# MODELING AND IDENTIFYING FACTORS ASSOCIATED WITH FATAL CRASHES INVOLVING VEHICLES WITH ADVANCED DRIVER ASSISTANCE SYSTEMS

by

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ABSTRACT

HARDIK RAMESHBHAI GAJERA. Modeling and Identifying Factors Associated with Fatal Crashes Involving Vehicles with Advanced Driver Assistance Systems. (Under the direction of DR. SRINIVAS S. PULUGURTHA)

Recent advancements in vehicular technology are expected to enhance traffic safety by either warning the drivers or by automating the tasks related to driving to reduce the human driver's involvement. The driver warning systems (DWSs) are designed to warn drivers in unsafe situations such as forward collision, lane departure, or when changing lanes with vehicles in blind spot areas. These features only warn the driver but cannot perform the driving tasks. Advanced driver assistance systems (ADASs) can perform driving tasks such as accelerating, braking, and steering, thereby eliminating the role of the human driver in performing these tasks. However, ADASs currently require drivers to remain seated and regain control when the vehicle demands.

A plethora of research is available on the operational and safety benefits of the DWSs and ADASs. Most of these studies focus on calibrating the driving behavior parameters to mimic vehicles with particular DWS or ADAS using microsimulation software or a driving simulator. Some researchers also performed field tests using vehicles equipped with DWSs or ADASs but in a controlled environment. The efficiency of DWSs or ADASs tested in laboratories or controlled environments may vary depending on driving conditions and the complexity of driving tasks, demanding research on the factors affecting crash occurrence when driving such vehicles in normal driving conditions with other vehicles.

Existing literature documents numerous studies focused on identifying factors affecting fatal crashes. The studies on fatal crashes show that factors such as roadway geometry, traffic control devices, vehicular characteristics, and other on- and off-road characteristics affect fatal crash occurrence. The factors related to the driver, such as attentiveness, distraction, and fatigue,

also affect the crash occurrence. Although the DWSs and ADASs are designed to enhance safety, recent crash data shows that vehicles equipped with these systems still get involved in crashes. The reason for the same has been identified as either disengagement of the features or the risk other drivers possess to the drivers of vehicles with DWSs or ADASs. In addition, change in drivers' behavior due to ADASs is also one of the factors influencing crash occurrence. The existing literature shows a dearth of research conducted to identify the factors influencing fatal crashes and fatal crash occurrence, considering the real-world crash data of vehicles equipped with varying DWSs and ADASs. Therefore, a comprehensive analysis considering the reported fatal crash data is imperative as it will help identify how the factors affecting fatal crash occurrence vary depending on the number and type of DWSs or ADASs equipped in the vehicles. In addition, conducting a study using a particular DWS or ADAS and the corresponding crash type for which the particular feature is designed would provide insights into the overall effectiveness of these features in terms of traffic safety. The findings from the study will assist in improving safety and proactively planning for infrastructure at higher penetration of vehicles with DWSs or ADASs.

The objectives of the research, therefore, are (1) to collect and comprehensively evaluate data pertaining to the vehicles equipped with individual DWS and ADAS, (2) to identify, model, and compare factors affecting fatal crashes involving vehicles with individual DWS, and ADAS, (3) to identify, model, and compare factors affecting fatal crashes involving vehicles with one or more DWSs and ADASs with vehicles without any warning or assistance systems, and (4) to examine the effect of traffic characteristics, geometric characteristics, on-network, and off-network characteristics, and vehicle characteristics on the safety of vehicles with varying numbers of DWSs and ADASs present in the vehicles involved in fatal crashes.

The fatal crash data is used to accomplish these objectives. The fatal crash data contains Vehicle Identification Numbers (VINs) of all vehicles involved in crashes, with information about all DWSs and ADASs equipped in the vehicles. In addition, the fatal crash data is more detailed and accurate than other crash severity data. Therefore, using only fatal crashes would provide reliable model estimates.

The fatal crash data from 2016 to 2020 were obtained from the Fatality Analysis and Reporting System (FARS) database and considered for analysis and modeling in this study. Using VINs of all vehicles involved in crashes, information about vehicular characteristics such as type and the number of DWSs or ADASs was retrieved from the National Highway Traffic Safety Administration (NHTSA) database. The vehicular information is combined with fatal crash data to classify vehicles based on various DWSs or ADASs equipped in vehicles. In this study, DWSs such as Forward Collision Warning System (FCWS), Blind Spot Monitoring (BSM), Lane Departure Warning (LDW), and ADASs such as Lane-Keeping Assist (LKA), Adaptive Cruise Control (ACC), and Pedestrian Automatic Emergency Braking (PAEB) system were considered for the analysis.

The combined dataset was further divided into three separate datasets, (a) multivehicle crashes, (b) single-vehicle and lane departure-related crashes, and (c) pedestrian crashes, to facilitate the analysis for different DWSs and ADASs depending on the type of crashes for which they are designed to enhance safety. A descriptive analysis of divided datasets was conducted, which showed that the proportion of crashes involving vehicles with DWSs or ADASs was less than 3% of the entire dataset. The locations of crashes were mapped to identify the spatial variation of crashes involving vehicles with various DWSs and ADASs. The temporal trends in the number of crashes involving vehicles with DWSs and ADASs were also plotted. The data visualization results showed that crashes involving vehicles with a particular DWS or ADAS vary spatially and temporally. Therefore, a comprehensive methodological framework to incorporate unobserved heterogeneity due to varying spatial, temporal, and driving behavior characteristics is proposed.

The aspect of heterogeneity was addressed in three parts. Nearest neighbor analysis was conducted for each year of crash data of a particular dataset to account for spatial heterogeneity and sample crashes involving vehicles without a DWS or ADAS. The three nearest neighbors were obtained as the most optimal. The data from nearest neighbors and corresponding crashes involving vehicles with DWSs or ADASs were considered for modeling.

The dependent variable in this study is either ordinal (number of DWSs or ADASs) or binary (with or without DWS or ADSA), depending upon the type of DWS and ADAS and the corresponding crash type for which a particular feature is designed. Logistic regression is the most appropriate modeling approach for these types of problems and was therefore used in the study. A fixed parameter and correlated random parameters ordered logit models were developed to identify factors affecting fatal crashes involving vehicles equipped with one or more DWSs and ADASs. In the case of pedestrian, single-vehicle and roadside departure-related crashes, a fixed and correlated binary logistic regression modeling approach was employed for vehicles with and without PAEB and LDW systems. The sole reason for developing random parameters model was to incorporate unobserved heterogeneity in modeling.

To account for temporal heterogeneity, a temporal variable in the form of linear effect of time elapsed was included while modeling. Driver-related parameters in the dataset were considered as random parameters in correlated random parameters models to incorporate heterogeneity due to varying driving behavior. The goodness of fit indices such as Log-likelihood statistics and McFadden pseudo-r-square were used to compare and identify the best-fitted model amongst fixed and correlated random parameters models. Further, partial effects were obtained to derive inferences from the models.

The results of the analysis conducted to identify factors affecting fatal crashes involving vehicles with and without DWSs or ADASs indicated that correlated random parameters models (ordered logit and binary logit) better fit the crash data. The correlated random parameters ordered logit model was significantly better compared to the fixed parameters ordered logit model. However, the difference in the goodness of fit indices was not statistically significant when the correlated random parameters binary logit model and fixed parameters binary logit model were compared, indicating that the improvement in model fit because of variation in driving behavior is not significant.

The partial effects of models showed that vehicles with one or more DWSs or ADASs are more likely to get involved in fatal crashes in urban areas and on interstates. The probability of fatal crash occurrence for vehicles with LDW or PAEB during adverse weather conditions, such as ice, snow, smoke, or fog, was lower than for vehicles without those features. In wet or snowy road conditions, vehicles with DWSs, such as FCWS or BSM, and ADASs, such as LKA and ACC, are safer than vehicles without those features. However, vehicles with LDW and PAEB are unsafe during wet road surface conditions. On the other hand, vehicles with BSM, FCWS, LKA, or ACC are less likely to get involved in fatal crashes in conditions when the vehicle is skidding laterally or longitudinally before the crash. Similarly, the probability of fatal crash occurrence for vehicles with LDW is less when a vehicle is skidding longitudinally before the crash. In contrast, vehicles with PAEB are safer when the vehicle is skidding laterally before a crash.

During critical road conditions, such as in the presence of work zones, vehicles with an ADAS or LDW are safer compared to vehicles without those features. In addition, vehicles with

DWSs and ADASs, except those with PAEB, are safer at intersections than normal vehicles. In crashes related to speeding or driving under the influence of alcohol, vehicles with DWSs or ADASs are less likely to get involved in fatal multivehicle crashes. However, drivers traveling at a higher speed than the speed limit are more likely to get involved in fatal crashes in single-vehicle or lane departure-related and pedestrian-related crashes.

From the results of all models, females and elderly drivers are more likely to get involved in fatal crashes when driving vehicles with any DWS or ADAS. In addition, it is notable that the probability of crash occurrence for vehicles with any DWSs or ADASs has increased from 2016 to 2020, showing that it is necessary to take precautionary measures to ensure better safety at higher penetration of these vehicles in the future.

The data processing framework, methodological findings, and study results help identify the factors affecting fatal crashes involving vehicles with one or more DWSs or ADASs. The results of this study also highlight critical factors affecting fatal crash occurrence for vehicles equipped with individual or multiple DWSs and ADASs. The results help identify the potential areas for improvement in vehicular technologies for the industry. It also provides insights about factors related to road geometry and on-road and off-road characteristics to the practitioners, assisting them in better preparing the infrastructure for fully automated vehicles in the future.

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# DEDICATION

*To my Family – for always being supportive.*

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| | |
|---|---|
| AADT | Annual Average Daily Traffic |
| ABS | Automated Braking System |
| ACC | Adaptive Cruise Control |
| ADAS | Advanced Driver Assistance System |
| DWS | Driver Warning System |
| BSM | Blind Spot Monitoring |
| AV | Automated Vehicle |
| CDC | Centers for Disease Control and Prevention |
| FARS | Fatality Analysis Reporting System |
| FCWS | Forward Collision Warning/Mitigation System |
| LDW | Lane Departure Warning |
| LKA | Lane-Keeping Assistance |
| NHTSA | National Highway Traffic Safety Administration |
| PAEB | Pedestrian Automatic Emergency Braking |
| SAE | Society of Automotive Engineers |
| VIN | Vehicle Identification Number |

# CHAPTER 1 INTRODUCTION

This chapter presents details including the background and motivation, problem statement, research significance, objectives of the research, and organization of this Dissertation.

## 1.1 Background and Motivation

In the United States, vehicles with driver warning systems (DWSs) and advanced driver assistance systems (ADASs) have rapidly grown in the past decade. From common vehicle models to luxury cars, the majority of the manufacturers provide options to add DWSs, such as blind spot monitoring (BSM), lane departure warning (LDW), and forward collision warning system (FCWS). The manufacturers also provide options to equip vehicles with ADASs, such as adaptive cruise control (ACC), lane-keeping assistance (LKA), and pedestrian automatic emergency braking (PAEB) systems. The primary reason behind the increasing number of vehicles with these features is motor vehicle crashes, with human errors as a cause of approximately 94% of crashes (NHTSA, 2017). Motor vehicle crashes are among the top ten causes of fatalities in the United States (NCIPC, 2020), increasing safety and operational concerns.

In 2019, over 2.35 million commuters were either injured or disabled, and approximately 36,000 people lost their lives by getting involved in fatal road crashes (NHTSA, 2019). According to the report by the Centers for Disease Control and Prevention (CDC), the total cost of medical care and productivity losses due to vehicular crashes (injuries and fatalities) was reported to exceed $75 billion in the United States (NCIPC, 2018). Commuters are getting involved in crashes primarily due to their fault or someone else's fault while driving, regardless of their familiarity with the road conditions (Gajera et al., 2023a).

The factors related to driver errors, such as improper lookout when driving, speeding, drinking and driving, and inattentiveness, are among the major causes of crashes. As vehicles with DWSs or ADASs provide additional warning or assistance to the drivers, vehicles equipped with these features are expected to enhance traffic safety and operation. The vehicles with different combinations of ADASs to automate either steering, acceleration, and braking or all driving tasks are known as automated vehicles (AVs). In the past few years, a plethora of research work focusing on the effects of individual ADAS or AVs on traffic safety and operation has been published by researchers working in the field of transportation (Gajera et al., 2023b).

While utilizing an ADAS and sitting idle in the driver's seat, drivers may engage in secondary tasks, like using mobile phones or other devices, which can lead to cognitive distractions. This can adversely affect drivers' attention and judgment (De Winter et al., 2014). Hence, it is crucial to analyze the changes in driver behavior when operating vehicles equipped with ADASs, as well as examine the safety benefits provided by these systems (Smiley, 2000).

Investigating the effect of vehicles with either one or multiple ADASs or DWSs on fatal crashes will help identify the factors affecting the crashes and provide insights about the involvement of AVs equipped with varying smart features designed to enhance safety in certain types of crashes. Moreover, it is important to recognize that the effects of DWSs, such as FCWS, BSM, and LDW and ADASs, such as ACC, LKA, and PAEB, on fatal crashes might differ from the anticipated benefits observed during field tests conducted while developing these features.

A comprehensive safety assessment to examine the trends in crashes involving vehicles with varying DWSs or ADASs to identify underlying risk factors affecting crashes involving vehicles with different DWSs and ADASs and compare them with factors influencing crashes involving non-automated vehicles will provide useful insights to the manufacturers and practitioners. By doing so, manufacturers and practitioners can make appropriate modifications to existing DWSs and ADASs and develop new policies to enhance safety on the road.

### 1.2 Problem Statement

Vehicular technologies and driver interactions are expected to evolve more than they have evolved in the past in the next few decades due to ongoing technological enhancements and research in the automobile industry. Recent and ongoing vehicle advancements have raised expectations regarding operational performance, environmental benefits, safety enhancement, and user comfort. As human error is the leading cause of motor vehicle crashes in the United States, DWSs and ADASs are expected to reduce the number of crashes caused due to driving errors through the gradual removal of the human driver's role in performing driving-related tasks and decision-making.

Although the deployment of vehicles with varying DWSs and ADASs has increased over recent years, fully AVs are yet to be a reality. Apart from a few test vehicles, fully AVs are not available in the market for users. The safety benefits of vehicles with varying DWSs and ADASs also depend on the driver's reliance on the features and their willingness to use them while driving. Additionally, some recent crashes involving vehicles with multiple ADASs resulting in deaths indicated that ADASs may not always be effective. Potential reasons for the same are related to the ability of ADASs to sense and control the driving tasks irrespective of the geographic location, geometric condition, traffic condition, and lighting condition.

Understanding the effect of the transition from no automation to vehicles with DWSs and ADASs on traffic safety could be more challenging than expected, considering data limitations and their lower penetrations in the market. Conducting a comprehensive safety analysis to examine the trends in fatal crashes and identifying potential risk-causing factors, coupled with the ongoing advancements in DWSs and ADASs, is the first task. Modeling analysis to identify risk factors associated with vehicles equipped with varying DWSs and ADASs when compared to vehicles without any DWS or ADAS during their crash involvement is an important step to determine the overall difference in safety that DWSs and ADASs provide. Recent fatal crash data (FARS, 2020) shows that vehicles with DWSs, such as LDW, FCWS, and BSM, and vehicles with ADASs, such as ACC, PAEB, FCWS, and LKA, are still getting involved in types of fatal crashes for which they were designed to provide additional assistance or warning. The variation in crash involvement also gets influenced due to drivers' familiarity with these features and their driving behavior. Therefore, there is a need to analyze crash data and identify various factors that contribute to crashes involving vehicles with varying DWSs and ADASs.

Due to the potential reduction in driving economies and the transition to fully AVs, the driving behavior when driving vehicles with varying technologies would also vary. Therefore, it is also necessary to incorporate heterogeneity due to spatial and temporal variation in crash data and varying driving behaviors. Conducting a similar analysis would help develop a readiness plan to proactively address the anticipated safety challenges in the upcoming years when the penetration of vehicles with DWSs and ADASs is expected to increase.

## 1.3 Research Significance

With the increasing penetration of vehicles with DWSs and ADASs over time, practitioners and industry experts need to identify their impacts on the infrastructure, safety, and operations to smoothen the transition from no automation to the scenario with fully AVs. A plethora of existing research on DWSs shows their benefits in terms of safety. However, a limited number of studies were conducted using real-world crash data of vehicles with DWSs and ADASs to determine the crash risk factors involving these vehicles.

Most of the studies on DWSs and ADASs to date focused on a simulation-based approach using either microsimulation software or driving simulators to generate virtual conditions involving vehicles with varying ADASs and identifying their impact under varying driving conditions and penetration rates. The cited reason for using such tools is the lack of availability of real-world data on vehicles with AVs. Some automobile manufacturing companies and researchers also tried to conduct studies using test vehicle data (Boggs et al., 2020; Chen et al., 2021). However, those studies were conducted primarily in selected areas, and almost negligible studies considered the involvement of these vehicles with varying ADASs in fatal crashes (Gajera et al., 2022; Gajera et al., 2023a). This Dissertation highlights factors affecting fatal crashes involving vehicles with varying DWSs and ADASs. The effect of the driver characteristics such as age, gender, and drink and drive also provides an idea about variation in crash risk for different drivers. Incorporating heterogeneity while modeling and comparing the risk-causing factors for vehicles with and without DWSs and ADASs will also provide insights into the overall safety benefits of these features and required modifications in vehicular technologies.

In order to identify the effect of various DWSs and ADASs on crashes, it is necessary to obtain information about DWSs and ADASs in vehicles. Fatal crash data is often more detailed and contains useful information such as Vehicle Identification Numbers (VINs), which are required to extract the information about DWSs and ADASs equipped in the vehicles involved in crashes. Besides it also contains detailed information about all the factors affecting crashes, including details about vehicular, road, crash, and driver characteristics. Therefore, considering fatal crash data would provide detailed insights about the risk-causing factors and be considered for the analysis.

The descriptive statistics of the crash data provide an overview of the number of crashes involving vehicles with varying DWSs or ADASs. The modeling results help compare the fatal crash occurrence for vehicles with and without DWSs and ADASs and identify the factors affecting the occurrence of fatal crashes involving these vehicles. The information about heterogeneity due to varying driving behavior is facilitated by comparing models with fixed and random driving behavior parameters. The findings help identify the factors related to the vehicle, road geometry and crashes for implementing policies to improve the safety of the existing transportation system and also serve as an overview of the current involvement of vehicles with DWSs and ADASs in fatal crashes.

The scope of this Dissertation is limited to fatal crashes and identifying and comparing factors affecting fatal crashes involving vehicles with varying combinations of DWSs and ADASs.

## 1.4 Research Objectives

The goal of this study is to identify factors affecting fatal crashes involving vehicles with different combinations of DWSs and ADASs to enhance safety. The objectives of the proposed research are:

1. To collect and comprehensively evaluate fatal crash data pertaining to vehicles with individual DWS and ADAS,
2. to identify, model, and compare factors affecting fatal crashes involving vehicles with individual DWS and ADAS,

3. to identify, model, and compare factors affecting fatal crashes involving vehicles with one or more DWSs and ADASs with vehicles without any warning or assistance systems, and,
4. to examine the effect of traffic characteristics, geometric characteristics, on-network and off-network characteristics, and vehicle characteristics on the safety of vehicles with varying numbers of DWSs and ADASs present in the vehicles involved in fatal crashes.

### 1.5 Organization of the Report

The remainder of the report comprises five chapters. Chapter 2 summarizes a comprehensive literature review of factors affecting fatal crashes, DWSs, ADASs, levels of automation, the effect of DWSs and ADASs on safety and operations, the effect of DWSs and ADASs on crash occurrence, limitations of the past research and need of the research on vehicles with DWSs and ADASs. All the methods used in this study are explained in Chapter 3. Chapter 4 contains information about the study area, data collection, data processing framework used in this study, and data visualization. The descriptive statistics of the datasets used in this study and the goodness of fit indices of models are provided in Chapter 5, along with the modeling results and discussion. The findings from this study, policy recommendations, scientific contributions, limitations of the study, and future scope of work are discussed in Chapter 6.

# CHAPTER 2 LITERATURE REVIEW

This chapter presents an overview of past studies associated with factors affecting fatal crashes, DWSs and ADASs, levels of automation, and the effect of DWSs and ADASs on safety and operations. Further, additional discussions related to studies using microsimulation and real-world data on the effect of DWSs and ADASs on safety are also discussed in this chapter.

## 2.1 Factors Influencing Fatal Crashes

Many researchers in the past focused on identifying factors influencing fatal crashes. The factors related to on-road and off-road characteristics identified in the past research are the dimension of the median (Molan et al., 2019), day of the week (Siskind et al., 2011), side traffic barriers (Penmetsa and Pulugurtha, 2018, 2019; Molan et al., 2020), speed limit (Wagenaar et al., 2007; Tagar and Pulugurtha, 2021), road infrastructure (Noland and Oh, 2004; Tagar and Pulugurtha, 2021), highway class (Chen et al., 2019), road alignment (Siskind et al., 2011), socio-demographic characteristics near the crash location (Noland and Oh, 2004), traffic control (Siskind et al., 2011), and adverse weather conditions (Pisano et al., 2008; Saha et al., 2016). Besides, some researchers also evaluated the effect of red-light cameras (Pulugurtha and Otturu, 2013; Hu and Cicchino, 2017), road surface (Pulugurtha et al., 2010, 2012; Tay, 2015; Chen et al., 2017), intersection type (Chen et al., 2017), and annual average daily traffic (AADT) (Pulugurtha and Nujjetty, 2012; Chen et al., 2017) on crashes at intersections. The aforementioned studies focused on either identifying the factors related to crashes or conducting a before and after analysis to determine the improvement in traffic safety.

In addition to the crash and road characteristics, other factors such as vehicle characteristics (presence of advanced features, safety standards and ratings, size, and type of vehicle) are also amongst factors influencing crash occurrence and injury severity. Secondary safety devices such as seat-belts (Farmer et al., 1997; Crandall et al., 2001; Cummings, 2002), airbags (Crandall et al., 2001), and antilock braking systems (Farmer et al., 1997) are generally considered as measures to reduce the injury when involved in a crash because their presence can only reduce the severity of injury to the driver and passengers. These devices do not affect the crash occurrence of a vehicle.

Other than road and vehicular characteristics, driver characteristics also affect fatal crash occurrence. Human errors are one of the most frequent causes of crashes in the United States (NHTSA, 2019). The causes of human error primarily vary depending on driver characteristics such as age, gender, and experience of a driver. Teen drivers are generally found to be aggressive and inexperienced, making them more vulnerable to crashes (Mathew et al., 2022). Findings from the research on teen drivers indicate that the crash rate per mile driven and crash rate per number of license holders for teen drivers are higher than for adults (Williams et al., 2005). In contrast, elderly drivers are found to have poor reaction time, ability to divide attention between multiple tasks, and vision (Gruber et al., 2013), due to which their probability of getting involved in a crash is higher compared to young drivers (Meng and Siren, 2012). In addition to age, several other factors, such as gender, distracted driving, and driving under the influence of alcohol or drugs, are also among the factors influencing the likelihood of getting involved in a crash. Therefore, considering driving behavior while analyzing crash data is necessary to get useful insights about variations in crash risk based on driver characteristics.

## 2.2 DWSs, ADASs and Levels of Automation

Existing literature contains a plethora of research on DWSs, ADASs, and AVs with varying levels of automation. The DWS provides a warning to the drivers departing their travel lane or making dangerous maneuvers, such as changing lanes while having a vehicle in a blind spot area or late-braking while having vehicles in front. The field tests on vehicles equipped with a DWS showed significant improvement in terms of safety. However, they are still getting involved in crashes primarily because of human errors irrespective of the warnings provided by the DWSs, due to which the manufacturers are shifting towards the development of ADASs to perform driving tasks and eliminate the role of human drivers from steering, accelerating, and braking.

The number of vehicles equipped with DWSs and ADASs has increased rapidly in the past few years while transitioning from non-automated to fully AVs. The FCWS warns the vehicle in potential forward collision conditions, reducing the likelihood of getting involved in rear-end collisions (Jermakian, 2011). The ACC system can control the vehicle's acceleration and deceleration to drive while maintaining a significant gap from the leading vehicle (Li et al., 2017a). Therefore, ACC also affects the vehicle's likelihood of getting involved in a rear-end collision. The ACC works either on radar or lidar-based detection. In case if the leading vehicle slows down, the radar detects the movement and applies brakes to maintain a safe gap. If there is no vehicle in front of a vehicle with ACC, it travels at a speed set by the driver (Eichelberger and McCartt, 2014).

The LDW system warns drivers of conditions when a vehicle departs a lane. However, LKA pushes the vehicle toward the center of the lane instead of providing a warning when departing the lane. The PAEB system determines the path of a pedestrian using either a camera or radar and warns the driver if a pedestrian walks in the path of a moving vehicle and collision is imminent (Eichelberger and McCartt, 2014). If the driver does not react promptly, the PAEB feature automatically engages the brake, avoiding a potential pedestrian crash (Eichelberger and McCartt, 2014).

The BSM system, also known as the side view assist system, warns the driver during conditions when any vehicle or object is present in the vehicle's blind spot area (Jermakian, 2011). The BSM system is designed to improve safety by warning the driver of sideswiping or rear-to-side collisions.

The vehicles equipped with a specific combination of ADASs qualify for level 1 and level 2 of levels of automation defined by SAE (SAE, 2018). Per the Society of Automotive Engineers (SAE), AVs will integrate on roads using six different automation levels (SAE, 2018). Vehicles without any smart features are categorized as level 0 vehicles (SAE, 2018; Jakob, 2018; Choksey and Wardlaw, 2021). Vehicles with ADASs, such as ACC and LKA, qualify for level 1 and level 2 automation based on the number of ADASs present in the vehicle (Jakob, 2018; Choksey and Wardlaw, 2021).

The vehicles with DWSs and ADASs are expected to reduce the number of crashes by providing additional warnings and assistance to the drivers. Vehicles equipped with these features are also known as smart vehicles due to their ability to interact with other vehicles and infrastructure through sensing. Due to additional assistance provided by vehicles with ADASs, they are driving the existing market because of the increasing emphasis on safety and operations. However, before transiting to the scenario with fully AVs, it is necessary to identify the safety effect of each DWS and ADAS and their combinations to improvise the technology and ultimately enhance the safety effectiveness of these vehicles.

### 2.3 Effect of ADASs and AVs on Safety

Several researchers examined the effects of individual ADAS on safety. Examples include studies to identify the effect of the automated braking system (ABS) (Eichelberger and McCartt, 2014), LKA (Jermakian, 2011), ACC (Eichelberger and McCartt, 2014; Li et al., 2017a), FCWS (Jermakian, 2011), and crash avoidance technology (Eichelberger and McCartt, 2014) on safety. Vehicles with ADASs can enhance traffic safety, as human error is the primary reason for crashes. The safety benefits are maximized at higher penetration of vehicles with smart features.

Researchers in the past used microsimulation to identify the effect of vehicles with different ADASs on safety (Dijkstra et al., 2010; Fan et al., 2013). Fitch et al. (2014) investigated the effectiveness of using various DWSs in multiple near-crash scenarios with FCW and LDW systems. The results showed that vehicles with multiple smart features are safer than others. Li et al. (2016) investigated the effect of ACC while integrating it with variable speed limit signs. They compared it with non-automated vehicles for five scenarios varying from 10% to 100% penetration rate. The results showed vehicles with ACC yield higher safety by reducing time exposed time to collision (TET) and time-integrated time to collision (TIT) by 77.5% and 77.3%, respectively.

Researchers in the past also evaluated the safety effects of AVs on safety using surrogate safety assessment models (Deluka Tibljaš et al., 2018; Virdi et al., 2019). While evaluating partially automated vehicles, Kikuchi et al. (2003) considered the effects of using ACC in platooning based on the different positioning of the vehicle using microsimulation. The results showed reduced reaction times for both vehicles equipped with ACC and without ACC, and both were observed to enhance safety. Similarly, Derbel et al. (2012) investigated the effect of mixed traffic including vehicles equipped with ACC for different crash scenarios. The results showed enhanced safety and reduced crash risk when vehicles with ACC were involved in a crash. Further, Jeong et al. (2014) studied the effect of an inter-vehicle safety warning information system (ISWS). The ISWS system communicates hazardous maneuvers of vehicles that could potentially lead to a crash. The driver behaviors captured using probe vehicle data were incorporated into the

PTV Vissim simulation software, and a surrogate safety assessment using SSAM tool was used to assess the number of conflicts. Rear-end conflicts were observed to reduce with the penetration rate while the congestion increased.

While most studies showed enhanced safety benefits of ADASs, some also showed that they are still not safer than non-automated vehicles in several scenarios (Favarò et al., 2017; Gajera et al., 2022). Teoh and Kidd (2017) conducted a comparative analysis of the driving potential of human drivers and vehicles with ADAS. Favarò et al. (2017) compared real-world crashes involving non-automated vehicles and fully AVs considering crash frequency. The study showed that non-automated vehicles ran more moles compared to AVs before involving in a crash. Genders and Razavi (2016) showed that the market penetration of AVs under 40% contributes to safety. However, higher penetration rates reduce the safety benefits. Rahman et al. (2019) investigated the effect of fully and partially AVs on safety. They identified that for higher safety benefits of partially and fully AVs, a market penetration of 30% or more is needed.

To analyze the effects of vehicles on safety, several researchers used different parametric as well as non-parametric models such as the negative binomial model (Gaweesh et al., 2019), spatial autoregressive model (Gaweesh et al., 2019), modified negative binomial regression (Kim et al., 2007), multivariate adaptive regression (Gaweesh et al., 2019), bootstrap-based binary logistic regression (Sze et al., 2014), fixed-parameters logit model (Anastasopoulos and Mannering, 2011), random parameters logit model (Anastasopoulos and Mannering, 2011; Venkataraman et al., 2013; Hou et al., 2022), grouped random parameters logit model (Itani et al., 2020), and intelligent driver model (Li et al., 2017b). These modeling techniques were used to analyze crash data and identify factors affecting crash severity. Amongst these modeling techniques, the grouped random parameters ordered logit model is considered superior to other models while analyzing ordered dependent variables.

