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Influence of Level 1 and Level 2 Automated Vehicles on Fatal Crashes and Fatal Crash Occurrence

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Mineta Transportation Institute

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16. Abstract

Connected and automated vehicles (CAVs) are expected to improve safety by gradually reducing human decisions while driving. However, there are still questions on their effectiveness as we transition from almost 0% CAVs to 100% CAVs with different levels of vehicle autonomy. This research focuses on synthesizing literature and identifying risk factors influencing fatal crashes involving level 1 and level 2 CAVs in the United States. Fatal crashes involving level 0 vehicles—ones that are not connected and automated—were compared to minimize unobserved heterogeneity and randomness associated with the influencing risk factors. The research team used the fatal crash data for the years 2016 to 2019 for the analysis. A partial proportionality odds model is developed using crash, road, and vehicle characteristics as the independent variables and the fatal crash involving a vehicle with a specific level of automation as the dependent variable. The results of this research indicate that level 1 and level 2 CAVs are less likely to be involved in a fatal crash at four-way intersections, on two-way routes with wide medians, at nighttime, and in poor lighting conditions when compared to level 0 vehicles. However, they are more likely than level 0 vehicles to be involved in a fatal crash with pedestrians and bicyclists. Comparative analysis between vehicles with smart features and other vehicles indicated that pedestrian automatic emergency braking (PAEB) and lane-keeping assistance (LKA) improve the safety by reducing possible collision with a pedestrian and roadside departure, respectively. Contrarily, vehicles with other smart features are still highly likely to be involved in fatal crashes. This research adds to the growing body of literature that will identify potential areas for improvement in the safety of vehicular technologies and road geometry.

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Executive Summary

Connected and automated vehicles (CAVs) have started to penetrate into the existing transportation system in the past few years. They have the potential to reduce human errors, which is the primary cause of crashes, by either aiding drivers through the use of smart features or by fully eliminating the role of humans in driving at higher levels of automation. The research on CAVs and their potential effects on safety and operations has been analyzed by many researchers using simulation techniques. However, identifying the factors that affect crash occurrence would help answer outstanding questions related to the overall safety effectiveness of CAVs.

The studies on fatal crash occurrence in the past have shown that road geometry, traffic control devices, and the speed of vehicle are common factors causing crashes. With the inclusion of CAVs equipped with smart features, the factors affecting crashes may vary. However, the current literature documents little to no research on the factors influencing fatal crashes and fatal crash occurrence considering real-world crash data of level 1 and level 2 CAVs. Further, the efficiency of smart features tested in laboratories or in controlled environments may vary depending on driving conditions. Thus, there is a need to identify the factors influencing fatal crashes involving vehicles with varying levels of automation and the effectiveness of various smart features in improving safety to proactively plan for infrastructure at higher penetrations, improve safety, and reduce the number of fatal crashes. The objectives of this research, therefore, are (1) to collect and comprehensively evaluate data pertaining to the levels of vehicle automation and what each level entails from a safety perspective, considering selected models/makes, their manufacture year, and specifications; (2) to research the trends in the penetration of level 1 and level 2 CAVs; and (3) to model the effect of level 1 and level 2 CAVs on fatal crashes and fatal crash occurrence.

Fatal crash data for 2016–2019 was obtained from the Fatality Analysis Reporting System (FARS) database and vehicle identification numbers (VINs) of all vehicles involved in crashes were extracted. Using the VINs, smart features in each vehicle involved in a crash were retrieved from the National Highway Traffic Safety Administration (NHTSA) database by creating a tool in Python. Crash related datafiles and data of smart features were combined to form a complete dataset for modeling. Using the Society of Automobile Engineers (SAE) International levels of automation, each vehicle was classified into a level of automation based on the smart features in the vehicle.

For the purpose of comparison of crashes involving level 1 and level 2 CAVs with level 0 vehicles, three nearest fatal crashes involving level 0 vehicles were identified and considered as corresponding samples for level 0 crashes in modeling. A proportional odds (PO) test was carried out to identify the slopes of different independent variables and it was identified that some of the independent variables have unequal (varying) slopes. Thus, a partial proportional odds (PPO) model was developed to identify the factors influencing crashes involving level 1 and level 2 CAVs compared to crashes involving level 0 vehicles. To identify the effectiveness of various smart features, which are designed to enhance safety for corresponding types of crashes, comparative analysis was carried out between vehicles equipped with features and other vehicles involved in fatal crashes.

The results from the PPO model indicate that level 1 and level 2 CAVs are less likely to be involved in crashes at four-way intersections, on two-way routes with medians, at nighttime, and in conditions with poor lighting compared to level 0 vehicles. In contrast, the CAVs have higher odds of being involved in crashes with non-motorists such as pedestrians and bicyclists compared to level 0 vehicles. The CAVs were also found to be more involved in crashes on one lane routes compared to level 0 vehicles. The results from the comparative analysis indicated that adaptive cruise control (ACC) and forward collision warning system (FCWS) are not efficient in improving safety in case of rear-end collisions. However, vehicles with pedestrian automatic emergency braking (PAEB) and lane-keeping assistance (LKA) are efficient in improving safety by reducing collisions with pedestrians and roadside departures, respectively. The findings and results from this research could be used in identifying the factors affecting fatal crashes involving CAVs, and potential areas for improvement in vehicular technologies as well as road geometry.

1. Introduction

In the United States, motor vehicle crashes are one of the top ten causes of death,[1] resulting in congestion and increasing safety concerns. In 2019, over 2.35 million people were injured or disabled, and 36,096 people lost their lives solely because of road crashes.[2] The cost of one fatality related to a motor vehicle crash is $1,704,000, while the cost of evident injury is $28,500.[3] According to the Centers for Disease Control and Prevention (CDC), the cost of medical care and productivity losses due to motor vehicle crashes (injuries and fatality) was reported to be more than $75 billion in the United States.[4] Drivers are at risk of being involved in a crash, regardless of whether they drive the safest vehicle or on familiar roads in normal conditions.

Several factors related to driver errors, such as improper lane changes, excessive speed, and inattentiveness while driving, cause many crashes. According to Traffic Safety Facts from the National Highway Traffic Safety Administration (NHTSA), approximately 94% of crashes in the United States between 2005 and 2007 were caused due to human errors.[5] Connected and automated vehicles (CAVs) are expected to enhance traffic safety and operation by reducing human involvement in various driving tasks with the help of assistance provided by smart features. In the past few years, a plethora of research work focusing on the effects of CAVs on traffic safety, operation, and human involvement have been published by researchers working in transportation. However, level 1 and level 2 CAVs are already penetrating the market, and their effects on crash occurrence needs to be identified.

The smart features engaged in CAVs reduce the involvement of humans in driving and could potentially eliminate human errors. However, driver reliance on these features may also result in inattentiveness while driving. While sitting idle in the driving seat, drivers may use mobile phones or perform other secondary tasks, which could result in cognitive distractions, affecting attention and judgment.[6] Thus, it is also important to examine changes in driver's behavior while driving vehicles equipped with varying levels of automation to determine the potential safety effects of the smart features.[7] Further, the attentiveness of drivers has also been found to vary based on individuals age and gender, as well as road environment.[8]

Investigating the factors affecting crashes involving level 1 and level 2 CAVs provide insights on the involvement of CAVs equipped with smart features designed to enhance safety in certain types of crashes. Furthermore, the findings of this study also help to identify the involvement of CAVs in crashes, which would help manufacturers and practitioners modify existing CAVs and design new policies.

1.1 Problem Statement

Motor vehicles and driver interactions are likely to change significantly in the next few decades, perhaps more than they have in the past. Recent and ongoing advances in vehicle automation technology have created very high expectations regarding highway performance, safety improvements, and environmental benefits. As human error is the leading cause of road crashes in the United States, CAVs are expected to reduce the number of crashes caused by drivers through the gradual removal of the role of human decisions in driving.

Although the deployment of driving assistance and autopilot features has increased over recent years, fully automated CAVs are not yet a reality, apart from a few test vehicles. Without a high penetration rate, the safety benefits of CAVs may not be maximized. Furthermore, the safety benefits also depend on how heavily the driver relies on driver assistance, autopilot, and other smart features. Additionally, some recent crashes involving vehicles with collision avoidance and autopilot systems, resulting in deaths, indicate that CAVs may not yet be effective all of the time. Potential reasons are related to disengagement and smart features abilities to sense and control the CAV irrespective of the geographic location, geometric configurations, environmental and traffic conditions, and time of day.

Understanding the effect of the transition from no CAVs to level 1 and level 2 CAVs, and ultimately all CAVs, on the overall safety of the transportation system could be more challenging than expected. A comprehensive safety analysis to examine the trends in crashes over time in conjunction with the advancements in vehicle technology is the first step. Such analysis should be complemented with modeling to identify factors associated with level 1 and level 2 CAV crash involvement when compared to non-automated (level 0) vehicles. Therefore, there is a need to analyze crash data and identify factors that play a role in crashes involving level 1 and level 2 CAVs. Due to the potential reduction in driving efforts and the transition to CAVs, the conventional perception of ownership of vehicles can also be influenced over time. Therefore, there is a need to examine the market trends, probable shift to CAVs (mode shift), and projected effect of vehicles with different levels of automation on crashes. This will help in developing a readiness plan to proactively address anticipated safety challenges in future years.

