Examination of Independent Contributions of Driver, Crash, Vehicle and Geometric Characteristics to Driver Fatalities

by

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A thesis
submitted to the Faculty of Graduate Studies
in partial fulfilment of the requirements for the
Degree of Master of Science
in

Civil Engineering

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May 2018

Author's Declaration Page

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners. I understand that my thesis may be made electronically available to the public.

ABSTRACT

In 2016, the National Highway Traffic Safety Administration (NHTSA) had recorded a total of 37,461 road-related mortalities within the United States alone. To alleviate the effects of road fatalities concerning economy and health, numerous factors must be scrutinized for their distinct contribution to such events. In Bédard et al. (2002), the authors examined the independent contribution of driver, vehicle, and crash factors to driver fatalities. Findings established that older drivers, higher travelling speed, seatbelts, vehicle wheelbase, model year and blood alcohol content have a direct or indirect effect on driver fatalities. This research study extends the previous work from Bédard et al. (2002) by applying 17 years of extra crash data. Additional variables not found in the original Bédard et al. (2002) study, such as geometric aspects, crash characteristics, atmospheric, light, and road surface conditions are also considered. This research also examines the impact of geometric factors on mortality trends for collisions with fixed objects. Crash data were obtained from the Fatality Analysis Reporting System (FARS). To assess the relationship between the various factors and driver fatalities, univariate and multivariable logistic regression are used to compute odds ratios (adjusted and unadjusted). Also, Poisson regression was carried out to determine the expected total number of driver fatality counts based on roadway geometric factors. Results from univariate and multivariate regressions indicate that increased driver ages, increased vehicle speeds, increased vehicle ages, females, left-side crashes, and BAC $\geq$ 0.15 mg/L were associated with higher odds of driver fatalities. Conversely, drivers wearing shoulder and lap belts were found to have lower odds of fatalities. Poisson regression showed that curved alignment, dry weather, dark conditions, minor arterial roads, male drivers, non-junctions, weekends, passenger cars (sedans), and 20 -29 and 80+ years age categories to have a significant impact on driver fatality counts. Furthermore, based on research results some countermeasures are recommended such as, providing driver simulator, and on-road driving evaluation training programs, emergency medical services (EMS) without any delays, and keeping fixed objects away from the roadway and others.

ACKNOWLEDGEMENTS

Even if I put all elegant words in here, I cannot sufficiently express my gratitude towards my advisors, Dr. Pernia, Dr. Bédard, and Mr. Sacha Dubois. I would like to thank them for their endless guidance, support, and understanding. Their beyond-measure encouragement and faith for me made everything possible. It is well worth saying that such an opportunity to work with them is a privilege.

I would also like to thank Mr. Bruce Weaver, Dr. Jian Deng and Dr. Sam Salem, for the guidance and support.

I would like to express my special gratitude to my mother, my father and Vibha Jindal for their continuous support, encouragement, and friendship. I am exclusively grateful for their patience.

Finally, there are lots of names that I cannot put all here but their continuous support and existence is deeply appreciated.

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CHAPTER 1: INTRODUCTION

1.1. Background

Approximately 102 people in the United States died each day from road crashes in 2016, contributing to the highest crash rate among developed nations as the National Highway Traffic Safety Administration (NHTSA, 2017) reported. Highway crashes and their impacts have been identified to be of a big concern for global health. The National Highway Traffic Safety Administration (NHTSA, 2017) recorded a total of 37,133 fatalities related to crashes, and a total economic impact cost of automobile crashes within the United States approximated to be over $800 billion for the same period. This total included human costs (such as preparedness to pay to avoid pain, suffering, and grief); the direct impact to the economy through lost productivity; the medical costs linked with injuries from crashes; insurance administrative costs, property and vehicle damage costs; and police costs (NHTSA, 2017).

Moreover, crashes against fixed objects have been determined to be the major cause for the majority of the severe reported injuries (Kadilar, 2016; Ximiao, 2012; Penmetsa & Pulugurtha, 2017). As a result, many states in the United States are adopting an international road safety project vision zero with the objective of developing a highway system with no fatalities or severe injuries (Belin, Tillgren, & Vedung, 2012). The core principle of vision zero is that "Life and health can never be exchanged for other benefits within the society".

Therefore, to decrease the number of traffic fatalities, substantial research had been carried out by various authors on the numerous variables affecting crashes such as driver characteristics (Bédard et al., 2002; Dupont et al., 2010; Rzeznikiewiz, Tamim & Macpherson, 2012), road characteristics (Garrido et al., 2014), vehicular characteristics (Mathis, 2011; Yasmin, Eluru, & Pinjari, 2015; Hasnine et al., 2016), as well as environmental and socio-economic factors (Clarke et al., 2010a; Azadeh, Zarrin, & Hamid, 2016; Guilhermina, Nagui & Margarida, 2012). These authors proposed that differences in individual traits play a significant role in safe driving. Factors like age, gender, risk perception, personality, abuse of traffic rules, excessive speed, non-use of seat belt, and some health conditions were established to be correlated with varying risk of traffic fatality (Bédard et al., 2002; Dupont et al., 2010; Clarke et al., 2010b; Høye, 2016; Lee, 2017; Kadilar, 2014).

Furthermore, the majority of the existing research has recognized driver characteristics such as reckless driving behaviour, distraction during driving, and impaired driving to be the major fatal crashes contributors, especially for young drivers (Lombardi, Horrey, & Courtney, 2017; Penmetsa & Pulugurtha, 2017). Thus, notwithstanding the efforts made by stakeholders to manage road safety through risk assessment, training, or provision of guidance for safe driving in recent years lives have still been lost as a result of traffic fatalities. While generally the mentioned studies identified several individual's characteristics as contributors to safer driving behaviour than others, the current study tries to fill in the gap in knowledge by investigating how a better understanding of these differences would enable organizations to consider them in their road safety measures and policies, and possibly contributing to an increased effectiveness in reducing road traffic fatalities.

This research is divided into three parts. In the first part, Bédard et al., (2002) is replicated. In the second part, univariate and multivariate logistic regressions are used to calculate the total number of driver fatalities with fixed objects. Also, geometric variables are added in the analysis, and multivariate logistic regression is used to evaluate the number of driver fatalities with fixed objects as a whole model. Finally, in the third part, the analysis shows the total number of driver fatality counts with fixed objects on additional variables and Poisson Regression is used to calculate Incidence Rate Ratios and Coefficients of each variable respectively. Furthermore, countermeasures were identified to reduce driver fatality risks and driver fatality involvement and are displayed in last section of chapter 4.

1.2. The Selected Research Subject

Several factors have been identified over the years to impact the risk of driver fatality in the event of a crash; these factors include:

Driver characteristics: Age, gender, blood alcohol content, and restraint use.

Crash characteristics: Direction of impact and vehicle speed at impact, intersection type, nature of lane, road surface, street lighting, road speed limit, roadway type, vehicle movement, the presence of the red-light camera, speed limit, shoulder type.

Vehicle characteristics: Weight, length, model year, vehicle age and airbags

Environmental characteristics: Day of week, time of day, and weather conditions.

Nevertheless, it had been a challenge for researchers to evaluate the independent influence of these factors on crash fatalities. In their research, Bédard et al., (2002) acknowledged that analyses on environmental factors required data on a large number of variables as well as a large sample size to have control over possible confounding variables as well as a large sample size to have control over the possible confounding variables and to offer accurate risk assessments. Moreover, the outcomes of previous projects by various authors (Hadland et al., 2016, Chen & Chen et al., 2011) on crash and environmental factors suggested that crash location, road function class, light conditions, road surface conditions, road alignment, and speed limit have a significant influence on driver fatalities.

Thus, the current research will add key environmental and roadway factors as well as several new crash variables to the identified characteristics affecting driver fatalities by Bédard et al. (2002). This will help to investigate the independent contributions of different variables that may be directly or indirectly relate to driver fatalities.

1.3. Problem Statement

In the last two years, there has been a significant increase in fatalities according to the latest NHTSA (2017) report. However, new road safety programs helped in the increase of seatbelt usage and the reduction of impaired driving, thus substantially lowering the number of road fatalities over the same years (2016 and 2017).

Furthermore, vehicle engineering improvements and new technologies like airbags and anti-lock braking systems have also contributed to a significant reduction of crash fatalities NHTSA (2017). Nonetheless, with the significant fatalities increase in 2015 (35,485) and 2016 (37,461) compared to 2014 (32,894) that decade-long decrease of 21% has been reduced by over one-third NHTSA (2017). Hence, there is an urgent need to find the possible causes of this recent increase as well as ways to try to reduce crash fatalities.

Furthermore, past researchers have suggested several elements combine to generate conditions that contribute to crashes (Bédard et al., 2002). They identified three groupings of factors that contributed to crashes: driver, vehicle, and crash factors. Driver factors include the engagements taken by, or the state of, the vehicle driver, including violation of traffic laws, speeding, in addition to being affected by age, gender, blood alcohol content, and restraint use. Crash environment factors characteristics that contribute to, or are related to fatalities, include the design of the roadway (such as narrow lanes, medians, the lack of shoulders, access points, curves, or intersections); fixed hazards (such as trees, poles, or embankments alongside the road); and road conditions (such as rain, snow, ice, or fog).

Vehicle factors can include any vehicle-related failures existing in the vehicle or the vehicle design such as weight, vehicle age, and airbags (Guilhermina, Nagui, & Margarida, 2012).

In this sense, this study will update Bédard et al., (2002) work in regard to the independent contribution of different variables towards driver fatalities to help interpret the trend. In addition, this study will compare driver fatality risk and driver fatality involvement which will provide an insight of the independent contribution of several variables to driver fatalities, which will help to consider different countermeasures in order to reduce the number and severity of crashes.

1.4. Research Approach and Objectives

The objectives of this research study are;

(1) To replicate the original analysis of Bédard et al. (i.e., the independent contributions of driver, crash, and vehicle characteristics to driver fatalities with fixed objects using the same data from 1975 to 1998.

(2) To investigate the independent contributions of driver, crash and vehicle characteristics to driver fatalities considering update data from 1975 to 2015.

(3) To consider additional crash variables (i.e., weather and geometric conditions) in the analysis and to determine the independent contribution of each variable as a whole model.

(4) To investigate the contribution of geometric and environmental factors in determining the total number of driver fatality counts with fixed objects.

(5) To provide countermeasures for the concerns according to the results.

This research includes a two-stage approach to achieve the objectives. In the first stage, the analysis will use univariate and multivariate logistic regression models on scrutinising identified variables on previous work by Bédard et al. (2002). Moreover, variables on crash characteristics identified from the last 17 years of data are also considered. Logistic regression was undertaken to calculate odds ratios (both adjusted and unadjusted) with 99% confidence intervals. The second stage of analysis will use a Poisson regression model to analyze driver fatality counts which are derived through coefficients and incidence rate ratios. Then possible countermeasures will be recommended according to the results from the two stages approach.

1.5. Outline of the Thesis

This thesis comprises of five chapters. Chapter 1 describes background information on fatality crashes and factors contributing to driver fatalities on many roads. The objectives and outline of the report are also included in this chapter. Chapter 2 presents the literature review on risk factors contributing to vehicle crashes resulting in driver fatalities and the various statistical models used. Chapter 3 explains the databases utilized as well as the methodology with an examination of univariate and multivariate logistic regression, Odds Ratio, and Poisson regression model. The analysis of the results and countermeasures will be presented in Chapter 4. Finally, conclusions are presented in Chapter 5, which also describes the main findings and contributions, limitations, and recommendations for future studies.

CHAPTER 2: LITERATURE REVIEW

This chapter presents two parts: firstly, a detailed literature review of factors affecting road fatalities, and secondly, a review and derivations of the statistical models used in the analysis.

2.1. Factors Affecting Road Fatalities

Over the last forty years, research projects have been carried out to identify significant factors that may be of influence on the increase in road fatalities (Kadilar et al., 2014). Similarly, various methods have been considered in these projects to explore the impact of these factors on road casualties. In the study by Bédard et al. (2002), data were obtained from the FARS database (1975-1998), to examine driver fatalities as a result of single-vehicle collisions with fixed objects. Their multivariate logistic regression findings established a positive correlation between fatal injuries and various variables like age, BAC levels, restraint use, travelling speed, vehicle model year, and direction of impact (Bédard et al., 2002).

Moreover, in the international traffic research analysis of Lord and Mannering et al., (2010), the majority of road crash research relies on count-data modelling techniques and their analysis is framed to examine the risk factors influencing crashes (age, airbag, etc.) over a specified time-frequency (year, month, etc.). Furthermore, recent studies suggest that the severity of injuries has been increased by variables such as terrain (topography), traffic volume, atmospheric conditions, light conditions, as well as road grade and speeding on highways (Anarkooli & Hosseinlou et al., 2016). Several factors were established to cause a road fatality including driver, crash, geometric and vehicle characteristics. To reduce fatalities, independent contribution of these factors need to be evaluated. Several studies were explored which justifies the contribution of these factors towards a fatality, which are displayed in the following subsections.

2.1.1. Driver Characteristics

Driver factors identified in the literature that influence road fatality included age, gender, blood alcohol content, restraint use, drug use, aggression, thoroughness in decision-making, driving confidence, attitudes, risk perception, social deviance, stress, experience, live events, fatigue, physiology, and ethnicity. These findings are explained in the following subsections.

Age

Bédard et al. (2002) found that older drivers (aged 65 and older) had higher odds of severe injuries and fatalities in comparison with younger drivers. Indeed, the fatality of odds calculated by univariate logistic regression for older drivers aged 80 years and older was higher by five times than drivers aged 40 to 49 (Bédard et al., 2002). Similarly, a research project by Lombardi et al. (2017) used pooled data from the FARS database for the years 2011-2014 to compute summary statistics which included yearly crash rates. Controlling for covariates (independent variables), the authors used a multivariate logistic regression model to estimate age and gender-linked differences in crash risks. To evaluate crash involvement ratios (CIRs), an induced exposure analysis was done for all fatal crashes. The comparison of the older and younger drivers was made for crash factors through a multivariate Poisson regression model. It was established through the multivariate regression models that crash rates per 100,000 drivers were highest for drivers aged over 85 years (9.89/100,000), followed by drivers aged 20 years (8.93/100,000).

Moreover, teen and older drivers aged over 55 years were over-involved in the studied crashes, while drivers between 20 and 54 years old were under-involved. Similar results were observed for CIRs with drivers under 20 years being under-involved, and drivers between 20-54 years being over-involved. CIRs increased with increasing age after 55 years and reached a maximum value of 1.61 male and 1.63 female for drivers 85+ years.

Research by Clarke, Ward, Bartle, and Truman (2010b) considered data from over 2000 crashes involving 60-years-old and above from the United Kingdom. The data were drawn from three police units in the UK Midland region for the years 1994–2007. The researchers used coding and cross-flow structuring to group the data into various crash factor categories. The analysis was done through qualitative judgment methodology. The findings suggested that for drivers aged above 70 years, the blameworthiness ratios appeared to increase with increasing age and drivers aged over 85 years were four times more likely to contribute to a fatal crash. The authors concluded that older drivers had visual problems to spot other road users, hence leading to a crash. Likewise, Brorsson et al. (1993) investigated the influence of age to explain the risk of crashes. The research also examined other factors related to driver, road, and vehicle. Their data were for single-vehicle crashes resulting in severe injuries as per 1984 Sweden police reports. The data on crash exposure were derived from a travel survey conducted in 1984 by Statistics Sweden. Brorsson et al. (1993) employed various statistical techniques including Poisson distribution and odds ratio at 95% confidence levels, and some tables used Fisher's exact test and ordinary Chi-square. Results established that drivers in their late teenage years (18-19 years) had six times more fatality risk than the average fatality risk for a single vehicle collision, whereas, in comparison with those aged 25-54 years, they had a ten times greater chance of crashing off the road. Moreover, on weekend nights, the drivers aged 18-19 years had 49 times greater than the average risk for single-vehicle collisions.

Similar findings were established by Norris et al., (2000), who used a sample of 1000 adults drawn from four southeastern US cities. Data were collected every six months from 1991 to 1995. The analysis used both bivariate relations and logistic regression models to generate multivariate models and chi-square tests. The results established that younger drivers aged between 19 and 39 years were twice more likely to be involved in a road crash than older adults aged between 56 and 88 years. The authors in this project applied the multivariate model to examine risky behaviours and situational factors; nonetheless, while the age impact somewhat declined in strength when more factors were included into the analysis, the younger drivers had an overall bigger risk of fatal crashes.

More recent research carried out by Zhang et al. (2013), used data for the years 2006 to 2010 obtained from the Guangdong Provincial Security Department in the Guangdong Province of China. The authors used logistic regression analyses and multivariate stepwise logistic regression for identifying significant factors as well as estimating the adjusted odds ratios (ORs) while confounding factors such as traffic violations and driver fatigue were controlled for. The crash involvement risk was established to decrease with increasing driving experience, suggesting younger drivers were at an increased risk than the older drivers.

Generally, all these previous research projects have consistently demonstrated that younger drivers were more likely to be involved in traffic crashes while older drivers were more vulnerable to fatal injuries

Gender

Previous research considering gender as a factor affecting fatal crashes have consistently demonstrated that male drivers are more likely to be involved in fatal crashes than female drivers. Abdel-Aty and Abdelwahab et al., (2004) examined the effects of gender differences in vehicle crash fatalities through the use of two popular artificial neural network paradigms: the fuzzy adaptive resonance theory (ART), and the multilayer perceptron (MLP) neural networks. Their research included driver, vehicle, and environmental factors as independent variables, while the dependent variable was driver fatality. Data were obtained for 1996 and 1997 Central Florida crash databases. The analysis involved the ordered prohibit models.

Their findings indicated that female drivers suffered more fatal injuries than their male counterparts, but male drivers had higher involvement.

Also, Islam and Mannering et al., (2006) examined the effect of the driver, gender and age on fatal single-vehicle crash using multinomial logit estimation models for the state of Indiana. The project used police-reported data for crashes occurring in Indiana for the year 1999. They further controlled for confounding effects of crashes involving multiple crashes. The analysis involved ordered prohibit and ordered logit models. They established statistically significant variances in fatalities amongst male and female drivers of different ages with young male drivers suffering increased and more fatalities than females.

Additional research was carried out by Obeng (2011) using data obtained from the Greensboro Department of Transportation from 1999 to 2002. The analysis used fixed effects ordered probability models to examine gender differences in crash fatality risk at signalised junctions. The findings indicated significant gender differences in the fatality effects of seatbelt use, airbag deployment, and driver condition. The gender differences were in terms of the independent variable's effects (such as a deployed airbag) which were established to generally be higher for females than males when increasing fatality risks, and minor for females when reducing fatality risks. Moreover, Santamariña-Rubio et al. (2014) utilized a cross-sectional examination to compare road fatal injury risk in both women and men, by age, vehicle, and severity, using data from Catalonia for the years 2004 to 2008 from Catalan regional government dataset. Their analysis involved the Poisson regression models. It was established that for young drivers, men were at a higher risk when compared to women in the same category, while for the older groups, women were at more risk than men. Overall, it was concluded that men were at a higher fatality risk than women.

A comparable view was established by Dee & Sela et al., (2003) who examined the impact of gender and higher speed limits on fatalities using panel data. The project generated state-by-year data on total crash-related fatalities for the US over the 1982 to 1999 period (observing 864 cases) from the FARS database. The analysis employed a semi-log model for estimation. The project established higher fatality rates with increasing severity for females by nearly 10% but had a minor and statistically insignificant impact among males. Furthermore, it was also suggested that the positive influence sharply varied by age. Particularly, the increases in speed limits increased significantly the fatality rates among females aged 25–44 years (nearly by 14.8%). Conversely, the speed limits increase to 65 MPH significantly reduced fatalities among males aged 25–44 (nearly 10.3%). However, the estimated fatality impacts of these speed limit policies for males, in general, were found statistically insignificant.

From these studies on gender, there is no clear consensus on who between men and women is at a higher risk for fatality or injury severity whereas some established higher risks for females sustaining severe injuries or fatal crashes, compared to males.

Alcohol and Drug Use

The research examining the effect of alcohol and drug use by drivers on fatalities consistently demonstrated that younger drivers were more likely to be involved in drug and/ or alcohol-related crashes mainly because of their willingness to take driving risks such as over speeding, dangerous overtaking, etc. (McGwin & Brown et al., 1999). Furthermore, in their examination of alcohol and driving, McGwin and Brown et al., (1999) used data from all police-recorded road crashes occurring during the year 1996 in the state of Alabama. Data were provided by the Crash Analysis Reporting Environment (CARE), and for each crash, an analysis of the driver, vehicle and street characteristics was performed. The crash data from FARS were analysed using two methods: per person-mile of travel (PMT) and per licensed driver, then the population at greater risk. The results from the PMT model established that young drivers at higher BAC levels were at higher risks of fatal crashes. They showed a tendency of risk-taking which included speeding, following other drivers too closely, and dangerous overtaking.

Moreover, Caetano & Clark et al., (2000) surveyed the patterns of drunk-driving among Whites, Hispanic, and Afro-Americans. The study used a sample from the 1995 National Alcohol Survey. They further applied post-stratification weights to ensure the data were distributed according to the population. The Software for Survey Data Analysis (SUDAAN) statistical program was used in this project, which approximates a population-averaged model. According to the authors, consuming more than ten drinks in a week and being male had a large risk for crash-related fatality across all ethnic groups. Certainly, it was established that alcohol-related problems would likely affect males more than females, and males were likely to be drunk-driving. Moreover, the alcohol-impaired driving sociodemographic predictors were largely ethnic specific, with Hispanics at a higher risk. A high BAC was particularly dangerous because both the risk of fatal injury and a driving error were highly elevated when compared with sober drivers. Also, Stübig et al. (2012) documented that drug-driving seemed to be the most dominant cause of crashes contributing nearly one-third of all fatalities. In their research, the authors postulated that alcohol intoxication contributed to different crash kinematics, a higher injury severity score, and higher preclinical fatality when compared with sober drivers. They conducted a medical and a technical examination of alcohol intoxicated drivers on the crash scene and also at the main hospital of admission for severe injuries. They carried out alcohol testing with either BAC or breath alcohol tests in a regular laboratory test. The Accident Research Unit evaluated 37,365 road crashes between 1999 and 2010. Statistical analysis was done using GraphPad Prism, and the significance level was fixed at $p < 0.05$. Moreover, student's t-test and Fisher's exact test were carried out in cases of the normal distribution, while the Manne-Whitney-U- und Wilcoxon-test were used for skew distributed data. Finally, a Chi-Square test was performed for contingency analysis. The most significant finding for the project was the fatality rate as a result of crashes in drivers with alcohol use was twice as many to sober drivers. Additionally, the results indicated that drivers with higher BAC content sustained severe injuries at a higher relative impact speed.

Likewise, Hadland et al. (2016) examined alcohol policies and BAC-related crash fatalities among young drivers in the US (≤ 20 years) using 2000 to 2013 data from FARS. The authors used the Alcohol Policy Scale (APS) data across all states within the US, developed with the help of interdisciplinary Delphi panel. Their analysis examined APS scores related to fatalities of ≤20 years old people occurring in crashes involving a driver with BACs of ≥0.08%. Their analysis used the alternating logistic regression algorithm models and the SAS software version 9.3. It was established that there were 23,757 BAC-related fatalities reported (as defined by ≥1 driver involved in the crash had BAC ≥0.08%), of which 11,006 (46.23%) fatalities were drivers, and 81.7% of those were males. Generally, the ratio suggested that from 2000 to 2013, more than 1 in every 4 crash fatalities were BAC related (involving a driver with a BAC ≥0.08%), and greater than 50% involved a driver with BAC >0. Additionally, the authors observed that almost 50% of all BAC-related fatalities occurred at night and during the weekends (Friday 6 pm to Monday at 6 am).

From the research on alcohol and drug use, researchers appear to agree that higher BAC levels have a positive influence on fatalities, and especially for males and young drivers.

Seat Belt Use

In comparing age and seatbelt use in fatal crashes, it was generally observed that the use of the seatbelt was less probable among the young drivers than it was amongst the older drivers

(Bédard et al., 2002). As a result, it was suggested that the use of seat-belts increased with age. Also, Shinar et al. (2001) observed safe driving behaviours using two samples of 1250 adults. The samples were obtained using interviews conducted between 1994 and 1995. The surveys were carried out by the Princeton Research Associates for Prevention Magazine. The statistical analysis used a four-way ANOVAs test, whereas the methodology pooled categories into three predictor variables. The ANOVA on seatbelt use indicated that female drivers reported higher adherence rates for the use of seatbelt with 78% as compared to 67% for male drivers. The authors furthermore observed that, while for female reported use of seatbelt increased with their income level, it did not increase with the level of income for male drivers. Moreover, the use of seatbelt was observed to increase with age.

Similarly, Begg and Langley et al., (2000) investigated the use of seatbelt and risk-driving linked behaviours in New Zealand. The research was part of the Dunedin Multidisciplinary Health and Development Study (DMHDS) which used a longitudinal examination of the health, attitudes, development, and behaviour of a 1037 sample cohort. The sample was taken from the obstetric hospital, Dunedin, New Zealand. Data were collected from the age of 3, with follow-up evaluations every two years until the subjects were 15 years old, then again at 18 years and 21 years old. Whereas the assessment by DMHDS involved other behaviours, road safety was a major issue. The last assessment at age 21, questions focused on the self-reported use of seatbelt as a driver, the front seat, and rear-seat passengers. The analyses were performed using SAS in which chi-square tests examined differences between various groups and Fisher's Exact Test was also used. The significance level was set at $p \leq 0.01$, and the variables satisfying these criteria were entered into a multivariate logistic regression model. Generally, it was established that female drivers recorded higher seatbelt usage than male. The findings from among male drivers indicated front seatbelt users were considerably less likely than non-users to engage in the risky driving behaviour, after drinking alcohol or using Marijuana. However, there were no significant statistical differences, on these variables, between women front seatbelt non-users and users.

An additional similar project on the seatbelt use was recently carried out by Høye et al., (2016). The anticipated effects of increasing use of seat belt on the number of light car driver fatalities were projected for three scenarios of increased seatbelt use in Norway. The impact of seat belts on fatality were examined in log-odds of a meta-analysis that was focused on 24 studies from 2000 or newer. The analysis used the Cochran's Q-test for heterogeneity, summary effects, confidence levels, and sensitivity analysis. The author established that seat belts decrease both non-fatal and fatal injuries by 60% for drivers while reducing 44% for rear seat passengers. Both these results were statistically significant.

