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CHARACTERISTICS AND CONTRIBUTING FACTORS OF EMERGENCY VEHICLE CRASHES

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Industrial Engineering

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by
Naji Abdelwanis
December 2013

Accepted by:
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ABSTRACT

The purpose of this study is to determine the contributing factors and characteristics associated with emergency vehicle crashes in order to generate insights about the emergency crashes.

This dissertation consists of three approaches to address the purpose. In the first analysis a binary logistic regression model was used to identify the critical factors associated with EV crashes that resulted in fatality compared to those that did not. Crashes at intersections, ambulances, drivers older than 50-years-old, and straight movement were significantly related to EV fatal crashes. The results suggest that drivers older than 50-years-old are more likely to be involved in fatality crashes than younger drivers for the emergency drivers which are different from the prior studies which demonstrated that younger drivers tend to be more likely to involve in vehicle crashes than older drivers for the general population.

In the second analysis, an ordered regression model was used to identify critical factors that contributed to the severity of injuries that EV occupants experience in crashes as well as the effect of driver distraction and driver fatigue on the severity of injury in EV crashes. The analysis found that male occupants are less likely to be severely injured in emergency crashes. Additionally, emergency occupants are more likely to be more severely injured when the vehicle speed exceeded 50 mph. Regardless of vehicle type or crash type; occupants in the front of the vehicles were more likely to be severity injured. Seat belt use was associated with emergency vehicle occupants being 4.17 times more likely to have less severe injuries. The result suggests that when the emergency crashes

occurred at a stop sign or traffic signal, the vehicle occupants were more likely to be severely injured. Head-on collisions were more likely to result in severely injured occupants than all other crash types. Occupants who were involved in emergency crashes with fatigued, sleepy, or distracted drivers were also more likely to be severely injured. Nighttime emergency crashes were more likely to result in more severely injured occupants. Crashes that occurred on curved road were more likely to lead to severely injured occupants. This analysis also demonstrates that emergency vehicle drivers are susceptible to similar effects of driver distraction and fatigue on crash types and safety outcomes that other commercial drivers and non-commercial drivers experience.

The third analysis employed a multinomial logit model was used to identify the disparities among types of EV (e.g., police, ambulance, and fire trucks) in terms of the types of crash. The differences in the manner of collision for the EV has been considered in order to evaluate the influence of the common factors such as environmental factors, driver behavior, vehicle type, and crash description on crash types of EV. The result of this analysis suggest that intersections, curved roads, crash time between (12-6 PM), and estimated speed of 50 MPH or more were significantly associated with EV crashes. Head-on collisions were more likely associated with fatality than the angular and single vehicle collisions, which supports what has been demonstrated in previous analysis. The results also suggest that EV were more likely to be in head-on collisions in urban areas than single vehicle collisions, and were more likely to be in angular collisions than single vehicle collisions in urban areas. In daylight, EVs were less likely to be in single vehicle collisions when compared to angular collisions, and less likely to be single vehicle collisions than head-on collisions. This analysis also suggests that police cars were more likely to be in single vehicle collisions than angular collisions and head-on collisions. EVs were more likely to be in angular collisions when compared to head-on collisions at intersections, and were more likely to be in angular collisions when compared to single collisions at intersections. When an EV driver was distracted, the EVs were more likely to be in head-on collisions than in single vehicle collisions, and were more likely to be in angular collisions than in single vehicle collisions. On dray road, EV were more likely to be in head-on collisions when compared to single vehicle collisions, and were more likely to be in angular collisions when compared to single vehicle collisions on dry roads.

This dissertation contributes to the literature related to safety transportation by identifying the critical factors associated with emergency crashes. The analyses presented in this dissertation have identified several significant factors that are associated with emergency crashes in terms of fatal crashes, injuries sustained in these crashes, and the crash type. Interestingly, these results show some disparities from what would be expected based on the existing literature. The first analysis suggests that intersection, ambulance, seat belt use and speeding were similar to what have been addressed in the literature. The results of this study suggest that drivers older than 50-years-old were more likely to be involved in fatality crashes than younger drivers for this particular group from the general drivers' population. Additionally, weather, road surface condition, and light condition were not significantly related to emergency fatal crashes in SC which is different from the other studies. The second analysis found that variables such as occupant's gender, speed, seatbelt usage, distraction, driver fatigue or sleep, weather, curve road, head on collision and time of the crash were significantly contributed to severity injury resulted from EV crashes. This finding was similar to previous studies.

However, variables such as occupant age, vehicle type, occupant setting positions and rural/urban locations were not significantly related to severity injury in emergency vehicle crashes, which contradicts what has been shown in prior studies. The prior studies suggested that angular collisions are more likely to result in more severities, however, this results illustrate that head-on collisions were 2.39 times more likely to result in severely injured occupants than other crash types. Results also suggest that front occupants are more likely to be severely injured in EV crashes, which differs from prior studies that suggest rear occupants are more likely to be severely injured in EV crashes. This analysis also shows that occupants riding in an EV with a distracted, fatigued, or sleepy driver were more likely to be severely injured which have not addressed before in emergency literature.

The third model analysis provides insight about three common crash types (head-on collisions, angular collisions and single vehicle collisions) involving EVs, which have not been evaluated yet in the prior studies in this field. The results of multinomial logit support what has been demonstrated in second analysis, which suggested that head-on collisions were significantly associated with severity of injury in EV crashes. Head-on collisions were shown to be more likely associated with fatality than the angular and single vehicle collisions. Additionally this analysis suggests that if the driver is distracted then the EVs were more likely to be in head-on collisions. The results also suggest that EV were more likely to be in angular collisions than head-on collisions at intersections, and were more likely to be head-on collisions than single vehicle collisions. This analysis is the first research been conducted to determine the effect of variables such environmental conditions, crash descriptions, vehicle attributes, road features on EV crash types. This analysis might provide insights about latent factors associated with high risk of EV crash types.

In conclusion, in additional to what has been demonstrated in prior studies, the results of this dissertation suggest that factors such as distractions, fatigue and sleepiness, and head-on collisions are significantly associated with EV crashes. Further research should be built on this dissertation to evaluate what types of distractions significantly influence EV crashes as well as the relation between distraction and EV head-on collisions. Schedules of EV drivers also might need to be explored to identify the causes of fatigue and sleepiness among EV drivers. Even though several studies have been conducted to determine the critical factors that contribute to ambulance crashes in rural areas, more evaluation of those factors might be still needed.

DEDICATION

I would like to dedicate my dissertation to the soul of my father Shoaib Abdelwanis who always stood with and supported my dream to purse my PhD in the United States of America. He passed away just one week after I arrived to the USA. Your memory always inspires me to succeed. Thanks for all you have done for my family and me. May Allah accept you amongst his beloved servants and forgive all your small and big sins. May Allah rest your soul in peace and grant you the best place in Paradise. Ameen.

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I am truly blessed to have such a wonderful and devoted family, and without them I would not have been able to achieve this wonderful accomplishment. My sincerest gratitude to my wonderful wife Naaima, for standing with me through both the good and the difficult times, and helping to keep me and our beloved children always happy and upbeat. I must express my deep appreciation to my beloved children (Ayaa, Ala, Mohamed and Ahmed) for all the sacrifices they made in support of their father. I deeply appreciate your heartwarming care and love that helped me preserve through any

difficulties. I am proud to have such an incredible family. May God bless and bring peace, pleasure and prosperity to all of you.

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CHAPTER ONE: INTRODUCTION

Scope

Safety while in transit remains one of the most important challenges that face the emergency response domain. There has been a substantial focus on emergency transportation in the literature, yet the rate of emergency vehicle crashes remains high (Burke et al., 2001; Custalow and Gravitz, 2004; Maguire et al., 2002; Sanddal et al., 2010). Emergency vehicles (EVs) include police cars, ambulances and fire trucks, but can also include other more specialized vehicles. The objectives of this research are to analyze EV crashes to determine crash risk factors and resulting crash-related injury severity under different driving conditions in order to better understand and evaluate the risks associated with emergency response crashes.

Vehicle crash data in South Carolina (SC) from 2001 to 2010 reported by Department of Public Safety were used for this dissertation. The database contains variables related to environmental conditions, crash descriptions, vehicle attributes, road features, and person descriptions for every crash. South Carolina represents a relatively small proportion of the U.S. population, but is over represented in terms of crashes and crash related fatalities (NHTSA, 2007). The South Carolina Department of Public Safety maintains a database of all crashes that resulted in a police report which included an injury or at least 1,000 dollars property damage.

The results of this dissertation help to address the critical factors associated with EV crashes. In addition, these results could have significant impact on reducing severities and fatalities associated with emergency vehicle crashes. Furthermore, these findings can be used to develop new guidance for decisions related to emergency transportation safety.

Significance and broader impacts

In addition to impeding the ability of EVs to respond to emergencies, emergency vehicle crashes (EVCs) have a great impact on US economy. In 2000, the total cost of EVCs has been estimated to be about 230.6 billion dollars (Blincoe, et al., 2002; Census, 2006). According to the National Highway Traffic Safety Administration (NHTSA), the number of people killed in vehicle crashes has declined from 33,883 people in 2009 to 32,885 people in 2010 (NHTSA, 2010). However, the number of people injured in vehicle crashes has increased to 2.24 million in 2010 from 2.22 million in 2009 (NHTSA, 2010). Several studies showed that the use of seat-belts has reduced the number of fatalities and injuries by preventing the vehicle occupants from hitting inside the vehicle or being ejected out from the vehicle (Abbas, Hefny, and Abu-Zidan, 2011; Cummings, 2002). Seatbelts and airbags mitigate injury severity in crashes, which results in a greater number of injuries and fewer fatalities (Crandall, Olson, and Sklar, 2001). Alcohol consumption, speeding, and not wearing a seatbelt continue to be associated with crashes that cause injuries and fatalities, which cost the U.S. economy about 141 billion dollars in 2000 (Blincoe et al., 2002; Yau, 2004). The cost associated with emergency medical crashes is estimated at about 500 dollars million each year in the U.S. (Eckstein, 2004; Heyward, Stanley, and Ward, 2009). Additionally, the costs of firefighter line of duty deaths have been estimated at between $900,000 and $1.2 million per incident (Sanddal, Albert, Hansen, and Kupas, 2008). Therefore, it is important to evaluate the crash factors associated with EVCs in order to understand how to mitigate the severity among both occupants and vehicles' crews, and thus, decrease the cost of crash sequences.

CHAPTER TWO: LITERATURE REVIEW

Past research has classified crash characteristics into categories such as environmental factors, driver behavior, vehicle type, and crash description (Bédard, Guyatt, Stones, and Hirdes, 2002; Maguire, 2011; Romano, Peck, and Voas, 2012; Slattery and Silver, 2009). These factors, which are related, have different impacts on vehicle crashes. Environmental characteristics include crash location, weather, road and light conditions. These environmental factors usually impact driver behaviors based on aspects such visibility, ability to control the vehicle, and work zones. Driver behaviors are related to the driver's characteristics (e.g., demographic and physiological factors) that affect the driver's performance on the roads. Vehicle type is also an important factor to consider, as it provides insights about which types of vehicles are more likely to be involved in crashes. Crash descriptions provide information that can be used to identify the contributing factors to the crashes.

Environmental Crash Characteristics

Characterizing the nature and circumstances of vehicle crashes may provide insights that lead to a better understanding of crashes and may lead to improved infrastructure and safety interventions. Many studies have identified environmental crash factors as weather conditions, time of the crash, day of the crash, road surface conditions, traffic density, and lighting conditions (Lam, 2004; Maguire, 2011; Ray and Kupas, 2005). Adverse weather may affect a driver's visibility and maneuverability to control the vehicle which may lead to crashes (Mueller and Trick, 2012; Qiu and Nixon, 2008). Morgan and Mannering, (2011) found that female drivers 45-years-old or older were more likely to be injured when they involved in vehicle crashes that took place on wet, snow, or ice roads, while male drivers 45-years-old or older were less likely to be injured. Previous studies have demonstrated that fatigue, drowsiness, alcohol, and poor visibility are critical factors related to night crashes, which makes night time driving more risky than the daytime driving (Chipman and Jin, 2009; Williamson, Feyer, Mattick, Friswell, and Finlay-Brown, 2001). According to Lord, Manar, and Vizioli, (2005) as the vehicle occupancy ratio and traffic density increase the risk of crashes increases. Therefore, understanding these factors and how they contribute to vehicle crashes is important to identify which critical factors lead to emergency crashes.