1.2 Research Objectives

The objectives of the proposed research are as follows:

- To collect and comprehensively evaluate data pertaining to the levels of vehicle automation and what each level entails from a safety perspective, considering selected models/makes, their manufacture year, and specifications.

- To research the trends in the penetration of level 1 and level 2 automated vehicles (AVs).

- To model the effect of level 1 and level 2 CAVs on fatal crashes and fatal crash occurrence.

The descriptive statistics from crash data provide an overview of the number of crashes involving level 1 and level 2 CAVs. The PPO model results compare the CAVs with level 0 vehicles and identify the factors affecting occurrence of fatal crashes involving level 1 and level 2 CAVs. The findings also help in identifying the factors related to vehicle, road geometry, and crash, for implementing policies to improve the safety of the existing transportation system and serve as an overview of current involvement of CAVs in fatal crashes.

1.3 Organization of the Report

The remainder of the report comprises six chapters. Chapter 2 summarizes past literature related to the effects of CAVs on safety, factors affecting fatal crashes, occurrence of fatal crashes, and market penetration trends of CAVs. Further, the effects of CAVs on the occurrence of fatal crashes is summarized along with the limitations of past research. Chapter 3 presents the methodological framework adopted for this research. Chapter 4 describes the study area, data collection, and processing methods along with the descriptive statistics of the data used in this research. Chapter 5 discusses the modeling technique used and the results from the partial proportional odds (PPO) model of level 1 and level 2 CAVs. The summary of vehicles equipped with various smart features and their efficiency in reducing fatal crashes is presented in Chapter 6. Chapter 7 presents the summary of this research, along with conclusions and the scope of future research.

2. Literature Review

This chapter presents an overview of past research associated with factors affecting fatal crashes, levels of automation, and the effects of CAVs on traffic safety and operations. Further, additional discussions related to studies on the effect of CAVs on mode choice, trip generation, and penetration of CAVs into the automobile market are presented.

2.1 Factors Influencing Crashes

In the past, many researchers focused on identifying factors influencing crashes, such as the dimension of medians,[9] side traffic barriers,[10] speed limits,[11] road infrastructure,[12] highway class, demographic characteristics[13] and adverse weather conditions.[14,15] Some researchers also evaluated the effects of red-light cameras,[16,17] road surface,[18] intersection type,[19] and annual average daily traffic (AADT) on crashes at intersections.[19,20] These studies are a few examples efforts on identifying the factors related to crashes or using before and after analysis to determine improvements in traffic safety.

In addition to the road and geometry-related factors, vehicle characteristics (smart features, safety standards, size, and type of vehicle) also influence crash injury severity. However, most vehicle safety devices are considered as secondary measures as their existence cannot prevent a vehicle from getting involved in a crash. Their sole purpose is to reduce the effect of a crash on the drivers and passengers. For example, vehicle safety devices such as seatbelts,[21-23] airbags,[22] and antilock braking systems[21] reduce injury severity in a crash.

A report published by the NHTSA shows that more than 94% of all motor vehicle crashes are caused by human error.[2] The causes of human error generally vary for different age groups. Teen drivers (below 20 years of age) generally get involved in crashes because of their immaturity, lack of skills, inexperience, and aggressive driving nature. Thus, the crash rate per miles driven and crash rate per number of license holders are higher for teens than for adults.[24] In contrast, elderly drivers (above 65 years) generally suffer from age or health-related problems which affect their reaction time, ability to divide attention between multiple tasks, and vision,[25] due to which their chances of getting involved in a crash are higher compared to adult drivers.[26] In addition to age, several other factors such as gender, distracted driving, and driving under the influence of alcohol or drugs also influence the likelihood of getting involved in crashes.

2.2 Levels of Automation

CAVs are expected to reduce the number of crashes caused by drivers through the gradual removal of the role of human decisions in driving. CAVs are characterized as smart vehicles that can interact with other vehicles and infrastructure to avoid any possible crashes resulting from human errors like inattentiveness, distracted driving, or aggressive driving. They are driving the existing market because of increasing emphasis towards safety, advancement of the vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) connectivity, and introduction of the internet of things (IoT) in the automobile industry.

According to the Society of Automotive Engineers (SAE) International, CAVs will integrate on roads using six different automation levels.[27] Vehicles without any smart features are categorized as level 0 (or non-CAVs). Vehicles that the driver could control but with features to assist the driver in handling lateral movement by ensuring that the vehicle stays in the lane or linear movement by controlling the acceleration and braking function qualifies as level 1. Partially automated (level 2) vehicles have automated functions that can control both acceleration and steering, but, driver has to steer, accelerate or break when needed to maintain safety.[27-29]

Level 3 vehicles should perform all driving tasks under limited circumstances such as driving on freeways or straight routes. Simultaneously, the human driver has to control the vehicle at any time, especially when there are multiple lane markings (mostly at intersections). Level 4 and level 5 vehicles are not yet available in automobile markets for vehicle owners. Still, several automobile manufacturers are working on developing such vehicles that have the capabilities of self-driving and require limited to no human efforts in performing driving tasks.[27]

2.3 Operational and Safety Effects of CAVs

Several studies have evaluated the effect of CAVs on road operational performance by considering various measures such as the average speed,[30] travel time and travel time reliability,[31-33] number of stops,[34] and delay at nodes or intersections in a particular network.[34] A few researchers have evaluated the safety effects of CAVs using surrogate safety assessment model (SSAM).[35,36] Some researchers identified the effects of smart features of CAVs on safety. Examples include the effects of automated braking system (ABS),[37] lane-keeping assistance (LKA),[38] adaptive cruise control (ACC),[37,39] forward collision warning system (FCWS),[38] and crash avoidance technology[37] on safety. To analyze the effects of vehicles on safety, researchers have developed different parametric and non-parametric models such as negative binomial model,[40] spatial autoregressive model,[40] modified negative binomial regression,[41] multivariate adaptive regression,[40] bootstrap-based binary logistic regression,[42] random parameter models,[43] and intelligent driver models.[44]

Based on the detailed review of previous research studies, microscopic simulation is the most common method adopted to evaluate the safety effects of CAVs.[45] However, accurately calibrated models and appropriate surrogate safety measures are required to improve the degree of reliability of the simulation results.[45] This is not feasible for this study due to the insignificant number of CAVs in use in the transportation system at this time. Although level 1 and level 2 CAVs are available in recent years, only a few studies have used real-world data to identify CAVs safety effectiveness.

There are limited studies comparing the safety effects of CAVs with level 0 vehicles. Researchers have conducted a comparative analysis of the driving potential of human drivers and CAVs using real world data of crash rate per million vehicle miles travelled.[46] There are potential barriers that CAVs must overcome to eliminate human interaction while performing driving tasks in a real-world scenario. CAVs are considered to be safe and efficient, but are still involved in crashes. The potential reasons they are mostly involved in crashes include disengagement of automated features, false detection of objects, and perception discrepancies.[47,48] Additionally, some recent crashes involving vehicles with collision avoidance and autopilot systems, resulting in deaths, indicate that CAVs may not be yet effective all of the time.

2.4 Penetration of CAVs

The benefits of CAV technology largely depend on a higher market penetration rate. The CAVs are expected to enhance traffic safety and operational performance of a transportation system through reduced reaction times, shorter gaps between vehicles (platooning), and efficient route choices. Market penetration is the percent of CAVs in the total fleet mix. Over the years, market penetration may vary from level 1 (partial automation) to level 5 (full automation). A few studies aimed to predict market penetration over time by analyzing technology trends and travel preferences.[49,50] Lavasani et al. (2016)[49] developed a market penetration model based on the adoption patterns of other technologies such as smartphones and the internet. Assuming CAVs are available in 2025, the study results indicate 7% CAV penetration in 2035 and 75% CAV penetration in 2060 in the United States.[49]

Similarly, Chen et al. (2016) also found that it would take between 12 and 25 years for 75% penetration of CAVs.[50] Kröger et al. (2019) used a vehicle technology diffusion model and presented existing trends and extreme adoption scenarios for the year 2035 in United States and Germany.[51] The penetration of CAVs based on the existing trend scenario was projected to be 10% and 8% for United States and Germany, respectively. However, considering the extreme adoption scenario, the CAVs penetration rate is expected to be higher (38%) in Germany compared to the United States (29%) due to a higher share of luxury cars and quicker fleet turnover. Bansal and Kockelman (2017) surveyed 2,167 Americans using a stated preference survey about CAV technologies.[52] The results suggest that privately-owned CAVs would have 24.8% penetration by 2045, assuming an annual reduction of 5% in the price of a CAV. However, the share jumps to 87.2% if prices decline by 10% every year.

