AVs might find it challenging to deal with the complexity of stop-controlled intersection rules. Finally, crash narratives also show that, in many crashes from Group 6, a vehicle was stopped waiting for a passenger, which might indicate a poor choice of location, as discussed by Kutela et al. (2022). Considering Group 7, the results show "v1 stop - v2 back up - v2 contact v1" as the second most common sequence of event in the group, suggesting that AVs might find it challenging to deal with human violations, such as backing up from a parked position, as observed in the crash narratives.

Vehicle Crossings

Group 8 represents predominantly crashes involving vehicles crossing paths, as seen in the group's most common sequence of events by the AV event "v2 run stop sign/red light", and by the HDV events "v1 cross junction" and "v2 other veh: from crossing across path". The similarities between AV and HDV crashes can be seen with "broadside" (76.2% in AV8 crashes) and "angle" (87.4% in HDV crashes) being the most common values for the variables "Collision Types", and "yes" (100% in AV crashes and 89.4% in HDV crashes) being the most common value for the variable "Intersection". The main difference between the group's AV and HDV data is the presence of the event "v2 run stop sign/red light" only for the AV dataset. However, the HDV variable "Violation" shows that the violations related to the rules of the road are also an important factor for the HDV cluster (9.8%), when compared to the overall data (1.2%). Another important difference is that over two-thirds of AV crashes occurred during dark lighting (67.6%) against nearly three-fourths of HDV crashes occurring during daylight (73.1%).

The above results show significant differences regarding event encoding between AV and HDV crashes. The main differences are the existence of the event "v2 run stop sign/red light" exclusively for AV crashes and the events "v1 unknown" or "v2 unknown" exclusively for HDV crashes. Despite these differences, the higher proportion of red light or stop sign violations (variable "VIOLATION") in the HDV dataset, when compared to the overall data, helps the connection between AV and HDV clusters into the same group. Furthermore, although AV crash narratives suggest that the crashes are caused by a red light or stop sign violation from a second vehicle involved, the proportion of such violations in the AV dataset (2.2% of all AV crashes) is nearly double the proportion in the HDV dataset (1.2% of all HDV crashes). This result suggests that AVs need to anticipate and/or respond better to other vehicles running stop signs or red lights at intersections.

Lane Changes

Group 9 represents predominantly crashes involving lane changes, as seen in Tables 1 and 2 by the AV9-10 events "v1 change lanes" and "v2 change lanes" and by the HDV15-16 event "v1 change lanes”. The similarities between AV and HDV crashes can be observed in "side swipe" (67.5% for AV9-10 and 82.7% for HDV15-16) being the most common value for the variable "Collision Types" and "no" being the most common value for the variable "Intersection". The main differences between the Group's AV and HDV data are a higher proportion of AV crashes during dark lighting (41.2%) when compared to HDV crashes (23.1%), and a higher presence of other types of crashes in the AV data, such as "rear end" and "head on" crashes. The HDV crashes of Group 9 are divided into two clusters (HDV15 and HDV16), due to differences in the direction of the movement. Considering AV crashes, the clusters differ by the vehicle that initiates the movement (AV or HDV), with the AV being responsible for 33.3% of the crash initiations. An additional variable that also contributes to the understanding of HDV crashes is the lower proportion of speeding (5.2% against 20.9% overall).

The results presented above align with the findings of Wang et al. (T. Wang et al., 2024) regarding the challenge AVs face with lane change movements. Group 9 is also the group that better relates AV and HDV crashes, considering the same number of clusters for each dataset (2), similar events (e.g., "v1 change lanes", "v1 contact v2/MVT"), and similar distribution for the available crash variables. Although there is not enough information about crash rates to affirm that AVs are not safer than HDVs in this context, the results suggest that AVs have challenges similar to those of HDVs during lane change maneuvers. For example, while cluster AV9 might be suggesting a failure in the lane changing plan, cluster AV10 might be suggesting the inaccurate identification of the other vehicle’s lane change intention, as discussed by Liu et al. (2021).

