Driverless Accidents: Studying and Analyzing Autonomous Vehicle Incident Reports in California and Other States

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Abstract

In recent years, there have been considerable advancements in Autonomous Vehicles (AVs), including in artificial intelligence (AI). However, using opaque AI technology can impose risks, leading to unsafe driving maneuvers and car accidents. Therefore, it is necessary to analyze the safety and efficiency of these AVs. This research paper presents a comprehensive analysis of autonomous vehicle accidents occurring in the United States and with a focus on accidents reported from California. Through this study, we aim to identify patterns, trends, and contributing factors associated with AV accidents. Through this research, we want to create a more informed analysis of AV accidents and provide insights to policymakers, industry stakeholders, and researchers working in the field.

Introduction

Recent advancements in artificial intelligence (AI) have accelerated the development of autonomous vehicles (AVs). One of the benefits of AVs is to provide safe, efficient, and accessible services. However, current deployed self-driving vehicles have not proven to be safe, as evidenced in recent accidents [1].According to a recent study, perceived safety, trust in technology, and control over the vehicle are critical psychological factors that determine the public's willingness to adopt AVs (Yuen et al. 2020). One of the big problems in addressing and assessing AV safety is that they are complex systems built out of many (possibly opaque) parts.

AVs rely on a combination of sensors, including LiDAR, radar, and cameras, to perceive their environment. However, these sensors can be susceptible to errors due to adverse weather conditions, poor lighting, or obstructions. Ensuring AVs can accurately detect and interpret their surroundings under all conditions is crucial for safety. At the same time, AI systems that drive AVs must also make complex ethical considerations and risk assessments, particularly in unavoidable collision scenarios. Improvements in these algorithms are essential to ensure that AVs make the safest possible decisions in every situation. This is especially important for regulatory compliance. If an AV gets into an accident, auditors, regulators and the public will want to know what happened and why.

Governments and regulatory bodies must establish comprehensive safety standards and testing protocols to ensure AVs meet high safety benchmarks before being deployed on public roads. Continuous monitoring and updating of these standards based on real-world data and technological advancements are necessary. A key part of regulatory oversight is to analyze past AV accidents for trends, patterns, and analysis.

California has been at the forefront of this technological revolution by enacting regulations allowing the testing and deployment of autonomous vehicles on public roads in 2014 (DMV 2024). From 2014 to 2018, the state has made incremental regulation updates by consistently conducting a series of public hearings and workshops. In 2019, the state also passed regulations for testing and deploying autonomous motor trucks that weigh less than a certain amount. Thanks to this proactive regulatory approach, the state has drawn many tech businesses and startups to test their AV technology. Since then, California has witnessed a steady increase in AV presence and activity from companies such as Waymo, Cruise, General Motors, Mercedes Benz, etc (Favarò et al. 2017).

The Department of Motor Vehicles (DMV) California publicly releases datasets about vehicle disengagement and crash reports. The former provides summaries of instances when a human driver had to take control of the vehicle due to technology failure or safety concerns. While several researches have been conducted on the disengagement dataset (Zhang, Yang, and Zhou 2022)(Favarò, Eurich, and Nader 2018)(Sinha et al. 2021), our focus for this research will be on the crash reports. On the other hand, the National Highway Traffic Safety Administration (NHTSA) has established a framework for publicly releasing data on crashes involving AVs and vehicles equipped with advanced driver assistance systems (ADAS). The Standing General Order issued in 2021 requires manufacturers and operators of vehicles with Level 2 ADAS and Levels 3-5 Automated Driving Systems (ADS) to report certain crashes to NHTSA. This includes crashes when the systems are engaged at least 30 seconds before the incident. In this study, we also include data from the NHTSA about the vehicles equipped with ADS as

[1]https://www.theguardian.com/technology/2023/nov/08/cruise-recall-self-driving-cars-gm

they fall under the same category of vehicles from CA DMV reports.

These reports provide factors that may have contributed to the accident, including but not limited to time, location, mode of the vehicle movement (s), road surface conditions, weather conditions, and lighting conditions. However, many reports have information that is "Not Available" or labeled as "Other" with no definition for the same. While, in total, around 379 reports were analyzed from the DMV and approximately 700 reports from the National Highway Traffic Safety Administration (NHTSA), many had missing information or did not follow a uniform format.