Nieuwenhuijsen et al. (2018), in their study on penetration of CAVs, generated three possible scenarios by varying parameters such as consumer's attitude towards CAVs, economic growth, technological developments, and policies related to CAVs.[53] In the base scenario, varying policies related to CAVs and car-sharing success rates were tested. It was estimated that in 2025, the market share of level 1 and level 2 CAVs would be 21% and 51% respectively. In the other two scenarios, positive attitudes towards CAVs, strong economic growth, and higher technological enhancements were considered, and it was projected that in 2025, market penetration of level 1 and level 2 CAVs would be 8% and 24% under conservative, and 3% and 10% under the progressive scenario.[53]

2.5 Limitations of Past Research

Understanding the effect of the transitions from level 0 to level 1 and some level 2 CAVs to all CAVs on the overall safety of the transportation system could be more challenging than expected. A comprehensive safety analysis to examine the trends in crashes in conjunction with advancements in vehicle technology is the first step. It should be complemented with synthesizing and identifying risk factors associated with fatal crashes involving level 1 and level 2 CAVs when compared to level 0 vehicles. Therefore, this research focuses on bridging this research gap by synthesizing and identifying risk factors influencing fatal crashes involving level 1 and level 2 CAVs compared to level 0 vehicles. Further, identification of makes of all level 1 and level 2 CAVs involved in fatal crashes would also provide information to the practitioners as well as industrial experts for future vehicular and policy modifications.

While the penetration of CAVs into the market is expected to increase over time, they currently account for hardly 1% of the vehicles using the transportation system. A quick comparison of vehicles involved in fatal crashes indicate that level 1 and level 2 CAVs are involved in ~1.8% of fatal crashes from 2016 to 2019 in the United States. Considering all level 0 vehicles involved in fatal crashes for comparative analysis could skew the research findings. The influence of risk factors on crash involvement could be controlled by using crashes involving level 0 vehicles within the vicinity of level 1 and level 2 CAVs. Such a nearest neighbor-based study design will help to identify and better understand the role of risk factors influencing fatal crashes involving level 1 and level 2 CAVs compared to level 0 vehicles. It will also help minimize the effect of unobserved heterogeneity and randomness associated with the influencing risk factors.

3. Methodology

This chapter presents the methodology to identify and compare the factors influencing fatal crashes involving level 1 and level 2 CAVs with level 0 vehicles.

3.1 Study Area and Data Collection

The study area for the research was selected to maximize the number of level 1 and level 2 crashes to assess the effects of spatially varying geometric characteristics. To examine the safety effects of level 1 and level 2 CAVs on the United States' transportation system, samples from all states were considered for analysis in the present research. For identifying the sale and penetration of level 1 and level 2 CAVs, various statistical datasets and the current literature on market penetration was reviewed.

To identify the effect of various levels of automation on fatal crashes, fatal crash data of United States was collected from the Fatality Analysis and Reporting System (FARS) database. Fatal crash data from 2016 to 2019 was considered for the purpose of modeling. Further, to identify the smart features in vehicles involved in fatal crashes, the vehicle identification number (VIN) of all the vehicles was used and data pertaining to smart features was retrieved from the NHTSA database.

3.2 Data Processing

This step involved processing the raw data obtained from FARS and NHTSA databases. The raw FARS data was divided into separate files related to crash, vehicle, pedestrian, and other characteristics. Initially, the data obtained in separate files from 2016 to 2019 was linked using the case ID and year, which were the common fields in all files. Further, the data from each year was combined to form a common dataset. Some of the samples had missing values or not-reported data, and were subsequently removed.

The VIN of all vehicles in the combined dataset was extracted as a separate file and data related to all vehicles based on VIN was obtained using a Python script. A loop was created to identify information of all the vehicles in a single trial. The loop looks up each VIN in the input list, connects with the VIN dataset of NHTSA, and returns the information of all smart features in the form of a list. Finally, the retrieved data including the VINs and information about smart features engaged in vehicle was joined with the FARS dataset.

Level 1 and level 2 vehicles made up only ~1.8 % of the obtained dataset. Further, various regions were identified to have no crashes involving level 1 or level 2 vehicles. Thus, for a more balanced comparison, and to minimize the spatial variance in the geometric characteristics, for every crash involving a level 1 or level 2 vehicle, three nearest neighbors (level 0 crashes) were identified. Samples involving one or more CAVs with different levels of automations were also identified and considered as separate data points in the analysis. Before modeling, the samples with unknown or unidentified values were eliminated. Chapter 4 provides a detailed overview of the study area, data collection, and processing.

3.3 Synthesizing the Safety Effects of CAVs

The factors affecting level 1 and level 2 CAVs may vary due to vehicular characteristics. Thus, both levels of automation were considered as separate categories. A variable indicating the highest level of automation amongst all vehicles involved in a crash was considered as the dependent variable. The partial proportional odds (PPO) model is popular amongst various logistic regression models because it provides flexibility by considering varying slopes of the independent variables. As the level of automation is considered as the dependent variable, the PPO model provides flexibility to model the factors which may not get affected due to level 2 automation compared to level 1 automation with equal slope along with unequal slopes for other variables. Thus, a PPO model was developed using level of automation as a dependent variable and factors related to road geometry, crash and vehicular characteristics, as well as pedestrians and bicyclists involved in crash as independent variables. Chapter 5 provides an overview of the results.

3.4 Analysis of Safety Provided by Smart Features

The projected safety benefits of CAVs due to the presence of smart features also needs to be evaluated to identify the pros and cons of the CAVs. To identify the effect of smart features on the occurrence of fatal crashes, vehicles equipped with various smart features were identified using the smart features data obtained from the NHTSA database. Likewise, the purpose for which smart features were designed and the corresponding crash types they could mitigate were also identified. The involvement of vehicles with and without smart features was summarized in Chapter 6 to assess the overall improvement in safety due to presence of smart features.

4. Study Area, Data Collection, and Processing Methods

This chapter provides an overview of the study area, data, and data processing. Descriptive statistics are also presented in this chapter.

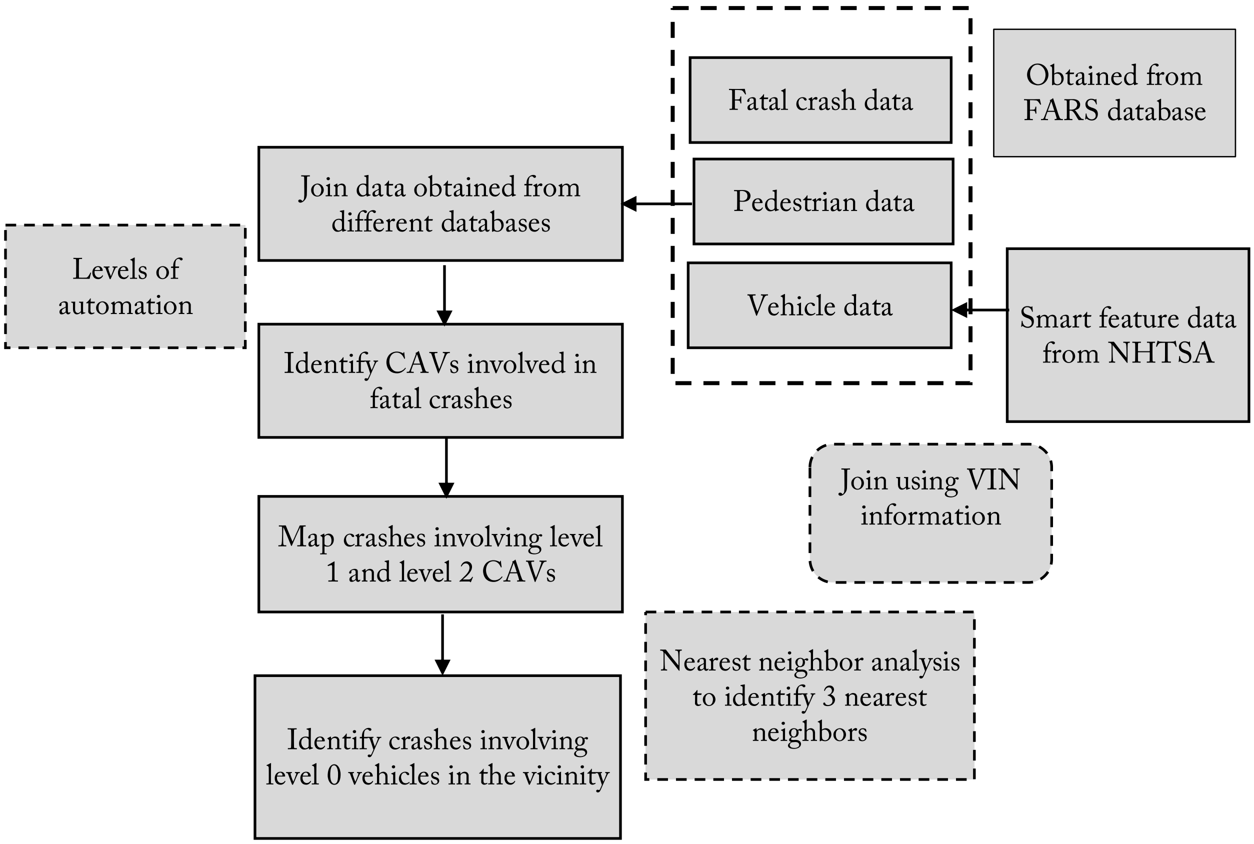
4.1 Study Area and Data Collection

The data pertaining to fatal crashes in the United States from 2016 to 2019 was obtained from the FARS database. The FARS database contains information related to fatal crashes including information on the vehicles involved in the crashes, pedestrian involvement in the crashes, and other factors. The geometric condition of the road on which each crash occurred, the weather conditions, and time of day are also included in the database. Further, the information related to smart features in vehicles involved in each crash was obtained separately from the NHTSA database using VIN.