For the studies on seatbelt use, it was observed that seatbelt use increased with increasing age, and females were more likely to wear seatbelts than males. However, seatbelt use was suggested to reduce non-fatal and fatal driver injuries by nearly 60%.

2.1.2. Vehicle Characteristics

Airbags

In the study by Bédard et al. (2002), airbag data failed to demonstrate beyond the protective effect of seatbelts, using their univariate and multivariate logistic regression model. It was established that the earlier vehicle models fitted with first-generation airbags were mostly large luxurious vehicles. However, it was not clear what benefits, if any, the airbags offered to drivers, and if specific groups of drivers were negatively affected by triggered airbags. Research in the last two decades had demonstrated that frontal airbags decreased the risk of the driver and passenger fatalities in vehicle crashes (Kahane et al., 2006). Also, the research on airbag compares two types of airbags; sled-certified (fitted after 1998 vehicle models) and first-generation airbags (for models older than 1998). According to the analysis by Kahane et al., (2006), non- or improper- use of seat-belts, or drivers leaning toward the airbags at the time of deployment were factors noted to contribute to air bag-induced fatalities. The analysis by Kahane et al., (2006) was based on FARS data obtained for the years 1994 to 2004, and they used the double-pair comparison of the selected variables. The study established the airbag-induced fatalities per registered vehicle to decrease among sled-certified cars. Risk of driver fatalities per registered cars was identical for drivers of vehicles with sled certification compared to those with first generation (Kahane et al., 2006).

A similar examination on airbags was done by Olson, Cummings, and Rivara et al., (2006). Utilizing a matched cohort design, the researchers predicted risk fatality ratios using airbag generations versus no airbag, adjusting for seating position, gender, restraint use, age, and all crash and vehicle characteristics. The sample consisted of 128,208 US vehicle users involved in fatal crashes between 1990 and 2002. The analysis used Stata 8 software to perform a likelihood ratio test for heterogeneity, while the risk ratios compared both airbags within subgroups, with data considered significant at a two-sided α of 0.05. Generally, first-generation airbags were linked with a 10% decrease of fatality risk for drivers, whereas sled airbags were linked with an 11% decrease in comparison to no airbag.

Moreover, a substantial decrease in fatality was attributed to the combined use of airbags and seat belts by Crandall, Olson, and Sklar et al., (2001). Driver airbags reduced frontal crash fatality by one fourth; whereas using a seat belt decreased fatality by three fourths. Moreover, frontal collision, airbag deploying and driver using a seat belt reduced the driver's fatality risk by over 80%. The research included crashes involving two vehicles reported to the FARS between 1992 and 1997. The authors used bivariate analyses that involved categorical variables by performing a crude matched-pairs analysis. Moreover, conditional logistic regression models were used to estimate odds ratios, while the final regression model entered vehicle weight and vehicle model age as continuous variables. The statistical significance was validated by either a p-value or a two-tailed 95% confidence interval (Crandall, Olson, & Sklar et al., 2001).

Generally, the research on airbag influence on fatalities suggests that airbag deploying reduced the driver's fatality risk. However, when the crash occurs then airbags are deployed, and drivers lean forward but they are pushed back by airbags, and they have a higher chance of fatal injury on the backside of the head. There was no significant difference between the two types of airbags examined.

Weight and Length

When considering vehicle characteristics about fatality risk, the most common related characteristic is vehicle size (weight and length). Whereas vehicle weight and length are greatly correlated, the most studied attribute is weight. Bédard et al. (2002) tested the benefit of wheelbase length after controlling for other vital variables and found a 10-inch wheelbase increase translated into a 10 percent decline in the fatality odds. In an earlier, Levine et al. (1999) established that every 1000 lbs increase in car weight implied the driver could survive an additional 6 mph front impact collision in comparison to other vehicles, whereas wheelbase length was related inversely to the impact speed. Their examination used FARS data on fixed object crashes between 1986 and 1995. The analysis compared characteristics using both ANOVA and logistic regression methods.

Additionally, a more recent analysis by Classen et al. (2007) conducted a mixed method project of the possible risk factors that decrease driving safety. They examined FARS data for 2003 to identify factors associated with fatality vs no fatality. Based on the descriptive analysis, binary logistic regression, and bivariate analysis models the researchers found that drivers of passenger vehicles (for example sedan) had approximately 2 times higher odds of fatality, while drivers of light trucks or vans had about 23% fatality reduced odds, in comparison to drivers of sports utility cars. Similarly, using the same 2003 FARS data, Awadzi et al. (2008) established that drivers of passenger vehicles had about 2.96 greater odds of fatality in comparison to drivers of sports utility cars. This research used Univariate analyses, bivariate analyses, and Multinomial logistic regression at 95% confidence ratios. Also, they observed other variables like female drivers, BAC levels, seatbelt use, airbag deployment, and fixed road objects to increase the odds of fatalities.

In another research, Finsion et al. (2002) investigated how vehicle weight and type were correlated with fatalities in crashes. Their binary exploration results indicated that heavier weight of cars reduced the probability of fatality, and drivers of passenger vehicles were more probable to suffer fatality than drivers in vans or pickup trucks. The project used the Maine Crash Outcome Data Evaluation System (CODES) 1996 database, and the analysis was done based on the population-based rates per driver with license and bivariate analysis of crash, vehicle, and driver characteristics. The multivariate logistic analysis was performed based on fatality reports and severe injuries sustained.

There is an agreement that bigger vehicles are innately safer than mini/ smaller vehicles in a crash scenario. The above researchers consequently concluded that in general terms weight was more protective to the driver in crashes than the length of the vehicle. This means that the SUV's are safer than sedans.

Model Year

Bédard et al. (2002) established that older model year cars were associated with an increased fatality risk of 5 percent for every 5 years. Previous researchers also reported that the most recent models were safer (Levine et al., 1999; using the methods above; Robertson, 1996). Robertson et al., (1996) reported a correlation between vehicle age and fatalities using 1975 to 1991 FARS data. The study used ordinary least squares regression to estimate the impact of vehicle age, BAC, and seatbelt use on fatalities. It was established that driver fatalities had been reduced significantly by safety features and standards included in newer vehicle models, contributing to increased crashworthiness. Based on recent literature, findings have established a correlation between vehicle age and fatalities.

As far as the model year is concerned, a recently concluded project by Glassbrenner et al., (2012) quantified the advantages of the improved protection offered by new model vehicles and their influence to historically lower fatality rates that have happened in the US in recent history (comparing a 2000 model year and a 2008 model year vehicle after travelling for 100000 miles). The data from 1975 to 2010 were obtained from the FARS, GES, the National Household Travel Survey, and the Federal Highway Administration. The analysis was done using ANOVA and logistic regression models. It was established that the probability of crashing after 100,000 miles of driving had declined from 30% in a 2000 model year vehicle to 25% in a 2008 model year vehicle (Glassbrenner et al., 2012). Similarly, Kahane et al., (2015) examined the impact of model year on fatalities. This research embraced an NHTSA statistical model (individual effectiveness estimates, focusing on % reductions) to investigate in greater detail the efficiency of nineteen different Federal Motor Vehicle Safety Standards (FMVSS) ranging from the year 1960 to 2012 using the FARS database data from 1975-2012. The report established that car safety technologies had reduced fatality rates significantly making new model vehicles safer than older models. This was further supported by NHTSA (2013) examinations of vehicle models from 1992 to 2011 using FARS data for 2005 to 2011. The analysis was done using Multivariate logistic regression models. As far as fatality risk and model year are concerned, the report noted that on condition of being involved in a crash, the likelihood of an older model year vehicle driver being fatally injured was more in comparison to the newer model year vehicle drive.

Based on the mentioned findings, there is a correlation between vehicle age and fatalities, with newer vehicle models offering more safety than older models.

Vehicle Age

The NHTSA (2013) report also established that drivers of an older vehicle had more probabilities of being fatally injured when compared to the newer vehicle drivers. The research model estimated that the driver of a vehicle older than 18 years at the time of the accident was 71% more probable to be injured fatally than the driver of a 3 years old or less vehicle. Earlier, Lécuyer and Chouinard et al., (2006) had examined vehicle age and crashworthiness in Canada. Their project included data from the National Collision Data Base (NCDB) for the years 2000 to 2003. The analysis was done by dividing fatal injuries by the vehicle age group. It was established that fatalities rose rapidly with an increase in vehicle age, excluding for vehicles of 0-2 years old. This was attributed as an indication of vehicle deteriorating with age as well as older vehicles being poorly maintained and more susceptible to mechanical failures.

Similarly, it has been demonstrated that mechanical failures contribute substantially or directly to crashes by approximately 6% according to Redhe and Nilsson et al., (2002). The authors tested the applicability of linear response surface approximations to examine the impact mechanical performance of finite element vehicle models (relation to crashworthiness). Also, a report by Haworth et al. (1997) determined in Australia that the odds of fatality were 2.5 times more for an occupant driving a pre-1978 car than a newer vehicle. This research used data collected in collaboration with the local police units, state coroners' officers, and Monash University accident research Centre. The analysis was done using the Odds ratio at 95% confidence levels.

The findings on vehicle age suggested that as the vehicles aged, the condition of critical safety components deteriorated and consequently, the probabilities of fatality contributed by mechanical failure increased.

2.1.3. Crash Characteristics

In the last two decades, crash characteristics have become a major concern in traffic safety research.

Direction of Impact

Majority of the existing literature on crash impact direction has grouped the variable into four classes: front, left and right side, rear-end and others. Wang et al. (2017) using a 5-year police-reported data from the Wuhan Traffic Management Bureau from 2008 to 2012 examined the impact of various factors on fatality, including the direction of impact. Statistical analysis was done using Wilcoxon rank sum statistics, chi-square test and Cramer's V test, as well as spatial stratified heterogeneity analyses, and stratified logistic regression analysis. The results established that driver side impact when compared to the front, passenger side and rear-end impact had a stronger correlation with driver fatality.

Similarly, Bédard et al. (2002) established that two-thirds of driver-side impacts were fatal, irrespective of age. Driver opposing-side and rear-end impacts were fatal for 31.3% and 38.4% respectively. The fatalities ratio following rear and driver-side impacts was independent of age and increased with age for both opposing-side and front impacts (Bédard et al., 2002). In a different study, Samaha and Elliott et al., (2003) examined side crashes using the NASS/CDS dataset, FARS, and GES databases from 1990 to 2001 crash data. The researchers used conditional logistic regression analyses and found that driver side impact had a higher fatality rate when compared to other impact types and passenger vehicles were riskier in comparison to minivans and trucks.

Generally, research on direction impact has observed that driver side impact has a higher fatality, followed by frontal impact than the other sides.

Vehicle Speed at Impact

The role of speed in fatality odds has been validated through various studies (Milton & Mannering et al., 1998; Elvik et al., 2013). According to Elvik et al., (2013) in his re-analysis of the correlation between fatality rates and mean traffic speed: the faster the vehicle travels on the road, the higher the likelihood of the driver crashing. As vehicle speed increases, the distance needed for stopping increases, and there is a higher chance another driver will misjudge how fast the speeding vehicle is travelling (Elvik et al., 2013). The analysis used a consolidated database of 115 studies which presented 526 estimates of the relationship between speed and road safety. Nilsson et al., (2004) used a cross-sectional study examining data from SCB/SIKA database in Sweden ranging from 1997-1999 to compare with a past Power Model on safety and speed. Linear regression analysis was used to examine crash injuries, speed, and safety. It was established that the fatality outcome from a crash is directly correlated to the pre-collision speed of the vehicle, irrespective of whether speeding was a contributing factor in the crash. This is because when a crash occurs, the vehicle experiences a swift change of speed.

This was also established by Milton and Mannering et al., (1998) in research including highway data from 1992 thru 1993 from the Washington State. Data were obtained from the Washington State highway system through the Washington State Department of Transportation's (WSDOT's) and the Transportation Information and Planning Support system (TRIPS). The analysis was performed using the negative binomial regression model. It was established that crashes increased with increasing speeds, whereas, trucks often slower were associated with being overtaken and contributing to more risk-taking by other vehicles moving faster.

Additionally, examining vehicle impact speed on fatality, it was established that the driver of the vehicle keeps moving at the previous speed of the crashed vehicle until stopped, by either having smashed into the interior of the vehicle, hitting an exterior object after being flung from the vehicle, or getting restrained by a triggered airbag or seat belt (Jurewicz et al., 2016). Their study reviewed the recent international research on the correlation between impact velocity change (delta-v), the probability of fatal and serious injury (MAIS3+) and impact speeds across many common crash dynamics. Higher the speed at which the driver body must absorb the released energy in the crash, the higher the chances of fatality outcomes (Jurewicz et al., 2016). Nilsson et al., (2004) and Elvik et al., (2013) established that lower mean road speeds in reaction to the reduction of the speed limit contributed to decreased fatality outcomes. Moreover, examining data from 1998 thru 2001, obtained from DTEI database in Australia, and analysed using Poisson distribution, Kloeden et al., (2001) identified relationships confirming that the chances of driver fatality increased with their speed over the specified speed limit.

Majority of the studies on vehicle speed at impact suggested that even small speed reductions could contribute to significant reductions in traffic fatalities. Furthermore, it was established that fatalities increased with increasing speeds.

Intersection Type

The intersection type is divided according to driver's angle of turn; straight, orthogonal (turns that are perpendicular at their point of intersection), and non-orthogonal (turns that are not perpendicular at their point of intersection) intersections. The various studies on intersection defined a 15 m to 20 m radius from the intersection center as 'within proximity of intersection' (close to the turning point) in their spatial data analysis (Schneider, Ryznar, & Khattak et al., 2004; Miranda-Moreno, Strauss, & Morency et al., 2011). The non-orthogonal intersections were linked with a higher fatality risk by Choi et al., (2010). His analysis included data from the National Motor Vehicle Crash Causation Survey data from 2005 thru 2007. Statistical analyses were performed using descriptive analysis, configural frequency analysis, and generalised logit model. It was established that non-orthogonal intersection permitted limited visibility to drivers in comparison to orthogonal and straight intersections. Drivers had less time to prepare when reacting to likely hazards when turning at an acute angle in a non-orthogonal road intersection because of limited visibility.

Furthermore, when the intersection angle between two streets is obtuse (offering better driver visibility), the other angle of the intersection is usually acute (offering limited driver visibility) according to Chipman et al. (2005). Chipman and her colleagues examined the risk of right-angled intersection crashes in British Columbia, Canada. Data were obtained from police reports for 2002. The odds ratio was calculated using Stata 8. They established an observed delay when drivers were reacting at non-orthogonal road intersections which explained partially this phenomenon of limited visibility. Reducing the time required to prepare to enter an intersection had been linked to higher fatalities.

Nonetheless, there was a possibility that travelling speed could be higher in obtuse intersections, contributing to higher impact fatalities as established by Wang and Abdel-Aty et al., (2006). This research used the negative binomial regression to model rear-end crash occurrences at signalized intersections. This research used over 3 years (2000, 2001, 2002) of longitudinal data which included 208 signalised intersections and 476 signalized intersections spatially correlated along different locations in the state of Florida. Higher fatalities were connected to heavy traffic, having more left and right-turn lanes on major roads, and higher speed limits.

Generally, the studies on intersection type propose that higher fatalities are connected to busy highways, which have more left and right-turn lanes, and higher speed limits. Non-orthogonal intersection turns (left turns) are also linked with higher fatalities.

Relation to Junction

The junction is a point where two or more lanes meet and separate from each other. Lane departure crashes have been established as the most common crash types, responsible for 1.6 million road crashes per year, which is equivalent to more than a quarter of all crashes according to a report by Mehler et al. (2014). Data used in the research are from July 2015 thru March 2017 and used from vehicle technology questionnaire, which was administered to Long road participants at baseline. Investigating the 2004 GES data, Najm et al. (2007) demonstrated that the lane departure without prior manoeuvring the vehicle was the second most frequent pre-crash scenario, contributing to 20% of pre-crash scenarios for light-vehicles. Their data set included crashes leading to fatalities with an objective to model pre-crash scenarios by crash contributing factors (economic cost, the frequency of occurrence, etc.). Najm et al. (2007) established that the common lane departure scenario was in speed locations in rural roads and the road alignment was determined as straight in about 74% of the crashes. Mastinu & Plöchl et al., (2017) also evaluated that lane departures fatalities were established to arise from driver relinquishing steering, inattention, or loss of control, uncalculated overtaking, and sudden evasive maneuvers.

Additionally, there is some research which indicates the effect of lane width, which analyses the wider lanes versus narrower lanes. A report by the National Cooperative Highway Research Program (NCHRP) consists of more than 7000 accidents, and 972 million Vehicle-miles of travel (VMT) assessed during their research concluded that all projects that consisted of lane widths ≥10 feet contributed in reducing crash rates (Harwood et al., 1990). Furthermore, Potts, Harwood, and Richard et al., (2007) used the NCHRP Project 17-26 database to obtain crash data for major roads in Minnesota and Michigan. Negative Binomial Regression Model was used for the analysis which found no suggestion, except in limited cases, that narrower lanes increased the frequency of crashes. The analysis of lane widths conducted was not statistically significant or demonstrated that narrow lanes were correlated with lower crash frequencies.

Noland et al., (2003) also determined that wider lanes caused nearly 900 additional traffic fatalities each year. The data used were a cross-sectional time-series data of all US states from the years 1987 thru 1990. The analysis was done using a fixed effects negative binomial regression model accounting for data heterogeneity. Noland concluded that at wider lanes, drivers tend to be too comfortable which can contribute to over speeding and inattention. Moreover, Penmetsa and Pulugurtha et al., (2017) carried out a study to evaluate fatalities on non-interstate roads in North Carolina. Data on crashes against fixed object were obtained from the Highway Safety and Information system (HSIS) for the years 2011 to 2013. The analysis used a logistic regression model to calculate the odds ratios. The authors argued that the percentage of fatalities on non-interstate roads was very high in comparison to the interstate roads. The study indicated that 93.5% of fatalities against fixed objects in North Carolina occurred on non-interstate roads, contributing to 15.6% of overall road-related fatalities.

However, on interstate roads drivers are more exposed to a risk for a fatality due to higher speed limits as compare to non-interstate roads according to Dillon et al., (2012). Dillon analysed FARS data from 1981 to 2009 for 48 US states. The fixed effects models and the ordinary least squares (OLS) were used for analysis. On the contrary, using multiple regression analysis and examining 1976 to 1988 FARS database, Garber and Graham et al., (1990) established that drivers were likely to retain higher speeds after departing interstates with lower speed limits thus increasing crash rates and in turn more fatalities.

The studies on relation to junction and lane widths have suggested that lane departures without prior manoeuvring as the most common crash scenario, while wider lanes (>10 feet) were linked to higher fatalities. Higher speed limits also form as one of the main reasons for the fatalities.

Roadway Alignment

Examining the impact of roadway alignment on fatalities on road crashes, Stimpson et al., (1987) stated that fatalities at horizontal curves occur from an interaction of several factors: the selection of improper speed, the failure to maneuver through curves with a super-elevation higher than three degrees and being unaware of roadway geometry sudden changes. The study used data from 1969 thru 1975, obtained from Science Applications, Inc. The analysis was done using stepwise multiple linear regression program. Moreover, Fitzsimmons and Lindheimer et al., (2012) examined the contribution of horizontal curves towards fatalities of road crashes on two-lane highways in Kansas. Data were obtained from the Kansas Department of Transportation database for 2006 to 2010. The analysis was done using descriptive statistics and odds ratio at 95% confidence intervals. It was identified that drivers of large trucks were at more risk of manoeuvring through rural horizontal curves as a result of cargo shift also of rolling over because of vehicle length, size, and performance of engine when vertical curvature exists. Additionally, crash rates are increased up to 4 times on horizontal curves as compared to the rates on tangent sections, all other factors being equal according to a roadway alignment report by Zegeer et al., (1987).

A comprehensive review of the literature by Glennon et al., (1985) established that the average horizontal curve crash rate on two-lane rural roads was 3 times more than on tangent sections. Furthermore, recent research by Hummer et al., (2010) used North Carolina HSIS data from 2003 to 2005, and frequency distribution was used for analysis. It was established that curve crashes have more than 3 times the fatality crash rate of all roads within the state. Moreover, Bauer and Harwood et al., (2014) examined different combinations of vertical and horizontal curve alignments using the Washington State HSIS crash records for the year 2003 to 2008. The data were analysed using a negative binomial distribution and the generalised linear model. It was established that fatality risk increased with reducing horizontal curve length, reducing horizontal curve radius, increasing difference in grade, and increasing grade percentage.

Nonetheless, Torbic et al., (2004) report sponsored by the NCHRP established horizontal curves as a significant safety problem for drivers of both large trucks and passenger vehicles on two-lane roadways. While Campbell, Richard, and Graham et al., (2008) suggested that horizontal curve sections at rural roads are more prone to fatalities because they had a smaller radius. Speed limits of 55 mph on horizontal curves is high to manoeuvre through especially for large trucks which cause them to rollover. Fixed objects like fences or trees obstructing clear-zones, and restricted sight distance also plays an important factor to increase the fatalities rate on horizontal curves.

Generally, roadway alignment research suggests fatalities increase with reducing horizontal curve length and reducing the horizontal curve radius. Proper sight distance and speed to manoeuvre the horizontal curves also plays an important part of safety. Horizontal curves should be kept at a minimum angle, which makes the driver easy to pass through them while maintaining the same speed limit.

Surface Conditions

The effect that surface conditions will have on crash fatality depends on various factors. Morgan and Mannering et al., (2011) analysed the effect of various weather possibilities (dry, wet, snow/ice covered) on roadway conditions and their impact on fatal crashes. They obtained crash data from Indiana police reports for 2007 and 2008. The analysis using a mixed logit model observed that roadway conditions influenced fatality depending on risk-taking behaviours and age. As an example, men aged <45 years had increased odds of fatal injuries. Similarly, a literature review carried by Andrey et al., (2003) stated that almost all of the included articles had indicated an increase in crash frequency during adverse roadway conditions but that the ratio of the increase varied widely. They noted that this variation might have been as a result of different statistical methods applied or the difference in drivers' detection of and reactions to observed deteriorations in roadway conditions.

Additionally, Eisenberg et al., (2004) used a negative binomial regression approach to analyse the mixed effects of rainfall on the roadway surface and crashes in the US. Data were obtained from the FARS database for 1975 to 2000. Results indicated lagged effects to be significant during sleet events (for example if it rained previous-day and present-day, the number of fatalities related to rain would be less the present-day than it would be if it had not rained the previous-day), proposing that drivers collect information that enables them to adjust to changes in road conditions. The temporal foundations of this severe-weather process adjustment had also been proposed by Andrey and Yagar et al., (1993). They used data from 1979 – 1983, which were collected from 15000 accidents that occurred during 169 rain events. Andrey and Yagar et al., used a sample approach to justify the fact that fatality risk increases by 70% during rainy conditions rather than normal conditions.

In determining resulting fatalities as a result of roadway conditions change, there seems to be a complex problem resulted by the fact that variances in roadway friction under different conditions can have a huge impact on dissipation of crash forces (Morgan & Mannering et al., 2011). This proposed a complex interaction between the various driver-linked elements and crash physics. This had been reported by Eisenberg, and Warner et al., (2005) who established that snowy roadway conditions contributed to fewer fatalities than dry roadway fatalities. Their study used FARS data for 1975 to 2000 for all states in the US. The analysis was done through negative binomial regression models using multivariate analysis and bivariate analysis. They established the first day of snow to be significantly more fatal for drivers than ensuing snowy days, especially for elderly drivers and proposing differences in adaptation, by age, across the driver population.

In summary, adapting to weather-generated changes in roadway conditions is a complex process which could be affected by many factors (Eisenberg et al., 2004). The weather has therefore been identified in the past research to play a key role in fatalities related to roadway conditions. These include bad visibility, slippery roadways, and other severe weather conditions. It was established that dry roadway conditions were the most fatal, followed by wet and snowy conditions (Morgan & Mannering et al., 2011). This was because drivers tend to be more cautious with speed in severe conditions. However, severe conditions appeared to contribute to more non-fatal crashes than dry conditions.

Light Conditions

Lighting conditions play a very important role. Lighting conditions help the drivers' visibility to spot roadway components like fixed objects, and oncoming traffic (Anarkooli & Hosseinlou et al., 2016). Their study examined various light conditions in rural two-lane roads in the state of Washington using data obtained from the HSIS dataset (2009 to 2011). Crash outcomes were modelled used ordered prohibit and indicated that the fatality of crashes highly increased when the crashes occurred at dark intersections. However, the traffic location variable was established to be statistically insignificant under sufficient light condition. Furthermore, shoulder width on rural two-lane roads was established as positively related to increased fatalities in dark-lighted conditions. With regard to light conditions interaction with crash types and their effects on fatalities, head-on collision with another vehicle or crash on fixed objects was found to be highly fatal in darkness than in sufficient light conditions. Finally, the impact of rear-end crashes on fatality was established as opposite between dark, dark-lighted, and daylight conditions, such that darkness increased the likelihood of drivers being involved in rear-end fatal crashes.

Furthermore, it is predictable that darkness obstructs drivers' visibility, allowing reduced time for last-minute braking and manoeuvring in moments before a crash, resulting in more fatalities. In this sense, Khorashadi et al. (2005) using 4 years (1997-2000) of California crash data captured the influence of light conditions by applying indicator variables that represented various times of day as the independent variables. The data were obtained from the TASAS database. Their study used a multinomial logit analysis and proposed that fatal crashes during morning hours were less fatal when compared to crashes in dark non-light conditions for both rural and urban areas.

Another research by (Chen & Chen et al., 2011), using 10 years of data from the HSIS database for 1991 to 2000 and mixed logit models, established that non-bright light conditions greatly increased the probability of fatalities in crashes. Similarly, Zhu and Srinivasan et al., (2011) established using an ordered-prohibit model that crashes occurring in conditions that were “dark but lighted” (from 7:30 p.m. to about 5:30 a.m.) were fatal relative to daylight and dark lighting conditions. Their study obtained 2001 to 2003 data from the LTCCS which was released in 2006. On the contrary, using data from the Florida Traffic Crash Records database for 2006, Xie et al. (2012) indicated surprisingly that darkness increased drivers' probabilities of involvement in non-fatal crashes. Their analysis used a multinomial logit model and the latent class model. They concluded that drivers have a habit of being more guarded when it is dark and in the absence of streetlights.