Logistic regression is proven reliable in modeling the relations between dependent and independent variables in many traffic safety studies (Zhang et al., 2000; Al-Ghamdi, 2002). There are a few studies in the highway safety domain, where logistic regression models were developed to identify the effect of independent variables on dependent variable. Kim et al. (2000a) identified behavioral predictors of vehicle crashes and injury severity. Kim et al. (2000b) used logistic regression modeling to identify the effect of different demographic factors associated with motorcycle crashes. Dissanayake and Lu (2002) also used a binary logit regression model to analyze the severity of young driver crashes as the dependent variable has only two values. Likewise, the binary logistic regression models were used to compare vehicles with and without the PAEB and LDW systems to assess their safety effectiveness in this study.

### 2.4 Summary and Limitations of Past Research

The increasing number of fatalities in motor vehicle crashes emphasize the need for identifying factors affecting fatal crashes. Researchers in the past studied fatal crash data and identified several factors related to road geometry, vehicles, drivers, and on- and off-road characteristics that directly or indirectly affect fatal crashes. However, the recent advancements in vehicular technology, especially the inclusion of ADASs, are expected to enhance safety, due to which research on ADASs is gaining popularity in the past few years.

Most studies in the past related to individual DWS, ADAS and AVs were carried out using simulation analysis. The simulation analysis includes either microsimulation software or driving simulators (Gouribhatla and Pulugurtha, 2022) to mimic the behavior of AVs and identify their effect on traffic operations and safety. The review of studies on microsimulation analysis showed mixed results, primarily due to varying assumptions and considerations related to each study. Another reason for the varying results from these studies is the varying accuracies of model calibration and the use of different surrogate safety measures, which significantly affect the degree of reliability of the microsimulation results (Sinha et al., 2020).

The effectiveness of ADASs also varies depending on factors related to road geometry, crash occurrence, and vehicle. Thus, using real-world crash data involving information about factors affecting crashes may yield clearer results compared to microsimulation techniques as it also considers the human errors by drivers of non-automated vehicles and vehicles with ADASs, which are already penetrating the existing transportation system.

The studies on identifying factors affecting the severity of crashes using crash data and parametric and non-parametric approaches showed better results than simulation-based studies, mainly due to consideration of affecting factors through existing data. However, the use of parametric and non-parametric approaches to analyze the effect of DWSs and ADASs is limited, primarily because of the lack of crash data availability. Amongst the techniques used to analyze crash data, correlated random parameters modeling is statistically superior because it allows parameters to vary across observations and also incorporates correlation between varying parameters while modeling.

The recent analysis using fatal crash data showed that many vehicles with one or more DWSs and ADASs still get involved in fatal crashes. Thus, a comprehensive safety assessment using crash data and considering all the factors affecting fatal crashes is useful in gaining insights on the factors affecting fatal crashes involving vehicles equipped with one or more DWSs and ADASs.

## 2.5 Contribution of the Research

There are potential barriers that AVs have to overcome to eliminate human interaction while performing driving tasks in a real-world scenario. Vehicles with DWSs or ADASs are considered safe and efficient but are still involved in crashes. The potential reasons for their involvement in crashes include disengagement of automated features, false detection of objects, and perception discrepancies (Xu et al., 2019; Sinha et al., 2021). Additionally, some recent crashes involving vehicles with DWSs or ADASs, resulting in deaths, indicate that smart features may not always be effective.

Understanding the effect of ADASs on the transportation system's overall safety while transitioning from no automation to full automation could be more challenging than expected. In addition, a comparison of DWSs and ADASs will provide an idea about the effectiveness of automation compared to warning systems. The first step is a comprehensive safety analysis to examine the spatial and temporal trends in crash data, including vehicles equipped with varying DWSs or ADASs. It should be complemented with the modeling to identify the risk factors affecting fatal crashes involving vehicles with and without DWSs and ADASs.

Therefore, this Dissertation focuses on bridging the research gap by identifying risk factors influencing fatal crashes involving vehicles with a DWS, an ADAS, and combinations of multiple DWSs or ADASs and synthesizing the difference in factors affecting fatal crashes involving vehicles with and without any DWS or ADAS. The research findings highlight factors related to on-road and off-road characteristics and vehicular characteristics, providing information about factors contributing to crashes involving various types of vehicles (with and without DWS or

ADAS), which would be helpful to practitioners in making policy decisions and to industry experts in further modifying the underlying technologies.

The literature also indicates unobserved heterogeneity in crash data could affect the model results. The methodological framework used in this study incorporates three significant aspects due to which unobserved heterogeneity in crash data arises, making the model estimates more accurate. The comparison of the fixed parameters binary or ordered logit model and correlated random parameters binary or ordered logit model provides an overview of how the effect of DWSs and ADASs on various types of fatal crashes could vary. In addition, it also provides information about how the unobserved heterogeneity in crash data due to varying driving behavior affects the modeling results and accuracy. A comparative analysis of vehicles with one and two DWSs or ADASs is also provided to quantify the difference DWSs or ADASs could result in terms of safety compared to vehicles with single or no DWS or ADAS.

# CHAPTER 3 STUDY METHODOLOGY

This chapter illustrates the methodology adopted in this study. It includes an overview of the methodological framework, including data collection, data processing, data preparation for modeling purposes, heterogeneity in crash dataset, and considerations while modeling to account for heterogeneity.

## 3.1 Methodological Framework

Figure 3-1 illustrates the methodological framework adopted for identifying the factors affecting fatal crashes involving vehicles with various DWSs and ADASs.

The first step is defining the problem and conducting a literature review to gain insights on existing research on DWSs and ADASs. From the existing literature review, research gaps are identified and discussed in Chapter 2. After identifying the research gaps, the objectives of this study were formulated and the data was collected for the analysis. The collected data includes fatal crash data obtained from the Fatality Analysis Reporting System (FARS) database and information about smart features retrieved from the National Highway Traffic Safety Administration (NHTSA) database. The combined dataset was processed further to remove samples with unknown or null details. Detailed information about data processing is provided in Chapter 4. To visualize the spatial and temporal trends in crashes, data visualization was conducted and is presented in Chapter 4.

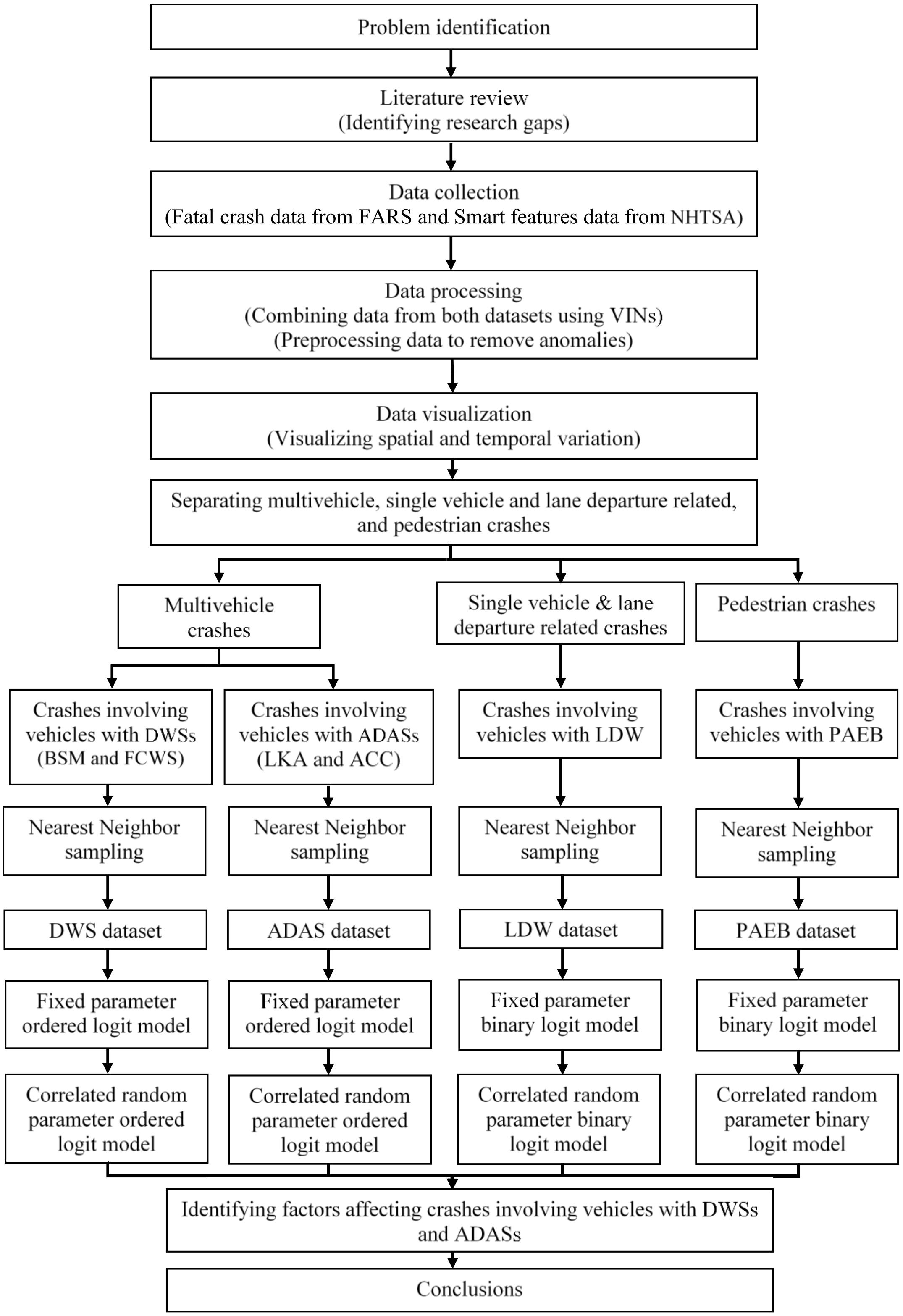


**Figure 3-1. Methodological framework for the analysis to identify factors affecting fatal crashes involving vehicles with various DWSs and ADASs.**

Each DWS or ADAS is designed to enhance safety for a particular crash type. For example, PAEB system is designed to enhance safety in case of vehicle – pedestrian crashes. Therefore, determining the effect of PAEB including multivehicle crashes would not provide exact idea about the effectiveness of the feature. Hence, the dataset was further divided in three datasets to determine the effect of various DWSs and ADASs on fatal crash occurrence. The three datasets include multivehicle crashes, lane departure related or single-vehicle crashes, and pedestrian crashes respectively.

The DWSs BSM and FCWS are designed to enhance safety in case of multivehicle crashes. Therefore, from multivehicle crashes database, vehicles with either BSM or FCWS were considered as vehicles with one DWS and vehicles with both features are considered as vehicles with two DWSs. Similar chronological order was used in case of vehicles with LKA and ACC. Vehicles with LDW and without LDW are coded as 1 and 0 respectively in lane departure related and single-vehicle crashes dataset. Vehicles with PAEB were coded as 1 and vehicles without PAEB were coded as 0 in pedestrian crash dataset. A descriptive statistics analysis was carried out to determine the frequency and percentage of samples for each DWS and ADAS. The results of descriptive statistics showed that number of vehicles with DWS or ADAS was very low (less than 3%) of the entire dataset, making it difficult to compare with vehicles without DWS or ADAS.

Further, as identified in the literature review, the crash dataset contains heterogeneity, and therefore, the heterogeneity needs to be incorporated for reliable model estimates. To account for spatial heterogeneity in the crash dataset and to sample vehicles without DWSs or ADASs corresponding to vehicles with DWSs or ADASs, a nearest neighbor analysis was carried out. Detailed information about nearest neighbor analysis is provided in Chapter 4. After conducting nearest neighbor analysis, the dataset for vehicles with DWS and corresponding neighbors was merged to develop the DWS dataset. Similar analysis was conducted for all the datasets.

Fixed parameters ordered logit and correlated random parameters ordered logit models were developed for DWS and ADAS dataset as the dependent variables in both the cases were ordered. For LDW and PAEB datasets, fixed parameters binary logit model and correlated random parameters binary logit model were developed. The modeling results were discussed in chapter 6 along with identified factors affecting fatal crashes for each model. Finally, conclusions were provided in Chapter 7.

### 3.2 Heterogeneity in Crash Dataset

From the literature review, it is identified that crash dataset contains heterogeneity due to spatial variation in locations of crashes, temporal variation in time of crashes, and variation due to driver characteristics. The heterogeneity in crash dataset can be broken down in three aspects as shown in Figure 3-2.

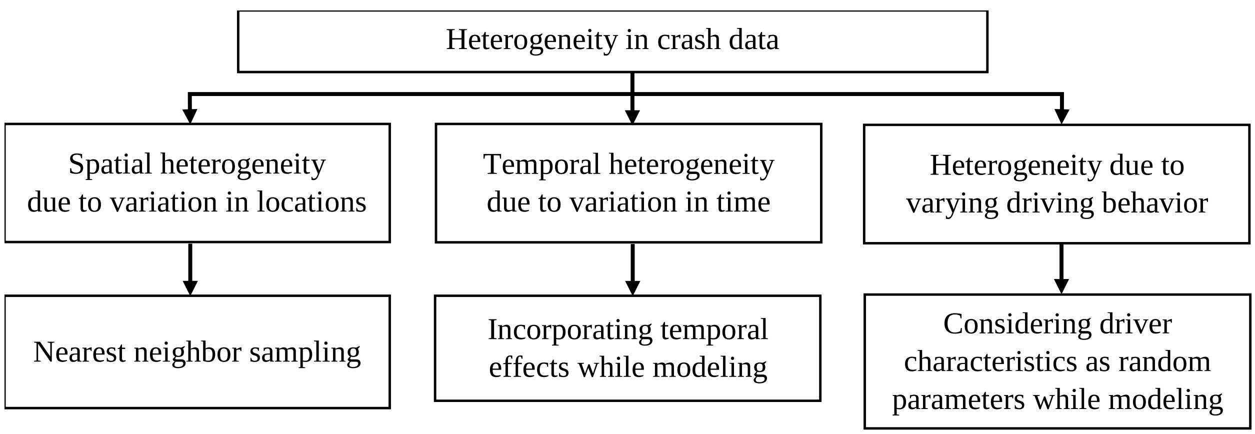


**Figure 3-2. Method to incorporate unobserved heterogeneity in modeling approach.**

As shown in Figure 3-2, the heterogeneity in crash dataset is incorporated while modeling in three stages. Initially, nearest neighbor sampling is used while sampling vehicles without any DWS or ADAS corresponding to vehicles with DWSs or ADASs. Nearest neighbor sampling optimizes number of nearest neighbors and provides the nearest corresponding samples for each crash involving vehicle with DWSs or ADASs. Detailed description of nearest neighbor analysis is provided in Chapter 4.

The temporal heterogeneity primarily arises if crash data considered for analysis is for large time period. In present study, five-year crash data (2016 to 2020) is considered. Therefore, to account for temporal heterogeneity, a temporal variable “Year of crash” in the form of linear effects of time elapsed was incorporated in modeling. The variable was coded as 1 for 2016, 2 for 2017, 3 for 2018, 4 for 2019, and 5 for 2020. Doing so provides estimates for year which describes the variation in probability of crash occurrence over the study years.

Every individual has a different driving style and experience. The variation in driving behavior for each individual gives rise to heterogeneity in crash dataset. Correlated random parameters modeling technique is adopted to account for heterogeneity due to variation in driving behavior. Variables related to driving behavior parameters such as age, gender, drink and drive were kept as random parameters for all models, allowing them to vary across observations. To account for possible correlation between various random parameters, a correlated random parameters modeling technique is used. It is explained in the next section.

### 3.3 Modeling Techniques

The study objective includes identifying the factors affecting fatal crashes involving vehicles with varying DWSs and ADASs. Thus, logistic regression techniques, which are most suitable for the analysis of categorical variables, were explored as the potential analytical method.

Amongst logistic regression techniques, random parameters logistic regression is identified to have higher accuracy than other modeling techniques as it accounts for heterogeneity due to unobserved variables in the modeling (Anastasopoulos and Mannering, 2011). Further, a correlated random parameter modeling approach is used to account for the possible correlations between the random parameters. Therefore, correlated random parameters modeling is identified to be the most suitable as it allows parameters to vary across each observation (random parameters) and it also incorporates correlation between random parameters in modeling.

Both fixed parameters and correlated random parameters models are developed in this study. The fixed parameters ordered logit model is useful to compare the effect of unobserved heterogeneity incorporated through correlated random parameters with the base model which does not have any random parameters.

Depending upon the type of DWS and ADAS and the corresponding crash type for which a particular feature is designed, dependent variable in this study is either ordinal (number of DWSs or ADASs) or binary (with or without a DWS or ADAS). Therefore, ordered logistic and binary logistic regression models were developed. Fixed parameter and correlated random parameter models are developed in both the cases. The interpretations for both the logistic regression techniques used in this study are unidirectional, meaning the indicator variables are not predicting the modeled variable. However, the variation in coefficients of the indicator variables is compared for the different categories of the modeled variable. Moreover, partial effects were estimated for each model to explain the influence of dependent variables on categories of independent variables. The description of the modeling technique is provided in next subsection.

*3.3.1. Fixed and Correlated Random Parameters Ordered Logit Models*

Ordered probability models (ordered probit or logit model), a class of logistic models, are regression models which can be used when the modeled variable has three or more categories, and the order of different categories is important (Sasidharan and Menéndez, 2014). As the DWSs provide warning messages to the drivers while ADASs perform certain driving tasks, the level of safety effectiveness is different for both systems. Thus, two separate models were developed. In the first model, the number of DWSs in the vehicles involved in fatal crashes was considered as the modeled variable. In the second model, the number of ADASs in the vehicles involved in fatal crashes was considered as the modeled variable.

The order is determined depending on the information and assistance provided to the driver while performing various driving tasks (number of features available in the vehicle). Fixed parameters ordered logit model provides flexibility to compute the marginal effects (direct and cross marginal effects) for continuous or indicator variables and is also computationally less expensive compared to random parameters models. Thus, the fixed parameters ordered logit model is developed first.

Let us assume $i$ ($i$ = 1,2,3,…..$N$, $N$= ) be an index to represent the observation and $k$ ($k$ = 0,1,2,…..$S$, $S$= 2) be the index to represent number of DWSs or ADASs in vehicle $i$. The variable $k$ takes a value ($k$ = 0) for 'vehicles without any DWS or ADAS,' ($k$ = 1) for 'vehicles with one DWS or ADAS,' and ($k$ = 2) for 'vehicles with two DWSs or ADASs.' In the ordered outcome framework, the actual number of features in vehicle ($Y_i$) is assumed to be associated with a continuous latent variable ($Y_i^*$). The latent propensity is represented as a linear function in Equation (1).

$$Y_i^* = \beta X_i + \varepsilon_i \tag{1}$$

where $X_i$ is the vector of observed independent variables, $\beta$ is the vector of estimable parameters and $\varepsilon$ is the random error term. The latent propensity is mapped to the actual categories of dependent variable by the $\psi_k$ thresholds ($\psi_k = -\infty \; and \; \psi_k = \infty$). In equation (1), the term $\beta$ is assumed to be fixed across observations. Therefore, Equation (1) converges to a fixed parameters ordered logit model.

As the driver characteristics such as driver fatigue, drivers' prior experience and expertise in driving, driver's age and gender, and their reaction times accounts for possible unobserved heterogeneity, random parameters model is a vital option for modeling as it facilitates incorporating unobserved heterogeneity in dataset while modeling (Milton et al., 2008; Venkataraman et al., 2013, 2014; Mannering and Bhat, 2014; Mannering et al., 2016; Hou et al., 2018). The random parameters ordered logit model assumes parameters in the model to vary across the observation, and the variation follows a specific distribution. In addition, it also provides the flexibility to vary the mean and variance across observations of the dataset (Hou et al., 2022).

To relax the fixed parameters assumptions, i.e., the effect of $(\beta)$ is the same across observations, a correlated random parameters approach was employed, wherein the $(\beta)$ was allowed to vary systematically across each observation. The correlated random parameters can be expressed as shown in Equation (2) (Ali et al., 2022).

$$\beta_i = \beta + \Omega\phi \tag{2}$$

where $\beta$ is the mean of the random parameter, $\Omega$ is a lower triangular Cholesky matrix containing information about covariances and it also accounts for possible correlations amongst the coefficients, and $\phi$ is a column vector of independent standard normally distributed variables. It is assumed that $\beta_i$ follows a multivariate normal distribution with mean $\beta$ and a covariance matrix $\Omega\Omega'$. In this study, unrestricted form of Cholesky matrix is used, which allows to capture correlations between multiple random parameters.

One of the practical limitations of this modeling framework is that the effect of the independent variables on latent propensity cannot quantify the effect of each variable on the probability of various categories of dependent variable (Washington et al., 2020). Therefore, average marginal effects are computed to obtain the effect of explanatory variables for each ordinal outcome. For an explanatory variable $X_i$, the average marginal effects are estimated using the difference in the estimated probabilities when the variable is changing from zero to one, while all other variables ($\overline{X_l}$) are equal to the average values of the sample observations. The average marginal effects for the indicator variable is mathematically expressed as shown in Equation (3) (Washington et al., 2020).

$$AME = P(Y = k|\overline{X_l},\ X_i = 1) - P(Y = k|\overline{X_l}, X_i = 0) \quad (3)$$

The random function can follow any distribution, such as normal, lognormal, uniform, Weibull, or triangular distribution. The selection of distribution influences the accuracy of the results. The existing literature shows that using normal distribution for random function provides better accuracy of the results. Therefore, random parameters are assumed to be normally distributed. The random values considered for modeling may affect the result outcomes, due to which multiple draws of the random sample must be tested for specific random functions.

The existing literature suggests that the Halton sequence approach is one of the best ways to draw random values (Halton, 1960; Bhat, 2003; Train, 2009). The Halton sequence is a sequence of dimensional numbers, and it is generated using the deterministic method. The Halton numbers are designed to give fairly even coverage through the domain of the selected distribution (Train, 2000). Thus, Halton draws were selected in this study instead of random draws of the selected distributions.

*3.3.2. Fixed and Correlated Random Parameters Binary Logit Models*

Let us assume *i* (*i* = 1,2,3,…..*N*, *N*= ) be an index to represent the observation and *k* be the index to represent whether a vehicle $i$ has PAEB or LDW. The variable *k* takes a value (*k* = 0) for 'vehicles without PAEB or LDW,' (*k* = 1) for 'vehicles with PAEB or LDW.' In the binary outcome framework, let ($U_i$) be the function which determines a vehicle has a PAEB or LDW or not. It can be mathematically expressed as shown in Equation (4).

$$U_i = \beta X_i + \varepsilon_i \tag{4}$$

where $X_i$ is the vector of observed independent variables, $\beta$ is the vector of estimable parameters and $\varepsilon$ is the random error term. In Equation (4), the term $\beta$ is assumed to be fixed across observations. Therefore, Equation (4) converges to a fixed parameters binary logit model.

As discussed earlier, driver characteristics accounts for possible unobserved heterogeneity. The random parameters model is suitable technique as it facilitates incorporating unobserved heterogeneity in dataset (Milton et al., 2008; Venkataraman et al., 2013, 2014; Mannering and Bhat, 2014; Mannering et al., 2016; Hou et al., 2018). The random parameters binary logit model assumes model parameters to vary across the observation, and the variation follows a specific distribution.

To relax the fixed parameter assumptions, i.e., the effect of $(\beta)$ is the same across observations, a correlated random parameters approach was employed, wherein the $(\beta)$ was allowed to vary systematically across each observation. The correlated random parameters can be expressed as shown in Equation (5) (Ali et al., 2022).

$$\beta_i = \beta + \Omega\phi \tag{5}$$

where $\beta$ is the mean of the random parameter, $\Omega$ is a lower triangular Cholesky matrix with information about covariances and correlations amongst coefficients, and $\phi$ is a column vector of independent standard normally distributed variables. It is assumed that $\beta_i$ follows a multivariate normal distribution with mean $\beta$ and a covariance matrix $\Omega\Omega'$. In this study, unrestricted form of Cholesky matrix is used, which allows to capture correlations between multiple random parameters.

The average marginal effects are computed to investigate the effect of explanatory variables on the probability of crash occurrence for vehicles with PAEB or LDW. For an explanatory variable $X_i$, the average marginal effects are computed similar to the ordered models as the difference in the probability estimates with the variable shifting from zero to one, when all other variables $(\overline{X_l})$ are equal to the average values. The average marginal effects for an indicator variable can be written as shown in Equation (3) (Washington et al., 2020).

In order to compare the goodness of fit of fixed and correlated random parameters models, indices such as McFadden Pseudo R-squared and Log-likelihood were considered. The McFadden pseudo-$\rho^2$ provides information about model fit for logistic regression models fitted using the method of maximum likelihood (McFadden, 1981). The comparison between models is to identify the difference between the accuracies of modeling methods and determine the model fit statistics rather than to compare the models with different modeled variables. The models with the highest McFadden pseudo R-squared and lowest Log-likelihood were considered as statistically better fit models. In addition, Log-likelihood ratio test was also conducted to determine whether the correlated random parameters models are significantly different from fixed parameters models or not.

# CHAPTER 4 STUDY AREA, DATA COLLECTION, DATA PROCESSING

This chapter presents the study area, data collection, data processing, and data visualization.

## 4.1 Study Area and Data Collection

The study area should be selected to get the maximum number of samples i.e., fatal crashes involving vehicles equipped with varying number of DWSs and ADASs. Further, the study area should be large enough to consider the spatial effects and the effect of varying geometry depending on the locations and road types. Thus, to identify the effect of DWSs and ADASs on safety for the United States transportation system, the whole United States is considered as the study area.

In order to identify the effect of various DWSs and ADASs on fatal crashes, crash data was collected from the FARS database. Further, the VINs of all the vehicles were used, and data on smart features were retrieved from the NHTSA database. The VINs data showed that the number of vehicles with ADASs, especially ACC and LKA, was much lower in the year 2016.

The FARS database contains information related to factors affecting crashes, vehicles involved in the crashes, pedestrian involvement in the crashes, the geometric condition of the road, weather conditions, and the time of the day. All the factors were considered initially for the analysis. Further, the FARS data were combined with the VIN information to generate a combined dataset involving information about all the variables.

## 4.2 Data Processing

This section includes information about processing raw data from the FARS and NHTSA databases to create a combined data set. It also included processing data to obtain separate datasets for analysis of multivehicle, lane departure or single-vehicle, and pedestrian involved crashes.

The raw FARS data are available in different files related to crashes, vehicles, pedestrians, and other characteristics. Initially, the obtained data in separate files for each year from 2016 to 2020 was linked using the assigned ID and year, which were the common fields in all files of the FARS database. The data from each year were combined in a complete dataset. Some of the samples had missing values or not-reported data, which were removed using filtering.

The VINs of all vehicles in the combined dataset were extracted as a separate file. A Python script was used to extract data related to DWSs and ADASs. Initially, a loop was created for extraction to identify all the vehicles' information in a single trial. The loop looks up a single VIN in the input list and connects it with the information from VIN dataset of NHTSA. The loop then returns the information of all smart features as a list. Further, the information in the list is transformed into a single raw data frame in the same loop. Finally, the data including the VINs and the information about smart features in the vehicle was combined with the FARS data.

The obtained dataset contained information about DWSs, such as LDW, FCWS, and BSM, along with information about ADASs, such as ACC, LKA, and PAEB. The dataset showed that various regions had no to a negligible number of crashes involving vehicles with DWSs or ADASs, compared to crashes involving vehicles without a DWS or ADAS. The samples involving one or more vehicles equipped with different DWSs or ADASs were also identified and considered as separate data points in the analysis. Before modeling, the samples with unknown or unidentified values were eliminated using a filtering technique to reduce the redundancies in the result. The data processing framework used in this study is summarized as shown in Figure 4-1.

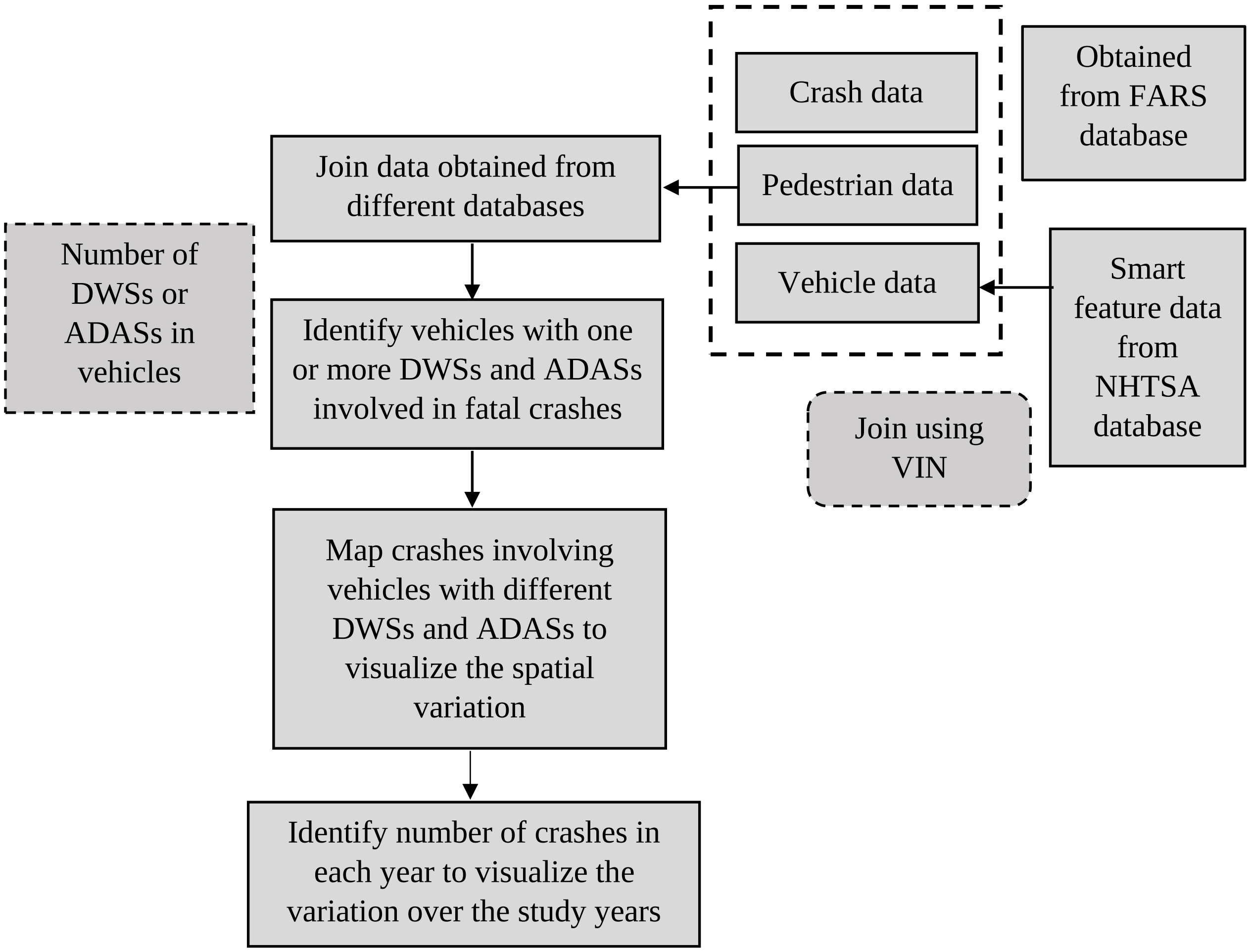


**Figure 4-1. Data processing framework.**

Using VIN's and the NHTSA VIN decoder the generic information on DWSs and ADASs availability for vehicles is obtained. However, there are limitations associated with this which needs to be handled meticulously. For instance, for most DWSs and ADASs, the VIN decoder provides DWS or ADAS availability for the vehicle as "Standard", "Optional", "Not Available", or has missing values. This is based on the make, model, model year, and trim level of the vehicle. If the code is "Standard", it is known that DWS or ADAS feature is on the vehicle. If the code is

"Not Available", DWS or ADAS is not available on the vehicle. To address this, only VIN code “Standard” was used in this study. DWS or ADAS and its type are provided to deal with specific crash types. For instance, PAEB a type of ADAS is effective only under pedestrian crashes. Similarly, LKA (type of ADAS) or LDW (type of DWS) is effective for single-vehicle or lane departure crashes. Therefore, to account for this aspect, the resultant crash data is bifurcated by type of crash.

