Autonomous Delivery Vehicle as a Disruptive Technology: How to Shape the Future with a Focus on Safety?

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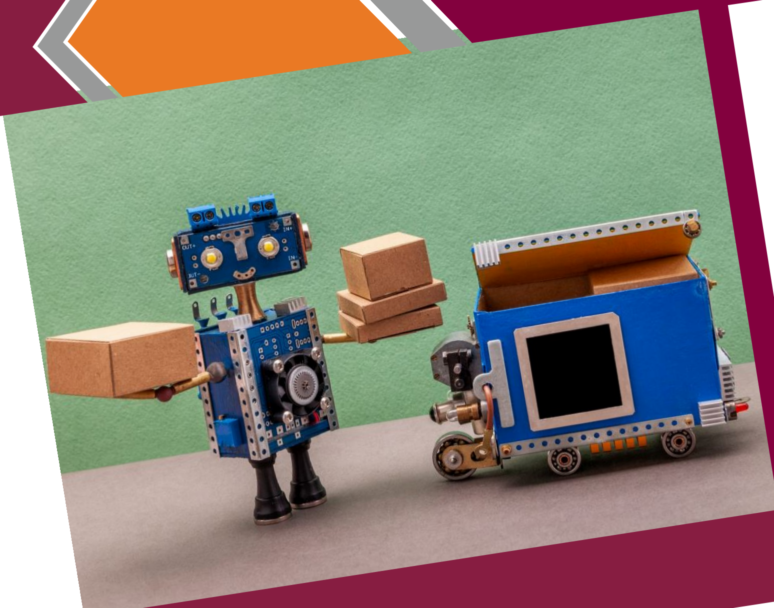

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The National Highway Traffic Safety Administration recently granted permission to deploy low-speed autonomous delivery vehicles (ADVs) on roadways. Although the mobility of ADVs is limited to low-speed roads and these vehicles are occupantless, frequent stops and mobility among residential neighborhoods cause safety-related concerns. There is consequently a need for a comprehensive safety impact analysis of ADVs. This study examined the safety implications and safety impacts of ADVs by using novel approaches. This research prepared several datasets such as fatal crash data, aggregated ADV trips and trajectories, and real-world crash data from the scenario design for an ADV-related operational design domain. Association rules mining was applied to the datasets to identify significant patterns. This study generated a total of 80 association rules that provide risk patterns associated with ADVs. The rules can be used as prospective benchmarks to examine how rule-based risk patterns can be reduced by ADVs that replace human-driven trips.</td></tr>
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Abstract

The National Highway Traffic Safety Administration recently granted permission to deploy low-speed autonomous delivery vehicles (ADVs) on roadways. Although the mobility of ADVs is limited to low-speed roads and these vehicles are occupantless, frequent stops and mobility among residential neighborhoods cause safety-related concerns. There is consequently a need for a comprehensive safety impact analysis of ADVs. This study examined the safety implications and safety impacts of ADVs by using novel approaches. This research prepared several datasets such as fatal crash data, aggregated ADV trips and trajectories, and real-world crash data from the scenario design for an ADV-related operational design domain. Association rules mining was applied to the datasets to identify significant patterns. This study generated a total of 80 association rules that provide risk patterns associated with ADVs. The rules can be used as prospective benchmarks to examine how rule-based risk patterns can be reduced by ADVs that replace human-driven trips.

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Introduction

The introduction of autonomous vehicle (AV) technologies has, and will continue to, influence many city design factors both in the U.S. and worldwide. AV technologies will provide new mobility concepts and opportunities, and will also improve the capacity and efficiency of transportation systems. The incorporation of AVs in future/smart cities may have many benefits. However, it is evident that the wide acceptance of AVs is dependent on ensuring the safety of their occupants and other road users. AV safety-related risks are typically addressed using the National Highway Traffic Safety Administration's (NHTSA's) different safety-related programs, which outline the use of "highly effective crash avoidance technologies" to prevent crashes. For the mass deployment of AVs, autonomous delivery vehicles (ADVs) can play a role in safety-related benchmarking, as these vehicles are occupantless and move mainly on low-speed roadways. Additionally, home delivery services are highly convenient for recipients, and they increase business opportunities for logistics service providers. However, these services result in social costs (for example, crash-related costs and air pollution) associated with the increased presence of delivery vehicles (e.g., vans and trucks) in residential areas.

With the large expansion of e-commerce, light deliveries have increased significantly in recent years. The ongoing COVID-19 pandemic has further highlighted the growing need for an automated delivery system. In 2020, NHTSA approved the deployment of low-speed ADVs with strict guidelines.[1] It is important to note that extensive safety issues have not been examined for these technologies. Additionally, ADVs' movements are limited to residential neighborhoods, which will generate safety issues due to the sheer number of conflict points created by the high density of driveways and presence of non-motorists. If the safety implications of AVs or ADVs are not widely addressed, the development and implementation of ADVs may result in a significant waste of resources for logistics service providers and vehicle developers. Therefore, a rigorous investigation of the associated safety issues is needed to determine the future scopes and applicability of ADVs.

ADVs have many advantages, such as reducing costs of delivery, releasing fewer harmful emissions, improving time efficiency, increasing traffic safety, and reducing congestion. This is due to their automated operation, dynamic route planning, and sensors that allow for a better understanding of the environment. For the mass deployment of AVs, it is usually emphasized that AVs will increase safety, as these vehicles will eliminate human errors. Morando et al. (2018) showed that AVs can reduce the number of conflicts at signalized intersections to 65% (a reduction of 20%). Fully automated vehicles do not need the assistance of human drivers. Thus, these vehicles have enormous potential in reducing the number of crashes by removing the

[1] https://www.nhtsa.gov/press-releases/nhtsa-grants-nuro-exemption-petition-low-speed-driverless-vehicle

human error component completely. AVs are able to map their surroundings using sensors as well as communicate with each other to further increase safety. Once most vehicles operating on roadways are AVs, the transportation system will become safer, more environmentally friendly, and more efficient. However, before the mass deployment of AVs for passenger transportation, it is expected that, in the early stages, AVs will first be widely used in cargo delivery or other light delivery efforts. This includes ADVs or automated delivery robots (ADRs) and automated delivery trucks (ADTs). In an online report, DHL noted that the logistics industry will have a chance to adopt AVs faster than any other industry due to the fact that delivery AV logistics are less complicated, and liability is less pressing since these AVs are delivering goods rather than human beings (DHL, 2014). The report mentions four AV application areas in the logistics industry: warehouse operations, outdoor logistic operations, line haul transportation, and last-mile delivery.

The objective of this study is to understand the safety-related issues associated with ADVs. In this study, the research team conducted a literature review; collected and integrated multiple datasets; aggregated ADV trips and trajectories, ADV-related collisions, and crowdsourced data from various sources; and performed safety implication and safety impact analysis of ADVs.

Literature Review

To date, most safety research on AVs has focused on passenger transport, and literature related to ADVs is limited. This study performed a scoping review on the safety of ADVs. The research team used two prominent citation indexing servers (Web of Science and Scopus) to identify relevant studies. The terms "automated delivery," "automated fleet," "automated robot delivery," "autonomous delivery," "autonomous fleet," and "autonomous robot delivery" were used in the title and keyword search options to identify the studies. Out of 197 articles, 41 relevant articles were selected for the final analysis. The selection was conducted by manually reading the study abstracts and conclusions. The studies ranged from design to operation, deployment, and safety. The current scoping review is limited to the following two topics:

- Crash prevention and safety
- Policymaking for ADVs

Several studies have reviewed the development, operational, and safety-related strategies of ADVs. Flämig (2016), for example, comprehensively introduced strategies to apply AVs to road freight transportation systems in public facilities. This study investigated to what extent AVs can be applied to road logistic systems. The study provided a historical understanding of in-house logistics, which helps in understanding why companies choose to use AVs in logistics systems. Moreover, it also introduces the navigation, safety, and control requirements for ADVs. Paddeu and Parkhurst (2020) explored the production phases of ADVs and presented a thorough review by focusing on their current and future development states. Research gaps regarding the identification of the advantages of ADVs in terms of economic benefits and development costs still exist. Moreover, the authors indicated that practice and policy barriers remain. Table 1 summarizes these two studies and Figure 1 presents the four different companies' ADVs.

Table 1. AV Related General Studies

Author	Research Problem	Method	Key Findings
Flämig (2016)	Overview of the current application and development history	Review paper	• Introduced how AVs can be applied to road freight transportation system on public facilities.
Paddeu and Parkhurst (2020)	Overview of emerging new technologies	Review paper	• Explored the developments in both surface and aerial ADVs. • A thorough review of automated urban freight transport systems. • Research gaps regarding the economic benefits of ADV and the developments cost still exist. • Barriers between practice and policy remain.

Safety of ADVs

Road safety and pedestrian safety are areas of primary concern for ADVs. While AVs have the potential to increase road safety with other AVs, evaluating the safety of pedestrians, interactions with common neighborhood surroundings, and overall safety impact is still a large issue. Many studies in this area use simulations to evaluate the safety impacts but come with limitations. This remains a major challenge due to the limited amount of real-world data available, as the deployment of ADVs is still done on a small scale. Witcher et al. (2021) investigated the consequences of crash risk and associated injuries. This study quantified that with a full market penetration rate of occupantless vehicles, fatalities can be reduced by 58.2% and injuries can be reduced by 61.8%. However, these quantified outcomes need to be justified as the results are based on several major assumptions and no real-world physical tests were performed. One of the limitations of Witcher et al. (2021) is that it did not perform any analysis using Nuro trajectory data (which can provide information on frequent stops, hard braking, and anomalies in trips) to validate the real-world safety impact.