Another study by Pahukula et al. (2015) focused on the time of day crash effects. Using the CRIS database in Texas for the years 2006 to 2010, their random parameters logit model established that fatality rates were higher when lighting conditions were good because drivers tend to drive at higher speeds when visibility is good.

Overall, the literature on light conditions suggests that lighting may or may not be a factor which increases drivers' probabilities of involvement in crashes. However, whether the crashes are fatal or not is still a debate with contrasting views.

Day of the Week

Past research focusing on the effects of day of the week impact on driver fatalities have mostly associated day of the week variable with BAC levels, according to a review of research by Lenne, Triggs, and Redman et al., (1999). They have used 28 participants with different BAC levels and at a different time of the day to formulate their results. The weekend has been established as the riskiest days, with Saturday indicating the highest recorded number of fatalities, averaging about 158 every Saturday as compared to a weekday. According to the FARS 2009 data examined by Walz and Daniels et al., (2011). They further suggested that higher fatalities were recorded on Saturdays because of drunk-driving. Similarly, Saturday has the recorded highest number fatalities rate in comparison to the percentage of vehicles on the road, about 1.2 deaths for every 100 million drivers (Walz & Daniels et al., 2011). Generally, almost one-third of all fatalities occurring on the weekend involved drivers with higher BAC levels. Nevertheless, during various hours of the day, these crashes happen more often. This was also in the earlier mentioned study by Hadland et al. (2016) examined alcohol policies and BAC-related crash fatalities among young drivers in the US (≤ 20 years) using 2000 to 2013 data from FARS.

Similar research was carried out in Ghana by Ackaah and Adonteng et al., (2011). They used Fatal Road Traffic Crashes (RTCs) Database for the period 2005 to 2007, and Micro-computer Accident Analysis Package software was used to calculate the risk factors associated with fatalities. Their findings with regard to the days of the week indicated that most fatalities were recorded on the weekends, with Saturday having the highest fatalities 16.8% followed by 15.9% on Sundays and Fridays recording 15.6%. In general, when combining the weekend together, including Friday, fatalities recorded were nearly one-half 48.3%. They further established December and November as the riskiest months with 10.4% and 9.8% respectively of all the recorded fatalities in Ghana (Ackaah & Adonteng et al., 2011).

Generally, the studies linked weekends (Fri 6 pm to Mon 6 am) with more fatalities than weekdays. Weekends also have a higher number of fatalities as compare to weekdays due to the increase in BAC level during weekends.

Pavement Type

The effect of skid resistance on fatality at various pavement types has been assessed through an analysis by Saplioglu et al. (2013): using regression analysis, their study indicated that there was a significant fatal crashes reduction with increasing pavement skid resistance. The research examined data from 2007 to 2011, obtained from the Isparta Municipal Department of Technical Services. Another study developed a pavement skid resistance crash model and texture depth crash model on a single roadway in the UK (Viner, Sinhal, & Parry, 2004). It established fatality rate was reduced by 65% with increasing pavement skid resistance from 0.35 to 0.6.

Moreover, to evaluate the impact of pavement condition factors on fatality, research by Chan et al. (2010) focused on asphalt roadways in urban locations with an 80 km/hr speed limit. The study used Tennessee Pavement Management System (PMS) and Accident History Database (AHD) to obtain crash data for the year 2006. Negative binomial regression was used for the analysis. The study further used the International Roughness Index (IRI) to measure the pavement condition. It was established that the fatality rate increased as the roadway condition deteriorated and particularly when other variables were included. The feasible explanation for this was that when the pavement surface was rough, the driver had more challenge with the pavement surface visibility in severe weather conditions which increased the chances of fatal crash occurrence.

Additionally, an exploratory study using a Pearson correlation analysis established a link between pavement type characteristics and fatalities in selected rural roads in Australia (Cairney & Bennett et al., 2008). The data were obtained from the VicRoads Crash stats system. Nonetheless, for signalized urban intersections in the same area, a different study by the same authors found there was no correlation between crash occurrence and pavement roughness. Similarly, this was further tested in Sweden by Ihs (2004), who assessed the influence of pavement roughness on crashes. The study findings indicated that higher IRI was related to a higher fatality rate. Also, an increase in fatalities at signalized intersections was established to be related with an increase in pavement roughness as a result of the presence of shoving, rutting, and pavement surface according to Larson et al. (2008). The research was done in Ohio, with data collected from 90 locations across the state. Single linear regression and multivariate linear regression models were utilized for the analysis. In addition, it was also suggested by Pahukula et al., (2015) that for fatal crashes with a fixed object, 61.8% happened on roadways with smooth asphalt, while 84.3% happened on dry roadway surface conditions.

Generally, the past studies on pavement type have suggested that fatal crashes occurred on pavements with poor pavement condition when compared to the smooth asphalt.

Past studies show that there is a direct or indirect contribution of each variable to driver fatalities. To decrease the fatal accidents, several variables were examined in our research individually and all together.

2.2. Statistical Methods

Regression is an analysis method of using data records to compute the relationship between a target variable, also known as the dependent variable, and a number of variables that are independent, also known as a covariate (Menard et al., 2010). The importance of quantifying the relationship between the dependent and the covariate variables is that the value of each covariate variable to the dependent variable value becomes known. After the value is known, what is needed is only the values of the covariate variables in order to make predictions for the dependent variable value. The objective of regression models is to produce the line that best fits the recorded data (Allison et al., 2012). The logic for this is that the recorded data varies and may never fit accurately on a line. Nevertheless, the regression line best fitted for the recorded data leaves the minimum amount of unexplained difference, like the distribution of points observed around the line. There are different types of regression analysis, with the most widely used including Logistic Regression, and Poisson Regression. These types of regressions will be discussed next. This section reviews the basic models of Univariate and Multivariate logistic regressions as well as the Poisson regression model.

2.2.1. Logistic Regression

Logistic regression analysis is convenient when the result is binary, which means a zero or one, of which one is considered a success (Allison et al., 2012). It may be widely used in studies examining the relationship concerning whether a fatality occurred in the gender, age, among other factors of the involved driver (Lord & Mannering et al., 2010). Models using logistic regression, calculate the occurrence probability of a dependent variable through the use of the given independent variable displayed in Equation 1. Thus, the expected resultant variable 'Y' is non-fatal (or value equal to 0) or fatal (or value equal to one).

$$Pr\ (Y = 1/X = x) \tag{1}$$

In this case, (Pr) is the conditional probability which is demonstrated as a function of x. If the relationship between x and $Pr\ (Y = 1/X = x)$ is assumed to be linear in equation 1, a difficulty arises. In this case, a value increase of x would decrease or increase the probability value (Allison, 2012). However, the probability value can only lie between 1 and 0 as linear models are often unbounded. Nevertheless, there is a likelihood of the probability falling outside those limits. The greatest way to mitigate this issue is by using logistic regression. Besides the outcome, it can be observed that some independent variables may have a vital influence on the outcome, representing them as $X_1\ X_2, \dots, Xp$. The relationship between the independent variables and the outcome is characterized by the distribution of the conditional probability of Y given that $X_1\ X_2, \ldots, X_p$.

Logistic regression is often applied for modelling the probabilities of an event (Menard et al., 2010): in our case, fatality or no fatality. The occurrence of fatality is a dichotomous variable, in which there are two odds: fatality occurred, or it did not occur. The fatality in this occurrence variables will be coded using 0,1 for example,

Yi = 1 ⇐⇒ driver i died in the crash. (from Equation 1)

Yi = 0 ⇐⇒ driver i did not die in the crash. (from Equation 1)

While there are many methods used to measure the probability of a specific event, the current study used the log-odds favouring fatality. A logistic regression analysis will model the likelihood of an outcome centered on individual attributes (Allison et al., 2012). The likelihood function is used which is the probability distribution of observed data expressed as a function of statistical parameters (independent variables). It describes odds of obtaining the observed data for all parameters, and is used to identify the particular parameter values (independent variables) that are most plausible in observed data. Therefore, likelihood ratio, demonstrates chance logarithm from which odds ratio is calculated from the log favouring the event in Equations 2 and 3:

$$log(Y = 1) = log\frac{P(Y = 1)}{P(Y = 0)} = log\frac{\pi}{1 - \pi} \qquad [2]$$

Note,

$$log(Y = 1) = -log(Y = 0) = log\frac{\pi}{1 - \pi} \qquad [3]$$

Whereby log(Y) in Equations 2 and 3 is any number which ranges between -∞ and ∞, moreover, a log of -∞ would imply that there is a certainty of a crash being non-fatal, while increased log implies an increased belief in the fatality occurrence. At the same time, a log of 0 is equal to 1/2 probability while the log of ∞ implies the certainty of fatality occurring represented in Equations 2 and 3.

There is a need to model $P\ (Y = 1)$ based on the predictor (independent) variables $X_1, X2, \ldots X_P$ (in this case $P = 1$ for the univariate logistic $P = 1$). For linear regression analysis, Equation 4 was used:

$$E(Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p \qquad [4]$$

$E(Y) = Outcome\ or\ dependent\ variable,$

$\beta_0, \beta_1, \beta_2$ & β_p $= parameters\ and$

X_1, X_2 & X_p $= independent\ variables.$

Nonetheless, for a dichotomous *Y = (0 or 1), E(Y) = P (Y = 1)* from equation 4. The above equation cannot be used for multivariate since the left-hand side (LHS) represents a number which is between 0 and 1, whereas the right-hand side (RHS) is hypothetically a number ranging between $-\infty$ and ∞. The solution is, therefore, to substitute the LHS with log EY represented in Equation 5:

$$log\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p \qquad [5]$$

So as to achieve a simple analysis of the above intercept in Equation 5, a situation is needed whereby the other factors ($\beta_1 \ldots \beta_P$) vanish. This would happen in a situation where X_1, $X_2, .., X_P$ are all equivalent to 0. Thus, β_0 may be interpreted as:

β_0 is the log favouring Y = 1 when X1 = X2... = XP = 0

2.2.2. Univariate Logistic Regression

In order to obtain a simple β_1 interpretation, there is a need to determine a way to eliminate β_0 from the equation (Menard et al., 2010). Since the log scale has the following regression Equation 6.

$$log(Y = 1) = \beta_0 + \beta_1 X_1 \qquad [6]$$

Where:

Log (Y= 1) = Outcome or dependent variable,

β_0 & β_1 = parameters,

X_1 = independent variable

This implies the difference in the log can be considered at different X_1 values explained in Equation 7, for example, m+n and m.

$$\log(Y = 1 \,\middle|\, X_1 = m + n) - log) \\ = \beta_0 + \beta_1(m + n) - \beta_0 + \beta_1 = m\beta_1 \tag{7}$$

Where,

X_1 = independent variable,

m+n and m = Values for X_1,

By putting n = 1 above, an interpretation can be made of β1: β1 as the log-additive change favoring Y = 1 in the event X_1 gets increased by 1 unit.

2.2.3. β1 Log Ratio

Therefore, β1 is interpreted in terms of m+n and m in Equation 8:

$$log\left(\frac{(Y = 1|X_1 = m + n)}{(Y = 1|X_1 = m)}\right) = m\beta_1 \tag{8}$$

2.2.4. Multivariate Logistic Regression Coefficients

In multivariate logistic regression, the regression coefficients interpretation is similar to the above univariate regression interpretation. β_0 was previously dealt with. Overall, the coefficient β_K (which corresponds to the variable X_K) may be interpreted as the additive variation in the log favouring Y = 1 in the condition that X_K is increased by 1 unit, while there is no change to the other predictor variables in equation 7 (Menard et al., 2010).

2.2.5. Poisson Regression

There is a similarity between Poisson regression and regular multiple regression apart from in an observed count, the dependent (Y) variable, follows the Poisson distribution (Winkelmann et al., 2010). Hence, the likely (Y) values are positive integers: 0, 1, 2, 3, etc. Furthermore, it is supposed that large counts are unusual. Therefore, Poisson regression can be compared to logistic regression, which similarly has a response variable that is discrete. Nevertheless, the response is not restricted to particular values like in logistic regression (Cameron & Trivedi et al., 2013).

2.2.6. The Poisson Distribution

The Poisson distribution is used to model the odds of (y) events (such as fatality, non-fatal, or crash) with the formula:

$$Pr(Y = y|\mu) = \frac{e^{-\mu}\mu^{y}}{y!} \qquad (y = 0,\ 1,\ 2\ldots) \qquad [9]$$

Note a single parameter (μ) specifies the Poisson distribution. This is the mean incidence rate of a rare event for each unit of exposure. Moreover, the exposure may be space, time, volume, area, distance, or population size. Since the exposure is regularly a time-frequency, the symbol (t) is used to symbolize the exposure. However, when no value of exposure is given, an assumption is made to be one (Cameron & Trivedi et al., 2013). In addition, the (μ) parameter can be construed as the possibility of a new incident of the event within a specified (t) period of exposure. The likelihood of (y) events is there given by:

$$Pr(Y = y|\mu, t) = \frac{e^{-\mu t}(\mu t)^{y}}{y!} \qquad (y = 0,\ 1,\ 2\ldots) \qquad [10]$$

There is a distribution property that the variance and mean are equal.

2.2.7. The Poisson Regression Model

Poisson regression is used to calculate counts where the dependent (Y) variable is an observed count. Thus, the possible values of Y are the nonnegative integers: 0, 1, 2, 3, and so on. In the Poisson regression, which is also known as a log-linear model, the Poisson incident rate μ is determined by a set of p regressor factors represented in Equation 11 (the X's) (Winkelmann et al., 2010, NCSS).

$$\mu = t\exp(\beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p) \qquad [11]$$

Where,

μ = Poisson distribution,

t = time frequency,

$X_1, X_2\ \&\ X_p = independent\ variables\ and$

$\beta_0, \beta_1, \beta_2\ \&\ \beta_p\ = parameters$

Notice that frequently, X_1=1 and then β_1 is the *intercept*. Furthermore, the $\beta_1, \beta_2, \ldots, \beta_k$ regression factors are unknown parameters and are determined from a data set. Hence,

$\beta_1, \beta_2, \ldots, \beta_k$ are labeled estimates. Consequently, the essential Poisson regression model (using this notation) for an observation (i) is displayed in Equation 12,

$$Pr(Y_i = y_i | \mu_i, t_i) = \frac{e^{-\mu_i t_i}(\mu_i, t_i)^{y_i}}{y_i!} \qquad [12]$$

where,

$$\mu_i = t_i \mu(X_i' \beta)\ t_i exp(\beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki}) \qquad [13]$$

Poisson distribution (μ_i) is used to model count data. There are different set of independent variables which contribute to model total counts, which means that the Poisson distribution is calculated by several independent variables. In other words, for a given set of values of the regressor variables (independent variables), Poisson distribution is calculated in Equations 12 and 13.

2.2.8. Maximum Likelihood Estimation

The maximum likelihood in Equation 14 is used to estimate the regression coefficients (Winkelmann et al., 2010, NCSS). The likelihood function logarithm is.

In Equation 14, "y" is the response variable vector, and $\widehat{\mu_i}$ is equal to vector fitted values, calculated from MLE's, $\hat{\beta}$ by exponentiating the linear prediction η = $X_i' \widehat{\mu_i}$.

$$ln[L(y, \beta)] = \sum_{i=1}^{n} y_i\, ln[t_i \mu(X_i' \beta)] - \sum_{i=1}^{n} t_i \mu(X_i' \beta) - \sum_{i=1}^{n} ln(y_i!) \qquad [14]$$

Notice that various statistical software may disregard the last part because it does not include the regression factors, thus their computed log-likelihoods may look different. The formation of the likelihood equations may be done by taking the derivatives in line with each regression factor and setting the outcome = 0. If this is done, the outcome may be a number of nonlinear equations that states no closed-form solution. Hence, there must be the use of an iterative algorithm to find the number of regression factors that maximize the log-likelihood. If the iteratively reweighted least squares (IRLS) method is used, a solution can be established in six iterations (Cameron & Trivedi et al., 1998).

2.2.9. Maximum Likelihood Estimates (MLE's) distribution

If the usual maximum likelihood theory is applied, the asymptotic MLE's distribution is multivariate normal explained in Equations 15 and 16:

$$\hat{\beta}\ N(\beta, \beta V_{\hat{\beta}}) \quad [15]$$

$$V\hat{\beta} = \left(\sum_{i=1}^{n} \mu_i X_i X_i'\right)^{-1} \quad [16]$$

Note that the mean and variance in the Poisson model are equal. Thus, the data practically may always reject this limit. Frequently, the variance > mean, in what is referred to as over-dispersion. In the model, the variance increase is characterized by a constant multiple of the covariance matrix displayed in Equation 17:

$$V\hat{\beta} = \phi\left(\sum_{i=1}^{n} \mu_i X_i X_i'\right)^{-1} \quad [17]$$

where ϕ is estimated using

$$\hat{\emptyset} = \frac{1}{n-k}\sum_{i=1}^{n} \frac{(y_i - \hat{\mu}_i)^2}{\hat{\mu}_i} \quad [18]$$

2.2.10. Goodness of Fit Test

The overall model performance is measured using two chi-square tests: (1) the Pearson statistic (Equations 19 & 20),

$$P_p = \sum_{i=1}^{n} \frac{\left(y_i - \hat{\mu}_i\right)^2}{\hat{\mu}_i} \quad [19]$$

and (2) the deviance statistic,

$$D_p = \sum_{i=1}^{n} \left\{ y_i ln\left(\frac{y_i}{\hat{\mu}_i}\right) - (y_i - \hat{\mu}_i) \right\} \quad [20]$$

Both tests are relatively chi-square distributed with $n-k$ degrees of freedom (Cameron & Trivedi, 2013). Moreover, when there is a rejected test, there is a substantial lack of fit, while when there is no rejected test, there is no lack of fit suggestion. In addition, $P_p$is only chi-square distributed in the analysis of a grouped data, and frequently is also used to test over-dispersion.

2.2.11. Deviance

The deviance is double the variance between the maximum attainable log-likelihood and the fitted model's log-likelihood. In regular multiple regression, this is the sum of residual squares (Cameron & Trivedi, 2013). To this end, in Poisson regression, it is a generalized sum of squares. The formulae are in Equation 21:

$$D(y, \hat{\mu}) = 2\{LL_y - LL_{\hat{\mu}}\} \qquad [21]$$

2.2.12. Pseudo R-squared Measures

It is worth noting the R-squared statistic is not extended to Poisson regression models. Nevertheless, there has been a suggestion of several pseudo-R-squared tests. The tests measures have a property in such a way, when used in the linear model, they are considered as equivalent to the linear model R-squared (Cameron & Trivedi, 2013). Consequently, the most popular measure is three model function of the log-likelihoods represented in Equations 22 to 25:

$$R^2 = \frac{LL_{fit} - LL_0}{LL_{max} - LL_0} \qquad [22]$$

Notice that LL_0 = Log-likelihood intercept−only model, LL_{fit} = log-likelihood current model,

$$LL_0 = \sum_{i=1}^{n} y_i \, 1n[t_i\hat{\mu}] - \hat{\mu}\sum_{i=1}^{n} t_i - \sum_{i=1}^{n} 1n(y_i!) \qquad [23]$$

where $\hat{\mu} = \frac{\sum_{i=1}^{n} y_i}{\sum_{i=1}^{n} t_i}$,

$$LL_{max} = \sum_{i=1}^{n} y_i \, 1n[t_i y_i] - \sum_{i=1}^{n} t_i y_i - \sum_{i=1}^{n} 1n(y_i!) \qquad [24]$$

$$LL_{fit} = \sum_{i=1}^{n} y_i \, 1n[t_i\hat{\mu}(X_i'\beta)] - \sum_{i=1}^{n} t_i\hat{\mu}(X_i'\beta) - \sum_{i=1}^{n} 1n(y_i!) \qquad [25]$$

Where, and LL_{max} = possible maximum Log-likelihood. Furthermore, LL_{max} occurs if the actual responses (the y_i's) = the predicted responses (the μ_i's). Note that, this R-squared value varies between 0 and 1, with one occurrence of a perfect fit. Also, it should be noted that it assumes the model has an intercept.

CHAPTER 3: METHODOLOGY

This chapter begins with a description of the source of crash data. Next, geometric variables selected for the analysis are described. In the statistical analysis section data, interpretation and various methods used are explained. In the last part of the chapter, the procedure for countermeasures is presented.

3.1. Source of Data

FARS is a national database containing comprehensive data about crashes on public roads within the United States. FARS is a yearly database on crash situations that result in at least one fatality occurring in less than a month after the crash (NHTSA, 2017). FARS is, therefore, a census database of all crash fatalities in the United States. FARS includes annual data from 1975 onward. The datasets in FARS comprise files which include a crash file, a driver file, a vehicle file, and a file on each person involved. These data may be applied in answering many questions on vehicle safety, drivers, roadway conditions, traffic situations, and roadways, at both national and state levels.

The crash file contains all information regarding the crash situation (such as pavement types, lighting conditions, weather conditions, time of day, among others) about each crash. The vehicle file contains information (such as vehicle types, vehicle weight, and vehicle model year) regarding all vehicles involved in each crash. Lastly, the person file has information concerning all vehicle occupants (such as age, gender, drivers and passengers, physical address, pedestrians, injury severity for each person, among others) who had been involved in each crash. In addition, the FARS database includes more specific geographical data (such as city, county, state, latitude, and longitude) for every crash. The FARS crash data are available from the NHTSA website for download.

The analysis presented was based on driver fatalities. Passengers were not considered in the current analysis which eliminates the effect of seating position. Seating position will affect the risk of a fatal injury, with the rear seats to be the safest location in the vehicle (Bédard et al., 2002). Single vehicle crashes were used to eliminate the risk of fatality which is dependent on the characteristics of another vehicle(s).

Crashes are included in FARS only if there is a fatality; if there are only drivers as sole occupants in single-vehicle crashes, then this would have led to a sample of 85% driver fatalities possibly biasing the outcomes of the analyses. Therefore, to solve this problem analysis was performed on crashes where at least 2 vehicle occupants were present. In all circumstances, there will be one fatality in a crash but not necessarily the driver dies. This research considers driver fatalities for single-vehicle crashes with fixed objects with 2-7 occupants.

3.2. Variable Selection

This research included the variables used in the previous study by Bédard et al., 2002. These variables are related to driver fatalities with fixed objects, and Table 3.1 shows the list of variables.

Table 3.1: Variables from previous study by Bédard et al., 2002.

Variables	
• Age	• Vehicle deformity
• Gender	• Vehicle use
• Alcohol use	• Weight
• Direction of impact	• Wheelbase
• Restraint use	• Model year
• Airbags	• Vehicle age

Dupont et al., (2010) & Wang et al., (2017) suggested that geometric variables such as roadway alignment, roadway conditions, roadway type, and roadway function, among others, are linked with driver fatalities. Therefore, this research added the key environmental and roadway factors from literature review to the list of variables to be evaluated in the analysis. Table 3.2 shows the potential variables selected and their availability in the FARS database.

Table 3.2: Variables with availability considered in the analysis.

Variables	**Availability**
• Roadway Alignment (Curved, Straight, Unknown)	• Added to the analysis.
• Roadway Conditions (Dry, Not Dry, Unknown)	• Added to the analysis.
• Light Conditions (Daylight, Dark)	• Added to the analysis.
• Day of the Week (Weekday, Weekend, Missing)	• Added to the analysis.

Table 3.2: Variables with availability considered in the analysis. (Cont.)

• Roadway Function (Interstate, Principal arterial, Freeways and expressways, principal artery, Principal arterial, other)	• Added to the analysis.
• Data Year Analysis (every 5-year increment)	• Added to the analysis.
• Interstate vs Non-Interstate roads	• Covered in Roadway Function.
• Relation to Junction (Non-Junction, Intersection, Intersection-related, Driveway, Alley etc.)	• Attribute code is changed after the year 2009.
• Intersection type	• Data recorded for years 2010 to 2013 only in FARS manual.
• Nature of Lanes	• Not in FARS manual
• Number of Lanes	• Data recorded for years 1975 to 2009, from 2010 attribute is changed
• Street lighting	• Not in FARS manual
• Vehicle movement	• Not in FARS manual
• Presence of the red-light camera	• Not in FARS manual
• Shoulder type	• Not in FARS manual
• Traffic Control Devices	• Data for Traffic Control Devices is discontinued in FARS manual.
• Access Points (Passing, Merging, Turning, etc.)	• Not in FARS manual
• Signage	• Not in FARS manual
• Surface Friction	• Not in FARS manual
• Grade	• Known as roadway profile till 2009 and then changed into Roadway Grade. Discontinuity of Data.
• Cross section	• Not in FARS manual
• Weather	• Covered under light conditions
• Visibility	• Covered under light conditions
• Area Type (Urban, Suburban, Rural)	• Covered under roadway function
• Terrain (Flat, Rolling, Mountainous)	• Covered under roadway type.
• Roadway Segments	• Not in FARS manual
• Special Facilities	• Not in FARS manual

The variables listed above were considered to be added in the analysis, but they were shortlisted due to different reasons such as not enough information available in FARS or not been recorded or have been discontinued after a certain number of years. Another reason for not including some of these variables is that they have a different attribute (code) after a certain number of years. Attributes for fixed objects and weather conditions are listed in Appendices A and B respectively. The final list of variables added in the analysis is shown in Table 3.3.

Table 3.3: Additional variables included in this research.

- Roadway Alignment (Curved, Straight, Unknown)
- Roadway Conditions (Dry, Not Dry, Unknown)
- Light Conditions (Daylight, Dark)
- Day of the Week (Weekday, Weekend, Missing)
- Roadway Type (Asphalt, Concrete, Brick, Dirt, Gravel, Other)
- Roadway Function (Interstate, Principal arterial, Freeway and expressway, Principal artery, others.
- Data Year Analysis (every 5-year increment)

3.3. Statistical Analysis

The statistical analysis is divided into three different parts. In the first part univariate and multivariate logistic regressions are used to replicate Bédard et al., 2002 previous study. The second part consists of two different sections. First, the work of Bédard et al., 2002, is updated considering additional 17 years of data. Secondly, additional variables are added into the analysis to calculate the Odds Ratio for driver fatalities with fixed objects by Univariate and Multivariate Logistical Regressions. Odds ratio (OR) is a measure of association between an exposure and outcome. The odds ratio represents the odds that an outcome will occur given a particular exposure, compared to the odds of occurring in the absence of exposure. Generally, the Odds ratio is Odds of exposure in one group by Odds of exposure in another group. In the original and replicated analysis, the Odds ratio is determined by using the independent variables crash, driver, and vehicle characteristics and the dependent variable driver fatality.