The VIN data showed that only 85 out of 52,714 vehicles involved in the crash in 2016 had either LKA, ACC, or PAEB systems. Therefore, the crash data of previous years was not considered, and data from 2016 to 2020 was used in this study. Figure 4-2 shows the location of fatal crashes from 2016 to 2020 involving vehicles with one or more DWSs.

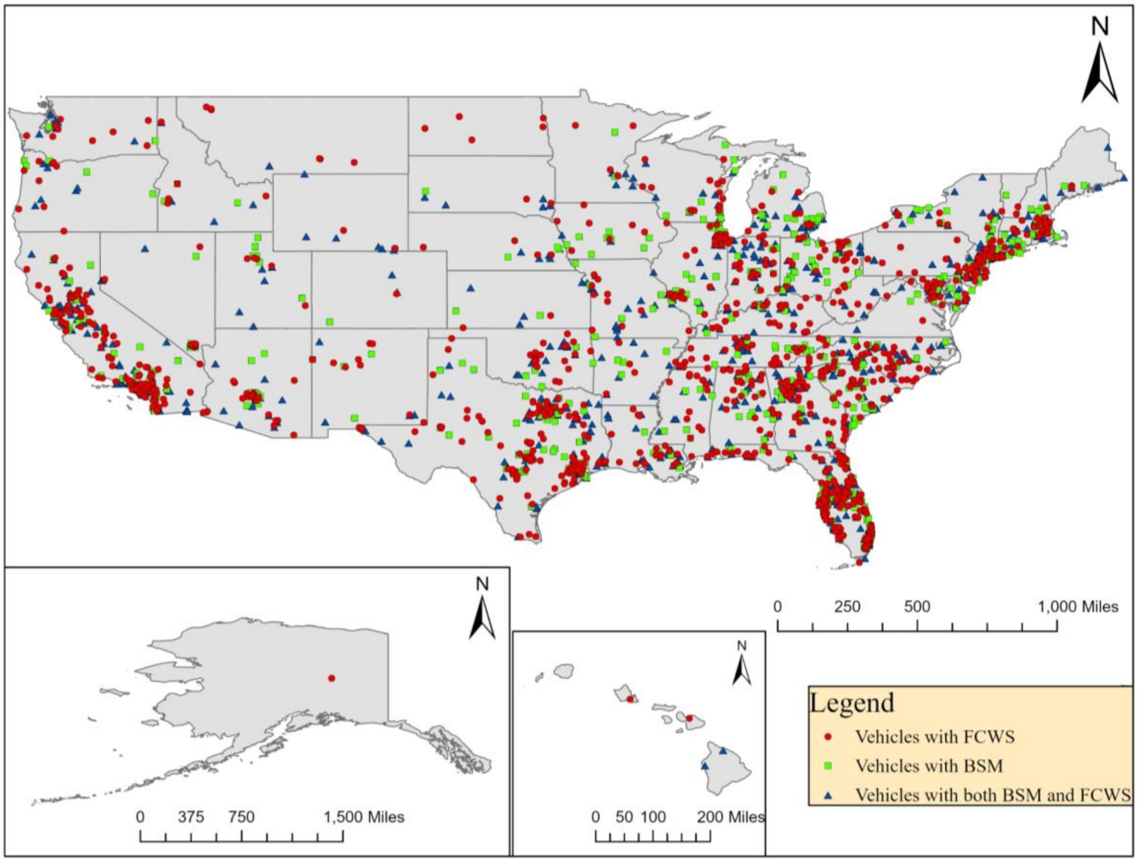


**Figure 4-2. Spatial variation of fatal crashes involving vehicles with one or more DWSs.**

The major clusters, including vehicles with one or multiple DWSs involved in fatal crashes, are in the eastern regions, as shown in Figure 4-2. The number of crashes involving vehicles with DWSs in central and mountain regions is low compared to both east and west coasts. The figures showing locations of fatal crashes involving vehicles with individual DWSs are shown separately in Appendix A.

Figure 4-3 shows the location of crashes in the United States from 2016 to 2020 involving vehicles with one or more ADASs. The trends in the case of vehicles with ADASs are similar to those with DWSs, with higher density clusters near the east and west coasts. However, the number of fatal crashes in the central region involving vehicles with ADASs is low compared to the fatal crashes involving vehicles with DWSs.

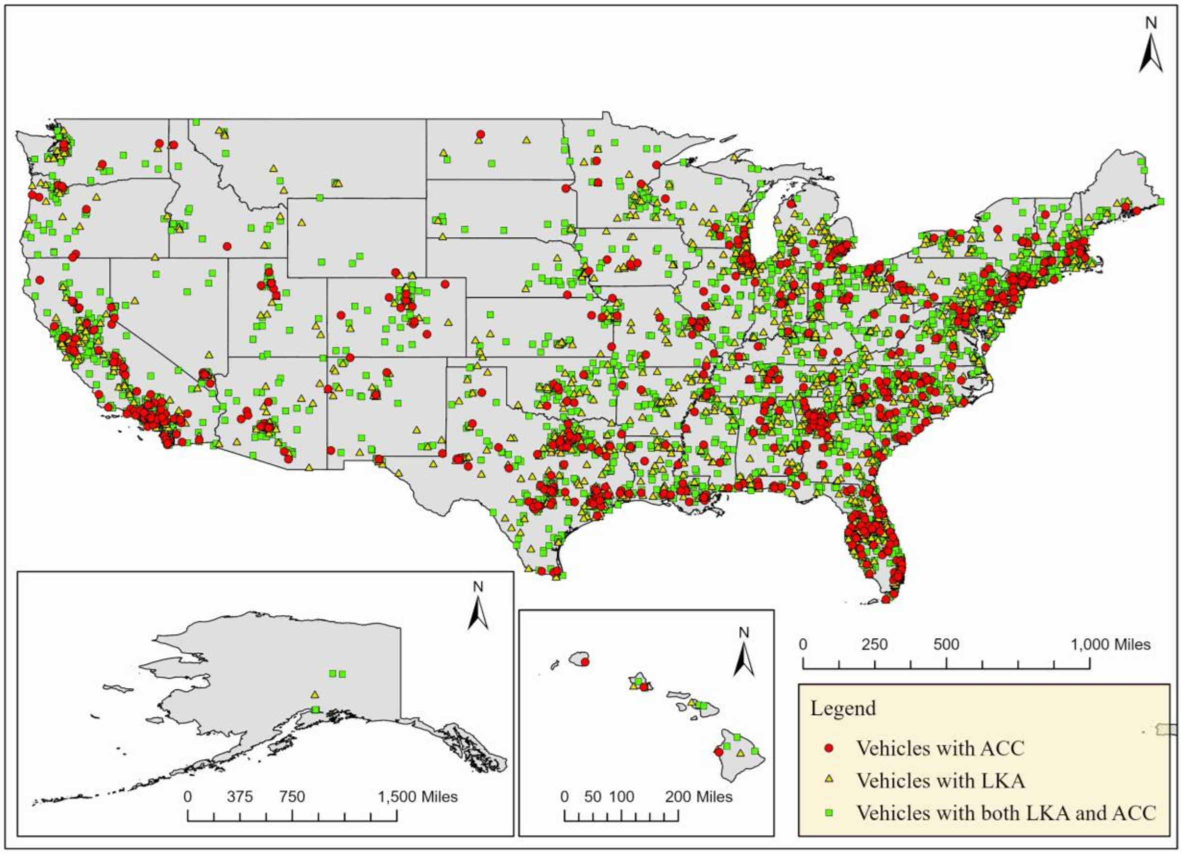


**Figure 4-3. Spatial variation of fatal crashes involving vehicles with one or more ADASs.**

Although the location shows crashes throughout the considered time period, it is necessary to identify the trends in fatal crashes with the time. Thus, number of crashes involving vehicles with various ADASs is shown in Figure 4-4. Figure 4-4 illustrates that the number of crashes involving vehicles with various ADASs, such as ACC, LKA, and PAEB, increased from 2016 to 2020. In addition, the involvement of vehicles with LKA in fatal crashes increased rapidly compared to the involvement of vehicles with PAEB, which is due to the lower penetration of vehicles with PAEB in the existing system. Crashes involving vehicles with LKA increased from 33 in 2016 to 2,437 in 2020. Similarly, the number of crashes involving vehicles with ACC and PAEB increased from 36 and 16 in 2016 to 2,093 and 1,484 in 2020, respectively. The increasing involvement of vehicles with ADASs, as shown in Figure 4-4, indicates a requirement to identify potential factors affecting their crash involvement.

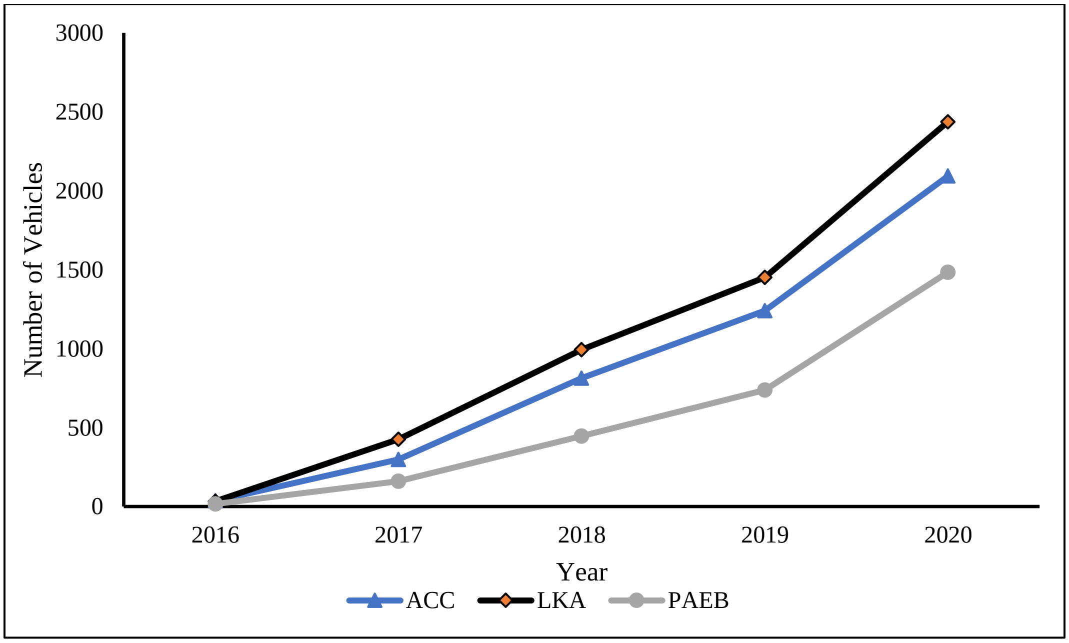


**Figure 4-4. Temporal variation of fatal crashes involving vehicles with ADASs.**

To compare the fatal crash involvement of vehicles with DWSs and ADASs and visualize the temporal variation in the number of crashes, crashes involving vehicles with DWSs per year is plotted as shown in Figure 4-5. Figure 4-5 also shows that the involvement of vehicles with DWSs in fatal crashes increased over the years. However, there was a sudden increase in the involvement after 2019 for the three considered DWSs. Thus, vehicles with DWSs were also considered in the analysis for comparison with vehicles with ADASs.

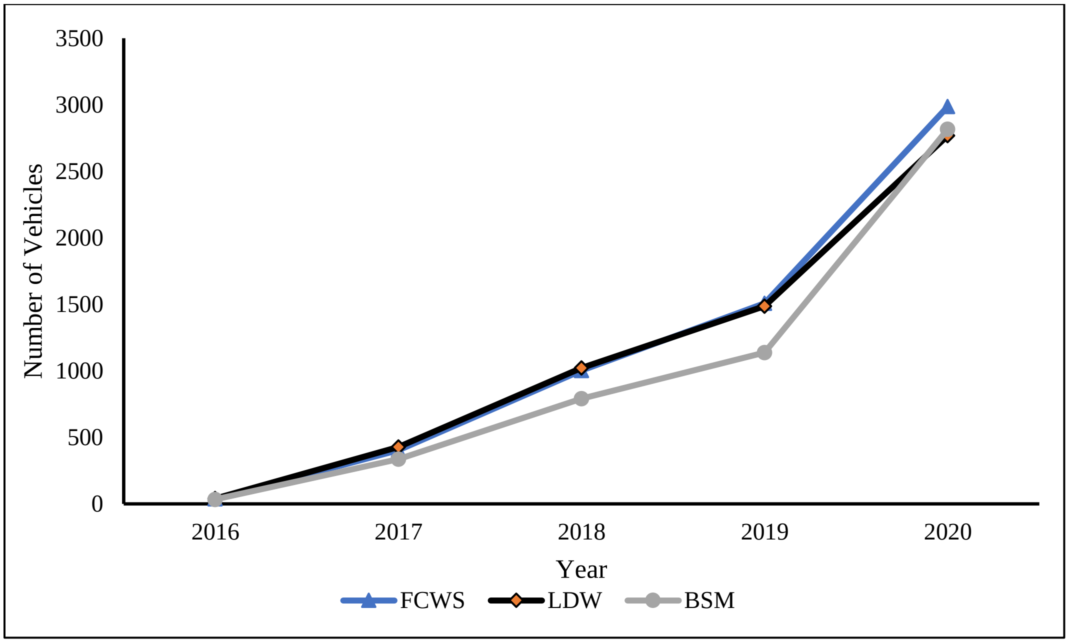


**Figure 4-5. Temporal variation of fatal crashes involving vehicles with DWSs.**

To model the effect of various DWS and ADAS, separate datasets were generated based on the crash type. Multivehicle crashes were separated to determine the effect of number of DWSs and ADASs on safety. The LDW and PAEB systems were not considered in the analysis of number of DWSs and ADASs as the LDW provides warning to vehicles departing lane or roadway, which generally influences single-vehicle crashes or crashes related to lane departure and PAEB is designed to prevent pedestrian crashes. To determine the effect of vehicles with LDW on single-vehicle and lane departure related fatal crash occurrence, dataset with all single-vehicle crashes and lane departure related multivehicle crashes is separated and used for modeling. In case of PAEB, all pedestrian crashes were considered for modeling. The final modeling framework includes four models: Model 1 to determine effect of number of DWSs, Model 2 to determine effect of number of ADASs, Model 3 to determine the effect of LDW on single-vehicle and lane departure related fatal crashes; and, Model 4 to determine the effect of PAEB on pedestrian crashes.

As the number of crashes involving vehicles with DWSs and ADASs varies spatially as well as temporarily, descriptive analysis is carried out to identify the frequency and proportion of samples in each categories of the indicator variables. The descriptive analysis results showed that proportion of crashes involving vehicles with varying number of DWSs or ADASs is less than 3% of the total number of samples. Therefore, for even comparison of vehicles with and without DWSs and ADASs, a sampling is required to select representative crashes involving vehicles without DWSs and ADASs.

Nearest neighbor analysis is recommended in the existing literature for sampling in cases where sample size is too large (Cover and Hart, 1967). In the nearest neighbor analysis, the number of nearest neighbors from locations of crashes involving vehicles with DWSs or ADASs is optimized to identify the optimum number of crashes. The optimization considers the average distance of $i^{th}$ nearest neighbors from all crashes. The use of nearest neighbor sampling also ensures that the comparison groups (crashes involving vehicles with and without DWS and ADAS) are in spatial proximity as past research findings indicates that crashes are correlated spatially (Aguero-Valverde and Jovanis, 2006; Mitra, 2009). Therefore, the nearest neighbor analysis was used for sampling crashes involving vehicles without DWSs or ADASs for modeling. The optimum number of nearest neighbors is identified as three and the maximum distance of third neighbor (in entire dataset) is within 3,300 feet.

The snapshot of three nearest neighbors corresponding to a crash involving vehicle with DWSs or ADASs is shown in Figure 4-6. The nearest neighbor sampling is carried separately for each year (i.e., 2016, 2017, 2018, 2019, 2020) and type of crash (i.e., multivehicle, single-vehicle and pedestrian crashes).


**Figure 4-6. Nearest Neighbor Sampling (3 Nearest Neighbors).**

The snapshot provides representation of ArcGIS interface with information on how nearest neighbors are sampled in ArcGIS using the nearest neighbor table tool. To determine the variation in frequency and percentage of samples across various categories of independent variables, descriptive statistics analysis was carried out at model level. The results of descriptive statistics are presented in the next chapter.

# CHAPTER 5 RESULTS AND DISCUSSIONS

This chapter presents the results to determine the effect of DWSs and ADASs on fatal crash occurrence. It includes the following.

1. Descriptive analysis results for developed models by crash type and smart features.
2. The goodness of fit indices to compare fixed and correlated random parameters model.
3. Model results
    - Analysis of multivehicle crashes involving vehicles with and without DWSs.
    - Analysis of multivehicle crashes involving vehicles with and without ADASs.
    - Analysis of single-vehicle and lane departure-related crashes involving vehicles with and without LDW.
    - Analysis of pedestrian crashes involving vehicles with and without PAEB.

As discussed previously, four datasets were created to determine factors affecting fatal crashes and identify the effect of various DWSs and ADASs on safety. Four models were developed, which included one model for each dataset. Model 1 includes multivehicle crashes involving vehicles with and without DWSs. The DWSs considered for model 1 are BSM and FCWS since both the features remain engaged all the time and are designed to improve safety in case of multivehicle crashes. Model 2 includes multivehicle crashes involving vehicles with and without ADASs. The ADASs considered in Model 2 are LKA and ACC. Again, both features are designed to automate driving-related tasks, preventing multivehicle crashes. Model 3 includes single-vehicle and lane departure-related crashes involving vehicles with and without LDW. One of the reasons for developing a separate model for LDW is that the LDW feature comes with a button on the steering wheel to turn it on or off. Therefore, the feature does not remain engaged all the time, and it depends on the driver whether to use it or not. Another reason is that LDW prevents vehicles from departing the lane, which is a primary cause of single-vehicle roadside departure or lane departure-related crashes. Therefore, considering single-vehicle and lane departure-related crashes in the case of the model for LDW would provide a better idea about how LDW would affect factors related to single-vehicle and lane departure-related fatal crashes and the overall difference in fatal crash occurrence for vehicles with and without LDW. Model 4 includes pedestrian crashes involving vehicles with and without PAEB. The PAEB feature is designed to prevent vehicle-pedestrian crashes. Therefore, only pedestrian crashes are considered in the case of the model for PAEB.

Since multiple models are developed to determine the effect of various DWSs and ADASs on safety, from here onwards, the model numbers are considered in the results and discussion section.

## 5.1 Descriptive analysis

A descriptive analysis was conducted to identify the frequency distribution across different categories of independent variables for each model. The frequency as well as percentage of samples in each category of the four models are shown in Table 5-1.

**Table 5-1. Frequency and percentage of samples with varying number of DWSs and ADASs in the modeling datasets.**

| Model # | Variable | Category | Frequency (%) |
|---|---|---|---|
| Model 1 | Presence of DWSs | No FCWS or BSM | 6366 (72.696) |
| | | Either FCWS or BSM | 1628 (18.591) |
| | | Both FCWS and BSM | 763 (8.713) |
| Model 2 | Presence of ADASs | No LKA or ACC | 4757 (73.162) |
| | | Either LKA or ACC | 649 (9.982) |
| | | Both LKA and ACC | 1096 (16.856) |
| Model 3 | Presence of LDW system | No | 1613 (71.721) |
| | | Yes | 636 (28.279) |
| Model 4 | Presence of PAEB system | No | 749 (72.158) |
| | | Yes | 289 (27.842) |

The descriptive statistics summarized in Table 5-1 indicate the frequency and percentage of samples for various categories of dependent variables in four models. In model 1, the proportion of vehicles with two DWSs is lowest (8.71%), followed by vehicles with one DWS (18.59%). In the case of Model 2, the proportion of vehicles with two ADASs is higher than that of vehicles with one ADAS. In all the models, the proportion of vehicles without any DWS or ADAS varies from 71.72% to 73.16%. The primary reason for a similar proportion of vehicles without DWS or ADAS in each model is the use of nearest neighbor sampling, which is optimized at three nearest neighbors for all the models. Therefore, the proportion of vehicles without DWS or ADAS in each model should be 75%. However, there are instances in the dataset where the nearest neighbor for two crashes involving vehicle with DWSs or ADASs is similar. Therefore, duplicate records are eliminated, and the resulting proportion of vehicles without DWS or ADAS for each model is slightly lower than the ideal proportion i.e., 75%.

The frequency of vehicles equipped with two ADAS (LKA and ACC) is higher than that of vehicles with two DWSs (FCWS and LDW). However, the frequency of vehicles with one

ADAS is lower than those with one DWS, indicating that fatal crash involvement of vehicles with multiple ADASs is higher than vehicles with single DWS. Another reason could be the higher penetration of vehicles with two ADASs than vehicles with one ADAS. The descriptive statistics results of the dataset used for each model are discussed in the following sections.

### *5.1.1. Descriptive statistics results of dataset for Model 1*

The descriptive statistics of all the variables related to driver, road, and crash characteristics included in Model 1 is shown in Table 5-2.

**Table 5-2. Descriptive statistics results of the dataset used for Model 1.**

| Variables | Frequency (Percentage) |
|---|---|
| **Driver characteristics** | |
| Age (Less than 24 years) | 1,392 (15.896) |
| Age (>=24, <=40 years) | 2,765 (31.575) |
| Age (>40, <=65 years) | 3,112 (35.537) |
| Age (Greater than 65 years) | 1,488 (16.992) |
| Drink and drive related | 923 (10.54) |
| Not related to drink and drive | 7,834 (89.46) |
| Gender (Female) | 2,781 (31.757) |
| Gender (Male) | 5,976 (68.243) |
| **Road characteristics** | |
| Area type (Urban) | 5,248 (59.929) |
| Area type (Rural) | 3,509 (40.071) |
| Functional class (Interstate) | 1,149 (13.121) |
| Functional class (Freeway or expressway) | 408 (4.659) |
| Functional class (Principal arterial) | 3,394 (38.758) |
| Functional class (Minor arterial) | 2,062 (23.547) |
| Functional class (Major collector) | 1,029 (11.751) |
| Functional class (Minor collector) | 196 (2.238) |
| Functional class (Local) | 519 (5.927) |
| Intersection | 5,231 (59.735) |
| Non-intersection | 3,526 (40.265) |
| Number of lanes (No traffic way access) | 84 (0.959) |
| Number of lanes (One lane) | 85 (0.971) |
| Number of lanes (Two lanes) | 5,001 (57.109) |
| Number of lanes (Three lanes) | 1,281 (14.628) |
| Number of lanes (Four lanes) | 1,112 (12.698) |

| Variables | Frequency (Percentage) |
|---|---|
| Number of lanes (Five lanes) | 842 (9.615) |
| Number of lanes (Six lanes) | 209 (2.387) |
| Number of lanes (Seven or more lanes) | 143 (1.633) |
| Work zone | 254 (2.901) |
| No work zone | 8,503 (97.099) |
| **Crash characteristics** | |
| Light condition (Daylight) | 5,387 (61.517) |
| Light condition (Dark) | 3,008 (34.35) |
| Light condition (Dawn) | 173 (1.976) |
| Light condition (Dusk) | 189 (2.158) |
| Pre-crash stability (Tracking) | 6,682 (76.305) |
| Pre-crash stability (Skidding laterally) | 148 (1.69) |
| Pre-crash stability (Skidding longitudinally) | 103 (1.176) |
| Pre-crash stability (Not specific) | 1,824 (20.829) |
| Surface condition (Dry) | 7,483 (85.452) |
| Surface condition (Wet) | 1,036 (11.831) |
| Surface condition (Ice, snow, mud, dirt, oil, or water) | 238 (2.718) |
| Season (Winter) | 1,863 (21.274) |
| Season (Spring) | 1,939 (22.142) |
| Season (Summer) | 2,511 (28.674) |
| Season (Fall) | 2,444 (27.909) |
| Speeding | 978 (11.168) |
| Not speeding | 7,779 (88.832) |
| Time of the day (12 AM to 3 AM) | 597 (6.817) |
| Time of the day (3 AM to 6 AM) | 524 (5.984) |
| Time of the day (6 AM to 9 AM) | 947 (10.814) |
| Time of the day (9 AM to 12 PM) | 1,106 (12.63) |
| Time of the day (12 PM to 3 PM) | 1,500 (17.129) |
| Time of the day (3 PM to 6 PM) | 1,815 (20.726) |
| Time of the day (6 PM to 9 PM) | 1,297 (14.811) |
| Time of the day (9 PM to 12 AM) | 971 (11.088) |
| Weather condition (Clear) | 6,576 (75.094) |
| Weather condition (Cloudy) | 1,281 (14.628) |
| Weather condition (Rain) | 668 (7.628) |
| Weather conditions (Snow, fog/smoke/smog, or other adverse condition) | 232 (2.649) |
| Manner of collision (Head-on) | 2,439 (27.852) |
| Manner of collision (Rear-end) | 1,799 (20.544) |
| Manner of collision (Angle) | 3,825 (43.679) |
| Manner of collision (Sideswipe - opposite direction) | 389 (4.442) |
| Manner of collision (Sideswipe - same direction) | 305 (3.483) |

Most drivers involved in a fatal crash fall within the age range of 24 to 65 years, with the highest percentage in the 40 to 65 years category. It suggests that middle-aged drivers are more frequently involved in crashes. Additionally, a considerable proportion of crashes (10.54%) are related to drinking and driving incidents. Male drivers account for a higher percentage (68.243%) than their female counterparts (31.757%), indicating potential disparities in driving behavior and a tendency for risk-taking.

Road characteristics reveal that crashes are more prevalent in urban areas (59.929%) compared to rural areas (40.071%). The functional class of roads indicates that multivehicle crashes in the dataset primarily occurred on principal and minor arterials. Intersections account for a substantial portion of crashes (59.735%). The number of lanes also influences crash occurrence, with roads having two lanes being the most common (57.109%).

Crash characteristics shed light on various factors contributing to crashes. Daylight conditions (61.517%) and dry surface conditions (85.452%) are predominant in crash incidents. The most frequent manner of collision is the "Angle" category (43.679%). The analysis also highlights the significance of driver behavior, with speeding being a factor in 11.168% of crashes. Moreover, crashes occur more during peak afternoon hours (3 PM to 6 PM), indicating the importance of considering the time of day in crash prevention strategies.

### *5.1.2. Descriptive statistics results of the dataset for Model 2*

The descriptive statistics of all the variables related to driver, road, and crash characteristics included in Model 2 is shown in Table 5-3.