Crash prevention is important for ADVs, as safety-related issues are always the most important public concern about new technology. Since ADVs mostly operate in neighborhoods with high population densities, safety is a major concern of ADV operation, especially regarding safe interactions between ADVs and pedestrians. ADV companies like Nuro have emphasized reducing physical harm when ADVs strike pedestrians (Nuro, 2021). Moreover, NHTSA has identified 12 autonomous driving system safety elements (NHTSA, 2017), and Nuro has explained how they are working to respond to these safety elements in their safety report. RethinkX suggested that there will be at least a 90% decrease in crashes involving AVs compared with conventional vehicles based on current safety data (RethinkX, 2017). Hawkins (2017) reported that Tesla's crash rate was reduced to approximately 40% after autopilot was introduced in 2015. However, there are critics who believe that a 90% decrease in crashes is too optimistic, and that AVs will also bring about other risks that can potentially jeopardize traffic safety. Mueller et al. (2020) suggested that AVs can prevent up to 34% of traffic crashes and that this number will be more if technology can eliminate all traffic violations. Groves and Kalra (2017) developed an online tool to show how many fatalities the deployment of AVs can reduce under different scenarios, but no scenario reached a 90% decrease. ADVs can play a role here, as these vehicles are occupantless and the trips are limited to low-speed roadways. However, it is difficult to estimate a certain percentage of crash reduction for ADVs, as ADV operators are not open-sourcing their trajectory data or data associated with safety-critical issues such as hard braking, collisions, or near-collisions.

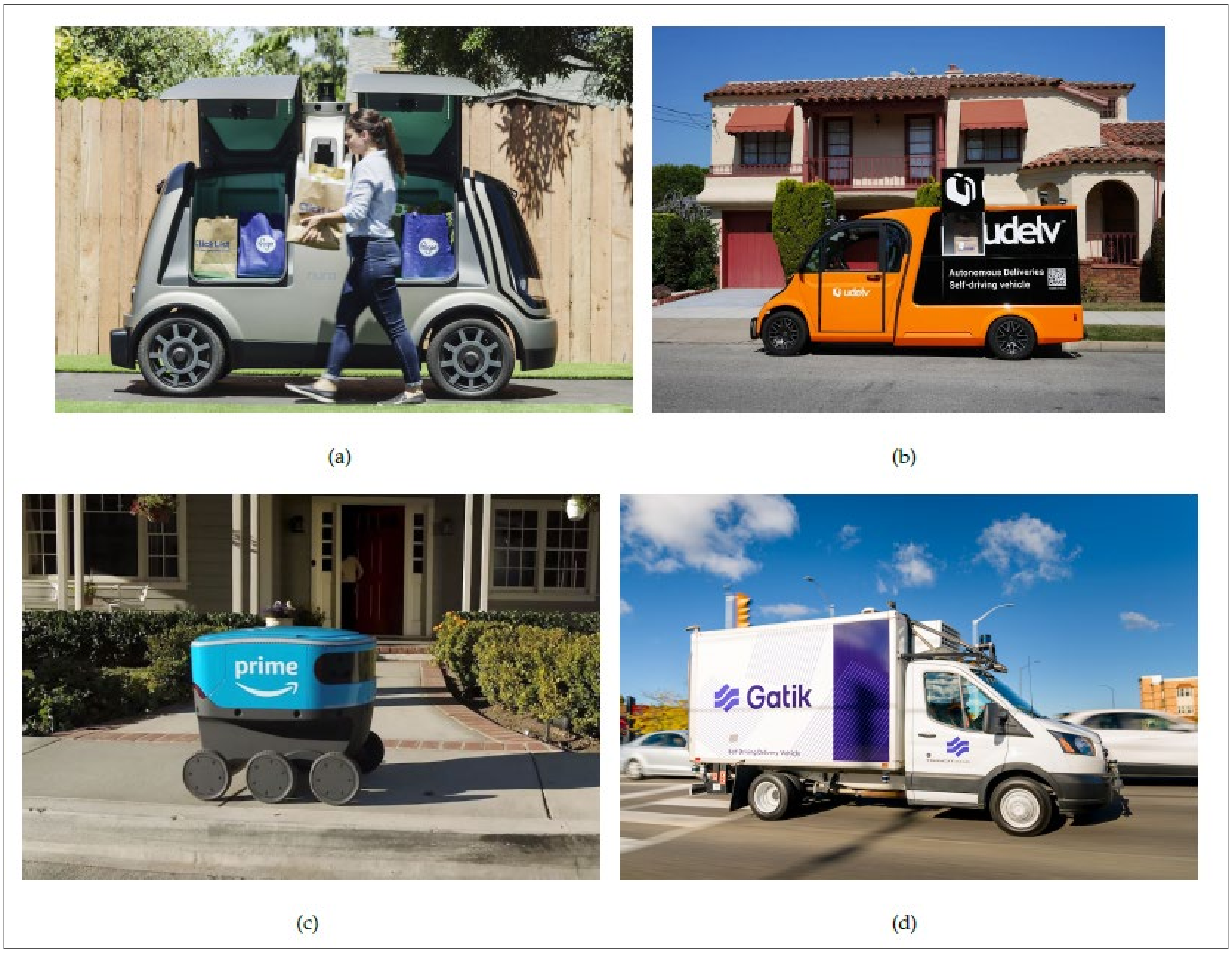

Figure 1. ADVs by different ADV operators.

Currently, studies directly related to ADV safety impact are few in number. However, some of the safety features of ADVs are similar to those of general AVs. In this section, several papers related to AV safety are reviewed. Morando et al. (2018) applied a simulation-based surrogate safety measure approach to study the safety impacts of AVs. They found that under a high market penetration rate, AVs can substantially improve the overall safety level, although AVs tend to operate with smaller headway to improve roadway capacity. Ye and Yamamoto (2019) applied the heterogeneous flow model to investigate the impact of connected and autonomous vehicles (CAVs) on roadway safety. The results indicate that an increase in the market penetration rate can bring extra benefits to traffic safety. Moreover, more cautious car following strategies can further improve safety. Papadoulis et al. (2019) developed a decision-making CAV control algorithm using VISSIM. The Surrogate Safety Assessment Model (SSAM) was implemented to evaluate the safety effects of the algorithm. The results show that, even at a low market penetration rate, CAVs can significantly reduce traffic conflicts. Katrakazas et al. (2019) developed a novel risk assessment approach under the framework of interaction-aware motion models and Dynamic Bayesian Networks (DBNs) which combines a network-level collision estimate with real-time estimates of vehicular risks. Findings revealed that there is an improvement of up to 10% in the interaction-conscious model if traffic conditions are categorized as collision-prone. Summaries of these studies can be found in Table 2.

Table 2. Studies Focusing on Crash Prevention and Safety

Author	Research Problem	Method	Key Findings
Morando et al. (2018)	Explore the safety impact of AVs	Simulation-based surrogate safety measure approach	• AVs can significantly improve safety level under high penetration rate. • At signalized intersection, AVs reduce conflict counts from 20% to 65% with penetration rate between 50% and 100%. • At roundabout, AVs reduce conflict numbers by 29% to 64% with 100% penetration rate.
Ye and Yamamoto (2019)	Investigate the impact of connected AVs on traffic safety	Heterogeneous Flow Model	• Applied heterogeneous flow model to examine the safety impact of connected AVs. • More cautious car following strategy can further enhance safety.
Papadoulis et al. (2019)	Develop a decision-making CAV control algorithm	SSAM	• SSAM is implemented to evaluate the safety effects of the algorithm. • Even at lower penetration rates, the introduction of CAVs can still significantly reduce traffic conflicts.
Katrakazas et al. (2019)	Develop real-time risk assessment method for AVs	Interaction-Aware Motion Models, DBN	• Developed a novel risk assessment approach. • There is an improvement of up to 10% in the interaction-conscious model, if traffic conditions were considered collision-prone.

Public Acceptance of ADVs

Another important ADV topic is public acceptance. Since ADVs are an emerging technology, consumers still have many related doubts and uncertainties. To deploy ADV services more effectively, it is necessary to understand what factors affect the public's decision to accept or reject ADVs as a new delivery form, and companies can use these findings to address people's concerns accordingly. Pani et al. (2020) analyzed the public acceptance of ADVs and conducted a thorough review of public feedback using the representative sample of 483 Portland customers' desires, faith, attitudes, and willingness to pay (WTP). This study offers realistic guidelines for promoting the mass adoption of carbon-friendly delivery vehicles by defining the latent class WTP determinants. Kapser and Abdelrahman (2020) suggested that ADVs may be a resource drain if they are not generally embraced as a viable delivery alternative. Structural equation modeling was carried out using quantitative data obtained via an online survey methodology (n =

501); results showed that price sensitivity is the best indicator of consumer adoption, followed by performance expectancy, hedonic motivations, potential risk, social factors, and facilitating policies. However, no effects of effort expectation could be identified. Kapser et al. (2021) investigated the difference between men's vs. women's ADV acceptance during the COVID-19 pandemic. They extended the Unified Theory of Acceptance and Use of Technology (UTAUT2) by including gender as a moderator. Then, structural equation modeling was applied to analyze the data collected from the questionnaire. The findings concluded that price sensitivity is an important factor in consumers' ADV acceptance in Germany and that perceived risk plays a decisive role in ADV acceptance among female consumers in Germany. Table 3 provides a brief overview of these studies.