The third part consists of three sections. The first section consists of raw fatality counts of drivers with fixed objects. The second and third sections use Poisson Regression to calculate driver fatality counts which were interpreted from Incidence Rate Ratios and Coefficients.

3.3.1. Replication of Bédard et al., 2002 (1975 to 1998)

In this part, the work done by (Bédard et al., 2002), considering data from 1975 to 1998 was replicated. Raw data were transferred in IBM SPSS, and then Data-year was fixed, data-year ranges for the year 1975 to 1998. Then the frequencies command was used to sum the number of instances within a particular category.

Identification of Minimum Occupants was required to include a minimum of 2 occupants and a maximum of 7 occupants. This will allow to have the possibility of not only drivers dying in the crash, and if there are only drivers as sole occupants in single-vehicle crashes, then this would have led to a sample of 85% driver fatalities possibly biasing the outcomes of the analyses as mentioned earlier.

Next step is to use frequency command in order to calculate the total number of cases for 2-7 occupants. Moving forward with the analysis, the next step is to code fixed objects according to 2011 to 2015 manual, and it is used for coding the fixed objects in the analysis. FARS manual 2011 to 2015 is used because this is the latest version which has the most recent and up-to-date information for the data since 1975. Fixed objects are labelled as “1” and the others as “0”. The list of fixed objects used in the analysis is listed in Appendix A. The frequency of fixed objects is determined later to calculate the total number of cases which were used in the analysis.

The types of vehicles used in the analysis were also shortlisted into cars, light trucks/SUV’s and vans. Age was recoded from 0 to 80+ years and divided into 7 groups starting from 0 thru 19, 20 thru 29, and so on, missing values for age were recoded as “99”. Sex was recoded as “1” for males and “2” for females, and other was recoded as “8” & missing values were recoded as “9”. Fatal Injuries were recoded as “1” and non-fatal injuries by “0”. There are a total of 9 tables for this replication work from which 8 are calculated by cross tabulation. The first table is generated by cross-tabulation of fatalities by age category and sex.

The second table is a cross tabulation between fatalities by Blood Alcohol Content (BAC) and age group. BAC is recoded into several groups starting from 0 to 6. First group which has “0.0” BAC was represented by label “0”, second group with “0.01-0.04” BAC was represented by label “1”, third group with a BAC level of “0.05-0.09” was represented by label “2”, fourth group with a BAC level of “0.10-0.14” was represented by label “3”, and so on till the last group which has BAC “0.30+” which was labelled as “6”. Once the BAC is recoded, the second table is generated.

The third variable considered is Impact. FARS recorded impact point initial and impact point principal prior to 2010. Impact point initial is the clock point on the vehicle associated with that collision. If this is the only collision event for the vehicle then it was also the impact point principal, otherwise, impact point principal was the clock point on the vehicle associated with the collision event which produced the most severe incidence of injury or property damage.

FARS now records initial damaged area and most damaged area (FARS manual)

The clock point diagram (displayed below in Figure 3.1) identifies the (areas) of impact. Attributes “01-12” refer to the points on a clock. Impact variable was calculated in two parts, Impact 1 and Impact 2. Impact 1 is coded as the most harmful impact point (Principle), and Impact 2 is coded as the direction of impact. Impact 2 is used to calculate the driver side because the literature indicates that this side is considered as the most dangerous (fatal) of all. Bédard et al., 2002, used Impact 1 (Principle) in their analysis but Impact 2 was used in this analysis because FARS stopped recording the most harmful impact point Impact 1 (Principle) after 2011.

For Impact 2, front side is coded “1”, which is “11,12,1” according to the clock point diagram, right side is coded as “2” which represents “2,3,4” according to Figure 3.1, left side is coded as “3” which is “8,9,10” according to the diagram, and “4” is the code for rear side which represents “5,6,7” according to the diagram. “9” is used as code for non-collision, other, or unknown. Cross-tabulation of fatalities by direction of impact is performed to generate the third table.

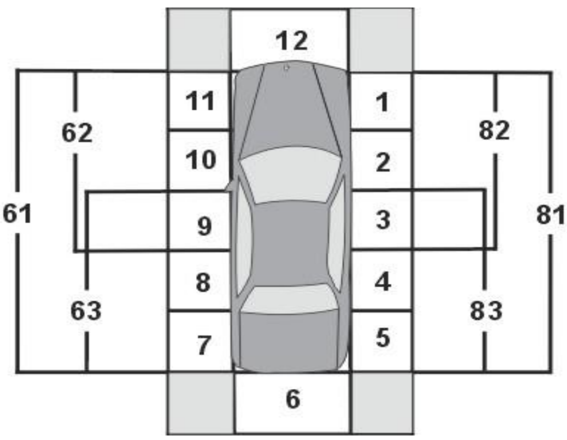

Figure 3.1: Areas of impact element values diagram (FARS manual, 2010).

Furthermore, the next variable considered in the analysis is Seat-belt. No seat belt was coded as “0”, Shoulder belt as “1”, Lap belt as “2”, Shoulder and lap belt as “3”, other (e.g., helmet, child safety seat, used but unknown) as “8” and “9” was used for missing values. Cross-tabulations of fatalities with restraint use and age group is performed to attain the fourth table. Similarly, airbags were coded as “0” for not deployed and “1” for deployed. Cross-tabulations of fatalities with airbags deployment with age group is performed to generate the fifth table.

Moreover, vehicle deformity is recoded for no damage, minor damage and functional damage equal to 0 and, disabling damage equal to 1. Missing values are coded as 8 and 9 which represent reported and unknown respectively. In the end, cross-tabulation is performed for fatalities by vehicle deformity and age group to generate the sixth table. Travel speed is the next variable and is calculated by recoding vehicle speed into different groups. These groups are coded as miles per hour with a particular value such as 0 thru 34 miles per hour (mph) = 0, 35 thru 59 (mph) = 1, 60 thru 152 = 3, and other = 9.

Cross-tabulation of fatalities by vehicle speed and age group is represented in the seventh table. Next, descriptive statistics such as weight, wheelbase, model year, vehicle age are represented in the eighth table. Weight, wheelbase and model year were directly extracted from the FARS database, and vehicle age was obtained by subtracting the vehicle model year from the calendar year at the time of the crash. For example, a 2000 model year vehicle crashed in 2009 had an age 9 at the time of the crash. A vehicle with age calculated as a negative one, is considered as zero. The negative one is due to model year vehicles released midway in the previous year. Finally, the ninth table is obtained by univariate and multivariate logistic regressions which are calculated by unadjusted and adjusted Odds Ratio model with 99 percent Confidence Interval (CI). Additionally, this analysis is a replication of (Bédard et al., 2002) study, in which the authors also used a 99 % CI.

3.3.2. Updated Work (data from 1975-2015)

The second analysis consists of two sections. The first section includes the replication analysis from the first section except that additional years of data are used. The data ranges from 1975 to 2015, including an additional 17 years of data.

Section two consists of expanding the original analysis from Bédard et al., (2002) by adding new variables. Data used in the analysis range from 1982 to 2014 because some of the variables considered did not have information from earlier or later years such as no travel speed data in 1980 or 81 and Road Function was not recorded prior to 1982, nor recorded from 2015 onward. The Odds ratio (OR) with 99% confidence interval of a fatality was calculated with univariate statistics (unadjusted OR) for each variable to establish whether the driver, vehicle and crash characteristics were linked with fatalities. Then a multivariate statistic (adjusted OR) for the crash, driver, and vehicle characteristics was performed. Both the adjusted and unadjusted Odds ratio with 99% CI were examined to determine if a variable is associated with a fatality or not. The statistically significance for each variable associated with driver fatality risk was tested using ($P<0.01$), and variables which were not statistically significant were removed from the model.

3.3.3. Poisson Regression Analysis (Data from 1982 to 2014)

The analysis consists of three subsections. In the first subsection, total fatality counts with a fixed object by each factor included in the model are displayed in the results; these are simply raw counts. In the second subsection, driver fatality counts in terms of Poisson regression Coefficients are interpreted and in the third subsection, Incidence-Rate Ratios (IRR's) for driver fatality counts which are simply the exponentiated coefficients are considered respectively. Basically, Poisson regression helps to determine the strength of the relationship between one dependent variable and a series of other changing variables. In this case, the dependent variable was the total number of counts for driver fatalities, and the independent variables were crash, and geometric factors. Driver factors were not considered due to sample size concerns (smaller sample size). Poisson regression was used in the analysis because the data satisfied all the necessary conditions, and in the third analysis, total number of fatality counts are calculated as an outcome when in previous two analyses the outcome was to calculate driver fatality risk. The mean and variance of the data were the same. Counts were positive integers (i.e. whole numbers) 0 or greater (0,1,2,3…k). Also, the technique does not work with fractions or negative numbers because the Poisson distribution is a discrete distribution. Additionally, Y values are counts and need to be positive integers, while the explanatory variables must be continuous, dichotomous or ordinal.

The variables listed in Table 3.3 were considered in the analysis as factors for the total number of driver fatality counts with fixed objects Variables used by Bédard et al., (2002), were not included in this analysis except age and gender because by doing so the sample size was reduced due to the substantial number of cases for each variable i.e., in other words each variable have millions of cases which reduce the sample size. Reduction in sample sizes results in unreliable values for results. The third analysis was carried out in STATA instead of IBM SPSS. STATA is better when the sample sizes are small. Data were filtered for the analysis for the years 1982 to 2014 to eliminate years missing values and then fatality counts per crash were computed. Single-car crashes were coded to eliminate the risk of fatality which that are dependent on the characteristics of another vehicle(s). Driver fatality counts were calculated from Coefficients and Incidence Rate Ratios in terms of Poisson Regression. Variables used in the analysis are statistically significant with respect to driver fatality counts and a $P < 0.05$ is used to measure the level of significance with a 95% CI. Lastly, Wald chi2 which represents the degree of freedom and Psuedo-R2 which is a statistic generated in ordinary least squares as goodness of fit measure are displayed.

3.4. Countermeasures Identification

The main objective of the present study was to identify the independent driver, crash and vehicle factors and circumstances that increase driver fatality risk. Through gaining knowledge of the actions, circumstances, or situations that increase fatality risks, countermeasures were identified to reduce fatality risks and involvement. Risk levels were evaluated in absolute terms if appropriate exposure data were accessible (for instance, crashes per vehicle age and model year) or based on relative risk (for instance, an increase in driver fatality risk as a result of BAC levels exceeding legal limits compared to sober drivers.).

The researcher analysed previous studies on driver fatality risks and driver involvement through literature review and various countermeasures proposed by various authors were identified. Results from previous parts of this study aided in sorting out key crash contributors and identification of any interactions. Then, the review identified methods that can be implemented to reduce driver fatality and to manage roads and junctions. Finally, the identified results and countermeasures of different authors were compared to the current research results. If the results did not support the identified countermeasure, the countermeasure management would be abandoned. The studies that were analysed for the identification of road safety countermeasures for management are illustrated below in Table 3.4.

Table 3.4: Countermeasures management.

Analysed Studies	Examined Countermeasure Management
1. American Association of Retired Persons (AARP); American Automobile Association (AAA)	- Older Drivers Training programs
2. Bédard et al. (2002); Lee et al., (2017)	- Training drivers on Airbag Safety
3. Bédard et al. (2002); Lee et al., (2017)	- Training drivers on Seatbelt Safety

Table 3.4: Countermeasures management. (Cont.)

4. Hadland et al. (2016)	- Management of Drunk-driving
5. FHWA (2018); Whitworth et al., (2004)	- Improving curved road design, Installing Roadside barriers
6. Dillon et al., (2012); (DMV, 2018)	- Controlling traffic at non-junctions
7. Chen & Chen et al., 2011; FHWA (2018); IESNA, 2005	- Improving roadway lighting systems

CHAPTER 4: RESULTS AND ANALYSIS

This chapter presents the results of the analyses and countermeasures. Results are divided into three parts. First part replicates previous work by (Bédard et al., 2002), considering data from 1975 thru 1998. The second part presents an updated analysis of Bédard and colleagues, (2002) work by including an additional 17 years of data from 1975 thru 2015 and also adding additional variables in the data analysis. The third part presents driver fatality counts for additional variables considering data from 1982 to 2014. Lastly, countermeasures are presented.

4.1. Replication of Bédard et al. (2002) Work

The analysis used univariate and multivariate logistic regressions to investigate the independent influence of driver, crash, and vehicle characteristics on fatalities considering data from 1975 to 1998.

Age and Gender

Table 4.1 shows the results from Bédard et al., (2002) study and Table 4.2shows the results from the replication work done in this research. Results presented in both tables indicate that the highest number of reported fatalities was among male drivers who were below the age of 30 years. The analysis also showed that a larger number of older adults had a higher fatality risk than young adults. Moreover, there was no significant difference across both genders for drivers aged below 40 years and those aged 80 years and older, while a higher percentage of drivers aged between 40 years and 79 years reported more fatal injuries for male drivers than female drivers. Moreover, there was no major difference between the results from Bédard et al., (2002) study and the replicated work when the overall percentages are examined but there is the large difference when absolute counts are examined. This research considered 40536 non-fatal cases and 40774 fatal cases while for Bédard et al., (2002) included 56772 non-fatal cases and 53065 fatal cases. The difference in number of counts can be explained by the fact that fixed objects considered in both studies can be different because attribute codes for fixed objects could have changed with the passage of time. The list of fixed objects used in this analysis are listed in Appendix A (as mentioned earlier). Furthermore, number of counts are decreasing in updated analysis, but it does not affect the driver fatality risk because age and gender in Table 4.1and 4.2 are calculated by cross-tabulation, which do not represent Odds ratio for driver fatalities.

Table 4.1: Fatalities by gender and age category.

Gender	Age (Years)							
	0-19	20-29	30-39	40-49	50-64	65-79	80+	Total
Male								
Non-Fatal	13801 (54.9)	18994 (51.5)	5845 (49.0)	2427 (47.4)	1903 (46.3)	1549 (47.5)	377 (46.6)	44896 (51.5)
Fatal	11318 (45.1)	17878 (48.5)	6091 (51.0)	2689 (52.6)	2211 (53.7)	1713 (52.5)	432 (53.4)	42332 (48.5)
Female								
Non-Fatal	3311 (54.4)	3779 (52.7)	1945 (50.9)	994 (49.5)	966 (52.0)	749 (53.4)	130 (49.4)	11874 (52.5)
Fatal	2774 (45.6)	3386 (47.3)	1877 (49.1)	1016 (50.5)	892 (48.0)	653 (46.6)	133 (50.6)	10731 (47.5)
Total								
Non-Fatal	17112 (54.8)	22773 (51.7)	7791 (49.4)	3422 (48.0)	2869 (48.0)	2298 (49.3)	507 (47.3)	56772 (51.7)
Fatal	14092 (45.2)	21265 (48.3)	7969 (50.6)	3705 (52.0)	3103 (52.0)	2366 (50.7)	565 (52.7)	53065 (48.3)

[a] Total number of cases are slightly higher than men and women data together as gender data were missing for approximately 200 cases.

Table 4.2: Fatalities by gender and age category (replicated 1975-1998).

Gender	Age (Years)							
	0-19	20-29	30-39	40-49	50-64	65-79	80+	Total
Male								
Non-Fatal	9792 (54.10)	13730 (50.10)	4177 (46.40)	1597 (43.20)	1170 (41.50)	1097 (45.60)	378 (49.10)	31941 (49.10)
Fatal	8299 (45.90)	13686 (49.90)	4822 (53.60)	2096 (56.80)	1647 (58.50)	1308 (54.40)	392 (50.90)	32250 (50.20)
Female								
Non-Fatal	2536 (53.10)	2713 (50.10)	1328 (46.80)	654 (45.70)	666 (49.80)	585 (53.70)	113 (49.60)	8595 (50.20)
Fatal	2243 (46.90)	2704 (49.90)	1509 (53.20)	778 (54.30)	671 (50.20)	504 (46.30)	115 (50.40)	8524 (49.80)
Total								
Non-Fatal	12328 (53.90)	16443 (49.97)	5505 (46.51)	2251 (43.92)	1836 (44.20)	1682 (48.13)	491 (49.20)	40536 (49.85)
Fatal	10542 (46.10)	16390 (50.03)	6331 (53.49)	2874 (56.08)	2318 (55.80)	1812 (51.87)	507 (50.8)	40774 (50.1)

Alcohol Use by Age

Driver fatalities related to BAC with age are presented in Table 4.3 andTable 4.4 below. Similar to Bédard et al., (2002) findings (Table 4.3), results for this research show that the percentage of sober drivers sustaining fatal injuries is 64.3% for adult drivers aged below 20 years and 87.1% for adult drivers aged 80 years and above. In relation to the age category of 30–39 years, the ratio of fatal injuries to non-fatal injuries for drivers was 2.64 at a BAC level of zero. At a BAC of 0.05–0.09, the ratio was 0.81. However, at a BAC level of 0.30 or higher, the ratio was 6.52. This pattern remained consistent for the rest of the age categories. Also, the overall relationship between fatality risk and BAC formed a 'U'-shape almost similar to the study from (Bédard et al., 2002). Thus, the overall risk for fatal injuries initially reduced with an increase to BAC, touching its lowest at 48.60% at the BAC level of 0.05-0.09. This then increased correspondingly with BAC levels reaching its highest proportion of 85.90% at a BAC level of 0.30 or higher.

Table 4.3: Fatalities by BAC against age (Bédard et al., 2002).

BAC	Age (Years)							
	<20	20-29	30-39	40-49	50-64	65-79	80+	Total
0								
Non-Fatal	1882 (35.8)	1308 (34.6)	456 (27.6)	279 (26.4)	248 (19.9)	218 (16.9)	31 (11.5)	4422 (30.4)
Fatal	3381 (64.2)	2469 (65.4)	1194 (72.4)	778 (73.6)	996 (80.1)	1071 (83.1)	2469 (65.4)	10127 (69.6)
0.01–0.04								
Non-Fatal	544 (50.0)	607 (52.7)	122 (42.1)	40 (32.8)	20 (22.5)	16 (27.6)	3 (25.0)	1352 (48.1)
Fatal	543 (50.0)	544 (47.3)	168 (57.9)	82 (67.2)	69 (77.5)	42 (72.4)	9 (75.0)	1457 (51.9)
0.05–0.09								
Non-Fatal	1016 (50.1)	1506 (53.6)	353 (54.3)	81 (39.7)	36 (36.0)	5 (13.9)	2 (28.6)	2999 (51.4)
Fatal	1012 (49.9)	1302 (46.4)	297 (45.7)	123 (60.3)	64 (64.0)	31 (86.1)	5 (71.4)	2834 (48.6)
0.10–0.14								
Non-Fatal	1301 (45.6)	2345 (46.9)	590 (47.0)	178 (42.0)	70 (34.0)	13 (27.7)	0 (0.0)	4497 (45.9)
Fatal	1553 (54.4)	2654 (53.1)	665 (53.0)	246 (58.0)	136 (66.0)	34 (72.3)	4 (100)	5292 (54.1)
0.15–0.19								
Non-Fatal	813 (35.8)	2154 (39.0)	701 (37.6)	213 (36.0)	85 (32.1)	17 (27.9)	1 (25.0)	3984 (37.6)
Fatal	1460 (64.2)	3371 (61.0)	1162 (62.4)	378 (64.0)	180 (67.9)	44 (72.1)	7 (75.0)	6598 (62.4)

Table 4.3: Fatalities by BAC against age (Bédard et al., 2002). (Cont.)

0.20–0.29								
Non-Fatal	301 (23.0)	1303 (26.0)	626 (27.2)	196 (21.6)	92 (22.4)	19 (23.5)	0 (0.0)	2537 (25.3)
Fatal	1005 (77.0)	3717 (74.0)	1678 (72.8)	710 (78.4)	319 (77.6)	62 (76.5)	1 (100)	7492 (74.7)
0.30+								
Non-Fatal	15 (12.2)	83 (15.3)	59 (13.9)	28 (12.4)	10 (9.4)	4 (28.6)	0 (0.0)	199 (13.9)
Fatal	108 (87.8)	458 (84.7)	365 (86.1)	197 (87.6)	96 (90.6)	10 (71.4)	2 (100)	1236 (86.1)

Table 4.4: Fatalities by BAC against age (replicated 1975-1998).

BAC	Age (years)							
	0-19	20-29	30-39	40-49	50-64	65-79	80+	Total
0.0								
Non-Fatal	1612 (35.7)	1057 (34.60)	353 (27.50)	208 (25.60)	190 (19.80)	169 (16.30)	32 (12.90)	3621 (30.40)
Fatal	2899 (64.3)	1998 (65.40)	931 (72.50)	606 (74.40)	769 (80.20)	869 (83.70)	217 (87.10)	8289 (69.60)
0.01-0.04								
Non-Fatal	428 (49.6)	497 (53.30)	102 (42.10)	31 (32.00)	16 (23.50)	13 (29.50)	3 (25.00)	1090 (48.30)
Fatal	435 (50.4)	436 (46.70)	140 (57.90)	66 (68.00)	52 (76.50)	31 (70.50)	9 (75.00)	1169 (51.70)
0.05-0.09								
Non-Fatal	787 (50.3)	1224 (53.40)	305 (55.20)	65 (39.20)	26 (32.10)	3 (10.30)	3 (37.50)	2413 (51.40)
Fatal	778 (49.7)	1069 (46.60)	248 (44.80)	101 (60.80)	55 (67.90)	26 (89.70)	5 (62.50)	2282 (48.60)
0.10-0.14								
Non-Fatal	998 (45.8)	1904 (46.80)	477 (46.90)	149 (40.20)	56 (34.60)	10 (22.70)	2 (40.00)	3596 (45.80)
Fatal	1182 (54.2)	2162 (53.20)	541 (53.10)	222 (59.80)	106 (65.40)	34 (77.30)	3 (60.00)	4250 (54.20)
0.15-0.19								
Non-Fatal	607 (36.00)	1744 (38.70)	594 (38.10)	181 (35.60)	69 (31.50)	13 (27.70)	3 (42.90)	3211 (37.70)
Fatal	1079 (64.00)	2757 (61.30)	966 (61.90)	327 (64.40)	150 (68.50)	34 (72.30)	4 (57.10)	5317 (62.30)
0.20-0.29								
Non-Fatal	237 (23.30)	1039 (25.70)	520 (26.70)	146 (19.90)	73 (22.10)	14 (22.20)	2 (28.60)	2031 (24.90)
Fatal	779 (76.70)	3009 (74.30)	1428 (73.30)	586 (80.10)	258 (77.90)	49 (77.80)	5 (71.40)	6114 (75.10)
0.30+								
Non-Fatal	13 (13.33)	68 (16.20)	48 (13.30)	23 (12.60)	8 (10.40)	2 (22.20)	0 (00.00)	162 (14.10)
Fatal	85 (86.70)	352 (83.80)	313 (86.70)	159 (87.40)	69 (89.60)	7 (77.80)	2 (100.00)	987 (85.90)

Direction of Impact

Out of the total direction of impact crashes reported, approximately 28740 fatal cases involved front crashes representing the highest number of fatalities per direction of an impact as displayed in Table 4.5 (Bédard et al., 2002). In the replicated work (Table 4.6), the highest number of fatalities was also for the fatal front impact direction with a total of 22414. Impacts on the right-side were reported for 3653 fatal crashes, for the left side (the driver-side) crash impacts had 6276 fatal crashes, and lastly, rear-end impacts recorded 960 fatal crashes. At best, both analyses showed over two-thirds of drivers failed to survive left-side impacts regardless of age category. Whereas, other analysis of Bédard et al. (2002) illustrated by Table 4.5 indicated that fatality proportion following all directions of impact also progressed with increasing age category before decreasing for drivers aged more than 65 years. Nonetheless, there were no observed differences in fatality risks and proportions in both results. However, this could be as a result of fewer data available for older driver categories. In this analysis (Table 4.6), direction (Impact1) has been used to examine the direction of impact instead of principle (Impact 2) used by Bédard et al., (2002) since impact 2 was not recorded anymore by FARS after 2011. Furthermore, to maintain continuity in the data Impact 1 is used for replicated analysis data were used from 1995 to 1998 and for updated analysis data were used from 1995 to 2015. Nonetheless, there were no observed differences in fatality risks and proportions for results from this research and the study from Bédard et al. (2002).

Table 4.5: Fatalities by impact direction against age (Bédard et al., 2002).

Impact	Age (years)							
	0-19	20-29	30-39	40-49	50-64	65-79	80+	Total
Front impact								
Non-Fatal	8371 (54.8)	11883 (51.9)	4428 (49.8)	2118 (48.9)	1903 (48.9)	1683 (49.2)	418 (48.1)	30804 (51.7)
Fatal	6893 (45.2)	10992 (48.1)	4464 (50.2)	2214 (51.1)	1990 (51.1)	1736 (50.8)	451 (51.9)	28740 (48.3)
Right-side impact								
Non-Fatal	3813 (72.2)	4669 (69.3)	1319 (63.8)	488 (62.1)	365 (61.0)	234 (64.3)	35 (57.4)	10923 (68.7)
Fatal	1471 (27.8)	2064 (30.7)	749 (36.2)	298 (37.9)	233 (39.0)	130 (35.7)	26 (42.6)	4971 (31.3)
Rear impact								
Non-Fatal	623 (63.8)	754 (58.7)	284 (61.1)	146 (67.6)	97 (64.2)	65 (65.0)	4 (33.3)	1973 (61.6)
Fatal	354 (36.2)	530 (41.3)	181 (38.9)	70 (32.4)	54 (35.8)	35 (35.0)	8 (66.7)	1232 (38.4)

Table 4.5: Fatalities by impact direction against age (Bédard et al., 2002). (Cont.)

Left-side impact								
Non-Fatal	1316 (33.1)	1565 (30.7)	555 (32.3)	212 (29.8)	155 (32.4)	92 (32.2)	14 (27.5)	3909 (31.7)
Fatal	2665 (66.9)	3535 (69.3)	1164 (67.7)	499 (70.2)	323 (67.6)	194 (67.8)	37 (72.5)	8417 (68.3)

Table 4.6: Fatalities by impact direction against age (replicated 1975-1998).