AV-unique Contexts

Figure 4 shows three Groups (10, 11, and 12) with contexts unique to the AV dataset. Group 10 represents predominantly rear end crashes following a lane change in front of the AV, as seen by the AV events "v2 change lanes", "v1 decelerate", and "v3 contact v1" in the group’s most common sequence of events. The group has a higher proportion of rear end crashes (85.7% against 53.3% overall), crashes during daylight (73.3% against 54.3% overall), and crashes with the presence of traffic signals (63.6% against 32.1% overall). This result indicates that Group 10 (represented by AV cluster 11) has similarities with HDV cluster 12 and could have been considered part of Group 7 (rear end crashes following the stopping of the vehicle in front). However, the pre-crash movement "v2 change lanes" makes AV cluster 11 unique, which can be explained by a difference in avoidance maneuver between AVs and HDVs in this particular context, in which AVs might have difficulty dealing with the presence of a close following vehicle, as discussed by Lee et al. (2023). Harder braking can also explain this result, leading to a violation of expectancy from the following vehicle.

Group 11 represents predominantly rear end crashes in which both vehicles were initially stopped before the following vehicle starts moving, as seen by the AV events "v1 stop", "v2 stop", and "v2 contact v1" in the group’s most common sequence of events. The group has a higher proportion of the values "rear end" (91.3% against 53.3% overall)," daylight" (69.2% against 54.3% overall), "yes" (95.7% against 67.9% overall), and "signal" (58.1% against 32.1% overall), for the variables "Collision Types", "Lighting", "Intersection", and "Traffic Control", respectively. An additional variable that adds to the understanding of AV crashes is crashes during rain (15.4% against 2.8% overall). The crash narratives from this cluster show that, in many crashes, an HDV rolled forward and collided with the AV after both vehicles were stopped at a red light. Driver's attitudes towards AVs, including the novelty effect of the technology, might explain the observed behavior, as discussed by Chen et al. (2020). For example, the AV crash narratives show many instances of road users directly trying to damage or incapacitate the AV.

Finally, Group 12 represents predominantly side swipe crashes on narrow streets, as seen by the AV events "v2 from opposing", "v2 pass v1 on left", and "v2 contact v1" in the group's most common sequence of events. The group has a higher proportion of the values "side swipe" (87.5% against 25.7% overall)," daylight" (69.2% against 54.3% overall), and "no" (75% against 32.1% overall), for the variables "Collision Types", "Lighting", and "Intersection", respectively. Additional variables also add to the understanding of AV crashes, such as crashes during clear weather (100% against 88.3% overall). Other than the challenge faced by AV in narrow streets, the results presented above might be explained by the test ODD used by the manufacturers, which might focus on particular types of streets.

Temporal and Manufacturer-specific Trends

This section presents the temporal and manufacturer-specific evaluation of the groups discussed above. The findings are particularly relevant in a mixed-fleet environment, offering valuable insights for directing the future of AV development and guiding public sector regulation and policy development.

Temporal Trends

Figure 5 shows the temporal trends for each of the groups detailed above, including crash counts (Figure 5a) and the proportion of crashes (Figure 5b). The first observable trend in Figure 5a is the increase in AV crash reporting, which aligns with the increase in miles driven by these vehicles and the number of test vehicles. The clear exception for the trend is 2020, with the reduced AV testing (and human-driven vehicles on the road) caused by the COVID-19 pandemic.

