Potential Reduction of Fatal Crashes in South Carolina due to Automated Vehicles

Final Report

by

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DISCLAIMER

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16. Abstract

Since 1995, several countries and states have implemented roadway traffic safety projects with the goal of achieving a highway system with no fatal or serious injury crashes. South Carolina's Target Zero plan is multifaceted in that it identifies several preventative measures to reduce fatalities. A common thread of these programs is that they are aspirational and there is not an expectation that zero fatalities will ever be a reality. While there are many contributors to fatal crashes, by far the biggest contributor is driver error. In South Carolina, the first contributing factor in nearly 85% of fatal crashes is driver related. Thus, to approach a target of zero fatalities will require eliminating drivers from the equation—or at least making drivers error-free. This research focuses on how 2019 South Carolina fatal crash data could be impacted hypothetically by different scenarios of autonomous vehicle (AV) safety applications. A detailed review of contributing factors to 919 2019 fatal crashes in South Carolina along with a review of site characteristics for each crash was conducted. A deterministic approach was used to calculate the effects of different AV levels on each of the fatal crashes. The approach was based primarily on literature findings with regard to the safety effectiveness of vehicle characteristics for each level. The estimated reduction in fatal crashes ranged from 10% to 23% for level 1 to nearly 95% for level 5 AV. The underlying assumption in terms of AV level is that the entire population of vehicles fall within that AV category.

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EXECUTIVE SUMMARY

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This research focuses on how 2019 South Carolina fatal crash data could be impacted hypothetically by different scenarios of autonomous vehicle (AV) safety applications. A detailed review of contributing factors to 919 2019 fatal crashes in South Carolina along with a review of site characteristics for each crash was conducted. A deterministic approach was used to calculate the effects of different AV levels on each of the fatal crashes. The approach was based primarily on literature findings with regard to the safety effectiveness of vehicle characteristics for each level. The estimated reduction in fatal crashes ranged from 10% to 23% for level 1 to nearly 95% for level 5 AV. The underlying assumption in terms of AV level is that the entire population of vehicles fall within that AV category.

CHAPTER 1

Introduction

1.1 Fatal Crashes in the US and an Approach to Eliminate Them

According to the National Highway Traffic Safety Administration (NHTSA) (NHTSA, 2012), “fatal crash” refers to a crash involving a motor vehicle leading to the death of at least one person within 30 days after the crash. Based on this definition, 38,824 people lost their lives in U.S. roadway crashes in 2020. This number is the highest total since 2007 and represents a 6.8% increase from 2019 fatalities (36,355) (Stewart, 2022). What is particularly surprising with this increase is that it happened even though there was a decrease of 11 percent in total vehicle miles traveled (VMT) in 2020 from 2019 due to the COVID pandemic and a 22 percent decrease in police reported crashes (Stewart, 2022). While there have been many technological advances in vehicles to make them safer, the recent spike in fatal crashes indicates that more needs to be done. South Carolina (SC) had the highest rate of U.S. traffic fatalities per 100 million VMT (1.97) in 2020, which is nearly 50% greater than the national rate (1.34). Almost all other southern states also have fatality rates well above the national rate (Stewart, 2022).

In 1995, a multi-national roadway traffic safety project called “Vision Zero” started in Sweden. The goal of the project was to achieve a highway system with no fatal or serious injury crashes. A core principle of Vision Zero is that “Life and health can never be exchanged for other benefits within society” (‘Road Safety: Vision Zero on the move’, 2012). Canada’s Road Safety Strategy 2025 has a similar long-term vision of making Canada’s roads “the safest roads in the world.” It encourages road safety stakeholders from all levels of government as well as the private sector and non-governmental stakeholders to collaborate and unite efforts to improve safety (*Canada’s Road Safety Strategy 2025.*, 2016). SC’s Target Zero initiative is the state’s vision to zero traffic fatalities and identifies several preventative measures to reduce fatalities (*Target Zero Traffic Deaths*, 2020). A common thread of these programs is that they are aspirational and there is no expectation that zero fatalities will ever be a reality. While there are many contributors to fatal crashes, by far the biggest contributor is driver error. Driver error

Figure 1: South Carolina’s Target Zero Initiative

contributes to well over 90% of all crashes including fatal crashes (AASHTO, 2010). In South Carolina, the first contributing factor in nearly 85% of fatal crashes is driver related (SCDPS, 2018). Thus, to approach a target of zero roadway fatalities will require eliminating drivers from the equation—or at least making drivers error free. Autonomous vehicles (AVs) have the potential to do just that. AVs are the most significant technological advancement in personal transport since the proliferation of seatbelts. AV technologies have gone from a vision to a reality with most new cars incorporating some AV elements.

This research focuses on how 2019 South Carolina fatal crash data could be impacted hypothetically by different scenarios of AV safety applications. This research attempts to quantify how each of the AV levels can potentially reduce the number of fatal crashes by decreasing drivers' errors or eliminating their roles.

CHAPTER 2

Literature Review and Methodology

2.1 Autonomous Vehicle Levels

According to the Society of Automotive Engineers (SAE) (*SAE Levels of Driving Automation^{TM} Refined for Clarity and International Audience*, 2021), there are six levels of driving automation. Level 0 (L0) refers to vehicles that have no automation with a few exceptions illustrated in Table 1. Level 1 (L1) vehicles are equipped with longitudinal or lateral control. Level 2 (L2) vehicles involve simultaneous longitudinal and lateral control. Truly autonomous driving occurs in level 3–5 vehicles. Level 3 (L3) vehicles have L2 abilities and can operate fully autonomously in certain circumstances but require the driver to take control when the driving system requests it. In level 4 (L4) vehicles, drivers receive fewer takeover requests than in L3 vehicles since the driving system works in more situations. Level 5 (L5) vehicles are fully autonomous, and the driving system works in every situation (Teoh, 2020). Each mentioned level has different safety applications (features) shown in Table 1.