Table 3. Studies Focusing on Public Perception

Author	Research Problem	Method	Key Findings
Pani et al. (2020)	Evaluate public acceptance of ADR during COVID-19 pandemic	Latent Class Analysis (LCA)	• Analyzed the public acceptance of the ADRs and carried out a thorough review using the representative sample of 483 Portland customers. • Offered realistic guidelines for promoting the mass adoption of carbon- friendly delivery vehicles.
Kapser and Abdelrahman (2020)	Investigate user acceptance of ADVs in Germany	Structural Equation Modelling (SEM)	• Used an expanded UTAUT2 to research the public acceptance of ADVs among users in Germany. • Carried out structural equation modeling using quantitative data obtained via an online survey. • Price sensitivity has been found to be the best indicator of consumer adoption, followed by hedonic motivations, potential risk, social factors, performance expectancy, and facilitating polices.
Kapser et al. (2021)	Investigate the difference between ADV acceptance of male and female in Germany	Structural Equation Modelling (SEM)	• Used an expanded UTAUT2 with gender as a moderator. • Carried out structural equation modeling using quantitative data obtained via questionnaire. • Price sensitivity has been found to be the best indicator of consumer adoption and perceived risk is a decisive factor for female consumers.

In general, a limited number of studies have focused solely on ADVs. It is important to note that ADVs are usually deployed on low-speed roadways with an enormous number of conflict points due to the presence of driveways and non-motorists. There is a need for additional studies to address the safety and operational issues of ADVs. Among the ADV-related studies reviewed in this paper, many studies are associated with the ADV network and system operation design. This is reasonable because right now there is still no mass deployment of ADVs. Researchers are more interested in designing efficient and safe ADV network and operation systems to prepare for the mass deployment of ADVs in the future. The current study used several datasets to understand the safety implications and safety impacts of ADVs.

Data Collection

The objective of this study is to understand the safety-related issues associated with ADVs. Due to the limited available large-scale vehicle movement data from ADV operators, this study used alternative datasets to achieve the research objectives. This study performed two levels of safety analysis: (1) safety implication analysis using datasets that imply the scenarios of ADVs, and (2) safety impact analysis using datasets from real-world ADVs. To perform the safety implication and safety impact analysis, the research team selected the following datasets:

- Fatality Analysis Reporting System (FARS) [2016–2020]
- Crash Report Sampling System (CRSS) [2016–2020]
- California AV and ADV collision Data [2014–2020]
- Waymo Open Data
- Third-party ADV Trajectory Data (sample data)

Brief overviews of these datasets are described below.

Fatality Analysis Reporting System (FARS)

NHTSA's crash data collection program consists of a wide range of datasets such as the CRSS, FARS, Crash Investigation Sampling System (CISS), Special Crash Investigations (SCI), Non-Traffic Surveillance (NTS), the Crash Injury Research & Engineering Network (CIREN), and special studies conducted to address various safety topics. The FARS contains detailed information on fatal traffic crashes within the 50 States, the District of Columbia, and Puerto Rico.[2] To be included as an entry in the FARS database, a crash must involve a motor vehicle traveling on a roadway and must result in the death of an occupant or a non-occupant of a vehicle within 30 days of the occurrence of the traffic crash. NHTSA has a cooperative agreement with an agency in each State's government to provide information on all qualifying fatal crashes in the State. As FARS provides comprehensive details of the fatal crashes and entities associated with each of these crashes, FARS data acquires information from several sources such as:

- Police Crash Reports
- Death Certificates
- State Vehicle Registration Files
- Coroner/Medical Examiner Reports
- State Driver's Licensing Files
- State Highway Department Data
- Emergency Medical Service Reports

[2] https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/811992

- Vital Statistics and other State Records

FARS contains variables at several levels, such as crash, vehicle, and event. Note that the variable codes are modified slightly each year, and variable codes with all changes are documented in a code manual. FARS data does not contain personally identifying information, such as names, addresses, or social security numbers. However, the VINs of the involved vehicles are provided. FARS data are publicly available in an FTP weblink.[3]

Crash Report Sampling System (CRSS)

CRSS is based on the National Automotive Sampling System General Estimates System (NASS GES),[4] which was recently discontinued. This dataset is a probability sample of traffic crashes, which are reported by law enforcement entities, involving all types of motor vehicles, pedestrians, and cyclists. This dataset is not limited to fatal crashes. As it contains all severity levels (fatal, incapacitating injury, non-incapacitating injury, minor injury, and no injury), it provides a representative sample of all police-reported crashes. As there is a need for all severity level representative crash information in the U.S., this study used this dataset to estimate the overall crash scope and trends, identify key safety concerns, identify patterns, and form the foundation for benefit-cost analysis of potential countermeasures and strategies.

California AV Collision Data

All real-world AV collisions that occurred in California are publicly available on the website of the California Department of Motor Vehicles (CA DMV)[5]. Based on California regulations, the CA DMV have allowed AV manufacturers with testing permits to test their AVs (in the presence of a human driver) on public roadways since September 16, 2014. On April 2, 2018, the State further approved testing without a human driver. As a mandate, the AV manufacturers need to provide to the DMV a complete report of any traffic collisions within 10 business days of the occurrence of the collision event. The research team manually extracted traffic crash information from the PDF report documents. The data collection period was limited to 2014–2021. The frequency of the AV collision reports indicates a rise in AV collisions due to the higher exposure of AVs in recent years (2020 is the exception due to COVID-19-related restrictions).

Waymo Open Data

In recent years, some studies used Waymo open data[6] (Hu et al., 2022; Scanlon et al., 2021). The Waymo Open Dataset contains large-scale and high-resolution sensor data collected by Waymo AVs in multiple cities in the U.S. Waymo released a total of 1,000 scenarios in 2019, and more

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[3] https://www.nhtsa.gov/file-downloads?p = nhtsa/downloads/FARS/
[4] https://www.nhtsa.gov/crash-data-systems/crash-report-sampling-system
[5] https://www.dmv.ca.gov/portal/vehicle-industry-services/autonomous-vehicles/autonomous-vehicle-collision-reports/
[6] https://waymo.com/open/data/

segments were released later. The scenarios vary by different facility type (for example, urban interstate, urban arterial, and urban collector), different situations such as daylight, dark condition (with or without lighting), and different weather conditions, including inclement weather conditions. The sensor data were collected by five Lidar (1 mid-range and 4 short-range) and five cameras (front and sides), where Lidar and camera were calibrated and synchronized (Hu et al., 2022). Additionally, Waymo provides many 3D ground truth bounding boxes (labels) for Lidar data with object annotation.

The research team downloaded data from the Waymo Open Dataset website.[7] Each segment contains 200 frames with a time interval of 0.1 seconds between two consecutive frames. Information in a single frame contains an enormous amount of information, including timestamp, roadway environment context, images, annotated information, Lidar points, and Lidar labels.

Third-Party ADV Trajectory Data

The research team collected a sample of ADV trajectory dataset from an ADV operator. The trips contain both conventional and automated trips. The dataset contains a total of 640,285 event information elements (see more details in the Safety Impact Analysis section) from January–June 2021 in Dallas, TX. The dataset contains trajectory information from 650 ADV trips. However, some of the trips contain very few trajectory points. Using a threshold of 500 trajectory points per trip, the key event parameters were determined for 99 unique trips.

Safety Implication Analysis

Operational Design Domain of ADV

The ODD defines the specific operating domains in which the Automated Driving System (ADS) is designed to perform (see Figure 2). The ODD determines the state(s) in which AVs are able to operate in different scenarios, where scenarios are associated with physical infrastructure components, operational constraints, objects, connectivity, environmental conditions, and zones such as construction zones. ADSs will rely on the real-time decision-making of the ODD protocol to determine the levels of automation and disengagement needs.