**Table 5-3. Descriptive statistics results of the dataset used for Model 2.**

| **Variables** | **Frequency (Percentage)** |
|---|---|
| **Driver characteristics** | |
| Age (Less than 24 years) | 857 (13.181) |
| Age (>=24, <=40 years) | 2,121 (32.621) |
| Age (>40, <=65 years) | 2,406 (37.004) |
| Age (Greater than 65 years) | 1,118 (17.195) |
| Drink and drive related | 767 (11.796) |

| Variables | Frequency (Percentage) |
|---|---|
| Not related to drink and drive | 5,735 (88.204) |
| Gender (Female) | 2,014 (30.975) |
| Gender (Male) | 4,488 (69.025) |
| **Road characteristics** | |
| Area type (Urban) | 3,942 (60.627) |
| Area type (Rural) | 2,560 (39.373) |
| Functional class (Interstate) | 894 (13.75) |
| Functional class (Freeway or expressway) | 328 (5.045) |
| Functional class (Principal arterial) | 2,454 (37.742) |
| Functional class (Minor arterial) | 1,514 (23.285) |
| Functional class (Major collector) | 800 (12.304) |
| Functional class (Minor collector) | 140 (2.153) |
| Functional class (Local) | 372 (5.721) |
| Intersection | 2,541 (39.08) |
| Non-intersection | 3,961 (60.92) |
| Number of lanes (No traffic way access) | 71 (1.092) |
| Number of lanes (One lane) | 66 (1.015) |
| Number of lanes (Two lanes) | 3,747 (57.628) |
| Number of lanes (Three lanes) | 876 (13.473) |
| Number of lanes (Four lanes) | 871 (13.396) |
| Number of lanes (Five lanes) | 590 (9.074) |
| Number of lanes (Six lanes) | 175 (2.691) |
| Number of lanes (Seven or more lanes) | 106 (1.63) |
| Work zone | 223 (3.43) |
| No work zone | 6,279 (96.57) |
| **Crash characteristics** | |
| Light condition (Daylight) | 3,897 (59.935) |
| Light condition (Dark) | 2,328 (35.804) |
| Light condition (Dawn) | 120 (1.846) |
| Light condition (Dusk) | 157 (2.415) |
| Pre-crash stability (Tracking) | 4,927 (75.777) |
| Pre-crash stability (Skidding laterally) | 131 (2.015) |
| Pre-crash stability (Skidding longitudinally) | 82 (1.261) |
| Pre-crash stability (Not specific) | 1,362 (20.947) |
| Surface condition (Dry) | 5,551 (85.374) |
| Surface condition (Wet) | 758 (11.658) |
| Surface condition (Ice, snow, mud, dirt, oil, or water) | 193 (2.968) |
| Season (Winter) | 1,357 (20.871) |
| Season (Spring) | 1,419 (21.824) |
| Season (Summer) | 1,866 (28.699) |
| Season (Fall) | 1,860 (28.607) |
| Speeding | 854 (13.134) |
| Not speeding | 5,648 (86.866) |
| Time of the day (12 AM to 3 AM) | 473 (7.275) |
| Time of the day (3 AM to 6 AM) | 394 (6.06) |
| Time of the day (6 AM to 9 AM) | 643 (9.889) |

| Variables | Frequency (Percentage) |
|---|---|
| Time of the day (9 AM to 12 PM) | 832 (12.796) |
| Time of the day (12 PM to 3 PM) | 1,110 (17.072) |
| Time of the day (3 PM to 6 PM) | 1,319 (20.286) |
| Time of the day (6 PM to 9 PM) | 942 (14.488) |
| Time of the day (9 PM to 12 AM) | 789 (12.135) |
| Weather condition (Clear) | 4,869 (74.885) |
| Weather condition (Cloudy) | 974 (14.98) |
| Weather condition (Rain) | 463 (7.121) |
| Weather conditions (Snow, fog/smoke/smog, or other adverse condition) | 196 (3.014) |
| Manner of collision (Head-on) | 1,804 (27.745) |
| Manner of collision (Rear-end) | 1,380 (21.224) |
| Manner of collision (Angle) | 2,800 (43.064) |
| Manner of collision (Sideswipe - opposite direction) | 290 (4.46) |
| Manner of collision (Sideswipe - same direction) | 228 (3.507) |

Driver characteristics play a significant role in crash occurrences. Most drivers involved in the crashes in the dataset for Model 2 fall within the age range of 24 to 65 years, with the highest percentage in the 40 to 65 years category. Additionally, a significant portion of crashes (11.796%) is related to drink and drive incidents, emphasizing the importance of addressing this dangerous behavior and through strict enforcement and education campaigns the impact of this can be controlled. Male drivers account for a higher percentage (69.025%) than female drivers (30.975%), indicating potential differences in driving behavior and risk-taking tendencies.

Road characteristics show that crashes are more prevalent in urban areas (60.627%) compared to rural areas (39.373%). The functional class of roads reveals that multivehicle crashes in the dataset mostly occurred on principal and minor arterials. Intersections account for a significant portion of crashes (39.08%). The number of lanes also influences crash occurrence, with roads having two lanes being the most common (57.628%).

Crash characteristics shed light on various factors contributing to crashes. Crashes predominantly occurred during daylight (59.935%) and under dry surface conditions (85.374%).

The most common manner of collision is the "Angle" category (43.064%). The analysis also highlights the significance of driver behavior, with speeding being a factor in 13.134% of crashes. Time of the day shows higher crashes during peak afternoon hours (3 PM to 6 PM).

### *5.1.3. Descriptive statistics results of the dataset for Model 3*

The descriptive statistics of all the variables related to driver, road, and crash characteristics included in Model 3 is shown in Table 5-4.

**Table 5-4. Descriptive statistics results of the dataset used for Model 3.**

| Variables | Frequency (Percentage) |
|---|---|
| **Driver characteristics** | |
| Age (Less than 24 years) | 458 (20.365) |
| Age (>=24, <=40 years) | 786 (34.949) |
| Age (>40, <=65 years) | 718 (31.925) |
| Age (Greater than 65 years) | 287 (12.761) |
| Drink and drive related | 652 (28.991) |
| Not related to drink and drive | 1,597 (71.009) |
| Gender (Female) | 588 (26.145) |
| Gender (Male) | 1,661 (73.855) |
| **Road characteristics** | |
| Area type (Urban) | 1,105 (49.133) |
| Area type (Rural) | 1,144 (50.867) |
| Functional class (Interstate) | 378 (16.807) |
| Functional class (Freeway or expressway) | 140 (6.225) |
| Functional class (Principal arterial) | 542 (24.1) |
| Functional class (Minor arterial) | 449 (19.964) |
| Functional class (Major collector) | 362 (16.096) |
| Functional class (Minor collector) | 104 (4.624) |
| Functional class (Local) | 274 (12.183) |
| Number of lanes (No traffic way access) | 23 (1.023) |
| Number of lanes (One lane) | 42 (1.867) |
| Number of lanes (Two lanes) | 1,612 (71.676) |
| Number of lanes (Three lanes) | 242 (10.76) |
| Number of lanes (Four lanes) | 170 (7.559) |
| Number of lanes (Five lanes) | 120 (5.336) |
| Number of lanes (Six lanes) | 28 (1.245) |
| Number of lanes (Seven or more lanes) | 12 (0.534) |
| Work zone | 59 (2.623) |
| No work zone | 2,190 (97.377) |

| Variables | Frequency (Percentage) |
|---|---|
| **Crash characteristics** | |
| Light condition (Daylight) | 1,112 (49.444) |
| Light condition (Dark) | 1,043 (46.376) |
| Light condition (Dawn) | 44 (1.956) |
| Light condition (Dusk) | 50 (2.223) |
| Pre-crash stability (Tracking) | 1,417 (63.006) |
| Pre-crash stability (Skidding longitudinally) | 755 (33.57) |
| Pre-crash stability (Not specific) | 77 (3.424) |
| Surface condition (Dry) | 1,865 (82.926) |
| Surface condition (Wet) | 287 (12.761) |
| Surface condition (Ice, snow, mud, dirt, oil, or water) | 97 (4.313) |
| Season (Winter) | 490 (21.787) |
| Season (Spring) | 486 (21.61) |
| Season (Summer) | 608 (27.034) |
| Season (Fall) | 665 (29.569) |
| Speeding | 704 (31.303) |
| Not speeding | 1,545 (68.697) |
| Time of the day (12 AM to 3 AM) | 296 (13.161) |
| Time of the day (3 AM to 6 AM) | 207 (9.204) |
| Time of the day (6 AM to 9 AM) | 230 (10.227) |
| Time of the day (9 AM to 12 PM) | 212 (9.426) |
| Time of the day (12 PM to 3 PM) | 317 (14.095) |
| Time of the day (3 PM to 6 PM) | 365 (16.229) |
| Time of the day (6 PM to 9 PM) | 330 (14.673) |
| Time of the day (9 PM to 12 AM) | 292 (12.984) |
| Weather condition (Clear) | 1,645 (73.144) |
| Weather condition (Cloudy) | 362 (16.096) |
| Weather condition (Rain) | 179 (7.959) |
| Weather conditions (Snow, fog/smoke/smog, or other adverse condition) | 63 (2.801) |
| Manner of collision (Single-vehicle roadside departure) | 1,491 (66.296) |
| Manner of collision (Head-on) | 375 (16.674) |
| Manner of collision (Rear-end) | 78 (3.468) |
| Manner of collision (Angle) | 205 (9.115) |
| Manner of collision (Sideswipe - opposite direction) | 55 (2.446) |
| Manner of collision (Sideswipe - same direction) | 45 (2.001) |

Drivers within the age range of 24 to 40 years constitute the highest percentage (34.949%) of crashes, followed by drivers aged over 40 but less than or equal to 65 years (31.925%). Moreover, a significant proportion of crashes (28.991%) are related to drink and drive incidents, emphasizing the need for targeted interventions to address this risky behavior. Male drivers

(73.855%) are more frequently involved in crashes compared to their female counterparts (26.145%).

Urban areas (49.133%) experience slightly fewer crashes than rural areas (50.867%). Principal and minor arterials are the most common types of roads where crashes occur, with interstate roads accounting for 16.807% of the crashes. Furthermore, intersections contribute significantly to crash occurrences (12.183%), highlighting the importance of implementing effective intersection safety measures. The majority of crashes happen on roads with two lanes (71.676%).

Examining crash characteristics, it is evident that crashes predominantly occur during daylight (49.444%) and under dry surface conditions (82.926%). The most common manner of collision is a single-vehicle roadside departure (66.296%). Additionally, speeding plays a significant role in crashes, accounting for 31.303% of cases.

### *5.1.4. Descriptive statistics results of the dataset for Model 4*

The descriptive statistics of all the variables related to driver, road, and crash characteristics included in Model 4 is shown in Table 5-5.

**Table 5-5. Descriptive statistics results of the dataset used for Model 4.**

| Variables | Frequency (Percentage) |
|---|---|
| **Driver characteristics** | |
| Age (Less than 24 years) | 180 (17.341) |
| Age (>=24, <=40 years) | 352 (33.911) |
| Age (>40, <=65 years) | 376 (36.224) |
| Age (Greater than 65 years) | 130 (12.524) |
| Drink and drive related | 69 (6.647) |
| Not related to drink and drive | 969 (93.353) |
| Gender (Female) | 308 (29.672) |
| Gender (Male) | 730 (70.328) |
| **Road characteristics** | |
| Area type (Urban) | 891 (85.838) |

| Variables | Frequency (Percentage) |
|---|---|
| Area type (Rural) | 147 (14.162) |
| Functional class (Interstate) | 152 (14.644) |
| Functional class (Freeway or expressway) | 52 (5.01) |
| Functional class (Principal arterial) | 404 (38.921) |
| Functional class (Minor arterial) | 228 (21.965) |
| Functional class (Major collector) | 82 (7.9) |
| Functional class (Minor collector) | 18 (1.734) |
| Functional class (Local) | 102 (9.827) |
| Intersection | 286 (27.553) |
| Non-intersection | 752 (72.447) |
| Number of lanes (No traffic way access) | 3 (0.289) |
| Number of lanes (One lane) | 23 (2.216) |
| Number of lanes (Two lanes) | 411 (39.595) |
| Number of lanes (Three lanes) | 202 (19.461) |
| Number of lanes (Four lanes) | 176 (16.956) |
| Number of lanes (Five lanes) | 154 (14.836) |
| Number of lanes (Six lanes) | 43 (4.143) |
| Number of lanes (Seven or more lanes) | 26 (2.505) |
| Work zone | 19 (1.83) |
| No work zone | 1,019 (98.17) |
| **Crash characteristics** | |
| Light condition (Daylight) | 221 (21.291) |
| Light condition (Dark) | 779 (75.048) |
| Light condition (Dawn) | 23 (2.216) |
| Light condition (Dusk) | 15 (1.445) |
| Pre-crash stability (Tracking) | 887 (85.453) |
| Pre-crash stability (Skidding laterally) | 75 (7.225) |
| Pre-crash stability (Skidding longitudinally or not specific) | 76 (7.322) |
| Surface condition (Dry) | 901 (86.802) |
| Surface condition (Wet) | 130 (12.524) |
| Surface condition (Ice, snow, mud, dirt, oil, or water) | 7 (0.674) |
| Season (Winter) | 286 (27.553) |
| Season (Spring) | 203 (19.557) |
| Season (Summer) | 232 (22.351) |
| Season (Fall) | 317 (30.539) |
| Speeding | 76 (7.322) |
| Not speeding | 962 (92.678) |
| Time of the day (12 AM to 3 AM) | 95 (9.152) |
| Time of the day (3 AM to 6 AM) | 113 (10.886) |
| Time of the day (6 AM to 9 AM) | 89 (8.574) |
| Time of the day (9 AM to 12 PM) | 52 (5.01) |
| Time of the day (12 PM to 3 PM) | 61 (5.877) |
| Time of the day (3 PM to 6 PM) | 112 (10.79) |
| Time of the day (6 PM to 9 PM) | 274 (26.397) |
| Time of the day (9 PM to 12 AM) | 242 (23.314) |
| Weather condition (Clear) | 789 (76.012) |

| Variables | Frequency (Percentage) |
|---|---|
| Weather condition (Cloudy) | 165 (15.896) |
| Weather condition (Rain) | 67 (6.455) |
| Weather conditions (Snow, fog/smoke/smog, or other adverse condition) | 17 (1.638) |

The descriptive statistics results in Table 5-5 include only pedestrian crashes, providing valuable insights into the characteristics of such incidents. Drivers in the age range of 40 to 65 years account for the highest percentage (36.224%) of pedestrian crashes, followed by drivers in the age range of 24 to 40 years (36.224%). Additionally, a small proportion of pedestrian crashes (6.647%) are related to drink and drive incidents, underscoring the need for interventions targeting this dangerous behavior. Male drivers (70.328%) are more frequently involved in crashes compared to their female counterparts (29.672%).

Shifting the focus to road characteristics, it is apparent that the majority of pedestrian crashes occur in urban areas (85.838%) compared to rural areas (14.162%). Principal arterials constitute the most common road type where pedestrian crashes occur (38.921%), followed by minor arterials (21.965%). Intersections also play a significant role, contributing to 27.553% of pedestrian crashes. The analysis of the number of lanes indicates that roads with two lanes (39.595%) have a higher frequency of pedestrian crashes.

It is observed that pedestrian crashes frequently occur during dark conditions (75.048%) and under dry surface conditions (86.802%). The most prevalent pre-crash stability condition is tracking (85.453%). Furthermore, pedestrian crashes exhibit seasonal variations, with fall (30.539%) being the season with the highest number of pedestrian crashes. Speeding contributes to a notable proportion of pedestrian crashes (7.322%).

The descriptive statistics provided in the analysis reveal notable variations in the frequency and percentage of samples across different categories of independent variables. While these statistics offer valuable insights into the distribution of factors, drawing direct inferences regarding the influencing factors for various types of crashes involving vehicles with and without DWSs or ADASs solely based on these statistics is not feasible. The complexity and interplay of multiple variables necessitate a more comprehensive approach.

To gain a deeper understanding of the critical factors influencing the occurrence of fatal crashes for vehicles with varying numbers of DWSs or ADASs, it is essential to employ modeling techniques and conduct further analysis. Incorporating modeling-driven analysis facilitates identifying the intricate relationships between different variables and determining significant factors that impact crash outcomes. Using a modeling approach also enables a more precise exploration of the data, providing insights beyond surface-level descriptive statistics.

The modeling-driven analysis allows for a more rigorous and comprehensive investigation, enabling practitioners to make informed decisions and develop targeted interventions to enhance road safety and mitigate the risks associated with crashes involving vehicles with varying DWSs or ADASs.

**5.2 Goodness of fit indices comparison**

Log-Likelihood and McFadden pseudo R-squares are used to measure the goodness of fit for different models developed in the study. The results of goodness of fit indices are shown in Table 5-6. Table 5-6 shows that the Log-likelihood values for the correlated random parameters model are lower for all the models compared to the log-likelihood of fixed parameters models, indicating that correlated random parameters models are better in all the cases. The McFadden Pseudo R-squared values for all correlated random parameters models are higher compared to fixed parameters models indicating the same.

**Table 5-6. Goodness of fit test results.**

| Goodness of Fit Index | Model Type | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|---|
| **Log likelihood Function** | Fixed Parameters Model | -6138.570 | -4584.504 | -1083.047 | -506.629 |
| | Correlated Random parameters model | -6124.668 | -4572.380 | -1076.154 | -502.602 |
| **Restricted log-likelihood** | | -6631.102 | -4933.469 | -1339.440 | -613.930 |
| **McFadden Pseudo R-squared** | Fixed Parameters Model | 0.074 | 0.071 | 0.191 | 0.175 |
| | Correlated Random parameters model | 0.076 | 0.073 | 0.197 | 0.181 |

The comparison of the goodness of fit indices shows that correlated random parameters models are superior in terms of model fit compared to fixed parameters ordered or binary logit models. In the case of both ordered models (model for DWSs and ADASs), the log-likelihood statistics of fixed and correlated random parameters model is statistically significant, meaning the difference in both the models is significant. However, in the case of both binary models, although the log-likelihood statistics and McFadden R-squared value shows that the correlated random parameters model is better, the difference in log-likelihood statistics is not significant. The results are not significantly improved after incorporating heterogeneity due to varying driver characteristics in the case of both binary logit models.

Further, partial effects are determined for all the models to compare the factors identified using fixed and correlated random parameters models. The partial effects of all the models show that in the case of fixed parameters and correlated random parameters models, the partial effects vary, but the overall effect of factors on fatal crash occurrence (for all categories of dependent variables) is the same. The variables indicating vehicles with one or more DWSs are safe in the case of fixed effects models are also showing the same in the case of correlated random parameters models. Considering the better fit in the correlated random parameters model, the results of same are discussed. The results of fixed parameters logit models and their partial effects are provided in Appendix B.

## 5.3 Modeling Results

### *5.3.1 Analysis for multivehicle crashes involving vehicles with and without DWSs*

The correlated random parameters model to identify the factors affecting multivehicle fatal crashes involving vehicles with and without DWSs is shown in Table 5-7.

**Table 5-7. Correlated random parameters ordered logit Model 1 estimates.**

| Variables | Coefficient | Standard error | *z*-value | *p*-value |
|---|---|---|---|---|
| Constant | -3.898 | 0.175 | -22.320 | 0.000 |
| Year | 0.584 | 0.026 | 22.310 | 0.000 |
| Area type (Urban) | 0.240 | 0.061 | 3.910 | 0.000 |
| Season (Winter) | -0.086 | 0.081 | -1.060 | 0.288 |
| Season (Spring) | -0.050 | 0.075 | -0.660 | 0.509 |
| Season (Fall) | 0.171 | 0.069 | 2.470 | 0.014 |
| Time of the day (12 AM to 3 AM) | -0.140 | 0.164 | -0.860 | 0.392 |
| Time of the day (3 AM to 6 AM) | -0.204 | 0.164 | -1.250 | 0.212 |
| Time of the day (9 AM to 12 PM) | 0.306 | 0.115 | 2.650 | 0.008 |
| Time of the day (12 PM to 3 PM) | 0.227 | 0.110 | 2.070 | 0.039 |
| Time of the day (3 PM to 6 PM) | 0.175 | 0.105 | 1.660 | 0.096 |
| Time of the day (6 PM to 9 PM) | 0.106 | 0.122 | 0.870 | 0.385 |
| Time of the day (9 PM to 12 AM) | -0.047 | 0.147 | -0.320 | 0.748 |
| Manner of collision (Head-on) | 0.215 | 0.077 | 2.790 | 0.005 |
| Manner of collision (Rear-end) | 0.029 | 0.082 | 0.360 | 0.721 |
| Manner of collision (Sideswipe - opposite direction) | 0.114 | 0.132 | 0.860 | 0.388 |
| Manner of collision (Sideswipe - same direction) | 0.247 | 0.153 | 1.610 | 0.107 |
| Speeding | -0.139 | 0.093 | -1.490 | 0.136 |
| Number of lanes (No trafficway access) | 0.318 | 0.274 | 1.160 | 0.245 |
| Number of lanes (one lane) | 0.304 | 0.257 | 1.180 | 0.237 |
| Number of lanes (Three lanes) | 0.025 | 0.083 | 0.300 | 0.766 |
| Number of lanes (Four lanes) | 0.242 | 0.085 | 2.840 | 0.005 |
| Number of lanes (Five lanes) | 0.211 | 0.094 | 2.230 | 0.026 |

| | | | | |
|---|---|---|---|---|
| Number of lanes (Six lanes) | 0.165 | 0.174 | 0.950 | 0.341 |
| Number of lanes (Seven or more lanes) | 0.268 | 0.214 | 1.260 | 0.209 |
| Surface condition (Wet) | -0.048 | 0.136 | -0.350 | 0.725 |
| Surface condition (Ice, snow, mud, dirt, oil or water) | -0.652 | 0.266 | -2.450 | 0.014 |
| Pre-crash stability (Skidding laterally) | -0.157 | 0.215 | -0.730 | 0.466 |
| Pre-crash stability (Skidding longitudinally) | -0.483 | 0.282 | -1.710 | 0.087 |
| Pre-crash stability (Not specific) | -0.263 | 0.073 | -3.600 | 0.000 |
| Functional class (Interstate) | 0.284 | 0.093 | 3.060 | 0.002 |
| Functional class (Freeway or expressway) | 0.376 | 0.127 | 2.970 | 0.003 |
| Functional class (Minor arterial) | -0.096 | 0.069 | -1.380 | 0.167 |
| Functional class (Major collector) | -0.123 | 0.092 | -1.330 | 0.184 |
| Functional class (Minor collector) | 0.173 | 0.177 | 0.980 | 0.328 |
| Functional class (Local) | 0.058 | 0.120 | 0.480 | 0.631 |
| Intersection | -0.138 | 0.071 | -1.940 | 0.053 |
| Work zone | 0.160 | 0.158 | 1.020 | 0.310 |
| Light condition (Dark) | 0.248 | 0.109 | 2.270 | 0.023 |
| Light condition (Dawn) | -0.175 | 0.215 | -0.810 | 0.415 |
| Light condition (Dusk) | 0.182 | 0.195 | 0.930 | 0.350 |
| Weather condition (Cloudy) | -0.041 | 0.079 | -0.520 | 0.603 |
| Weather condition (Rain) | 0.011 | 0.165 | 0.060 | 0.949 |
| Weather condition (Snow, fog/smoke/smog, or other adverse condition) | 0.494 | 0.194 | 2.540 | 0.011 |
| **Means of random parameters** | | | | |
| Drink and drive | -0.429 | 0.101 | -4.250 | 0.000 |
| Gender (Female) | 0.684 | 0.055 | 12.370 | 0.000 |
| Age (Less than 24 years) | -0.296 | 0.084 | -3.520 | 0.000 |
| Age (>40, <=65 years) | -0.347 | 0.068 | -5.100 | 0.000 |
| Age (Greater than 65 years) | 0.196 | 0.078 | 2.500 | 0.013 |
| **Diagonal elements of Cholesky matrix** | | | | |
| Drink and drive | 0.453 | 0.092 | 4.900 | 0.000 |
| Gender (Female) | 0.779 | 0.051 | 15.180 | 0.000 |
| Age (Less than 24 years) | 0.387 | 0.069 | 5.650 | 0.000 |
| Age (>40, <=65 years) | 0.383 | 0.047 | 8.210 | 0.000 |
| Age (Greater than 65 years) | 0.197 | 0.060 | 3.310 | 0.001 |
| **Below diagonal elements of Cholesky matrix** | | | | |
| Gender (Female) - Drink and drive | 0.242 | 0.050 | 4.830 | 0.000 |
| Age (Less than 24 years) - Drink and drive | -0.619 | 0.073 | -8.510 | 0.000 |
| Age (Less than 24 years) - Gender (Female) | -0.484 | 0.071 | -6.830 | 0.000 |
| Age (>40, <=65 years) - Drink and drive | -0.890 | 0.054 | -16.560 | 0.000 |
| Age (>40, <=65 years) - Gender (Female) | 0.194 | 0.050 | 3.910 | 0.000 |
| Age (>40, <=65 years) - Age (Less than 24 years) | -0.385 | 0.047 | -8.250 | 0.000 |

| | | | | |
|---|---|---|---|---|
| Age (Greater than 65 years) - Drink and drive | -0.209 | 0.062 | -3.340 | 0.001 |
| Age (Greater than 65 years) - Gender (Female) | -0.912 | 0.066 | -13.820 | 0.000 |
| Age (Greater than 65 years) - Age (Less than 24 years) | 0.030 | 0.059 | 0.510 | 0.612 |
| Age (Greater than 65 years) - Age (>40, <=65 years) | -0.253 | 0.060 | -4.240 | 0.000 |
| **Threshold parameters for probabilities** | | | | |
| Threshold parameters for probabilities | 1.644 | 0.039 | 42.530 | 0.000 |

The estimates show that most variables are statistically significant at more than 90% confidence level. To ensure the identifiability of the classification thresholds, the threshold delineating vehicles without any DWS and vehicles with one DWS is fixed to zero. The threshold delineating vehicles with one and two DWSs is identified to be 1.644. The coefficients show the loading for a particular variable in the model, which determines the number of DWSs in the vehicles using the established thresholds. A negative coefficient value indicates that the presence of a particular variable is shifting the predictions towards vehicles without any DWS while a positive coefficient indicates the presence of a specific variable is adding to the estimates towards one or more DWSs.

The *p*-value of all the means of random parameters is less than 0.013, indicating that all the random parameters are highly significant. The diagonal elements of the Cholesky matrix and the below diagonal elements of the Cholesky matrix indicate the correlation between various variables and the significance of the correlation. All other possible combinations of random parameters are significantly correlated except for ages greater than 65 years and less than 24 years. It shows that incorporating a correlated parameters model in the present case, which considers the correlation between variables, is better.

The model coefficients are not directly interpretable regarding their contribution to the crash occurrence. Therefore, partial effects were obtained, as shown in Table 5-8.

**Table 5-8. Partial effects of correlated random parameters Model 1.**

| Variables | Y = 0 | | Y=1 | | Y=2 | |
|---|---|---|---|---|---|---|
| | Partial effect | *p*-value | Partial effect | *p*-value | Partial effect | *p*-value |
| Year | -0.099 | 0.000 | 0.071 | 0.000 | 0.028 | 0.000 |
| Area type (Urban) | -0.040 | 0.000 | 0.029 | 0.000 | 0.011 | 0.000 |
| Season (Winter) | 0.014 | 0.281 | -0.010 | 0.282 | -0.004 | 0.277 |
| Season (Spring) | 0.008 | 0.506 | -0.006 | 0.507 | -0.002 | 0.504 |
| Season (Fall) | -0.030 | 0.015 | 0.021 | 0.015 | 0.008 | 0.017 |
| Time of the day (12 AM to 3 AM) | 0.023 | 0.374 | -0.017 | 0.378 | -0.006 | 0.366 |
| Time of the day (3 AM to 6 AM) | 0.033 | 0.188 | -0.024 | 0.192 | -0.009 | 0.176 |
| Time of the day (9 AM to 12 PM) | -0.055 | 0.012 | 0.039 | 0.011 | 0.016 | 0.017 |
| Time of the day (12 PM to 3 PM) | -0.040 | 0.047 | 0.028 | 0.044 | 0.012 | 0.053 |
| Time of the day (3 PM to 6 PM) | -0.030 | 0.106 | 0.022 | 0.103 | 0.009 | 0.112 |
| Time of the day (6 PM to 9 PM) | -0.018 | 0.395 | 0.013 | 0.392 | 0.005 | 0.401 |
| Time of the day (9 PM to 12 AM) | 0.008 | 0.746 | -0.006 | 0.746 | -0.002 | 0.744 |
| Manner of collision (Head-on) | -0.037 | 0.007 | 0.027 | 0.006 | 0.011 | 0.008 |
| Manner of collision (Rear-end) | -0.005 | 0.722 | 0.004 | 0.722 | 0.001 | 0.723 |
| Manner of collision (Sideswipe - opposite direction) | -0.020 | 0.401 | 0.014 | 0.398 | 0.006 | 0.409 |
| Manner of collision (Sideswipe - same direction) | -0.044 | 0.129 | 0.031 | 0.122 | 0.013 | 0.145 |
| Speeding | 0.023 | 0.123 | -0.016 | 0.126 | -0.006 | 0.117 |
| Number of lanes (No trafficway access) | -0.058 | 0.282 | 0.041 | 0.269 | 0.018 | 0.310 |
| Number of lanes (one lane) | -0.056 | 0.272 | 0.039 | 0.260 | 0.017 | 0.299 |
| Number of lanes (Three lanes) | -0.004 | 0.767 | 0.003 | 0.767 | 0.001 | 0.768 |
| Number of lanes (Four lanes) | -0.043 | 0.007 | 0.030 | 0.006 | 0.013 | 0.009 |
| Number of lanes (Five lanes) | -0.037 | 0.033 | 0.026 | 0.031 | 0.011 | 0.039 |
| Number of lanes (Six lanes) | -0.029 | 0.362 | 0.021 | 0.356 | 0.009 | 0.375 |
| Number of lanes (Seven or more lanes) | -0.049 | 0.239 | 0.034 | 0.229 | 0.014 | 0.261 |
| Surface condition (Wet) | 0.008 | 0.722 | -0.006 | 0.723 | -0.002 | 0.721 |
| Surface condition (Ice, snow, mud, dirt, oil or water) | 0.091 | 0.002 | -0.067 | 0.003 | -0.024 | 0.001 |
| Pre-crash stability (Skidding laterally) | 0.025 | 0.446 | -0.018 | 0.450 | -0.007 | 0.435 |
| Pre-crash stability (Skidding longitudinally) | 0.071 | 0.045 | -0.052 | 0.050 | -0.019 | 0.032 |
| Pre-crash stability (Not specific) | 0.043 | 0.000 | -0.031 | 0.000 | -0.012 | 0.000 |
| Functional class (Interstate) | -0.051 | 0.004 | 0.036 | 0.003 | 0.015 | 0.005 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Functional class (Freeway or expressway) | -0.070 | 0.006 | 0.049 | 0.005 | 0.021 | 0.010 |
| Functional class (Minor arterial) | 0.016 | 0.161 | -0.011 | 0.162 | -0.004 | 0.158 |
| Functional class (Major collector) | 0.020 | 0.172 | -0.015 | 0.175 | -0.006 | 0.166 |
| Functional class (Minor collector) | -0.031 | 0.349 | 0.022 | 0.343 | 0.009 | 0.363 |
| Functional class (Local) | -0.010 | 0.635 | 0.007 | 0.634 | 0.003 | 0.638 |
| Intersection | 0.023 | 0.051 | -0.017 | 0.052 | -0.007 | 0.051 |
| Work zone | -0.028 | 0.329 | 0.020 | 0.324 | 0.008 | 0.342 |
| Light condition (Dark) | -0.043 | 0.026 | 0.031 | 0.025 | 0.012 | 0.029 |
| Light condition (Dawn) | 0.028 | 0.391 | -0.020 | 0.396 | -0.008 | 0.379 |
| Light condition (Dusk) | -0.032 | 0.372 | 0.023 | 0.366 | 0.009 | 0.387 |
| Weather condition (Cloudy) | 0.007 | 0.600 | -0.005 | 0.600 | -0.002 | 0.598 |
| Weather condition (Rain) | -0.002 | 0.949 | 0.001 | 0.949 | 0.001 | 0.949 |
| Weather condition (Snow, fog/smoke/smog, or other adverse condition) | -0.094 | 0.022 | 0.065 | 0.017 | 0.029 | 0.037 |
| Drink and drive | 0.066 | 0.000 | -0.048 | 0.000 | -0.018 | 0.000 |
| Gender (Female) | -0.124 | 0.000 | 0.087 | 0.000 | 0.037 | 0.000 |
| Age (Less than 24 years) | 0.047 | 0.000 | -0.034 | 0.000 | -0.013 | 0.000 |
| Age (>40, <=65 years) | 0.057 | 0.000 | -0.041 | 0.000 | -0.016 | 0.000 |
| Age (Greater than 65 years) | -0.034 | 0.016 | 0.024 | 0.015 | 0.010 | 0.019 |

The partial effects shown in Table 5-8, along with the p-value, indicate that the effect of variables on crashes involving vehicles with one or more DWSs compared to vehicles without DWSs is varying. The negative values of partial effects indicate that vehicles without DWSs have less probability of getting involved in a fatal multivehicle crash according to particular variables. The variable year is added to the model to account for the temporal heterogeneity. It shows that the probability of fatal crash occurrence for vehicles without any DWS decreased over the study years. However, for vehicles with one or more DWSs, the probability of fatal crash occurrence increased. Considering that the penetration of vehicles with DWSs increased over the study years in the data, it is apparent that the partial effect for the variable “year of crash” is positive for one or more than one DWSs.