Table 1. Safety applications of different levels of vehicles

Level of Vehicle	Safety Application
Level 0	Warnings (NHTSA, 2020)(Kockelman *et al.*, 2016) Autonomous Emergency Braking (AEB) (*SAE Levels of Driving Automation™ Refined for Clarity and International Audience*, 2021)
Level 1	Warnings (NHTSA, 2020)(Kockelman *et al.*, 2016) Lane Keeping Assist (LKA) or Adaptive Cruise Control (ACC) (*SAE Levels of Driving Automation™ Refined for Clarity and International Audience*, 2021)(NHTSA, 2020) Autonomous Emergency Braking (AEB) (*SAE Levels of Driving Automation™ Refined for Clarity and International Audience*, 2021)
Level 2	Warnings (NHTSA, 2020)(Kockelman *et al.*, 2016) Lane Keeping Assistance (LKA) Adaptive Cruise Control (ACC) Autonomous Emergency Braking (AEB) (*SAE Levels of Driving Automation™ Refined for Clarity and International Audience*, 2021)

Level 3	Warnings (NHTSA, 2020)(Kockelman *et al.*, 2016) Traffic Jam Pilot (TJP) (*SAE Levels of Driving Automation™ Refined for Clarity and International Audience*, 2021) Highway Pilot (HWP) (Thorn *et al.*, 2018) Autonomous Emergency Braking (AEB) (*SAE Levels of Driving Automation™ Refined for Clarity and International Audience*, 2021)
Level 4	Like level 5 vehicles but needs a driver in limited situations (*SAE Levels of Driving Automation™ Refined for Clarity and International Audience*, 2021)(NHTSA, 2020)
Level 5	Fully autonomous system works in all situations (*SAE Levels of Driving Automation™ Refined for Clarity and International Audience*, 2021)(NHTSA, 2020)

According to Table 1, level 0 vehicles are only equipped with safety warning applications that may include one or more of the following warning systems: Forward Collision Warning (FCW), Control Loss Warning (CLW), Road Departure Crash Warning (RDCW), Blind Spot Warning (BSW), Lane Departure Warning (LDW), Lane Change Warning (LCW), and Do Not Pass Warning (DNPW) (NHTSA, 2020)(Kockelman *et al.*, 2016). These safety applications alert drivers through visual and auditory warnings depending on the manufacturer and model year of the vehicles (Lerner *et al.*, 2014). Also, some level 0 vehicles have Autonomous Emergency Braking (AEB), where the vehicle can automatically engage braking when there is an obstruction or a pedestrian on the roadway (*SAE Levels of Driving Automation™ Refined for Clarity and International Audience*, 2021).

Level 1 vehicles are equipped with level 0 safety applications (Warnings and AEB) and either Lane Keeping Assistance (LKA) or Adaptive Cruise Control (ACC) (*SAE Levels of Driving Automation™ Refined for Clarity and International Audience*, 2021; NHTSA, 2020). LKA helps the vehicle not leave its travel lane unintentionally. This application uses sensor information and adjusts steering, brakes, or both to help the vehicle return to the travel lane (*Driver Assistance Technologies*, 2016). ACC helps the vehicle maintain a predefined distance from the vehicle ahead by adjusting the speed. Level 2 vehicles are equipped with level 0 safety applications (Warnings and AEB) and both LKA and ACC (*SAE Levels of Driving Automation™ Refined for Clarity and International Audience*, 2021).

Level 3 vehicles are equipped with level 0 safety applications (Warnings and AEB), Traffic Jam Pilot (TJP) (Lerner *et al.*, 2014), and Highway Pilot (HWP) (Thorn *et al.*, 2018). TJP and HWP help vehicles drive autonomously in congested traffic situations and highways, respectively (*SAE Levels of Driving Automation™ Refined for Clarity and International Audience*, 2021; Thorn *et al.*, 2018). Both of these applications have some limitations that require the driver to take over control of the vehicles. Level 4 vehicles are highly automated where drivers only need to drive in limited situations (*SAE Levels of Driving Automation™ Refined for Clarity and International Audience*, 2021; NHTSA, 2020). Level 5 vehicles can drive automatically in all situations without human intervention (*SAE Levels of Driving Automation™ Refined for Clarity and International Audience*, 2021; NHTSA, 2020).

2.2 Impacts of Autonomous Vehicles on Safety

This section discusses the impacts of different levels of AVs and their safety applications on vehicle crash reduction as reported in the extant literature. Generally, scholars have used three approaches to determine the safety impacts of AVs: survey, simulation, and analysis. Several survey-based studies explored the public's opinions about AVs' potential benefits (Bansal, Kockelman and Singh, 2016; Ahmed *et al.*, 2020), AVs' potential drawbacks (Bansal, Kockelman and Singh, 2016; Ahmed *et al.*, 2020), and likelihood of AV adoption (Shabanpour *et al.*, 2018). The most closely tied to the present study was Kockelman et al. (2016) who used two national and two state surveys (Texas) to assess people's opinions about current and future connected and automated vehicle (CAV) technologies. They designed a matrix to measure the effectiveness of different safety applications on crashes based on the KABCO scale using three estimation categories: conservative, moderate, and aggressive. According to their matrix, the effectiveness of FCW & Cooperative Adaptive Cruise Control (CACC), CLW, RDCW & LKA, BSW & LCW, and DNPW for fatal crashes are 0.7-0.9, 0.4-0.6, 0.3-0.7, 0.7-0.9, and 0.6-0.8 from conservative to aggressive estimates, respectively (Kockelman *et al.*, 2016). Bansal et al. (2016) studied the opinions of Austin residents towards levels 3 and 4 AVs. They concluded that more than 60% of respondents expect fewer roadway crashes using level 4 vehicles. Respondents' opinions indicated that the most significant advantage of AV technology is the reduction of crashes while system or equipment failure was the greatest concern. Shabanpour et al. (2018) applied a survey to evaluate the preferences of respondents for using fully AVs and found that factors such as income, age, crash experience, parking cost, household size, and residential area play a significant role in choosing fully AVs over other alternatives. Ahmed et al. (2020) conducted a survey that indicated that 66% of respondents expect to see a reduction in crashes due to AVs and 68% expect reduced crash severity. However, over 70% percent were concerned about the failure of systems in bad weather and crashes resulting from the failure of systems. Several other researchers designed surveys to study individuals' opinions about AVs in other countries (Schoettle and Sivak, 2014; Kyriakidis, Happee and De Winter, 2015; Daziano, Sarrias and Leard, 2017; Haboucha, Ishaq and Shiftan, 2017).

Several scholars used simulation to evaluate potential impacts of AVs on the reduction of crashes. Using VISSIM, Morando et al. (2018) measured the safety of fully autonomous AVs and concluded that 50% to 100% penetration levels of AVs could decrease conflicts by 20% to 65% at signalized intersections. They also concluded that a 100% penetration level of AVs would reduce conflicts by 29% to 64% at roundabouts. Papadoulis et al. (2019) applied a control algorithm in VISSIM to evaluate the impact of CAV penetration levels on traffic conflicts. They showed 25%, 50%, 75%, and 100% market penetration could decrease traffic conflicts by 12-47%, 50-80%, 82-92%, and 90-94%, respectively. Mousavi et al. (2020) proposed a microsimulation model to evaluate the safety impact of AV movements near an unsignalized intersection. They showed that the number of conflicts decreased even in congested situations compared to the movement of regular vehicles.