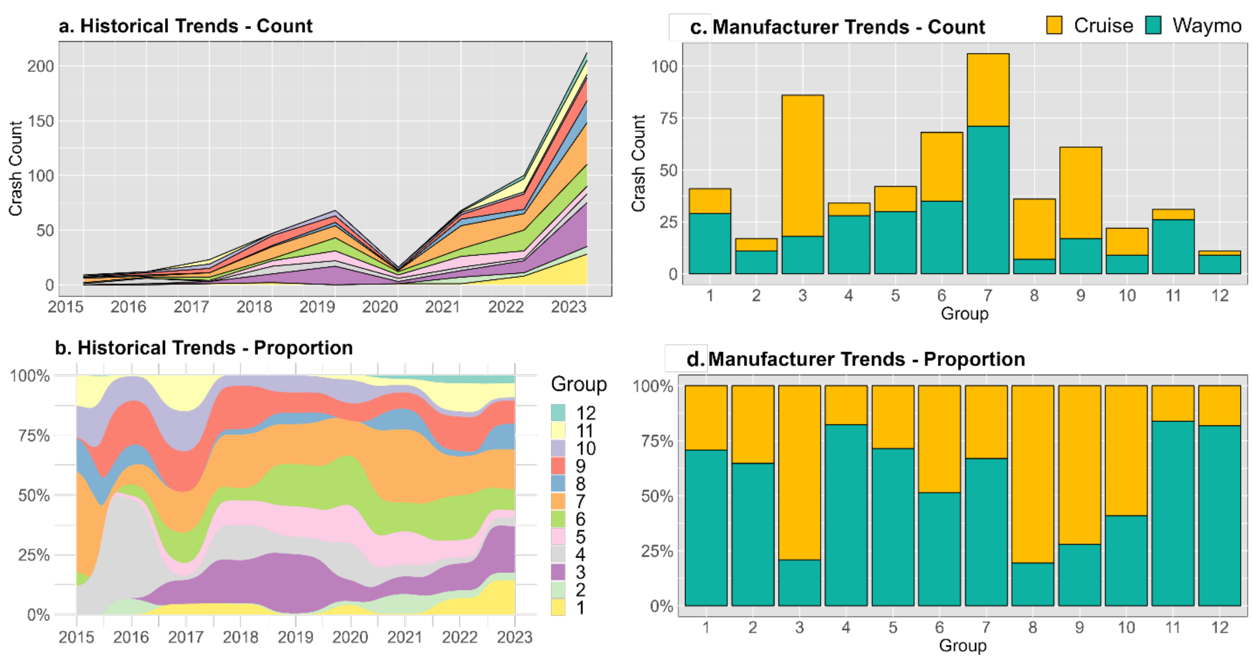


Figure 5. Historical and Manufacturer trends for AV crashes by group.

Considering the yearly proportion of crashes contributed by each group shown in Figure 5a, Groups 4 (right-turns) and 5 (left-turns) show a decline in their proportional contribution in recent years. This result might be associated with enhancements in the manufacturers' algorithms designed to mitigate human expectancy issues related to these movements, thereby reducing the number of rear-end collisions involving AVs in these scenarios. However, Groups 6 and 7 (rear end crashes following a stopping or stopped vehicle in front), which also reflect human expectancy challenges and related rear-end collisions, have remained relatively stable in terms of crash proportion over time. These findings highlight the complexity of designing systems that match the driving behavior of the general population while maintaining a desirable level of safety.

Group 3 (diverse types of vehicle contact), which has also remained relatively stable over time, underscores the importance of high-quality data on crash narratives and the derived sequence of events. More specifically, the diversity of crashes observed within this group hinders the understanding of specific temporal trends.

On the other side of the spectrum, Groups 1 (collision with objects), 11 (rear end crashes following the stopping of both vehicles involved), and 12 (collision in a narrow road) show an increase in their proportional contribution in recent years. The results for Group 1 might indicate a collateral effect of the changes observed in Groups 4 and 5, with increased aggressiveness from AVs resulting in a higher percentage of collisions with objects on the road. For Group 11, the rise in crash proportion might be related to an increasingly adverse environment for AV operation, with a growing number of aggressive actions from humans towards AVs observed in the existing crashes. Finally, the results for Group 12 might also indicate an increase in aggressiveness from AVs, as well as increased testing in challenging locations.

Manufacturer Trends

Figure 5 also presents the specific challenges faced by each of the two manufacturers (Cruise and Waymo) analyzed in this research. Groups 3 (unknown or diverse vehicle contact) and 8 (running a red light/stop sign) are particularly challenging for Cruise vehicles, with more than 75% representation of the crashes in these groups. On the other hand, Groups 4 (right-turns), 11 (rear end crashes following the stopping of both vehicles involved), and 12 (collision on a narrow road) are particularly challenging for Waymo vehicles.

Interestingly, as presented above, Groups 11 and 12 are happening proportionally more in recent years, which might indicate a bigger challenge from Waymo in terms of public acceptance and trust (Group 11), and the recent choice of testing environment (Group 12). Group 4, on the other hand, indicates an improvement over time in the manufacturer's performance at right-turn movements. The present analysis, however, must be cautious given the self-reported nature of AV crash narratives, although a higher level of encoding was used to address this bias, by aggregating similar narrative items into the same code.

Expectancy Violations in AV Crashes

Narratives in the AV crash data were reviewed to identify the presence of expectancy violations. Narratives of AV Crashes representing Turning Movements (Groups 4 and 5) and Vehicle Crossings (Group 8) indicate expectancy violation played a role in the crashes.