The road geometry and location-related variables such as urban areas, number of lanes (one to seven or more lanes), and functional class (intestate, freeways and expressways, and local) show that vehicles with one or more DWSs have a higher probability of crash occurrence. In contrast, on major collector, major arterial, and minor arterial roads, and at intersections, vehicles with one or more DWSs have a lower probability of crash occurrence than vehicles without DWSs. During night time, in winter and spring seasons, in conditions when a driver is speeding, in wet, ice or snow, or muddy road surface conditions, in conditions when a vehicle is skidding laterally or longitudinally, during dawn light conditions, and in cloudy weather conditions, vehicles with one or more DWSs have a lower probability of crash occurrence. Similarly, in drink and drive-related crashes, vehicles with one or more DWSs are safer than those without DWSs.

The driver characteristics-related variables are highly significant and show that the probability of crash occurrence is higher for females when driving vehicles with one or more DWSs. Similarly, for elderly drivers (age greater than 65 years), the probability of crash occurrence when driving a vehicle with DWSs is higher. In contrast, for teens and younger drivers, the probability of fatal crash occurrence is lower when driving vehicles with DWSs. Potential reasons for the same could be the familiarity of younger drivers with warning systems and their reaction time after receiving alerts from the DWS.

*5.3.2 Analysis for multivehicle crashes involving vehicles with and without ADASs*

The correlated random parameters model to identify the factors affecting multivehicle fatal crashes involving vehicles with one or more ADASs and without ADAS is shown in Table 5-9.

**Table 5-9. Correlated random parameters ordered logit Model 2 estimates.**

| Variables | Coefficient | Standard error | *z*-value | *p*-value |
|---|---|---|---|---|
| Constant | -3.481 | 0.208 | -16.710 | 0.000 |
| Year | 0.543 | 0.031 | 17.350 | 0.000 |
| Area type (Urban) | 0.294 | 0.070 | 4.200 | 0.000 |
| Season (Winter) | 0.046 | 0.095 | 0.490 | 0.627 |
| Season (Spring) | -0.038 | 0.090 | -0.420 | 0.676 |
| Season (Fall) | 0.234 | 0.082 | 2.860 | 0.004 |
| Time of the day (12 AM to 3 AM) | -0.151 | 0.195 | -0.780 | 0.437 |
| Time of the day (3 AM to 6 AM) | -0.183 | 0.194 | -0.940 | 0.345 |
| Time of the day (9 AM to 12 PM) | 0.068 | 0.139 | 0.490 | 0.624 |
| Time of the day (12 PM to 3 PM) | 0.007 | 0.133 | 0.050 | 0.957 |
| Time of the day (3 PM to 6 PM) | -0.004 | 0.128 | -0.030 | 0.977 |
| Time of the day (6 PM to 9 PM) | 0.002 | 0.149 | 0.010 | 0.990 |
| Time of the day (9 PM to 12 AM) | -0.242 | 0.176 | -1.380 | 0.169 |
| Manner of collision (Head-on) | 0.296 | 0.091 | 3.250 | 0.001 |
| Manner of collision (Rear-end) | 0.034 | 0.097 | 0.350 | 0.728 |
| Manner of collision (Sideswipe - opposite direction) | 0.057 | 0.161 | 0.360 | 0.722 |
| Manner of collision (Sideswipe - same direction) | 0.270 | 0.178 | 1.520 | 0.130 |
| Speeding | -0.170 | 0.102 | -1.660 | 0.098 |
| Number of lanes (No trafficway access) | -0.291 | 0.341 | -0.850 | 0.395 |
| Number of lanes (one lane) | 0.709 | 0.277 | 2.560 | 0.010 |
| Number of lanes (Three lanes) | 0.106 | 0.094 | 1.120 | 0.261 |
| Number of lanes (Four lanes) | 0.075 | 0.095 | 0.790 | 0.431 |
| Number of lanes (Six lanes) | 0.043 | 0.189 | 0.230 | 0.820 |
| Number of lanes (Seven or more lanes) | 0.084 | 0.243 | 0.350 | 0.728 |
| Surface condition (Wet) | -0.051 | 0.165 | -0.310 | 0.759 |
| Surface condition (Ice, snow, mud, dirt, oil or water) | -0.705 | 0.337 | -2.090 | 0.036 |
| Pre-crash stability (Skidding laterally) | -0.474 | 0.240 | -1.980 | 0.048 |
| Pre-crash stability (Skidding longitudinally) | -0.437 | 0.338 | -1.290 | 0.196 |
| Pre-crash stability (Not specific) | -0.264 | 0.085 | -3.110 | 0.002 |
| Functional class (Interstate) | 0.165 | 0.108 | 1.520 | 0.127 |
| Functional class (Freeway or expressway) | 0.188 | 0.148 | 1.270 | 0.203 |
| Functional class (Minor arterial) | -0.191 | 0.083 | -2.320 | 0.020 |
| Functional class (Major collector) | -0.270 | 0.108 | -2.510 | 0.012 |
| Functional class (Minor collector) | 0.395 | 0.198 | 2.000 | 0.046 |
| Functional class (Local) | -0.126 | 0.142 | -0.890 | 0.375 |
| Intersection | -0.089 | 0.086 | -1.030 | 0.303 |

| | | | | |
|---|---|---|---|---|
| Work zone | -0.109 | 0.175 | -0.620 | 0.532 |
| Light condition (Dark) | 0.107 | 0.133 | 0.800 | 0.422 |
| Light condition (Dawn) | -0.069 | 0.246 | -0.280 | 0.777 |
| Light condition (Dusk) | -0.115 | 0.226 | -0.510 | 0.611 |
| Weather condition (Cloudy) | -0.236 | 0.096 | -2.470 | 0.014 |
| Weather condition (Rain) | 0.052 | 0.200 | 0.260 | 0.794 |
| Weather condition (Snow, fog/smoke/smog, or other adverse condition) | 0.172 | 0.240 | 0.720 | 0.474 |
| **Means of random parameters** | | | | |
| Drink and drive | -0.580 | 0.117 | -4.950 | 0.000 |
| Gender (Female) | 0.754 | 0.065 | 11.520 | 0.000 |
| Age (Less than 24 years) | -0.610 | 0.120 | -5.100 | 0.000 |
| Age (>40, <=65 years) | -0.285 | 0.076 | -3.760 | 0.000 |
| Age (Greater than 65 years) | 0.060 | 0.094 | 0.630 | 0.527 |
| **Diagonal elements of Cholesky matrix** | | | | |
| Drink and drive | 0.110 | 0.108 | 1.020 | 0.307 |
| Gender (Female) | 0.719 | 0.062 | 11.620 | 0.000 |
| Age (Less than 24 years) | 1.383 | 0.111 | 12.480 | 0.000 |
| Age (>40, <=65 years) | 0.625 | 0.054 | 11.520 | 0.000 |
| Age (Greater than 65 years) | 0.153 | 0.071 | 2.150 | 0.031 |
| **Below diagonal elements of Cholesky matrix** | | | | |
| Gender (Female) - Drink and drive | 0.278 | 0.060 | 4.640 | 0.000 |
| Age (Less than 24 years) - Drink and drive | -0.491 | 0.099 | -4.970 | 0.000 |
| Age (Less than 24 years) - Gender (Female) | 0.586 | 0.096 | 6.120 | 0.000 |
| Age (>40, <=65 years) - Drink and drive | 0.039 | 0.057 | 0.690 | 0.487 |
| Age (>40, <=65 years) - Gender (Female) | 0.216 | 0.058 | 3.750 | 0.000 |
| Age (>40, <=65 years) - Age (Less than 24 years) | -0.129 | 0.052 | -2.490 | 0.013 |
| Age (Greater than 65 years) - Drink and drive | 0.485 | 0.078 | 6.190 | 0.000 |
| Age (Greater than 65 years) - Gender (Female) | -0.370 | 0.076 | -4.900 | 0.000 |
| Age (Greater than 65 years) - Age (Less than 24 years) | 0.884 | 0.079 | 11.240 | 0.000 |
| Age (Greater than 65 years) - Age (>40, <=65 years) | 0.116 | 0.071 | 1.620 | 0.104 |
| **Threshold parameters for probabilities** | | | | |
| Threshold | 0.743 | 0.028 | 26.630 | 0.000 |

The estimates show similar results as shown in Model 1, indicating that the majority of variables possess statistical significance at a level exceeding 90%. To ensure the distinguishability of the thresholds, the fixed threshold between vehicles without one and no ADAS is set to zero.

The threshold separating vehicles with one and two ADASs is identified as 0.743. The coefficients represent the loading of a specific variable in the model, which delineates predictions of the number of ADASs in vehicles based on the established thresholds. A negative coefficient value implies that a particular variable shifts the predictions toward vehicles without any ADAS. In contrast, positive coefficients indicate that the presence of a specific variable contributes to the estimations of one or two ADASs. The constant for the model is -3.481 showing without any additional variable, the model would predict a vehicle without any ADAS, which is a base category of the dependent variable.

In the case of Model 2, the *p*-value for all the means of random parameters except age greater than 65 years is less than 0.001, indicating the high significance of these random parameters. Considering that the other two categories of variable age are highly significant, all three categories were considered random parameters in the model. The diagonal and below-diagonal elements of the Cholesky matrix reflect the correlation between various variables and the significance of that correlation. The diagonal elements of all random parameters are statistically significant except for variable drink and drive, indicating no correlation between random values following normal distribution considered for the variable drink and drive. The below diagonal elements are also statistically significant except for two combinations (age between 40 and 65 years and drink and drive and age greater than 65 years and age 40 to 65 years). Since the majority of the correlations are statistically significant, the exceptions in the correlation matrix are kept while modeling to incorporate the collinearity between random parameters in the model estimates.

Similar to Model 1, the model estimates do not directly show the crash occurrence likelihood. Therefore, partial effects were derived as presented in Table 5-10.

**Table 5-10. Partial effects of correlated random parameters Model 2.**

| Variables | Y = 0 | | Y=1 | | Y=2 | |
|---|---|---|---|---|---|---|
| | Partial effect | *p*-value | Partial effect | *p*-value | Partial effect | *p*-value |
| Year | -0.091 | 0.000 | 0.036 | 0.000 | 0.055 | 0.000 |
| Area type (Urban) | -0.048 | 0.000 | 0.019 | 0.000 | 0.029 | 0.000 |
| Season (Winter) | -0.008 | 0.629 | 0.003 | 0.628 | 0.005 | 0.630 |
| Season (Spring) | 0.006 | 0.674 | -0.002 | 0.675 | -0.004 | 0.673 |
| Season (Fall) | -0.040 | 0.005 | 0.016 | 0.005 | 0.025 | 0.006 |
| Time of the day (12 AM to 3 AM) | 0.024 | 0.419 | -0.010 | 0.427 | -0.014 | 0.414 |
| Time of the day (3 AM to 6 AM) | 0.029 | 0.321 | -0.012 | 0.332 | -0.017 | 0.314 |
| Time of the day (9 AM to 12 PM) | -0.012 | 0.628 | 0.005 | 0.626 | 0.007 | 0.630 |
| Time of the day (12 PM to 3 PM) | -0.001 | 0.957 | 0.000 | 0.957 | 0.001 | 0.957 |
| Time of the day (3 PM to 6 PM) | 0.001 | 0.977 | 0.000 | 0.977 | 0.000 | 0.977 |
| Time of the day (6 PM to 9 PM) | 0.000 | 0.990 | 0.000 | 0.990 | 0.000 | 0.990 |
| Time of the day (9 PM to 12 AM) | 0.038 | 0.146 | -0.016 | 0.155 | -0.023 | 0.139 |
| Manner of collision (Head-on) | -0.051 | 0.002 | 0.020 | 0.001 | 0.031 | 0.002 |
| Manner of collision (Rear-end) | -0.006 | 0.729 | 0.002 | 0.729 | 0.003 | 0.730 |
| Manner of collision (Sideswipe - opposite direction) | -0.010 | 0.726 | 0.004 | 0.724 | 0.006 | 0.727 |
| Manner of collision (Sideswipe - same direction) | -0.048 | 0.155 | 0.018 | 0.137 | 0.030 | 0.167 |
| Speeding | 0.027 | 0.085 | -0.011 | 0.090 | -0.016 | 0.082 |
| Number of lanes (No trafficway access) | 0.045 | 0.351 | -0.018 | 0.368 | -0.026 | 0.339 |
| Number of lanes (one lane) | -0.141 | 0.025 | 0.049 | 0.007 | 0.093 | 0.040 |
| Number of lanes (Three lanes) | -0.018 | 0.271 | 0.007 | 0.265 | 0.011 | 0.275 |
| Number of lanes (Four lanes) | -0.013 | 0.438 | 0.005 | 0.434 | 0.008 | 0.441 |
| Number of lanes (Six lanes) | -0.007 | 0.822 | 0.003 | 0.821 | 0.004 | 0.823 |
| Number of lanes (Seven or more lanes) | -0.014 | 0.734 | 0.006 | 0.730 | 0.009 | 0.736 |
| Surface condition (Wet) | 0.008 | 0.756 | -0.003 | 0.757 | -0.005 | 0.755 |
| Surface condition (Ice, snow, mud, dirt, oil or water) | 0.096 | 0.007 | -0.041 | 0.012 | -0.055 | 0.005 |
| Pre-crash stability (Skidding laterally) | 0.069 | 0.021 | -0.029 | 0.028 | -0.040 | 0.016 |
| Pre-crash stability (Skidding longitudinally) | 0.064 | 0.136 | -0.027 | 0.155 | -0.037 | 0.122 |
| Pre-crash stability (Not specific) | 0.042 | 0.001 | -0.017 | 0.001 | -0.025 | 0.001 |
| Functional class (Interstate) | -0.028 | 0.140 | 0.011 | 0.132 | 0.017 | 0.145 |
| Functional class (Freeway or expressway) | -0.033 | 0.224 | 0.013 | 0.211 | 0.020 | 0.232 |
| Functional class (Minor arterial) | 0.031 | 0.017 | -0.013 | 0.018 | -0.019 | 0.016 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Functional class (Major collector) | 0.043 | 0.007 | -0.017 | 0.009 | -0.025 | 0.006 |
| Functional class (Minor collector) | -0.073 | 0.068 | 0.027 | 0.049 | 0.046 | 0.080 |
| Functional class (Local) | 0.020 | 0.359 | -0.008 | 0.366 | -0.012 | 0.354 |
| Intersection | 0.015 | 0.300 | -0.006 | 0.301 | -0.009 | 0.299 |
| Work zone | 0.018 | 0.519 | -0.007 | 0.525 | -0.011 | 0.515 |
| Light condition (Dark) | -0.018 | 0.426 | 0.007 | 0.424 | 0.011 | 0.428 |
| Light condition (Dawn) | 0.011 | 0.773 | -0.005 | 0.775 | -0.007 | 0.772 |
| Light condition (Dusk) | 0.019 | 0.599 | -0.008 | 0.604 | -0.011 | 0.595 |
| Weather condition (Cloudy) | 0.038 | 0.010 | -0.015 | 0.011 | -0.022 | 0.009 |
| Weather condition (Rain) | -0.009 | 0.797 | 0.003 | 0.795 | 0.005 | 0.798 |
| Weather condition (Snow, fog/smoke/smog, or other adverse condition) | -0.030 | 0.492 | 0.012 | 0.481 | 0.018 | 0.500 |
| Drink and drive | 0.085 | 0.000 | -0.036 | 0.000 | -0.049 | 0.000 |
| Gender (Female) | -0.136 | 0.000 | 0.051 | 0.000 | 0.085 | 0.000 |
| Age (Less than 24 years) | 0.089 | 0.000 | -0.037 | 0.000 | -0.052 | 0.000 |
| Age (>40, <=65 years) | 0.047 | 0.000 | -0.019 | 0.000 | -0.028 | 0.000 |
| Age (Greater than 65 years) | -0.010 | 0.532 | 0.004 | 0.529 | 0.006 | 0.534 |

The partial effects and their p-values, as shown in Table 5-10, indicate that the effect of variables on crashes involving vehicles with one and two ADASs compared to vehicles without DWSs is different for all the variables. The interpretation of partial effects is similar to the interpretations described in section 5.3.1.

The penetration of vehicles with ADASs is increasing over the study years (2016 – 2020). Hence, a variable year is added while modeling to determine the effect of features on fatal crashes over the years. The results show that over the study years, the likelihood of crash occurrence for vehicles with one and two ADASs has increased. The increment is higher in the case of vehicles with two ADASs compared to vehicles with one ADAS. The results emphasize the trends shown in Figure 4-4, which indicates that penetration of vehicles with one or more ADASs increased over the study years, resulting in a higher number of crashes involving vehicles with one or more ADASs.

The results show that in urban areas, the probability of a crash involving a vehicle with one or two ADASs is higher than vehicles without any ADAS, possibly due to the higher penetration of vehicles with ADASs in urban areas. The road geometry-related variables, such as the number of lanes (one to seven or more lanes) and functional class (intestate, freeways and expressways, and minor collector), show that the probability of fatal crash occurrence is higher for vehicles with one or more ADASs. For all the variables, the probability is higher for vehicles with two ADASs than vehicles with one ADAS. In contrast, on major arterial, minor arterial roads, and local roads, at intersections, and at work zones, vehicles with one or more ADASs have a lower probability of crash occurrence than vehicles without ADAS. Notably, the results of work zone-related crashes vary in Model 1 and Model 2, showing that vehicles with ADASs are safer at work zones, whereas vehicles with DWSs are not safer at work zones.

Vehicles with one as well as two ADASs have a lower likelihood of getting involved in fatal crashes during the spring season, night, afternoon, and evening time, in conditions when the driver is speeding, in drink and drive related crashes, in wet, ice or snow, or muddy road surface conditions, in conditions when the vehicle is skidding laterally or longitudinally, in dawn or dusk light conditions, and in cloudy weather conditions. In contrast, during adverse weather conditions, or dark lighting conditions, the likelihood of fatal crash occurrence is higher for vehicles with one or more ADASs, which is possibly due to poor detection capabilities of smart features during these conditions as identified in the existing literature.

The driver characteristics are significant and show that the probability of crash occurrence is higher for females when driving vehicles with one or more ADASs. Similarly, the probability of crash occurrence when driving a vehicle with ADASs is higher for older drivers (age greater than 65 years). In contrast, the probability of fatal crash occurrence is lower when driving a vehicle with ADASs for teens and younger drivers. The driver characteristics related variables showed similar results in Model 1 and Model 2, indicating that familiarity of drivers with technology highly affects their probability of crash occurrence when driving vehicles with DWSs or ADASs.

*5.3.3 Analysis for single-vehicle and lane departure-related crashes involving vehicles with and without LDW*

The correlated random parameters model to identify the factors affecting single-vehicle and lane departure related fatal crashes involving vehicles with and without LDW is shown in Table 5-11.

**Table 5-11. Correlated random parameters ordered logit Model 3 estimates.**

| Variables | Coefficient | Standard error | *z*-value | *p*-value |
|---|---|---|---|---|
| Constant | -3.665 | 0.280 | -13.100 | 0.000 |
| Year | 0.709 | 0.045 | 15.690 | 0.000 |
| Area type (Urban) | 0.321 | 0.090 | 3.560 | 0.000 |
| Season (Winter) | -0.050 | 0.131 | -0.380 | 0.703 |
| Season (Spring) | -0.015 | 0.121 | -0.120 | 0.902 |
| Season (Fall) | 0.135 | 0.113 | 1.200 | 0.231 |
| Time of the day (12 AM to 3 AM) | -0.242 | 0.230 | -1.050 | 0.292 |
| Time of the day (3 AM to 6 AM) | -0.276 | 0.228 | -1.210 | 0.227 |
| Time of the day (9 AM to 12 PM) | -0.070 | 0.201 | -0.350 | 0.727 |
| Time of the day (12 PM to 3 PM) | -0.364 | 0.186 | -1.960 | 0.050 |
| Time of the day (3 PM to 6 PM) | -0.363 | 0.177 | -2.050 | 0.041 |
| Time of the day (6 PM to 9 PM) | -0.607 | 0.193 | -3.140 | 0.002 |
| Time of the day (9 PM to 12 AM) | -0.424 | 0.227 | -1.870 | 0.062 |
| Manner of collision (Head-on) | 0.530 | 0.149 | 3.550 | 0.000 |
| Manner of collision (Rear-end) | 0.648 | 0.232 | 2.800 | 0.005 |
| Manner of collision (Sideswipe - opposite direction) | 0.325 | 0.262 | 1.240 | 0.216 |
| Manner of collision (Sideswipe - same direction) | 0.331 | 0.315 | 1.050 | 0.293 |
| Speeding | 0.095 | 0.098 | 0.970 | 0.331 |
| Number of lanes (No trafficway access) | 0.205 | 0.517 | 0.400 | 0.692 |
| Number of lanes (one lane) | -0.344 | 0.345 | -1.000 | 0.319 |
| Number of lanes (Three lanes) | -0.005 | 0.141 | -0.040 | 0.971 |

| | | | | |
|---|---|---|---|---|
| Number of lanes (Four lanes) | -0.026 | 0.166 | -0.150 | 0.877 |
| Number of lanes (Six lanes) | 0.402 | 0.327 | 1.230 | 0.219 |
| Number of lanes (Seven or more lanes) | 0.131 | 0.642 | 0.200 | 0.838 |
| Surface condition (Wet) | 0.129 | 0.204 | 0.630 | 0.528 |
| Surface condition (Ice, snow, mud, dirt, oil or water) | -0.316 | 0.339 | -0.930 | 0.351 |
| Pre-crash stability (Skidding Longitudinally) | -0.309 | 0.309 | -1.000 | 0.318 |
| Pre-crash stability (Not specific) | 0.047 | 0.127 | 0.370 | 0.714 |
| Functional class (Interstate) | 0.079 | 0.139 | 0.570 | 0.568 |
| Functional class (Freeway or expressway) | 0.064 | 0.183 | 0.350 | 0.728 |
| Functional class (Minor arterial) | -0.018 | 0.127 | -0.140 | 0.888 |
| Functional class (Major collector) | -0.188 | 0.141 | -1.330 | 0.182 |
| Functional class (Minor collector) | -0.193 | 0.229 | -0.850 | 0.398 |
| Functional class (Local) | 0.105 | 0.156 | 0.670 | 0.501 |
| Work zone | -0.250 | 0.292 | -0.860 | 0.391 |
| Light condition (Dark) | 0.254 | 0.181 | 1.400 | 0.162 |
| Light condition (Dawn) | 0.033 | 0.348 | 0.090 | 0.925 |
| Light condition (Dusk) | 0.126 | 0.284 | 0.440 | 0.658 |
| Weather condition (Cloudy) | -0.289 | 0.129 | -2.230 | 0.026 |
| Weather condition (Rain) | -0.322 | 0.246 | -1.310 | 0.191 |
| Weather condition (Snow, fog/smoke/smog, or other adverse condition) | -0.023 | 0.317 | -0.070 | 0.942 |
| **Means of random parameters** | | | | |
| Gender (Female) | 0.399 | 0.096 | 4.150 | 0.000 |
| Age (Less than 24 years) | -0.208 | 0.120 | -1.730 | 0.085 |
| Age (>40, <=65 years) | -0.200 | 0.108 | -1.850 | 0.065 |
| Age (Greater than 65 years) | 0.601 | 0.140 | 4.300 | 0.000 |
| Drink and drive | -0.152 | 0.109 | -1.400 | 0.163 |
| **Diagonal elements of Cholesky matrix** | | | | |
| Gender (Female) | 0.881 | 0.139 | 6.340 | 0.000 |
| Age (Less than 24 years) | 0.061 | 0.136 | 0.450 | 0.655 |
| Age (>40, <=65 years) | 0.150 | 0.114 | 1.310 | 0.190 |
| Age (Greater than 65 years) | 0.635 | 0.164 | 3.860 | 0.000 |
| Drink and drive | 0.177 | 0.116 | 1.530 | 0.127 |
| **Below diagonal elements of Cholesky matrix** | | | | |
| Gender (Female) - Age (Less than 24 years) | 1.242 | 0.159 | 7.800 | 0.000 |
| Gender (Female) - Age (>40, <=65 years) | -0.986 | 0.136 | -7.250 | 0.000 |
| Age (Less than 24 years) - Age (>40, <=65 years) | 0.256 | 0.114 | 2.250 | 0.025 |
| Gender (Female) - Age (Greater than 65 years) | 0.509 | 0.164 | 3.100 | 0.002 |
| Age (Less than 24 years) - Age (Greater than 65 years) | 0.898 | 0.172 | 5.210 | 0.000 |

| | | | | |
|---|---|---|---|---|
| Age (>40, <=65 years) - Age (Greater than 65 years) | 0.482 | 0.166 | 2.900 | 0.004 |
| Gender (Female) - Drink and drive | -0.382 | 0.132 | -2.900 | 0.004 |
| Age (Less than 24 years) - Drink and drive | 0.149 | 0.125 | 1.190 | 0.234 |
| Age (>40, <=65 years) - Drink and drive | 0.765 | 0.129 | 5.910 | 0.000 |
| Age (Greater than 65 years) - Drink and drive | -0.018 | 0.116 | -0.150 | 0.880 |

The estimates in the group random parameters binary logit model developed to determine factors affecting fatal crashes involving vehicles with and without LDW show that most of the variables are statistically significant at more than a 90% confidence level. Negative estimates contribute to the prediction of vehicles without LDW, and positive estimates for any variable contribute to the prediction of a vehicle with LDW.

The results of Model 3 show that the probability of crash occurrence for vehicles with LDW has increased over the study years, and the variation is statistically significant at a 99% confidence level. Similar to Model 2, the means of random parameters are statistically significant for all the random parameters except drink and drive. Further, the correlation results show that the diagonal element of the Cholesky matrix for ages less than 24 years, ages between 40 to 65 years, and drinking and driving are not significant at a 90% confidence level. There is no correlation across the observations for particular variables. However, all below the diagonal elements of the Cholesky matrix representing the correlation between various random parameters are statistically significant at a 95% confidence level except for the correlation between age less than 24 years and drink and drive and age greater than 65 years and drink and drive. Similar to Model 2, considering the significance of the majority of the correlations and means of random parameters, all the random parameters are included in the model.

In the case of Model 3, the estimates represent the contribution of various variables in the model prediction of vehicles with and without LDW and not the effect of individual factors on the probability of crash occurrence. Therefore, partial effects for both models with binary dependent variables are estimated. The partial effects for Model 3, along with p and z statistics and standard error of the estimates, are shown in Table 5-12.