[7] https://waymo.com/open/download/

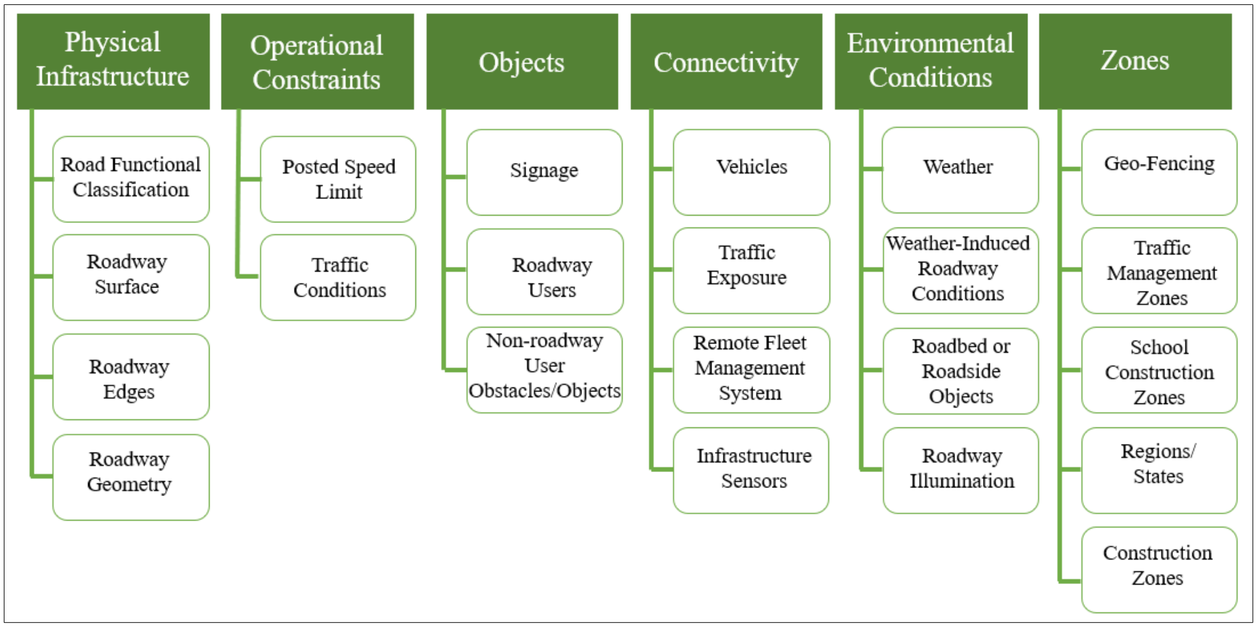

Figure 2. Framework of ODD (Source: Thorn et al., 2018).

The ODD for the ADV was limited to roadways with posted speed limits at or below 45 mph. The expected functionality of ADVs is generally limited to the collection and delivery of goods from a local grocery or distribution center to the nearest neighborhood. ADVs are categorized as light vehicles. Additionally, ADV trips need to be limited to non-interstate roadways. The ADVs have unique features such as low mass, no occupant needs, and lower structural safety features to protect ADV in-vehicle occupants.

In this study, the research team determined FARS ADV ODD scenarios (defined in Table 4) to perform a safety implication analysis. The ADV ODD scenario is the tradeoff between using large datasets with small and ODD-specific datasets. The larger datasets can represent the crash population; however, these data are not adequate in representing the specific ODD scenarios.

Analyzing FARS and CRSS for ADV Safety Implication

Real-world collisions demonstrate a situation where human drivers failed to avoid a collision. The prospective safety implication approach relies on a core principle: any crash and crash-induced injury can be avoided by avoiding the scenario that generates the crash potential. Safety implication analysis can be done by exploring similar real-world scenarios by understanding the patterns of contributing factors. The parameters of these prospective scenarios associated with any crash event can be benefitted by replacing the occurrence patterns and associated risk with ADV elements. ADVs have three key safety features: smaller size and lighter weight with low-speed thresholds, improved crashworthiness characteristics, and being occupantless. These safety benefits can be evaluated by understanding real-world crash patterns.

Table 4 lists a definition of ADV ODD scenarios so that the real-world FARS and CRSS data can be extracted to perform the safety implication analysis. During 2016–2020, there were

172,237 fatal crashes. The CRSS-provided non-weighted crash count during 2016–2020 is 259,077. By applying the ADV ODD scenario, 37,692 fatal crashes were identified as ADV ODD-relevant fatal crashes. Similarly, 55,221 non-weighted crashes were identified from the CRSS. The vehicles involved in these crashes are 43,683 and 73,440, respectively, for these two datasets.

Table 4. Defining ADV ODD for FARS and CRSS Crash Filtering

Functional Class	FARS	CRSS
ADV ODD Definition	Light vehicles and posted speed limit (less than 50 mph) and non-interstate roadways and vehicle models not older than 2000	Light vehicles and posted speed limit (less than 50 mph) and non-interstate roadways and vehicle models not older than 2000 and non-fatal and non-property damage only
All Crashes (2016–2020)	172,237	259,077
ADV ODD Defined Crashes (2016–2020)	37,692	55,221
All Vehicles Involved in Crashes (2016–2020)	263,647	457,314
ADV ODD Defined Vehicles Involved in Crashes (2016-2020)	43,683	73,440

The following section provides details on the FARS-data-only analysis to avoid biased interpretation. This is mostly because CRSS data presents a sample and not the whole population of all injury levels. For ADV ODD scenarios (as defined in Table 4), only non-interstate roadways were considered. Current ADV companies limit their trips on such roadways. Here, FARS ADV ODD scenario shows that around 39% of these fatal crashes occurred on principal arterials and 45% occurred on local, minor arterial, and minor collector roadways (see Table 5).

Table 5. FARS ADV ODD Scenario for Different Functional Classes

Functional Class	2016	2017	2018	2019	2020	Total
Principal Arterial - Other	3,254	3,384	3,418	3,416	3,692	17,164
Major Collector	1,140	1,082	1,196	1,088	1,215	5,721
Minor Collector	294	295	301	312	254	1,456
Minor Arterial	2,291	2,422	2,579	2,491	2,795	12,578
Local	1,267	1,532	1,340	1,228	1,306	6,673
Trafficway Not in State Inventory	22	10	20	19	20	91
Total	8,268	8,725	8,854	8,554	9,282	43,683

Of the 43,683 vehicles involved in fatal crashes, full-scale market penetration of ADVs were predicted to reduce single-vehicle-related collisions (a collision not involving a motor vehicle) fatalities by approximately 27.6% (see Table 6). This is mostly due to the occupantless nature of the ADVs.

Table 6. FARS ADV ODD Scenario for Different Crash Types

Crash Types	2016	2017	2018	2019	2020	Total
Not a Collision with Motor Vehicle	3,916	4,003	4,169	4,005	4,328	12,088
Angle	2,504	2,806	2,666	2,668	2,936	13,580
Front-to-Front	996	1,017	1,079	1,075	1,129	5,296
Front-to-Rear	516	556	599	487	530	2,688
Rear-to-Side	17	4	6	8	10	45
Sideswipe	272	304	300	283	317	1,476
Others	47	35	35	28	32	161
Total	8,268	8,725	8,854	8,554	9,282	43,683

Table 7 lists the number of occupants in fatal crashes by year. Around 65% of fatal crashes are associated with vehicles having a single occupant. ADVs provide significant safety implications in reducing single-occupant-related crashes associated with day-to-day grocery shopping and other non-commute trips, as these vehicles will be occupantless.

Table 7. FARS ADV ODD Scenario by Number of Occupants

Number of Occupants	2016	2017	2018	2019	2020	Total
0	15	17	18	15	14	79
1	5,384	5,530	5,817	5,537	6,066	28,334
2	1,864	1,942	1,880	1,855	1,976	9,517
3 or more	1,005	1,236	1,139	1,147	1,226	2,923
Total	8,268	8,725	8,854	8,554	9,282	43,683

Association Rules Mining

To understand the safety implications of ADVs, this study applied association rules mining methods to the FARS ADV Scenario data. Association rules mining has been gaining popularity in transportation safety analysis in recent years (Das et al., 2021; Kong et al., 2020; Montella et al., 2021). Association rules are very effective for a large set of unsupervised data, as they offer key intuitions for insightful decision making. The research team used the 'apriori' algorithm to generate the rules. A large dataset with several categorical variables with no defined response variable can be considered unsupervised data. Association rules mining can generate the most frequent patterns of the variable categories, which are described as rules with some performance measures such as support, confidence, and lift. This algorithm applies a "bottom-up" approach in which frequent subsets are expanded one item at a time by using a breadth-first search following a Hash tree structure (Das et al., 2021; Kong et al., 2020).

Consider $I = \{i_1, i_2, i_3, \ldots\ldots i_n,\}$ as a set of N distinctive items or attributes (for example, daylight is an attribute of 'lighting condition' variable). Let D be a set of transactions where each transaction T consists of a set of items or attributes, such that $T \in I$. Each transaction is associated with only an identifier. An association rule can be expressed as *Antecedent (left side of the rule) → Consequent (right side of the rule)* or $A \rightarrow B$, where $A \in I$ and $B \in I$. For association rules mining, the most common performance measures are support (S), confidence (C), and lift (L).