On a national scale, there is a large-scale distinction in regulations for AVs (West and Karsten 2018). Only a few states now have extensive laws that control the development and use of autonomous cars. States like Arizona (ADOT 2024), Texas (TDOT 2024), and Florida (FSHMV 2024) have also become significant centers for AV testing, driven by their regulatory frameworks, which, in many cases, are designed to attract AV companies by offering a less restrictive environment than California. Under a series of executive orders, Arizona has had a relatively unrestricted AV testing and deployment process since 2015 (ADOT 2024). This emphasizes the state's commitment to serving as a pro-innovation hub for developing technologies. Florida's regulations are also less restrictive, allowing companies to test and deploy AVs more quickly than in California (Terwilleger 2015).

This research paper seeks to address the need to understand AV failures by thoroughly analyzing AV accidents in the United States from 2016 to 2024. California Department of Vehicles (DMV) releases official accident reports certified by the manufacturer of the AV involved in the accident. By examining factors such as weather, road conditions, accident locations, type of accidents, etc, this research aims to provide insights into the complexities of AV safety and inform strategies to mitigate risks associated with autonomous driving.

Previous Work

In (Favarò, Eurich, and Nader 2018), the authors analyze disengagement reports and collisions involving AVs, focusing on the California DMV mandate that trained human drivers should remain behind the wheel during testing, regardless of autonomy level and how often the drivers take control of the vehicle. It highlights the types of reports required for post-testing failures and accidents, providing a good basis for understanding regulatory impacts on AV safety.

(Almaskati, Kermanshachi, and Pamidimukkala 2024) is more of a survey on crash report analyses done by various California DMV data studies. It includes statistics on crash types common to AVs, such as rear-end and sideswipe collisions. The authors also look into the different behavioral patterns of AVs compared to human drivers (in other vehicles involved in the accident) that might contribute to these incidents. Authors of (Favarò, Eurich, and Nader 2018) take a comprehensive look at the frequency and types of disengagements in AVs, their causes, and how they relate to accident rates. These events are crucial for evaluating the performance and safety of AVs, as they provide insights into situations where the technology cannot handle certain driving conditions or unexpected scenarios.

(Abdel-Aty and Ding 2024) comprehensively compares accidents involving AVs and human-driven vehicles (HDVs). It analyzes the conditions under which these accidents occur, such as weather and road types. It discusses the outcomes, suggesting AVs result in fewer severe injuries than HDVs. On the other hand, (West and Karsten 2018) discusses the legal aspects of AVs in traffic, focusing on the regulatory impact and how it shapes the deployment and integration of autonomous driving technologies. While it does not focus on any technical aspect of AVs, the authors explore the role of national and state regulations in shaping the legal landscape for AVs, which could provide insights into how legal factors impact AV accidents and their analyses. (Liu et al. 2021) analyzes the differences in pre-crash scenarios between AVs and conventional vehicles, providing insights into the common types of accidents that occur and the factors leading up to these accidents. It discusses the higher likelihood of certain types of crashes with AVs compared to traditional vehicles.

Methodology

First, the data ic collected from the CA DMV and NHTSA website. This includes all the reports generated between the years 2019 to 2024. In the next step, we analyze these documents. Finally, data analysis can be done using visualization tools such as seaborn and matplotlib to parse the data. We also use scipy, a fundamental algorithms library for statistical analysis.

Data Collection and Processing

The CA DMV website provides a list of all the accident reports submitted to the DMV by the manufacturers and verified by the relevant authority. The reports before 2019 can be requested from the DMVs archival team that is available to the general public. We use the beautifulsoup library to scrape the website and get the available documents. The archived documents are not available directly on the website but can be requested via email. The documents post-2019 can be parsed by using PyPDF2, which is a Python library that can parse check-boxes and text-boxes in PDFs. On the other hand, the reports before 2019 are scanned. As a result, we use OCR to read through the PDFs and collect the data. The script collects all forms of data from text boxes with event descriptions (location, time, details of accident) to check-boxes about the accident (mode of car, movement, weather, visibility). On the other hand, the NHTSA provides data in the form of an excel sheet that is equivalent to the parsed data from CA DMV.