4.2 Data Processing

The data related to all the parameters was obtained from the FARS and NHTSA databases. The data processing used for this research is summarized as shown in Figure 1.

Figure 1. Data Processing Framework

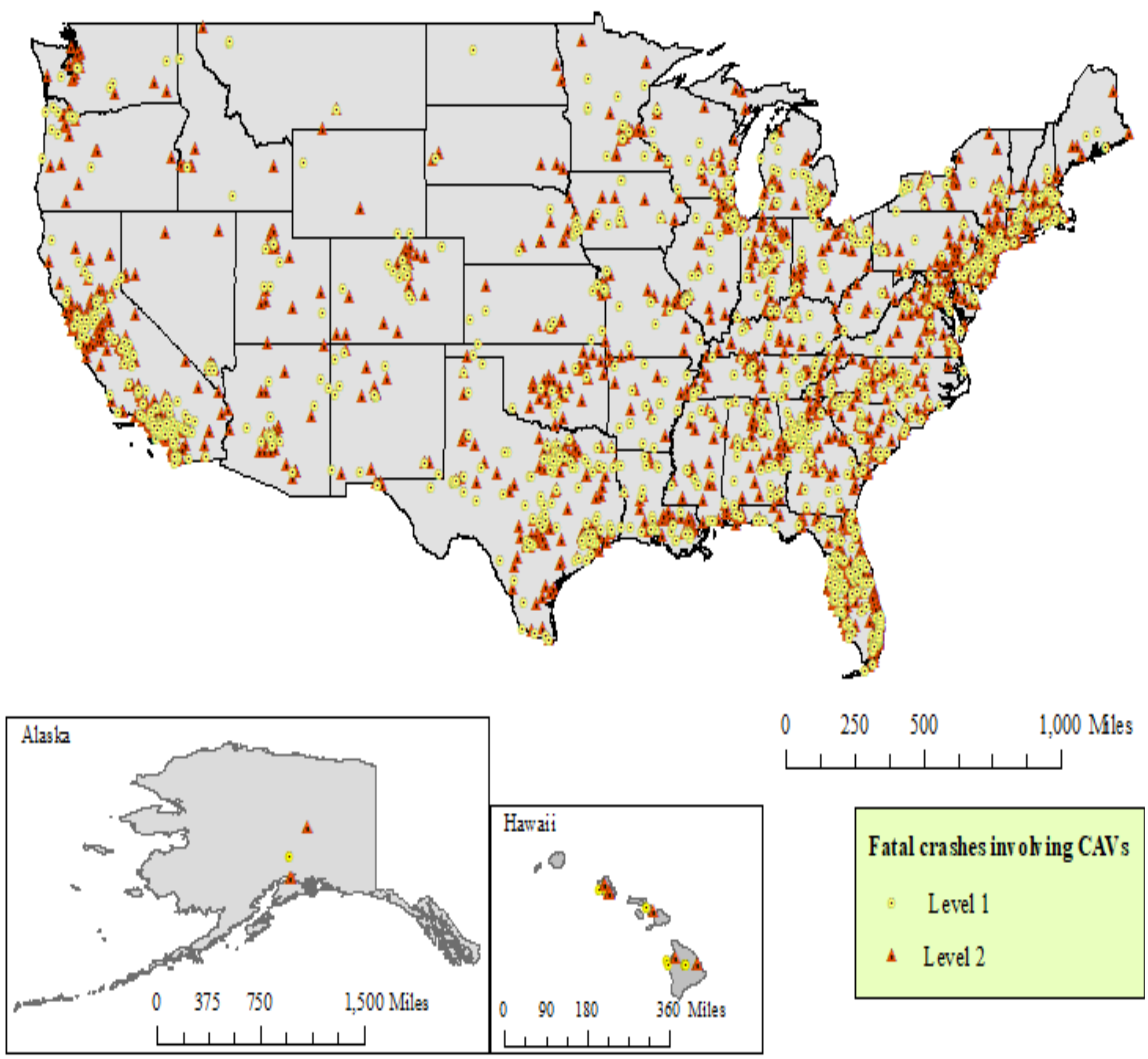


The crash database consisted of several files with different crash parameters related to vehicles, pedestrians, drivers, and visibility while driving. All datasets share a common case number, which was used to compile the full dataset used in this research. A Python script was developed to generate a loop including all the VINs, which directly calls the NHTSA database and returns all the information related to smart features such as ACC, LKA (sometimes referred to as lane centering assistance), pedestrian automatic emergency braking (PAEB), and FCWS.

The data obtained from the NHTSA database had information about several features engaged in vehicles. As per the six levels of automation described by SAE International,[27, 28] the vehicles were classified into three different groups: level 0, level 1, and level 2. The vehicles without the LKA or ACC were classified as level 0 vehicles. The vehicles with either LKA or ACC were classified as level 1 CAVs, whereas vehicles with both LKA and ACC features were classified as level 2 CAVs. Information about engagement of features in a crash was not available in the dataset.

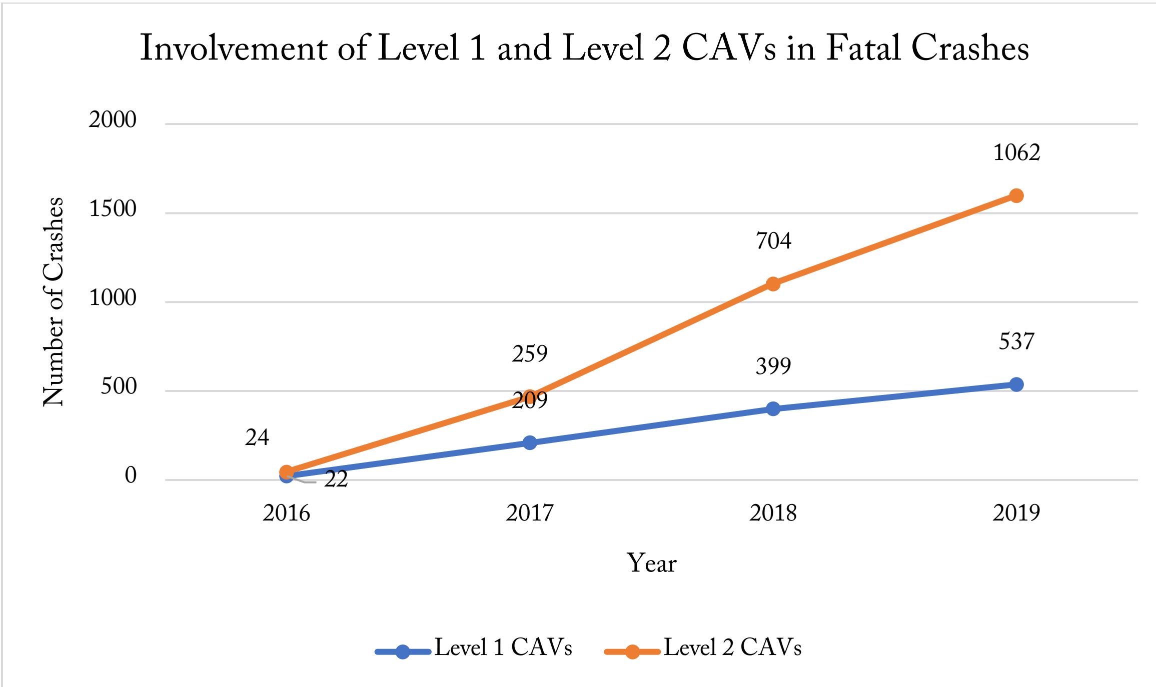
The VIN data showed that a limited number of level 1 and level 2 CAVs were involved in fatal crashes before 2016. While not many level 1 and level 2 CAVs were purchased by vehicle owners prior to 2016, the number has increased considerably in recent years. Further, the crash data also indicated that only 46 out of 52,714 vehicles involved in a crash in 2016 qualified as either level 1 or level 2 automation. Therefore, the crash data of previous years was not considered and only data for the years 2016 to 2019 was used for the analysis. In case of a crash involving both a level 1 and level 2 CAVs, it was considered in both the categories to capture the effect of vehicular characteristics on crash occurrence. Figure 2 shows the location of all crashes involving level 1 and level 2 CAVs in the United States. The total number of fatal crashes involving level 1 or level 2 CAVs was 2,428 (~1.8%) compared to 136,471 (~98.2%) fatal crashes involving level 0 vehicles.