El-Hansali et al. (2021) used a "surrogate safety assessment model" (SSAM) in combination with VISSIM to evaluate the impacts of AVs on some safety measures such as number of conflict points, "time to collision" (TTC), and "post-encroachment time" (PET). They found that AVs could decrease "rear-end conflict points" and "total conflict points" by 13% and 8.6%, respectively. They estimated that AVs could reduce the rate of annual crashes by 12%, PET by 35.8%, and TTC by 20.4%. They did not address any specific level of AVs. Virdi et al. (2019) proposed a microsimulation approach to measure the safety of CAVs using a SSAM. They showed that conflicts at different types of intersections could be decreased significantly by increasing the penetration level of CAVs. Rahman (2019) used simulation to assess the operational and safety advantages of CAVs in various traffic conditions, weather situations, and roadways. He concluded that increasing CAV market penetration can improve mobility and safety. Moreover, he found that noticeable safety benefits can only be achieved with at least a 30% market penetration rate. Zhang et al. (2021) proposed a SSAM to evaluate the safety impact of using CAVs on a freeway. They used VISSIM to simulate the behaviors of CAVs and regular vehicles. They concluded that safety indicators such as the number of conflicts, acceleration, and velocity difference did not significantly improve when the penetration level of CAVs was less than 50%. The safety indicators improved substantially for penetration levels greater than 70%. Kusano and Gabler (2015) used simulation to evaluate the impact of FCW and LDW safety applications on crashes and injury reduction. They showed that 0% to 67% of crashes and 2% to 69% of drivers' moderate to fatal injuries can be prevented depending on different TTC values if the FCW market penetration rate is 100%. They also found that 11% to 23% of lane departure accidents and 13% to 22% of drivers' severe to fatal injuries can be prevented if the LDW market penetration rate is 100%.

Several researchers used different analysis techniques to evaluate the impact of CAVs on crash reduction. Xiao et al. (2021) used a meta-analysis approach to assess the safety improvement of connected vehicle technology. They considered different safety indicators such as TTC and "time exposed time-to collision" (TET). They showed that nationally 2351 fatal crashes can be eliminated by 2025 and 5337 fatal crashes can be eliminated by 2035 with predicted market penetration levels for those two years, where the rate of fatal crash reduction differs by state depending on income and predicted market penetration. They estimated that the rate of fatal crash reduction in South Carolina would range from 6.3-6.49% in 2025 and 12.2-12.78% in 2035. Sternlund (2017) analyzed 104 fatal crashes that occurred in Sweden in 2010. They concluded that LDW systems could prevent 33% to 38% of single-vehicle and head-on fatal collisions. In another study, LKA plus lane departure warning (LDW) was estimated to reduce head-on and single vehicle injury crashes by 53% in conditions without ice or snow, and on roads with speed limits between 43 mph to 75 mph (Sternlund *et al.*, 2017). Scanlon et al. (2016) concluded that LKA systems can theoretically decrease road departure crashes by 32% and serious injuries to drivers by 28% in the USA, but those percentages can reach 78% and 65%, respectively if all roads had lane marking and wide shoulders. Utriainen et al. (2020) simulated that LKA could potentially prevent 27% of fatal crashes.

Most recent model vehicles are equipped with systems that provide driver alert warnings such as lane departure warning, driver drowsiness alertness, forward collision warning (FCW), rear collision warning (RCW), blind spot monitoring, and curve-adaptive headlights (Highway Loss Data Institute, 2018). Such warning can alert drivers and theoretically significantly contribute to crash avoidance (Highway Loss Data Institute, 2018).

2.3 Summary of Literature

This study focuses on quantifying a potential reduction of fatal crashes in South Carolina. While surveys provide valuable information on perceived safety and public acceptance of CAV technologies, they do not have a scientific basis for estimating the magnitude of safety benefits.

Prior simulation modeling studies focused mainly on reductions in conflicts with different penetrations of CAVs but did not predict fatalities. While crashes are rare, random events, fatal crashes are roughly 150 times rarer than reported vehicle crashes. Further, the simulation modeling approach assumes that traffic crashes are a function of conflicts. While this is true for the majority of all crashes, it is not true for fatal crashes. Nearly half of South Carolina's fatal crashes involve roadway departure and nearly a third are the result of impaired driving. Many of these fatal crashes are single vehicle crashes where conflicts with other vehicles do not contribute to the fatal crash (SCDPS, 2018).

One of the analysis approaches used in the literature was a meta-analysis where a synthesis of the findings of different studies was used to estimate an overall effect. Because of the diversity in the effectiveness of the technologies for different AV levels, an analysis methodology similar to meta-analysis was chosen for this research.

2.4 General Methodology

The methodology has two main components. The first dissects the typology of contributors to fatal crashes including performing a site characterization of where these fatal crashes occur. The second component is to analyze the distributions of the contributors and site characteristics and then determine how these distributions can be positively affected by the introduction of AVs into the traffic stream.

Fatal crash data from 2019 provides the basis for the analysis. The acquisition and processing of this crash data is discussed in Chapter 3. Site characterization is a major reason why a larger database such as FARS is not used here. Robust site characterization requires detailed analysis of crash reports including narratives by the reporting officer and investigation into the site characteristics where the crash occurred. The site characterization methodology involved using Google Earth and Google Street View to characterize roadway factors that may have contributed to the fatal crashes. Site characteristics include limited sight distance, geometric elements, traffic control and safety devices, and other physical elements (e.g., presence of trees). Much of this information is not available in a crash report.

The crash reduction assessment methodology combines a number of different approaches depending on contributing factors, harmful events, and AV level. For some fatal crashes, improved reaction time may reduce the severity to no fatality or eliminate the crash all together. Literature (Levin and Boyles, 2016) suggests that reaction times are lower for autonomous drivers compared to human drivers. Lower reaction times will result in lower impact speeds which may make the collision survivable. More details on this approach and other approaches are given in the assessment section.

CHAPTER 3

Data Acquisition, Summarization, and Site Characterization

3.1 Sources of Data

South Carolina crash reports (Form TR-310) follow the Model Minimum Uniform Crash Criteria (MMUCC) guidelines (*MMUCC Guideline: Model Minimum Uniform Crash Criteria*, 2012). The crash report includes a variety of characteristics and data elements including crash, person, roadway, and several other data elements. Many of these data elements are uploaded into a digital database. Based on the crash reports, some of the crash characteristics considered for this study include crash type (e.g., angle, head-on, rear-end), first harmful event (FHE), most harmful event (MHE), roadway surface condition (RSC), weather conditions (WCC), light condition (ALC), and contributing factor fields that are analogous to MMUCC contributing circumstances (*SAE Levels of Driving Automation™ Refined for Clarity and International Audience*, 2021). For this research, SCDOT provided 2019 digital crash data. Additionally, the researchers acquired copies of 2019 fatal crash reports from the South Carolina Department of Motor Vehicles (SCDMV). In total, there were 919 fatal crash reports provided. These crash reports included enforcement officer narrative and diagrams not available in the digital files. The researchers also requested and received South Carolina Highway Patrol Multi-Disciplinary Accident Investigation Team (MAIT) reports that were available for over 200 of the 2019 fatal crashes. The digital 2019 crash data were geocoded into ArcGIS based on longitude and latitude and mapped in Google Earth.