Characteristics of Rural and Urban Crashes

Although the transportation related fatality rate has been declined recently in the U.S. the number of fatalities in rural crashes is still high (Clark and Cushing, 2004). Speeding and not using seatbelts have a substantial role in this issue (Zwerling et al., 2005). Another factor that may contribute to a higher fatality rate may relate to the distance between the crash location and trauma center (Zwerling et al., 2005). Rural crashes tend to occur with vehicle striking fixed objects, on narrow roads without shoulders, unlit roads, on snow-covered road, at T-intersections and in adverse weather. In addition, rural crashes are more likely to be head-on crashes (Heyward et al., 2009; Ray and Kupas, 2007; Zwerling et al., 2005). Compared to rural crashes, urban crashes are more likely to occur in rain, on wet roads, with streetlights, at intersections, at traffic signals and involve more vehicles, and rear-end or angular collisions (McCartt, Northrup, and Retting, 2004; Ray and Kupas, 2007). Head-on crashes occur in rural areas more than urban areas because traffic streams are not always divided (Ray and Kupas, 2007; Zwerling et al., 2005). Vehicle crashes in rural areas are more likely to occur in poor lighting roads (Abdel-Aty, Ekram, Huang, and Choi, 2011). Poor lighting might increase the likelihood of vehicle crashes in rural areas because rural areas have less roadway lighting than in urban areas. Crashes in rural areas are also more likely to be single vehicle collision with fixed obstacles or head-on collisions rather than angular or rear-end collisions (Zwerling et al., 2005). Several studies found that crashes in rural areas tend to be more severe in terms of injury or death to vehicle occupants (Sanddal et al., 2008; Xie, Zhao, and Huynh, 2012). For example, in 2005, rural areas represent over than 60% of fatal crashes in Florida (Xie et al., 2012). The study found that variables such as age, not wearing a seatbelt, light conditions and speeding lead to increase driver injury severity in rural areas. According to Zwerling et al., (2005) fatal crash incidence density in rural areas are two times greater than in urban areas due to head-on collisions, collisions with fixed objects, and delay in response to reach trauma centers.

Driver characteristics

There are several factors that affect driving performance and subsequent crash risks including: age (Roenker et al., 2003; Williams and Tison, 2012), gender (Shope and Bingham, 2008; Williams, 2003), driving experience (Custalow and Gravitz, 2004), consumption of alcohol or drugs (Rakauskas et al., 2008; Ronen et al., 2010; Weiss, Ellis, Ernst, Land, and Garza, 2001), and fatigue and distraction (Liu and Wu, 2009; Neyens and Boyle, 2008; Sheridan, 2004). These factors are important because they reflect driver skills and ability to control the vehicle under different circumstances. Prior studies have shown that younger drivers tend to be at a higher risk of crashes compared to older drivers (Shope and Bingham, 2008; Williams, 2003); however, older drivers are more likely to have cognitive or diseases defects (Hu, Trumble, Foley, Eberhard, and Wallace, 1998). Massie, Green, and Campbell, (1997) suggest that female drivers may be less likely to be in fatal crashes per mile driven compared to male drivers. However, female drivers were more likely to be in non-fatal crashes than male drivers. Compared to older female drivers, older male drivers were more likely to be severely injured in vehicle crashes (Hill and Boyle, 2006).

Prior studies have shown that cognitive factors relevant to driving have an effect on a driver's dynamic interaction to operate and control the vehicle, which may lead to fatal crashes (Anstey, Horswill, Wood, and Hatherly, 2012; Jackson, Croft, Kennedy, Owens, and Howard, 2012). Driver distraction and inattention have a negative impact on a driver's performance which increases the likelihood of crashes (Neyens and Boyle, 2008). Driver distraction takes driver's attention away from driving tasks which may result in fatal crashes (Horberry, Anderson, Regan, Triggs, and Brown, 2006; Kaber, Liang, Zhang, Rogers, and Gangakhedkar, 2012). Inattention is one of leading causes of vehicle crashes because it increases the response time to process the primary task (Dozza, 2012; Jackson et al., 2012). Thus, understanding these factors helps to identify the driver factors that contribute to emergency crashes and how they are related under different circumstances.

Compared to daytime, nighttime driving has been identified as a contributing factor associated with vehicle crashes particularly for teenage drivers (Shope and Bingham, 2008). Also, having a passenger present has been shown to increase the likelihood of crash risk for teen drivers (e.g., willingness to engage in risky behaviors and general risk taking) (Shope and Bingham, 2008). Paleti, Eluru, and Bhat, (2010) identified several factors associated with teenage drivers being more likely to behave aggressively including: not wearing seatbelt, driving under the influence of alcohol, not having a valid license, and driving a pick-up truck. However, when there are more than two passengers 20-years-old or older, the teenage driver is less likely to be involved in a severe crash (Paleti et al., 2010). Other studies have focused on distractions that have a negative impact on driver's performance and resulting in increased the likelihoods vehicle crashes. For example, Neyens and Boyle, (2008) identified visual, auditory, biomechanical, and cognitive as four elements of driving distraction that can affect a driver's likelihood of specific crash types and injury severity. The authors found that cell phones and passengers have a negative impact on teenage drivers, which may increase the likelihood of more severe crashes among this age group. The presence of secondary tasks and the eyes off the road also have been identified as critical factors that lead to slower drivers reaction times (Dozza, 2012). In another study Horberry et al., (2006) found that performing additional tasks in the vehicle while driving decreases the driver's performance. The authors suggest that a driver cannot maintain the speed limit and will not be able to respond to unexpected hazard as quickly when performing additional tasks while driving. The authors also classified the distraction into the following categories: distraction under the driver's control (e.g., tuning the radio), uncontrolled distraction (e.g., receiving a phone call), and external vehicle distraction (e.g., roadside advertisement). Compared to internal technology such as CDs and radio, talking on a cell phone does not require as much eyes off the road time as turning the radio or seeking for a particular CD while driving (Horberry et al., 2006). This might related to the fact that drivers sometimes spend more time searching for CDs or looking for specific channel than on cell phones. Older drivers (60-75-years-old) tend to drive more cautiously than teenagers in complex environment because they cannot respond to hazard as quickly (Horberry et al., 2006). Text messaging while driving has a negative impact on driving performance, particularly among young drivers who tend to interact more with the technology (Horberry et al., 2006; Rudin-Brown, Young, Patten, Lenné, and Ceci, 2012). Additionally, among the other age groups, teenage drivers for both male and female have high crash rate (Lyon, Pan, and Li, 2012; Neyens and Boyle, 2008; Romano et al., 2012; Williams and Tison, 2012). The literature also shows that teenage crashes are associated with several factors such as inexperience, drugs, nighttime and weekend driving, non-use of seatbelts, speeding and distraction (Chen, Baker, and Li, 2006; Foss RD, 2001; Shope and Bingham, 2008; Williams, 2003).

Clarke, Ward, Bartle, and Truman, (2009) found that emergency drivers are more likely to be involved in crashes involving time pressure and speeding as a result of their type of work. Ambulance drivers are less likely to be severely injured compared to police and fire truck drivers (Savolainen, Dey, Ghosh, Karra, and Lamb, 2009). The authors suggest that speeding and not using seatbelts were associated with this issue. Thus, identifying the emergency drivers' characteristics in crashes will provide insights about critical factors that contribute to emergency crashes, fatalities, and injuries.

Vehicle type and crash description

The vehicle type and series of crash events are also important factors that affect the resulting injuries and outcomes. Vehicle types (e.g., car, truck, van, bus, motorcycle) have different crash outcomes or injuries that should be considered. For instance, vans or buses may have more occupants and may have an increased frequency of injuries due to the number of occupants. However, motorcycle occupants have high risk of more severe injury (Neyens and Boyle, 2012; Tay, Rifaat, and Chin, 2008). Using naturalistic data in a study of what factors may affect driver's response time for evasive maneuvers in real traffic, Dozza found that the respond time for truck drivers is quicker than the car drivers (Dozza, 2012). The author suggests that the truck drivers may have more experience than the light car drivers (Dozza, 2012). Additionally, classification of vehicle types helps to identify the safety issues related to each type in order to mitigate the severity of injuries. Understanding the chain of events that lead to a crash helps to identify the driver's errors and the environment before and after the crash. Crash description can be classified based on number of vehicles involving in a crash or based on crash type (e.g., angular crash, head-on crash, or rear-end crash) (Neyens and Boyle, 2012; Romano et al., 2012). Ambulances have been shown to be more likely involved in angular collisions with more occupants, while similar sized vehicles were more likely involved in rear-end collisions with fewer occupants (Ray and Kupas, 2005). Using vehicle types and crash descriptions helps identify which common vehicle type are involving in more severe crashes as well as the crash location and the other factors that lead to crash severity.

Emergency Vehicles

EV crashes are of great concern among emergency providers especially since they are already responding to an emergency. EVs include ambulances (EMV), fire trucks (FT), police cars (PC), and other official vehicles associated with emergency response. NHTSA reported that from 1991 to 2000 there more than 300,000 EV crashes, resulting in almost 1,600 fatalities (Custalow and Gravitz, 2004; Ray and Kupas, 2007). Another study has shown that for three year (1994 -1996) about 2,500 crashes for over 26,000-lb gross vehicle weight occur annually in the U.S. Of those crashes about 1,076 result in injuries and fatalities including an average of 6 firefighters and 15 civilians per year (Campbell, 1999). The author suggests that civilians were 4times more likely to be killed compared to fire truck occupants. Emergency medical vehicles also have a high rate of crashes. Based on a descriptive analysis of fatal ambulance crashes in the U.S. between 1987 and 1997, there were a total of 405 fatalities and 838 injuries (Kahn, Pirrallo, and Kuhn, 2001). Ambulance occupants have been shown to face high risk of severe injuries or death in crashes (Becker, Zaloshnja, Levick, Li, and Miller, 2003; Lenné, Triggs, Mulvihill, Regan, and Corben, 2008). Several factors have been associated with the risk of injuries in these crashes including time pressure to respond to emergencies and driving in unknown areas which might increase uncertainty (Becker et al., 2003; Custalow and Gravitz, 2004; Heyward et al., 2009; Maguire, Hunting, Smith, and Levick, 2002; Savolainen et al., 2009). Failing to use appropriate safety restraint devices especially in the rear patient compartment is also a critical factor that increases severity injuries among ambulance occupants (Becker et al., 2003; Heyward et al., 2009; Maguire et al., 2002). Thus, identifying the emergency crash factors will help to give more insight about critical factors that contribute to emergency crashes and injury. Figure 1 shows the important factors that are generally associated with EV crashes. In general, environmental factors significantly affect all other factors such as driver, vehicle, and roadways characteristics. Driver behavior also has a critical impact on vehicle dynamics, via the vehicles movement on the road. In the short term, vehicle type and vehicle dynamics have important effects on the road. It is the combination of all these factors which characterize the EVCs. The driver will react based on any changes of the vehicle movement and emergency status in order to maintain the EV goes smoothly on the road. Also if the vehicle inters a curve road or run out of the road the driver will receive these changes by his/her perceptions and will adapt his/her behavior based on the new circumstances. Therefore, a chain of sequences events that may occur simultaneously that result in an EV crash.