Figure 2. Fatal Crashes Involving Level 1 and Level 2 CAVs (2016–2019) in the United States



The number of crashes involving level 1 and level 2 CAVs increased from 22 and 24, respectively, in 2016 to 537, and 1,062 in 2019. Figure 3 shows the yearly number of fatal crashes involving level 1 and level 2 CAVs. It is noticeable that level 2 crashes are almost double the number of level 1 crashes in 2019 which may be due to the increasing penetration of level 2 CAVs compared to level 1 CAVs. The involvement of level 1 and level 2 CAVs in fatal crashes also varied based on the make and model of the vehicle. The number of level 1 and level 2 CAVs involved in fatal crashes is summarized in Appendix 1.

Figure 3: Yearly Fatal Crashes in United States Involving Level 1 and Level 2 CAVs



If the sample size is uneven Cover and Hart recommend using nearest neighbors for the analysis.[54] The number of neighbors selected for comparison should be large enough to reduce the chances of biased estimates. Selecting neighbors in proportion to the samples in the reference group (in this research crashes involving level 1 and level 2 CAVs) ensures that points are close enough to provide accurate estimates.[54] This is also driven by past research findings that crashes are spatially correlated.[55,56] Considering fatal crashes involving level 0 vehicles within the vicinity of crashes involving level 1 and level 2 CAVs also minimizes unobserved heterogeneity and randomness associated with influencing risk factors. Therefore, to compare the CAVs with non-CAVs and to identify an appropriate sample size for crashes involving level 0 vehicles corresponding to crashes involving level 1 and level 2 CAVs, the three nearest neighbors from locations of crashes involving level 1 or level 2 CAVs were identified using the 'nearest neighbor' tool in ArcGIS Pro. Further, the samples with null values amongst identified crashes involving level 1 and level 2 CAVs and nearest neighbors involving level 0 vehicles were filtered to remove the samples with not-specific, unknown, or unidentified values as per the FARS database.

4.3 Descriptive Statistics

A descriptive analysis was carried out to compute the frequency distribution amongst the different categories of the independent variables. The frequency and percentage for various categories of variables in the dataset were considered for identifying the suitable technique for analysis. Table 1 shows the descriptive statistics of the crashes involving pedestrian, bicyclists, and vehicles.

Table 1. Frequency and Distribution of Variables Related to Persons, and Vehicles Involved in Crashes

Variable	Category	Frequency (%)
Level of automation	0	10,127 (80.66)
	1	863 (6.87)
	2	1,565 (12.47)
Vehicles involved	1	3,974 (31.65)
	2	5,835 (46.48)
	3	1,728 (13.76)
	>=4	1,018 (8.11)
Pedestrian involved	No	10,841 (86.35)
	Yes	1,714 (13.65)
Bicyclist involved	No	12,309 (98.04)
	Yes	246 (1.96)

The descriptive statistics show that the majority of crashes involved either 1 or 2 vehicles. However, 8.11% crashes involved more than four vehicles. In addition, pedestrian involvement in fatal crashes is higher compared to the involvement of bicyclists. The proportion of level 1 and level 2 CAVs involved in fatal crashes is 6.87% and 12.47%, respectively.

The variables related to time, location, and functional class of the road on which crashes occurred are shown along with the frequency and percentages in Table 2. They indicate that the majority of the crashes occurred on two lane routes, and at non-junction locations compared to other route types and locations of route. Further, crashes in the urban areas are higher compared to the rural areas. The temporal variation of crashes also indicates that the number of crashes is higher on Friday, and Saturday compared to other days of week. The number of crashes is also higher from 3:00 PM to 9:00 PM compared to other time periods. However, the variation is marginal amongst all the categories of time of day and day of the week due to which relying on descriptive statistics may not provide clear idea about the factors influencing fatal crashes.

The descriptive statistics of factors related to safety, traffic control measures, and other factors is summarized in Table 3. They indicate that normal conditions such as dry road surface, vehicle traveling straight before the crash, and tracking (stable) vehicle before the crash occur with higher frequencies compared to other categories of corresponding variables. The categories of all the variables were observed to identify the ideal conditions as per the past literature and were considered as base categories.

Table 2. Frequency and Distribution of Variables Related to Time and Location of Crashes

Variable	Category	Frequency (%)
Day of the week	Monday	1,753 (13.96)
	Tuesday	1,540 (12.27)
	Wednesday	1,636 (13.03)
	Thursday	1,778 (14.16)
	Friday	2,022 (16.11)
	Saturday	2,010 (16.01)
	Sunday	1,816 (14.46)
Time of the day	0:00–2:59 am	1,209 (9.63)
	3:00–5:59 am	1,026 (8.17)
	6:00–8:59 am	1,277 (10.17)
	9:00–11:59 am	1,333 (10.62)
	12:00–2:59 pm	1,821 (14.5)
	3:00–5:59 pm	2,152 (17.14)
	6:00–8:59 pm	2,011 (16.02)
	9:00–1:59 pm	1,726 (13.75)
Area type	Rural	4,591 (36.57)
	Urban	7,964 (63.43)
Functional class	Interstate	2,121 (16.89)
	Principal arterial—other freeways and expressways	810 (6.45)
	Principal arterial—other	4,400 (35.05)
	Minor arterial	2,618 (20.85)
	Major collector	1,288 (10.26)
	Minor collector	315 (2.51)
	Local	1,003 (7.99)
Number of lanes	Non-trafficway or driveway access	94 (0.75)
	One lane	172 (1.37)
	Two lanes	6,910 (55.04)
	Three lanes	1,925 (15.33)
	Four lanes	1,705 (13.58)
	Five lanes	1,238 (9.86)
	Six lanes	333 (2.65)
	Seven or more lanes	178 (1.42)
Portion of the road on which crash occurred	Acceleration/deceleration lane	16 (0.13)
	Crossover-related	28 (0.22)
	Driveway access related	512 (4.08)
	Entrance/exit ramp related	236 (1.88)
	Intersection-related	3,837 (30.56)
	Non-junction	7,614 (60.65)

Variable	Category	Frequency (%)
	Other location within interchange area	95 (0.76)
	Railway grade crossing	20 (0.16)
	Through road	197 (1.57)
Type of intersection	Three-way intersection	1,263 (10.06)
	Four-way intersection	2,550 (20.31)
	Roundabout, traffic circle, or multiple-way intersection	24 (0.19)
	Not an intersection	8,718 (69.44)
Presence of work zone	No	12,203 (97.2)
	Yes	352 (2.8)
Trafficway type	One-way trafficway	140 (1.12)
	Two-way, not divided	5,850 (46.59)
	Two-way, not divided with a continuous left-turn lane	851 (6.78)
	Two-way, divided, positive median barrier	2,492 (19.85)
	Two-way, divided, unprotected (painted > 4 feet) median	469 (3.74)
	Two-way, divided, unprotected median	2,437 (19.41)
	Entrance/exit ramp	222 (1.77)
	Non-trafficway or driveway access	94 (0.75)

Table 3: Frequency and Distribution of Variables Related to Safety, and Crash Related Factors

Variable	Category	Frequency (%)
Vehicle at fault	No	4,801 (38.24)
	Yes	7,754 (61.76)
Hit and run	No	12,355 (98.41)
	Yes	200 (1.59)
Rollover	No	10,932 (87.07)
	Yes	1,623 (12.93)
Manner of collision	Angle	3,336 (26.57)
	Front-to-front	1,918 (15.28)
	Front-to-rear	1,712 (13.64)
	Rear-to-side	39 (0.31)
	Sideswipe—opposite direction	241 (1.92)
	Sideswipe—same direction	378 (3.01)
	The first harmful event was not a collision with a motor vehicle in transport	1,421 (11.32)
	Not a collision with motor vehicle in-transport	3,510 (27.96)
Damage to the vehicle	No damage	254 (2.02)
	Minor damage	1,163 (9.26)
	Functional damage	1,568 (12.49)
	Disabling damage	9,570 (76.22)
Light condition	Daylight	6,380 (50.82)
	Dark—lighted or unknown light	2,713 (21.61)
	Dark—not lighted	2,927 (23.31)
	Dawn	259 (2.06)
	Dusk	276 (2.2)
Fatalities in crash	1	11,443 (91.14)
	2	890 (7.09)
	>2	222 (1.77)
Speeding	No	10,543 (83.97)
	Yes, exceeded speed limit	1,101 (8.77)
	Yes, too fast or racing	911 (7.26)
Traffic control device	No control	9,926 (79.06)
	Traffic control signal (on colors) with pedestrian signal	296 (2.36)
	Traffic control signal (on colors) without or unknown pedestrian signal	1,373 (10.94)
	Stop sign	625 (4.98)
	Warning sign	156 (1.24)
	Other regulatory sign	68 (0.54)
	Flashing traffic control signal	40 (0.32)

Variable	Category	Frequency (%)
	Highway traffic signal	9 (0.07)
	Railway crossing device or school zone device	26 (0.21)
	Yield sign or person	36 (0.29)
Presence of curve	Straight	10,352 (82.45)
	Curve	2,109 (16.8)
	Non-trafficway or driveway access	94 (0.75)
Surface condition	Dry	10,774 (85.81)
	Wet	1,435 (11.43)
	Ice/frost	92 (0.73)
	Snow	86 (0.68)
	Mud, dirt, or gravel	40 (0.32)
	Oil or water	34 (0.27)
	Non-Trafficway or Driveway Access	94 (0.75)

5. Synthesizing the Safety Effects of Level 1 and Level 2 CAVs

As all the variables were categorical variables, logistic regression techniques, which are most suitable for analysis of categorical variables were explored to identify the potential analysis method.