Impact	Age (Years)							
	0-19	20-29	30-39	40-49	50-64	65-79	80+	Total
Front								
Non-Fatal	6070 (53.50)	8632 (50.10)	3117 (46.50)	1415 (45.20)	1239 (45.30)	1266 (48.70)	391 (49.50)	22130 (49.70)
Fatal	5276 (46.50)	8601 (49.90)	3593 (53.50)	1718 (54.80)	1494 (54.70)	1333 (51.30)	399 (50.50)	22414 (50.30)
Right Side								
Non-Fatal	2668 (72.00)	3332 (68.30)	998 (63.60)	334 (59.60)	240 (60.00)	158 (64.20)	49 (65.30)	7779 (68.00)
Fatal	1037 (28.00)	1544 (31.70)	572 (36.40)	226 (40.40)	160 (40.00)	88 (35.80)	26 (34.70)	3653 (32.00)
Left side								
Non-Fatal	949 (32.80)	1070 (28.80)	355 (28.30)	115 (23.10)	88 (27.70)	58 (29.00)	17 (30.90)	2652 (29.70)
Fatal	1941 (67.20)	2643 (71.20)	899 (71.70)	383 (76.90)	230 (72.30)	142 (71.00)	38 (69.10)	6276 (70.30)
Right Side								
Non-Fatal	470 (63.10)	517 (55.20)	172 (54.30)	75 (60.50)	40 (51.30)	36 (58.10)	3 (30.00)	1313 (57.80)
Fatal	275 (36.90)	420 (44.80)	145 (45.70)	49 (39.50)	38 (48.70)	26 (41.90)	7 (70.00)	960 (42.20)

Restraint Use

Roughly, 82.24% of crash data related to restraint use reported that drivers were not wearing a seatbelt. The remaining 17.76% had a three-point belt on (shoulder and lap). The results for restraint use for (Bédard et al.,2002) and replicated work are presented below in Table 4.7 and Table 4.8, respectively. According to these results, the percentage of fatalities for drivers not wearing seatbelts varied from a low of 49.20% for young drivers aged below 20 years to a high of 62.30% for drivers aged between 50 and 64 years. Conversely, the percentage of fatalities for drivers wearing seat belts varied from a low of 32.30% for drivers aged below 20 years to as high as 43.80% for older drivers aged 80 years or more.

Table 4.7: Fatalities by restraint use against age (Bédard et al., 2002).

Restraint	Age (years)							
	0-19	20-29	30-39	40-49	50-64	65-79	80+	Total
No seatbelt								
Non-Fatal	11766 (52.2)	15431 (48.7)	4925 (44.8)	1923 (41.1)	1531 (40.9)	1054 (43.4)	240 (42.5)	36870 (48.1)
Fatal	10771 (47.8)	16277 (51.3)	6057 (55.2)	2754 (58.9)	2212 (59.1)	1373 (56.6)	325 (57.5)	39769 (51.9)
Shoulder only								
Non-Fatal	76 (55.5)	94 (54.3)	25 (48.1)	10 (35.7)	13 (46.4)	16 (57.1)	3 (42.9)	(237 (53.2)
Fatal	61 (44.5)	79 (45.7)	27 (51.9)	18 (64.3)	15 (53.6)	12 (42.9)	4 (57.1)	216 (47.7)
Lap only								
Non-Fatal	201 (63.4)	253 (65.2)	122 (62.6)	55 (63.9)	69 (63.9)	52 (51.5)	11 (64.7)	763 (63.2)
Fatal	116 (36.6)	135 (34.8)	73 (37.4)	26 (32.1)	39 (36.1)	49 (48.5)	6 (35.3)	444 (36.8)
Shoulder & lap								
Non-Fatal	2092 (68.7)	2661 (66.6)	1318 (67.9)	799 (69.5)	732 (64.7)	760 (59.6)	160 (55.4)	8522 (66.4)
Fatal	954 (31.3)	1336 (33.4)	624 (32.1)	351 (30.5)	400 (35.3)	515 (40.4)	129 (44.6)	4309 (33.6)

Table 4.8: Fatalities by restraint use against age (replicated 1975-1998).

Restraint	Age (Years)							
	0-19	20-29	30-39	40-49	50-64	65-79	80+	Total
No seatbelt								
Non-Fatal	8324 (50.80)	11234 (47.00)	3653 (42.80)	1337 (38.10)	1007 (37.70)	738 (41.80)	246 (45.50)	26539 (46.30)
Fatal	8068 (49.20)	12647 (53.00)	4878 (57.20)	2173 (61.90)	1664 (62.30)	1029 (58.20)	295 (54.50)	30754 (53.70)
Shoulder belt								
Non-Fatal	68 (55.30)	83 (55.00)	23 (51.10)	7 (33.30)	9 (45.00)	10 (47.60)	3 (37.50)	203 (52.20)
Fatal	55 (44.70)	68 (45.00)	22 (48.90)	14 (66.70)	11 (55.00)	11 (52.40)	5 (62.50)	186 (47.80)
Lap belt								
Non-Fatal	161 (66.50)	176 (64.20)	77 (59.20)	37 (62.70)	45 (64.30)	36 (50.00)	9 (69.20)	541 (62.90)
Fatal	81 (33.50)	98 (35.80)	53 (40.80)	22 (37.30)	25 (35.70)	36 (50.00)	4 (30.80)	319 (37.10)

Table 4.8: Fatalities by restraint use against age (replicated 1975-1998). (Cont.)

Shoulder and lap								
Non-Fatal	1823 (67.70)	2108 (64.00)	888 (63.30)	508 (63.50)	479 (59.90)	601 (57.60)	144 (56.30)	6551 (63.70)
Fatal	871 (32.30)	1184 (36.00)	515 (36.70)	292 (36.50)	321 (40.10)	443 (42.40)	112 (43.80)	3738 (36.30)

Airbags

Results in Table 4.9 and Table 4.10 indicate that airbags appeared to have a non-protective impact on drivers aged below 40 years in general. Specifically, airbags seemed slightly advantageous to drivers aged 20– 29 years and those aged 40-64 years but appeared slightly disadvantageous for drivers aged 80 years or more. The data in both analyses appeared to establish an inverted U-shape curve. Please note that 65% of the cases are missing for Bédard et al., (2002) study and 50% of the cases are missing for the replicated study.

Table 4.9: Fatalities by airbag against age (Bédard et al., 2002).

Air Bag Status	Age (years)							
	0-19	20-29	30-39	40-49	50-64	65-79	80+	Total
Bag not deployed								
Non-Fatal	5263 (55.9)	7067 (52.1)	3043 (50.4)	1435 (49.1)	975 (48.9)	899 (50.6)	242 (48.8)	18924 (52.3)
Fatal	4160 (44.1)	6490 (47.9)	2998 (49.6)	1485 (50.9)	1020 (51.1)	879 (49.4)	254 (51.2)	17286 (47.7)
Bag deployed								
Non-Fatal	355 (56.3)	489 (53.7)	211 (49.9)	118 (51.5)	110 (55.6)	115 (47.3)	22 (44.9)	1420 (52.9)
Fatal	276 (43.7)	422 (46.3)	212 (50.1)	111 (48.5)	88 (44.4)	128 (52.7)	27 (55.1)	1264 (47.1)

Table 4.10: Fatalities by airbag against age (replicated 1975-1998).

Air Bag Status	Age (Years)							
	0-19	20-29	30-39	40-49	50-64	65-79	80+	Total
Not Deployed								
Non-Fatal	4133 (55.30)	5311 (50.90)	2135 (48.10)	950 (44.90)	637 (44.70)	651 (48.50)	229 (50.40)	14046 (50.70)
Fatal	3345 (44.70)	5127 (49.10)	2308 (51.90)	1167 (55.10)	787 (55.30)	690 (51.50)	225 (49.60)	13649 (49.30)
Deployed								
Non-Fatal	32 (55.60)	443 (52.90)	166 (47.20)	87 (46.50)	69 (47.30)	96 (45.90)	21 (48.80)	1211 (51.20)
Fatal	263 (44.40)	395 (47.10)	186 (52.80)	100 (53.50)	77 (52.70)	113 (54.10)	22 (51.20)	1156 (48.80)

Vehicle Deformity

The data on vehicle deformity for the replicated work indicated that the majority of all crashed vehicles were deformed severely with 37934 fatal cases and 37103 non-fatal cases reported in comparison to 2482 fatal and 3057 non-fatal cases for less-severe deformities. Similar to Bédard et al., (2002) results (Table 4.11), the replicated work show consistently that more fatalities occurred among drivers of vehicles deformed severely (Table 4.12). Moreover, among drivers of vehicles severely deformed, fewer percentages of driver fatalities aged below 20 years were reported in comparison to other age categories. The percentage of vehicles with severe deformities varied with driver's age, forming an inverted U-shape curve for the older driver age categories. The ratio of vehicles deformed severely to those with less severe deformities decreased gradually with increasing age for drivers older than 30 years. Specifically, for young drivers below 20 years, the number of fatalities from severely deformed crashes was 16.68 times that of fatalities from less severe deformed crashes. This ratio reduces to 14.38 for drivers aged between 30 and 39 years, and 7.82 for those aged 80 years and more.

Table 4.11: Fatalities by vehicle deformity against age (Bédard et al., 2002).

Vehicle Deformity	Age (years)							
	0-19	20-29	30-39	40-49	50-64	65-79	80+	Total
Severe								
Non-Fatal	15723 (54.2)	20674 (50.9)	6818 (47.8)	2927 (46.1)	2445 (46.1)	1996 (48.4)	431 (46.4)	51014 (50.7)
Fatal	13281 (45.8)	19962 (49.1)	7434 (52.2)	3423 (53.9)	2862 (53.9)	2127 (51.6)	498 (53.6)	49587 (49.3)
Less Severe								
Non-Fatal	1205 (63.2)	1885 (62.7)	884 (65.6)	458 (64.2)	401 (65.4)	271 (56.9)	72 (55.0)	5176 (63.2)
Fatal	701 (36.8)	1122 (37.3)	464 (34.4)	255 (35.8)	212 (34.6)	205 (43.1)	59 (45.0)	3018 (36.8)

Table 4.12: Fatalities by vehicle deformity against age (replicated 1975-1998).

Vehicle Deformity	Age (years)							
	0-19	20-29	30-39	40-49	50-64	65-79	80+	Total
Severe								
Non-Fatal	11385 (53.60)	15150 (49.70)	4960 (45.80)	2032 (43.40)	1647 (43.60)	1496 (47.90)	433 (49.30)	37103 (49.40)
Fatal	9860 (46.40)	15347 (50.30)	5866 (54.20)	2653 (56.60)	2133 (56.40)	1629 (52.10)	446 (50.70)	37934 (50.60)

Table 4.12: Fatalities by vehicle deformity against age (replicated 1975-1998). (Cont.)

Less Severe								
Non-Fatal	810 (57.80)	1152 (56.10)	484 (54.30)	198 (49.60)	178 (52.00)	164 (50.90)	71 (55.50)	3057 (55.20)
Fatal	591 (42.20)	903 (43.90)	408 (45.70)	201 (50.40)	164 (48.00)	158 (49.10)	57 (44.50)	2482 (44.80)

Vehicle Speed

The analysis of vehicle speed indicated that higher speeds are associated with increased fatalities regardless of age category as represented by Table 4.13 and Table 4.14. Results of both analyses indicate that younger drivers had less fatality risk than other age categories drivers at all speed levels. For the replicated work, drivers younger than 20 years had fatality risk of 29%, at speeds lower than 55kph, while drivers 80 years and above had 49.20% fatality risk. Moreover, at 56-95kph speed category, drivers below 20 years had 39.3% fatality risk and drivers aged 50-64 years had fatality risk of 49.9%. This trend was observed in all other speed levels. Furthermore, the percentage of fatalities in different categories of speed varied with increasing age, with the largest number of fatal crashes occurred at speeds of 112+kph (70+mph) among all other age categories, similar to findings for Bédard et al. (2002). Moreover, 57.7% data were missing for driver fatalities with fixed objects in replicated analysis.

Table 4.13: Fatalities by vehicle speed against age (Bédard et al., 2002).

Vehicle Speed in kph (mph)	Age (years) 0-19	20-29	30-39	40-49	50-64	65-79	80+	Total
<56 (35)								
Non-Fatal	207 (75.5)	279 (72.3)	183 (71.8)	124 (71.3)	114 (62.0)	129 (62.0)	34 (50.7)	1070 (69.1)
Fatal	67 (24.5)	107 (27.7)	72 (28.2)	50 (28.7)	70 (38.0)	79 (38.0)	33 (49.3)	478 (30.9)
56–95 (35–59)								
Non-Fatal	2734 (62.4)	3659 (59.9)	1587 (56.5)	805 (55.0)	781 (53.4)	650 (51.6)	121 (49.2)	10337 (58.3)
Fatal	1648 (37.6)	2451 (40.1)	1222 (43.5)	658 (45.0)	682 (46.6)	610 (48.4)	125 (50.8)	7396 (41.7)
96–111 (60–69)								
Non-Fatal	1582 (57.7)	2094 (54.2)	814 (52.5)	338 (50.2)	248 (46.4)	201 (51.8)	24 (39.3)	5301 (54.0)
Fatal	1162 (42.3)	1772 (45.8)	736 (47.5)	335 (49.8)	286 (53.6)	187 (48.2)	37 (60.7)	4515 (46.0)
112+ (70)								
Non-Fatal	2431 (47.6)	3115 (44.2)	799 (38.1)	257 (33.6)	111 (32.8)	52 (37.1)	2 (13.3)	6767 (43.7)
Fatal	2674 (52.4)	3925 (55.8)	1299 (61.9)	2674 (52.4)	227 (67.2)	88 (62.9)	13 (86.7)	10900 (56.3)

Table 4.14: Fatalities by vehicle speed against age (replicated 1975-1998).

Vehicle speed in kph (mph)	Age (years)							
	0-19	20-29	30-39	40-49	50-64	65-79	80+	Total
<56 (35)								
Non-Fatal	132 (71.00)	148 (66.40)	87 (62.10)	50 (58.10)	61 (59.80)	84 (58.30)	30 (50.80)	592 (63.00)
Fatal	54 (29.00)	75 (33.60)	53 (37.90)	36 (41.90)	41 (40.20)	60 (41.70)	29 (49.20)	348 (37.00)
56-95 (35-59)								
Non-Fatal	2138 (60.70)	2768 (57.60)	1156 (53.60)	536 (50.30)	522 (50.10)	468 (49.60)	114 (51.10)	7702 (56.00)
Fatal	1385 (39.30)	2035 (42.40)	1001 (46.40)	530 (49.70)	519 (49.90)	475 (50.40)	109 (48.90)	6054 (44.00)
96-111 (60-69)								
Non-Fatal	1253 (56.30)	1679 (53.30)	622 (49.90)	253 (47.80)	183 (42.90)	174 (51.50)	31 (47.70)	4195 (52.60)
Fatal	972 (43.70)	1470 (46.70)	624 (50.10)	276 (52.20)	244 (57.10)	164 (48.50)	34 (52.30)	3784 (47.40)
112+ (70+)								
Non-Fatal	1891 (47.80)	2473 (43.90)	656 (37.70)	198 (33.10)	86 (30.90)	43 (36.10)	11 (34.40)	5358 (43.30)
Fatal	2066 (52.20)	3164 (56.10)	1085 (62.30)	400 (66.90)	192 (69.10)	76 (63.90)	21 (65.60)	7004 (56.70)

Vehicle Attributes

Vehicle attributes investigated included wheelbase, weight, model year, and vehicle age. Table 4.15 andTable 4.16 present descriptive statistics of the data extracted from the FARS database. Results for replicated work indicate that the vehicle weight means is 1342.54 kg with a standard deviation of 303.50 and maximum weight recorded as 2665 kg. Furthermore, wheelbase mean is 268.21 cm with a standard deviation of 24.44 and minimum size of 199.9 cm. The mean model year is 1980.36 with a standard deviation of 8.14: the oldest was a 1900 model year vehicle, and newest was a 1999 model year vehicle. Similar to findings for Bédard et al. (2002), vehicle attributes show that the majority of crashed vehicles are passenger cars, while the majority of vehicles had been produced earlier than 1980. For the analyses, vehicle age was obtained by subtracting the vehicle model year from the crash year as mentioned before, and a mean of 7.17 was recorded with a standard deviation of 5.56. All the variables were considered normally distributed except age which was transformed by a one unit change for every 5-years for the model year and 25 cm of wheelbase.

Table 4.15: Descriptive statistics for vehicle attributes (Bédard et al., 2002).

Variable	Mean	S.D.	Minimum	Maximum
Weight (kg)	1361	311	492	2659
Wheelbase (cm)	271.1	24.9	200	428
Model year	1979	8.45	1900	1999
Age	7.17	5.56	-1	84

Table 4.16: Descriptive statistics for vehicle attributes (replicated 1975-1998).

Variable	Mean	S.D.	Minimum	Maximum
Weight (kg)	1342.54	303.50	493.18	2665
Wheelbase (cm)	268.21	24.44	199.90	427.99
Model year	1980.36	8.14	1900	1999
Age	7.37	5.69	0	84

Univariate and Multivariate Logistic Regressions

Table 4.17 (Bédard et al., 2002) and Table 4.18 (replicated) present the univariate logistic and multivariate logistic regression results when investigating the independent influence of crash, driver, and vehicle characteristics to fatalities. Data were entered into the univariate and multivariate models, and Odd's Ratio (adjusted and unadjusted) were calculated. The analysis included similar variables considered in Bédard et al. (2002), study. Several variables were entered and sequentially removed if they were not statistically significant (P< 0.01) same as (Bédard et al., 2002) study. Vehicle weight and vehicle wheelbase are highly correlated with each other; hence wheelbase was entered. Wheelbase was chosen due to the replication study as the same was considered in Bédard et al. (2002) study. The other reason for choosing it is that there are more available cases for wheelbase than vehicle weight. Airbags were not considered in the analysis because 50% of total cases were missing for airbags. Variables such as (driver age, gender, BAC, direction of impact, airbag deployment, restraint use, travelling speed, vehicle model year, vehicle wheelbase) were considered in the analysis. The reference categories have an OR of 1. Furthermore, age by gender results shows that an increase in driver age is linked with an increase in the odds of a fatality. In this sense, drivers aged below 30 years had lower odds of sustaining fatal injuries than drivers aged above 30 years and drivers aged 80 years or more had the highest odds of fatalities compared with reference category group of 40-49 years. Generally, women had higher odds of fatality than men with adjusted OR 1.54 times greater than men which is a reference category, meaning that women have 1.54 greater odds of dying in a crash than men. Similar to the study by (Bédard et al., 2002) BAC results showed that odds of fatality decreases with the increase in

BAC level till 0.05-0.09 and then odds of fatality increases with an increase in BAC concentrations reaching at 3.16 at 0.30+ BAC level, which forms a "U" curve. BAC level of 0.30 or more has three times more risk of sustaining fatal injuries than BACs of 0 (reference category). Furthermore, driving at 56-95kph had odds of 1.36 (25.6% more risk than <55kph) driver fatalities, while 96-111kph had 55.3% greater odds of fatalities risk than <55kph. Moreover, BAC level for replicated analysis with adjusted OR is displayed in Figure 4.1, which reveals that OR decreases as the BAC increases up to 0.10-0.14 (0.54) and then OR increases abruptly reaching its peak at BAC level 0.30+ (3.16). This reveals that OR is three times more compared to the base category 0.

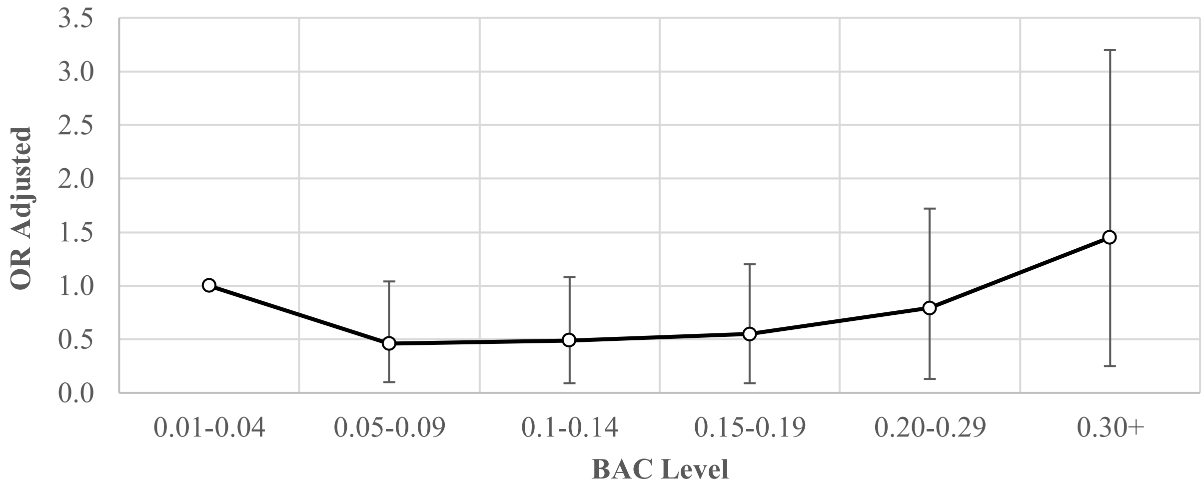

Figure 4.1: Replicated analysis adjusted OR for BAC level.

In reference to the direction of impact, right-side crash impacts and rear-end crash impacts have lower odds of fatal injuries as compared to front-impact crashes which is considered as reference category. Nevertheless, crashes on the left side had adjusted OR more than double that frontal crashes, meaning that the odds are 2.26 higher for a driver to sustain fatal injuries from left side impact than frontal impact. In this sense, odds of driver fatalities were reduced for right side and rear-end crashes by 0.48 and 0.72 respectively compared to front side (reference category). This also supports the results by Bédard et al., (2002). Restraint results established that drivers wearing a lap belt and shoulder belts had lower OR than the drivers with no seat belt (reference category). This meant that odds of driver fatalities were reduced by 23.1% when wearing shoulder belt (OR=0.66), 25.6% for lap belt (OR=0.82), and by 51.3% when wearing shoulder and lap belt (OR=0.48). Furthermore, when comparing travelling speeds at impact against the 55kph speed limit (reference category), the OR increased with higher speeds meaning that the odds of driver fatality increased with increasing speed. This was a similar finding to the results for by Bédard et al., (2002) study. For example, drivers travelling at 112kph or higher (OR=2.64) had 136% more risk to sustain fatal injuries than those traveling at 55kph or below. Also, driving at 56-95kph had odds of 1.36 (25.6% more risk than <55kph) of driver fatalities, while 96-111kph had 55.3% greater odds of fatalities risk than <55kph. Moreover, similar to Bédard et al., (2002) findings, an increase of 5 years to the vehicle model year increased the fatality odds by 3% (OR=1.03) while a 25cm wheelbase increment reduced the risk of fatality by 9% (OR=0.90). All variables were statistically significant except age category for 30-39 years old (0.02), restraint use for left and right side with the p value of (0.19) and (0.14) respectively, speed category of >56 mph (0.15) and model year (0.01).

Furthermore, replicated analysis have 24 degrees of freedom and the chi-square value is equal to 2336.45 with $p < 0.01$ which indicates that the model is statically significant, and a good fit.

Several graphs are generated which reveals difference in adjusted OR's such as: age category, direction of impact and vehicle speed. These graphs interpret driver fatality risk compare to independent variables. Each variable has reference category one and other categories are compared to reference category. These graphs give an insight of the trends for adjusted OR's, to depict the highest and lowest OR for driver fatalities, which will help to predict the variable which has higher and lower contribution for driver fatalities with fixed objects. For example in terms of vehicle impact, the left side have double OR compare to front side (reference category), which indicates that driver fatality risk is higher when crash occurs on driver side are compared to front side and right side have lower OR compare to right side which suggests that driver fatality risk is lower when crash occurs on right side. These graphs are displayed in Appendix C.

Table 4.17: Results of the univariate logistic regressions (unadjusted) and multivariate logistic (adjusted) with driver fatality (N=10143) as the dependent variable (OR and 99% CI).

Variable	Unadjusted OR	99% CI	Adjusted OR	99% CI
Age (Years)				
<20	0.73	0.59-0.90	0.78	0.62 –0.99
20-29	0.71	0.57–0.87	0.76	0.60 –0.95
30-39	0.83	0.66 –1.05	0.84	0.66–1.07
40-49	1	1.00–1.00	1	1.00–1.00
50-64	1.48	1.07–2.04	1.73	1.23–2.44
65-79	1.68	1.16–2.42	2.33	1.58–3.43
80+	3.35	1.38–8.15	4.98	2.01–12.37
Gender				
Male	1	1.00–1.00	1	1.00–1.00
Female	1.48	1.31 –1.67	1.54	1.35 –1.76
BAC				
0	1	1.00–1.00	1	1.00–1.00
0.01–0.04	0.49	0.39-0.61	0.49	0.39-0.62
0.05–0.09	0.46	0.39-0.55	0.49	0.41-0.58
0.10–0.14	0.53	0.46-0.61	0.54	0.46-0.64
0.15–0.19	0.78	0.68-0.90	0.8	0.68-0.94
0.20–0.29	1.39	1.18-1.64	1.37	1.14-1.64
0.30+	3.15	1.99-5.00	3.16	1.96-5.09
Impact				
Front side	1	1.00–1.00	1	1.00–1.00
Right side	0.47	0.41-0.53	0.48	0.42-0.55
Rear end	0.72	0.56-0.91	0.72	0.56-0.93
Left side	2.11	1.81-2.46	2.26	1.92-2.65
Restraint				
None	1	1.00–1.00	1	1.00–1.00
Shoulder Belt	0.82	0.47-1.45	0.66	0.36-1.21
Lap belt	0.79	0.49-1.26	0.82	0.50-1.36
Shoulder & lap belt	0.58	0.51-0.65	0.46	0.39-0.53
Travelling Speed(kph)				
<56	1	1.00–1.00	1	1.00–1.00
56-95	1.19	0.84-1.67	1.36	0.94-1.96
96-111	1.32	0.94-1.87	1.68	1.15-2.45
112+	1.84	1.31-2.58	2.64	1.82-3.83
Model Year				
5-year increment	1.02	0.99-1.05	1.05	1.01-1.09
Wheelbase				
25cm increment	0.96	0.92-1.02	0.9	0.85-0.95

Table 4.18: Results of the univariate logistic regressions (unadjusted) and multivariate logistic regressions (adjusted) with driver fatality (N=11481) as the dependent variable (OR and 99% CI).