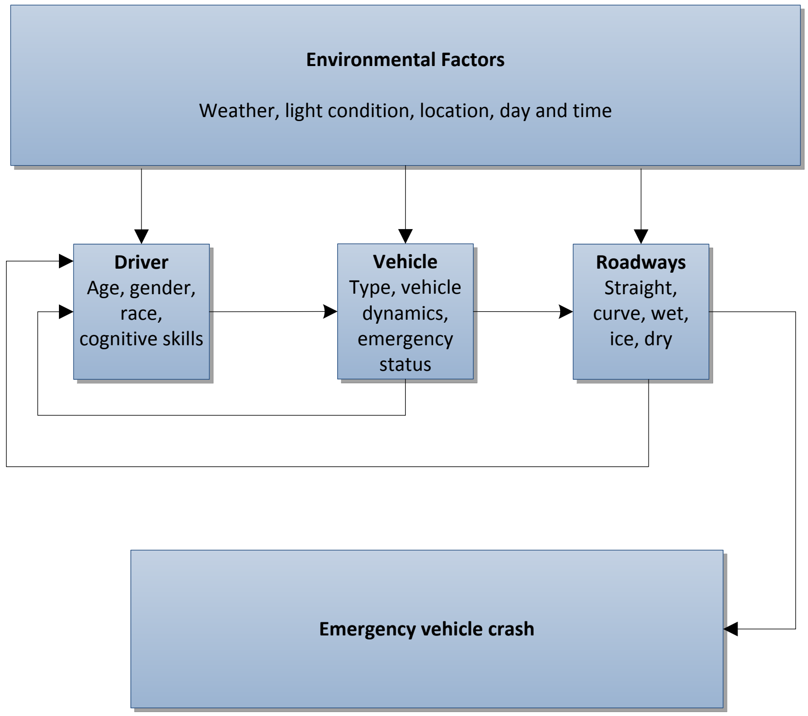

Figure 1. Relationship between common crash factors with emergency crash characteristics.

Characteristics of emergency vehicle crashes

EV crashes are similar to crashes involving other types of vehicles in terms of violations charged and prior driving records (Kahn et al., 2001). According to Ray and Kupas, (2005) crash factors involving EV crashes in Pennsylvania are similar to those of similar-sized vehicles in terms of environmental condition and road surface condition. Using the same data, they compared ambulance crashes in rural and urban areas. They found that day and time of the crash were similar between ambulances in rural and urban areas. Light conditions in general were also similar; however, rural ambulance crashes were more likely to occur under darkness (Ray and Kupas, 2007). Emergency rural crashes tend to occur on snowy roads at nighttime with poor lighting. Also, the rural crashes tend to be collisions with fixed objects and are more severe, whereas crashes in urban areas are more likely to involve more than one vehicle and more individuals (Sanddal et al., 2008; Xie et al., 2012). Emergency crashes tend to take place at four-way intersections and traffic signals in urban area, while in rural areas they tend to occur at T-intersection. Compared to other vehicle crashes, emergency crashes tend to occur during daylight, in clear weather conditions, in urban area, while emergency crashes are more likely occur in the evenings or during weekends in rural area (Ray and Kupas, 2005). Crashes occurring in clear weather might relate to drivers paying less attention to the driving task (Savolainen et al., 2009). It has been shown that majority of fatal medical emergency crash victims are unrestrained rear occupants (Becker et al., 2003; Ray and Kupas, 2005) which may relate to medical procedures and the equipment used to treat patients in the rear compartment. Ray and Kupas, (2007) found that 75% of EV crashes in rural areas was due drivers' errors compared to 93% in urban areas. Several factors might contribute to this issue such as stress to reach driver's destination on time as well as failure of other vehicles to yield the right of the way during the emergency response which may be especially problematic at intersections (Savolainen et al., 2009). Custalow and Gravites suggest that of 206 ambulance crashes, 37% involved drivers who have less than three years of driving experience and 71% involved drivers who had a record of multiple collisions (Custalow and Gravitz, 2004).

Ambulances have high risk among the other emergency transportation. For instance, ambulance fatality rate has been estimated to be 2.5 to 4.8 times the national average of all other occupants in vehicles (Maguire et al., 2002; Savolainen et al., 2009). Compared to the other EVs, police cars were more likely to involve speeding with nonuse of seatbelts crashes resulting in more severe injuries (Savolainen et al., 2009). Between 1991 and 2000 there were 300 fatal ambulance crashes that involved 816 occupants in the US (Proudfoot, Romano, Bobick, and Moore, 2003). In another study of ambulance crash data between 2007 and 2009 found that 466 EV crashes occurred with 79 fatalities and 358 injuries in the US (Sanddal, Sanddal, Ward, and Stanley, 2010). The occupational fatality rate for ambulance was estimated at 12.7 per 100,000 ambulance works per year which exceeds the other public service workers at 7.7 per 100,000 compared to the national average of 5.0 per 100,000 during the same time period (Maguire et al., 2002). Thus, as the literature has shown, EV crashes are still challenges that should continue to be the focus of research. Identifying factors associated with emergency crashes can help to provide more facts about emergency crashes to the decision makers in order to prevent crashes and mitigate the severity among emergency occupants.

CHAPTER THREE: RESEARCH OBJECTIVES AND DATA SOURCES

This chapter presents a brief overview of framework and method of analysis used in this dissertation. Problem statements, hypothesis, followed by the statistical models used for the analysis are presented.

Problem statement and research questions

EVs operate under highly uncertain circumstances. That is, ambulances must respond to emergency calls quickly, often in adverse weather, in disaster or severe environmental conditions in order to respond to emergencies. Previous research has identified several important factors associated with emergency crashes. Understanding these factors and how they relate to each other will lead to the identification of the most critical factors that contribute to the occurrence of EV crashes as well as the crash outcomes. Additionally, understanding these crashes will identify the similarities and disparities of EV crash categories that exist.

The objectives of this research are to evaluate the important factors that have been identified in literature and how they contribute to emergency crashes. The crash database for EV crashes in SC between 2001 and 2010 will be used for the research analysis. The crash database contains a plethora of information about traffic crashes in SC. The database contains variables related to environmental conditions, crash description, vehicle attributes, road features and driver factors for vehicle crashes in SC.

The research questions addressed in this dissertation are as follows:

- What are the main factors contributing to fatalities in EV crashes?

- What factors are significant predict EV occupant injury severity?
- What crash factors are associated with EV crash types?

Characteristics of South Carolina

According to American Road and Transportation Builders Association (ARTBA), SC has about 66,024 miles of roads and about 9,270 numbers of bridges. In 2012, the population of SC was estimated at about 4.7 million, which is about 1.5% of the USA population (U.S. Census Bureau, 2012).

According to South Carolina's Information Highway (SCIWAY, 2010), SC has about 31,189 square miles (40th largest state) with an estimated population of 153.6 per square mile. Columbia, the capital of SC, has a population of 129,272 in 2010, and is the largest city. About 76% of the SC population lives in urban areas (SCIWAY, 2010). Figure 2 shows the map including all highways that go through the state of SC.

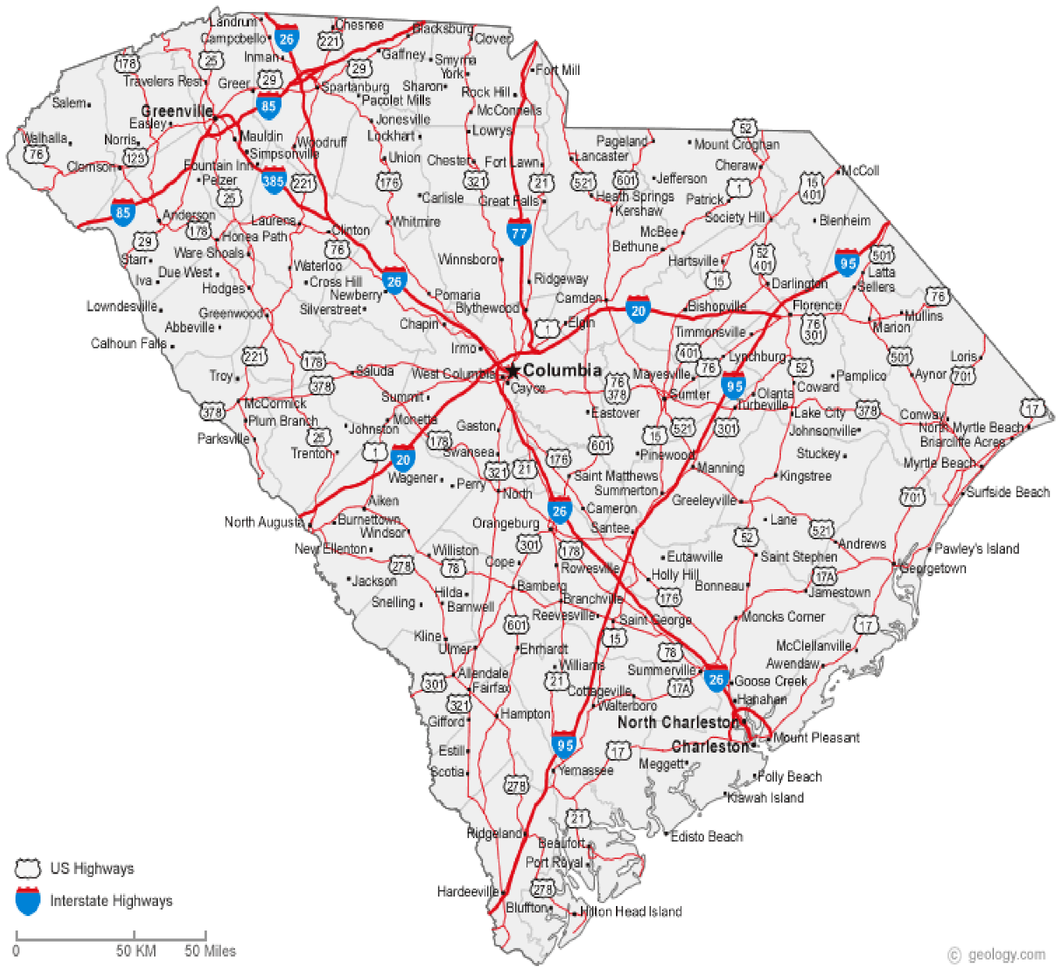

Figure 2. The South Carolina highway and interstate system
(Source: http://geology.com)

South Carolina Crash Data

Although, SC has small population, it is over presented in vehicle crashes (NHTSA, 2007). The crash data used in this dissertation is from the SC Department of Public Safety (SCDPS). The crash data includes all vehicle crashes in SC from 2010-2010 with minimum level of property damage. The database also includes all related factors associated with vehicle crashes in SC such as the important variables that have been addressed in prior research as well as SC characteristics. Emergency crashes have been extracted from the data for research purpose.

There are several limitations associated with crash data that guide the types of analysis and the type of research that it facilitates. For example, the data does not contain any information related to driver's record, experience, or any previous action prior to the crashes, so it is not possible to account for driver experience or exposure. The data also does not contain any information related to purpose of the trip or the distances that have being traveled, the starting point, or the destination. The data does not contain any information about the emergency statues during the crashes (Emergency lights on or off), so it is not clear whether the EVs were on calls during a crash. In addition, the data does not include any data related to rural and urban areas, however, an area with populations of less than 50,000 will be considered as rural (U.S. Census Bureau, 2010). Based on this classification there are just six cities that could be counted as urban areas. Though this classification between rural and urban areas exists cross the US, it is still challenge to classify SC areas based on one approach. For instance a city such as Greenwood might be more urban than rural, but it is classified as rural. Since the existing data doses not classify the crash area based on rural and urban areas, another developing definition of SC rural areas done by department of commerce (Bunch, January, 2008) was used in this analysis. Based on this definition there are 16 urban areas and 29 rural areas in SC. The larger database has been reduced to include only emergency crashes. The reduced data includes 11,531 EV crashes in SC between 2001 and 2010. Of those crashes, 9,201 (79.7% of the total) were police vehicles, 1,358 (11.7% of the total) were ambulances and 972 (8.4% of the total) were fire trucks.