3.2 Contributing Factors of Fatal Crashes

There are three major factor categories that contribute to crashes: 1) driver related, 2) roadway related, and 3) vehicle related factors. Table 2 summarizes a data dictionary of selected codes associated with the crash characteristics used to determine contributing factor categories for each crash. Common contributing factors associated with driver-related crashes that are coded into SC crash reports include driving too fast for conditions, failing to yield the right-of-way, running off the road, aggressive driving, and driving under the influence. Harmful events considered to be driver related include wrong side or wrong way, and over-correcting/over-steering. Additionally, several road element codes related to environmental contributors, including obstructions, roadway surface condition, and stationary objects coded as harmful events (e.g., ditches, trees, and utility poles), were classified under the road environment category. Striking traffic control devices was not included as an environmental contributor. Vehicle-related contributing factor codes include mechanical issues, tire blowout/condition, and other defects related to the vehicle.

Table 2: Fatal Crash Data Coding Dictionary Guide (South Carolina Crash Data Dictionary, 2010)

	Driver/Human	**Environmental/Roadway**	**Vehicle**
Harmful Event ▪ FHE ▪ MHE	13= Over-Correcting 16= Under the Influence	Fixed Object: 49= Fence 54= Light Lum. Support 55= Mailbox 56= Median Barrier 58,59= Other Fixed Obj. 60= Tree 61= Utility Pole Natural Elements: 14= Swerving to Avoid Obj. 20,21= Animals 38,39= Other Movable Obj. Roadway Elements: 40,42= Bridge Components 44= Culvert 46,47= Ditch/Embankment	3= Downhill Runaway 4= Equipment Failure 18= Other Non-Collision
Contributing Factor ▪ PRC ▪ OCF1 ▪ OCF2 ▪ OCF3 ▪ OCF4	***16= Under the Influence*** Inattentive: 1= Disregarded Signal 2= Distracted/Inattention 7= Fatigued/Asleep 19= Cell Phone Aggressive Driving: 3= Too Fast for Conditions 4= Exceeded Speed Limit 8= Followed Too Closely 12= Aggressive Driving Violations/ Maneuvers: 5= Failed to Yield ROW 6= Run Off Road 9= Improper Turn 13= Overcorrect. /Oversteer. 14= Swerving To Avoid Obj. 15= Wrong Side/Wrong Way 18= Improper Lane Use/Chg. 28= Other Improper Action	Roadway Elements: 30= Debris 31= Non-Hwy Work 32= Obstruct. In Roadway 33= Road Surf. Condition (Wet) 34= Rut, Hole, Hump 35= Shoulders 36= Traffic Cont. Device (Miss.) 37= Work Zone (Constr./Main.) 38= Worn, Travel Polish. Surf 48= Unknown Roadway Factor 62= Obstruction Non-Motorist: 50= Non-Motor. Inattentive 51= Lying/Illegal In Rdwy 52= Non-Mot. Fail Yield ROW 53= Not Visible (Dark Clothing) 54= Non-Motor. Disregarded 55= Improper Crossing 56= Darting 57= Non-Mot. Wrong Side Road 58= Other Non-Mot. Factor 59= Non-Motorist Unknown 66= Non-Mot. Under Influence 67= Other Person Under Infl. Other: 60= Animal in Road 61= Glare 63= Weather Condition 68= Other Environ. Factor	70= Brakes 71= Steering 72= Power Plant 73= Tires/Wheels 74= Lights 75= Signals 76= Windows/Shield 77=Restraint Systems 78= Truck 79= Cargo 80= Fuel System 88= Other Vehicle Defect 89= Unknown Vehicle Def.

	Other: 10= Medical Related 29= Unknown	69= Unknown Environ. Factor	
Light Condition ▪ ALC		*Covered in contributing factors with dark clothing	
Road Surface Condition ▪ RSC		*If RSC= 2 or "Wet" and Contrib. Factor= 3 or "Too Fast for Conditions"	

Table 3 provides a breakdown of the percentage of the 2019 South Carolina fatal crashes as a primary contributing factor (PCF) or a general contributing factor which includes PCFs and other contributing factors (OCFs). The table indicates that more than half of the 2019 South Carolina crashes happened because drivers were driving too fast for conditions, driving under the influence (DUI), or failed to yield right of way. This suggests that an autonomous driver that is immune to impaired driving and follows all traffic laws all of the time would have a significant positive impact on roadway fatal crashes as long as there are no system failures.

Table 3. Contributing factors and their percentage in the 2019 South Carolina fatal crashes

Element	Contributing Factors	% of fatal crashes (PCF)	% of fatal crashes (PCF & OCF1-4)	Element	Contributing Factors	% of fatal crashes (PCF)	% of fatal crashes (PCF & OCF1-4)
Dri	Too Fast for Conditions	21.4%	24.5%	Ve	Brakes	0%	0.2%
	DUI	20.8%	22.1%		Fuel System	0%	0.1%

	Failed To Yield Right of Way	10.6%	11.2%	Environment	Lying &/Or Illegally in Rdwy	9.8%	11.0%
	Wrong Side/Wrong Way	8.2%	12%		Improper Crossing	1.7%	2.7%
	Run Off Road	4.8%	28.7%		Not Visible (Dark Clothing)	1.2%	5.7%
	Disregarded Sign/Signal	3.3%	3.8%		Non-Motorist Under Influence	1.0%	2.1%
	Aggressive Driving	2.8%	4.7%		Animal In Rdwy	1.0%	1.1%
	Exceeded Speed Limit	2.6%	16.4%		Non-Motorist Failed to Yield	0.4%	0.8%
	Improper Lane Usage/Change	2.3%	2.9%		Obstruction In Rdwy	0.2%	0.2%
	Other Improper Action	1.1%	1.5%		Non-Motorist Wrong Side	0.2%	0.6%
	Medical Related	0.9%	1.0%		Non-Motorist Disregarded	0.2%	0.3%
	Distracted/Inattention	0.7%	5.2%		Other Non-Motorist Factor	0.2%	0.2%
	Fatigued/Asleep	0.4%	1.1%		Obstruction	0%	0.1%
	Improper Turn	0.2%	0.7%		Rut, Hole, Bump	0.2%	0.2%
	Swerving To Avoid Object	0.1%	0.5%		Other Roadway Factor	0.1%	0.2%
	Followed Too Closely	0.1%	0.1%		Road Surface Condition	0.1%	0.3%
	Over-Correcting/Steering	0.1%	3.8%		Weather Condition	0%	0.7%
	Vision Obscured	0%	0.1%		Non-Motorist Inattentive	0%	0.4%
Veh	Tires/Wheels	0.4%	0.7%		Debris	0%	0.3%
	Lights	0.3%	0.5%		Darting	0.3%	0.3%
	Other Vehicle Defect	0.1%	0.1%				