Variable	Unadjusted OR	99% CI	Adjusted OR	99% CI
Age (Years)				
<20	0.68	0.54-0.85	0.74	0.58 –0.95
20-29	0.66	0.52–0.82	0.72	0.56 –0.91
30-39	0.79	0.62 –1.02	0.79	0.61–1.03
40-49	1	1.00–1.00	1	1.00–1.00
50-64	1.38	0.97–1.97	1.60	1.11–2.32
65-79	1.50	1.01–2.21	2.09	1.39–3.15
80+	2.12	0.92–4.90	3.01	1.27–7.11
Gender				
Male	1	1.00–1.00	1	1.00–1.00
Female	1.43	1.26 –1.63	1.51	1.31 –1.74
BAC				
0	1	1.00–1.00	1	1.00–1.00
0.01–0.04	0.46	0.36-0.58	0.46	0.36-0.58
0.05–0.09	0.46	0.39-0.55	0.49	0.40-0.59
0.10–0.14	0.54	0.46-0.63	0.55	0.46-0.65
0.15–0.19	0.76	0.65-0.89	0.79	0.66-0.93
0.20–0.29	1.46	1.23-1.74	1.45	1.20-1.75
0.30+	3.78	2.28-6.26	3.68	2.19-6.19
Impact				
Front side	1	1.00–1.00	1	1.00–1.00
Right side	0.55	0.48-0.63	0.55	0.48-0.64
Rear end	0.73	0.56-0.95	0.72	0.54-0.95
Left side	2.02	1.71-2.40	2.11	1.77-2.52
Restraint				
None	1	1.00–1.00	1	1.00–1.00
Shoulder Belt	0.77	0.41-1.46	0.71	0.36-1.39
Lap belt	0.72	0.43-1.18	0.74	0.40-1.25
Shoulder & lap belt	0.58	0.50-0.66	0.48	0.41-0.56
Travelling Speed(kph)				
<56	1	1.00–1.00	1	1.00–1.00
56-95	1.16	0.79-1.71	1.25	0.83-1.90
96-111	1.30	0.88-1.93	1.53	1.01-2.34
112+	1.79	1.22-2.64	2.36	1.56-3.58
Model Year				
5-year increment	1.00	0.97-1.04	1.03	0.99-1.07
Wheelbase				
25cm increment	0.98	0.93-1.03	0.91	0.86-0.97

4.2. Updated Work (1975-2015)

This section includes two sections. The first presents the results when considering additional 17 years of data in the logistic regression to investigate the independent influence of crash, driver, and vehicle characteristics on driver fatalities: from 1975 to 2015 and in the second subsection additional variables were included in calculating the multivariate and univariate logistic regression.

4.2.1. Additional Data

Age and Gender

When comparing age and gender fatality risk (Table 4.19), the analysis established older drivers to be at higher risk of fatal crash involvement similar to findings without the additional years of data. Results also indicate that younger drivers less than 30 years of age have the highest number of fatalities in both males and females. Males have a total of 22020 fatalities for the age group 20-29, and on the other hand, female have 4738 fatalities for the same age group. The age group of 50 years to 64 years old had the highest fatality likelihood with 58.50% which is also similar to findings in part one. The analysis also well found no significant difference in fatality risk for both males and females in the age group of $\geq$ 20 years to <30 years. Similar to part one, results indicate that a larger proportion of older adults were fatally injured when compared with younger adults. In addition, fewer female drivers were fatally injured among older age groups compared to male groups, as illustrated in Table 4.10. Nonetheless, female drivers < 20 years had a higher fatality risk (46.30%) than male drivers in the same category (45.70%), but overall more male drivers are fatally injured compared to female drivers. Total number of non-fatal cases are 68102 and fatal cases are 68766, which shows that total number of driver fatal and non-fatal cases increased by 55,558 when additional 17 years of data are considered compared to part one which has 40536 non-fatal and 40774 fatal cases respectively.

Table 4.19: Fatalities by gender and age category.

Gender	Age (Years)							
	0-19	20-29	30-39	40-49	50-64	65-79	80+	Total
Male								
Non-Fatal	15141 (54.30)	22071 (50.10%)	7052 (46.80)	3351 (44.10)	2379 (41.50)	1831 (44.00)	795 (47.30)	52620 (49.50)
Fatal	12738 (45.70)	22020 (49.90)	8014 (53.20)	4249 (55.90)	3349 (58.50)	2326 (56.00)	885 (52.70)	53581 (50.50)

Table 4.19: Fatalities by gender and age category. (Cont.

Female								
Non-Fatal	4186 (53.70)	4771 (50.20)	2554 (48.40)	1433 (47.50)	1264 (48.20)	1016 (52.70)	258 (50.30)	15482 (50.50)
Fatal	3609 (46.30)	4738 (49.80)	2726 (51.60)	1585 (52.50)	1361 (51.80)	911 (47.30)	255 (49.70)	15185 (49.50)
Total								
Non-Fatal	19327 (54.20)	26842 (50.10)	9606 (47.20)	4784 (45.10)	3643 (43.60)	2847 (46.80)	1053 (48.00)	68102 (49.80)
Fatal	16347 (45.80)	26758 (49.90)	10740 (52.80)	5834 (54.90)	4710 (56.40)	3237 (53.20)	1140 (52.00)	68766 (50.20)

Alcohol Use by Age

The results on the fatalities by alcohol use against age are presented in Table 4.20 below. It shows that fatality risk for sober drivers increased from a percentage of 61.7% for drivers aged below 20 years to a high of 86% for drivers aged 80 years and higher. Nevertheless, the overall fatality risk and BAC correlation formed a ‘U’-shaped curve which is similar to the results from the previous section (replicated work). This means that the overall fatality risk decreases with an increase of BAC, reaching a low point of 47.70% at a BAC level of 0.05-0.09 before correspondingly increasing with BAC levels to a peak percentage of 82.20% for BAC levels of 0.30 or more. This pattern remained consistent for age categories between 20 years and 64 years, which was the case for the findings in previous section. For drivers aged below 20 years, the lowest fatality risk was recorded at BAC levels of 0.01-0.04 (49.4%) contradicting the results of part one in which the lowest fatality risk was recorded at BAC levels of 0.05-0.09 (49.7). The ratio of fatally injured drivers to non-fatally injured drivers for age group 20-29 is 1.65 at BAC level zero, the ratio decreases to 0.83 at BAC level 0.05-0.09, and then achieving peak 4.20 at BAC level 0.30+. This pattern is also consistent with other age groups. The findings of this subsection with updated data are also similar to the results from previous replicated research.

Table 4.20: Fatalities by BAC against age.

BAC	Age (years)							
	0-19	20-29	30-39	40-49	50-64	65-79	80+	Overall
0								
Non-Fatal	3329 (38.3)	2494 (37.70)	964 (33.50)	584 (29.50)	540 (24.10)	387 (19.30)	84 (14.00)	8382 (33.50)
Fatal	5353 (61.70)	4127 (62.30)	1914 (66.50)	1394 (70.50)	1705 (75.90)	1617 (80.70)	517 (86.00)	16627 (66.50)

Table 4.20: Fatalities by BAC against age. (Cont.)

0.01-0.04								
Non-Fatal	672 (50.6)	839 (53.30)	193 (44.30)	78 (37.10)	34 (22.50)	18 (22.80)	4 (16.00)	1838 (48.30)
Fatal	656 (49.4)	736 (46.70)	243 (55.70)	132 (62.90)	117 (77.50)	61 (77.20)	21 (84.00)	1966 (51.70)
0.05-0.09								
Non-Fatal	1155 (50.4)	2025 (54.60)	536 (55.00)	178 (46.20)	79 (38.90)	13 (24.10)	7 (43.80)	3993 (52.30)
Fatal	1136 (49.6)	1684 (45.40)	438 (45.00)	207 (53.80)	124 (61.10)	41 (75.90)	9 (56.30)	3639 (47.70)
0.10-0.14								
Non-Fatal	1451 (46.6)	3173 (48.50)	853 (47.70)	334 (42.00)	123 (36.10)	21 (30.00)	4 (44.40)	5959 (47.10)
Fatal	1666 (53.4)	3369 (51.50)	934 (52.30)	461 (58.00)	218 (63.90)	49 (70.00)	5 (55.60)	6702 (52.90)
0.15-0.19								
Non-Fatal	838 (36.2)	2733 (38.70)	954 (38.50)	388 (37.60)	122 (28.70)	18 (22.80)	5 (38.50)	5058 (37.70)
Fatal	1479 (63.8)	4333 (61.30)	1527 (61.50)	643 (62.40)	303 (71.30)	61 (77.20)	8 (61.50)	8354 (62.30)
0.20-0.29								
Non-Fatal	334 (23.2)	1620 (25.50)	803 (26.30)	317 (22.40)	138 (22.50)	19 (21.30)	4 (30.80)	3235 (24.90)
Fatal	1104 (76.8)	4745 (74.50)	2248 (73.70)	1098 (77.60)	475 (77.50)	70 (78.70)	9 (69.20)	9749 (75.10)
0.30+								
Non-Fatal	31 (20.10)	137 (19.20)	100 (17.20)	50 (15.20)	24 (15.80)	4 (23.50)	1 (33.30)	347 (17.80)
Fatal	123 (79.9)	576 (80.80)	481 (82.80)	279 (84.80)	128 (84.20)	13 (76.50)	2 (66.70)	1602 (82.20)
0.20-0.29								
Non-Fatal	334 (23.2)	1620 (25.50)	803 (26.30)	317 (22.40)	138 (22.50)	19 (21.30)	4 (30.80)	3235 (24.90)
Fatal	1104 (76.8)	4745 (74.50)	2248 (73.70)	1098 (77.60)	475 (77.50)	70 (78.70)	9 (69.20)	9749 (75.10)
0.30+								
Non-Fatal	31 (20.10)	137 (19.20)	100 (17.20)	50 (15.20)	24 (15.80)	4 (23.50)	1 (33.30)	347 (17.80)
Fatal	123 (79.9)	576 (80.80)	481 (82.80)	279 (84.80)	128 (84.20)	13 (76.50)	2 (66.70)	1602 (82.20)

Direction of Impact

The majority of cases for the direction of impact variable involved frontal crashes which also have the highest number of fatalities as presented on Table 4.21. Furthermore, the highest fatality risk was established to be left-side impacts irrespective of age category which is similar to results from previous section (replicated work). The highest left-side fatality risk proportion was 76.80% for drivers aged 40 to 49 years, followed by 72.80% for drivers aged

50 to 64 years. Also similar to previous section results, the right-side recorded the lowest fatality risk proportion, with only 28.10% reported for drivers younger than 20 years, and overall risk of 32.20% of all crashes. The rear-end impacts had a fatality risk proportion of 41.70 %, with the highest risk recorded as 48.40% for drivers between 50 and 64 years old. Moreover, the risk of fatality following all impact directions progressed with an increase in an age before decreasing for drivers aged 65 years and older. As indicated previously, direction (impact 2) was used instead of principle (impact 1) for the analysis.

Table 4.21: Fatalities by impact direction against age.

Impact	Age (Years)							
	0-19	20-29	30-39	40-49	50-64	65-79	80+	Total
Front								
Non-Fatal	9079 (54.00)	12960 (50.10)	5000 (47.40)	2639 (45.70)	2130 (44.80)	1915 (48.00)	754 (49.50)	34477 (49.80)
Fatal	7749 (46.00)	12908 (49.90)	5541 (52.60)	3131 (54.30)	2624 (55.20)	2071 (52.00)	768 (50.50)	34792 (50.20)
Right Side								
Non-Fatal	4000 (71.90)	5093 (68.10)	1574 (64.40)	668 (60.50)	409 (57.80)	259 (64.30)	92 (65.20)	12095 (67.80)
Fatal	1567 (28.10)	2381 (31.90)	869 (35.60)	437 (39.50)	299 (42.20)	144 (35.70)	49 (34.80)	5746 (32.20)
Left side								
Non-Fatal	1447 (32.40)	1663 (28.30)	554 (28.10)	219 (23.20)	163 (27.20)	93 (27.40)	31 (30.10)	4170 (29.20)
Fatal	3013 (67.6)	4211 (71.70)	1421 (71.90)	726 (76.80)	436 (72.80)	246 (72.60)	72 (69.90)	10125 (70.80)
Rear								
Non-Fatal	783 (63.90)	911 (56.30)	289 (54.50)	156 (57.60)	82 (51.60)	56 (54.90)	11 (61.10)	2288 (58.30)
Fatal	443 (36.10)	707 (43.70)	241 (45.50)	115 (42.40)	77 (48.40)	46 (45.10)	7 (38.90)	1636 (41.70)

Restraint Use

The restraint use data established that 56% of all drivers not wearing a seatbelt at the time of crash sustained fatal injuries which are slightly higher than the 53.7% in part one. Additionally, for those wearing lap and shoulder belt, 39.30% turned out fatal, a 3% increase from the results in part one. The findings for restraint use are presented in Table 4.22 below. Because the majority of drivers were wearing a three-point belt, the analyses compared the use of three-point belt against no belt. The fatality proportion for drivers with no seatbelt varied from a low of 50.9% for the youngest drivers (<20 years) to as high as 66.4% for drivers aged 50 to 64 years. On the contrary, the fatality risk for drivers with seatbelt varied from 33% for the youngest drivers (<20 years) to a high of 47.7% for drivers aged ≥80 years. Furthermore, the ratio difference between the fatalities of drivers with no belts and those with three-point belts varied correspondingly with age, forming an inverted U-shaped curve similar to the results in part one.

Table 4.22: Fatalities by restraint use against age.

Restraint	Age (Years)							
	0-19	20-29	30-39	40-49	50-64	65-79	80+	Total
No seatbelt								
Non-Fatal	11177 (49.10)	15885 (45.00)	5416 (41.10)	2324 (36.80)	1476 (33.60)	911 (37.10)	347 (41.70)	37536 (44.00)
Fatal	11608 (50.90)	19397 (55.00)	7747 (58.90)	3984 (63.20)	2923 (66.40)	1547 (62.90)	486 (58.30)	47692 (56.00)
Shoulder belt								
Non-Fatal	129 (57.30)	177 (55.30)	57 (52.80)	21 (37.50)	22 (50.00)	21 (56.80)	6 (33.30)	433 (53.60)
Fatal	96 (42.70)	143 (44.70)	51 (47.20)	35 (62.50)	22 (50.00)	16 (43.20)	12 (66.70)	375 (46.40)
Lap belt								
Non-Fatal	200 (65.80)	238 (61.70)	107 (57.50)	52 (56.50)	58 (60.40)	48 (48.50)	12 (60.00)	715 (60.40)
Fatal	104 (34.20)	148 (38.30)	79 (42.50)	40 (43.50)	38 (39.60)	51 (51.50)	8 (40.00)	468 (39.60)
Shoulder and lap								
Non-Fatal	5255 (67.00)	6555 (63.40)	2776 (62.90)	1791 (60.10)	1674 (56.70)	1506 (54.90)	537 (52.30)	20094 (62.20)
Fatal	2593 (33.00)	3782 (36.60)	1636 (37.10)	1188 (39.90)	1276 (43.30)	1236 (45.10)	490 (47.70)	12201 (39.30)

Airbags

A great amount of airbag-related data were missing compared to other variables, only 70,370 cases were reported from a total of 138991 cases. A total of 49.8% deployed airbag cases turned out fatal to drivers as Table 4.23 indicates. In addition, 50.2% of cases with airbag not deployed were fatal, showing a small margin of airbag protection. However, when comparing age categories, deployed airbags did not have a protective impact on drivers <20 years (45.8% overall), while it appeared advantageous to drivers aged 50–64 years (54.70% overall). At the same time, results indicated that deployed airbags were less fatal for drivers aged 80 years or higher (51.70%) when compared with drivers aged 65 to 79 years. Unlike the results established in part one, deployed airbags had 0.7% higher fatalities than non-deployed airbags for drivers <20 years and 2.3% for drivers 80+ years. Generally, the crash data formed an inverted U-shape curve almost comparable to part one results, the highest point of both curves (airbag deployed and not deployed) reported for drivers aged between 50 and 64 years. There is not a huge difference in fatalities as displayed in Table 4.23 for both cases when the airbags are deployed and when not deployed, however, when deployed the overall percentage of fatal crashes decreases as compared to air bags not deployed which is similar to the replicated analysis results.

Table 4.23: Fatalities by airbag against age.

Airbag status	Age (Years)							
	0-19	20-29	30-39	40-49	50-64	65-79	80+	Total
Not Deployed								
Non-Fatal	6215 (54.9)	8557 (50.10)	3438 (47.50)	1846 (45.50)	1232 (42.80)	935 (45.10)	402 (50.50)	22625 (49.80)
Fatal	5107 (45.1)	8536 (49.90)	3795 (52.50)	2215 (54.50)	1644 (57.20)	1138 (54.90)	394 (49.50)	22829 (50.20)
Deployed								
Non-Fatal	3052 (54.20)	4821 (50.70)	1796 (48.50)	1045 (47.50)	847 (45.30)	632 (46.10)	304 (48.30)	12497 (50.20)
Fatal	2581 (45.80)	4687 (49.30)	1905 (51.50)	1157 (52.50)	1024 (54.70)	740 (53.90)	325 (51.70)	12419 (49.80)

Vehicle Deformity

The deformity of vehicles is ranked using a four-point scale, with severe deformity recorded as the worst. During the analysis of the vehicle deformity variable, data were grouped either as less severe or severe. Overall, more than 90% of all vehicles investigated had been severely deformed, and similar to part one, more fatalities occurred in this category as shown in Table 4.24. Fewer percentages of fatalities for drivers younger than 30 years (53.30) were reported in vehicles severely deformed when compared to the age of 50 -64 years with a total of 57.00%, this pattern was also established in part one results. As well, the ratio of vehicles severely deformed increased initially with increasing age before decreasing for older drivers thus forming an inverted U-shape curve. The proportion of vehicles severely deformed when compared to vehicles with less severe deformities, decreased gradually with increasing age. For the youngest drivers (<20 years), the proportion of fatalities for severe deformities was 46.20% compared to 40.50% from less severe deformities resulting in fatal injuries. This proportion increased to 53.30% for severe deformities and 45.40% for less severe deformities for drivers aged 30-39 years. Moreover, the proportion increased with age as for the results from part one. To this end, the highest proportions of fatalities were observed for 50 to 64 years category with 57% and 48.90% for fatal severe and less severe deformities respectively, and the proportion began to reduce with increasing age with 51.40% and 45.90% fatalities reported for severe and less severe deformities in that order for drivers aged ≥80 years. Data show a curve forming an inverted “U” shape which forms same pattern as part one.

Table 4.24: Fatalities by vehicle deformity against age.

Vehicle deformity	Age (years)							
	0-19	20-29	30-39	40-49	50-64	65-79	80+	Total
Less Severe								
Non-Fatal	1204 (59.50)	1720 (55.80)	754 (54.60)	361 (50.60)	300 (51.10)	262 (51.3)	124 (54.10)	4725 (55.40)
Fatal	819 (40.50)	1362 (44.20)	626 (45.40)	352 (49.40)	287 (48.90)	249 (48.7)	105 (45.90)	3800 (44.60)
Severe								
Non-Fatal	17946 (53.80)	24900 (49.70)	8762 (46.70)	4378 (44.60)	3317 (43.00)	2551 (46.4)	968 (48.60)	62822 (49.40)
Fatal	15410 (46.20)	25183 (50.30)	10019 (53.30)	5448 (55.40)	4390 (57.00)	2951 (53.6)	1024 (51.40)	64425 (50.60)

Vehicle Speed

The vehicle speed analysis associated higher speeds with more fatal injuries regardless of driver age as outlined in Table 4.25. Results indicate that younger the driver the higher the odds of not sustaining fatal injuries which is similar to results from part one. This pattern for age remained for speed categories below 96kph, and the same pattern was also observed in part one results. Interestingly, the fatality ratio for drivers aged 80 years and higher decreased in comparison to other age groups for speeds of 96kph or higher. For part one results, this decrease was not observed as fatalities for 80+ old drivers increased at speeds higher than 112kph. At speeds <56kph, drivers younger than 20 years had a 28.3% risk of fatalities while drivers ≥80 years had 46.40% risk. Moreover, at ≥56kph to ≤95kph, the proportion of fatalities for drivers <20 years increased to 38.60% and for drivers ≥80 years increased to 52.40%. Furthermore, the risk for young drivers increased to 43.30% while for older drivers reduced to 48.90% at speeds ≥ 96kph to 111kph. In addition, for all drivers (except ≥80-year-old drivers) the largest proportion of fatal injuries were observed at speeds of >111kph which are similar to the results of part one.

Table 4.25: Fatalities by vehicle speed against age.

Vehicle speed in kph (mph)	Age (years) 0-19	20-29	30-39	40-49	50-64	65-79	80+	Total
<56 (35)								
Non-Fatal	205 (71.70)	225 (65.80)	136 (63.60)	88 (54.40)	100 (56.50)	124 (55.90)	59 (53.60)	937 (60.00)
Fatal	81 (28.3)	117 (34.20)	78 (36.40)	68 (43.60)	77 (43.50)	98 (44.10)	51 (46.40)	570 (40.00)
56-95 (35-59)								
Non-Fatal	3192 (61.4)	4243 (57.60)	1796 (53.40)	1002 (50.70)	882 (48.30)	739 (49.60)	226 (47.60)	12080 (53.90)
Fatal	2005 (38.60)	3128 (42.40)	1566 (46.60)	976 (49.30)	945 (51.70)	750 (50.40)	249 (52.40)	9619 (46.10)
96-111 (60-69)								
Non-Fatal	2003 (56.70)	2695 (53.50)	1030 (48.40)	521 (47.60)	386 (44.50)	285 (50.60)	70 (51.10)	6990 (50.70)
Fatal	1528 (43.30)	2347 (46.50)	1096 (51.60)	574 (52.40)	481 (55.50)	278 (49.40)	67 (48.90)	6371 (49.30)
112+ (70+)								
Non-Fatal	3122 (48.40)	4400 (44.80)	1285 (40.80)	545 (37.20)	302 (36.20)	146 (38.60)	51 (47.70)	9851 (42.70)
Fatal	3323 (51.60)	5421 (55.20)	1868 (59.20)	920 (62.80)	533 (63.80)	232 (61.40)	56 (52.30)	12353 (57.30)

Vehicle Attributes

The vehicle attributes investigated included wheelbase, weight, model year, and vehicle age as presented by Table 4.26. The descriptive statistics of the data extracted directly from the FARS database indicate the mean weight to be 1402.09 kg, with a maximum weight of 3534.09 kg and a minimum weight of 493.18 kg. The mean weight is higher than the results in part one in which the mean weight was equal to 1342.54. Furthermore, the mean for wheelbase was 273.94 cm, with a standard deviation of 28.61cm. The maximum wheelbase recorded was 460.50 cm, which is 32cm more than the maximum wheelbase recorded in part one. In addition, data for the model year had a mean of 1986.95, with the oldest vehicle model being 1900 and the newest model being for 2016. Also, vehicle age had a mean of 8.12 years at the time of the crash, with the oldest vehicle being 86 years old.

Table 4.26: Descriptive statistics for vehicle attributes.

Variable	Mean	S.D.	Minimum	Maximum
Weight (kg)	1402.09	324.49	493.18	3534.09
Wheelbase (cm)	273.94	28.61	186.69	460.50
Model year	1986.95	11.28	1900	2016
Age	8.12	6.03	0	86

Univariate and Multivariate Logistic Regressions

The analysis applied univariate and multivariate logistic regressions to examine the independent influence of driver, crash, and vehicle characteristics to fatal injuries. Table 4.27 illustrates the results of these regressions. The analysis included similar variables examined by Bédard et al. (2002). However, an additional 17 years of data were added to cover the time frame 1975 to 2015. Vehicle age was entered and sequentially removed since it was not statistically significant P< 0.01 significance level as in Bédard et al., (2002) study. Vehicle weight and vehicle wheelbase are highly correlated with each other, hence wheelbase was entered. Wheelbase was chosen to be consistent with the replication study and Bédard et al., (2002) study. As previous work, there are more available cases for wheelbase than vehicle weight. Airbag was eliminated from this part of the analysis because there are 50% of total cases missing as indicated in part one. Variables which were not statically significant with fatal injuries were removed using a P< 0.01. Variables statistically significant such as driver age, gender, BAC, direction of impact, airbag deployment, restraint use, travelling speed, vehicle model year, vehicle wheelbase were considered in the analysis. Variables significance are displayed in Table 4.27. Results of the multivariate regression model are presented in Table 4.27 which has 17731 total number of cases. For comparison purposes, unadjusted ORs obtained with univariate regressions for each variable are presented. Adjusted ORs obtained with the multivariate regression are used to explain the results which compare base categories with other groups for each variable. Adjusted OR are normally used to interpret results of multivariate logistic regressions.

Base categories also known as reference categories have an OR of 1. I the variable has an OR > 1 than the odds of exposure are greater among cases than controls, if the OR < 1 then the odds of exposure are lower among cases than exposure, and if OR = 1 then the odds of exposure to the risk factor are the same in both groups.

Results indicate that increase in driver age were correlated with greater odds of a fatality, similar to results of age categories for part one. Drivers below the age of 30 years had the lowest odds of fatality risk with odds ratio (OR) of 0.65 while drivers 50-64 and 65-79 have higher odds of fatality with OR of 1.52 and 1.81 respectively compared to the reference category group of 40-49 years. Age group of 80+ years old had the highest odds of fatal injuries with OR of 3.47 when compared to group of 40-49 years. Overall, comparable to part one, female drivers had higher fatality odds than male drivers (reference category) with an OR of 1.45. Meaning female drivers had 145.6% odds of sustaining fatal injuries.