Groups 4 and 5 represent crashes during right and left turn movements, respectively. The collision type was predominantly rear end: 88.9% and 83.3% for Groups 4 and 5, respectively. Seventy-six out of the 555 AV crashes belong to these two groups. Narratives from two of the crashes are presented below:

- "*While in autonomous mode, the Waymo AV was stopped at a red traffic light… After the traffic light turned green, the Waymo AV began to proceed and then came to a stop as it yielded to oncoming traffic also entering the intersection. A passenger vehicle behind the Waymo AV then made contact with the stationary Waymo's rear bumper at approximately 5 MPH*."

- "*The Waymo AV was preparing to make a right-on-red from … onto … and was yielding to cross-traffic when a passenger vehicle made contact with the Waymo AV's rear bumper at approximately 3 MPH."*

The predominance of rear end crashes and the example narratives suggest additional caution from AVs during turns, which can lead to rear end crashes. This is also supported by the discussions of Boggs et al.(2020a) and Wang & Li (2019), and might be associated with several factors, such as the misjudgment from the AVs regarding the conflicts on the road (Boggs, et al., 2020b; Junghans et al., 2021), the misjudgment from the following vehicles regarding the braking behavior of AVs (Boggs, et al., 2020b; Liu et al., 2021; Novat et al., 2023), and difference between yielding behavior of AVs and HDVs (Liu et al., 2024).

Group 8 represents predominantly crashes involving vehicles crossing paths. Thirty-six out of the 555 AV crashes belong to Group 8. Narratives from two crashes are presented below:

- "*The Audi rolled through the stop-sign and struck the right rear quarter panel and right rear wheel of the Lexus AV. Prior to the collision; the Lexus AV's autonomous technology began applying the brakes in response to its detection of the Audi's speed and trajectory. Just before the collision, the driver of the AV disengaged Autonomous Mode and took manual control of the vehicle*."

- *"A Cruise autonomous vehicle ("AV"), operating in driverless autonomous mode, was traveling…. As the AV was passing through the intersection .. on a green light, a fire truck with emergency lights traveling … entered the intersection and made contact with the AV, damaging the front and rear passenger side of the AV. Police and Emergency Medical Services (EMS) were called to the scene. The AV was towed from the scene."*

AV crash narratives suggest that the crashes in Group 8 are caused by a red light or stop sign violation from a second vehicle involved. This result suggests that HDVs are violating expectancies of AVs. The second crash narrative suggests that the AV violated the expectancy of the fire truck traveling with emergency lights.

In summary, two kinds of expectancy violations were observed in AV crashes:

1. AV violating expectancy: Hesitation/caution in permissive turning movements and not yielding to emergency vehicles.
2. HDV violating expectancy: Running stop signs or red lights at intersections.

While the following expectancy violations were not observed in the AV crash narratives, the research team would recommend incorporating them into future research on the safety impacts of expectancy violations:

1. Change interval at signalized intersections: Difference in AV and HDV response to change interval when the vehicle is present in the dilemma zone could result in crashes.
2. Turning vehicles yielding to pedestrians/bicyclists at intersections: Extra cautious yielding or stopping of turning AVs for pedestrians/bicyclists could result in rear end crashes.

CHAPTER 4. Conclusions and Recommendations

The present study applied Crash Sequence Analysis to identify patterns in AV and HDV crashes. Data from 555 AV crashes and 39,270 HDV crashes were used. Overall data analysis shows that intersections are much more challenging to AVs than to HDVs (despite likely differences in exposure), with nearly twice the proportion of crashes occurring at intersections (68.5% for AV against 34.9% for HDV). Other interesting observations are the higher proportion of rear end crashes and the much lower severity for AV crashes.