**Table 5-12. Partial effects of correlated random parameters Model 3.**

| **Variables** | **Partial effect** | **Standard error** | ***z*-value** | ***p*-value** |
|---|---|---|---|---|
| Year | 0.132 | 1.854 | 15.350 | 0.000 |
| Area type (Urban) | 0.060 | 0.119 | 3.550 | 0.000 |
| Season (Winter) | -0.009 | -0.008 | -0.380 | 0.703 |
| Season (Spring) | -0.003 | -0.002 | -0.120 | 0.902 |
| Season (Fall) | 0.025 | 0.030 | 1.200 | 0.231 |
| Time of the day (12 AM to 3 AM) | -0.045 | -0.024 | -1.050 | 0.293 |
| Time of the day (3 AM to 6 AM) | -0.051 | -0.019 | -1.210 | 0.228 |
| Time of the day (9 AM to 12 PM) | -0.013 | -0.005 | -0.350 | 0.727 |
| Time of the day (12 PM to 3 PM) | -0.068 | -0.039 | -1.960 | 0.050 |
| Time of the day (3 PM to 6 PM) | -0.068 | -0.044 | -2.040 | 0.041 |
| Time of the day (6 PM to 9 PM) | -0.113 | -0.067 | -3.130 | 0.002 |
| Time of the day (9 PM to 12 AM) | -0.079 | -0.041 | -1.860 | 0.063 |
| Manner of collision (Head-on) | 0.099 | 0.067 | 3.560 | 0.000 |
| Manner of collision (Rear-end) | 0.121 | 0.017 | 2.790 | 0.005 |
| Manner of collision (Sideswipe - opposite direction) | 0.061 | 0.006 | 1.240 | 0.216 |
| Manner of collision (Sideswipe - same direction) | 0.062 | 0.005 | 1.050 | 0.293 |
| Speeding | 0.018 | 0.022 | 0.970 | 0.330 |
| Number of lanes (No trafficway access) | 0.038 | 0.002 | 0.400 | 0.692 |
| Number of lanes (one lane) | -0.064 | -0.005 | -1.000 | 0.319 |
| Number of lanes (Three lanes) | -0.001 | 0.000 | -0.040 | 0.971 |
| Number of lanes (Four lanes) | -0.005 | -0.001 | -0.150 | 0.877 |
| Number of lanes (Six lanes) | 0.075 | 0.004 | 1.230 | 0.219 |
| Number of lanes (Seven or more lanes) | 0.024 | 0.001 | 0.200 | 0.838 |
| Surface condition (Wet) | 0.024 | 0.012 | 0.630 | 0.528 |
| Surface condition (Ice, snow, mud, dirt, oil or water) | -0.059 | -0.008 | -0.930 | 0.351 |
| Pre-crash stability (Skidding Longitudinally) | -0.058 | -0.008 | -1.000 | 0.318 |
| Pre-crash stability (Not specific) | 0.009 | 0.012 | 0.370 | 0.714 |

| | | | | |
|---|---|---|---|---|
| Functional class (Interstate) | 0.015 | 0.010 | 0.570 | 0.568 |
| Functional class (Freeway or expressway) | 0.012 | 0.003 | 0.350 | 0.728 |
| Functional class (Minor arterial) | -0.003 | -0.003 | -0.140 | 0.888 |
| Functional class (Major collector) | -0.035 | -0.023 | -1.330 | 0.183 |
| Functional class (Minor collector) | -0.036 | -0.007 | -0.840 | 0.399 |
| Functional class (Local) | 0.020 | 0.010 | 0.670 | 0.501 |
| Work zone | -0.047 | -0.005 | -0.860 | 0.391 |
| Light condition (Dark) | 0.047 | 0.089 | 1.400 | 0.161 |
| Light condition (Dawn) | 0.006 | 0.000 | 0.090 | 0.925 |
| Light condition (Dusk) | 0.023 | 0.002 | 0.440 | 0.658 |
| Weather condition (Cloudy) | -0.054 | -0.035 | -2.230 | 0.026 |
| Weather condition (Rain) | -0.060 | -0.019 | -1.310 | 0.190 |
| Weather condition (Snow, fog/smoke/smog, or other adverse condition) | -0.004 | 0.000 | -0.070 | 0.942 |
| Gender (Female) | 0.074 | 0.078 | 4.130 | 0.000 |
| Age (Less than 24 years) | -0.039 | -0.032 | -1.730 | 0.084 |
| Age (>40, <=65 years) | -0.037 | -0.048 | -1.850 | 0.065 |
| Age (Greater than 65 years) | 0.112 | 0.058 | 4.270 | 0.000 |
| Drink and drive | -0.028 | -0.033 | -1.430 | 0.153 |

The partial effects for the variable year show that the probability of crash occurrence for vehicles with LDW increased with the increase in time (from 2016 to 2020). The reason for the same is the increasing number of vehicles in the sample over the study years, as shown in Figure 4-5.

In the case of both the models with binary variables, the positive value of partial effect indicates a higher likelihood of fatal crash occurrence for vehicles with particular DWS or ADAS. In Model 3, the positive coefficient shows a higher probability of crash occurrence for vehicles with DWS. For example, the partial effect of 0.06 for urban areas shows that vehicles with LDW are 6% more likely to get involved in a fatal single-vehicle or lane departure-related crash than vehicles without LDW. Similarly, during the fall season, vehicles with LDW have a 2.5% higher probability of fatal crash occurrence than vehicles without LDW. In contrast, the likelihood of crash occurrence for vehicles with LDW is 0.95 and 0.3% less in winter and spring compared to vehicles without LDW.

Unlike the results of Model 1 and Model 2, the results of Model 3 show that for single-vehicle or lane departure crashes, vehicles with LDW are safer during daytime and nighttime compared to vehicles without LDW. Similarly, the likelihood of fatal crash occurrence for vehicles with LDW is higher when the driver is speeding, which is contradictory compared to vehicles with BSM, FCWS, LKA, or ACC.

The probability of crash occurrence for vehicles with LDW is higher than those without LDW on roads with six or more lanes, during wet surface conditions, on interstates, freeways and expressways, and local roads, and during dark, dawn, or dusk light conditions. In contrast, the likelihood of single-vehicle or lane departure related fatal crash occurrence is lower for a vehicle with LDW compared to vehicles without LDW on roads with one to four lanes, during icy, snowy, or muddy road surface conditions, in conditions when the vehicle is skidding longitudinally, on minor arterial, major collector, and minor collector roads, at work zones, and during cloudy, rainy, or other adverse conditions. This means that vehicles with LDW are safer in the most adverse weather or road surface conditions.

The driver characteristics are significant and show that females and drivers with ages greater than 65 years are more likely to get involved in a fatal crash when driving a vehicle with LDW compared to vehicles without LDW. In contrast, the likelihood of fatal crash occurrence is lower for drivers with age less than 65 years when driving a vehicle with LDW. In drink and drive relate crashes, the likelihood of fatal crash occurrence is lower when driving a vehicle with LDW. It is noteworthy that for elderly drivers, the likelihood of fatal crash occurrence is 11% higher when driving a vehicle with LDW than those without LDW.

*5.3.4. Analysis for pedestrian crashes involving vehicles with and without PAEB*

The correlated random parameters model to identify the factors affecting fatal pedestrian crashes involving vehicles with and without PAEB system is shown in Table 5-13.

**Table 5-13. Correlated random parameters ordered logit Model 4 estimates.**

| **Variables** | **Coefficient** | **Standard error** | ***z*-value** | ***p*-value** |
|---|---|---|---|---|
| Constant | -3.987 | 0.517 | -7.710 | 0.000 |
| Year | 0.683 | 0.066 | 10.270 | 0.000 |
| Area type (Urban) | 0.332 | 0.214 | 1.550 | 0.120 |
| Season (Winter) | 0.043 | 0.200 | 0.220 | 0.829 |
| Season (Spring) | -0.106 | 0.211 | -0.500 | 0.614 |
| Season (Fall) | 0.752 | 0.183 | 4.100 | 0.000 |
| Time of the day (12 AM to 3 AM) | 0.332 | 0.386 | 0.860 | 0.390 |
| Time of the day (3 AM to 6 AM) | 0.735 | 0.353 | 2.080 | 0.037 |
| Time of the day (9 AM to 12 PM) | 0.079 | 0.437 | 0.180 | 0.857 |
| Time of the day (12 PM to 3 PM) | 0.235 | 0.424 | 0.560 | 0.579 |
| Time of the day (3 PM to 6 PM) | 0.087 | 0.354 | 0.250 | 0.805 |
| Time of the day (6 PM to 9 PM) | 0.557 | 0.323 | 1.730 | 0.084 |
| Time of the day (9 PM to 12 AM) | 0.422 | 0.339 | 1.240 | 0.214 |
| Speeding | 0.261 | 0.234 | 1.120 | 0.264 |
| Number of lanes (No trafficway access) | 2.555 | 1.372 | 1.860 | 0.063 |
| Number of lanes (one lane) | 0.146 | 0.541 | 0.270 | 0.788 |
| Number of lanes (Three lanes) | 0.032 | 0.175 | 0.180 | 0.854 |
| Number of lanes (Four lanes) | 0.026 | 0.181 | 0.150 | 0.885 |
| Number of lanes (Six lanes) | -0.325 | 0.328 | -0.990 | 0.323 |
| Number of lanes (Seven or more lanes) | 0.196 | 0.352 | 0.560 | 0.577 |
| Surface condition (Wet) | 0.023 | 0.309 | 0.070 | 0.941 |
| Pre-crash stability (Skidding laterally) | -0.443 | 0.287 | -1.540 | 0.123 |
| Pre-crash stability (Skidding longitudinally) | 0.047 | 0.241 | 0.200 | 0.845 |
| Functional class (Interstate) | -0.035 | 0.200 | -0.170 | 0.862 |
| Functional class (Freeway or expressway) | 0.085 | 0.307 | 0.280 | 0.782 |
| Functional class (Minor arterial) | -0.262 | 0.178 | -1.470 | 0.141 |
| Functional class (Major collector) | 0.088 | 0.278 | 0.320 | 0.751 |
| Functional class (Minor collector) | 0.388 | 0.563 | 0.690 | 0.491 |
| Functional class (Local) | -0.167 | 0.250 | -0.670 | 0.505 |

| | | | | |
|---|---|---|---|---|
| Work zone | -0.741 | 0.542 | -1.370 | 0.172 |
| Light condition (Dark) | -0.325 | 0.302 | -1.080 | 0.282 |
| Light condition (Dawn) | 1.137 | 0.521 | 2.180 | 0.029 |
| Light condition (Dusk) | -1.370 | 0.704 | -1.950 | 0.052 |
| Weather condition (Cloudy) | -0.178 | 0.203 | -0.880 | 0.382 |
| Weather condition (Rain) | 0.199 | 0.417 | 0.480 | 0.633 |
| Weather condition (Snow, fog/smoke/smog, or other adverse condition) | -0.038 | 0.655 | -0.060 | 0.954 |
| Intersection | 0.065 | 0.158 | 0.410 | 0.679 |
| **Means of random parameters** | | | | |
| Gender (Female) | 0.014 | 0.153 | 0.090 | 0.928 |
| Age (Less than 24 years) | -0.085 | 0.199 | -0.430 | 0.669 |
| Age (>40, <=65 years) | -0.405 | 0.165 | -2.450 | 0.014 |
| Age (Greater than 65 years) | 0.388 | 0.209 | 1.850 | 0.064 |
| Drink and drive | 0.022 | 0.333 | 0.060 | 0.948 |
| **Diagonal elements of Cholesky matrix** | | | | |
| Gender (Female) | 1.874 | 0.234 | 8.000 | 0.000 |
| Age (Less than 24 years) | 1.170 | 0.254 | 4.620 | 0.000 |
| Age (>40, <=65 years) | 0.971 | 0.177 | 5.470 | 0.000 |
| Age (Greater than 65 years) | 0.752 | 0.249 | 3.020 | 0.003 |
| Drink and drive | 0.137 | 0.415 | 0.330 | 0.741 |
| **Below diagonal elements of Cholesky matrix** | | | | |
| Gender (Female) - Age (Less than 24 years) | -0.171 | 0.234 | -0.730 | 0.463 |
| Gender (Female) - Age (>40, <=65 years) | 0.564 | 0.176 | 3.210 | 0.001 |
| Age (Less than 24 years) - Age (>40, <=65 years) | -1.271 | 0.188 | -6.760 | 0.000 |
| Gender (Female) - Age (Greater than 65 years) | -0.127 | 0.252 | -0.500 | 0.614 |
| Age (Less than 24 years) - Age (Greater than 65 years) | 0.129 | 0.240 | 0.540 | 0.590 |
| Age (>40, <=65 years) - Age (Greater than 65 years) | -0.273 | 0.238 | -1.150 | 0.250 |
| Gender (Female) - Drink and drive | 1.323 | 0.475 | 2.790 | 0.005 |
| Age (Less than 24 years) - Drink and drive | -0.151 | 0.463 | -0.330 | 0.745 |
| Age (>40, <=65 years) - Drink and drive | 0.305 | 0.429 | 0.710 | 0.477 |
| Age (Greater than 65 years) - Drink and drive | -0.307 | 0.420 | -0.730 | 0.465 |

The grouped random parameters binary logit model developed to determine factors affecting fatal pedestrian crashes involving vehicles with and without LDW shows that the majority of the variables are statistically significant at more than a 90% confidence level. The interpretation of model coefficients is similar to Model 3.

The results of the model for pedestrian crashes show that the probability of crash occurrence for vehicles with PAEB has increased over the study years, and the variation is statistically significant at a 99% confidence level. Unlike Model 2, the means of random parameters are statistically significant only for drivers aged 40 to 65 years and greater than 65 years. For all other random parameters, the means are not statistically significant. Further, the correlation results show that the diagonal element of the Cholesky matrix for all variables except drink and drive are statistically significant at a 99% confidence level. In the case of correlation between various random parameters, as shown in the results for below diagonal elements of the Cholesky matrix, the correlation between female and age less than 24 years, female and age greater than 65 years, age less than 24 years, and age greater than 65 years, age from 40 to 65 years and age greater than 65 years, age all categories of variable age with drink and drive is not significant. The correlation between these variables is not significant, and hence correlated random parameters model does not improve the results significantly by incorporating these correlations in the model estimation procedure.

The partial effects for Model 4 are estimated to determine the factors affecting fatal crashes involving pedestrians and vehicles with and without PAEB and to compare the results. The partial effects for Model 4, along with p and z statistics and standard error of the estimates, are shown in Table 5-14.

**Table 5-14. Partial effects of correlated random parameters Model 4.**

| **Variables** | **Partial effect** | **Standard error** | ***z*-value** | ***p*-value** |
|---|---|---|---|---|
| Year | 0.122 | 1.780 | 10.200 | 0.000 |
| Area type (Urban) | 0.059 | 0.218 | 1.550 | 0.120 |
| Season (Winter) | 0.008 | 0.009 | 0.220 | 0.829 |
| Season (Spring) | -0.019 | -0.016 | -0.500 | 0.614 |

| | | | | |
|---|---|---|---|---|
| Season (Fall) | 0.135 | 0.176 | 4.110 | 0.000 |
| Time of the day (12 AM to 3 AM) | 0.059 | 0.023 | 0.860 | 0.389 |
| Time of the day (3 AM to 6 AM) | 0.132 | 0.061 | 2.080 | 0.037 |
| Time of the day (9 AM to 12 PM) | 0.014 | 0.003 | 0.180 | 0.857 |
| Time of the day (12 PM to 3 PM) | 0.042 | 0.011 | 0.560 | 0.579 |
| Time of the day (3 PM to 6 PM) | 0.016 | 0.007 | 0.250 | 0.805 |
| Time of the day (6 PM to 9 PM) | 0.100 | 0.113 | 1.730 | 0.084 |
| Time of the day (9 PM to 12 AM) | 0.075 | 0.075 | 1.250 | 0.213 |
| Speeding | 0.047 | 0.015 | 1.120 | 0.264 |
| Number of lanes (No trafficway access) | 0.457 | 0.006 | 1.860 | 0.063 |
| Number of lanes (one lane) | 0.026 | 0.002 | 0.270 | 0.788 |
| Number of lanes (Three lanes) | 0.006 | 0.005 | 0.180 | 0.854 |
| Number of lanes (Four lanes) | 0.005 | 0.003 | 0.150 | 0.885 |
| Number of lanes (Six lanes) | -0.058 | -0.010 | -0.990 | 0.323 |
| Number of lanes (Seven or more lanes) | 0.035 | 0.004 | 0.560 | 0.577 |
| Surface condition (Wet) | 0.004 | 0.002 | 0.070 | 0.941 |
| Pre-crash stability (Skidding laterally) | -0.079 | -0.025 | -1.540 | 0.124 |
| Pre-crash stability (Skidding longitudinally) | 0.008 | 0.003 | 0.200 | 0.845 |
| Functional class (Interstate) | -0.006 | -0.004 | -0.170 | 0.862 |
| Functional class (Freeway or expressway) | 0.015 | 0.003 | 0.280 | 0.782 |
| Functional class (Minor arterial) | -0.047 | -0.044 | -1.470 | 0.141 |
| Functional class (Major collector) | 0.016 | 0.005 | 0.320 | 0.751 |
| Functional class (Minor collector) | 0.069 | 0.005 | 0.690 | 0.491 |
| Functional class (Local) | -0.030 | -0.013 | -0.670 | 0.505 |
| Work zone | -0.133 | -0.010 | -1.360 | 0.174 |
| Light condition (Dark) | -0.058 | -0.187 | -1.080 | 0.282 |
| Light condition (Dawn) | 0.203 | 0.019 | 2.180 | 0.029 |
| Light condition (Dusk) | -0.245 | -0.015 | -1.940 | 0.052 |
| Weather condition (Cloudy) | -0.032 | -0.022 | -0.870 | 0.382 |
| Weather condition (Rain) | 0.036 | 0.010 | 0.480 | 0.633 |
| Weather condition (Snow, fog/smoke/smog, or other adverse condition) | -0.007 | 0.000 | -0.060 | 0.954 |
| Intersection | 0.012 | 0.014 | 0.410 | 0.679 |
| Gender (Female) | 0.002 | 0.003 | 0.090 | 0.928 |
| Age (Less than 24 years) | -0.015 | -0.011 | -0.430 | 0.669 |
| Age (>40, <=65 years) | -0.072 | -0.112 | -2.450 | 0.015 |
| Age (Greater than 65 years) | 0.069 | 0.037 | 1.850 | 0.064 |
| Drink and drive | 0.004 | 0.001 | 0.060 | 0.948 |

The partial effects for the variable year show that the probability of crash occurrence for vehicles with PAEB increased over the study years (from 2016 to 2020). The reason for the same is the increasing number of vehicles in the sample over the study years, as shown in Figure 4-4. The increment in the probability of crash occurrence over the study years is lowest in Model 4 compared to all other models, which is due to the lower penetration of PAEB over the study years compared to other DWSs or ADASs.

The positive value of partial effects in Model 4 shows a higher probability of crash occurrence for vehicles with PAEB. In urban areas, the likelihood of getting involved in pedestrian crashes is 5.95% higher for vehicles with PAEB than those without PAEB. Similarly, during the fall season, vehicles with PAEB have a 13.5% higher probability of getting involved in a fatal crash than a vehicle without PAEB. In contrast, the likelihood of pedestrian crashes for a vehicle with PAEB is 1.9% less in the spring than for a vehicle without PAEB.

Unlike Model 3, Model 4 shows that vehicles with PAEB are not safer during daytime and nighttime compared to vehicles without PAEB. Similarly, when a driver is speeding, the likelihood of fatal crash occurrence for vehicles with PAEB is higher, which is contradictory compared to vehicles with BSM, FCWS, LKA, or ACC and similar to vehicles with LDW.

The probability of fatal pedestrian crash occurrence for vehicles with PAEB is higher compared to vehicles without PAEB in the case of roads with one to four lanes or more than seven lanes, during wet road surface conditions, when a vehicle is skidding longitudinally, at intersections, on freeways and expressways, major collector, and minor collector roads, and during dawn light conditions, and rainy weather conditions. In contrast, on roads with six lanes, in conditions when a vehicle is skidding laterally, the likelihood of fatal pedestrian crash occurrence is lower for vehicles with PAEB compared to vehicles without PAEB on interstates, minor arterial, and local roads, at work zones, and during dark or dusk light conditions, during cloudy or other adverse conditions such as snow, fog/smoke/smog. This means that vehicles with PAEB are safer in most adverse weather conditions.

Females and drivers with age greater than 65 years are more likely to get involved in fatal pedestrian crashes for vehicles with PAEB compared to vehicles without PAEB. In contrast, the likelihood of fatal pedestrian crash occurrence is lower for drivers with age less than 65 years when driving a vehicle with PAEB. For crashes related to drink and drive, the likelihood of fatal crash occurrence is higher for vehicles with PAEB. For elderly drivers, the likelihood of fatal crash occurrence is 6.9% higher when driving a vehicle with PAEB compared to vehicles without PAEB.

# CHAPTER 6 CONCLUSIONS

Traffic crashes are among the top ten causes of fatalities in the United States. Existing literature documents that human errors are one of the primary causes of crashes in the United States. Varying driving behaviors due to variations in experience, reaction times, age, gender, and on-road and off-road characteristics are also associated with crash occurrence. Through the "Vision Zero" strategies, agencies worldwide under the Safe System Approach (SSA) aim to implement strategic and emerging technology-based solutions to reduce traffic-related crashes and fatalities.

Recent advancements in vehicle technologies are expected to change existing traffic systems fundamentally. DWSs and ADASs have drawn much attention from researchers in transportation engineering and other disciplines, particularly investigating the potential benefits of vehicles with varying DWSs or ADASs. Vehicles with DWSs or ADASs are expected to mitigate human errors while performing driving-related tasks by either providing warning to drivers in unsafe situations or by eliminating the role of human drivers from performing various driving tasks, thereby reducing traffic-related crashes and fatalities.

The existing literature shows numerous benefits of DWSs and ADASs in terms of safety. However, most of the existing studies on DWSs or ADASs are related to simulation analysis or analysis of test vehicles operating in a controlled environment. Although vehicles with DWSs or ADASs are expected to reduce traffic-related crashes, the crash data of the United States from the 2016 to 2020 shows that more than 5,000 vehicles equipped with either DWS or ADAS got involved in a fatal crash for which those DWSs or ADASs were designed to enhance the safety, demanding research on identifying potential causes and factors affecting those crashes. This study focuses on identifying fatal crashes involving vehicles equipped with DWSs or ADASs and determining the factors affecting fatal crashes involving vehicles with and without particular DWS or ADAS.

The methodology involved collecting fatal crash data for the United States from 2016 to 2020. After collecting the fatal crash data, the VINs of all the vehicles involved in fatal crashes were used to retrieve information about DWSs or ADASs in the vehicles. Depending on the Make, Model, and year of a vehicle, some vehicles offer the buyer an option for adding on a particular DWS or ADAS. Whereas for other models, the features are standard and come with a particular model. Vehicles with "standard" features are considered in this study.

The crash dataset was separated into three datasets based on crash types. The first dataset included all multivehicle crashes, in which DWSs, such as FCWS and BSM, and ADASs, such as LKA and ACC, play a vital role in enhancing safety. The second dataset was explicitly used to determine the effect of the LDW feature. It included single-vehicle and lane departure-related crashes, in which the LDW feature provides additional safety per its design. The third dataset included pedestrian crashes involving vehicles with and without the PAEB system. After segregating datasets, spatial maps, and temporal variation plots were developed to visualize the spatial and temporal variation in crashes. The trends showed that crashes varied throughout the United States, and the number of crashes involving vehicles with particular DWS or ADAS increased over the study years.

In separated datasets, descriptive statistics analysis showed that the share of vehicles equipped with particular DWS or ADAS was less than 3% in all datasets. Therefore, for even comparison and to eliminate spatial heterogeneity, nearest neighbor analysis was conducted for each dataset and each year of the crash. Per the nearest neighbor sampling results, three nearest neighbors (crashes involving vehicles without DWSs or ADASs) corresponding to each crash involving a vehicle with DWSs or ADASs were considered for modeling. After conducting nearest neighbor analysis, separate descriptive analysis was conducted for each dataset to determine the variation in frequency and proportion of samples in each category of independent variables and to identify the most suitable modeling technique.

The dependent variable was ordinal for models to identify the effect of DWSs or ADASs on multivehicle crashes. Therefore, fixed and correlated random parameters ordered logit models were employed in this study. Using a correlated random parameters model ensures the incorporation of heterogeneity due to varying driving behaviors and possible correlation between the random parameters. The dependent variable was binary in the case of models to identify the factors affecting crashes involving vehicles with LDW and PAEB. Therefore, fixed and correlated random parameters binary logit models were developed for those datasets.

The fixed and correlated random parameters modeling results provided valuable insights into the factors affecting fatal crashes involving vehicles with and without particular DWSs or ADASs. The following are the concluding remarks.

- Although vehicles with varying DWSs or ADASs are designed to enhance traffic safety in particular crash types, they are still involved in the same type of fatal crashes.
- Due to spatial and temporal heterogeneity in crash data, modeling results may be most accurate if various types of heterogeneity are incorporated when modeling.
- The trends in crash data showed that the number of fatal crashes involving vehicles with DWSs or ADASs varies spatially and temporally; using the methodological framework proposed in this study would help break down and incorporate various types of heterogeneity in crash datasets when modeling.

- Descriptive statistics analysis conducted in this study shows that the frequency and proportion of samples for various crash types varies; therefore, crash modeling is necessary to gain deeper insights into factors affecting fatal crashes and identify their effect on the probability of crash occurrence.
- The models developed in this study to determine the effect of vehicles with one or more DWSs or ADASs on factors affecting fatal crash occurrence showed that correlated random parameters ordered logit models significantly improve the model accuracy compared to fixed parameters ordered logit models.
- Although correlated random parameters binary logit models employed in the study provided better model accuracies than fixed parameters binary logit models, the Chi-square test results showed that both (fixed and correlated random parameters) models are not significantly different. The improvement in model accuracy by incorporating unobserved heterogeneity due to varying driving behavior parameters does not significantly improve the model fit.
- The factors affecting fatal crashes involving vehicles with zero, one, and two DWSs or ADASs varied over the study years. The probability of crash occurrence of vehicles with DWSs and ADASs increased over the study years, possibly due to the increasing penetration of vehicles with DWSs and ADASs in the transportation system.
- Vehicles equipped with one or more DWSs or ADASs are more likely to be involved in fatal crashes in urban areas and on interstates.
- Vehicles with LDW or PAEB features have a lower probability of being involved in fatal crashes during adverse weather conditions, such as ice, snow, smoke, or fog, than vehicles without these features.

- During wet or snowy road conditions, vehicles equipped with DWSs features like FCWS or BSM and ADASs features like LKA and ACC are safer than vehicles without these features. However, vehicles with LDW and PAEB are unsafe on wet road surfaces.
- Vehicles equipped with BSM, FCWS, LKA or ACC are less likely to be involved in fatal crashes in conditions where the vehicle is skidding laterally or longitudinally before a crash. Similarly, the likelihood of fatal crashes involving vehicles with LDW is lower when the vehicle is skidding longitudinally before the crash. On the other hand, vehicles with PAEB are safer when the vehicle is skidding laterally before a crash.
- The modeling results indicated that the effect of vehicles with DWSs and ADASs on a crash occurrence at work zones varies significantly. Vehicles equipped with ADASs or LDW are safer compared to vehicles without these features.
- At intersections, vehicles with DWSs and ADASs, except those with PAEB, are safer compared to vehicles without any DWS or ADAS.
- In crashes related to speeding or driving under the influence, vehicles equipped with DWSs or ADASs are less likely to be involved in fatal multivehicle crashes. However, drivers who exceed the speed limit are more likely to be involved in single-vehicle or lane departure-related and pedestrian-related fatal crashes.
- Female and elderly drivers are more likely to be involved in fatal crashes when driving vehicles with any DWSs or ADASs, demanding modifications in vehicular technology considering those drivers.
- The effect of driver age, gender, and drink and drive on fatal crash occurrence varied across observations. Incorporating these variables as random parameters while modeling yields better model estimates.

### 6.1 Practical Implications

The factors affecting various types of fatal crashes involving vehicles with different DWSs or ADASs, as highlighted in the study results, could be used by practitioners for making policy decisions and modifying the existing infrastructure before higher penetration of vehicles with warning and assistance systems in the transportation system. The modeling results of vehicles with and without LDW showed that vehicles with LDW still get involved in fatal crashes. One of the potential reasons for the same could be the underutilization of the feature because the option could be turned on or off by the drivers. Making policy decisions mandating these warning features could help enhance safety.

DWSs provides warnings to the drivers who responsible for performing various driving tasks, meaning they are enhancing safety by providing additional warning to the drivers (decision makers). Considering the usefulness of DWSs during adverse weather and road conditions as shown in the study results, policymakers can make decisions to mandate using these features in those circumstances to enhance safety.

The method used in this study relies on information about the VINs provided in the crash dataset. Considering the increasing penetration of vehicles with varying DWSs and ADASs, practitioners could consider planning to involve VIN number-related details in the dataset for varying levels of injury severity to gain deeper insights about factors affecting crash severity in the future.

The factors affecting fatal crashes involving vehicles with and without DWSs or ADASs could be used by industry experts to enhance the vehicular technology related to these warning and assistance systems to enhance their safety under critical circumstances identified in this study.

## 6.2 Scientific Contribution of the Study

This study focuses on an analysis of crash data involving various types of vehicles. The data preparation and processing framework used in this study to determine vehicles with and without DWSs and ADASs using VINs could be used by researchers in the future to determine vehicle-specific information for any dataset which contains VINs. The methodological framework used in this study provides an overview of various types of unobserved heterogeneity in crash data, along with a step-wise method to incorporate it while modeling. Separate consideration of heterogeneity due to spatial, temporal, and driving behavior variation while modeling provides an overview of the contribution of each aspect of unobserved heterogeneity in model accuracy. The temporal trends of fatal crashes involving vehicles with varying DWSs and ADASs show that the number of fatal crashes involving these vehicles increased over the study years. This study to identify the factors affecting fatal crashes involving vehicles with various DWSs and ADASs is the first of its kind to conduct crash data driven analysis. The factors identified in this study provide useful insights about required modifications in vehicular technology and can be used by researchers in the future.

## 6.3 Limitations and Scope for Future Work

The crash data from 2016 to 2020 were considered for the analysis. The trends in the number of crashes involving vehicles with DWSs and ADASs were increasing, demanding future research at higher penetration of these vehicles to get better insights about factors affecting fatal crashes. Further, due to data limitation, all vehicles with ADASs or LDW as standard features were considered in the analysis, considering that vehicles with these features should always use them. Using details of whether a particular feature was on or not at the time of the crash would provide more abstract results related to factors affecting crash occurrence for those vehicles.

The crash dataset used in this study included only fatal crashes as fatal crash data is more detailed and includes VIN information. Considering crash data of varying injury severity levels to determine the factors affecting injury severity is also a future research scope.

Another limitation of the study is that complete data on vehicles without DWSs or ADASs is not utilized since the penetration of vehicles with DWSs and ADASs was very low compared to those without DWS or ADAS. A study using all the crashes could be conducted at higher penetration of vehicles with DWSs and ADASs to gain detailed insights about the crash data.

One of the objectives of this study was to identify factors affecting fatal crashes involving vehicles with and without a particular DWS or ADAS. Statistical methods are used in this study since they provide detailed insights about each factor and its effect on the probability of crash occurrence. Using advanced machine learning or deep learning methods to determine the probability of crash occurrence could be another approach to explore and is identified as the future scope of the work.