Furthermore, alcohol use results show more fatalities as BAC levels increased, like a BAC level ≥0.30 indicates three times more fatality risk than BAC level of 0 (reference category), which are similar to part one. Furthermore, the travelling speed at impact variable was compared against the 55kph speed limit, and results showed that odds increased for higher speeds, hence supporting previous part one findings. In this sense, crashes at 112kph or higher had more than double the odds (2.57) of a fatality than crashes happening at speeds below 56kph. Moreover, BAC level for replicated analysis with adjusted OR curve is displayed in Figure 4.2, which reveals that OR decreases as the BAC increases up to 0.10-0.14 (0.53) and then OR increases abruptly reaching its peak at BAC level 0.30+ (3.47). This reveals that OR is three times more compared to the base category 0. Results also supports the findings of previous replicated analysis.

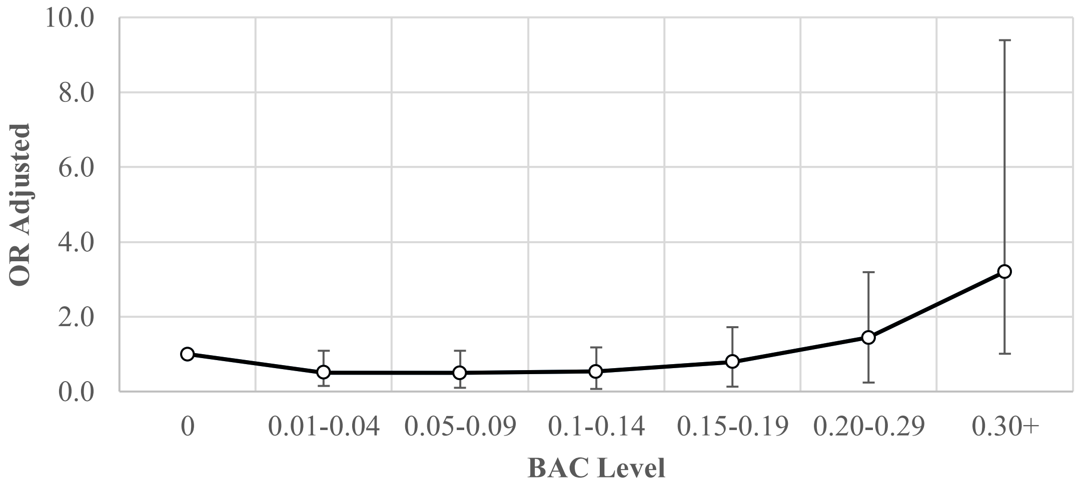

Figure 4.2: Updated analysis adjusted OR for BAC level.

In addition, the direction of impact variable compared the rear, left, and right-side impacts against frontal impact which is considered as the reference category. Both the left-side crash and rear-end crash impacts reported low odds of fatal injury, with left-side impacts having 30% reduced chance of fatality, and rear-end crashes having 52.2% reduced the chance of fatality. However, left side crashes had an OR almost doubled that of frontal crashes, meaning that left side crashes had 2.34 odds of fatalities. These results are in support of findings from part one that had established driver-side impacts as having the highest risk of fatal crashes.

Additionally, seatbelt data results established that most drivers were wearing a three-point belt at the time of the crash. Similar to part one results, drivers wearing shoulder and lap belt had a lower OR than drivers with no seatbelt with 0.42 odds of a fatality which is a reference category. Similarly, drivers with a lap belt had 0.67 fatality odds, and those with shoulder belt had 0.77 odds of a fatality. As well, increasing the vehicle model year by 5 years increased the driver fatality odds by 4.9% for all categories, while increasing wheelbase by 25cm reduced the risk of fatality by a 6.8% rate. Both the vehicle model year and wheelbase results were in support of previous part one findings.

Furthermore, the intercept or constant model compares chi-square of replicated analysis and updated analysis values. Updated analysis has chi-square 39 degrees of freedom equal to 2378.39 and $p < 0.01$ which indicates that model is statically significant and a good fit. It also indicates that model improves on model fit compare to previous replicated analysis fit as the chi-square value improved.

Several graphs are generated which reveals difference in adjusted OR's such as: age category, direction of impact and vehicle speed. These graphs interpret driver fatality risk compare to independent variables. Each variable has reference category one and other categories are compared to reference category. These graphs give an insight of the trends for adjusted OR's, to depict the highest and lowest OR for driver fatalities, which will help to predict the variable which has higher and lower contribution for driver fatalities with fixed objects and also compares with results of previous analysis. For example, in terms of vehicle impact right side, rear side, and left side compare to front side (reference category). Left side have double OR compare to reference category, which predicts that driver fatality risk is higher when crash occurs on driver side compare to front side and right side have lower OR compare to right side which suggests that driver fatality risk is lower when crash occurs on right side. These results were also similar to previous replicated analysis. These graphs are displayed in Appendix D.

Table 4.27: Results of the univariate logistic regressions (unadjusted) and multivariate logistic regression (adjusted) with driver fatality (N=17731) as the dependent variable (OR and 99% CI).

Variable	Unadjusted OR	99% CI	Adjusted OR	99% CI	P>|z|
Age(Years)					
<20	0.64	0.54-0.76	0.65	0.54-0.78	0.01
20-29	0.63	0.54-0.75	0.65	0.54-0.77	0.01
30-39	0.76	0.63-0.91	0.73	0.60-0.89	0.01
40-49	1	1.00-1.00	1	1.00-1.00	0.01
50-64	1.30	1.01-1.67	1.52	1.16-1.99	0.01
65-79	1.35	1.00-1.81	1.81	1.32-2.47	0.01
80+	2.39	1.28-4.40	3.47	1.82-6.61	0.01
Gender					
Male	1	1.00-1.00	1	1.00–1.00	0.01
Female	1.40	1.27-1.55	1.45	1.30-1.62	0.01
BAC					
0	1	1.00-1.00	1	1.00–1.00	0.01
0.01–0.04	0.51	0.42-0.61	0.51	0.41-0.62	0.01
0.05–0.09	0.48	0.42-0.56	0.50	0.43-0.58	0.01
0.10–0.14	0.54	0.48-0.61	0.53	0.46-0.60	0.01
0.15–0.19	0.80	0.71-0.91	0.79	0.69-0.90	0.01
0.20–0.29	1.52	1.32-1.74	1.44	1.23-1.67	0.01
0.30+	3.55	2.35-5.34	3.20	2.09-4.89	0.01
Travelling Speed(kph)					
<56	1	1.00-1.00	1	1.00–1.00	0.01
56-95	1.25	0.93-1.67	1.36	0.99-1.86	0.01
96-111	1.46	1.08-1.96	1.72	1.25-2.38	0.01
112+	1.93	1.45-2.59	2.57	1.87-3.54	0.01
Impact					
Front side	1	1.00-1.00	1	1.00–1.00	0.01
Right side	0.46	0.42-0.52	0.47	0.42-0.53	0.01
Rear end	0.69	0.57-0.85	0.7	0.56-0.86	0.01
Left side	2.14	1.88-2.43	2.34	2.05-2.68	0.01
Restraint					
None	1	1.00-1.00	1	1.00–1.00	0.01
Shoulder Belt	0.79	0.50-1.26	0.67	0.41-1.09	0.01
Lap belt	0.78	0.50-1.23	0.77	0.48-1.24	0.06
Shoulder & lap belt	0.55	0.50-0.61	0.42	0.37-0.47	0.01
Model Year					
5-year increment	1.00	0.98-1.02	1.04	1.02-1.07	0.01
Wheelbase					
25cm increment	0.98	.94-1.02	0.93	0.89-0.97	0.01

4.2.2. Univariate and Multivariate Regressions Analysis for Additional Variables

Variables which were used in analysis one, and additional variables mentioned in Table 3.3 were added to determine Odds Ratio by using univariate and multivariate logistic regressions in order to scrutinize their independent influence to fatal injuries. These additional variables were added in the whole model also to determine the change in ORs for previous variables in regard to the additional variable. Table 4.28illustrates the results of this process. Univariate and Multivariate Logistic Regression was calculated with 95 % CI, which gives unadjusted and adjusted OR. Variables which were not statically significant associated with fatal injuries were removed using a P< 0.01 cut off. Variables such as (driver age, gender, BAC, direction of impact, airbag deployment, restraint use, travelling speed, vehicle model year, vehicle wheelbase, roadway alignment, weather, light conditions, day of the week, roadway type, roadway function, relation to junction and, vehicle type) were considered in the analysis. Variables significance are displayed in Table 4.28

Table 4.28: Results of the univariate logistic regressions (unadjusted) and multivariate logistic regression (adjusted) with driver fatality (N=20145) as the dependent variable (OR and 95% CI).

	Unadjusted OR	95% C.I.	Adjusted OR	95% C.I.	P>|z|
Age (Years)					
<20	0.66	0.59-0.75	0.74	0.64-0.84	0.01
20-29	0.66	0.59-0.74	0.70	0.62-0.80	0.01
30-39	0.77	0.68-0.88	0.75	0.66-0.86	0.01
40-49	1	1	1	1	0.01
50-64	1.30	1.09-1.55	1.45	1.21-1.75	0.01
65-79	1.43	1.16-1.76	1.71	1.37-2.14	0.01
80+	2.28	1.47-3.54	2.87	1.82-4.52	0.01
Gender					
Male	1	1	1	1	0.01
Female	1.31	1.22-1.41	1.43	1.32-1.55	0.01

Table 4.28: Results of the univariate logistic regressions (unadjusted) and multivariate logistic regression (adjusted) with driver fatality (N=20145) as the dependent variable (OR and 95% CI). (Cont.)

BAC					
0	1	1	1	1	0.01
0.01–0.04	0.50	0.44-0.57	0.48	0.42-0.56	0.01
0.05–0.09	0.49	0.44-0.54	0.48	0.43-0.54	0.01
0.10–0.14	0.56	0.51-0.61	0.52	0.47-0.58	0.01
0.15–0.19	0.83	0.76-0.91	0.73	0.66-0.82	0.01
0.20–0.29	1.64	1.48-1.80	1.38	1.23-1.55	0.01
0.30+	4.15	3.06-5.64	3.29	2.40-4.52	0.01
Travel Speed (mph)					
<35	1	1	1	1	0.01
35-59	1.28	1.04-1.58	1.35	1.07-1.71	0.01
60-69	1.52	1.23-1.88	1.79	1.41-2.27	0.01
70+	1.91	1.55-2.35	2.49	1.97-3.15	0.01
Surface Conditions					
Dry	1.01	0.93-1.09	0.93	0.85-1.01	0.09
Not Dry	1	1	1	1	0.01
Light Conditions					
Daylight	1.29	1.21-1.38	1.10	1.02-1.19	0.01
Dark	1	1	1	1	0.01
Day of the Week					
Work Day	1	1	1	1	0.01
Weekend	0.95	0.89-1.01	1.03	0.96-1.11	0.29
Roadway Type					
Brick, Gravel, Dirt,	1	1	1	1	0.01
Asphalt/Concrete	1.22	1.05-1.41	1.09	0.92-1.29	0.29
Roadway Function					
Interstate, Principal	1	1	1	1	0.08
Freeway and expressway, principle	0.92	0.77-1.10	1.07	0.88-1.30	0.49
Principal-arterial, other	0.94	0.84-1.06	1.03	0.9-1.17	0.57
Minor arterial	0.94	0.84-1.05	1.07	0.94-1.21	0.27
Collector	0.98	0.89-1.08	1.16	1.03-1.30	0.01
Local	0.90	0.82-1.00	1.16	1.03-1.31	0.01
Unknown	0.88	0.68-1.13	1.04	0.78-1.39	0.75

Table 4.28: Results of the univariate logistic regressions (unadjusted) and multivariate logistic regression (adjusted) with driver fatality (N=20145) as the dependent variable (OR and 95% CI). (Cont.)

Relation to Junction					
Non-Junction	1	1	1	1	0.01
Intersection, intersection related	0.88	0.78-1.00	0.92	0.80-1.06	0.26
Driveway, Alley	2.00	1.36-2.95	1.80	1.19-2.70	0.01
Entrance/Exit	1.05	0.81-1.35	1.18	0.89-1.65	0.24
Rail Grade Crossing, Crossover, Other or Unknown combined due to low number of cases)	1.05	0.79-1.39	1.18	0.86-1.60	0.29
Roadway Alignment					
Straight	1.03	0.97-1.09	0.99	0.92-1.05	0.78
Curved	1	1	1	1	0.01
Type of Vehicle					
Cars	1	1	1	1	
Light Trucks / SUVs	0.96	0.90-1.03	1.05	0.96-1.15	0.23
Vans	0.83	0.70-0.98	0.98	0.81-1.19	0.89
Number of Occupants					
2	1	1	1	1	0.01
3	0.57	0.53-0.62	0.60	0.55-0.64	0.01
4	0.45	0.41-0.50	0.49	0.44-0.54	0.01
5	0.34	0.30-0.40	0.35	0.30-0.41	0.01
6	0.33	0.26-0.42	0.35	0.27-0.46	0.01
7	0.26	0.17-0.39	0.27	0.17-0.41	0.01
8 or more occupants	0.32	0.21-0.48	0.36	0.23-0.55	0.01
Impact					
Front side	1	1	1	1	0.01
Right side	0.55	0.50-0.59	0.53	0.49-0.58	0.01
Rear end	0.74	0.64-0.86	0.76	0.65-0.89	0.01
Left side	2.0	1.87-2.27	2.22	2.00-2.45	0.01
Restraint					
None	1	1	1	1	0.01
Shoulder Belt	0.65	0.47-0.91	0.58	0.40-0.83	0.01
Lap belt	0.69	0.49-0.97	0.67	0.46-0.96	0.03
Shoulder & lap belt	0.52	0.49-0.56	0.43	0.40-0.46	0.01
Model Year	0.98	0.96-0.99	1.01	0.99-1.02	0.28
Wheelbase	0.97	0.94-0.99	0.94	0.91-0.97	0.01

Reference categories have an OR of 1 same as previous section. All the categories are compared to reference (base) categories, which have OR = 1 as mentioned in section one.

Using the 40-49 age category as a reference category, an increase in driver age was associated with greater odds of fatalities while younger drivers with age category of <20 years had the lowest odds of driver fatalities. For example, drivers with 80+ years old had adjusted odds of 2.28 for fatal injuries which is almost four times more than drivers <20 years which have adjusted odds of 0.66 similar to results of age categories for part one and two. Additionally, female drivers had slightly higher fatality odds than male drivers with a 1.31 more chance of sustaining fatal injuries, which is similar to the previous updated and replicated analysis. In support of the previous updated and replicated results, the general trend for OR is the same for BAC levels, but the OR had increased by 100% when additional variables are considered. BAC results indicated increased fatalities as BAC levels increased. In this sense, drivers at a BAC level of 0.30+ had four times more fatality odds than sober drivers, when compared to the previous updated analysis.

Moreover, BAC level for updated analysis with additional variables with adjusted OR is displayed in Figure 4.3, which reveals that OR decreases as the BAC increases up to 0.10-0.14 (0.53) and then OR increases abruptly reaching its peak at BAC level 0.30+ (3.47) this reveals that driver fatality odds is three times higher for drivers with BAC of 0.30+ compare to sober drivers. Results also supports the findings of previous replicated analysis. Moreover, BAC level for updated analysis with adjusted OR is displayed in Figure 4.3.

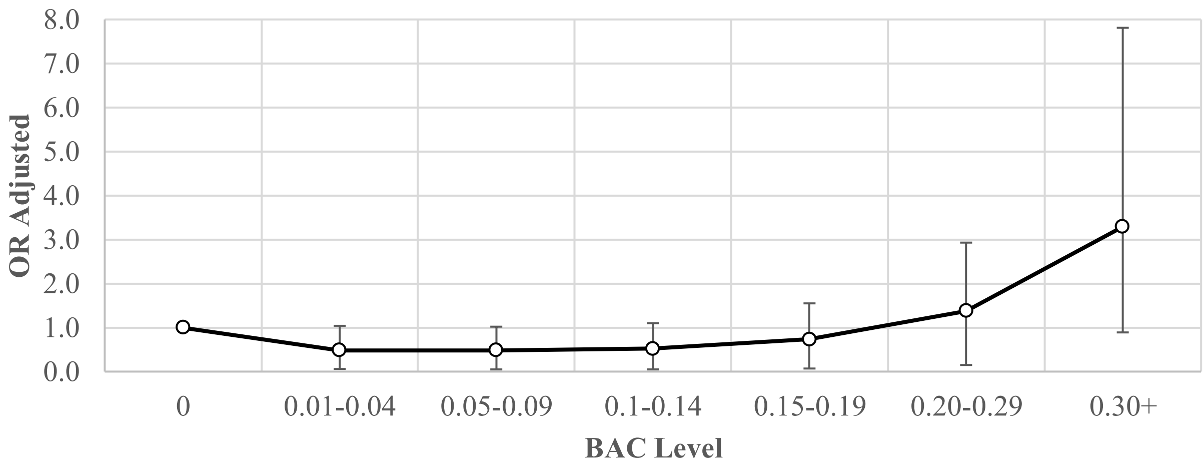

Figure 4.3: Updated analysis with additional variables adjusted OR for BAC level.

Moreover, travelling speed indicates that Odds of driver fatalities increases when speed increases. OR (1.91) is almost doubled when the speed is more than 70 mph when compared to the reference category of 35 mph. ORs also increases by 28% and 52% for the speed category of 35-59 mph and 60-69 mph respectively. These results are also similar to the previous updated and replicated analysis.

In addition, straight roadways are compared to curved roadways which is a reference category. Straight roadways have slightly higher odds (0.78) of fatalities than curved roadways, which represents that driver fatality risk is higher on straight roadways by 3%.

Also, weather conditions which are also known as surface conditions, compares not dry-roadway condition with dry roadway conditions. Weather conditions indicates that not-dry roadway conditions considered as a base group have similar odds of fatalities when compared to dry roadway conditions which have an OR of 1.01. Attributes for weather conditions are displayed in Appendix B.

Interestingly, light conditions indicate that daylight conditions (reference category) have 29 % higher driver fatality odds when compared to dark lighting conditions. Attributes for light conditions are displayed in Appendix B.

Furthermore, weekends have 0.95 times lower odds of driver fatality risk compared to the weekdays (reference category). In regard to roadway type, brick, gravel, or dirt (unpaved roadways) which are kept as the reference category are compared with asphalt/concrete (paved roadways). Asphalt or concrete pavements have 1.09 higher chance of driver fatality odds than brick, gravel, or dirt pavements.

Moreover, roadway function suggests that local roads have the lowest fatality odds of 0.90 when compared to interstate, principal (reference category) and also have the highest number of odds when compared to other categories. Principal arterial and Minor arterial have 6% driver fatality odds when compared to interstate, principal. Freeway expressway, principle and collector have 0.92 and 0.98 lower odds of driver fatality respectively, as shown in Table 4.19. In regard to relation to junction, non-junction is kept as a reference group and intersection/intersection related, driveway/alley, entrance/exit, and rail grade crossing are compared to the reference category. Results indicate that driveway/alley had twice the odds compared to non-junction. Entrance/exit and rail grade crossing also have 5% higher odds for driver fatalities. Intersection/intersection related have 0.88 times lower odds of driver fatalities when compared to reference category. Moreover, Figure 4.4represents adjusted OR curve in regard to relation to junction, which shows that driveway/alley have the highest OR when compared to non-junction.

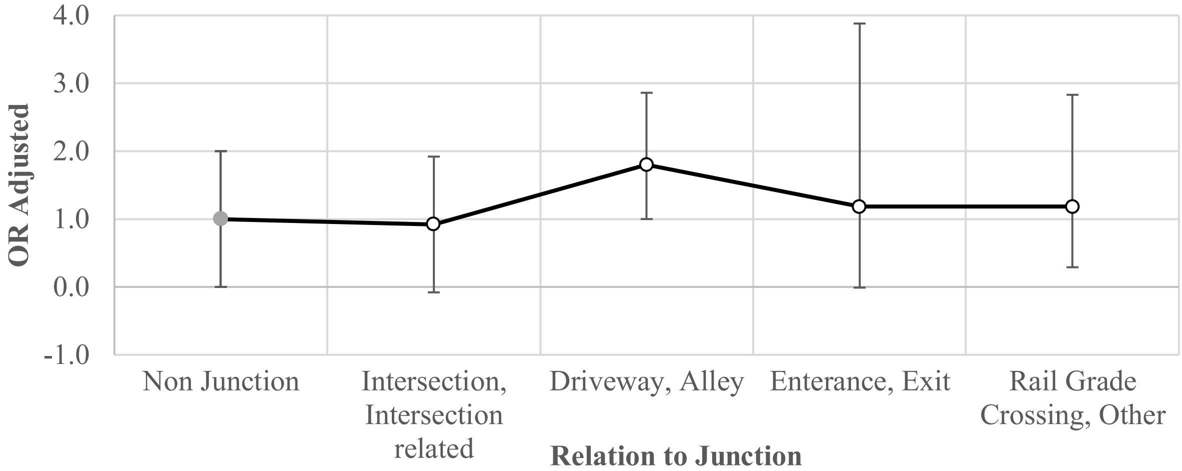

Figure 4.4: Updated analysis with additional variables adjusted OR for relation to junction.

Additionally, light trucks/SUV's and vans have lower odds of driver fatalities (0.96) and (0.83) respectively when compared to cars (reference category). Finally, the risks of driver fatalities appeared to decrease with increasing number of vehicle occupants. Generally, two occupants have the highest odds of driver fatality which is also the reference group compared to other occupants. Regarding the direction of impact, both the right-side crash impacts and rear-end had a lower odds risk of fatalities while left-side impacts had an OR more than double that of frontal impacts. This also supports previous findings that had determined left-side impacts as having higher odds.

Moreover, the direction of impact variable compared the rear, left, and right-side impacts against frontal impact which is considered as the reference category (same as the previous replicated analysis). Results indicated that the left side (driver side) Impact had twice the OR compared to the front side. Also, both the right side and rear side have low odds of (0.55) and (0.74) respectively which are similar to results from previous updated and replicated analysis.

In reference to seatbelt, results indicated that drivers wearing three-point seatbelts had the lowest odds of fatalities in a crash with OR of 0.433. Similarly, drivers wearing a shoulder belt (OR =0.574) or lap belt (OR=0.682) had lower fatality odds than drivers not wearing a seatbelt. These results are similar to results from previous replicated and updated analyses. Additionally, seatbelt results established that Odds of driver fatalities are higher when no seat belts (reference category) are used by drivers. Shoulder and lap-belt have the lowest OR at 0.52 in the whole group when compared to the reference category, which represents that Odds of driver fatalities decreases by almost 50% when shoulder and lap-belts are used.

Shoulder belt and lap-belt have almost similar OR of 0.65 and 0.69 respectively, which are also similar to the results from previous updated and replicated analysis. As well, increasing the vehicle model year by 5 years does not have any change in OR (1.01). While increasing wheelbase by 25cm reduced the risk of fatality by a 6% rate. Both the vehicle model year and wheelbase results were are in support of previous updated and replicated findings.

Furthermore, the intercept or constant model compares chi-square of updated analysis and updated analysis with additional variables values. Updated analysis with additional variables has chi-square 47 degrees of freedom equal to 2859.37 and $p < 0.01$ which indicates that the model is statically significant and is a good fit. It also indicates that model improves on model fit compare to previous replicated analysis fit as chi-square value improved.

Several graphs are generated which reveals difference in adjusted OR's such as: age category, direction of impact and vehicle speed. These graphs interpret driver fatality risk compare to independent variables. Each variable has reference category one and other categories are compared to reference category. These graphs give an insight of the trends for adjusted OR's, to depict the highest and lowest OR for driver fatalities, which will help to predict the variable which has higher and lower contribution for driver fatalities with fixed objects and also compares with results of previous analysis. For example, in terms of vehicle impact right side, rear side, and left side compare to front side (reference category). Left side have double OR compare to reference category, which predicts that driver fatality risk is higher when crash occurs on driver side compare to front side and right side have lower OR compare to right side which suggests that driver fatality risk is lower when crash occurs on right side. These results were also similar to previous updated and replicated analysis. These graphs are displayed in Appendix E.

4.3. Poisson Regression Analysis

This part is divided into three sections: the first section consists of tables with details of total driver fatality counts with a fixed object by each factor, the second section interprets the coefficients in terms of Poisson regression and the third section interprets the coefficients in terms of Incidence Rate Ratio (IRR) of each factor on driver fatality. As indicated previously, the years considered for these analyses are from 1982 to 2014.

4.3.1. Total Driver Fatality

Tables were developed to show the total number of counts for driver fatalities of each variable considered in this part. The total number of fatally injured drivers for the time period considered is 12,804. The number of driver fatalities increased gradually starting from 1982 until 2004, before gradually decreasing from 2005 to 2014. Total Percentage and Cumulative Percentage are used in this case. Cumulative Percentage for a frequency distribution is the percent of values at or below a particular category, as it is another way of expressing frequency distribution. In 2004, the count of driver fatalities was the highest with 535 fatalities recorded, representing a 4.18% increase from 2003 as represented in Table 4.29.

Table 4.29: Driver fatalities frequencies from 1982 to 2014.

Data Year	Frequency	Percentage	Cumulative Percentage
1982	209	1.63	1.63
1983	226	1.77	3.40
1984	251	1.96	5.36
1985	261	2.04	7.40
1986	285	2.23	9.62
1987	337	2.63	12.25
1988	357	2.79	15.04
1989	363	2.84	17.88
1990	379	2.96	20.84
1991	365	2.85	23.69
1992	354	2.76	26.45
1993	337	2.63	29.08
1994	465	3.63	32.72
1995	461	3.60	38.01
1996	489	3.82	36.32
1997	475	3.71	43.85
1998	452	3.53	47.38
1999	402	3.14	50.52
2000	491	3.83	54.35
2001	487	3.80	58.15
2002	505	3.94	62.10
2003	480	3.75	65.85
2004	535	4.18	70.02
2005	483	3.77	73.80
2006	128	1.00	74.80
2007	416	3.25	78.05
2008	478	3.73	81.78
2009	441	3.44	85.22
2010	490	3.83	89.05
2011	408	3.19	92.24
2012	355	2.77	95.01
2013	314	2.45	97.46
2014	325	2.54	100.00
Total	12,804	100.00	

Additionally, Table 4.30 displays roadway alignment trends which compare straight and curved roadway alignment in regard to driver fatality counts. Straight roads have 7331 (57.26%) fatalities compared to 5473 (42.74%) for curved roads. This shows that straight roads have 14.52% more driver fatality counts compared to curved roads. Total number of driver fatalities are more on curved roadways (57.26%) compared to straight roadways, this can be due to the higher number of straight segments than curved segments.