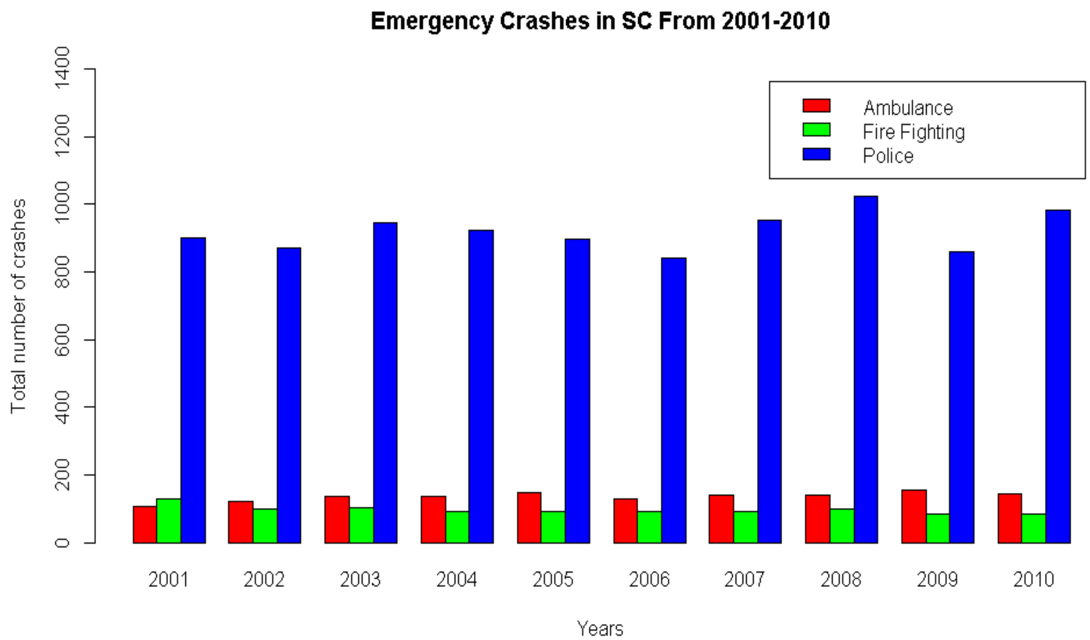

Figure 3. Emergency vehicle crashes in SC between 2001 and 2010.

CHAPTER FOUR: FATAL CRASHES

Motor vehicle crashes are the main cause of fatalities and injuries in the USA (Quinlan, Annest, Myers, Ryan, and Hill, 2004). From an engineering stand point, it is important to analyze the cause of this death in order to develop the safety system in motor vehicles, and can effectively mitigate fatalities. The main goal in this chapter is to identify the factors that are associated with fatalities resulting from EV crashes. The chapter describes the characters of fatal crashes involving EVs. Therefore, a binary logistic regression was used to identify the critical factors associated with emergency fatal crashes. The dependent variable for the binary logistic regression was a fatal crash, which has two levels a fatal crash [1] or not a fatal crash [0].

All explanatory variables were coded as binary dummy variables, therefore, when a variable is true [1] or is not true [0] for each factor. Each factor will be tested against all other factors included in the same category, therefore, when a factor occurs [1] will be considered in the model. Otherwise [0], the model will not count it. The explanatory variables were selected based on their importance in the relevant literature as well as road and driving environments.

Emergency fatal crashes

Although the SC mileage death rate (MDR)(the number of traffic fatalities per 100 million vehicle miles of travel) has been decreasing in recent years from 2.8 in 1990 to 2.1 per 100 million vehicle miles of travel in 2006, SC has been identified as having one of the highest mileage-based death rate in the US (SCDPS, 2007). According to SCDOT, (2007), it is estimated that on average three people die each day in motor vehicle crashes in SC. It was reported that one fatal crash occurs every nine hours and one injury crash occurs every 16.3 minutes (SCDOT, 2007). In 2006, about $2.82 billion dollars were estimated to be the economic loss due the vehicle crashes in SC (SCDOT, 2006). Thus, evaluating these crashes from different aspects such as EVs might help to understand the cause of this rate. In general, fatal crashes have been consistently higher in rural areas than urban areas (Zwerling et al., 2005). Several important factors were identified that contributed to fatality crashes such as speeding, lower seat belt usage and consumption of alcohol (Zwerling et al., 2005). EV crashes have been shown to be similar to crashes involving other types of vehicles in terms of fatal crashes; however, ambulance crashes were more likely to occur during emergency use and at intersections (Kahn et al., 2001). This may relate to the fact that emergency drivers tend to speed during the emergency and assume the other drivers will see the flashing lights and the siren and yield to the EV. However, in traffic signals the other drivers would assume they had the right when the traffic signal is green (Ray and Kupas, 2005), which may lead to high related crashes. According to Becker et al., (2003), unrestrained fire fighters are more likely to be severely injured or killed especially in emergency response than the other EV occupants. However, police fatal crashes provide a different picture. The authors found that seatbelt usage and emergency response were not significantly associated with fatal or injured occupants in police car crashes.

Analytical approach to the fatal crash model

A binary logistic regression model is used to build a predictive model based on explanatory factors for a binary variable. Logistic regression is used to predict the odds ratio of occurrence of an EV crash that results in a fatal crash compared to an EV crash that does not result in a fatality (see equation 1).

$$odds(Fatal\ crash) = \left(\frac{p}{1-p}\right) = \frac{Probability\ of\ fatal\ crash_i}{Probability\ of\ non-\ fatal\ crash_i} \tag{1}$$

where odds are a ratio of the probability of a fatal crash (p) to the probability of non-fatal crash ($1 - p$).

In logistic regression, the response variable is a log function of the probability, which is a natural logarithm of the odds. The natural log transforms the nonlinear term $\left(\frac{p}{1-p}\right)$ into a linear term between the probability the crash will result in fatality and the predictors (equation 2).

$$logit(p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{2}$$

The logit of a probability can be defined as the log of the odds of a fatal crash will occur rather than the crash will not be occurred. In other words, the dependent variable will have a value of one as in equation 3 (Brian S. Everitt and Torsten Hothorn, July 20, 2009);

$$p(x_1, x_2, \dots, x_n) = \frac{e^{(\beta_0 + \beta_1 x_1 + \cdots, + \beta_n x_n)}}{1 + e^{(\beta_0 + \beta_1 x_1 + \cdots, + \beta_n x_n)}} \tag{3}$$

The odds ratio can be defined as the likelihood that the EV fatal crash will occur under a particular exposure to the likelihood that the EV fatal crash will occur compared to the absence of that exposure (Szumilas, 2010). In the logistic regression, the coefficients are exponentiated in order to estimate the adjusted odds ratios. In the case that the regression coefficient for a parameter is negative, the crash is less likely to result in a fatality. However, when the coefficient is positive, the crash is more likely to result in a fatality. In the logistic regression, the confidence interval for the odds ratio (CI) can be calculated (Moore, MacCabe, and Craig, 2009) as follows:

$$\left(e^{b_i - z^* \times SE_{b_i}}, e^{b_i + z^* \times SE_{b_i}}\right) \tag{4}$$

When the confidence interval includes the value of one, the estimate is not significantly associated with the EV fatal crash. That is, the odds takes the value of one when the response variables are equally likely. However, when the interval does not include one, the estimate is significantly associated with EV fatal crash.

An adjusted odds ratio (AOR) is calculated to determine the odds associated with a variable when controlling or accounting for the other variables in a multivariate statistical model. For example, we can calculate the AOR for weather, controlling for age, gender, and distraction in order to evaluate the effect of weather on EV fatalities. Specifically the adjusted odds rates will be used to examine the influence of the predictors on the EV crash fatalities. AOR is calculating by taking the exponent of one of the parameters (the β_i in the equation 2) see equation (5).

$$AOR = e^{(\beta_i)} \tag{5}$$

The probability of an EV crash that will result in fatality is equally likely, when the AOR=1, if the AOR is greater than one, then the EV crash is more likely to result in fatality. When the AOR is less than one, then the EV crash is less likely to result in fatality. Additionally, AOR is bounded by zero.

It is important to determine how well the model fits the data. The Akaike Information Criterion (AIC) is used to measure the relative quality of the fit of a statistical model. The best fit will be shown by the model that yields the lowest AIC value (Yamaoka et al., 1978).

$$AIC = (-2)\log(\mathrm{L}) + 2(K) \tag{6}$$

where K is the number of estimated parameters included in the model (i.e., number of variables + the intercept). L is the maximized likelihood value. When the number of parameters is increased in AIC equation, the log likelihood is decreased. The Akaike Information Criterion accounts for the trade-off between the model's goodness of fit and the number of parameters included in the model (Bozdogan, 2000). For instance, two models can be compared. One model contains all predicts including gender of the EV driver can be compared to another model which does not contain the driver's gender. The model that has lowest AIC value will be the best fit model. It is important to notice that some important variables were included in the model even though their results might obvious expected. The purpose for including these variables, is to evaluate the relation of these variables with other important predictors, and also, because the absence of these variables would dramatically affected the model estimates and decreases the validity of the model.

Results of fatality model

The descriptive analysis shows that there were 11,531 EV crashes in SC from 2001-2010. Of those crashes about 79.7% were police cars, while 11.7% were ambulances and 8.4%.were fire trucks. Compared to the other EV, police cars represented about 69.62% of fatal crashes, while ambulances represented 20.25% and fire trucks 10.13%. Most of the fatal emergency crashes took place when the weather was clear 79.75%. Additionally, about 88.61% of the fatal emergency crashes occurred on dry roads. Also, the data shows that 45.57% of the fatal emergency crashes occurred during the daylight and 44.30% occurred in intersections. Compared to the other to other crash types, single vehicle collisions represented about 37.97% of EV crashes, while angular collisions represented about 21.52%, and 8.86% head-on collisions. About 63.29% of the fatal emergency crashes occurred in urban areas.

Table 1: Characteristics of fatal emergency crashes in South Carolina, 2001-2010.

Crash factors	Fatal Crashes		No fatal crashes	
	Numbers	(%)	Numbers	(%)
Vehicle type				
Ambulances	16	20.25	1342	11.72
Fire trucks	8	10.13	964	8.42
Police cars	55	69.62	9146	79.86
Total fatal crashes	79	100	11452	100
Clear weather	63	79.75	8959	78.23
Dry road surface conditions	70	88.61	9600	83.83
Intersections	35	44.3	3645	31.83
Stop sign/signal controlled intersections	29	36.71	3084	26.93
Daylight	36	45.57	6539	57.1
Head on	7	8.86	320	2.79
Rear-end	2	2.53	1670	14.58
Angle	17	21.52	2436	21.27
Single crashes	30	37.98	3214	28.07
Missing or others	23	29.11	3812	33.29
Urban areas	50	63.29	8420	73.52

The binary logistic regression model results:

The logistic regression results show that emergency crashes that took place at intersections were more likely lead to fatal crashes (AOR= 2.01) (See Table 2). As expected severe or totaled vehicles were more likely associated with fatality crashes than other levels of vehicle crashes (AOR=8.28). Ambulance crashes were 2.02 times more likely associated with fatalities than other EV. Restrained drivers were less likely associated with fatal crashes than unrestrained drivers (AOR=0.20). When the EV was moving essentially straight ahead it was 3.57 times more likely to result in fatal crashes than other movements. Older drivers (>50 years-old) were more likely associated with fatal crashes than young drivers (AOR=1.73). Fatal crashes were less likely to occur in areas where the speed limit was between (25 -35) mph (AOR=0.29).

Table 2: Factors associated with emergency fatality crashes in SC.

Parameter	Estimate	Std error	Z-value	AOR (95% CI)
(Intercept)	-5.37	0.44	-12.15	
Intersection	0.70	0.24	2.94	2.01 (1.25,3.18)
Ambulance	0.70	0.29	2.40	2.02 (1.1,3.49)
Seat belt used by driver	-1.61	0.31	-5.24	0.20 (0.11,0.38)
Severe or totaled vehicle	2.11	0.24	8.82	8.28 (5.18,13.29)
Movement straight ahead	1.27	0.33	3.84	3.57 (1.94,7.21)
Driver age >50	0.55	0.23	2.36	1.73 (1.1,2.73)
Speed Limit (25-35)mph	-1.22	0.33	-3.66	0.29 (0.15,0.54)
-2 Log-likelihood at intercept				945.18
-2 Log-likelihood at convergence				770.77

*All variables are significant at p<0.05.