* Veh: Vehicle, DUI: Driving Under Influence, Rdwy: Roadway

Based on the aggregated contributing factor category code assignment, percentages for each combination of contributing factor category pertaining to fatal crashes were calculated for 2019 South Carolina fatal crashes. Venn Diagram percentages (N=919) are summarized in Figure 2. As indicated in Figure 2, driver-related factors play a significant role in the majority of 2019 SC fatal crashes. The driver contributes to 86% of fatal crashes combined, with more than 59% of fatal crashes being attributed solely to the driver. Additionally, environmental contributing factors contribute to nearly 40% of fatal crashes. Lastly, vehicle factors contribute to only 1.5% of fatal crashes. While this driver contribution of 86% of fatal crashes is significant, it is actually lower than the driver contribution for all crashes in South Carolina (94.9) (Stanley, 2021), and values found for all crashes on previous studies (93% and 95%) (Treat et al., 1979; Highway Safety Improvement Program Manual- Safety: Federal Highway Administration, 2010). This is an indication of the significance of the contribution of the environment to fatal crashes—especially with regard to at-fault pedestrians.

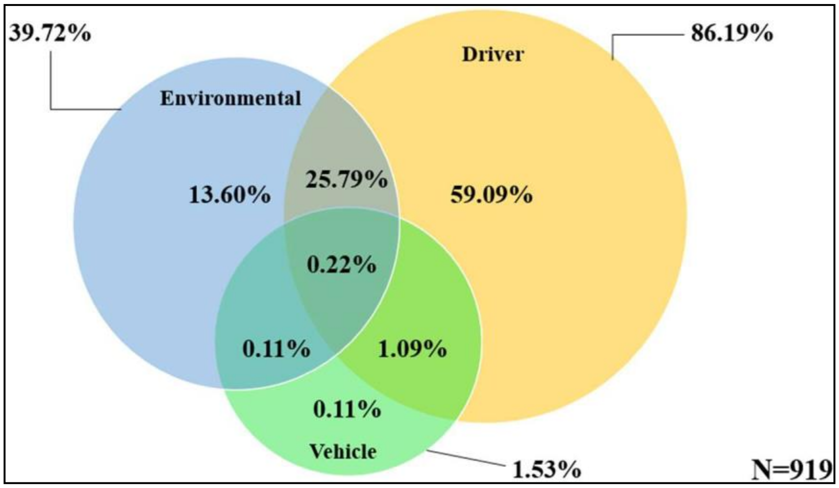

Figure 2: 2019 SC Fatal Crash Contributing Factor Venn Diagram (N=919).

3.3 Analysis of Fatal Crash Site Characteristics

The fatal crash reports and MAIT studies were examined to identify any site characteristics that may have contributed to the crash but were not coded in the reports. Investigating officer narratives and sketches were used in this analysis. Of particular interest were curve details and fixed objects within clear zones. For crashes in which curves potentially contributed to the crash, the estimated curve design speed was calculated by taking measurements within Google Earth. Google makes no claims to the accuracy of Google Earth maps, however based on information from the web, relative accuracy of about 3' per 1000' feet can be expected at the highest resolution. Equation 1 is used for estimating design speed for high-speed curves (AASHTO, 2018).

$$R = \frac{v^2}{15(e+f)} \quad (1)$$

Where R is the radius of the curve, v is the design speed, e is the design superelevation rate and f is the design friction coefficient. Design speed can be solved for by substituting values for R, e, and f. Design friction coefficients (f) are a function of speed and were retrieved from AASHTO design guidelines (AASHTO, 2018). A conservative value of 0.04 (4%) was used for superelevation (e).

To estimate curve radius, a chord length (*C*) and middle ordinate distance (M) are measured in Google Earth relative to the vehicle trajectory along the center of the travel lane (see Figure 3). The actual long chord (LC) is not needed to estimate radius. Only a chord along the curve is required. Ideally, a chord length as long as possible is preferred to minimize error, however it is difficult to precisely estimate the location of a curve's point of curvature (PC) and point of tangency (PT). The curve radius can be estimated using the Pythagorean Theorem with the variables identified in Figure 4, and by using Equations 2 and 3.

$$R^2 = (R - M)^2 + (\frac{C}{2})^2 \quad (2)$$

$$R = \frac{1}{2}M + \frac{C^2}{8M} \quad (3)$$

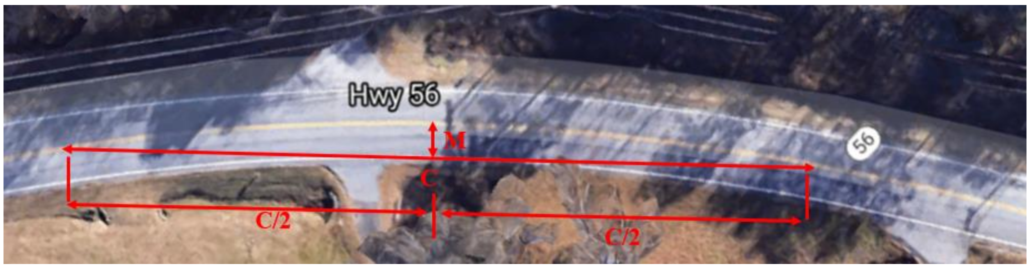

Figure 3: Chord length (*C*) and middle ordinate distance (M) measured in Google Earth

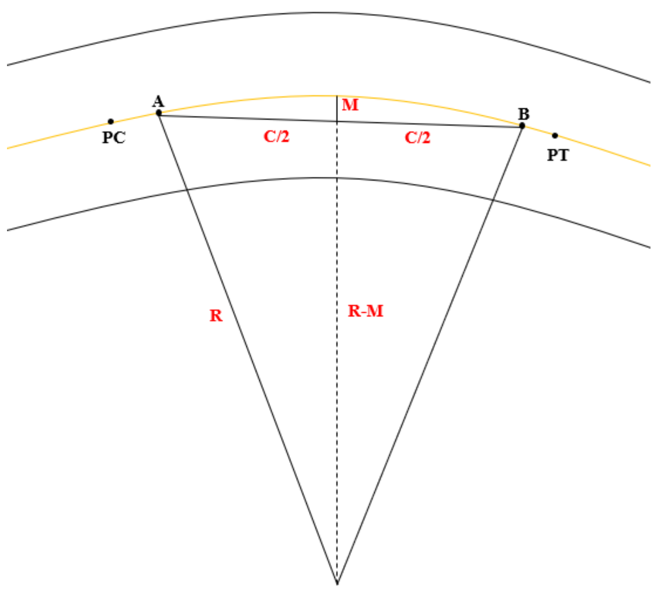

Figure 4: Curve radius estimation method

A fixed object that contributed to the fatal crash was located and its lateral distance from the edge of the travel lane was measured to determine if the object was in the roadway's clear zone. Suitable clear zones were based on the AASHTO design criteria (AASHTO, 2018).