Context-specific analysis shows that, although many groups contain both AV and HDV clusters, the types of crashes can differ significantly. The first observable result is the presence of clusters representing pedestrian and bicyclist crashes only in the HDV data, which suggests that AVs might be exercising additional caution around vulnerable road users or that the technology is better than human eye sight, which is either way very welcome and needed. A second trend is the difference in crash patterns between AVs and HDVs during right and left turns. For these movements, while rear end is the most common crash type for AV, angle is the most common for HDV crashes. This particular outcome might indicate greater caution and/or hesitation from AVs, and aggressive behavior from HDVs, which is in turn supported by the higher severity rate and the higher-than-average presence of speeding in these groups. A similar trend of rear end crashes is observed during the deceleration or stopping movement of AVs, which happen mostly at intersections and indicate a challenge for AVs. Another relevant observation is the greater presence of crashes involving red light/stop sign violations by a second vehicle involved in AV crashes; suggesting a failure from the AVs to anticipate other vehicle's violations. Finally, the results show three groups with contexts particular to the AV dataset, which include rear-end collisions following an HDV's lane change, rear-end collisions with both vehicles stopped, and sideswipes on narrow streets. These unique contexts can indicate both technological challenges and the difference in crash exposure caused by the manufacturer's ODD.

Narratives of AV Crashes representing Turning Movements and Vehicle Crossings indicate expectancy violation played a role in these crashes. AVs violated expectancy of HDVs with hesitation/caution in permissive turning movements and not yielding to emergency vehicles. HDVs violated expectancy of AVs by running stop signs or red lights at intersections. Expectancy violations could happen due to the difference in AV and HDV behavior during change interval at signalized intersections and while turning vehicles yield to pedestrians/bicyclists at intersections.

Systematic human-in-the-loop (HIL) experiments simulating AV-HDV-Pedestrian and AV-HDV interactions should be conducted to probe expectancy violations and safety impacts in future research.

References

Boggs, A. M., Arvin, R., & Khattak, A. J. (2020a). Exploring the who, what, when, where, and why of automated vehicle disengagements. Accident Analysis & Prevention, 136, 105406. https://doi.org/10.1016/j.aap.2019.105406

Boggs, A. M., Wali, B., & Khattak, A. J. (2020b). Exploratory analysis of automated vehicle crashes in California: A text analytics & hierarchical Bayesian heterogeneity-based approach. Accident Analysis and Prevention, 135. https://doi.org/10.1016/j.aap.2019.105354

California DMV. (2023). Autonomous Vehicle Collision Reports. https://www.dmv.ca.gov/portal/vehicle-industry-services/autonomous-vehicles/autonomous-vehicle-collision-reports/

Chen, H., Chen, H., Liu, Z., Sun, X., & Zhou, R. (2020). Analysis of Factors Affecting the Severity of Automated Vehicle Crashes Using XGBoost Model Combining POI Data. Journal of Advanced Transportation, 2020. https://doi.org/10.1155/2020/8881545

Dixit VV, Chand S, Nair DJ (2016) Autonomous Vehicles: Disengagements, Accidents and Reaction Times. *PLOS ONE*, 11(12)https://doi.org/10.1371/journal.pone.0168054

Gabadinho, A., Ritschard, G., Studer, M., & Muller, N. S. (2010). Mining sequence data in R with the TraMineR package: A user's guide.

Jin, X., & Han, J. (n.d.). K-Medoids Clustering. Encyclopedia of Machine Learning and Data Mining.

Junghans, M., Krauns, F., Sonka, A., Böhm, M., & Dotzauer, M. (2021). Comparison of safety and kinematic patterns of automated vehicles turning left in interaction with oncoming manually driven vehicles. Transactions on Transport Sciences, 12(3), 55–66. https://doi.org/10.5507/tots.2021.003

Kutela, B., Avelar, R. E., & Bansal, P. (2022). Modeling Automated Vehicle Crashes with a Focus on Vehicle At-Fault, Collision Type, and Injury Outcome. Journal of Transportation Engineering Part A: Systems, 148(6). https://doi.org/10.1061/JTEPBS.0000680

Kutela, B., Dzinyela, R., Haule, H., Sheykhfard, A., & Msechu, K. (2023). Leveraging autonomous vehicles crash narratives to understand the patterns of parking-related crashes. Traffic Safety Research, 4. https://doi.org/10.55329/fiqq8731

Lee, S., Arvin, R., & Khattak, A. J. (2023). Advancing investigation of automated vehicle crashes using text analytics of crash narratives and Bayesian analysis. Accident Analysis and Prevention, 181. https://doi.org/10.1016/j.aap.2022.106932

Liu, P., Guo, Y., Liu, P., Ding, H., Cao, J., Zhou, J., & Feng, Z. (2024). What can we learn from the AV crashes? – An association rule analysis for identifying the contributing risky factors. Accident Analysis and Prevention, 199. https://doi.org/10.1016/j.aap.2024.107492