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# APPENDIX A: SPATIAL VARIATION OF FATAL CRASHES

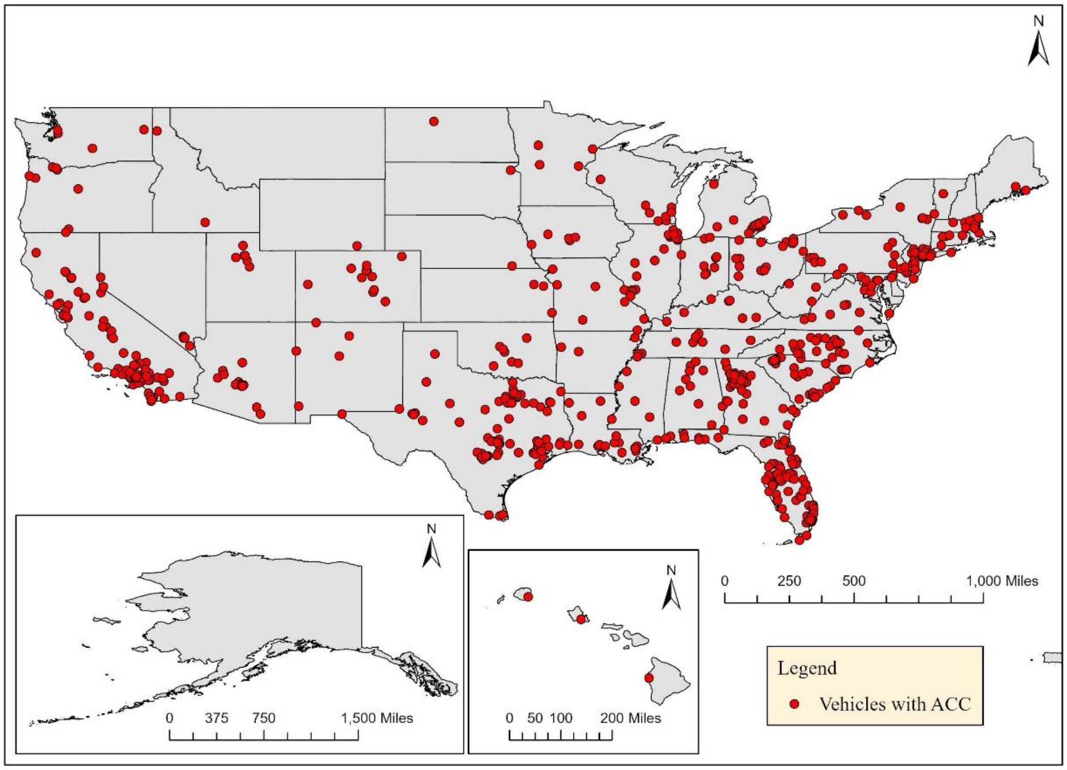


**Figure A-1. Fatal multivehicle crashes involving vehicles with ACC.**

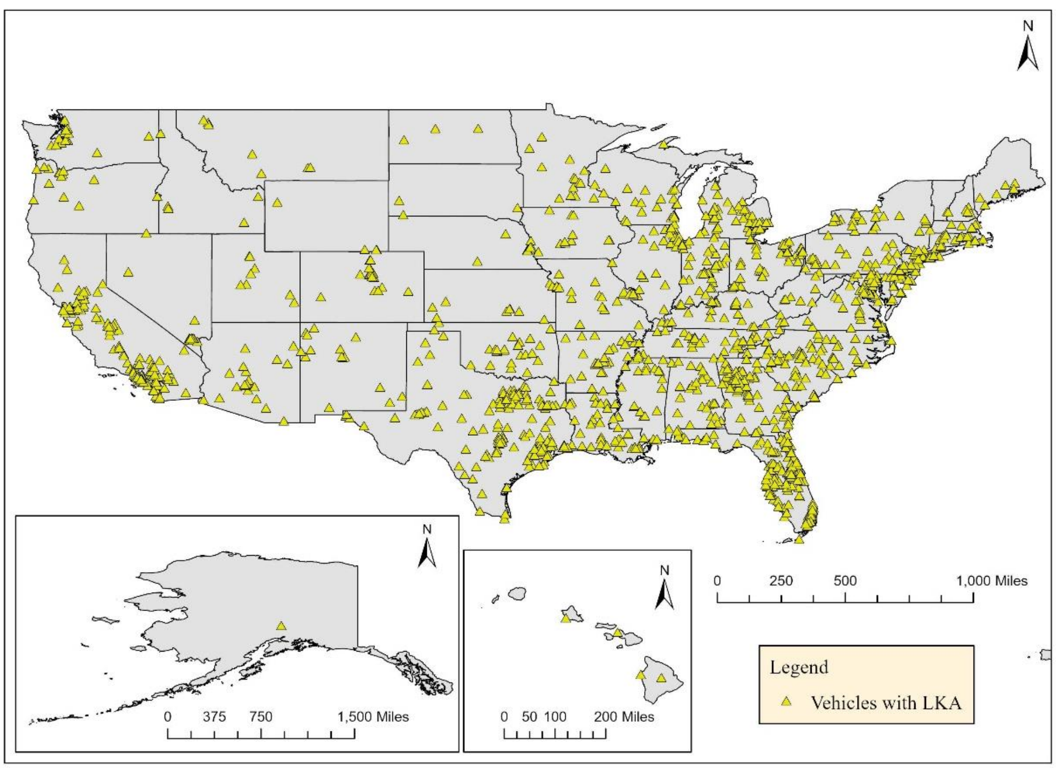


**Figure A-2. Fatal multivehicle crashes involving vehicles with LKA.**

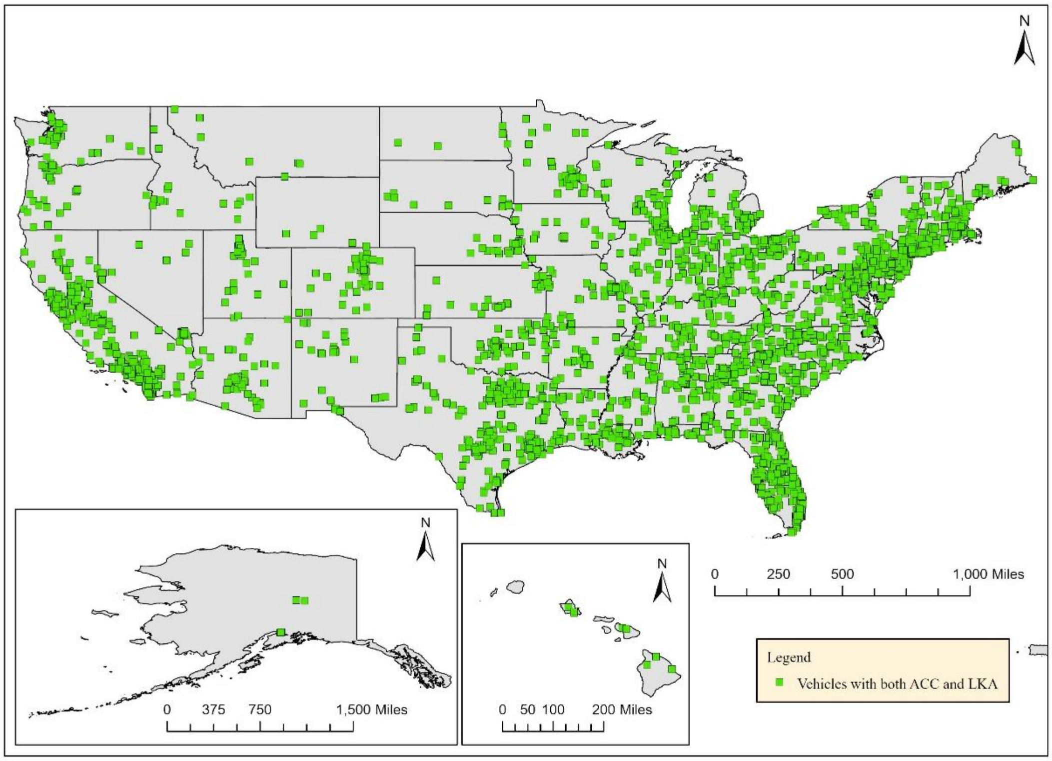


**Figure A-3. Fatal multivehicle crashes involving vehicles with both LKA and ACC systems.**

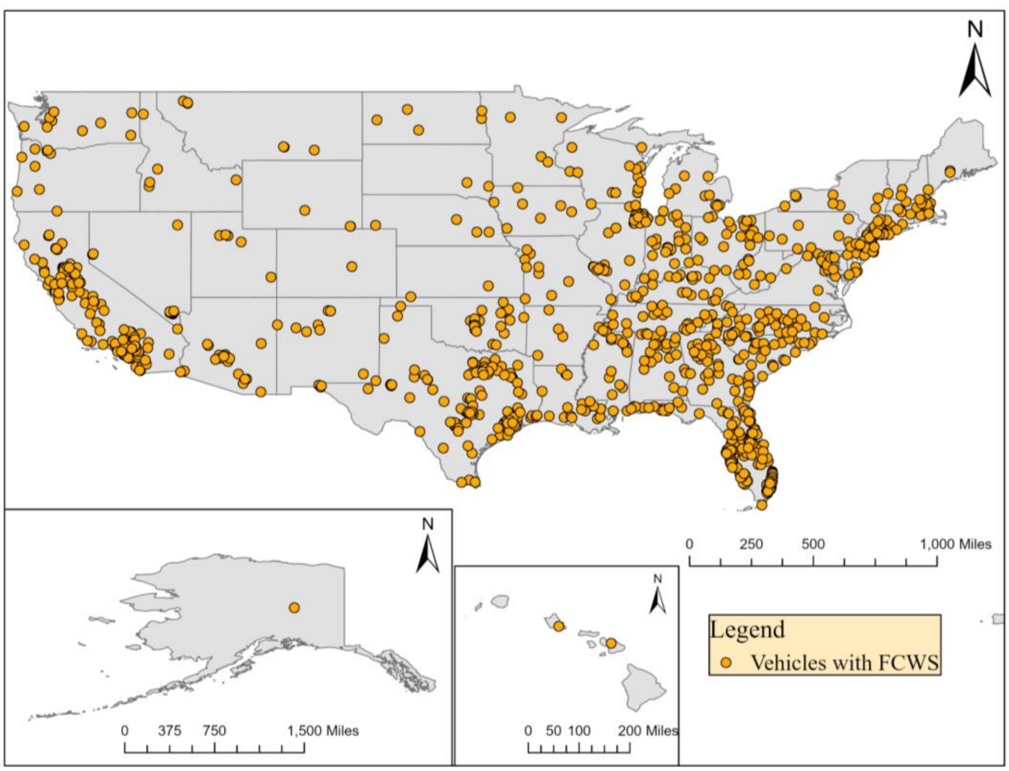


**Figure A-4. Fatal multivehicle crashes involving vehicles with FCWS.**

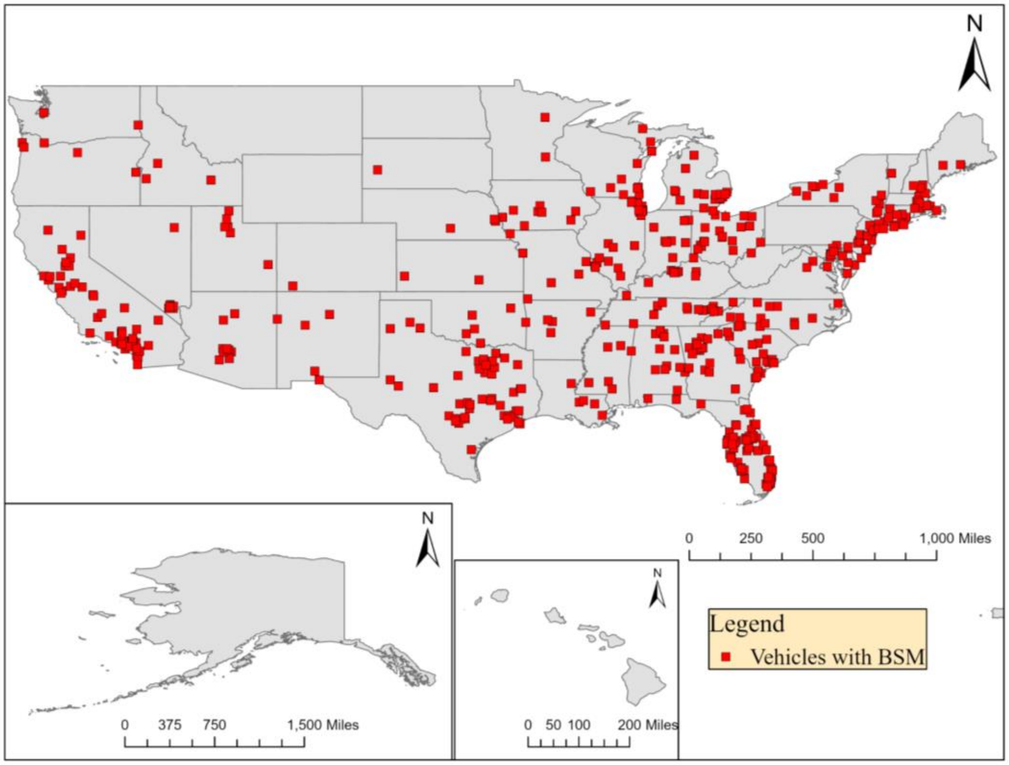


**Figure A-5. Fatal multivehicle crashes involving vehicles with BSM.**

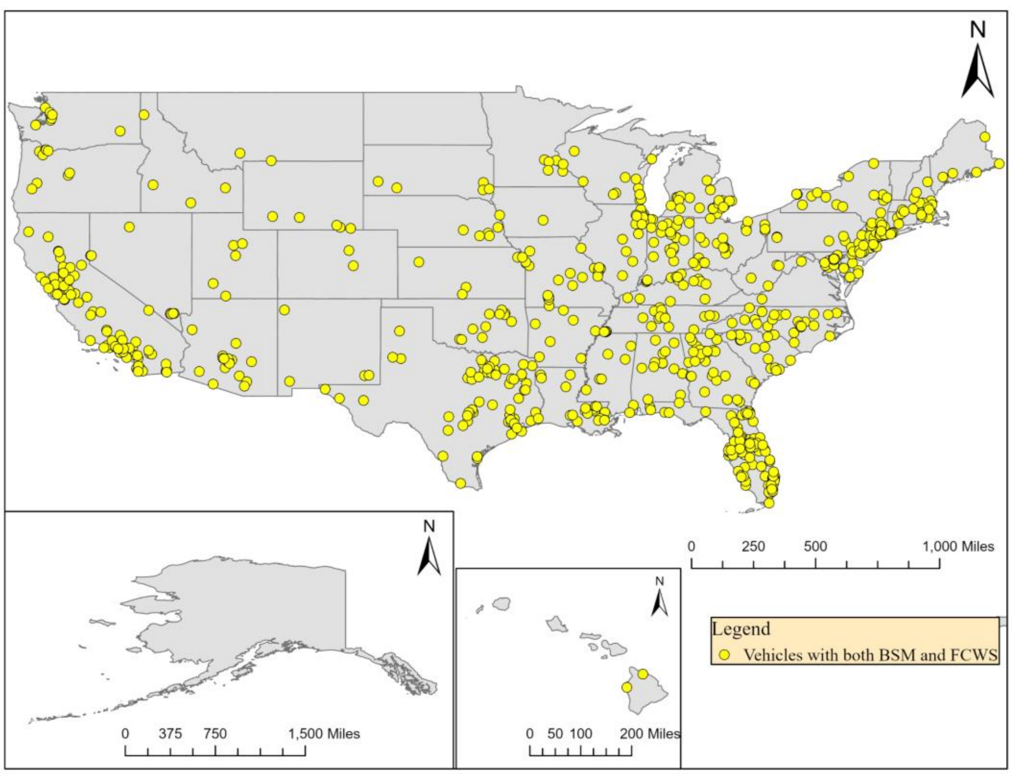


**Figure A-6. Fatal multivehicle crashes involving vehicles with both BSM and FCWS.**

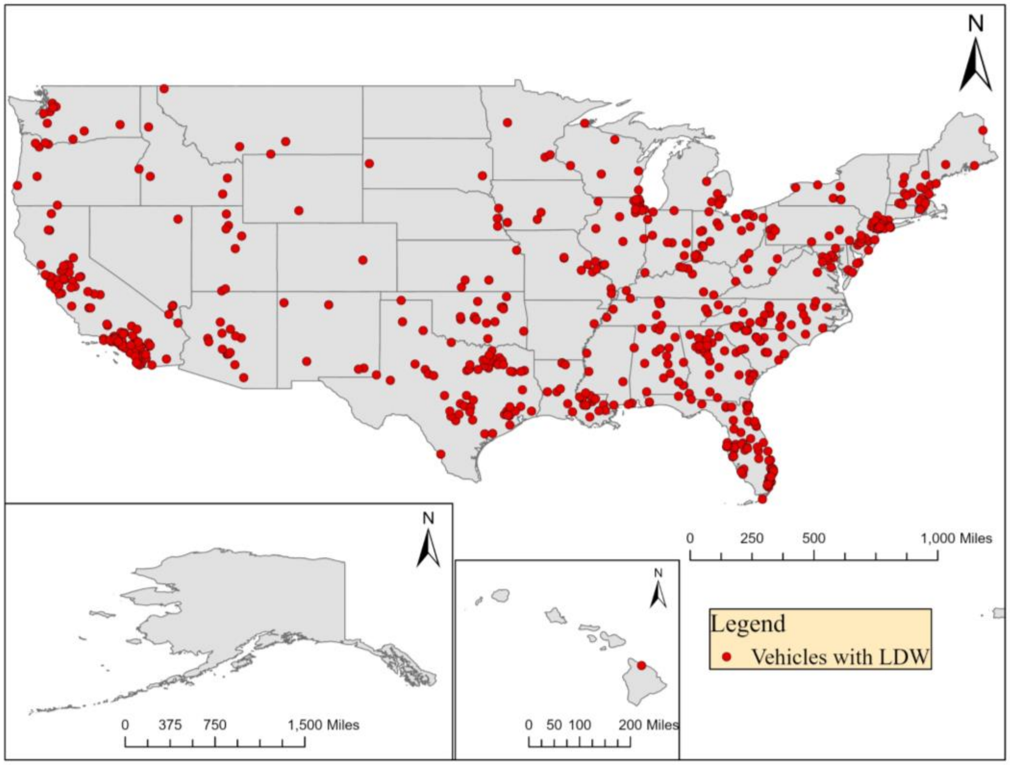


**Figure A-6. Fatal single-vehicle and lane departure crashes involving vehicles with LDW.**

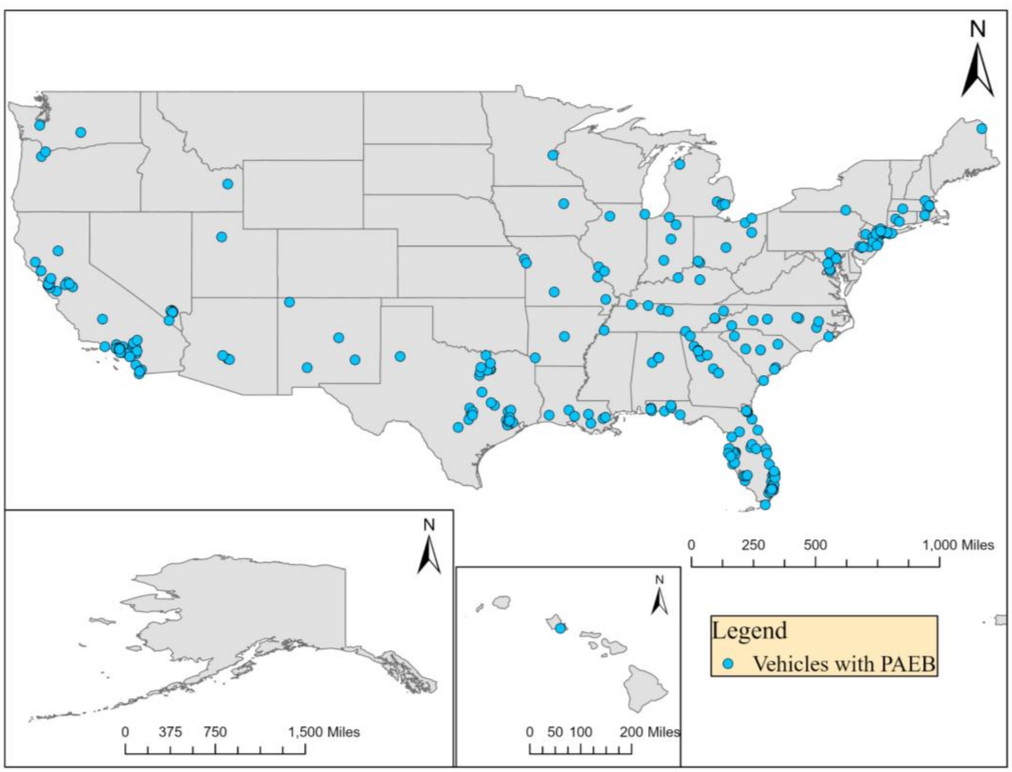


**Figure A-6. Fatal pedestrian crashes involving vehicles with PAEB.**

# APPENDIX B: FIXED PARAMETERS MODEL ESTIMATES

## Table B-1. Fixed Parameters Model 1 Estimates.

| Variables | Coefficient | Standard error | *z*-value | *p*-value |
|---|---|---|---|---|
| Constant | -3.566 | 0.162 | -22.050 | 0.000 |
| Year | 0.524 | 0.023 | 22.730 | 0.000 |
| Area type (Urban) | 0.214 | 0.058 | 3.670 | 0.000 |
| Age (Less than 24 years) | -0.174 | 0.078 | -2.220 | 0.026 |
| Age (>40, <=65 years) | -0.119 | 0.062 | -1.920 | 0.055 |
| Age (Greater than 65 years) | 0.262 | 0.074 | 3.540 | 0.000 |
| Gender (Female) | 0.659 | 0.052 | 12.710 | 0.000 |
| Season (Winter) | -0.085 | 0.076 | -1.120 | 0.264 |
| Season (Spring) | -0.056 | 0.072 | -0.780 | 0.435 |
| Season (Fall) | 0.142 | 0.066 | 2.140 | 0.032 |
| Time of the day (12 AM to 3 AM) | -0.159 | 0.156 | -1.020 | 0.308 |
| Time of the day (3 AM to 6 AM) | -0.208 | 0.155 | -1.340 | 0.179 |
| Time of the day (9 AM to 12 PM) | 0.263 | 0.110 | 2.390 | 0.017 |
| Time of the day (12 PM to 3 PM) | 0.192 | 0.105 | 1.830 | 0.067 |
| Time of the day (3 PM to 6 PM) | 0.151 | 0.101 | 1.490 | 0.137 |
| Time of the day (6 PM to 9 PM) | 0.076 | 0.117 | 0.650 | 0.514 |
| Time of the day (9 PM to 12 AM) | -0.073 | 0.141 | -0.520 | 0.605 |
| Manner of collision (Head-on) | 0.194 | 0.072 | 2.690 | 0.007 |
| Manner of collision (Rear-end) | 0.027 | 0.078 | 0.350 | 0.729 |
| Manner of collision (Sideswipe - opposite direction) | 0.070 | 0.131 | 0.540 | 0.592 |
| Manner of collision (Sideswipe - same direction) | 0.207 | 0.143 | 1.450 | 0.148 |
| Speeding | -0.104 | 0.087 | -1.200 | 0.230 |
| Number of lanes (No trafficway access) | 0.335 | 0.244 | 1.370 | 0.169 |
| Number of lanes (one lane) | 0.277 | 0.237 | 1.170 | 0.243 |
| Number of lanes (Three lanes) | 0.017 | 0.079 | 0.210 | 0.831 |
| Number of lanes (Four lanes) | 0.210 | 0.081 | 2.600 | 0.009 |
| Number of lanes (Five lanes) | 0.204 | 0.090 | 2.260 | 0.024 |
| Number of lanes (Six lanes) | 0.149 | 0.163 | 0.920 | 0.360 |
| Number of lanes (Seven or more lanes) | 0.239 | 0.192 | 1.240 | 0.214 |
| Surface condition (Wet) | -0.028 | 0.131 | -0.210 | 0.832 |
| Surface condition (Ice, snow, mud, dirt, oil or water) | -0.582 | 0.251 | -2.320 | 0.020 |
| Pre-crash stability (Skidding laterally) | -0.093 | 0.201 | -0.460 | 0.645 |
| Pre-crash stability (Skidding longitudinally) | -0.428 | 0.251 | -1.710 | 0.088 |
| Pre-crash stability (Not specific) | -0.242 | 0.069 | -3.510 | 0.001 |
| Drink and drive | -0.369 | 0.094 | -3.910 | 0.000 |

| Variables | Coefficient | Standard error | *z*-value | *p*-value |
|---|---|---|---|---|
| Functional class (Interstate) | 0.254 | 0.089 | 2.840 | 0.005 |
| Functional class (Freeway or expressway) | 0.350 | 0.119 | 2.930 | 0.003 |
| Functional class (Minor arterial) | -0.084 | 0.067 | -1.260 | 0.209 |
| Functional class (Major collector) | -0.106 | 0.087 | -1.220 | 0.224 |
| Functional class (Minor collector) | 0.152 | 0.172 | 0.880 | 0.378 |
| Functional class (Local) | 0.054 | 0.113 | 0.480 | 0.633 |
| Intersection | -0.123 | 0.067 | -1.830 | 0.067 |
| Work zone | 0.140 | 0.145 | 0.960 | 0.335 |
| Light condition (Dark) | 0.234 | 0.104 | 2.240 | 0.025 |
| Light condition (Dawn) | -0.174 | 0.211 | -0.820 | 0.410 |
| Light condition (Dusk) | 0.198 | 0.178 | 1.110 | 0.267 |
| Weather condition (Cloudy) | -0.046 | 0.077 | -0.600 | 0.550 |
| Weather condition (Rain) | -0.004 | 0.158 | -0.020 | 0.981 |
| Weather condition (Snow, fog/smoke/smog, or other adverse condition) | 0.437 | 0.186 | 2.350 | 0.019 |
| **Threshold parameters for probabilities** | | | | |
| Threshold | 1.478 | 0.035 | 42.170 | 0.000 |

**Table B-2. Fixed Parameters Model 1 Partial Effects.**

| Variables | Y=0 | | Y=1 | | Y=2 | |
|---|---|---|---|---|---|---|
| | Partial effect | *p*-value | Partial effect | *p*-value | Partial effect | *p*-value |
| Year | -0.096 | 0.000 | 0.063 | 0.000 | 0.033 | 0.000 |
| Area type (Urban) | -0.039 | 0.000 | 0.026 | 0.000 | 0.013 | 0.000 |
| Age (Less than 24 years) | 0.031 | 0.022 | -0.021 | 0.023 | -0.011 | 0.019 |
| Age (>40, <=65 years) | 0.022 | 0.052 | -0.014 | 0.053 | -0.007 | 0.051 |
| Age (Greater than 65 years) | -0.050 | 0.001 | 0.032 | 0.001 | 0.018 | 0.001 |
| Gender (Female) | -0.128 | 0.000 | 0.081 | 0.000 | 0.047 | 0.000 |
| Season (Winter) | 0.015 | 0.258 | -0.010 | 0.260 | -0.005 | 0.254 |
| Season (Spring) | 0.010 | 0.432 | -0.007 | 0.433 | -0.004 | 0.429 |
| Season (Fall) | -0.027 | 0.035 | 0.017 | 0.034 | 0.009 | 0.037 |
| Time of the day (12 AM to 3 AM) | 0.028 | 0.290 | -0.019 | 0.295 | -0.010 | 0.279 |
| Time of the day (3 AM to 6 AM) | 0.037 | 0.157 | -0.024 | 0.163 | -0.012 | 0.145 |
| Time of the day (9 AM to 12 PM) | -0.051 | 0.022 | 0.033 | 0.019 | 0.018 | 0.028 |
| Time of the day (12 PM to 3 PM) | -0.036 | 0.075 | 0.024 | 0.072 | 0.013 | 0.083 |
| Time of the day (3 PM to 6 PM) | -0.028 | 0.145 | 0.018 | 0.142 | 0.010 | 0.152 |
| Time of the day (6 PM to 9 PM) | -0.014 | 0.520 | 0.009 | 0.517 | 0.005 | 0.524 |
| Time of the day (9 PM to 12 AM) | 0.013 | 0.600 | -0.009 | 0.601 | -0.005 | 0.596 |
| Manner of collision (Head-on) | -0.037 | 0.008 | 0.024 | 0.008 | 0.013 | 0.010 |

| Variables | Y=0 | | Y=1 | | Y=2 | |
|---|---|---|---|---|---|---|
| | Partial effect | *p*-value | Partial effect | *p*-value | Partial effect | *p*-value |
| Manner of collision (Rear-end) | -0.005 | 0.730 | 0.003 | 0.729 | 0.002 | 0.730 |
| Manner of collision (Sideswipe - opposite direction) | -0.013 | 0.598 | 0.009 | 0.596 | 0.005 | 0.602 |
| Manner of collision (Sideswipe - same direction) | -0.040 | 0.166 | 0.026 | 0.157 | 0.014 | 0.182 |
| Speeding | 0.019 | 0.220 | -0.012 | 0.223 | -0.006 | 0.214 |
| Number of lanes (No trafficway access) | -0.067 | 0.200 | 0.042 | 0.182 | 0.025 | 0.229 |
| Number of lanes (one lane) | -0.054 | 0.272 | 0.035 | 0.257 | 0.020 | 0.297 |
| Number of lanes (Three lanes) | -0.003 | 0.832 | 0.002 | 0.831 | 0.001 | 0.832 |
| Number of lanes (Four lanes) | -0.040 | 0.012 | 0.026 | 0.011 | 0.014 | 0.015 |
| Number of lanes (Five lanes) | -0.039 | 0.030 | 0.025 | 0.027 | 0.014 | 0.035 |
| Number of lanes (Six lanes) | -0.028 | 0.376 | 0.018 | 0.369 | 0.010 | 0.388 |
| Number of lanes (Seven or more lanes) | -0.047 | 0.238 | 0.030 | 0.226 | 0.017 | 0.259 |
| Surface condition (Wet) | 0.005 | 0.832 | -0.003 | 0.832 | -0.002 | 0.831 |
| Surface condition (Ice, snow, mud, dirt, oil or water) | 0.092 | 0.005 | -0.062 | 0.007 | -0.029 | 0.003 |
| Pre-crash stability (Skidding laterally) | 0.017 | 0.637 | -0.011 | 0.639 | -0.006 | 0.632 |
| Pre-crash stability (Skidding longitudinally) | 0.070 | 0.052 | -0.047 | 0.059 | -0.023 | 0.039 |
| Pre-crash stability (Not specific) | 0.043 | 0.000 | -0.028 | 0.000 | -0.015 | 0.000 |
| Drink and drive | 0.063 | 0.000 | -0.042 | 0.000 | -0.021 | 0.000 |
| Functional class (Interstate) | -0.049 | 0.007 | 0.031 | 0.005 | 0.018 | 0.009 |
| Functional class (Freeway or expressway) | -0.070 | 0.006 | 0.044 | 0.004 | 0.026 | 0.010 |
| Functional class (Minor arterial) | 0.015 | 0.203 | -0.010 | 0.205 | -0.005 | 0.200 |
| Functional class (Major collector) | 0.019 | 0.214 | -0.013 | 0.217 | -0.007 | 0.208 |
| Functional class (Minor collector) | -0.029 | 0.394 | 0.019 | 0.387 | 0.010 | 0.407 |
| Functional class (Local) | -0.010 | 0.637 | 0.007 | 0.635 | 0.004 | 0.640 |
| Intersection | 0.023 | 0.066 | -0.015 | 0.066 | -0.008 | 0.065 |
| Work zone | -0.027 | 0.350 | 0.017 | 0.344 | 0.009 | 0.362 |
| Light condition (Dark) | -0.044 | 0.028 | 0.028 | 0.026 | 0.015 | 0.030 |
| Light condition (Dawn) | 0.031 | 0.388 | -0.020 | 0.394 | -0.010 | 0.375 |
| Light condition (Dusk) | -0.038 | 0.288 | 0.025 | 0.278 | 0.014 | 0.305 |
| Weather condition (Cloudy) | 0.008 | 0.546 | -0.006 | 0.548 | -0.003 | 0.544 |
| Weather condition (Rain) | 0.001 | 0.981 | 0.001 | 0.981 | 0.001 | 0.981 |
| Weather condition (Snow, fog/smoke/smog, or other adverse condition) | -0.089 | 0.030 | 0.055 | 0.022 | 0.033 | 0.046 |