Discussion of fatality model

The goal of this chapter was to provide a description of fatal crashes involving emergency vehicles. Several factors were founded to be significantly related to emergency vehicle fatal crashes; intersection, ambulance, seat belt use, severe or totaled vehicles, movement essentially straight ahead, drivers older than 50-years-old and speed limits between (25-35). The analysis suggests that EV drivers were more likely to be in fatal crashes at intersections. Previous studies found similar results associated with EV crashes at intersections (Kahn et al., 2001; Ray and Kupas, 2007; Savolainen et al., 2009). According to Kahn et al., (2001), ambulances were more likely associated with fatal crashes at intersections during emergency response which has been supported by this analysis. Also the current analysis supports previous studies that showed ambulances are more likely associated with fatal crashes than the other types of EV (Kahn et al., 2001; Ray and Kupas, 2005). The results related to older drivers are different for this particular group from the general drivers' population. For example, prior studies show that for the general population, younger drivers tend to be more likely involved in fatal crashes than older drivers (Shope and Bingham, 2008). Additionally, the literature has consistently shown that weather, road surface condition and light condition are significantly associated with emergency crashes (Eisenberg and Warner, 2005; Kilpeläinen and Summala, 2007; Savolainen et al., 2009). However, this analysis found these factors were not significantly related to EV fatal crashes. Although, male drivers have been shown to crash more than female drivers, regardless of the crash severity, assuming exposure is controlled (Savolainen et al., 2009); the current analysis showed that gender was not significantly associated with EV crash fatalities. Seatbelts use has been shown to be effective in reducing death in vehicle crashes (Studnek and Ferketich, 2007). This analysis found that drivers who used a seatbelt were less likely to be involved in fatal crashes. Crash descriptions and the manner of collisions have been consistently shown to be significantly related to EV crashes (Kahn et al., 2001; Ray and Kupas, 2005). The result of this analysis showed that these factors were not significantly related to emergency fatal crashes. Even though the literature has addressed that fatality crashes more likely in rural areas than urban areas (Ray and Kupas, 2007; Zwerling et al., 2005), this analysis found the locations of the crash was not significantly related to the likelihood of fatalities in EV crashes. This might relate to a small number of fatalities occurring in emergency crashes in SC. Estimated collision speed was also found to not significantly relate to emergency fatal crashes.

This analysis in this chapter has several limitations to be considered. First, the data does not contain any information related to driver's record or experience. The data also does not contain any information outside of the specific crash characteristics that might relate to an individual's exposure or existing health. This may be particularly important for passengers of emergency medical vehicles. The data also does not contain any information related to the length of the trip, the starting point or the destination, or the purpose of the trip. It is also not known if these crashes occurred when the EV was responding to an emergency call with siren and flash lights on or driving in normal traffic.

In conclusion, a binary logistic model was used to explore the critical factors associated with emergency fatal crashes. Several factors have been identified as critically contributed to with emergency fatal crashes. Intersections, ambulances, seatbelt usage, speeding, and older drivers were found to be significantly associated with fatal EV crashes. The results of this model illustrated that EV were more likely to be in crashes at intersections which support the prior research. Thus, visibility at intersection is still an issue that should be considered. This analysis found that older drivers were more likely associated with fatal crashes than young drivers for those particular groups which is different from general drivers' population studies. Movement essentially ahead also has been shown to be more likely associated with fatalities than the other types of movements. Additionally, ambulances were more likely associated with fatal crashes than the other EV types. Further analysis should be conducted to explore why older drivers were more likely associated with fatal crashes. In addition, research should be conducted to explore why crash types, locations, estimated speeds, and gender were not significantly associated with emergency fatal crashes. Safety in ambulances also should be considered, and hence, further assessment of the of ambulance driving process, driving training and driving guidance should be conducted. In this model EV crashes resulted in fatalities were considered. In other words, regardless of all EV crash victims (whether they EV occupants, other vehicles victims, or pedestrians) all fatalities were considered. Therefore, to assist safety process for EV occupants, it vital is important to explore the other levels of severity for the EV occupants in order to better understand what factors are significantly associated with increases of severity among EV occupants in crashes. Furthermore, it important to investigate EV crash types in order to identify the contributing factors with most common crash types such as single collisions, head-on collisions and angular collisions. In the next chapter, further investigation will be conducted in order to evaluate the effect of driver distraction and driver fatigue on the severity of injury resulted from EV crashes.

CHAPTER FIVE: SEVERTY CHARACTERSITICS

The purpose of this chapter is to estimate the effect that driver distraction and driver fatigue have on the severity of injury in EV crashes. There has been a substantial focus in the literature on emergency transportation (e.g., ambulances, police vehicles, and fire trucks), however little is known about driver distraction and driver fatigue influence crash characteristics and resulting injury severity. An ordered logistic regression model was used to predict the likelihood of a more severe injury for EV occupants

Severity Model

Prior studies have shown that cognitive factors relevant to driving have an effect on a driver's dynamic interaction to operate and control the vehicle (Anstey et al., 2012; Jackson et al., 2012). Driver distraction and inattention have been demonstrated as significant factors that affect driver's performance and increase the likelihood of crashes (Sheridan, 2004). Thus, understanding driver behavior helps to identify the factors that contribute to EV crashes and how they are related under different circumstances. Driver distraction has been shown to influence the teenage drivers' and their passengers' injury severity (Neyens and Boyle, 2008) as well as their crash types (Neyens and Boyle, 2007). Driver inattention has been identified as a contributing factor in ambulance crashes at urban areas (Maguire, 2011; Saunders and Heye, 1994). However, EV driver's distraction has not been explored yet. This chapter examines whether distraction is a significant factor associated with EV crashes or not.

Long driving hours and poor shift scheduling have been identified as important factors that contributed to this sleepiness and fatigue especially for commercial drivers, and thus, to commercial vehicle crashes. According to Liu and Wu, (2009) fatigued drivers are more likely associated with potential road hazard (any unexpected object on the road) while driving that may result in crashes. Fatigued drivers experience delayed reaction time and longer time recognizing hazards than non-fatigued drivers (Liu and Wu, 2009). Commercial drivers are more likely to be exposed to fatigue and sleepiness compared to the general public drivers (Arnold et al., 1997; Taylor and Dorn, 2006). Emergency drivers, like commercial drivers, have long work shifts and are also subject to sleepiness and fatigue which influence their driving performance (Vila, 2006). According to Taylor and Dorn, (2006), sleepiness, long work hours, stress and task demand are critical factors that contributed to fatigue. Studnek and Fernandez, (2008) found that sleepiness, time spent in ambulance, and call volume critically contributed to ambulance crashes. According to Maguire et al., (2002), many ambulance crashes were due to sleepiness that resulted from long work hours (16 to more than 24 hours). These findings suggest that sleepiness of emergency workers is still an issue that should be considered. Clarke et al., (2009) suggest that EV drivers are more likely to be involved in crashes related to time pressure and speeding. Due the nature of police and fire fighter works that require them to act quickly, both groups were less likely to wear seat belts compared to ambulance drivers, and hence, ambulance drivers were less likely to be more severely injured than police and fire truck drivers in crashes (Savolainen et al., 2009).

Although fatigue and driver distraction have been demonstrated as important factors contributing to vehicle crashes, there are still limited knowledge about the effects of these factors on EV vehicle crashes. Therefore, the objective of this chapter was to analyze crash-related injury severity for all EV occupants to better understand and evaluate the injury outcomes of crashes associated with driver distraction and driver fatigue.

Method of Severity Model

In the case the dependent variable has more than two categories and the categories have inherent order, an ordered logit model is used (see equation 7). In an ordinal logistic regression the probabilities, odds and logits are assumed to be cumulative which called proportional odds model (Das and Rahman, 2011). That is, the influences of explanatory factors are the same on all injuries categories on the logarithm scales (Citko, Milewska, Wasilewska, and Kaczmarski, 2012). In an ordinal logit model, the severity injury variable (S) is measured by unobserved latent continuous variable S^* resulted from an EV crash (i). The injury severity variable (S) is categorized into (j) categories. The general specification of injury severity model (O'Donnell and Connor, 1996) is

$$S_i^* = \beta x_{i+} \varepsilon_i \tag{7}$$

Where β is a vector of parameter to be estimated, and x_i is the matrix explanatories for individual EV crash i, and ε_i is a random error.

In ordinal logistic regression, it is expected that the high level of observed severity (S) will arise from S_i^*. This relation can be interpreted (Kockelman and Kweon, 2002) as following:

$$S_i = \begin{cases} 1\ if -\infty \le s_i^* \le \beta_1 \\ 2\ if\ \beta_1\ \le s_i^* \le \beta_2 \\ 3\ if\ \beta_2 \le s_i^* \le \beta_3 \\ 4\ if\ \beta_3 \le s_i^* \le \beta_4 \\ 5\ if\ \beta_4 \le s_i^* \le \infty \end{cases} \tag{8}$$

where [1] is no injury, [2] possible injury, [3] non-incapacitating, [4] incapacitating, and [5] fatality.

Thus, the cumulative logit probability$P(s_i \le i)$can be calculated for five levels of injury severities as following:

$$logit\ P(s \le 1) = ln \frac{P(s = 1)}{\sum_{i=2}^{5} P(s = i)}$$

$$logit\ P(s \le 2) = ln \frac{\sum_{i=1}^{2} P(s = i)}{\sum_{i=3}^{5} P(s = i)}$$

$$logit\ P(s \le 3) = ln \frac{\sum_{i=1}^{3} P(s = i)}{\sum_{i=4}^{5} P(s = i)}$$

$$logit\ P(s \le 4) = ln \frac{\sum_{i=1}^{4} P(s = i)}{P(s = 5)}$$

$P(s \le 5) = 1$, and hence, the logit undefined (9)

The cumulative logit model for the injury severities (s) (Citko et al., 2012) is

$$logit\ P(\text{s}\le i) = ln\left(\frac{\sum_{i=1}^{J} P_j}{\sum_{J+1}^{J} P_j}\right) = \alpha_i + \beta_1 x_1 + \cdots + \beta_n x_n,\ \ j = 1, \dots, J-1 \tag{10}$$

It should be noted that intercept α_i depends on the category j, while the estimates β_n do not depend on the category j.

The cumulative odds ratio can be calculated (Bender and Grouven, 1997) as following:

$$odds(s \leq j) = e^{\alpha_i} e^{(\beta_i x_i + \cdots + \beta_n x_n)}, i = 1, \ldots, n \tag{11}$$

where n is odds for each category j is different except for the intercepts.

An ordered logit regression model is used to estimate the influences of environment, crash types, vehicle in use, and driver characteristics on the injury severity of individuals in EV involved in a crash. In an ordered logit model, the cumulative probability of all injury levels is considered. Therefore, the response variable will count all the injury levels from the lowest level to the highest level. When a model parameter estimate is positive a higher order of the response variable is more likely to occur than a lower order of the response. While the negative estimate indicates that lower levels of the response variable is more likely to occur than the higher. The ordered logistic model was developed using the *polr* function in the statistical analysis in R software version R 2.15.1.

The dependent variable for the ordered logistic regression was vehicle occupant's injury severity which had 5 levels, including: no injury [1], possible injury [2], non-incapacitating [3], incapacitating [4], and fatality [5].

The explanatory variables considered in this analysis were selected based on the results of previous studies of EV crashes (Ray and Kupas, 2005; Ray and Kupas, 2007;

Sanddal et al., 2010). All of the explanatory variables included in this analysis were coded as dichotomous variables, therefore, each variable is either true [1] or is not true [0] for each factor. The categorization of urban or rural settings was not included in the database. Therefore, a crash was identified as a rural crash if it occurred in a county with 155 people per square mile or less per the definition by SC Department of Commerce (Bunch, January, 2008). Therefore, there are 15 urban counties and 31 rural counties in SC. It should be noted that the result of ordered logit include the t-value in the table because of the application of the *polr* function. As the numbers of samples are equal to 30 samples or more, t-distribution is approximately normal distribution, and hence, the numbers of predictors included in this model exceed 30 predictors, the t-value is approximately the z-distributions.