Many studies have proposed new and innovative interest measures for rule mining to generate interesting and insightful rules. Lift, the most common performance measure in association rules mining, measures how often A and B collectively occur compared to the expected value if they were statistically independent. A high lift value (greater than one) indicates independence between A and B. If the value of the lift is greater than 1, it indicates that A and B appear more frequently together in the data and are said to be positively dependent on each other. The equations of association rules mining are listed below (n indicates count):

Support of A,
$$\boldsymbol{S(A) = \frac{n(A)}{n}} \tag{1}$$

Support of B,
$$S(B) = \frac{n(B)}{n} \tag{2}$$

Support of rule A→ B,
$$S(\mathrm{A} \rightarrow \mathrm{B}) = \frac{n(AB)}{n} = S(\mathrm{B} \rightarrow \mathrm{A}) \tag{3}$$

Confidence of rule A→ B,
$$C(\mathrm{A} \rightarrow \mathrm{B}) = \frac{S(\mathrm{A} \rightarrow \mathrm{B})}{S(A)} \tag{4}$$

Confidence of rule B→ A,
$$C(\mathrm{B} \rightarrow \mathrm{A}) = \frac{S(\mathrm{A} \rightarrow \mathrm{B})}{S(B)} \tag{5}$$

Lift of A→ B,
$$L(\mathrm{A} \rightarrow \mathrm{B}) = \frac{C(\mathrm{A} \rightarrow \mathrm{B})}{S(B)} = \frac{C(\mathrm{B} \rightarrow \mathrm{A})}{S(A)} \tag{6}$$

For rules mining, it is critical to determine the thresholds of support and confidence measures. A very small support can generate a large number of rules, and rules with less frequencies of the combinations can affect the insightfulness of the data. After performing several trials, the research team used a minimum value of support and confidence of 0.01. By using this threshold, 563 rules were generated from the unsupervised learning framework. Around 80% of these rules have lift values higher than 1. Table A (see Appendix) shows the top 40 rules based on the 'lift' measure. The top three rules (based on the lift measures) are described below:

- The first rule (R#01), a 3-item rule with 2 antecedents and 1 consequent, has a lift measure of 2.868 (Support = 0.054, Confidence = 0.312, Count = 1,248). The support value of 0.054 indicates that among all events, 5.4% events are curve-related front-to-front non-intersection crashes. This rule indicates that the proportion of curve-related front-to-front ADV non-intersection collisions is 2.868 times the proportion of all AV collisions at curves in the complete dataset.
- The second rule (R#02), a 5-item rule with 4 antecedents and 1 consequent, has a lift measure of 2.689 (Support = 0.054, Confidence = 0.819, Count = 1,266). This rule indicates that the proportion of AV collisions at four-way signalized intersections (45

mph posted speed limit, two-way divided, straightly aligned roadways) is 2.689 times the proportion of all AV collisions at signalized intersections in the complete dataset.

- The third rule (R#03), a 4-item rule with 3 antecedents and 1 consequent, has a lift measure of 2.619 (Support = 0.109, Confidence = 0.798, Count = 2,531). This rule indicates that the proportion of AV collisions at four-way signalized intersections (two-way divided, straightly aligned roadways) is 2.619 times the proportion of all AV collisions at signalized intersections in the complete dataset. Note that the difference between R#03 and R#02 is the absence of posted speed limit (45 mph) in the antecedent of R#03.

The most frequent items in the top 40 rules are: TrWay = Two-Way Undivided: 21 times, Int = Four-Way Intersection: 18 times, TCD = Traffic control signal: 16 times, Int = Not an Intersection: 13 times, Coll = Front-to-Front: 13 times, Align = Straight: 12 times, PSL = 45 MPH: 11 times, Coll = Angle: 10 times, TCD = No Controls: 9 times, Wea = Clear: 9 times, Align = Curve: 9 times, TrWay = Two-Way Divided: 8 times, TCD = Stop Sign: 7 times, and PSL = 40 MPH: 1 time. Among the top 10 rules, the most frequent items are: Int = Four-Way Intersection: 7 times, TrWay = Two-Way Divided: 5 times, Align = Straight: 4 times, Coll = Angle: 4 times, TrWay = Two-Way Undivided: 3 times, Coll = Front-to-Front: 3 times, Int = Not an Intersection: 1 time, and TCD = No Controls: 1 time. The counts of these frequent attributes indicate the presence of these items or attributes in many rules. Due to their common presence in many rules, the most frequent attributes in the top rules can be considered significant contributing factors.

Safety Impact Analysis

The research team used three databases (California AV collision data, Waymo open data, and Third Party ADV trajectory data) to perform a safety impact analysis (safety analysis using real-world data such as California AV collision data, Waymo data, and sample data from ADV operators). California AV collision data was used to determine the patterns of contributing factors of collisions associated with delivery-inclusive AV companies. As Waymo is a delivery-inclusive company (note: Waymo trips were used for delivery purposes), this open-source big trajectory data can also provide safety impacts in terms of jerk. The research team also collected sample ADV trajectory data from a third-party data vendor. This was examined to provide the associations between hard braking, over speeding, and excessive over speeding.

Collision Patterns of Delivery Inclusive AV Company Operated AVs

California maintains a database of AV collisions. Most of the AV companies in California are delivery inclusive, except for a few companies such as Apple and Nissan. During 2014–2021, there were 394 AV collisions in California. Around 96% of these collisions were associated with delivery-inclusive AV companies. The companies with the highest total number of collisions were Cruise (166 collisions), Google/Waymo (151 collisions), and Zoox (37 collisions), followed by Lyft, Aurora, and Apple. Based on AV mileage information provided by these companies, it was found that AV collisions are associated with these companies' AV mileages. As exclusive ADV-related data is not readily available, the research team used delivery-inclusive AV collision data to perform the safety impact analysis. Note that few recent studies have analyzed California AV collision data to identify risk patterns (Das, 2020; Das et al., 2021; Rahman et al., 2021; Kutela et al, 2021).

Understanding patterns of the key contributing factors can provide insights into the safety impacts of ADVs. The research team selected 314 collisions by considering the following key variables:

- Prior mode of the ADV (automated or conventional)
- Prior condition of the ADV (moving, and stopped in traffic)
- Prior condition of the other vehicle (moving, stopped in traffic, and not reported)
- Weather condition (clear, cloudy, fog, rain, and not reported)
- Lighting condition (daylight, dark, dawn/dusk, and not reported)
- Collision type (rear-end, broadside, sideswipe, head-on, and others)

After performing several trials, the research team used a 0.05 minimum value of support and a 0.10 confidence. Using these thresholds, the rules mining identified 550 rules. The number of rules with a lift value great than 1 is 349. Table B (see Appendix) lists the top 40 rules. The top three rules (based on the lift measures) are described below:

- The first rule (R#01), a 3-item rule with 2 antecedents and 1 consequent, has a lift measure of 2.499 (Support = 0.057, Confidence = 0.207, Count = 18). This rule indicates that the proportion of collisions associated with an AV going straight and the other vehicle changing lanes is 2.499 times the proportion of all AV collisions associated with the other vehicle changing lanes in the complete dataset.
- The second rule (R#02), a 5-item rule with 4 antecedents and 1 consequent, has a lift measure of 1.862 (Support = 0.051, Confidence = 0.842, Count = 16). This rule indicates that the proportion of rear-end AV collisions associated with an AV in conventional mode—stopped in clear weather—is 1.862 times the proportion of all AV collisions associated with the other vehicle proceeding straight in the complete dataset.
- The third rule (R#03), a 6-item rule with 5 antecedents and 1 consequent, has a lift measure of 1.839 (Support = 0.086, Confidence = 0.931, Count = 27). This rule indicates that the proportion of rear-end AV collisions associated with an AV in autonomous mode and stopped, in clear weather and daylight with the other vehicle proceeding straight, is 1.862 times the proportion of all rear-end AV collisions in the complete dataset.

The most frequent items in the top 40 rules are: AV = Stopped: 31 times, Collision_Type = Rear End: 31 times, OtherVeh = Proceeding Straight: 27 times, Pre_Crash_Mode = Autonomous: 24 times, Lighting = Daylight: 18 times, Weather = Clear: 16 times, Pre_Crash_Mode = Conventional: 8 times, AV = Proceeding Straight: 3 times, Collision_Type = Side Swipe: 2

times, OtherVeh = Making Right Turn: 2 times, Lighting = Dark-Street Lights: 1 time, OtherVeh = Parked: 1 time, and OtherVeh = Changing Lanes: 1 time. Among the top 10 rules, the most frequent items are: Collision_Type = Rear End: 8 times, OtherVeh = Proceeding Straight: 7 times, AV = Stopped: 6 times, Lighting = Daylight: 6 times, Pre_Crash_Mode = Autonomous: 5 times, Weather = Clear: 4 times, Pre_Crash_Mode = Conventional: 4 times, AV = Proceeding Straight: 2 times, OtherVeh = Changing Lanes: 1 time, and Collision_Type = Side Swipe: 1 time.

Jerk Analysis on Waymo Open Dataset

The research team applied the ADV ODD scenario to filter the Waymo data suitable for ADV-related trajectories. To understand the suitability of the Waymo trajectory data, the research team performed jerk value analysis following the work by Punzo et al. (2011). The absolute jerk values larger than 15 m/s^3 were considered as not physically feasible. Also, more than one sign inversion in a one-second window was defined as an anomalous jerk sign inversion.

By limiting the data to the ADV ODD scenario (light vehicles and posted speed limit less than 50 mph and non-interstate roadways), the anomaly jerk proportion was determined to be 3.7% with a maximum jerk of 50 m/s^3 and minimum jerk of -50 m/s^3. The jerk analysis outcome shows that the dataset itself is not consistent by showing anomalies in the position-based data. The current analysis was limited to only position-based data. Future studies can also explore speed-based data. Note that the results of the jerk analysis conducted in this study should not be viewed as a comprehensive safety impact measure due to the assumptions made for the ADV-related scenarios.

Safety Critical Events from ADV Sample Dataset

The ADV sample dataset contains trajectory level information for three major events (hard braking, over speeding, and excessive over speeding). These trajectories of 99 unique trips were explored in this study. Based on the mean score for each event in each trip, ranks were provided for each trip by event. The top 40 trips, based on the lowest average ranks, are listed in Table C (see Appendix). For example, rule (T#01) indicates that there were 574 events with hard braking (mean value = 0.0592), over speeding (mean value = 0.4895), and excessive over speeding (mean value = 0.4495). The mean values indicate the proportions of events (such as hard braking, speeding, and over speeding) during the trip length. For example, over speeding with 0.4895 indicates that for around 49% of the trip's duration, the vehicles were over speeding. These safety-critical events represent 43% of all trajectory points and 6% of total trips. Note that over speeding is defined as being when the operating speed exceeds 1 to 3 mph from the posted speed limit, and excessive over speeding is defined when the operating speed exceeds 3 mph above the posted speed limit.