Statistical Analysis

The Chi-Square test is a statistical method used to determine if there is a significant association between two categorical variables. It's commonly used in hypothesis testing to compare observed data with data we expect to obtain according

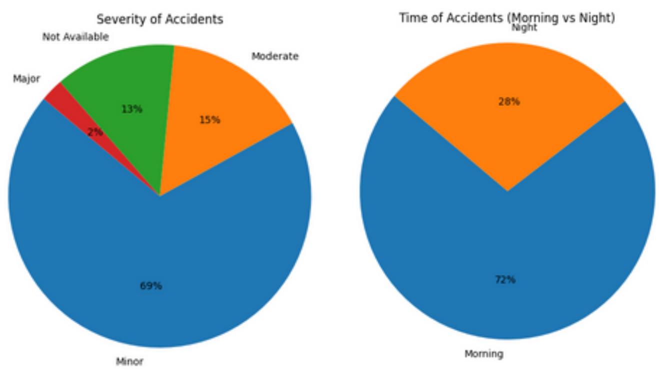

Figure 1: The distribution of the severity of accidents and time of the incidents

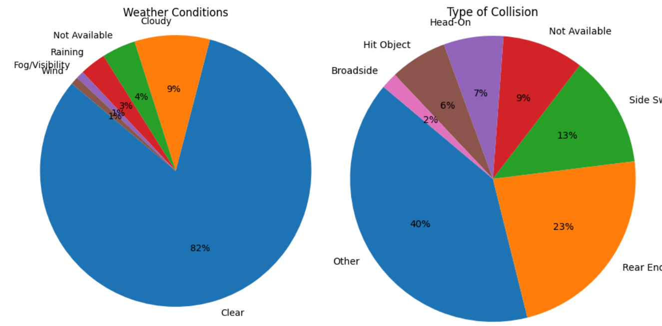

Figure 2: Distribution of the weather condition on the day of the incident and Distribution of the type of collision with secondary car/object

to a specific hypothesis. We used the Chi-Square Test of Independence to determine whether there is a significant relationship between two categorical variables. For example, it can test if the frequency of one categorical variable differs across the levels of another categorical variable (e.g. if voter preference differs by age group).

Results

The primary columns extracted from the PDFs include the time/date of the accident, the location of an accident, the severity of the accident, the weather during the accident, the location of the damage on the vehicle, and the mode/-movement of the car during the accident. Along with this the NHTSA also provided information such as speed limit of the road, speed limit before the accident along with the previously mentioned factors. Based on these, the following charts can be generated.

Figure 1 shows the distribution of the severity of accidents and time of the incidents, respectively. Most accidents have been categorized as Minor, meaning the AV did not get a lot of damage. This is followed by Moderate and, finally, Major. This shows that most accidents have not been catastrophic and are severely dangerous. Furthermore, most accidents were reported during the day (assuming time between 6:00 and 18:00 as daytime). This can be attributed to the amount of traffic during the day compared to night time, which is significantly higher. However, it would be more beneficial if the reports also included information about whether it was during daylight hours, as they only talk about visibility and street lighting, not sunlight.

Figure 2 shows the distribution of weather at the time of the accident. We can see that the weather does not have a significant effect on the incident itself. Considering the assumption that California weather also tends to follow the same distribution pattern, we can assume that weather does not contribute to the cause of the incident. The figure also shows the distribution of the type of collisions (point of view of the AV) that have taken place during the incident. The reports do not give a clear definition of “Other”; however, they cannot be categorized in any of the other categories. We can also see that most incidents are side-swipes or rear ends. This shows that most accidents have occurred due to mistakes or maneuvers made by the secondary vehicle, i.e., the human driven vehicle. This is also on par with the previous research, which has attributed most incidents to mistakes caused by secondary vehicle drivers (Ding et al. 2023).

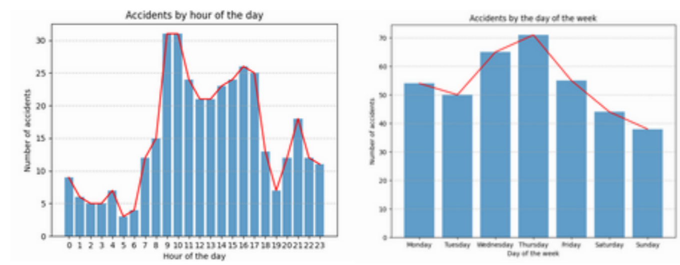

Figure 3: Number of accidents vs the hour at which the accidents vs the hour at which the incident took place for undamaged cars (on the left) and damaged cars (on the right)