In total, 188 crashes were coded by the officers as occurring on curves; however, the researchers could identify only 175 fatal crashes where a curve actually contributed. The discrepancy was due to miscoding. The researchers checked the radius and design speed of those curves and found that 24% (42) had a design speed less than the speed limit. And 47% (82) of the curves had a design speed less than 5 mph above the speed limit. Prior research on operating speeds indicates that drivers tend to drive at least 7-10 mph above the posted speed limit. With design speeds below or right at the posted speed limit, excess speed can become problematic. A statistical analysis of the 2019 fatal crash data indicates that a driver who is not speeding is 1.7 times more likely to be involved in a fatal crash if the design speed is less than the speed limit. This suggests that a driver might assume that they are traveling at a safe speed if they do not exceed the speed limit, however they still might be driving too fast for the conditions when maneuvering a tight curve. Adjustments were made to the contributing factor information based on the site characterization analysis to ensure that the AV assessment is based on accurate crash data. It is noteworthy that fully autonomous AVs (levels 4 and 5) leverage up to date spatial information including terrain and geometric alignment that can be used to ensure that the vehicle is driving at safe speeds to negotiate tight curves.

CHAPTER 4

Assessment of Automated Vehicle Impacts

This chapter discusses the assessment of impacts of different AV levels on fatal crash contributing factors and the corresponding reduction in fatal crashes that could potentially be experienced. The analysis used in assessing AV impacts on fatal crashes resulted in further categorizing contributing factors in terms of how they would be impacted for different AV levels. A detailed discussion on these categories and each analysis follows the discussion on assumptions in the next section.

4.1 Assumptions

The assessment of AV impacts on fatal crashes required the researchers to make a number of assumptions. While some of these assumptions will seem perfectly reasonable, others are ambitious. The goal of this research is to estimate fatal crash reduction assuming “ideal conditions” to determine what is possible if AVs work exactly as designed in all situations. An overall underlying assumption is that the maximum impact of a safety application on different contributing factors of a fatal crash can determine whether the fatal crash can be eliminated, or the severity decreased. The result is not necessarily binary when considering each fatal crash individually (e.g., fatal crash or not fatal crash). In some instances, a probability is calculated depending on the crash characteristics and the estimated ability of AVs to reduce the crash. Thus, if it is determined that a fatal crash’s reduction is 40% due to an AV safety impact, then that fatal crash becomes 0.6 fatal crashes. This is done for all fatal crashes for each of the AV levels and the remaining fatal crashes are summed. This “after” total is compared with that actual number of 2019 fatal crashes (919) to estimate the impact of AV for each level. The following are general assumptions used in the assessment.

1. When evaluating the fatal crash reduction effects of each AV level, 100% market penetration is assumed. This assumption allowed the team to isolate the effects of that particular AV level. In reality, there will likely be a mix of AV levels on the road. A probabilistic weighting approach may be suitable for predicting the effects of a mixed vehicle population, but this was not considered in this research.
2. In recent years, there have been a number of severe and fatal crashes that can be attributed in whole or in part to a failure of an AV safety application. This research

assumes that there will be no such failures and that all safety applications/automation work exactly as intended without any error or defect. While this is idealistic, AV systems will undoubtedly improve over time as we learn from system failures.

3. If there was a bicycle, motorcycle, or a truck as a primary unit in a crash, the effects of AVs were not calculated because of the lack of literature for developing a methodology.
4. Since there is uncertainty about the performance of level 4 AVs in the future (Litman, 2022; Sundararajan, Zohdy and Hamilton, 2016), this research assumes two possible scenarios. The first scenario (S1) assumes that these vehicles' autonomous driving system works only in dry weather, which corresponds to the following weather condition codes identified in the South Carolina crash data dictionary (*South Carolina Crash Data Dictionary*, 2010): 1. clear, no adverse conditions, 2. cloudy, 3. fog, smog, smoke, and 4. severe cross winds, high wind (*South Carolina Crash Data Dictionary*, 2010). The second scenario (S2) assumes that the level 4 AV works in both dry and rainy weather but not snowy weather. Since there were no fatal crashes in snowy weather in South Carolina in 2019, the second scenario (S2) works exactly the same as level 5 AVs in decreasing the number of fatal crashes. Thus, just level 4 vehicles working in the first scenario (S1) are evaluated here.
5. Level 3 highway pilot systems only work in non-congested conditions with the following limitations. First, the operational speed must be between 50 mph and 80 mph (Cho and Hansman, 2020). Second, the highway pilot system can only work on dry roadway surfaces, during daylight hours, with dry weather conditions (similar to S1 in level 4 vehicles) (Kremer *et al.*, 2021). For this research, it is assumed that level 3 highway pilot will be used only on restricted access roads such as interstate freeways if weather conditions are met. While this may not be conservative—in reality, drivers may choose not to use highway pilot in these situations—the researchers are taking a conservative approach in assuming that highway pilot will not be used on rural highways.
6. Automatic Emergency Braking exists in all levels of AVs. Consequently, all AVs can use their AEB system to reduce their speed in 1) fatal pedestrian crashes (using pedestrian AEB) and 2) rear-end collisions. It is assumed that this system has the same performance in all levels of AVs.

7. Level 1 AVs are equipped with warnings and AEB and either LKA (subcategory L1a) or ACC (subcategory L1b) but not both. Level 2 AVs are equipped with both. Some Level 2 vehicles, such as Teslas, may have hands free steering in some situations however this capability is not assumed to lower fatality rates based on manufacturer guidelines.

4.2 Contributing Factors Categories and Assessment

As discussed in Chapter 3, each of the 2019 South Carolina fatal crashes have one or more contributing factors that can be categorized as driver, environment, or vehicle. The analysis used in the assessment resulted in further categorizing contributing factors in terms of how they would be impacted for different AV levels. Seven different categories (A-G) were developed and are discussed in the following subsections.

4.2.1 Category A (Driver Related): 100% of fatal crashes are eliminated.

Category A contributing factors assume that all fatal crashes associated with the contributing factor can be eliminated. AVs are equipped with Automated Driving Systems (ADS) that include different sensors. By knowing their position on a roadway using GPS along with roadway attribute information stored in a spatial database, location-based speed limits can be determined. These systems can also use sensors such as cameras to detect traffic control devices such as speed limit signs. Safe speeds that may even be lower than posted speed limits can also be ascertained using sensed or accessed roadway geometry, sight distance, and terrain information (Varghese and Boone, 2015). The underlying assumption is that fully autonomous AVs will always operate at a safe speed. Thus, all fatal crashes with too fast for conditions or exceeding speed limit contributing factors are eliminated in level 5 AVs and also for select fatal crashes involving level 3 and level 4 AVs if they are driving autonomously. Category A also applies to many other driver-related contributing factors including DUI, aggressive driving, medical-related, distracted/inattention, disregarding a sign/signal, fatigued/asleep, failed to yield the right of way, improper turn, improper lane usage/change other improper action if the vehicle is driving autonomously (level 5 and select level 4 and level 3 fatal crashes).