Safe System Decision Support Tool

The Safe System approach for road safety originated in the Netherlands in the 1970s. Later, Sweden, Australia, and New Zealand adopted the Safe System. The concept behind the 'Safe System's approach is to build a road transport system that allows for human error and minimizes casualties following road crashes. The five pillars of the 'Safe System' approach are 'Safe Road Users,' 'Safe Road,' 'Safe Speeds,' 'Safe Vehicles,' and 'Post-Crash Care.' In contrast to traditional road safety approaches that primarily focus on road users and risky behaviors, the 'Safe System' approach provides a systematic method to reduce crash occurrences and subsequent injuries in the event of a crash. The U.S. DOT has adopted the Safe System approach as the guiding paradigm to address roadway safety in 2022.[8] A Safe System approach incorporates the following principles:

- Death and Serious Injuries are Unacceptable
- Humans Make Mistakes
- Humans Are Vulnerable
- Responsibility is Shared
- Safety is Proactive
- Redundancy is Crucial

The research team identified several key contributing factors by exploring association rules mining. Table 8 shows a Safe System-based ADV-related decision support matrix tool. This tool can be useful for both ADV operators and transportation agencies, and was developed in a way to link the research findings to an applicable tool. As the U.S. DOT is moving toward a Safe System approach, the current tool can work as a high-level decision support matrix to understand the impact of ADV-related safety issues. In addition to the score, responses can be added to each of the cells to help identify the specific issues of concern. This is intuitive in determining the key risk factors for infrastructure.

Seven critical factors were primarily determined as the risk factors for ADV mobility. These factors are rear-ended collisions, front-to-front collisions, AV in autonomous mode, AV in conventional mode, stopping of AVs, intersections, and others. It is important to note that the columns (e.g., rear-end) indicate risk measures in terms of crash, near-crash, or conflict. Once there is a score in each cell for the exposure, likelihood, and severity rows, the product of each column is calculated and entered in the final row, labeled 'total.' The purpose of this multiplicative process is that if a score of zero has been given for any component of a crash type (i.e., exposure, likelihood, or severity), that collision or conflict type scores zero (meaning that it has reached a Safe System). The sum of the total scores for each collision or conflict type is then added to the final cell on the right-hand side. This score is out of a possible 448 and represents two specific infrastructure-based Safe System pillars (safe road and safe speed). The closer that

[8] https://www.transportation.gov/NRSS

the score is to zero, the more the project in question is in alignment with the Safe System principles (see Table 9 for score details). Additional Safe System pillars (i.e., road users, vehicles, and post-crash care) are considered in the following rows, where prompts are given to direct the users to consider how the project interacts with road users, vehicles, and post-crash care. The research team also considered infrastructure pillars (safe road and safe speed) following the other three pillars in a way to provide a complete picture of the interactions and reasoning behind the scores.

Table 8. Proposed Safe System based ADV related Decision Support Tool

Risk Factors	Rear-end	Front-to-front	Autonomous Mode	Conventional Mode	AV Stopped	Intersection	Other	
Exposure	$\frac{\_\_}{4}$	$\frac{\_\_}{4}$	$\frac{\_\_}{4}$	$\frac{\_\_}{4}$	$\frac{\_\_}{4}$	$\frac{\_\_}{4}$	$\frac{\_\_}{4}$	
Likelihood	$\frac{\_\_}{4}$	$\frac{\_\_}{4}$	$\frac{\_\_}{4}$	$\frac{\_\_}{4}$	$\frac{\_\_}{4}$	$\frac{\_\_}{4}$	$\frac{\_\_}{4}$	
Severity	$\frac{\_\_}{4}$	$\frac{\_\_}{4}$	$\frac{\_\_}{4}$	$\frac{\_\_}{4}$	$\frac{\_\_}{4}$	$\frac{\_\_}{4}$	$\frac{\_\_}{4}$	
Product	$\frac{\_\_}{64}$	$\frac{\_\_}{64}$	$\frac{\_\_}{64}$	$\frac{\_\_}{64}$	$\frac{\_\_}{64}$	$\frac{\_\_}{64}$	$\frac{\_\_}{64}$	Total = $\frac{\_\_}{448}$
Pillar	**Contexts**							**Response**
Safe Road User	• Are road users likely to be alert and compliant? • What is the density of non-motorists?							--*
Safe Vehicle	• Has vehicle breakdown been catered for? • What is the distribution of multiple modes? • What is the vehicle ownership per household?							--
Post-crash care	• What is the distance to the nearest hospital? • Do emergency and medical services operate as efficiently and rapidly as possible?							--
Safe Roads	• What are the counts of fixed objects? • Number of driveways? • Is there on-street parking? • Is there any roundabout? • Is there a park nearby?							--
Safe Speeds	• What is the posted speed limit? • Is the operational speed much higher than posted speed limit?							--

*Note: *responses are kept blank.*

Table 9. Proposed Scoring Method

Road User Exposure	Crash likelihood	Crash severity
0 = there is no exposure to a certain crash type.	0 = there is only minimal chance that a given crash type can occur.	0 = should a crash occur, there is only minimal chance that it will result in a fatality or serious injury to the relevant road user involved.

Road User Exposure	Crash likelihood	Crash severity
1 = volumes of vehicles that may be involved in a particular crash type are particularly low, and therefore exposure is low. *AADT is < 400 vehicles per day (vpd).*	1 = it is highly unlikely that a given crash type will occur.	1 = should a crash occur; it is highly unlikely that it will result in a fatality or serious injury to any road user involved. *Kinetic energies must be fairly low during a crash.*
2 = volumes of vehicles that may be involved in a particular crash type are moderate, and therefore exposure is moderate. *AADT is between 400 and 1,000 vpd.*	2 = it is unlikely that a given crash type will occur.	2 = should a crash occur; it is unlikely that it will result in a fatality or serious injury to any road user involved. *Kinetic energies are moderate.*
3 = volumes of vehicles that may be involved in a particular crash type are high, and therefore exposure is high. *AADT is between 1,000 and 2,000 vpd.*	3 = it is likely that a given crash type will occur.	3 = should a crash occur; it is likely that it will result in a fatality or serious injury to any road user involved. *Kinetic energies are moderate but are not effectively dissipated.*
4 = volumes of vehicles that may be involved in a particular crash type are very high, or the road is very long, and therefore exposure is very high. *AADT is > 2,000 vpd.*	4 = the likelihood of individual road user errors leading to a crash is high given the infrastructure in place.	4 = should a crash occur; it is highly likely that it will result in a fatality or serious injury to any road user involved. *Kinetic energies are high enough to cause a fatal and serious injury crash.*

Conclusions

The research team found that ADV networks and operation designs had the most studies, likely due to a desire to lay the foundations of a larger production in the future. Despite public acceptance, policymaking, crash prevention and safety, and potential impacts and challenges being important topics, there are a limited number of studies covering these areas. ADVs are still new and are yet to be widespread and manufactured on a larger scale.

The results of this investigation should not be taken as definitive ADV safety implications and impacts. The research team considered important assumptions to determine the ADV ODD scenario and its representation in the real-world collision data, and notes that some of these assumptions cannot be fully reproduced in real-world scenarios. However, the findings of this study are meant to support constructive thinking into how innovative technologies such as ADVs may offer benefits that transcend the typical approaches used in vehicle safety, including passive and active safety measures. The research team does not expect the safety implications (around 27% reduction due to the reduction of single vehicle occupantless collisions) to be fully observed in the real-world deployment of ADVs.

For FARS ADV ODD scenarios, the most frequent attributes in the top 10 rules are four-way intersection, two-way divided roadways, straight alignment, angle collisions, two-way undivided, front-to-front collisions, and no traffic control devices. For California's AV collision data associated with delivery inclusive AV companies, the most frequent attributes in the top 10 rules are rear-end collisions, non-AV moving straight, AV in stopped condition, daylight, pre-crash mode as autonomous, clear weather, AV proceeding straight, non-AV changing lanes, and sideswipe collisions. The research team envisions that the results from the safety implications (rules from FARS ADV ODD scenario) and safety impacts (rules from California's AV collisions associated with delivery inclusive AV companies) analysis can provide some high-level benchmark rules on risk patterns to examine how crashes in these scenarios can be reduced by using ADVs to eliminating human-driven delivery-related trips. The research team also developed a Safe System-based ADV-related decision support tool, which can be used for infrastructure readiness for ADVs.

In this study, the research team was not able to explore large-scale ADV trajectory data due to the unavailability of such data. The research team collected some event trigger-related trajectory information from a third-party ADV company. However, this data is not suitable for locality feature-related exploration. Given the high frequency of non-motorist-related traffic crashes every year, it is important to examine the crash compatibility with vulnerable roadway users, given the less rigid structural requirements for ADV design. As ADV trips are more frequent in roadway networks with higher driveway densities and non-motorist trips, it is important to investigate large-scale ADV trajectory data from prominent ADV companies such as Nuro.