Liu, Q., Wang, X., Wu, X., Glaser, Y., & He, L. (2021). Crash comparison of autonomous and conventional vehicles using pre-crash scenario typology. Accident Analysis and Prevention, 159. https://doi.org/10.1016/j.aap.2021.106281

Monticello M Tesla's "Full Self-Driving Capability" Falls Short of Its Name. *Consumer Reports*, https://www.consumerreports.org/autonomous-driving/tesla-full-self-driving-capability-review-falls-short-of-its-name/

NHTSA. (2023). Standing General Order on Crash Reporting. https://www.nhtsa.gov/laws-regulations/standing-general-order-crash-reporting

Novat, N., Kidando, E., Kutela, B., & Kitali, A. E. (2023). A comparative study of collision types between automated and conventional vehicles using Bayesian probabilistic inferences. Journal of Safety Research, 84, 251–260. https://doi.org/10.1016/j.jsr.2022.11.001

Patel, R. K., Channamallu, S. S., Khan, M. A., Kermanshachi, S., & Pamidimukkala, A. (2023). An Exploratory Analysis of Temporal and Spatial Patterns of Autonomous Vehicle Collisions. Public Works Management and Policy. https://doi.org/10.1177/1087724X231217677

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., VanderPlas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, E. (2012). Scikit-learn: Machine Learning in Python. CoRR, abs/1201.0490. http://arxiv.org/abs/1201.0490

Petrovic, D., Mijailović, R., & Pešić, D. (2020). Traffic Accidents with Autonomous Vehicles: Type of Collisions, Manoeuvres and Errors of Conventional Vehicles' Drivers. Transportation Research Procedia, 45, 161–168. https://doi.org/10.1016/j.trpro.2020.03.003

Rousseeuw, P. J. (1987). Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. Journal of Computational and Applied Mathematics, 20, 53–65. https://doi.org/10.1016/0377-0427(87)90125-7

Song, Y. (2021). Traffic Crash Patterns and Causations Based on Sequence of Events: Preparing for a Transition into Automated Transportation. The University of Wisconsin-Madison.

Song, Y., Chitturi, M. V., & Noyce, D. A. (2021). Automated vehicle crash sequences: Patterns and potential uses in safety testing. Accident Analysis & Prevention, 153, 106017. https://doi.org/10.1016/j.aap.2021.106017

Song, Y., Chitturi, M. V., & Noyce, D. A. (2022). Intersection two-vehicle crash scenario specification for automated vehicle safety evaluation using sequence analysis and Bayesian networks. Accident Analysis & Prevention, 176, 106814. https://doi.org/10.1016/j.aap.2022.106814

Song, Y., Chitturi, M. V., & Noyce, D. A. (2023). Impact of event encoding and dissimilarity measures on traffic crash characterization based on sequence of events. Accident Analysis & Prevention, 185, 107016. https://doi.org/10.1016/j.aap.2023.107016

Tennant C, Howard S, Franks B, Bauer M, Stares S, Pansegrau P, Stysko-Kunkowska M, Cuevas-Badallo A (2017) Autonomous Vehicles–Negotiating a Place on the Road: A Study on How Drivers Feel about Interacting with Autonomous Vehicles on the Road.

Wang, S., & Li, Z. (2019). Exploring causes and effects of automated vehicle disengagement using statistical modeling and classification tree based on field test data. Accident Analysis and Prevention, 129, 44–54. https://doi.org/10.1016/j.aap.2019.04.015

Wang, T., Chen, J., Li, W., Chen, J., & Ye, X. (2024). A Precrash Scenario Analysis Comparing Safety Performance across Autonomous Vehicle Driving Modes. Journal of Advanced Transportation, 2024. https://doi.org/10.1155/2024/4780586

Ye, W., Wang, C., Chen, F., Yan, S., & Li, L. (2021). Approaching autonomous driving with cautious optimism: Analysis of road traffic injuries involving autonomous vehicles based on field test data. Injury Prevention, 27(1), 42–47. https://doi.org/10.1136/injuryprev-2019-043402

APPENDIX: Final Documentation of Outputs, Outcomes, and Impacts

USDOT Performance Indicators I

Three (3) transportation-related courses were offered during the study period by the PIs and the teaching assistant associated with the research project. These courses include CEE 370 (Transportation Engineering), CEE 572 (Transportation Operations), and CEE 679 (AI & Data Science in Transportation). One (1) graduate student participated in this research project during the study period.