5.1 Proportional Odds Model

The dependent variable is ordinal, and the aim of this research is to model and identify the risk factors influencing fatal crashes involving level 1 and level 2 CAVs compared to level 0 vehicles. Ordered probability models (ordered probit or logit model), a class of logistic models, are regression models which can be used when the dependent variable has three or more categories, and the order of different categories is important.[57] In this research, the fatal crashes involving vehicles with different levels of automation are analyzed. They follow a hierarchical order as various smart features in level 1 and level 2 CAVs make them safer.[38] Thus, ordered probability models were identified as more appropriate method for the present analysis.

The proportional odds (PO) modeling technique may also be appropriate for analysis of this problem as there are many parameters related to a fatal crash, and all of them may directly or indirectly influence the occurrence of a crash. The PO model provides the odds (likelihood) of occurrence of a particular event for a selected category compared to the base category (optimum condition). One of the fundamental assumptions of the PO model is that the independent variables influence all the categories of the dependent variable identically (equal slope). In other words, for a dependent variable, with order Y= 1, 2,….,p, where p>1, the PO model with 'n' independent variables (X1, X2,….Xn) has (p-1) intercepts with 'n' slopes. The PO model is mathematically expressed as shown in Equation 1.[58-61]

$$\ln\left(Y'_p\right) = logit[\pi(x)] = \ln\left(\frac{\pi(x)}{1-\pi(x)}\right) = \propto_p + \left(\beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_n X_n\right) \qquad (1)$$

The prediction of the PO model represents the expected logit for the category 'p' or above and Y'p represents the odds of being in higher categories. In order to estimate the probability, PO model predictions are required to be transformed as odds, which can be used to estimate probability using Equation 2.[61]

$$P(Y \geq p) = \frac{\exp\left(\ln\left(Y'_p\right)\right)}{1 + \exp\left(\ln\left(Y'_p\right)\right)} \qquad (2)$$

The categories of all the independent variables as well as dependent variables along with the frequency and percentages are obtained using Statistical Analysis System (SAS) analytics suite.[57]

5.2 Partial Proportional Odds (PPO) Model

Three fatal crashes involving level 0 vehicles, which were closest in locations to each fatal crash involving level 1 or level 2 CAV, were considered for analysis. Thus, it is assumed that the spatial heterogeneity associated with fatal crashes involving level 0 vehicles would also be associated with fatal crashes involving level 1 or level 2 CAV. Further, the severity level is the same amongst samples as only fatal crashes are considered for comparison. Thus, the partial proportional odds (PPO) model, which allows flexibility by providing unequal and equal slopes to different independent variables, was used instead of other statistical methods which account for heterogeneity.

Prior to developing the PPO model, an odds proportionality test was conducted using SAS. The test showed that all the independent variables are not influencing all the categories of the dependent variable (fatal crash involvements by the level of automation) identically. In other words, some of the factors affecting fatal crash occurrence are different in crashes involving level 1 and level 2 CAVs. The null hypothesis that all the independent variables have an identical effect on all dependent variables is rejected (p-value less than 0.05). Several independent variables have unequal slopes, which violates the basic assumption of equal slopes in the PO model. Thus, the PPO model was developed using SAS by identifying and assigning both equal and unequal slopes to the independent variables, as shown in Equation 3.

$$\ln\left(Y'_{\ p}\right) = \ln\left(\frac{\pi_p(x)}{1-\pi_p(x)}\right) = \propto_p + \left(\beta_{1p}X_1 + \beta_{2p}X_2 + \beta_{3p}X_3 + \cdots . \beta_{np}X_n\right) \quad (3)$$

5.3 PPO Model Results

The results of the PPO model indicate that all the variables shown in Table 4 are significant, except the number of lanes, at a 90% confidence level. Further, the individual significance of each category of the independent variable 'number of lanes' indicated that the category (road with one lane) is significant at a 99% confidence level, thus the parameter is not dropped from the model. The final model is developed considering all the variables mentioned in Table 4. It is the result of modeling using a backward elimination approach, which was considered to remove one variable at a time which were not significant to improve the model fit.

Table 4. Analysis of Effects

Independent variable	Wald chi-square	p-value
Vehicles involved	46.18	<.01
Pedestrian involved	7.81	0.01
Bicyclist involved	3.94	0.05
Day of the week	23.34	<.01
Time of day	17.38	0.02
Functional class	23.89	0.02
Manner of collision	138.21	<.01
Portion of the road on which crash occurred	19.57	0.01
Type of intersection	4.69	0.10
Fatalities in crash	12.01	<.01
Vehicle at fault	9.61	<.01
Rollover	15.34	<.01
Damage to the vehicle	15.37	0.02
Speeding	5.91	0.05
Traffic way type	82.45	<.01
Number of lanes	10.08	0.12
Traffic control device	15.02	0.09
Pre-crash stability of vehicle	23.89	<.01
Pre-crash movement of vehicle	10.41	0.06

The effects of the independent variables (Table 4) also indicates that number of vehicles involved, manner of collision, traffic way type, and pre-crash stability of the vehicle are the most significant independent variables. The results of the PPO model developed using SAS along with the odds ratio are summarized in Table 5. The Akaike information criterion (AIC) value of the PPO model shown in Table 5 is 14978. It was 15496 for the intercept-only model.

Further, the likelihood ratio and Wald chi-square statistic values are also statistically significant (p-value less than 0.01), which indicates that the model with independent variables is a better fit than the intercept-only model. The estimated results in Table 5 also show that three of the independent variables have varying slopes and their influence in fatal crashes involving level 1 and level 2 CAVs varies.

Table 5: Estimates and Odds Ratios for Models by the Level of Automation

Variable (Reference category)	Category	Estimate		Odds ratio	
		Level 1	Level 2	Level 1	Level 2
Intercept		-1.822*	-2.645*	-	-
Vehicles involved (1)	2	0.086		1.09	
	3	0.336*		1.4*	
	>=4	0.631*		1.879*	
Pedestrian involved (no)	Yes	0.283*		1.328*	
Bicyclist involved (no)	Yes	0.354**		1.425**	
Day of the week (Wednesday)	Monday	-0.011		0.989	
	Tuesday	-0.112		0.894	
	Thursday	-0.112		0.894	
	Friday	-0.067		0.935	
	Saturday	-0.027		0.974	
	Sunday	0.235**		1.265**	
Time of the day (9:00–11:59:00am)	0:00–2:59am	-0.302**		0.739*	
	3:00–5:59am	-0.176		0.838	
	6:00–8:59am	-0.182		0.833	
	12:00–2:59pm	-0.084		0.919	
	3:00–5:59pm	0.002		1.002	
	6:00–8:59pm	-0.004		0.996	
	9:00–11:59pm	-0.187**		0.829**	
Functional class (principal arterial—other)	Interstate	-0.026	-0.137	0.974	0.872
	Principal arterial—other freeways and expressways	0.127	0.238**	1.136	1.269**
	Minor arterial	0.06	0.055	1.062	1.057
	Major collector	0.064	0.037	1.066	1.038
	Minor collector	-0.01	0.251	0.99	1.286
	Local	0.093	0.105	1.097	1.111
Manner of collision (angle)	Front-to-front	0.227**		1.257**	
	Front-to-rear	-0.057		0.944	
	Rear-to-side	-0.669		0.512	
	Sideswipe—opposite direction	0.072		1.074	
	Sideswipe—same direction	0.074		1.077	
	The first harmful event was not a collision with a motor vehicle in transport	0.639**		1.894**	