4.2.2 Category B and C: 0% of fatal crashes are eliminated.

Category B assumes that the fatal crashes associated with the contributing factor cannot be eliminated. Fatal crashes where vehicle defects are a contributing factor are rare and unpredictable. This research assumes that these fatal crashes cannot be reduced or eliminated with AV technology in any level of AVs unless there are other contributing factors (Category B).

Category C assumes that the elimination/reducing the impact of the fatal crash associated with the contributing factor cannot be determined based on the current knowledge and literature review about AVs. These include animal in roadway, obstruction in roadway, rut, hole, and bump (Giarratana, 2016).

4.2.3 Category D: Pedestrian fatal crashes (Environment Related): Fatal crash reduction is variable

Category D contributing factors relate to crashes involving pedestrians and assumes that the probability of a pedestrian fatality can be changed with pedestrian AEB which is included in all AV levels. The approach to determine AV impacts on pedestrian fatal crashes is based on a study by Rosen and Sander (2009). They worked on the "German In-Depth Accident Study (GIDAS)" that included 490 pedestrian crashes from 1999 to 2007. Richards (2010) used logistic regression and proposed an S-curve graph for the probability of a pedestrian fatality versus vehicle speed. For this research, an S-curve equation was applied to crash data for each at-fault pedestrian crash where a 100% probability of pedestrian fatality occurrence equals the estimated collision speed reported in the fatal crash report. The original estimated collision speed was used from 2019 South Carolina fatal crash reports. Then, the following deceleration formula was used to calculate the impact of AEB on reducing the speed of an AV for that crash.

$$v_f = v_i + at \quad (4)$$

Where $v_i, v_f, a,$ and t are initial speed, final speed, acceleration/deceleration rate, and time. We assumed that the deceleration rate in emergency braking is the same for both regular and AVs and is equal to 8 m/s^2 (26.25 ft/s^2) (Kudarauskas, 2007). The reaction time for AVs is assumed to be 0.5 seconds (Khoury, Amine and Saad, 2019; Levin and Boyles, 2016). For typical drivers, reaction time varies by age. Driver age data in the crash reports was not available to the researchers. Thus, SC Census data was used to estimate the distribution of drivers' ages who were involved in fatal crashes. Using estimated reaction times from Wood and Zhang (2017) and the SC driver age distribution, a weighted average reaction time of 2.05 seconds was calculated and used in the analysis. This resulted in an average reduction in reaction time of 1.55 seconds (2.05 – 0.50) using AEB. Thus, the AV speed at collision can be calculated by:

$$v_2 = 1.467 * (v_1 - (1.55 * 26.25)) \tag{5}$$

Where v_1 is the estimated collision speed (ft/s) and v_2 is the reduced speed (mph) using AEB. If the reduced speed is zero, there will be no pedestrian collision. For speeds greater than zero, the probability of pedestrian fatality is calculated using Equation (6). This equation is based on the S-curve graph from Richards, (2010).

$$prob_{pedestrian\ fatality} = \frac{1}{1 + e^{\frac{\left(0.5 - \frac{v_2}{v_1}\right)}{0.0923}}} \tag{6}$$

Where $prob_{pedestrian\ fatality}$ is the probability of pedestrian fatality. As mentioned before, this equation was used to calculate the probability of a pedestrian fatality in each crash associated with pedestrians.

4.2.4 Category E: AEB Engaged (Driver): Fatal crash reduction is variable

Category E assumes that the impact of the fatal crash associated with contributing factors following too closely, and wrong side/wrong way can be decreased using the AEB systems which works for all levels. This methodology only applies to rear-end crashes or head-on crashes because research found little to no safety benefit of AEB in angle crashes/failure to yield (Doecke *et al.*, 2014).

Equation (7) was fitted to an S-curve graph from Richards's (2010) study to estimate the probability of a fatality given the speed of impact considering the speeds and directions of the vehicles and reduced speeds due to AEB engaging.

$$prob_{\ fatality} = \frac{1}{1 + e^{\frac{\left(0.5 - \frac{\Delta v_2}{\Delta v_1}\right)}{0.1}}} \tag{7}$$

This equation was applied to all rear-end and head-on collisions regardless of other contributing factors. Recall that only the contributing factor that experiences the greatest AV benefit is considered in the final calculation of reduced fatal crashes. Category E also applies to situations where ACC is engaged.

4.2.5 Category F: Warnings

Category F assumes that the impact of a fatal crash associated with a contributing factor can be decreased based on warning systems (lane departure, driver drowsiness alertness, FCW, RCW, blind spot monitoring, and curve-adaptive headlights) present at any automation level. Unless the accident happens in the first few minutes of the drive, the vehicle is able to assess a driver's alertness and if a collision is impending and give warnings to alert the driver to take action. Thus, this category assumes the elimination of certain fatal crashes associated with at least one of the following contributing factors fatigue/asleep, distracted/inattention, exceeded speed limit, and medical related, on a case-by-case basis looking at all crash contributing factors, estimated speed at collision, speed limit, and others factors based on reduction rates in the literature.

4.2.6 Category G: LKA

LKA uses a lane departure sensor to check the position of vehicles and turn the steering wheel toward the lane or brake if it is moved out of the lane (*Driver Assistance Technologies*, 2016). A study conducted in Finland (Utriainen, Pollanen and Liimatainen, 2020) considering four vehicle manufacturer LKA technologies, estimated that LKA could prevent 27% of head-on and single-vehicle fatal crashes, or 30% of single-vehicle and 24% of head-on crashes to be more exact. The assumptions of the study included fully visible lane markings, and favorable driver input and weather for the LKA operation. LKA is effective from 5 mph to 124 mph, depending on the car manufacturer. In this category, the effectiveness of LKA for fatal crashes in SC was based on the percentages of the aforementioned study on a case-by-case basis when the contributing factors included improper lane usage/change, wrong side/wrong way, or run off road.

4.2 Results and Discussion

Table 4 summarizes the fatal crash reduction categories associated with the various contributing factors of fatal crashes. The table is broken down by AV level and includes many cases where multiple categories may apply (e.g., A or B). The applicable category is dependent on the characteristics of each crash.