Figure 3 shows the distribution of the number of accidents by hour of the day for all cars and only damaged cars, respectively. We can see that most accidents happen between 7:00 to 18:00 hours, with peaks around 9:00 and 4:00. This can again be attributed to the number of cars on the roads during these hours, which would be higher than usual as commuters would be traveling to and from work. In both these graphs, another peak can be observed around 21:00 hours. It also shows the number of accidents vs. the day the incident occurred. There is a slight uptick in the number of accidents on Wednesdays and Thursdays. One hypothesis could be that since most places of accidents have been restricted to the Bay Area, where flexible work weeks and hybrid word settings are typical, people tend to work mainly during these days, causing more vehicles to be on the road.

Figure 4 is calculated using the NHTSA data and it shows the frequency of the accidents along with the speed posted at the roads and the speed at which the car was travelling. We can see in the graph on the left, that most cars with ADS mode were travelling on roads with speed between 20 mph to 40 mph. This also checks out since most states only allow fully autonomous modes in commercial districts and residential areas and not on public highways. On the other hand,

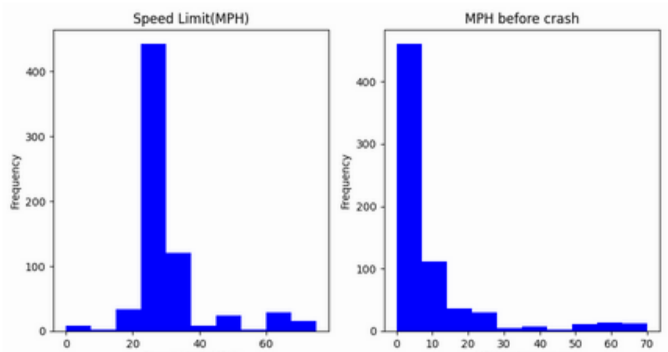

Figure 4: Frequency of the number of accidents vs posted speed limit on the roads and frequency of the number of accidents vs the speed of the car right before the accident

the speed of the vehicle right before crashing is usually between 0 mph to 20 mph. Either, this could be due to the fact that the vehicle was at standstill, explaining the uptick in the lower speed ranges or the vehicle slows down too rapidly. This would support the other statistic that most accidents are caused due to a secondary vehicle rear-ending the ATV.

Chi-Square Statistic

The Chi-Square (χ^2) test is a statistical method used to determine if there is a significant association between two categorical variables. This non-parametric test compares the observed frequencies in each category of a contingency table to the expected frequencies derived from the null hypothesis, which assumes no association between the variables.

$$x^2 = \sum \left(O_i - {E_i}^2/E_i\right)$$

P-value The P-value is a probability that measures the evidence against the null hypothesis. It is calculated based on the Chi-Square statistic and the degrees of freedom. The P-value indicates the likelihood of obtaining a Chi-Square statistic at least as extreme as the one observed, assuming that the null hypothesis is true.

• Low P-value (≤ 0.05): Indicates strong evidence against the null hypothesis, leading to its rejection. This suggests that there is a significant association between the variables.

• High P-value (> 0.05): Indicates weak evidence against the null hypothesis, leading to its acceptance. This suggests that there is no significant association between the variables.

Degrees of Freedom The degrees of freedom (df) in a Chi-Square test of independence are calculated based on the number of rows (r) and columns (c) in the contingency table:

$df = (r-1)x(c-1)$

The degrees of freedom determine the shape of the Chi-Square distribution and are essential for interpreting the Chi-Square statistic. They reflect the number of independent values or quantities that can vary in the analysis.

Table 1 shows the values generated by the Chi-square model. To understand the factors that most affect the outcome, which in our case is the type of damage on the car, we look for categories with a high chi-square value and a low p-value. This would indicate a significant association between the input category and the target. There is a substantial association between roadway conditions and the incidents involving Vehicle 1, indicating that certain roadway conditions may influence the likelihood of incidents. Weather conditions also significantly affect the incidents involving Vehicle 1, suggesting that adverse weather may increase the risk of accidents. Furthermore, lighting at the time of the incident significantly impacts the accidents involving Vehicle 1.