**Table B-3. Fixed Parameters Model 2 Estimates.**

| Variable | Coefficient | Standard error | *z*-value | *p*-value |
|---|---|---|---|---|
| Constant | -3.153 | 0.189 | -16.720 | 0.000 |
| Year | 0.474 | 0.027 | 17.830 | 0.000 |
| Area type (Urban) | 0.248 | 0.066 | 3.770 | 0.000 |
| Age (Less than 24 years) | -0.173 | 0.097 | -1.790 | 0.074 |
| Age (>40, <=65 years) | -0.158 | 0.071 | -2.210 | 0.027 |
| Age (Greater than 65 years) | 0.226 | 0.086 | 2.620 | 0.009 |
| Gender (Female) | 0.731 | 0.061 | 12.060 | 0.000 |
| Season (Winter) | 0.047 | 0.088 | 0.530 | 0.597 |
| Season (Spring) | -0.052 | 0.085 | -0.620 | 0.537 |
| Season (Fall) | 0.188 | 0.077 | 2.450 | 0.014 |
| Time of the day (12 AM to 3 AM) | -0.121 | 0.184 | -0.650 | 0.513 |
| Time of the day (3 AM to 6 AM) | -0.144 | 0.184 | -0.780 | 0.434 |
| Time of the day (9 AM to 12 PM) | 0.034 | 0.130 | 0.260 | 0.792 |
| Time of the day (12 PM to 3 PM) | -0.017 | 0.124 | -0.130 | 0.893 |
| Time of the day (3 PM to 6 PM) | -0.017 | 0.120 | -0.140 | 0.885 |
| Time of the day (6 PM to 9 PM) | -0.012 | 0.141 | -0.080 | 0.934 |
| Time of the day (9 PM to 12 AM) | -0.245 | 0.168 | -1.450 | 0.146 |
| Manner of collision (Head-on) | 0.258 | 0.085 | 3.010 | 0.003 |
| Manner of collision (Rear-end) | 0.039 | 0.091 | 0.430 | 0.669 |
| Manner of collision (Sideswipe - opposite direction) | 0.056 | 0.152 | 0.370 | 0.712 |
| Manner of collision (Sideswipe - same direction) | 0.253 | 0.168 | 1.500 | 0.132 |
| Speeding | -0.118 | 0.096 | -1.220 | 0.221 |
| Number of lanes (No trafficway access) | -0.259 | 0.301 | -0.860 | 0.389 |
| Number of lanes (one lane) | 0.579 | 0.263 | 2.210 | 0.027 |
| Number of lanes (Three lanes) | 0.086 | 0.090 | 0.960 | 0.335 |
| Number of lanes (Four lanes) | 0.050 | 0.091 | 0.560 | 0.579 |
| Number of lanes (Six lanes) | 0.041 | 0.183 | 0.230 | 0.821 |
| Number of lanes (Seven or more lanes) | 0.093 | 0.220 | 0.420 | 0.671 |
| Surface condition (Wet) | -0.063 | 0.154 | -0.410 | 0.683 |
| Surface condition (Ice, snow, mud, dirt, oil or water) | -0.664 | 0.301 | -2.200 | 0.028 |
| Pre-crash stability (Skidding laterally) | -0.384 | 0.228 | -1.690 | 0.092 |
| Pre-crash stability (Skidding longitudinally) | -0.343 | 0.302 | -1.130 | 0.257 |
| Pre-crash stability (Not specific) | -0.224 | 0.080 | -2.790 | 0.005 |
| Drink and drive | -0.521 | 0.109 | -4.790 | 0.000 |
| Functional class (Interstate) | 0.146 | 0.104 | 1.410 | 0.157 |
| Functional class (Freeway or expressway) | 0.177 | 0.138 | 1.280 | 0.200 |
| Functional class (Minor arterial) | -0.151 | 0.078 | -1.950 | 0.051 |

| Variable | Coefficient | Standard error | *z*-value | *p*-value |
|---|---|---|---|---|
| Functional class (Major collector) | -0.249 | 0.101 | -2.460 | 0.014 |
| Functional class (Minor collector) | 0.328 | 0.194 | 1.690 | 0.091 |
| Functional class (Local) | -0.088 | 0.135 | -0.650 | 0.516 |
| Intersection | -0.075 | 0.080 | -0.940 | 0.348 |
| Work zone | -0.066 | 0.164 | -0.400 | 0.686 |
| Light condition (Dark) | 0.089 | 0.127 | 0.700 | 0.483 |
| Light condition (Dawn) | -0.055 | 0.236 | -0.230 | 0.815 |
| Light condition (Dusk) | -0.100 | 0.214 | -0.470 | 0.639 |
| Weather condition (Cloudy) | -0.208 | 0.090 | -2.320 | 0.020 |
| Weather condition (Rain) | 0.058 | 0.186 | 0.310 | 0.755 |
| Weather condition (Snow, fog/smoke/smog, or other adverse condition) | 0.135 | 0.216 | 0.630 | 0.531 |
| **Threshold parameters for probabilities** | | | | |
| Threshold | 0.649 | 0.024 | 26.650 | 0.000 |

**Table B-4. Fixed Parameters Model 2 Partial Effects.**

| Variables | Y = 0 | | Y=1 | | Y=2 | |
|---|---|---|---|---|---|---|
| | Partial effect | *p*-value | Partial effect | *p*-value | Partial effect | *p*-value |
| Year | -0.087 | 0.000 | 0.029 | 0.000 | 0.058 | 0.000 |
| Area type (Urban) | -0.045 | 0.000 | 0.015 | 0.000 | 0.030 | 0.000 |
| Age (Less than 24 years) | 0.031 | 0.064 | -0.010 | 0.070 | -0.020 | 0.061 |
| Age (>40, <=65 years) | 0.029 | 0.025 | -0.010 | 0.026 | -0.019 | 0.025 |
| Age (Greater than 65 years) | -0.043 | 0.011 | 0.014 | 0.009 | 0.029 | 0.013 |
| Gender (Female) | -0.143 | 0.000 | 0.044 | 0.000 | 0.099 | 0.000 |
| Season (Winter) | -0.009 | 0.599 | 0.003 | 0.597 | 0.006 | 0.600 |
| Season (Spring) | 0.010 | 0.534 | -0.003 | 0.536 | -0.006 | 0.533 |
| Season (Fall) | -0.035 | 0.016 | 0.012 | 0.014 | 0.024 | 0.017 |
| Time of the day (12 AM to 3 AM) | 0.022 | 0.501 | -0.007 | 0.509 | -0.014 | 0.497 |
| Time of the day (3 AM to 6 AM) | 0.026 | 0.418 | -0.009 | 0.428 | -0.017 | 0.412 |
| Time of the day (9 AM to 12 PM) | -0.006 | 0.794 | 0.002 | 0.793 | 0.004 | 0.794 |
| Time of the day (12 PM to 3 PM) | 0.003 | 0.893 | -0.001 | 0.893 | -0.002 | 0.893 |
| Time of the day (3 PM to 6 PM) | 0.003 | 0.885 | -0.001 | 0.885 | -0.002 | 0.885 |
| Time of the day (6 PM to 9 PM) | 0.002 | 0.934 | -0.001 | 0.934 | -0.001 | 0.934 |
| Time of the day (9 PM to 12 AM) | 0.043 | 0.125 | -0.015 | 0.137 | -0.028 | 0.119 |
| Manner of collision (Head-on) | -0.049 | 0.003 | 0.016 | 0.003 | 0.033 | 0.004 |
| Manner of collision (Rear-end) | -0.007 | 0.671 | 0.002 | 0.670 | 0.005 | 0.672 |
| Manner of collision (Sideswipe - opposite direction) | -0.010 | 0.716 | 0.003 | 0.713 | 0.007 | 0.717 |

| Variables | Y = 0 | | Y=1 | | Y=2 | |
|---|---|---|---|---|---|---|
| | **Partial effect** | ***p*-value** | **Partial effect** | ***p*-value** | **Partial effect** | ***p*-value** |
| Manner of collision (Sideswipe - same direction) | -0.049 | 0.154 | 0.015 | 0.131 | 0.034 | 0.164 |
| Speeding | 0.021 | 0.210 | -0.007 | 0.218 | -0.014 | 0.207 |
| Number of lanes (No trafficway access) | 0.044 | 0.354 | -0.015 | 0.374 | -0.029 | 0.343 |
| Number of lanes (one lane) | -0.121 | 0.046 | 0.035 | 0.016 | 0.086 | 0.062 |
| Number of lanes (Three lanes) | -0.016 | 0.342 | 0.005 | 0.336 | 0.011 | 0.346 |
| Number of lanes (Four lanes) | -0.009 | 0.582 | 0.003 | 0.580 | 0.006 | 0.584 |
| Number of lanes (Six lanes) | -0.008 | 0.822 | 0.003 | 0.821 | 0.005 | 0.823 |
| Number of lanes (Seven or more lanes) | -0.017 | 0.678 | 0.006 | 0.672 | 0.012 | 0.681 |
| Surface condition (Wet) | 0.011 | 0.680 | -0.004 | 0.682 | -0.008 | 0.678 |
| Surface condition (Ice, snow, mud, dirt, oil or water) | 0.101 | 0.006 | -0.037 | 0.012 | -0.064 | 0.004 |
| Pre-crash stability (Skidding laterally) | 0.064 | 0.059 | -0.022 | 0.074 | -0.041 | 0.051 |
| Pre-crash stability (Skidding longitudinally) | 0.057 | 0.210 | -0.020 | 0.234 | -0.037 | 0.197 |
| Pre-crash stability (Not specific) | 0.040 | 0.004 | -0.014 | 0.005 | -0.026 | 0.003 |
| Drink and drive | 0.086 | 0.000 | -0.030 | 0.000 | -0.055 | 0.000 |
| Functional class (Interstate) | -0.028 | 0.168 | 0.009 | 0.158 | 0.019 | 0.173 |
| Functional class (Freeway or expressway) | -0.034 | 0.217 | 0.011 | 0.201 | 0.023 | 0.225 |
| Functional class (Minor arterial) | 0.027 | 0.046 | -0.009 | 0.049 | -0.018 | 0.045 |
| Functional class (Major collector) | 0.043 | 0.010 | -0.015 | 0.012 | -0.028 | 0.008 |
| Functional class (Minor collector) | -0.065 | 0.114 | 0.020 | 0.086 | 0.045 | 0.126 |
| Functional class (Local) | 0.016 | 0.508 | -0.005 | 0.514 | -0.010 | 0.504 |
| Intersection | 0.014 | 0.346 | -0.005 | 0.347 | -0.009 | 0.345 |
| Work zone | 0.012 | 0.681 | -0.004 | 0.684 | -0.008 | 0.679 |
| Light condition (Dark) | -0.016 | 0.486 | 0.005 | 0.483 | 0.011 | 0.487 |
| Light condition (Dawn) | 0.010 | 0.812 | -0.003 | 0.814 | -0.007 | 0.811 |
| Light condition (Dusk) | 0.018 | 0.630 | -0.006 | 0.636 | -0.012 | 0.627 |
| Weather condition (Cloudy) | 0.037 | 0.015 | -0.013 | 0.018 | -0.024 | 0.014 |
| Weather condition (Rain) | -0.011 | 0.758 | 0.004 | 0.756 | 0.007 | 0.759 |
| Weather condition (Snow, fog/smoke/smog, or other adverse condition) | -0.026 | 0.544 | 0.008 | 0.533 | 0.017 | 0.549 |

**Table B-5. Fixed Parameters Model 3 Estimates.**

| Variable | Coefficient | Standard error | *z*-value | *p*-value |
|---|---|---|---|---|
| Constant | -4.410 | 0.334 | -13.210 | 0.000 |
| Year | 0.828 | 0.051 | 16.320 | 0.000 |
| Area type (Urban) | 0.380 | 0.116 | 3.280 | 0.001 |
| Age (Less than 24 years) | -0.138 | 0.153 | -0.900 | 0.367 |
| Age (>40, <=65 years) | -0.045 | 0.133 | -0.340 | 0.733 |
| Age (Greater than 65 years) | 0.815 | 0.177 | 4.610 | 0.000 |
| Gender (Female) | 0.559 | 0.119 | 4.700 | 0.000 |
| Season (Winter) | -0.010 | 0.165 | -0.060 | 0.954 |
| Season (Spring) | 0.001 | 0.157 | 0.010 | 0.994 |
| Season (Fall) | 0.210 | 0.142 | 1.480 | 0.140 |
| Time of the day (12 AM to 3 AM) | -0.306 | 0.292 | -1.050 | 0.295 |
| Time of the day (3 AM to 6 AM) | -0.290 | 0.290 | -1.000 | 0.318 |
| Time of the day (9 AM to 12 PM) | -0.126 | 0.252 | -0.500 | 0.616 |
| Time of the day (12 PM to 3 PM) | -0.419 | 0.236 | -1.780 | 0.075 |
| Time of the day (3 PM to 6 PM) | -0.427 | 0.224 | -1.910 | 0.057 |
| Time of the day (6 PM to 9 PM) | -0.731 | 0.249 | -2.930 | 0.003 |
| Time of the day (9 PM to 12 AM) | -0.467 | 0.286 | -1.630 | 0.103 |
| Manner of collision (Head-on) | 0.597 | 0.191 | 3.120 | 0.002 |
| Manner of collision (Rear-end) | 0.783 | 0.289 | 2.710 | 0.007 |
| Manner of collision (Sideswipe - opposite direction) | 0.374 | 0.357 | 1.050 | 0.295 |
| Manner of collision (Sideswipe - same direction) | 0.337 | 0.400 | 0.840 | 0.399 |
| Speeding | 0.102 | 0.123 | 0.820 | 0.410 |
| Number of lanes (No trafficway access) | 0.159 | 0.643 | 0.250 | 0.805 |
| Number of lanes (one lane) | -0.351 | 0.390 | -0.900 | 0.368 |
| Number of lanes (Three lanes) | -0.067 | 0.184 | -0.370 | 0.714 |
| Number of lanes (Four lanes) | 0.021 | 0.213 | 0.100 | 0.920 |
| Number of lanes (Six lanes) | 0.495 | 0.430 | 1.150 | 0.250 |
| Number of lanes (Seven or more lanes) | 0.167 | 0.662 | 0.250 | 0.801 |
| Surface condition (Wet) | 0.137 | 0.260 | 0.530 | 0.598 |
| Surface condition (Ice, snow, mud, dirt, oil or water) | -0.360 | 0.397 | -0.910 | 0.365 |
| Pre-crash stability (Skidding Longitudinally) | -0.369 | 0.407 | -0.910 | 0.365 |
| Pre-crash stability (Not specific) | 0.065 | 0.164 | 0.400 | 0.689 |
| Drink and drive | -0.062 | 0.132 | -0.470 | 0.636 |
| Functional class (Interstate) | 0.056 | 0.176 | 0.320 | 0.752 |
| Functional class (Freeway or expressway) | 0.054 | 0.239 | 0.230 | 0.820 |
| Functional class (Minor arterial) | -0.058 | 0.161 | -0.360 | 0.717 |
| Functional class (Major collector) | -0.207 | 0.177 | -1.170 | 0.243 |
| Functional class (Minor collector) | -0.274 | 0.283 | -0.970 | 0.333 |

| Variable | Coefficient | Standard error | *z*-value | *p*-value |
|---|---|---|---|---|
| Functional class (Local) | 0.069 | 0.195 | 0.350 | 0.726 |
| Work zone | -0.311 | 0.343 | -0.910 | 0.364 |
| Light condition (Dark) | 0.275 | 0.231 | 1.190 | 0.235 |
| Light condition (Dawn) | 0.050 | 0.416 | 0.120 | 0.904 |
| Light condition (Dusk) | 0.123 | 0.392 | 0.310 | 0.754 |
| Weather condition (Cloudy) | -0.323 | 0.167 | -1.930 | 0.053 |
| Weather condition (Rain) | -0.394 | 0.317 | -1.240 | 0.214 |
| Weather condition (Snow, fog/smoke/smog, or other adverse condition) | -0.021 | 0.401 | -0.050 | 0.958 |

**Table B-6. Fixed Parameters Model 3 Partial Effects.**

| Variable | Partial effect | Standard error | *z*-value | *p*-value |
|---|---|---|---|---|
| Year | 0.132 | 0.008 | 15.770 | 0.000 |
| Area type (Urban) | 0.061 | 0.019 | 3.290 | 0.001 |
| Age (Less than 24 years) | -0.022 | 0.024 | -0.910 | 0.362 |
| Age (>40, <=65 years) | -0.007 | 0.021 | -0.340 | 0.733 |
| Age (Greater than 65 years) | 0.139 | 0.031 | 4.470 | 0.000 |
| Gender (Female) | 0.093 | 0.020 | 4.610 | 0.000 |
| Season (Winter) | -0.002 | 0.026 | -0.060 | 0.954 |
| Season (Spring) | 0.000 | 0.025 | 0.010 | 0.994 |
| Season (Fall) | 0.034 | 0.023 | 1.460 | 0.144 |
| Time of the day (12 AM to 3 AM) | -0.047 | 0.044 | -1.090 | 0.278 |
| Time of the day (3 AM to 6 AM) | -0.045 | 0.043 | -1.040 | 0.300 |
| Time of the day (9 AM to 12 PM) | -0.020 | 0.039 | -0.510 | 0.611 |
| Time of the day (12 PM to 3 PM) | -0.064 | 0.034 | -1.880 | 0.061 |
| Time of the day (3 PM to 6 PM) | -0.065 | 0.033 | -2.010 | 0.045 |
| Time of the day (6 PM to 9 PM) | -0.108 | 0.033 | -3.250 | 0.001 |
| Time of the day (9 PM to 12 AM) | -0.071 | 0.041 | -1.730 | 0.083 |
| Manner of collision (Head-on) | 0.100 | 0.033 | 3.030 | 0.002 |
| Manner of collision (Rear-end) | 0.135 | 0.052 | 2.590 | 0.010 |
| Manner of collision (Sideswipe - opposite direction) | 0.062 | 0.061 | 1.010 | 0.311 |
| Manner of collision (Sideswipe - same direction) | 0.056 | 0.068 | 0.820 | 0.414 |
| Speeding | 0.016 | 0.020 | 0.820 | 0.412 |
| Number of lanes (No trafficway access) | 0.026 | 0.107 | 0.240 | 0.809 |
| Number of lanes (one lane) | -0.053 | 0.056 | -0.950 | 0.342 |
| Number of lanes (Three lanes) | -0.011 | 0.029 | -0.370 | 0.712 |
| Number of lanes (Four lanes) | 0.003 | 0.034 | 0.100 | 0.920 |
| Number of lanes (Six lanes) | 0.083 | 0.076 | 1.100 | 0.269 |

| Variable | Partial effect | Standard error | *z*-value | *p*-value |
|---|---|---|---|---|
| Number of lanes (Seven or more lanes) | 0.027 | 0.110 | 0.250 | 0.804 |
| Surface condition (Wet) | 0.022 | 0.043 | 0.520 | 0.603 |
| Surface condition (Ice, snow, mud, dirt, oil or water) | -0.055 | 0.057 | -0.960 | 0.338 |
| Pre-crash stability (Skidding Longitudinally) | -0.056 | 0.059 | -0.960 | 0.338 |
| Pre-crash stability (Not specific) | 0.011 | 0.026 | 0.400 | 0.690 |
| Drink and drive | -0.010 | 0.021 | -0.480 | 0.635 |
| Functional class (Interstate) | 0.009 | 0.028 | 0.310 | 0.753 |
| Functional class (Freeway or expressway) | 0.009 | 0.039 | 0.230 | 0.821 |
| Functional class (Minor arterial) | -0.009 | 0.025 | -0.360 | 0.716 |
| Functional class (Major collector) | -0.032 | 0.027 | -1.190 | 0.234 |
| Functional class (Minor collector) | -0.042 | 0.042 | -1.000 | 0.315 |
| Functional class (Local) | 0.011 | 0.032 | 0.350 | 0.727 |
| Work zone | -0.048 | 0.050 | -0.950 | 0.341 |
| Light condition (Dark) | 0.044 | 0.037 | 1.190 | 0.233 |
| Light condition (Dawn) | 0.008 | 0.067 | 0.120 | 0.904 |
| Light condition (Dusk) | 0.020 | 0.064 | 0.310 | 0.758 |
| Weather condition (Cloudy) | -0.050 | 0.025 | -2.000 | 0.045 |
| Weather condition (Rain) | -0.060 | 0.046 | -1.320 | 0.188 |
| Weather condition (Snow, fog/smoke/smog, or other adverse condition) | -0.003 | 0.064 | -0.050 | 0.958 |

**Table B-7. Fixed Parameters Model 4 Estimates.**

| Variable | Coefficient | Standard error | *z*-value | *p*-value |
|---|---|---|---|---|
| Constant | -4.490 | 0.600 | -7.490 | 0.000 |
| Year | 0.737 | 0.070 | 10.540 | 0.000 |
| Area type (Urban) | 0.373 | 0.251 | 1.490 | 0.137 |
| Season (Winter) | 0.056 | 0.250 | 0.230 | 0.821 |
| Season (Spring) | -0.084 | 0.258 | -0.330 | 0.745 |
| Season (Fall) | 0.777 | 0.228 | 3.410 | 0.001 |
| Time of the day (12 AM to 3 AM) | 0.342 | 0.452 | 0.760 | 0.449 |
| Time of the day (3 AM to 6 AM) | 0.750 | 0.409 | 1.840 | 0.067 |
| Time of the day (9 AM to 12 PM) | -0.067 | 0.533 | -0.130 | 0.900 |
| Time of the day (12 PM to 3 PM) | 0.260 | 0.513 | 0.510 | 0.612 |
| Time of the day (3 PM to 6 PM) | 0.005 | 0.419 | 0.010 | 0.991 |
| Time of the day (6 PM to 9 PM) | 0.598 | 0.370 | 1.620 | 0.106 |
| Time of the day (9 PM to 12 AM) | 0.456 | 0.392 | 1.160 | 0.245 |
| Speeding | 0.345 | 0.297 | 1.160 | 0.246 |
| Number of lanes (No trafficway access) | 3.149 | 1.415 | 2.230 | 0.026 |

| Variable | Coefficient | Standard error | *z*-value | *p*-value |
|---|---|---|---|---|
| Number of lanes (one lane) | 0.164 | 0.585 | 0.280 | 0.780 |
| Number of lanes (Three lanes) | 0.024 | 0.211 | 0.110 | 0.909 |
| Number of lanes (Four lanes) | -0.008 | 0.224 | -0.040 | 0.970 |
| Number of lanes (Six lanes) | -0.409 | 0.440 | -0.930 | 0.352 |
| Number of lanes (Seven or more lanes) | 0.068 | 0.503 | 0.140 | 0.892 |
| Surface condition (Wet) | 0.042 | 0.366 | 0.110 | 0.909 |
| Pre-crash stability (Skidding laterally) | -0.431 | 0.361 | -1.190 | 0.233 |
| Pre-crash stability (Skidding longitudinally) | 0.112 | 0.291 | 0.380 | 0.700 |
| Functional class (Interstate) | 0.094 | 0.255 | 0.370 | 0.711 |
| Functional class (Freeway or expressway) | 0.056 | 0.365 | 0.150 | 0.879 |
| Functional class (Minor arterial) | -0.311 | 0.216 | -1.440 | 0.150 |
| Functional class (Major collector) | 0.204 | 0.307 | 0.670 | 0.506 |
| Functional class (Minor collector) | 0.516 | 0.611 | 0.840 | 0.399 |
| Functional class (Local) | -0.148 | 0.301 | -0.490 | 0.623 |
| Work zone | -0.786 | 0.598 | -1.310 | 0.189 |
| Light condition (Dark) | -0.344 | 0.357 | -0.970 | 0.334 |
| Light condition (Dawn) | 1.139 | 0.598 | 1.900 | 0.057 |
| Light condition (Dusk) | -1.818 | 0.891 | -2.040 | 0.041 |
| Weather condition (Cloudy) | -0.217 | 0.239 | -0.910 | 0.365 |
| Weather condition (Rain) | 0.238 | 0.471 | 0.510 | 0.613 |
| Weather condition (Snow, fog/smoke/smog, or other adverse condition) | -0.077 | 0.754 | -0.100 | 0.919 |
| Intersection | 0.098 | 0.188 | 0.520 | 0.603 |
| Gender (Female) | 0.215 | 0.172 | 1.250 | 0.213 |
| Age (Less than 24 years) | 0.026 | 0.235 | 0.110 | 0.914 |
| Age (>40, <=65 years) | -0.191 | 0.192 | -0.990 | 0.320 |
| Age (Greater than 65 years) | 0.548 | 0.253 | 2.160 | 0.031 |
| Drink and drive | 0.215 | 0.347 | 0.620 | 0.536 |

**Table B-8. Fixed Parameters Model 4 Partial Effects.**

| Variable | Partial effect | Standard error | *z*-value | *p*-value |
|---|---|---|---|---|
| Year | 0.119 | 0.012 | 10.190 | 0.000 |
| Area type (Urban) | 0.058 | 0.037 | 1.560 | 0.119 |
| Age (Less than 24 years) | 0.004 | 0.038 | 0.110 | 0.914 |
| Age (>40, <=65 years) | -0.031 | 0.031 | -1.000 | 0.316 |
| Age (Greater than 65 years) | 0.093 | 0.045 | 2.080 | 0.037 |
| Gender (Female) | 0.035 | 0.028 | 1.230 | 0.217 |
| Season (Winter) | 0.009 | 0.041 | 0.230 | 0.822 |

| Variable | Partial effect | Standard error | *z*-value | *p*-value |
|---|---|---|---|---|
| Season (Spring) | -0.013 | 0.041 | -0.330 | 0.743 |
| Season (Fall) | 0.132 | 0.040 | 3.340 | 0.001 |
| Time of the day (12 AM to 3 AM) | 0.057 | 0.078 | 0.740 | 0.462 |
| Time of the day (3 AM to 6 AM) | 0.130 | 0.074 | 1.760 | 0.078 |
| Time of the day (9 AM to 12 PM) | -0.011 | 0.085 | -0.130 | 0.899 |
| Time of the day (12 PM to 3 PM) | 0.043 | 0.088 | 0.490 | 0.621 |
| Time of the day (3 PM to 6 PM) | 0.001 | 0.068 | 0.010 | 0.991 |
| Time of the day (6 PM to 9 PM) | 0.100 | 0.063 | 1.590 | 0.112 |
| Time of the day (9 PM to 12 AM) | 0.076 | 0.066 | 1.150 | 0.252 |
| Speeding | 0.058 | 0.052 | 1.120 | 0.262 |
| Number of lanes (No trafficway access) | 0.535 | 0.173 | 3.090 | 0.002 |
| Number of lanes (one lane) | 0.027 | 0.098 | 0.270 | 0.784 |
| Number of lanes (Three lanes) | 0.004 | 0.034 | 0.110 | 0.909 |
| Number of lanes (Four lanes) | -0.001 | 0.036 | -0.040 | 0.970 |
| Number of lanes (Six lanes) | -0.062 | 0.063 | -1.000 | 0.319 |
| Number of lanes (Seven or more lanes) | 0.011 | 0.083 | 0.130 | 0.893 |
| Surface condition (Wet) | 0.007 | 0.060 | 0.110 | 0.909 |
| Pre-crash stability (Skidding laterally) | -0.066 | 0.052 | -1.280 | 0.202 |
| Pre-crash stability (Skidding longitudinally) | 0.018 | 0.048 | 0.380 | 0.704 |
| Drink and drive | 0.036 | 0.059 | 0.610 | 0.545 |
| Functional class (Interstate) | 0.015 | 0.042 | 0.370 | 0.714 |
| Functional class (Freeway or expressway) | 0.009 | 0.060 | 0.150 | 0.880 |
| Functional class (Minor arterial) | -0.049 | 0.033 | -1.480 | 0.138 |
| Functional class (Major collector) | 0.034 | 0.052 | 0.650 | 0.515 |
| Functional class (Minor collector) | 0.088 | 0.110 | 0.810 | 0.420 |
| Functional class (Local) | -0.024 | 0.047 | -0.500 | 0.617 |
| Work zone | -0.112 | 0.072 | -1.550 | 0.122 |
| Light condition (Dark) | -0.057 | 0.060 | -0.950 | 0.342 |
| Light condition (Dawn) | 0.205 | 0.113 | 1.810 | 0.070 |
| Light condition (Dusk) | -0.206 | 0.058 | -3.540 | 0.000 |
| Weather condition (Cloudy) | -0.034 | 0.037 | -0.930 | 0.353 |
| Weather condition (Rain) | 0.040 | 0.080 | 0.490 | 0.622 |
| Weather condition (Snow, fog/smoke/smog, or other adverse condition) | -0.012 | 0.119 | -0.100 | 0.918 |
| Intersection | 0.016 | 0.031 | 0.520 | 0.605 |