Variable (Reference category)	Category	Estimate		Odds ratio	
		Level 1	Level 2	Level 1	Level 2
	Not a collision with motor vehicle in-transport	-0.244*		0.783*	
Portion of the road on which crash occurred (non-junction)	Acceleration/deceleration lane	0.498		1.646	
	Crossover-related	-0.328		0.72	
	Driveway access related	-0.092		0.912	
	Entrance/exit ramp related	-0.422		0.656	
	Intersection-related	0.625		1.868	
	Other location within interchange area	0.589**		1.803**	
	Railway grade crossing	-0.535		0.586	
	Through road	0.494*		1.639*	
Type of intersection (not an intersection)	Three-way intersection	-0.678		0.508	
	Four-way intersection	-0.811**		0.445**	
	Roundabout, traffic circle, or multiple-way intersection	0		-	
Fatalities in crash (1)	2	0.283*		1.327*	
	>2	0.184		1.202	
Vehicle at fault (no)	Yes	-0.191**		0.826**	
Rollover (no rollover)	Yes	-0.325**	-0.228**	0.723**	0.796**
Damage to the vehicle (no damage)	Minor damage	0.132	0.521**	1.141	1.685**
	Functional damage	0.357*	0.611*	1.43*	1.843*
	Disabling damage	0.258	0.53**	1.294	1.699**
Speeding (no)	Yes, exceeded speed limit	0.166		1.181	
	Yes, too fast or racing	-0.136		0.872	
Traffic way type (two-way divided with positive median barrier)	One-way trafficway	0.002		1.002	
	Two-way, not divided	0.14		1.151	
	Two-way, not divided with a continuous left-turn lane	0.173		1.189	
	Two-way, divided, unprotected (painted > 4 feet) median	-2.395*		0.091*	
	Two-way, divided, unprotected median	0.404*		1.499*	
	Entrance/exit ramp	0.181		1.198	
	Non-trafficway or driveway access	0.394		1.482	
Number of lanes (two lanes)	Non-trafficway or driveway access	0		-	

Variable (Reference category)	Category	Estimate		Odds ratio	
		Level 1	Level 2	Level 1	Level 2
	One lane	0.723**		2.068**	
	Three lanes	0.057		1.059	
	Four lanes	0.014		1.015	
	Five lanes	0.011		1.011	
	Six lanes	-0.038		0.963	
	Seven or more lanes	0.001		1.001	
Traffic control device (no control)	Traffic control signal (on colors) with pedestrian signal	0.018		1.019	
	Traffic control signal (on colors) without or unknown pedestrian signal	0.089		1.093	
	Stop sign	0.319*		1.375*	
	Warning sign	-0.236		0.79	
	Other regulatory sign	-0.467		0.627	
	Flashing traffic control signal	0.223		1.249	
	Highway traffic signal	-1.334		0.263	
	Railway crossing device or school zone device	-0.112		0.894	
	Yield sign or person	0.689**		1.991**	
Pre-crash stability of vehicle (tracking)	Skidding laterally	-0.417*		0.659*	
	Skidding longitudinally	-0.443*		0.642*	
	Other vehicle loss of control	-9.692		<0.001	
	Pre-crash stability not specific	0.147**		1.159**	
Pre-crash movement of vehicle (stayed in original travel lane)	Stayed on road (left original travel lane)	-0.13		0.878	
	Departed road	-0.143		0.867	
	Remained off road	-0.348		0.706	
	Entered road	-0.6		0.549	
	Returned to road	-0.845**		0.43**	

Note 1: ** Significant at a 95% confidence level
Note 2: * Significant at a 90% confidence level

The negative value of estimates, e.g., for the portion of the road on which a crash occurred (crossover related) and speeding (too fast), indicate a lower likelihood of a particular outcome. The odds ratio for each parameter represents the odds of a specific outcome compared to the other outcomes. It was computed using the exponential of the estimate for a particular category. For example, for four-way intersections with an estimate (-0.81), the odds ratio is 0.0445 (e-0.081), indicating that a fatal crash involving a level 1 or level 2 CAV is less likely to occur at a four-way intersection compared to a fatal crash involving level 0 vehicle, than at any location on the route other than an intersection. Likewise, the odds of being involved in a fatal crash for level 1 or level 2 CAVs compared with level 0 vehicles are 1.64 times higher on through lanes than at non-junction locations, when keeping all other parameters constants.

Crashes were statistically significantly less likely to occur in two time of the day periods (9:00 pm to 11:59 pm and (0:00 am to 2:59 am) at a 95% confidence level compared with the reference time. Further, it is 27% more likely that fatal crashes involving CAVs occur on Sunday (weekend) than on Wednesday (weekday).

Pedestrians are the most vulnerable road users. The odds of a crash involving pedestrians or bicyclists was greater than 1, indicating a higher likelihood of fatal crashes involving CAVs and pedestrians or bicyclists. Further, from a safety perspective, head-on collisions are generally more severe than angle collisions and the likelihood of a head-on collision is higher compared to an angle collision. Among all the portions on the road, odds that fatal crashes will occur on a through road or at a location within the interchange area are higher.

CAVs are considered safer vehicles, and the model results in the case of rollovers also convey that the likelihood of level 1 and level 2 CAVs being involved in a rollover is less compared to no rollover. In addition, the odds of CAV crash involving minor, functional, and disabling damage is also high compared to no damage, which is as expected in case of a fatal crashes.

Road geometry plays an important role in the occurrence of a crash. The model results show that the likelihood of a fatal crash on a two-way divided road with a median wider than 4 feet is less compared to a two-way road with a positive median barrier. Contrarily, a two-way divided road with a positive median barrier is safer than the road with an unprotected median. Further, the likelihood of a fatal crash on a one-lane road is 107% higher compared to two-lane roads, and the odds of a fatal crash at a stop sign and yield sign are, respectively, 37% and 99% higher than at intersections with no traffic control.

The CAVs with smart features could also influence the driving behavior of drivers, as while relying on technology they could become less attentive, which may be why drivers are less attentive at locations with stop or yield signs. Finally, the likelihood of getting involved in a fatal crash while returning on the road is less compared to the vehicles traveling in the same lane.

The variables such as rollover, damage to the vehicle, and functional class with unequal slopes show that the response of level 1 and level 2 CAVs is not the same. Independent variables such as rollover and damage to the vehicle show that level 1 CAVs are safer than level 2 CAVs, whereas the odds ratio of different functional classes shows that level 2 CAVs are safer than level 1 CAVs on interstates, minor arterials, and major collectors. On principal arterials, minor collectors, and local roads, level 1 CAVs were found to be safer than level 2 CAVs. As level 2 CAVs have both LKA and ACC, they can provide enhanced safety in the case of freeways by controlling the acceleration as well as lane departure, which are often causes of crashes on freeways. Further, the odds of crashing for vehicles traveling too fast are less compared to vehicles that are not over-speeding in the case of CAVs, indicating that CAVs could provide better safety at high speeds, primarily due to the smart features.

6. Analysis of Effect of Smart Features on Fatal Crash Occurrence

The involvement of level 1 and/or level 2 CAVs in fatal crashes compared to level 0 vehicles varies with the smart features. Thus, based on the VIN, details regarding fatal crashes involving vehicles with smart features that are designed for performing specific tasks and enhancing safety were extracted. The ACC system controls acceleration and deceleration of vehicle to maintain a significant gap from the vehicle in front,[39] which affects the likelihood of the vehicle being involved in a rear-end collision. If the leading vehicle slows down, the sensor detects that movement and automatically applies brakes. If no vehicles are present in front, the vehicle travels at a set speed.[37] The LKA pushes the vehicle towards center of the lane if it is moving outside the lane and makes the driving task smoother. The PAEB system automatically engages brakes when it identifies a pedestrian in front of the vehicle and reduces chances of a crash with the pedestrian.[37] The blind spot monitoring (BSM) system, also known as side-view assist system, provides a warning to the driver when other vehicles or objects are present in the blind spot of the vehicle and improves the safety from sideswipe or rear-to-side collisions.[38] The FCWS provides a warning to the vehicle in the case of forward collision risk and reduces the chances of being involved in rear-end collisions when the driver is at fault.[38] The data for all the features and different collision types for which the specific features are designed for was extracted from the FARS database and summarized as shown in Table 6. Further, similar to the previous models, data for years 2016 to 2019 is used for the purpose of comparison.

In Table 6, the proportion of pedestrian crashes from all fatal crashes is higher than the corresponding proportion for vehicles equipped with a PAEB system. In the case of ACC and FCWS, the percentage of rear-end collisions is almost double compared to other vehicles without these features. Similarly, the proportion of sideswipe or rear-to-side collision of vehicles with BSM is also double compared to the data of all crashes. In the case of vehicles with LKA system, fatal crashes involving roadside departure are considered for the analysis. Crashes involving roadside departure include only cases when the vehicle runs off the road. Other cases where the vehicle ran off the road while trying to avoid collision with other vehicles/pedestrians or due to traction loss are not considered in this comparison. These trends can be mainly attributed to only considering fatal crash data in the evaluation. Considering injury crashes and property damage crashes in the evaluation could further improve the clarity of these findings.

Overall, smart features are designed to enhance safety and avoid particular types of crashes. However, research findings indicate that these smart features may not be yet effective all the time. Potential reasons are related to localization and the ability of features to sense and control the CAV irrespective of the geographic location and geometric, environmental, and traffic conditions.