Limitations

One of the main limitations of this study is the reliance on the available 1000 reports from the CA DMV and NHTSA, which may not capture all incidents or the full range of factors contributing to these accidents. Furthermore, the absence of detailed reports on specific variables, such as the vehicle's speed before the accident being uniformly given across all reports, restricts our ability to analyze the risk factors comprehensively. This limitation underscores the need for more granular data collection and reporting processes to enhance the accuracy and depth of future research.

Discussion

Through the research, we have found some specific key points that can be analyzed through the reports. We have found that most autonomous vehicles have faced accidents due to faults by secondary vehicles and that these accidents peak during specific periods of time during the day. Until more research can be done into discovering how autonomous vehicles can safely predict human behavior in driving, testing could be restricted to non-peak hours as this can prevent accidents and save manufacturers resources. An important data point that these reports can include is input from the secondary vehicle driver about the maneuvers they will be trying to make and what they thought the AV was trying to do. This could shed more light on what the AV was failing to predict. However, current reports do not share this information. We can also see that while most accidents happen during daylight and routine weather, adverse weather and roadway conditions impact the accident's intensity, as shown by the statistical model.

Conclusion

In this study, we have comprehensively analyzed autonomous vehicle (AV) accidents using data from the California Department of Motor Vehicles. Our findings align with previous studies indicating that key factors in AV accidents are environmental conditions and vehicle modes during and leading up to accidents. This analysis reaffirms AV technology's complex challenges and emphasizes the importance of continued scrutiny and regulatory oversight to ensure public safety.

In our analysis of accident data, we found that the majority of accidents are minor in severity. Most of the accidents occurred during daylight hours, likely due to higher traffic volumes during typical commuting hour. Weather conditions

Table 1: Table shows the vales generated from the Chi-square statistical model. Here, the model is created based on the correlation of the categories to the severity of damage caused to the ATV.

Sr No	Category	Column Chi-Square Statistic	P-value	Degrees of Freedom
1	Vehicle 1 was Moving	0.908145	0 0.635037	2
2	Number of Vehicles involved in Accident (w V1)	3.974395	1 0.409482	4
3	Vehicle 2 was Moving	2.025679	2 0.363186	2
4	Number of Vehicles involved in Accident (w V2	2.598746	3 0.627045	4
5	Car Mode	0.902937	4 0.636693	2
6	Weather Vehicle 1	10.859083	5 0.028194	4
7	Weather Vehicle 2	10.143427	6 0.118741	6
8	Lighting Vehicle 1	6.354899	7 0.041692	2
9	Lighting Vehicle 2	5.752518	8 0.218408	4
10	Roadway Surface Vehicle 1	4.909849	9 0.296673	4
11	Roadway Surface Vehicle 2	2.297175	10 0.681283	4
12	Roadway Conditions Vehicle 1	8.900118	11 0.179274	6
13	Roadway Conditions Vehicle 2	11.488584	12 0.003201	2
14	Movement Preceding Collision Vehicle 1	15.513618	13 0.746303	20
15	Movement Preceding Collision Vehicle 2	11.815424	14 0.922282	20
16	Type of Collision Vehicle 1	16.245501	15 0.180249	12
17	Type of Collision Vehicle 2	8.534318	16 0.576793	10

appear to have a minimal impact on the occurrence of accidents. Additionally, the analysis of speed data shows that AVs are generally operating within speed limits, particularly in areas where autonomous driving is permitted, but often experience collisions at lower speeds, likely due to sudden stops or the presence of stationary vehicles. The type of collision that occurred was predominantly side-swipes or rear-end incidents. This can be attributed to errors made by human drivers of secondary vehicles.

Our findings demonstrate the importance of continued monitoring and refinement of AV technology, particularly in interactions with human-driven vehicles. The insights gained from this data are crucial for enhancing safety measures and developing strategies to minimize the occurrence of accidents, especially in urban environments where AVs are increasingly being integrated. Future studies could benefit from more granular data, such as daylight conditions, to further refine the understanding of factors influencing AV accidents.

Acknowledgments

We thank the University of California, Santa Cruz, (UCSC) for extending support at all stages of this study. We are incredibly grateful to the Department of Computer Science and Engineering and the Graduate Office for their constant support. We also want to thank the Artificial Intelligence Explainability Accountability (AIEA) Lab at UCSC for their valuable input.

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