Results of ordered logit regression model predicting injury severity

There were 11,531 EV crashes in SC between 2001 and 2010. Within these crashes, there were 14,118 occupants of these EVs. Of these occupants about 73.94% were in police vehicles, 16.56% were in ambulances and 9.50% were in fire trucks (see Table 3). About 76.72% of EV crashes occurred in urban counties compared to about 23.28% in rural areas. Males represented about 81.92% of all the EV occupants involved in EV crashes. There were 2,547 injured occupants in these crashes and 23 of those experienced fatal injuries. About 92.73% of the EV occupants were involved in crashes that occurred on straight roads. About 84.23 percent of all the occupants were involved in EV crashes when the estimated speed was slower than 50 mph. The results also show that 84.13% of EV occupants were involved in crashes that occurred on dry roads, 78.11% occurred during clear weather, and about 75.73% occurred during daylight. The results show that about 26.77% of all EV occupants were involved in single crashes compared to angular crashes (21.71%), head-on crashes (3.00%) and rear-end crashes (14.87%). The results show that 5.69% of EV occupants were involved in crashes with distracted drivers, while less than 0.18% of the occupants were involved in crashes with fatigued or distracted drivers. Front occupants present about 10.67 of all the EV occupants involved in EV crashes.

Table 3: Characteristics of occupants in EV crashes involved in crashes in South Carolina between 2001 and 2010.

Crash factors	Injuries	(%)
Injury Severity		
No Injury	11548	81.80
Possible injury	1611	11.41
Non-incapacitating injury	724	5.13
Incapacitating injury	212	1.50
Fatality	23	0.16
Vehicle type		
Ambulances	2338	16.56
Fire trucks	1341	9.50
Police cars	10439	73.94
	14118	100
Clear weather	11028	78.11
Dry Road surface conditions	11878	84.13
Intersections	4667	33.06
Stop sign or signal controlled intersections	3979	28.18
Dark lighting conditions	3426	28.1
Curved roadway	1026	7.27
Rural area	3286	23.28
Crash type		
Head on	424	3.00
Rear-end	2099	14.87
Angle	3065	21.71
Single crash	3779	26.77
Sideswipe	881	6.24
Missing or others	3870	27.41
Male occupants	11565	81.92
Disabled damage	2961	20.97
Distraction	803	5.69
Fatigue or sleep	26	0.18
Front occupant	1506	10.67
Estimated collision speed>50 mph	2226	15.77

The ordered logit model results

The ordered logit mode results show that EV occupants are more likely to be severely injured when the vehicle's speed exceeds 50 mph (AOR =1.81) (see Table 4).

Additionally, if the vehicle's speed exceeds 50 mph on a curved road, the occupants were more likely to experience more severe injuries (AOR=2.1). EV occupants were more likely to be more severely injured when the crash occurred at traffic stop sign or traffic signal (AOR= 1.34) than those who involved in EV crashes that occurred at uncontrolled intersections. Head-on collisions were 2.39 times more likely to result in more severely injured occupants than other crash types. Regardless of vehicle type or crash type, occupants in the front seat of the vehicles were more likely to be more severely injured (AOR=1.37) than rear occupants. As expected, seat belts provided a protective effect, and were associated with EV occupants being 4.17 times more likely to have less severe injuries. Occupants involved in EV crashes with fatigued or sleepy drivers were 5.36 times more likely to be more severely injured. Additionally, when a driver was distracted, occupants of the EV vehicle were more likely to be more severely injured (AOR= 1.22). Occupants in ambulances were less likely to be more severely injured (AOR=0.51) than either police cars or fire trucks. However, occupants in ambulance crashes that took place in rural counties were more likely to be severely injured (AOR=1.55) than those involved in any other EV crash that occurred in urban counties. EV vehicle occupants were less likely to be severely injured in crashes that occurred on dry road (AOR=0.51). Occupants in EV crashes that occurred between 6pm and 12 pm were more likely to be severely injured (AOR=1.16) compared to other times. Additionally, curved road crashes were more likely to lead to severely injured occupants (AOR=1.31).

Table 4: Factors associated with an individual's injury severity in emergency vehicles involved in crashes in SC.

Parameter	Estimate*	Std. error	t-value	AOR (95% CI)
Intercept (1|2)**	-0.41	0.11	-3.77	
Intercept (2|3)	0.79	0.11	7.17	
Intercept (3|4)	2.29	0.12	18.78	
Intercept (4|5)	4.58	0.22	20.65	
Dry road	-0.68	0.08	-8.84	0.51 (0.44, 0.59)
Rain	-0.59	0.10	-6.02	0.55 (0.46, 0.67)
Intersection	0.23	0.06	3.73	1.26 (1.12, 1.43)
Ambulance	-0.66	0.08	-8.59	0.51 (0.44, 0.6)
Head on collision	0.65	0.11	5.72	1.92 (1.53, 2.39)
Front occupant	0.31	0.07	4.64	1.37 (1.2, 1.56)
Seat belt used	-1.43	0.07	-20.64	0.24 (0.21, 0.28)
Male occupant	-0.37	0.06	-6.66	0.69 (0.62, 0.77)
Rural area	0.06	0.06	1.05	ns
Stop sign or stop and go light	0.29	0.07	4.48	1.34 (1.18, 1.52)
Distraction	0.20	0.09	2.17	1.22 (1.02, 1.46)
Fatigued or asleep	1.68	0.35	4.78	5.36 (2.65, 10.6)
Curve collision	0.27	0.10	2.75	1.31 (1.08, 1.58)
Disabled damage	0.65	0.05	13.12	1.91 (1.73, 2.1)
Dark, no light	-0.41	0.06	-6.69	0.66 (0.59, 0.75)
Time of crash between (6-12PM)	0.15	0.05	2.81	1.16 (1.05, 1.29)
Speed limit (25-35)	-0.31	0.05	-6.24	0.73 (0.66, 0.81)
Estimated collision speed >50	0.59	0.07	8.94	1.81 (1.59, 2.06)
Ambulance in rural area	0.44	0.14	3.13	1.55 (1.18, 2.04)
Estimated collision speed >50 and	0.74	0.17	4.47	2.10 (1.52, 2.91)
-2 Log-likelihood at intercept				18,517.85
-2 Log-likelihood at convergence				17,390.53

*All variables are significant at $p<0.001$, unless noted as not significant (ns).

** [1]: no injury, [2]: possible injury, [3]: non-incapacitating, [4]: incapacitating, and [5]: fatal injuries

Discussion of severity model

South Carolina is over-represented in terms of traffic fatalities (NHTSA, 2007). It is reported that every 4.8 minutes there is a vehicle crash in SC. One person is killed every 8.4 hours in a crash and one person is injured every 10.5 minutes. In 2004, SC was ranked fifth highest in terms of the crash rate in the USA (SCDOT, 2007). In 2005, the cost of death from vehicle crashes in South Carolina was estimated about $1.01 billion (Center for Disease Control and Prevention, 2011). The goal of this analysis was to evaluate the effect of distraction and fatigue on EV crashes while accounting for other factors that have been shown to affect EV crashes.

The results of this analysis suggest that several factors including, speed, seatbelt usage, occupant sitting position, distraction, driver fatigue or sleep, weather, curve road, head-on collisions and time of the crash were significantly associated with the severity of injuries in EV vehicle crashes. Some of these results supported what has been shown in the literature, and others demonstrate some divergent results. For instance, several studies suggest that rear occupants in ambulances were more likely to be more severely injured (Becker et al., 2003; Kahn et al., 2001). However, the current analysis suggests that front occupants (in any EV vehicle type) are more likely to be severely injured than rear occupants. This might relate to the fact that the current study included police cars and fire trucks in addition to ambulances, however no significant main effect differences in the injury severity of occupants were found for the individual vehicle types.

This analysis demonstrates that for emergency vehicles, driver distraction, sleepiness, and driver fatigue are significantly associated with increases of severity among vehicle occupants in crashes. This support what has been addressed in the prior research about the negative impact of distraction, sleepiness and fatigue on driver's performance for the general population. It has been shown that ambulance crashes were more likely to result in more severe injuries in rural areas than in urban areas (Weiss et al., 2001) and this is supported by the current analysis, However, this analysis suggests that there is not a general difference in the injury severity for EV occupants in crashes in either urban or rural areas were not significantly associated with increases in the likelihood of more severe injuries for EV vehicle occupants.

Several studies suggested that EV vehicles are more likely to be involved in angular collisions (Kahn et al., 2001; Ray and Kupas, 2005). However, in the current analysis, single vehicle crashes were the most frequent crash type for EV vehicles. The current analysis also suggests that EV vehicles involved in head-on collisions were more likely to be associated with more severely injured occupants. Similar to other studies, this analysis suggests that EV crashes striking other vehicles were more likely to lead to more severely injured occupants than single vehicle crashes (Custalow and Gravitz, 2004; Ray and Kupas, 2005).

Although, the prior studies have consistently found that an individual's age and gender are important factors related to injury severity for the general population (Eby, 1995; Maguire et al., 2002; Ray and Kupas, 2007; Zwerling et al., 2005), this analysis did not find that these two factors significantly influenced the likelihood of more severe injuries for EV vehicle occupants when other crash, vehicle and environmental factors are accounted for in the model.

In addition to the limitations that discussed for the previous model, the distraction factors were included only under one variable (identified as a contributing factor to the crash) which categorized distraction into two categories: cell phone calls and distracted/inattention. The cell phones and distraction/inattention were combined into one variable in this analysis, so we are not able to discuss the specific sources of distractions and their resulting injury severity.

Regardless of the limitations, the analysis does demonstrate some interesting findings that warrant further investigation. For example, fatigue or sleepiness and driver distraction were significantly related to a higher likelihood of more severe injuries among EV occupants. When controlling for other factors, the results showed that occupants riding in an EV vehicle with a distracted or a fatigued or sleepy driver were more likely to be severely injured. This supports what have been found in previous studies on distraction, fatigued and sleepiness for other types of vehicles and drivers (Hanley and Sikka, 2012; Stutts, Wilkins, Scott Osberg, and Vaughn, 2003; Taylor and Dorn, 2006). These researches showed that distraction, fatigue and sleepiness have negative impact on driver's performance, and hence, have a strong influence on vehicle crashes. Drivers of EV may be distracted by the necessary communication with dispatchers; therefore, it is important to evaluate the communication process between EV drivers and dispatchers in order to avoid distraction among EV drivers. The results also demonstrated that EV occupants who were involved in crashes with a fatigued driver were more likely to be severely injured; this might be related to EV long shift hours. Long work hours and doing tasks under complicated environment might increase mental work load which results fatigue among emergency driver which affect their performance, and thus, might result in crash (Brookhuis and de Waard, 2001).

It is well known that EVs operate under highly unpredictable circumstances in which they must respond to emergency calls quickly while potentially in adverse weather, during disasters, or severe environmental conditions. Working for long hours under such this complex environment is more likely to result in high mental work load, fatigue, distraction and sleepiness, which influence EV driver's performance and increases the likelihood of vehicle crashes.

Conclusion of severity model

The purpose of this chapter was to determine the effect of driver distraction and driver fatigue on the severity of injury in EV crashes. The results suggested that intersections, distraction, driver fatigue or sleep, and head-on collisions have significant influences on the severity of injuries in EV crashes. The results also illustrate that EV fatigue and distraction still have negative impact on EV drivers. Therefore, further studies are needed to identifying type of distraction, sleepiness and fatigue factors, and work shift schedules factors that are associated with EV crashes. Identify these factors can help to provide more information about EV crashes to decision makers to mitigate fatalities and injuries associated with EV crashes. Additionally, this analysis suggests head-on collisions are significantly associated with EV occupants being injured. Thus, it is important to extend the research to explore why head-on collisions are significant associated with the severity of injury in EV crashes.