USDOT Performance Indicators II

Research Performance Indicators:

- Three journal articles have been published. One each in Accident Analysis and Prevention, IEEE Transactions on Intelligent Transportation Systems, and the Transportation Research Record. One article in under review with Safety Science.
- One conference presentation was made at the 2026 Transportation Research Board (TRB) Annual Meeting.

Leadership Development Performance Indicators: This research project generated two (2) academic engagements and one (1) industry engagement. The PIs held positions in six national and international organizations addressing issues related to the scope of this research, including Transportation Research Board Transportation Operations and Management Section, International Advisory Committee for International Symposium on Traffic and Transportation Theory, AAA Foundation for Traffic Safety's Safe Mobility Conference, ASCE Connected & Autonomous Vehicle Impacts Committee, IEEE Emerging Transportation Technology Testing Technical Committee, and International Symposium on Navigating the Future of Traffic Management. The PIs also held editorial positions in five international journals, *ASCE Journal of Transportation Engineering, Part A: Systems*, *IEEE Transactions on Intelligent Transportation Systems*, *Transportation Research Part B*, *Transportation Science*, and *Transportation Research Record*. he ASCE Transportation and Development Institute awarded Dr. David Noyce, the 2026 James Laurie Prize for contributions to the advancement of transportation engineering.

Education and Workforce Development Performance Indicators: The research outcomes, including the developed methodologies, will be incorporated into course content for CEE 572 (Transportation Operations) and CEE 679 (AI & Data Science in Transportation) at the University of Wisconsin-Madison. The students in these classes will soon be entering the workforce. Thereby, the research helped enlarge the pool of people trained to develop knowledge and utilize at least a part of the technologies developed in this research, and to put them to use when they enter the workforce.

Outputs

- Journal Article: Andriola, C., Chitturi, M., Noyce, D. A. (2026) Exploring Temporal and Manufacturer-specific Trends of Automated Vehicle Crashes Using Sequence of Events. *IEEE Transactions on Intelligent Transportation Systems, 1–5.* https://doi.org/10.1109/TITS.2026.3659741

- Journal Article: Andriola, C., Chitturi, M. V, Bill, A., & Noyce, D. A. (2025). Supporting the Safe System Approach Decision-Making Through Crash Sequence Analysis. *Transportation Research Record: Journal of the Transportation Research Board*. https://doi.org/10.1177/03611981251381766
- Journal Article: Andriola, C., Chitturi, M. V., Noyce, D. A. & Song, Y. (2025). How Similar or Different are Automated Vehicle and Human-driven Vehicle Crash Patterns? Findings from Crash Sequence Analysis. *Accident Analysis & Prevention, 222, 108239.* https://doi.org/10.1016/j.aap.2025.108239
- Conference Presentation: Andriola, C., Chitturi, M. & Noyce, D. A. (2026). The Challenges of Automated Truck Deployment: A Crash Sequence of Events Analysis Based on Semi-Truck Crashes. 105th Annual Meeting of the Transportation Research Board.

Outcomes

The outcomes of this project contribute to the advancement of understanding of safety of AVs. By applying crash sequence analysis, the study identified patterns in AV and HDV crashes and how similar or different they are. Additionally, this research identified scenarios where expectancy violations played a role in AV crashes. These scenarios can be used to test safety performance of AVs in AV-HDV and AV-HDV-pedestrian interactions and can support development of safer AVs. The findings also inform researchers and practitioners working at the intersection of traffic safety, AV development, and human factors. In addition, this project has contributed to graduate-level research training in CAV safety and data science, supporting workforce development in emerging transportation technologies.

Impacts

The application and dissemination of the project's outputs are anticipated to catalyze significant positive impacts on the transportation system safety. Laying the foundation for understanding and quantifying the interactions of AVs with other road users will enable the development of safer AVs that results in greater trust and consequently the eventual adoption of AVs in the broader society. AVs are expected to have a radical impact on the safety outcomes on our roadways. Through our research dissemination and education, this research will equip engineers, researchers, and professionals with the knowledge and skills to continue advancing the field of AV safety and development. This will ensure a sustained impact on the transportation system's safety, reliability, and efficiency.