Additional Products

The Education and Workforce Development (EWD) and Technology Transfer (T2) products created as part of this project are described below and are listed on the Safe-D website. The final project dataset is located on the SafeD Dataverse[9].

Education and Workforce Development Products

Undergraduate and graduate courses:

- TTI/Texas A&M/University of San Antonio (UTSA)/Texas State University (TXST): Some of the material will be included in the slides and class notes for the graduate course *CVEN 626 (Highway Safety)* at TAMU and *CE5493: Traffic Engineering* at UTSA, and *CE 4361: Highway Engineering* at Texas State University. At the time this report was written, the class notes had not been yet updated. These materials will be also made available on the GitHub repository of Dr. Subasish Das.

[9] Link will be provided later.

- TTI/Texas A&M: Some of the material has been included in Chapters 4-8 of the forthcoming textbook titled "Artificial Intelligence in Highway Safety" written by Dr. Subasish Das, which will be published by September 2022.
- UTC presentations: One presentation for the public will be hosted by the Safe-D UTC sometime in the fall of 2022.

Student Funding and Enrichment:

- TTI – one Ph.D. student, Zihang Wei, at Texas A&M University. Title of dissertation to be determined.
- TTI – one undergraduate student, Valerie Vierkant, at Texas A&M University.

For Zihang Wei, the project has been very beneficial. This project allowed Zihang to enhance his knowledge in safety analysis and statistics, learn new programming languages, and publish papers. Valerie Vierkant learned how to assemble different types of traffic and roadway data, perform data quality control checks, process and analyze data, link databases, and download data from Waymo and NHTSA.

Technology Transfer Products

The main technology transfer products from this study include the following:

- Three sample datasets.
- Webinar – At the conclusion of this project, the researchers will conduct a webinar to present the methodology and project findings to students and stakeholders.
- Conference Paper – The research team prepared a conference paper that will be presented at the 102nd Transportation Research Board annual meeting in 2023.
- Journal Article – The research team submitted one paper for publication. The team will submit another paper to a peer-review transportation engineering journal.

Data Products

This project used five different datasets to perform the analysis. ADV related operation design domain (ODD) scenarios were determined to examine the real-world collision data. This study generates a total of 80 association rules with high likelihood measures for these datasets. The rules can be used as the prospective benchmark rules to examine how these rule-based risk patterns can be replaced by ADVs by eliminating human-driven grocery related trips The dataset can be found here.

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Appendix

Table A. Top 40 rules for FARS ADV ODD Multi-Vehicle Scenario

Rules	Antecedent	Consequent	Supp.	Conf.	Lift	Count
R#01	Coll = Front-to-Front, Int = Not an Intersection	Align = Curve	0.054	0.312	2.868	1248
R#02	Int = Four-Way Intersection, TrWay = Two-Way Divided, PSL = 45 MPH, Align = Straight	TCD = Traffic control signal	0.054	0.819	2.689	1266
R#03	Int = Four-Way Intersection, TrWay = Two-Way Divided, Align = Straight	TCD = Traffic control signal	0.109	0.798	2.619	2531
R#04	Int = Four-Way Intersection, TrWay = Two-Way Divided	TCD = Traffic control signal	0.114	0.797	2.614	2644
R#05	Coll = Angle, Int = Four-Way Intersection, TrWay = Two-Way Divided, Align = Straight	TCD = Traffic control signal	0.079	0.78	2.56	1837
R#06	Coll = Angle, Int = Four-Way Intersection, TrWay = Two-Way Divided	TCD = Traffic control signal	0.083	0.777	2.55	1920
R#07	Coll = Front-to-Front, TCD = No Controls	Align = Curve	0.052	0.276	2.542	1204
R#08	Coll = Angle, Int = Four-Way Intersection, TrWay = Two-Way Undivided, Align = Straight	TCD = Stop Sign	0.061	0.307	2.528	1408
R#09	Coll = Front-to-Front, TrWay = Two-Way Undivided	Align = Curve	0.052	0.273	2.516	1202
R#10	Coll = Angle, Int = Four-Way Intersection, TrWay = Two-Way Undivided	TCD = Stop Sign	0.063	0.302	2.492	1461
R#11	TrWay = Two-Way Undivided, Align = Curve	Coll = Front-to-Front	0.052	0.559	2.457	1202
R#12	Int = Four-Way Intersection, PSL = 40 MPH	TCD = Traffic control signal	0.054	0.737	2.417	1248
R#13	Int = Not an Intersection, TrWay = Two-Way Undivided	Align = Curve	0.079	0.256	2.352	1837
R#14	Align = Curve	Coll = Front-to-Front	0.058	0.529	2.325	1338
R#15	Int = Not an Intersection, TrWay = Two-Way Undivided, PSL = 45 MPH, TCD = No Controls	Coll = Front-to-Front	0.066	0.528	2.318	1546
R#16	Int = Not an Intersection, TrWay = Two-Way Undivided, TCD = No Controls	Align = Curve	0.072	0.25	2.302	1676
R#17	Int = Not an Intersection, TrWay = Two-Way Undivided, PSL = 45 MPH	Coll = Front-to-Front	0.072	0.522	2.294	1671
R#18	PSL = 45 MPH, Align = Straight, TCD = Traffic control signal	TrWay = Two-Way Divided	0.066	0.606	2.244	1528
R#19	Int = Four-Way Intersection, PSL = 45 MPH, Align = Straight	TCD = Traffic control signal	0.091	0.682	2.239	2109
R#20	Coll = Angle, Wea = Clear, TrWay = Two-Way Undivided, Align = Straight	TCD = Stop Sign	0.052	0.271	2.237	1202
R#21	PSL = 45 MPH, TCD = Traffic control signal	TrWay = Two-Way Divided	0.068	0.603	2.234	1581

Rules	Antecedent	Consequent	Supp.	Conf.	Lift	Count
R#22	Int = Four-Way Intersection, PSL = 45 MPH	TCD = Traffic control signal	0.094	0.678	2.226	2189
R#23	Coll = Angle, TrWay = Two-Way Undivided, Align = Straight	TCD = Stop Sign	0.091	0.269	2.221	2128
R#24	Int = Four-Way Intersection, Wea = Clear, PSL = 45 MPH, Align = Straight	TCD = Traffic control signal	0.053	0.676	2.217	1227
R#25	Int = Four-Way Intersection, PSL = 45 MPH, TCD = Traffic control signal	TrWay = Two-Way Divided	0.056	0.597	2.209	1306
R#26	Int = Four-Way Intersection, Wea = Clear, PSL = 45 MPH	TCD = Traffic control signal	0.055	0.671	2.203	1275
R#27	TrWay = Two-Way Undivided, Align = Curve, TCD = No Controls	Int = Not an Intersection	0.072	0.909	2.19	1676
R#28	Int = Not an Intersection, TrWay = Two-Way Undivided, TCD = No Controls	Coll = Front-to-Front	0.142	0.495	2.172	3313
R#29	Int = Four-Way Intersection, TrWay = Two-Way Undivided, Align = Straight	TCD = Stop Sign	0.064	0.263	2.168	1480
R#30	Int = Not an Intersection, Wea = Clear, TrWay = Two-Way Undivided, TCD = No Controls	Coll = Front-to-Front	0.073	0.493	2.165	1699
R#31	Align = Curve, TCD = No Controls	Int = Not an Intersection	0.081	0.893	2.151	1887
R#32	Int = Not an Intersection, TrWay = Two-Way Undivided	Coll = Front-to-Front	0.151	0.487	2.141	3502
R#33	Int = Four-Way Intersection, TrWay = Two-Way Undivided	TCD = Stop Sign	0.066	0.259	2.14	1541
R#34	Int = Not an Intersection, Wea = Clear, TrWay = Two-Way Undivided	Coll = Front-to-Front	0.077	0.486	2.135	1782
R#35	Coll = Front-to-Front, PSL = 45 MPH, TCD = No Controls	Int = Not an Intersection	0.076	0.886	2.134	1768
R#36	Coll = Angle, Wea = Clear, TrWay = Two-Way Undivided	TCD = Stop Sign	0.055	0.258	2.131	1269
R#37	Coll = Angle, Wea = Clear, TrWay = Two-Way Undivided, Align = Straight, TCD = Traffic control signal	Int = Four-Way Intersection	0.057	0.873	2.12	1321
R#38	Coll = Angle, Wea = Clear, TrWay = Two-Way Undivided, TCD = Traffic control signal	Int = Four-Way Intersection	0.061	0.872	2.119	1422
R#39	Coll = Front-to-Front, TrWay = Two-Way Undivided, TCD = No Controls	Int = Not an Intersection	0.142	0.877	2.111	3313
R#40	Coll = Angle, Wea = Clear, Align = Straight, TCD = Traffic control signal	Int = Four-Way Intersection	0.106	0.866	2.103	2456

Table B. Top 40 Association Rules from California AV Collisions associated with Delivery Inclusive AV Companies