The goal of this chapter was to determine the effect of driver distraction and driver fatigue on the severity of injury in EV crashes. In the following chapter, a multinomial regression model will be used to evaluate the influences of crash important factors on the EV crash types.

CHAPTER SIX: EMERGENCY CRASH TYPES

This chapter presents the third model of the dissertation. Particularly, the purpose of this analysis is to explore the differences between the crash types involving EV. Multinomial regression is one of the sophisticated statistical tools that can be used to predict the disparities of vehicle crashes in the transportation literature. In this part of the dissertation, a multinomial model is used to predict the probability of different types of EV crashes (i.e., angular collisions with another vehicles, head on collision and single vehicle collisions) based on multiple independent variables.

Background

Analyzing and describing crash types have consistently demonstrated as important factors that can be used to explore the characteristics of vehicle crashes (Neyens and Boyle, 2007; Shankar, Mannering, and Barfield, 1996; Tay et al., 2008). Compared to rear end collisions, angular crashes are more likely to result in more severe injury (Z. Liu and Donmez, 2011). Single vehicle collisions and striking a fixed object are more common in rural areas than urban areas (Zwerling et al., 2005). These two types of crashes are more likely to result in more fatalities than the rear end and angular collisions (Zwerling et al., 2005). When more than two vehicles are involved in sideswipe crashes, number of severely injured occupants increases (Shankar et al., 1996). According to Bilston, Clarke, and Brown, (2011), crashes with fixed objects were more likely to result in serious spinal injury than other types of crashes that involve two or more vehicles.

In terms of fatalities resulted from rollover crashes, ambulances were similar to other public motor vehicles (Kahn et al., 2001). The authors also suggested that ambulances tend to strike other vehicles in fatal crashes regardless of emergency use status. According to Ray and Kupas, (2005) ambulance were more likely to be in angular collisions with more occupants, while similar sized vehicles were more likely to be involved in rear end collisions with less number of occupants. Urban ambulances are more likely to be involved in rear impact crashes, while rural ambulances are more likely to involve in front impact crashes (Weiss et al., 2001).

In general, EVs are more likely to be involved in angular collisions compared to the other types of vehicles (Savolainen et al., 2009). Several studies have been conducted to evaluate EV crashes using different statistical approaches; however, these studies have not identified the critical factors that are significantly associated with crash types of EV crashes. Therefore, it is important to determine the factors associated with the types of crashes that involved EVs in order to generate additional insight for the population.

Objectives

The purpose of this analysis is to evaluate the disparities of crash types of EV and what factors significantly relate to each crash type.

Dependent variables

The crash data includes the manner of collision variables from which the crash characterizes in different categories. The manner of collision contains eight types of crashes, which presented about 75% of all EV crashes. Three categories of crash types were considered which presented about 70 % of EV crashes that recorded under the manner of collision variable. These crash types have been classified into three categories as following:

- Angular collision: There are three types of angled collisions, angled in the same direction, angled in opposite directions and right angled. Angled in the same direction collision is defined as two vehicles striking at angled side (e.g., front of one vehicle strikes the other vehicle's side in the same directions). The angled opposite directions collision can be defined as two vehicles involving at angled side (e.g., front of one vehicle strikes the other vehicle's side in the opposite directions). Right angled collision resulting as two vehicles striking at the right angled side.
- Head on collision: This type of collision can be defined as front of one vehicle striking with the front end of other vehicle when they are traveling in the opposite directions.
- Single collision: This is defined as a crash of single vehicle (e.g., vehicle striking a fixed object, run off the roads, or a vehicle rollover).

These three types of crashes have been addressed in literature as the most common crashes compared with the other types of vehicle crashes (Bilston et al., 2011; Shankar et al., 1996; Ye, Pendyala, Washington, Konduri, and Oh, 2009). Head on collision has been identified as critical factors associated with severe crashes in the previous severity model, thus, it is important to go further with the investigations to explore the characteristics of each type of crashes and how they are related to crash injury severity.

Independent variables

Variables considered in this study selected based on the review of previous studies in which these factors have been examined as important factors contributed to EV crashes (Ray and Kupas, 2005; Ray and Kupas, 2007; Sanddal et al., 2008). The variables included in this study are driver, vehicle, weather and highway characteristics, light conditions and time of the crashes. Speed limit and estimated collision's speed, rural or urban areas also were included in the model. All predictors were set coded as binary variables, therefore, when variable is true [1] otherwise is [0] for each factor.

Data analysis

The analysis presented in this study was conducted in R 2. 15.1. using *mlogit* function to estimate the multinomial logistic regression model.

Method of crash type model

A multinomial logit model will be used to identify the disparities of EV crash categories that exist across the SC (see equation 12).

$$log\left(\frac{pi1}{pi3}\right) = \beta_1(X_i)$$

$$log\left(\frac{pi2}{pi3}\right) = \beta_2(X_i) \qquad (12)$$

$$log\left(\frac{pi1}{pi2}\right) = \beta_3(X_i)$$

The equations are mutually exclusive and exhaustive. Therefore, when two of the three equations are found the model can be created.

A multinomial regression is preferable technique used in crash analysis to predict unordered categories of the response variable based on the same combination of the explanatories to be examined (Neyens and Boyle, 2007). Like the binary logistic regression, multinomial logistic regression uses maximum likelihood estimation to evaluate the probability of categorical predictor variables. The model results will be used to estimate the odds of the response variables (crash types) occur in one category will be compared to the other categories. In this model the three crash categories will be compared to each other: angular collisions with another vehicles, head on collision, and single collisions not with other vehicle

1. Head on collisions compared to angular collisions,
2. Single collisions compared to angular collisions,
3. Head on collisions compared to single collisions.

Like the other logistic models, the parameter estimate has less influence to predict the logit if its value is close to zero (Shadfar and Malekmohammadi, 2013). The multinomial outcome usually shows all categories, however, one of the relationships will be used against the other types of crash types. For example, head-on collisions will be compared to angular collisions as well as to single vehicle collisions.

Results of crash types

As shown in the first model, between 2001 and 2010 there were 11531 EV crashes in South Carolina. Of those crashes 6,024 crashes represented the three types of vehicle crashes including in this analysis. About 2,453 were angular collisions, 327 head-on collisions and 3,244 single vehicle collisions. About 88% of the single vehicle collisions were police cars, while 6.3% were ambulance and 5.5% were fire trucks. Additionally, 77% of the angular collisions were police compare to 14.3 ambulances, and 8.5% fire trucks. The results also show that 76%.4 of the head-on collisions were police compare to 14.6 ambulances, and 8.8 fire trucks. About 78.8% of the angular collisions, 79.5% of head-on collisions and about 76.3% of single vehicle collisions occurred in clear weather. The results also show that 86% of the head-on collisions, 85.8% of angular collisions and about 79.5% of single vehicle collisions were on dry roads. About 89% of single vehicle collisions, 85.9% of head-on collisions and 85.2% of angular vehicle collisions were involved male drivers. Drivers less than 50-years-old were involved in 61.5% of single vehicle collisions, 60.2% of head-on collisions and 54.0% of angular collisions. About 53.5% of angular collisions occurred at intersections compared to 33.3% of head-on collisions and 11.8% of single vehicle collisions. About 78.8% of head-on collisions, 76.8 of angular collisions, and about 60.4% of single vehicle collisions took place in urban areas. About 17.6% of the angular collisions were resulted in fatalities compare to 2.1 % of the head-on collisions, and 0.92% single vehicle collisions

Table 5: Characteristics of EV crash types in South Carolina between 2001 and 2010.

Variables	Emergency crash types		
	Angular collision (%)	Head- on collision (%)	Single collision (%)
Vehicle type			
Ambulance	14.39	14.68	6.32
Fire Fighting	8.56	8.87	5.58
Police	77.05	76.45	88.1
	100%	100%	100%
Clear weather	78.88	79.51	76.39
Dry road surface	85.89	86.24	79.56
Intersection	53.57	33.33	11.87
Daylight	65.27	54.13	28.76
Male drivers	85.2	85.93	89.06
Younger drivers <50	54.02	60.24	61.56
Fatality	17.69	2.14	0.92
Urban areas	76.84	78.9	60.42
Curve roads	4.16	7.65	14
Distraction	5.75	4.89	1.66
Estimated speed >50 mph	6.16	11.93	37.95
Total number of crashes	2453	327	3244

Multinomial logit results

The multinomial logistic regression model results show that head-on collisions were 3.14 times more likely result in to fatality than angular collisions, and head-on collisions were 2.56 times more likely to result in a fatality injury when compared to single vehicle collisions (see table 6). The analysis also suggests that EVs were more likely to be single vehicle collisions (AOR=5.41) when its speed 50 mph or more compared to angular collisions and were more likely to be in single vehicle collisions (AOR=3.22) when compared to head-on collisions. When a driver was distracted, EVs were more likely to be in a head-on collision (AOR=2.05) or in an angular collision (AOR=2.04) than a single vehicle collision. If the driver of EV was identified as being aggressive, then they were 7.72 times more likely to be in a head-on collision compared.to a single vehicle collision and 5 times more likely to be in angular collisions when compared angular collisions to single vehicle collisions. In daylight, EVs were less likely to be in single vehicle collisions (AOR=0.38) when compared to angular collisions, and less likely to be single vehicle collisions (AOR=0.47) than head- on collisions. In urban areas, EVs were less likely to be in single vehicle collisions (AOR=0.70) when compared to angular collisions and were less likely to be in single vehicle collisions when compared to head-on collisions (AOR=0.54). Police cars were 1.32 time more likely to involve in single vehicle collisions when compared to angular collisions and 1.61 were more likely to be involved in single collisions when compared to head-on collisions. On dry roads, EVs were 1.59 times more likely to be in a head-on collision when compared to single vehicle collisions, and 1.40 times more likely to be in an angular collision when compared to single vehicle collisions. The model suggests that EVs were 2.56 times more likely to be in a head-on collision at an intersection than a single vehicle collision. However, EVs were less likely (AOR=0.46) be in head-on collisions when compared to angular collisions. Additionally, EVs were 5.5 times more likely to be angular collisions at intersections when compared to single vehicle collisions, and 2.17 were more likely to be in angular collisions at intersections when compared to head-on collisions. Between 12 PM and 6 PM, the EVs were more likely to be in angular collisions (AOR=1.69) when compared to single vehicle collisions, and were 1.40 times more likely to be in angular collisions than in head-on collisions. EVs were 1.66 times more likely to be in a head-on collision on curved roads than in an angular collision, while the EVs were less likely to be in head-on collisions on curve roads when compared to single vehicle collisions (AOR=0.62).

Table 6: Factors associated with EV crash types in SC.