Table 6: Comparison of Vehicles with Smart Features and All Vehicles

Safety features	Total crashes	Pedestrian crashes	Rear-end collisions	Rear-to-side collisions or sideswipe	Total vehicles involved	Roadside departure
# of Crashes	1,36,471	26,366 (19.32%)	9,650 (7.07%)	324 (1.70%)	2,09,375	30,374 (14.51%)
Crashes involving vehicles with PAEB system	1,327	217 (16.35%)	-	-	-	-
Crashes involving vehicles with FCWS	2,889	-	425 (14.71%)	-	-	-
Crashes involving vehicles with ACC	2,356	-	346 (14.69%)	-	-	-
Crashes involving vehicles with BSM	2,253	-	-	77 (3.42%)	-	-
Vehicles with LKA	-	-	-	-	2,845	288 (10.12%)

7. Summary & Conclusions

7.1 Summary

The risk factors influencing fatal crashes involving level 1 and level 2 CAVs compared to level 0 vehicles within vicinity were explored using PO and PPO models. The PO test showed that all the independent variables do not have equal slopes, and their effect on the dependent variable varies, which violated the basic assumption of the PO model. Thus, the PPO model was considered appropriate and developed using all the independent variables.

The factors such as rollover of vehicles, pre-crash movement of a vehicle, type of intersection, and pre-crash stability of a vehicle indicate that the likelihood of a fatal crash for level 1 and level 2 CAVs is less compared to level 0 vehicles. The CAVs are safer when vehicles depart the travel lane or skid laterally or longitudinally before the crash, indicating their safety benefits in snow or rainy weather. Level 1 and level 2 CAVs are safer on interstates and in conditions when the vehicle is moving too fast than the speed limit, ensuring their higher safety, especially on high-speed routes. Further, the odds of a fatal crash involving level 2 CAVs are less on minor arterial and major collectors than level 1 CAVs. In comparison, level 1 CAVs are safer on low-volume roads such as minor collectors and local roads. Further, the chances of a fatal crash involving CAVs on a two-lane road is lower than a road with single or multiple lanes.

The chances of level 1 or level 2 CAVs getting involved in a fatal crash with non-motorists such as pedestrians or bicyclists is higher than level 0 vehicles. One of the reasons behind the higher odds of getting involved in fatal crashes with non-motorists may be due to decreased attentiveness of drivers due to reliance on the technology. Similarly, the chances of a fatal crash involving a CAV at a flashing signal or stop sign is also higher than a level 0 vehicle. The odds of more than one fatality in crashes involving level 1 or level 2 CAVs are also higher compared to level 0 vehicles. CAVs are more likely to be involved in fatal crashes on different portions of the road, like in acceleration or deceleration lanes, intersections, and any location within interchange areas.

LKA usually works based on the information regarding lane markings provided by the cameras attached to the vehicle. Locations like intersections with multiple or no markings may increase the uncertainty of such systems when making decisions, which could be the potential reason for the high likelihood of fatal crashes at those locations. The likelihood of a rear-end collision or rear-to-side collision is less compared to a head-on collision or sideswipe collision.

The odds ratio of different variables such as functional class, traffic control devices, traffic way type, the portion of the road, and manner of collision vary significantly for level 1 and level 2 CAVs compared to level 0 vehicles. Therefore, an analysis to identify the effect of smart safety features was carried out. The findings indicate that the vehicles with smart features are still involved in specific types of crashes for which they are designed to avoid. Overall, parameters such as pre-crash stability and movement of a vehicle, and crash at high speed, which are primarily related to the vehicles, indicate that level 1 and level 2 CAVs are safer. In contrast, fatal crash involvement with non-motorists and at stop and yield signs where drivers have to make decisions (be attentive) had a higher likelihood of occurrence in level 1 and level 2 CAVs. Therefore, level 1 and level 2 CAVs are improving the overall safety of vehicles. At the same time, it also affects drivers' attentiveness, resulting in an increased likelihood of a fatal crash in some situations.

7.2 Conclusions

This research aimed to identify the effect of level 1 and level 2 CAVs on the occurrence of fatal crashes. A review of existing studies on the penetration of level 1 and level 2 CAVs, the effect of CAVs on mode choice and travel behavior, factors influencing fatal crashes, and the occurrence of fatal crashes was carried out. Fatal crash data obtained from the FARS database and smart feature data based on VINs retrieved from the NHTSA database were combined to identify the level 1 and level 2 CAVs. To identify the effect of levels of automation on fatal crash occurrence, a PPO model was developed comparing level 0 vehicles with level 1 and level 2 CAVs involved in fatal crashes. A comparative analysis of vehicles equipped with smart features and other vehicles was carried out to determine the efficiency of smart features designed to enhance safety in various types of crashes.

A nearest neighborhood analysis was carried out to identify crashes involving level 0 vehicles that occurred in the vicinity of crashes involving level 1 and level 2 CAVs. The PPO model was developed based on the identified sample of crashes involving level 1, level 2 CAVs, and three nearest crashes involving level 0 vehicles.

The results of the PPO model indicate that the involvement of level 1 and level 2 CAVs in fatal crashes with pedestrians and bicyclists is higher compared to level 0 vehicles which may be due to the inattentiveness or overreliance of drivers on smart features. Further, level 1 and level 2 CAVs have higher odds of getting involved in fatal crashes on one-lane routes and near locations with stop, yield, or flashing yellow signs. The CAVs were also found not to be safe in the case of head-on collision and collision with non-motorists.

The vehicles with smart features such as ACC and FCWS, which are designed to improve safety in the case of rear-end collisions, are getting involved in such collisions more than level 0 vehicles. However, LKA and PAEB systems are more efficient than level 0 vehicles in the case of roadside departures and crashes with pedestrians.

The findings of this research provide an overview of the factors influencing the occurrence of fatal crashes involving level 1 and level 2 CAVs. These research findings can assist automobile manufacturers in modifying the existing technologies underlying various smart features engaged in level 1 and level 2 CAVs. In addition, the overview provided by this research can aid practitioners and transportation engineers to better plan, design facilities, and modify existing policies.

7.3 Limitations and Future Scope

The primary purpose of this research was to identify the effect of smart features on safety. The safety performance of a vehicle may vary depending on the manufacturer of the vehicle and the type or functionality of the technology. For example, ACC works either based on a camera or radar. The effect of different technologies on which ACC works was not identified or explored in this research. Thus, an analysis incorporating the manufacturer and the type of technology as independent variables would provide insights on the variation in the safety performance of different vehicles with the same level of automation. Further, the PPO model used in this research is a fixed parameters model, which restricts parameters to remain the same for all observations. However, random parameters modeling allows each observation to have its own parameter estimate and can account for variability in individual crash-specific characteristics.[55] Such an approach would be more applicable as larger and more detailed datasets (with the type of technology and their functionality at the time of crash by vehicle manufacturer) become available.

The proportion of level 1 and level 2 CAVs is very low, as only 1.8% of all fatal crashes in the years studied involved either a level 1 or level 2 CAV. Therefore, most of the crashes involving level 1 and level 2 CAVs are with level 0 vehicles. Thus, analysis at higher penetration rates may yield different results and merits further investigation. In addition, the analysis considering only at fault vehicles would also provide insights about the risk driver possess to other drivers while driving vehicles with different levels of automation.

The effect of levels of automation was identified using the crash data covering four years in this research. However, analysis to accommodate the variation in risk factors influencing crashes with time may yield better results.

Appendix A

This appendix summarizes the make of level 1 and level 2 CAVs identified based on VIN from the FARS database.

Table A1. Vehicle Make Details of Level 1 and Level 2 CAVs Involved in Fatal Crashes

Make	Level 1 CAVs	Level 2 CAVs
Acura	2	21
Alfa Romeo	1	0
Audi	0	21
BMW	44	35
Buick / Opel	6	7
Cadillac	46	23
Chevrolet	305	19
Chrysler	16	27
Dodge	40	65
Ford	123	229
GMC	56	38
Honda	33	316
Hyundai	29	113
Infiniti	0	18
Jaguar	3	0
Jeep / Kaiser-Jeep / Willys- Jeep	72	159
KIA	145	14
Land Rover	1	17
Lexus	10	33
Lincoln	4	20
Mazda	3	43
Mercedes-Benz	2	77
Nissan/Datsun	3	6
Other Domestic Manufacturers	0	28
Other Import	6	5
Porsche	3	8
Subaru	20	123
Toyota	190	529
Volkswagen	4	38
Volvo	1	16

Abbreviations and Acronyms

AADT	Annual Average Daily Traffic
ABS	Automated Braking System
ACC	Adaptive Cruise Control
AIC	Akaike Information Criterion
BSM	Blind Spot Monitoring
CAV	Connected and Automated Vehicle
CDC	Centers for Disease Control and Prevention
FARS	Fatality Analysis Reporting System
FCWS	Forward Collision Warning System
LKA	Lane-Keeping Assistance
NHTSA	National Highway Traffic Safety Administration
PAEB	Pedestrian Automatic Emergency Braking
PO	Proportional Odds
PPO	Partial Proportional Odds
SAE	Society of Automotive Engineers
SAV	Shared Automated Vehicles
VIN	Vehicle Identification Number

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