Rules	Antecedent	Consequent	Supp.	Conf.	Lift	Count
R#01	AV = Proceeding Straight	OtherVeh = Changing Lanes	0.057	0.207	2.499	18
R#02	Pre_Crash_Mode = Conventional, AV = Stopped, Weather = Clear, Collision_Type = Rear End	OtherVeh = Proceeding Straight	0.051	0.842	1.862	16
R#03	Pre_Crash_Mode = Autonomous, AV = Stopped, OtherVeh = Proceeding Straight, Weather = Clear, Lighting = Daylight	Collision_Type = Rear End	0.086	0.931	1.839	27
R#04	Pre_Crash_Mode = Conventional, AV = Proceeding Straight, Weather = Clear	Collision_Type = Side Swipe	0.051	0.390	1.829	16
R#05	Pre_Crash_Mode = Conventional, AV = Stopped, Collision_Type = Rear End	OtherVeh = Proceeding Straight	0.061	0.826	1.827	19
R#06	Pre_Crash_Mode = Autonomous, AV = Stopped, OtherVeh = Proceeding Straight, Lighting = Daylight	Collision_Type = Rear End	0.096	0.909	1.795	30
R#07	Pre_Crash_Mode = Autonomous, OtherVeh = Proceeding Straight, Weather = Clear, Lighting = Daylight	Collision_Type = Rear End	0.124	0.907	1.791	39
R#08	Pre_Crash_Mode = Autonomous, OtherVeh = Proceeding Straight, Lighting = Daylight	Collision_Type = Rear End	0.137	0.896	1.769	43
R#09	Pre_Crash_Mode = Conventional, AV = Stopped, Lighting = Daylight, Collision_Type = Rear End	OtherVeh = Proceeding Straight	0.051	0.800	1.769	16
R#10	Pre_Crash_Mode = Autonomous, Lighting = Daylight, Collision_Type = Rear End	AV = Stopped	0.162	0.699	1.741	51
R#11	Pre_Crash_Mode = Autonomous, OtherVeh = Proceeding Straight, Lighting = Daylight, Collision_Type = Rear End	AV = Stopped	0.096	0.698	1.739	30
R#12	Pre_Crash_Mode = Autonomous, Weather = Clear, Lighting = Daylight, Collision_Type = Rear End	AV = Stopped	0.146	0.697	1.737	46
R#13	Pre_Crash_Mode = Autonomous, OtherVeh = Proceeding Straight, Weather = Clear, Lighting = Daylight, Collision_Type = Rear End	AV = Stopped	0.086	0.692	1.725	27
R#14	AV = Stopped, OtherVeh = Proceeding Straight, Weather = Clear, Lighting = Daylight	Collision_Type = Rear End	0.127	0.870	1.717	40
R#15	AV = Stopped, OtherVeh = Proceeding Straight, Lighting = Daylight	Collision_Type = Rear End	0.146	0.868	1.714	46
R#16	Pre_Crash_Mode = Autonomous, OtherVeh = Proceeding Straight, Lighting = Daylight	AV = Stopped	0.105	0.688	1.713	33
R#17	Pre_Crash_Mode = Autonomous, OtherVeh = Proceeding Straight, Weather = Clear, Lighting = Daylight	AV = Stopped	0.092	0.674	1.681	29
R#18	Pre_Crash_Mode = Conventional	OtherVeh = Parked	0.054	0.106	1.658	17
R#19	Pre_Crash_Mode = Autonomous, AV = Stopped, Weather = Clear, Lighting = Daylight	Collision_Type = Rear End	0.146	0.836	1.652	46
R#20	Pre_Crash_Mode = Autonomous, OtherVeh = Proceeding Straight, Collision_Type = Rear End	AV = Stopped	0.124	0.661	1.647	39

Rules	Antecedent	Consequent	Supp.	Conf.	Lift	Count
R#21	Pre_Crash_Mode = Autonomous, OtherVeh = Proceeding Straight, Weather = Clear, Collision_Type = Rear End	AV = Stopped	0.105	0.660	1.645	33
R#22	Pre_Crash_Mode = Autonomous, OtherVeh = Proceeding Straight	AV = Stopped	0.153	0.658	1.639	48
R#23	Pre_Crash_Mode = Autonomous, AV = Stopped, Lighting = Daylight	Collision_Type = Rear End	0.162	0.823	1.624	51
R#24	Pre_Crash_Mode = Conventional, AV = Proceeding Straight	Collision_Type = Side Swipe	0.057	0.346	1.622	18
R#25	Pre_Crash_Mode = Autonomous, OtherVeh = Proceeding Straight, Weather = Clear	AV = Stopped	0.131	0.651	1.622	41
R#26	Pre_Crash_Mode = Autonomous, AV = Stopped, OtherVeh = Proceeding Straight	Collision_Type = Rear End	0.124	0.813	1.605	39
R#27	Pre_Crash_Mode = Autonomous, Collision_Type = Rear End	AV = Stopped	0.207	0.644	1.604	65
R#28	Collision_Type = Rear End	OtherVeh = Making Right Turn	0.054	0.107	1.599	17
R#29	Pre_Crash_Mode = Autonomous, OtherVeh = Proceeding Straight	Collision_Type = Rear End	0.188	0.808	1.596	59
R#30	OtherVeh = Proceeding Straight, Lighting = Daylight, Collision_Type = Rear End	AV = Stopped	0.146	0.639	1.592	46
R#31	AV = Stopped, OtherVeh = Proceeding Straight	Collision_Type = Rear End	0.185	0.806	1.591	58
R#32	Pre_Crash_Mode = Autonomous, AV = Stopped, OtherVeh = Proceeding Straight, Weather = Clear	Collision_Type = Rear End	0.105	0.805	1.59	33
R#33	Pre_Crash_Mode = Autonomous, Weather = Clear, Collision_Type = Rear End	AV = Stopped	0.178	0.636	1.586	56
R#34	OtherVeh = Proceeding Straight, Weather = Clear, Lighting = Daylight, Collision_Type = Rear End	AV = Stopped	0.127	0.635	1.582	40
R#35	Pre_Crash_Mode = Conventional, AV = Stopped, OtherVeh = Proceeding Straight, Lighting = Daylight	Collision_Type = Rear End	0.051	0.8	1.58	16
R#36	Pre_Crash_Mode = Autonomous, OtherVeh = Proceeding Straight, Weather = Clear	Collision_Type = Rear End	0.159	0.794	1.567	50
R#37	Pre_Crash_Mode = Autonomous	OtherVeh = Making Right Turn	0.051	0.105	1.564	16
R#38	Pre_Crash_Mode = Conventional, AV = Stopped, OtherVeh = Proceeding Straight	Collision_Type = Rear End	0.061	0.792	1.563	19
R#39	AV = Stopped, OtherVeh = Proceeding Straight, Weather = Clear	Collision_Type = Rear End	0.156	0.79	1.561	49
R#40	AV = Stopped, Lighting = Dark-Street Lights	Pre_Crash_Mode = Autonomous	0.057	0.75	1.539	18

Table C. Event Information of Top 40 Trips Based on Average Ranking

Rules	Count	Hard Braking Mean	Hard braking Rank	Over-speeding Rank	Excessive Over-speeding Mean	Excessive Over-speeding Rank	Average Rank
T#01	574	0.0592	18	13	0.4495	13	17.67
T#02	929	0.0517	19	17	0.5802	17	18.00
T#03	2977	0.0390	22	22	0.6537	22	19.67
T#04	2140	0.0318	25	16	0.5575	16	20.00
T#05	7721	0.0284	27	18	0.6193	18	20.33
T#06	777	0.0257	29	14	0.5084	14	21.00
T#07	1915	0.0862	13	19	0.1102	19	21.67
T#08	2953	0.0474	21	45	0.8300	45	23.33
T#09	3692	0.0181	30	35	0.8226	35	23.67
T#10	2171	0.0170	33	12	0.1612	12	25.67
T#11	607	0.2010	9	23	0.0148	23	26.33
T#12	1074	0.0102	40	42	0.9097	42	27.67
T#13	1667	0.0078	48	8	0.2346	8	28.00
T#14	979	0.0061	57	10	0.2993	10	30.67
T#15	5866	0.0085	46	21	0.2659	21	31.00
T#16	646	0.0062	56	32	0.8173	32	31.67
T#17	8206	0.2516	6	38	0.0090	38	31.67
T#18	19895	0.0034	67	20	0.6544	20	33.67
T#19	6377	0.0804	15	47	0.0612	47	34.00
T#20	579	0.9655	2	55	0.0173	55	34.33
T#21	540	0.1000	11	58	0.1019	58	35.00
T#22	719	0.0028	72	11	0.3561	11	35.67
T#23	5760	0.0033	68	4	0.0736	4	37.00
T#24	1359	0.0177	32	37	0.0471	37	37.00
T#25	8752	0.0017	80	33	0.8235	33	39.33
T#26	34864	0.0043	63	1	0.0013	1	39.33
T#27	1530	0.0013	83	15	0.3895	15	40.33
T#28	568	0.0687	16	44	0.0000	44	40.33
T#29	10971	0.0014	82	30	0.7807	30	40.67
T#30	5273	0.0152	36	41	0.0315	41	40.67
T#31	6094	0.0005	87	9	0.2529	9	41.00
T#32	1707	0.0088	44	24	0.0006	24	41.00
T#33	2082	0.0005	88	7	0.1988	7	41.33
T#34	96810	0.0006	86	6	0.1066	6	42.00
T#35	2163	0.9986	1	62	0.0000	62	42.33
T#36	19206	0.0004	90	31	0.8018	31	43.00
T#37	4024	0.0017	79	50	0.9073	50	43.67
T#38	2729	0.0066	55	46	0.1832	46	43.67
T#39	570	0.3930	3	63	0.0000	63	43.67
T#40	6022	0.0028	71	40	0.4532	40	44.00