	Head-on vs. Angular				Single vs. Angular				Head-on vs. Single			
Coefficients:	Estimate	Std. Error	Pr (>|z|)	AOR (95% CI)	Estimate	Std. Error	Pr(>|z|)	AOR (95% CI)	Estimate	Std. Error	Pr (>|z|)	AOR (95% CI)
Intercept	-1.68	0.25	0.00		1.35	0.13	0.00		-3.03	0.25	0.00	
Cloudy	0.10	0.19	0.61	ns	-0.22	0.11	0.04	0.80 (0.64, 0.99)	0.32	0.19	0.10	ns
Fatality	1.15	0.47	0.01	3.14 (1.26, 7.85)	0.18	0.38	0.63	ns	0.96	0.45	0.03	2.61 (1.08, 6.34)
Intersection	-0.78	0.13	0.00	0.46 (0.36, 0.59)	-1.72	0.07	0.00	0.18 (0.15, 0.21)	0.94	0.13	0.00	2.56 (1.97, 3.33)
Dry roads	0.13	0.17	0.47	ns	-0.34	0.09	0.00	0.71 (0.60, 0.85)	0.47	0.17	0.01	1.59 (1.14, 2.24)
Police car	-0.19	0.14	0.19	ns	0.28	0.09	0.00	1.32 (1.11, 1.57)	-0.46	0.15	0.00	0.63 (0.47, 0.84)
Urban areas	0.24	0.15	0.10	ns	-0.36	0.07	0.00	0.70 (0.61, 0.81)	0.60	0.14	0.00	1.82 (1.37, 2.41)
Distraction	0.01	0.27	0.97	ns	-0.71	0.19	0.00	0.49 (0.34, 0.72)	0.72	0.30	0.02	2.05 (1.14, 3.69)
Aggressive Driving	0.44	0.43	0.31	ns	-1.60	0.40	0.00	0.20 (0.90, 0.44)	2.04	0.50	0.00	7.72 (2.87, 20.75)
Curve roads	0.51	0.24	0.03	1.66 (1.04, 2.63)	0.98	0.13	0.00	2.67 (2.07, 3.44)	-0.48	0.22	0.03	0.62 (0.40, 0.96)
Daylight	-0.23	0.14	0.10	ns	-0.97	0.08	0.00	0.38 (0.32, 0.44)	0.74	0.14	0.00	2.09 (1.58, 2.77)
Crash time (12-6) PM	-0.34	0.15	0.03	0.71 (0.53, 0.96)	-0.53	0.09	0.00	0.59 (0.50, 0.70)	0.19	0.16	0.23	ns
Estimated collision speed>50 mph	0.52	0.20	0.01	1.68 (1.15, 2.47)	1.69	0.10	0.00	5.41 (4.45, 6.59)	-1.17	0.18	0.00	0.31 (0.22, 0.44)
-2 Log likelihood at null	10328.92											
-2 Log likelihood at convergence	7948.539											

Discussions of crash type's model

The goal of this chapter was to determine the significant factors associated with crash types of emergency vehicles. The results of this analysis show that head-on collisions were more likely to result in fatalities than angular and single vehicle collisions for EVs and, this is different from the prior studies which suggested that single collisions and angular collisions were more likely to result in more fatalities for the general population (Zwerling et al., 2005). These results support the previous model outcomes which suggested that that EV vehicles involved in head-on collisions were more likely to be associated with more severely injured occupants.

Another factor might be related to this issue resulting from the current analysis is that EVs were more likely to be in head-on collisions in urban areas when compared to single vehicle collisions. Previous researches suggested that ambulances were more likely to be in head-on collisions in rural areas or single vehicle collisions, while the ambulances tend to be involved in angular collisions in urban areas (Ray and Kupas, 2007). However, this analysis found that EV were more likely to be in head-on collisions in urban areas than single vehicle collisions, and were more likely to be in angular collisions than single vehicle collisions in urban areas.

This analysis also suggests that police cars were more likely to be in single vehicle collisions than angular collisions and head-on collisions. This might be related to speed, especially when the police officers are responding to an emergency case as well as the number of vehicles on the roads in urban areas compared to rural areas. Similar to prior studies that suggested EVs were more likely to be in angular collisions at intersections (Kahn et al., 2001), this analysis suggests that EVs were more likely to be in angular collisions when compared to head-on collisions at intersections, and were more likely to be in angular collisions when compared to single collisions at intersections. This might be related to visibility at intersections particularly in urban areas. Even though there is much research about evaluating the effect of distraction on vehicle drivers (Maguire, 2011; Saunders and Heye, 1994), there is little research evaluating the effect of distraction on EV drivers. This analysis suggests that when an EV driver was distracted, the EVs were more likely to be in head-on collisions than in single vehicle collisions, and were more likely to be in angular collisions than in single vehicle collisions. EV drivers might be distracted by occupants, communication with dispatchers by radio, or using any other wireless devices. Previous research suggest that EV tend to be in crashes that on dry roads (Kahn et al., 2001, Ray and Kupas, 2007); however, the authors did not show what type of crashes were existed on their analyses. These results suggest that on dray road EV were more likely to be in head-on collisions when compared to single vehicle collisions, and were more likely to be in angular collisions when compared to single vehicle collisions on dry roads. (Kahn et al., 2001) found that ambulances were more likely to crash between noon and 6 PM; however, it is not clear what type of crashes were most frequent at this time. The model presented here suggests that between noon and 6 PM, the EVs were more likely to be in an angular collision when compared to a single vehicle collision, and were more likely to be in an angular collision when compared with a head-on collision.

Conclusion of crash type model

The purpose of this chapter was to determine the significant factors associated with crash types involving EVs. The results of this analysis suggest that intersections, curve roads, crash time between (12-6 PM), and estimated speed of 50 MPH or more were significantly associated with EV crashes. Head-on collisions were more likely associated with fatality than the angular and single vehicle collisions. This support what has been demonstrated in previous analysis which suggested that head-on collisions were significantly associated with severity of injury in EV crashes. Additionally this analysis suggests that EVs were more likely to be in head-on collisions than single vehicle collisions, if the driver is distracted. Therefore, distraction is still an issued that should be considered in further research to explore the relation between distraction and EV head-on collisions. The results also suggest that EV were more likely to be in angular collisions than head-on collisions and single vehicle collisions at intersections. Thus, visibility at intersections might need to be considered. Additionally, EV training programs should be evaluated in order to emphasize safety among emergency drivers. The results also suggest that when the EV's speed is 50 MPH or more, the EV were more likely to be in single vehicle collisions than the angular and head-on collisions. Therefore, it is important to investigate what type of EVs is more likely to be in single vehicle collisions when the speed is 50 MPH or more.

CHAPTER SEVEN: CONCLUSIONS

The overall purpose of this dissertation was to identify the critical factors and characteristics associated with crashes involving EVs. The important factors that have been identified in literature were evaluated in order to provide insight about how they contribute to EV crashes. Statistical models were applied to provide a better understanding of EV crashes. Crash data from South Carolina between 2001 and 2010 was used to determine the effect of variables such environmental conditions, crash descriptions, vehicle attributes, road features, and person descriptions on EV crashes in order to provide better explanations of how these factors contributed to EV crashes. Three areas of EV crash characteristics were considered are:

- Fatal crashes
- Occupant injury severity
- EV crash types

Three research questions addressed in this dissertation are:

- What are the main factors contributing to fatal EV crashes?
- What factors significantly predict EV occupant injury severity?
- What crash factors are associated with EV crash types?

Three regression models (logistic regression, ordered logit and multinomial logit) were used to analyze EV crashes from different perspectives:

In the first analysis, a binary logistic regression model was used to determine the effect of environmental conditions, crash descriptions, vehicle attributes, road features, and person descriptions on EV fatal crashes, and thus to answer the first question in the hypothesis. Intersections, ambulances, older EV drivers, and straight movement ahead were founded to be significantly associated with EV crashes that resulted in fatality. This analysis also illustrated that ambulances were more likely associated with fatal crashes than the other EV types Moreover, EVs were more likely to be in fatal crashes at intersections than other road locations.

The second analysis used an ordered logit model to determine the effect of driver distraction and driver fatigue on occupants' severity in EV crashes. The results of the ordered logit model illustrate that factors such as intersections, seatbelt usage, occupant sitting position, distraction, driver fatigue or sleep, weather, curve road, head-on collisions, time of the crash, ambulance in rural areas, and estimated speed > 50 mph were significantly associated with the severity of injuries in EV crashes. Unexpectedly, this analysis suggests that distraction, driver fatigue or sleepiness are significantly associated with a higher likelihood of more severe injuries among EV occupants.

In the third analysis, a multinomial logit model was used to identify the significant factors associated with crash types involving EVs. Results of this analysis suggests that intersections, curve roads, crash time between (12-6 PM), and estimated speed of 50 mph or more were significantly associated with EV crashes. Supporting the finding from the second analysis, head-on collisions were more likely associated with fatality than the angular and single vehicle collisions. Additionally this analysis suggests that when EVs were more likely to be in head-on collisions, if the drivers is distracted. Contradicting prior studies this analysis illustrated that head-on collisions were more likely to result in fatalities than angular and single vehicles collisions.

Research Contribution

This research explores the contributing factors and characteristics associated with EV crashes. The research provides comprehensive analysis of EV crashes that gives insights about these types of crashes. The results of this research have demonstrated several significant factors associated with the EV crashes in addition to what has been established in literature before.

It is expected that this research will be beneficial for safety transportation analysts in understanding the effect of crash factors such as weather condition, driver's attributes, crash descriptions, road surface conditions and other related factors to emergency crashes and types. Additionally, the results of this study can be useful not only to crash analysts, but also to training designers, civil engineers and other human factor researchers. First, training designers are expected to train and test drivers' capabilities to drive safely under different circumstances for emergency response, this study provides significant factors such as intersections, impact of distraction and fatigue, occupant setting positions that can be showed to drivers in order to consider when responding to emergency calls. Second, for civil engineers this study provides additional suggestions for road design that might help to decrease the vehicle crashes. Finally, this study provides suggestion might be used for further researches in the human factors field including designing collision avoidance systems and policies for EV safety. This research has identified fatigue and driver distraction as significant factors contributed to EV crashes. This analysis provides insight about the crash types involving EVs.

The previous models have found several factors associated with emergency crashes and the resulting injuries and fatalities. The first model suggests that older drivers were more likely associated with fatal crashes than young drivers for EVs, which is different from previous studies for the general population. Locations, estimated speeds, and gender were not significantly associated with emergency fatal crashes. Factors such as weather, road surface condition and light condition were consistently addressed in literature as significantly associated with emergency crashes (Eisenberg and Warner, 2005; Kilpeläinen and Summala, 2007; Savolainen et al., 2009), surprisingly, this analysis did not find these factors to be significantly relate to emergency fatal crashes.

The results of the second model suggest that head-on collisions were 2.39 times more likely to result in severely injured occupants than other crash types. This finding differs from the prior studies, which suggested that EV vehicles are more likely to be involved in angular collisions (Kahn et al., 2001; Ray and Kupas, 2005). Results also illustrate that front occupants are more likely to be severely injured in EV crashes, which contradict prior studies that suggest rear occupants are more likely to be severely injured in EV crashes (Becker et al., 2003; Kahn et al., 2001). This analysis also suggests that occupants riding in an EV with a distracted, fatigued, or sleepy driver were more likely to be severely injured which have not addressed before in emergency literature.

The results of the third model identify the critical factors associated with crash types involving EVs. Although several researches were evaluated EV crashes, crash types involving EV has not been explored yet. This research provides insight about three common crash types (head-on collisions, angular collisions and single vehicle collisions) involving EVs. The results of multinomial logit support what has been demonstrated in second model results, which suggested that head-on collisions were significantly associated with severity of injury in EV crashes. The results also illustrated that head-on collisions were more likely associated with fatalities than the angular and single vehicle collisions. Additionally this analysis suggests that when EVs were more likely to be in head-on collisions, if the drivers is distracted. The results also suggest that EV were more likely to be in angular collisions than head-on collisions at intersections, and were more likely to be head-on collisions than single vehicle collisions. This analysis is the first research been conducted to determine the effect of variables such environmental conditions, crash descriptions, vehicle attributes, road features on EV crash types.

Results of this dissertation could be used to develop new guidance in the emergency transportations domain.

Future research

Further research should investigate what types of distractions are critically associated with severe emergency crashes. Communication processes might be needed to reevaluate to reduce the distraction among EV drivers. It is important also to evaluate the cause of driver fatigue and sleepiness that have been identified as critical factors associated with EV crashes that result in severe injuries. Evaluating schedules of the drivers of EV might be necessary to explore the effect of fatigue and sleepiness during their duties. It would be beneficial also to continue research on ambulance crashes in rural areas to explore additional factors that might contribute to these types of EV crashes. Another area of research could be conducted to identify why older drivers were more likely associated with emergency fatal crashes than young drivers for this particular group. Further investigation is needed to explore the relation between distraction and EV head-on collisions.

It is important to also investigate what type of EVs is more likely to be in single vehicle collisions when the speed is 50 MPH or more than the other EVs and whether this type of crashes is related to vehicle size or locations.

Once the relationship between EV crashes and the contributing crash factors are fully understood, designing a system that protects individuals and prevent those types of crashes could be designed and implemented. Also designing a good warning system that can alert the driver of a hazard on the road (or a near-crash event) may promote safety in EV if EV crashes and their characteristics are understood.

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