Using information provided in Table 4, the researchers applied the relevant category crash reduction algorithms to the 2019 South Carolina (SC) fatal crashes and determined the estimated fatal crash reduction for each AV level. The results of this are presented in Table 5. The table shows that there are three distinct tiers of AV impacts on fatal crashes: 1) Full automation (L4 and L5); 2) Driver in full or almost full control with AV assistance (L1 LKA, L2, L3); and 3) Driver in full control with limited AV assistance (L1 ACC). By far the greatest impact on fatal crashes occurs in the first tier where vehicles are operating fully autonomously without any human influence. In this case, driver errors are eliminated and reaction time is improved considerably. For automation level 4, two scenarios were examined. The percent reduction in level 4, scenario 2 (S2) is the same as in level 5 because there were not any fatal crashes in snowy weather in SC in 2019. The 53 additional fatal crashes in level 4 S1 are because of weather conditions where driver intervention is required. For the second tier, the percent of fatal crash reduction decreased dramatically compared to the fully autonomous tier. There was not a lot of difference in fatal crashes in the AV levels included in the second tier. The primary difference in fatal crash reduction between level 2 and level 3 is the reduction in freeway fatal crashes experienced when level 3 vehicles are operating in full automation. For level 1, results indicate that LKA is more effective at reducing fatal crashes compared with ACC. In fact, there is very little difference in the fatal crash experience between L1 (LKA) and L2 or even L3 which is what the three levels are lumped together in tier 2. Tier 3 only includes ACC. Note that all levels include AEB.

Table 4 Fatal crash reduction categories and associated contributing factors for different AV levels

Aspec	**Contributing Factors**	**Level of automation**				
		L1*	**L2**	**L3**	**L4**	**L5**
Driver	Too Fast for Conditions	B or E	B or E	A or B or E	A or B	A (100%)
	DUI	B or E	B or E	A or B or E	A or B	A (100%)
	Failed to Yield Right of Way	B or E	B or E	A or B or E	A or B	A (100%)
	Wrong Side/Wrong Way	E	E	A or E	A or E	A (100%)
	Run Off Road	G or B or E	G or B or E	A or G or B or E	A or G or B	A (100%)
	Disregarded Sign/Signal	B or G	B or G	B or G	A or B	A (100%)
	Aggressive Driving	B or E	B or E	A or B or E	A or B	A (100%)
	Exceeded Speed Limit	B or E	B or E	A or B or E	A or B	A (100%)
	Improper Lane Usage/Change	B or G or E	B or G or E	A or B or G or E	A or B or G	A (100%)
	Other Improper Action (Driver)	B or E	B or E	A or B or E	A (100%)	A (100%)
	Medical Related	B or E	B or E	A or B or E	A or B	A (100%)
	Distracted/Inattention	F or E	F or E	A or F or E	A (100%)	A (100%)
	Fatigued/Asleep	F	F	F	A (100%)	A (100%)
	Improper Turn	C (0%)	C (0%)	C (0%)	A (100%)	A (100%)
	Swerving To Avoid Object	C (0%)	C (0%)	C (0%)	A (100%)	A (100%)
	Followed Too Closely	B or E	B or E	B or E	A (100%)	A (100%)
	Over-Correcting/Steering	C (0%)	C (0%)	C (0%)	A (100%)	A (100%)
Vehicle	Tires/Wheels	B (0%)	B (0%)	B (0%)	B (0%)	B (0%)
	Lights	B (0%)	B (0%)	B (0%)	B (0%)	B (0%)
	Other Vehicle Defect	B (0%)	B (0%)	B (0%)	B (0%)	B (0%)

Environmental/Roadway	Lying &/Or Illegally in Roadway	D	D	D	D	D
	Improper Crossing	D	D	D	D	D
	Not Visible (Dark Clothing)	D	D	D	D	D
	Non-Motorist Under Influence	D	D	D	D	D
	Non-Motorist Failed to Yield	D	D	D	D	D
	Non-Motorist Wrong Side	D	D	D	D	D
	Non-Motorist Disregarded	D	D	D	D	D
	Other Non-Motorist Factor	D	D	D	D	D
	Animal in Roadway	C (0%)	C (0%)	C (0%)	C (0%)	C (0%)
	Obstruction in Roadway	E	E	E	E	E
	Rut, Hole, Bump	C (0%)	C (0%)	C (0%)	C (0%)	C (0%)
	Other Roadway Factor	B (0%)	B (0%)	B (0%)	B (0%)	B (0%)
	Road Surface Condition	B (0%)	B (0%)	B (0%)	B (0%)	B (0%)
	Darting	B (0%)	B (0%)	B (0%)	B (0%)	B (0%)

*L1 AVs are either equipped with LKA or ACC.

Table 5: Number of fatal crash reduction in SC for each vehicle autonomation level

Level of AV	% of Fatal Crash Reduction	Number of Fatal Crash Reduction (out of 919)
Level 5	94.8%	871
Level 4 – Scenario 2 (S2)	94.8%	871
Level 4 – Scenario 1 (S1)	89.1%	818
Level 3	31.0%	285
Level 2	23.1%	213
Level 1a (LKA)	23.0%	212
Level 1b (ACC)	10.4%	97

From an AV standpoint, there are not many recommendations that can be made with regard to South Carolina except for better education about the benefits of autonomous vehicles. And while all levels provide some benefit in terms of fatal crash reduction, the quest for target 0 fatal crashes can only be achieved if all vehicles operate fully autonomously. Even then, over 5% of fatal crashes would remain. This is because AVs cannot react instantaneously in the event of an animal, pedestrian, or bicyclist moving into the path of a vehicle without any time to react. If AV is combined with connected vehicle and/or connected infrastructure, the AVs can potentially be alerted to pedestrians and animals in the area. An alert condition combined with lower speeds may be able to increase the % reduction of fatal crashes across all AV levels.

CHAPTER 5

Conclusions

AVs have the potential to induce a paradigm shift in the ground transportation system. This research focused on how 2019 South Carolina fatal crash data could be hypothetically impacted by different scenarios of AV safety applications. The detailed review of contributing factors of 919 2019 fatal crashes in SC along with a review of site characteristics for each crash was conducted and a deterministic approach was used to calculate the effects of different AV levels on each individual fatal crash. This research found that as much as 95% of the 2019 SC fatal crashes could have been avoided with 100% penetration of level 5 AVs on our roadway network and about 23% of fatal crashes if the vehicle is not driving autonomously but provides intervention with AV safety technologies such as AEB, ACC, and LKA. Between sequential AV levels, the largest difference in fatalities was estimated to be between levels 3 (31%) and 4 (89-95%) where the latter is anticipated to need driver intervention only based on weather conditions (rainy weather for the lower end of the range). Within automation level 1, for this crash data set, LKA was estimated to reduce approximately twice the fatalities as ACC. This research assumes that there will be no fatal crashes attributed to AVs and that all safety applications/automation work exactly as intended without any error or defect. While this is idealistic, AV systems will undoubtedly improve over time as we learn from system failures.

Technological advancement has brought AVs into reality and there is a likelihood that relationships between vehicles and drivers are likely to be reversed significantly in the future. With over 86% of 2019 South Carolina fatal crashes being caused in whole or in part by the driver, giving the vehicle more responsibility in the driving task promises to go along way into making Target Zero safety initiatives a reality.

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