Table 4.30: Driver fatalities trends on roadway alignment.

Roadway Alignment	Frequency	Percentage	Cumulative Percentage
Straight	7,331	57.26	57.26
Curved	5,473	42.74	100.00
Total	12,804	100.00	

Furthermore, when looking at pavement conditions, as shown in Table 4.31 below, dry pavements have the majority of crashes as they account for 77.88% (9972) of total crashes, compared to 22.12% (2832) recorded on not dry pavements. Dry roadways have higher driver fatality counts that could be explained by having lower, not dry conditions compared to dry conditions.

Table 4.31: Driver fatalities trends on pavement conditions.

Pavement Conditions	Frequency	Percentage	Cumulative Percentage
Dry	9,972	77.88	77.88
Not Dry	2,832	22.12	100.00
Total	12,804	100.00	

Moreover, data on lighting conditions indicate that the majority of crashes occurred during dark light conditions accounting for 60.82% of fatal crashes while daylight conditions constitute 39.18% of fatalities as Table 4.32 illustrates. Driver fatality counts are higher on dark light conditions probably due to the reduced time for last minute breaking and maneuvering which obstructs driver visibility which is also stated by Anarkooli & Hosseinlou et al., (2016).

Table 4.32: Driver fatalities trends on lighting conditions.

Light Condition	Frequency	Percentage	Cumulative Percentage
Daylight	5,017	39.18	39.18
Dark	7,787	60.82	100.00
Total	12,804	100.00	

In addition, asphalt and concrete are the major materials of pavement type (FHWA, 2012). Asphalt/Concrete account for 94.47% of fatal crashes and 5.53% of crashes occurred on brick, gravel, dirt, or another type of pavements as Table 4.33 demonstrates below.

Table 4.33: Driver fatality trends on pavement type.

Pavement Type	Frequency	Percentage	Cumulative Percentage
Brick, Gravel, Dirt, Other	708	5.53	5.53
Asphalt/Concrete	12,096	94.47	100.00
Total	12,804	100.00	

Table 4.34 shows that the number of fatal crashes occurring on collectors and local roads represent 24.01% and 23.18% of the total respectively. It also shows minor arterial roads with 15.82%, while interstate roads have 15.67% of fatalities counts. Principal arterial and other roads account for 14.96%, whereas freeway and expressway account for 4.37% of fatal crashes. Finally, unknown roads account for 1.98% of all fatalities. A maximum number of driver fatality counts are caused on Interstate roads followed by collector and local roads as a possible result to congestion and speeding also supported by Garber & Garber et al., (1990).

Table 4.34: Driver fatalities trends on roadway function.

Roadway Function	Frequency	Percentage	Cumulative Percentage
Interstate	2,007	15.67	15.67
Freeway and expressway	560	4.37	20.05
Principal arterial, other	1,916	14.96	35.01
Minor arterial	2,025	15.82	50.83
Collector	3,074	24.01	74.84
Local	2,968	23.18	98.02
Unknown	254	1.98	100.00
Total	12,804	100.00	

Count data in relation to junction established that non-junction areas have the highest fatality frequencies with 87.39% that could be a result of confusion of right of way. Intersections or related to intersections have 7.70% as presented in Table 4.35. Entrance or exit of junctions account for 2.01% of fatal crashes, while rail grade crossing, crossover, or other junctions have 1.6% fatalities count. Finally, driveway, alley and access roads have 1.19% fatal crashes.

Table 4.35: Driver fatalities trends in relation to junction.

Relation to Junction	Frequency	Percentage	Cumulative Percentage
Non-Junction	11,189	87.39	87.39
Intersection, intersection related	986	7.70	95.09
Driveway, Alley, Access, etc.	152	1.19	96.27
Entrance/Exit	257	2.01	98.28
Rail Grade Crossing, Crossover, Other	220	1.572	100.00
Total	12,804	100.00	

Additionally, count data indicate that weekends (approximately 65%) have the highest number of fatal crashes in comparison to weekdays (approximately 35%) as presented in Table 4.36. Considering the possibility that drivers drive under the influence of alcohol on weekends (Walz and Daniels et al., 2011).

Table 4.36: Driver fatalities trends on type of day.

Type of Day	Frequency	Percentage	Cumulative Percentage
Workday	4,523	35.32	35.32
Weekend	8,281	64.68	100.00
Total	12,804	100.00	

Furthermore, data on vehicle type (Table 4.37) indicate that cars (68%) have the highest number of fatalities as compared to SUVs/light trucks (27%) or Vans (5%). This could be due to the reason that total number of cars are more than any other vehicle type, and overall structure of cars can be weaker compared to SUVs/light trucks.

Table 4.37: Driver fatalities trends on vehicle type.

Vehicle Type	Frequency	Percentage	Cumulative Percentage
Cars	8,750	68.34	68.34
Light Trucks / SUVs	3,467	27.08	95.42
Vans	587	4.58	100.00
Total	12,804	100.00	

Moreover, count data on gender established that fatally injured male drivers account for approximately 71% of total fatalities while female drivers are 29% as Table 4.38 below illustrates. Research done by several authors (Islam and Mannering et al., 2016 and

Santamariña-Rubio et al., 2014) suggest that male drivers take higher risk while driving compared to female drivers.

Table 4.38: Driver fatalities trends by gender.

Sex	Frequency	Percentage	Cumulative Percentage
Male	9,061	70.77	70.77
Female	3,743	29.23	100.00
Total	12,804	100.00	

This section represents the total driver fatality counts on different crash variables. Data represent the contribution of each variable towards the driver fatality counts. Results indicate that straight roadways, dry surface conditions, and dark conditions have higher driver fatality counts. Moreover, in regard to days weekends have higher driver fatality counts compare to weekdays. Furthermore, non-junction, cars and male drivers have higher driver fatality counts.

4.3.2. Log of the Incidence Rate Ratio

This section interprets the driver fatality counts in terms of Poisson regression coefficients. One group in each variable is kept as a reference category which is taken as 0. Data from 1982 to 2014 were divided into 7 groups. Data groups are distributed with 5 years of data which will predict the trends for driver fatality counts in regard with different years. Driver fatalities count is the response variable in this Poisson regression which models the log of expected counts as a function of predictor variables. Coefficients (coeff.) are the estimated Poisson regression coefficients for the model. The number of observations used in this analysis is 12,804. Wald chi-square in the analysis represents 30 degrees of freedom for the model as shown in Table 4.39. The degree of freedom is equal to the number of predictor variables used in the analysis. The next step shows the p-value which indicates that the variables used are statically significant. Furthermore, Pseudo-R2 is represented in Table 4.39. Pseudo-R2 measures are relative measures among similar models indicating how well the model explains the data. Pseudo-R2 (0.07) suggests that the hypothesis could be rejected because the data are not Poisson distributed and do not fit the model. Furthermore, Poisson regression is dependent on the sample size and number of counts. Therefore, driver and vehicle characteristics were not included in the analysis because by doing so sample size was reduced as the number of observations were not as large as number of coefficients. The minimum sample size requirement was not met which is that the number of predictor variable combined should be at least as large as the number of coefficients. If the condition is not satisfied then the predictor variable is not estimable, therefore only geometric characteristics were considered in the analysis.

In this sense, FARS data are used in the analysis which is limited to fatal crashes and many variables are not recorded which could have an effect on driver fatality counts. Moreover, each variable is evaluated with the p-value. If the value is greater than 0.05, it means that the independent variables does not show a statistically significant relationship with the dependent variable with a 95% CI

Table 4.39: Poisson regression output.

Number of Observations	12,804
Wald χ^2 (30)	0.00
Prob> χ^2	0.01
Pseudo-R^2	0.0765

Results from the Poisson Regression analysis (Table 4.40) indicate that data year for group 1991 have driver fatality counts 0.70 greater driver fatality counts compared to the data year 1986, in other words, antilog value for data year group of 1991suggets that it have 5 times more driver fatality counts when compare to base group 1986. Data year 1991 is the only data year in which driver fatality counts are greater than the base year. Data years 1996 (0.50), 2000 (0.12), 2006 (0.07), 2011 (0.14), and 2014 (0.33) all have fewer driver fatalities counts compare to the base group. Table 4.40 shows that the log of fatality counts decreases with time. Additionally, the difference in logs of expected counts for curved roadway alignment is 0.52 times higher than for straight roads, implying that there are more fatalities for curved roads than straight roads. This result support the finding from part 2 analysis in which curved roadways have higher OR than straight roads.

Furthermore, not dry weather conditions have 0.48 times less expected driver fatalities log counts when compared to dry weather. Additionally, the difference in logs of driver fatality counts is 0.27 times greater in dark conditions when compare to light conditions. This result contradicts the finding from part 2 analysis in which not dry roadways (OR=1) and daylight (OR=1.10) have higher OR.

Also, asphalt/concrete pavements have almost double the logs of the expected count when compared to unpaved roads or brick roads. Asphalt/concrete pavements have an anti-log coefficient value of 4.36 which indicates that driver fatality counts are 4.36 times more on asphalt/concrete compare to unpaved roads which supports the finding of previous part 2 analysis in which Asphalt/concrete have 1.09 odds compare to unpaved roads.

In regard to interstate roadways with respect to other types of roadways, results indicate that minor arterials contribute to 0.64 times higher logs of expected driver fatalities which is also (the highest in the group) followed by the increase in the logs for collectors (0.36), locals (0.24), and principal arterials (0.19) compare to interstate roadways. On the other hand, freeways (0.30) and unknown roads (0.37) have reduce logs of driver fatality counts compare to interstate roadways. Furthermore, rail grade crossing/other and entrance/exit have 0.35 and 0.41 times fewer logs of expected driver fatality counts when compare to non-junction. Driveway and alley also have less driver fatality counts compare to non-junction with the same driver fatality log counts of 0.66. In regard to OR entrance/exit have highest odds of driver fatalities (1.18) compared to interstate roadways as indicated by part 2 results.

Moreover, log of driver fatalities count is 0.30 times greater for weekends compare to weekdays, which is also similar to previous part 2 results in which weekends have higher OR (1.03). Vehicle miles travelled (VMT) is also more on weekend nights as compared to a normal weekday night. Furthermore, cars (coefficient = 0.50) have the highest coefficient for log counts which is approximately 50 percent more when compared to vans (base) and 27 percent more when compare to SUV’s (coefficient – 0.22).

For age, the category of 40-49 years old is considered as reference group. As expected, younger adults have the highest logs of expected driver fatality counts. Age groups of 0-19 years and 20-29 years have 0.20 and 0.42 times greater logs of expected driver fatalities compare to the reference group. In relation, to gender, the difference in logs of expected driver fatality counts is 0.31 lower for females compare to males. In regard to previous analysis younger adults <20 years of age have lowest OR (0.74) and OR increases with an increase in age recorded highest at 80+ years age group (2.87).

Results from Poisson Regression indicates that curved roads, dry weather conditions, and asphalt/concrete pavements have higher logs of driver fatality counts. Results also suggest that minor arterials, non-junctions, weekends and, cars have higher driver fatality logs. Younger and older drivers and male drivers also have the highest driver fatality counts compared to middle age drivers and female drivers.

Table 4.40: Poisson log-likelihood ratios.

Driver Fatalities count	Coefficient	CI (95%) Lower	CI (95%) Upper	Z	P>|z|
Year (5-year increment)					
1986 (base)	0	0	0	0	0.01
1991	0.70	-0.00	0.15	1.73	0.08
1996	-0.57	-0.13	0.01	-1.49	0.13
2001	-0.12	-0.19	-0.05	-3.33	0.00
2006	-0.07	-0.15	-0.00	-2.09	0.03
2011	-0.14	-0.22	-0.07	-3.86	0.01
2014	-0.33	-0.41	-0.24	-7.63	0.01
Roadway Alignment					
Straight (base)	0				
Curved	0.52	-0.53	-0.44	2.98	0.00
Weather					
Dry (base)	0				
Not dry	-0.48	-0.53	-0.44	-23.85	0.01
Light Condition					
Daylight (base)	0				
Dark	0.27	0.24	0.30	16.44	0.01
Type of Roadway					
Brick, Gravel, Dirt (base)	0				
Asphalt/Concrete	0.64	0.57	0.72	17.13	0.01
Roadway Function					
Interstate (base)	0				
Freeway and Expressway	-0.30	-0.38	-0.22	-7.51	0.01
Principal Arterial, Other	0.19	-0.03	0.07	0.67	0.50
Minor Arterial	0.64	0.00	0.11	2.26	0.02
Collector	0.36	0.30	0.41	12.85	0.01
Local	0.24	0.18	0.29	8.67	0.01
Unknown	-0.37	-0.49	-0.25	-6.25	0.01
Relation to Junction					
Non-Junction (base)	0				
Intersection, (and related)	-0.66	-0.73	-0.60	-20.75	0.01
Driveway, Alley, Access, etc.	-0.66	-0.77	-0.55	-11.89	0.01
Entrance/Exit	-0.41	-0.52	-0.31	-7.62	0.01
Rail Grade Crossing, Crossover, Other	-0.35	-0.47	-0.23	-5.86	0.01
Relation to Junction					

Table 4.40: Poisson log-likelihood ratios. (Cont.)

Day of the week					
Workday (base)	0				
Weekend	0.30	0.26	0.33	17.2	0.01
Vehicle Type					
Vans (base)	0				
Cars	0.50	0.42	0.59	12.42	0.01
Light Trucks - SUVs	0.22	0.13	0.30	5.24	
AGECAT					
40-49 (base)	0				
0-19	0.19	0.14	0.25	7.32	0.01
20-29	0.42	0.37	0.47	15.7	0.01
30-39	0.06	0.01	0.11	2.35	0.01
50-64	0.09	0.03	0.15	2.92	0.01
65-79	0.19	0.12	0.26	5.6	0.01
80+	0.20	0.09	0.30	3.91	0.01
Sex					
Male (base)	0				
Female	-0.31	-0.34	-0.27	-17.69	0

4.3.3. Incident Rate Ratios (IRR)

This section presents the IRR data findings. Table 4.41 illustrates the IRR for various variables. IRR is obtained by exponentiating the Poisson regression coefficient and is another way to look at the driver fatality counts. The incidence rate ratio are simply the ratio of the number of events of one category to the number of events in the other category. IRR have same results but are displayed because they are easier to interpret and explain compare to coefficients. IRR shows the contribution of each variable towards the fatality counts of drivers. One group in each variable is kept as a reference category which is taken as 1. The reference category is taken as 1 for each variable in this section as rates cannot be compared with zero. If the risk ratio is 1 it suggests no difference or little difference in risk, if the risk ratio >1 it suggests an increased risk of that outcome in the exposed group, if the risk ratio < 1 it suggests a reduced risk in exposed group. Same variables used in Section 2 are used to calculate Incidence Rate Ratios as IRR's are obtained by exponentiating the coeff as mentioned before. The same variables were used as they were all statically significant in previous analysis. IRRs are displayed to interpret results displayed by coefficients properly and accurately.

From Table 4.41, it is observed that the IRR for data year group 1991-1995 is 1.07, when compare with the data year group 1986-1990 (base). It means that the data year group for 1991-1995 is expected to have a rate 0.07 times greater, or that the number of driver fatality counts are 0.07 times more in data year group of 1991 compared to base data year group. IRR for data year group of 1991 is the highest compare to all other groups (1996, 2001, 2006, 2011, 2014), which shows that total number of driver fatality counts are decreasing with increasing years. Additionally, IRR for curved roadway alignment is 0.05 times more than straight roads implying that number of driver fatality counts are less on straight roads which is very interesting as the raw fatality counts are more on straight roads, in other words this shows that when other factors are considered curved roads are more fatal compared to straight roads.

Furthermore, not dry weather compared to dry weather has a rate of 0.61 times lower driver fatalities. In addition, the number of driver fatality counts increase by 0.31 times if it is dark as compared to driving in daylight conditions. Similar to previous raw counts findings indicating that dark conditions have more driver fatalities. Also, IRRs for driver fatality counts are greater by 0.91 if roadways are made of asphalt or concrete when the other variables are held constant in the model compared to roadway type (base category).

Moreover, on roadway function, collectors and local streets contribute to the highest number of fatal crashes with an IRR of 0.43 and 0.27 times more for driver fatalities respectively, than interstates/principal arterials (base). Minor arterials (0.06), and principal arterials (0.01) also have a higher IRR for driver fatalities as compared to the interstate. Freeways and expressways have the lowest IRR (0.73) when compare to the base group making them the least fatal of all categories. Additionally, in relation to junction the analysis shows that rail grade crossing has IRR of 0.70 times lower for driver fatalities than non-junction (base). All other variables including intersections (0.51), driveways, and alleys (0.51) have lower IRRs compared to non-junction.

In addition, IRR is 1.35 for weekends as compare to weekdays, which indicates that weekends have a rate 0.35 times greater for driver fatalities compare to weekends. Furthermore, IRR of driver fatalities for cars is 0.66 times, and light trucks/SUV's is 0.24 times more when compared to vans (reference category).

Moreover, the age group of 20-29 have the highest IRR for driver fatalities of 0.52 compare to reference category age group of 40-49 years. Age groups of 0-19, 65-79, and 80+ have almost the same incidence rate ratios which are 0.22, 0.21 and, 0.22 respectively. Age groups for 30-39 years (0.06), and 50-64 years (0.09) have the lowest IRRs compared to the age group of 40-49 years. These results show that younger adults and old age drivers have the maximum fatality counts in the whole group.

In reference to gender, females compare to males have a rate of 0.73 times lower than that of males for driver fatalities. This shows that males are more fatally injured than females.

Results for IRRS also indicates that curved roads, dry weather conditions, and asphalt/concrete pavements have higher driver fatality counts, which are similar to results of previous section. Results also suggest that minor arterials, non-junctions, weekends and, cars have higher driver fatality counts. Younger drivers, older drivers and male drivers have the highest driver fatality counts compared to middle age drivers and female drivers, which also supports the findings from previous section.

Table 4.41: Incident rate ratios (IRR).

Fatalities Sum	IRR	CI (95%) – Lower	CI (95%) - Upper	Z	P>|z|
Year (5-year increment)					
1986 (base)	1				
1991	1.07	0.992	1.16	1.73	0.08
1996	0.94	0.87	1.01	-1.49	0.13
2001	0.88	0.81	0.94	-3.33	0.01
2006	0.92	0.85	0.99	-2.09	0.01
2011	0.86	0.80	0.93	-3.86	0.03
2014	0.71	0.65	0.78	-7.63	0.01
Roadway Alignment					
Straight (base)	1				
Curved	1.05	1.01	1.09	2.98	0.01
Weather					
Dry (base)	1				
Not dry	0.61	0.58	0.63	-23.85	0.01
Light Condition					
Daylight (base)	1				
Dark	1.31	1.27425	1.36	16.44	0.01
Type of Roadway					
Brick, Gravel, Dirt (base)	1				
Asphalt/Concrete	1.91	1.773826	2.05	171.3	0.01

Table 4.41: Incident rate ratios (IRR). (Cont.)

Roadway Function					
Interstate, Principal Arterial (base)	1				
Freeway and Expressway, Principal Arterial	0.73	0.67	0.79	-7.51	0.01
Principal Arterial, Other	1.01	0.96	1.07	0.67	0.50
Minor Arterial	1.06	1.00	1.12	2.26	0.02
Collector	1.43	1.36	1.52	12.85	0.01
Local	1.27	1.20	1.34	8.67	0.01
Unknown	0.68	0.61	0.77	-6.25	0.01
Relation to Junction					
Non-Junction (base)	1				
Intersection (and related)	0.51	0.48	0.54	-20.75	0.01
Driveway, Alley, Access, etc.	0.51	0.46	0.57	-11.89	0.01
Entrance/Exit	0.65	0.58	0.73	-7.62	0.01
Rail Grade Crossing, other	0.70	0.62	0.78	-5.86	0.01
Day of the week					
Workday (base)	1				
Weekend	1.35	1.30	1.40	17.2	0.01
Vehicle Type					
Vans (base)	1				
Cars	1.66	1.53	1.80	12.42	0.01
AGECAT					
40-49 (base)	1				
0-19	1.22	1.15	1.28	7.32	0.01
20-29	1.52	1.44	1.61	15.7	0.01
30-39	1.06	1.01	1.11	2.35	0.01
50-64	1.09	1.03	1.16	2.92	0.00
65-79	1.21	1.13	1.35	5.6	0.01
80+	1.22	1.10	1.35	3.91	0.01
Sex					
Male (base)	1				
Female	0.73	0.70	0.75	-17.69	0.01

4.4. Countermeasures

This section presents a summary of possible countermeasures available to enhance safety according to results obtained in the analysis.

4.4.1. Older and Younger Drivers

Results from this research analysis indicated that older drivers 80+ years and younger drivers in the categories 0-19, and 19-29 years of age are at higher risk of fatal injuries compare to other categories. This issue has been addressed in the last few years by the American Association of Retired Persons (AARP) and the American Automobile Association (AAA) by providing online learning driving programs such as an AARP driver safety course and an online defensive course from AAA senior driving) related to the road safety of older drivers (http://aaafoundation.org, https://www.aarp.org). In this sense, these programs should be available to older drivers who lack access to the internet or are not familiar with the internet. Similarly, these learning programs may be more efficient if family members of older people are aware of such programs on driving safety and encourage their older family members to participate. Furthermore, driver simulators and on-road driving evaluations training programs with individual feedback of on-road driving performance to older adult drivers should be provided, which should help older drivers to drive more efficiently and safely (Dennis P. McCarthy 2005). Moreover, older drivers will also have the opportunity of preparing for possible dangerous driving conditions without being physically at risk. Research performed by Martin Lavallière et al., (2012) also suggest that simulator trainings helped older drivers to improve their visual inspection strategies. Furthermore, driver safety training programs should become mandatory for every new driver. Also, that penalties for drivers caught under the influence of alcohol should increase.

Results also indicate that young drivers have higher odds of fatality when the BAC level is high. One recommendation to reduce the number of fatalities is that emergency medical services (EMS) should reach crash locations with minimum delays which could be achieved with the automatic crash notification technology (ACN) that will automatically notify call centre in the event of a crash (Lahausse, Julie A et al., 2008 and Cuddihy et al., 2007).

4.4.2. Airbags and Seatbelt

Results from this research indicate that the use of seatbelts reduce fatalities. Data establish that shoulder and lap belts offer a protective measure in crash scenarios compare to other types of seat-belts. Furthermore, this research also indicate that airbag deployment benefits are still being debated because 50% of the data were missing. This study suggests that dummy vehicle testing should be done on different fixed objects such as, poles, trees, rocks, etc., so that airbag deployment effects can be known from different scenarios. This will also help to know the effect of airbags on drivers with different heights and weights. Perez J et al., (1996), and Shkrum et al., (2002) concluded that airbag is deployed with great speed, up to 200mph which results in fatal accidents pushing driver backwards and sideways.

In addition, airbag deactivation systems could also be used to reduce airbag related fatalities by vehicle and policymakers which restrict activation of an airbag to situations when a light-weight child carrier seat is secured in the passenger seat using the seat belt (Fleming et al., 1999). Airbags deactivation systems include an occupant classification by using a weight sensor and non-occupancy sensor, and a seat belt condition sensor for detecting whether the seat-belt is fastened or not and airbag is deployed accordingly (Fleming et al., 1999).

Furthermore, NHTSA has regularly produced reports regarding road safety, which provide broad facts and statistics on crash risk factors about drivers, environmental structure, and vehicle technology. These reports should be more readily accessible and integrated into driving learning programs. Therefore, this research recommends driving learning programs for drivers emphasizing the safety benefits of the proper use of seatbelts and the importance of the airbag in your vehicle.

4.4.3. Drunk Driving

Also for this research, driving under the influence of alcohol has been linked with an increase in fatalities, especially for young drivers. Therefore, to reduce drunk driving several steps had been already initiated by state law, which states that driving above the legal Blood Alcohol Content (BACs) limit is prohibited as indicated by Zedor et al., (1989). Furthermore, courses could be introduced for a restrictive BAC policy which can help to reduce fatalities due to BAC-related crashes, which could be effective for drivers across age and gender. (Haland et al., 2016). In this sense, training programs could be introduced in high schools and colleges/universities, targeting young adults who are more prone to get involved in drunk driving. Moreover, it is also recommended a mandatory safety course related to drunk driving which should be attended by drivers every 5 years to remind drivers the fatal consequences of drunk driving. This could help to decrease drunk driving which can reduce fatalities (Li-Hui Chen et al., 2006). Further, it is recommended that a mandatory waiting period of ≥3 months before the intermediate phase (new drivers), a nighttime driving restriction, and either ≥30 hours of supervised driving or a passenger restriction could help to reduce fatalities as this could help to gain driving experience and could avoid risky situations probably due to improper lighting (Li-Hui Chen et al., 2006).

4.4.4. Curved Road Design

In addition, this study finding establish that curved roadway alignments have a higher risk for fatalities than straight segments of roadways. The US Department of Transportation Federal Highway Administration (FHWA) recently proposed a countermeasure that would see improvement of roadside design at curve sections (FHWA, 2018). This strategy incorporates numerous treatments that target the improvement of high-risk environment at the side of roads, alongside the outer sections of horizontal curves on roads. These treatments include adequate shoulder rumble strips, centerline rumble strips, adequate sight distance, edge drop-offs, skid resistance pavement surfaces, grooved pavement, lighting on the curve, widen the roadway, improvement or restoring superelevation, modifying horizontal alignment and to prohibit trucks with very long semitrailers on roads with horizontal curves that cannot accommodate truck off tracking.. Also, these treatments will prevent fatalities related to roadway departure by offering drivers the opportunity to safely recover and by decreasing the severity of the crash (Hummer et al., 2010 and Stimpson et al., 1987). Based on results from the analysis, this study recommends that the roadways should be free from fixed objects like poles or trees and adequate sight distance should be provided on the curves so that oncoming vehicles can be spotted from a far distance. Moreover, there should be enough lighting provided on the curves so that drivers can drive without any visual limitation at nighttime. Slope steepness and slope elevations at curves should be kept minimum so that it ensures the stability of the vehicle and drivers can regain control easily if needed. Furthermore, roadside barriers should be installed wherever fixed objects like a mountain or boulder are present which cannot be moved and where safe distance is not achieved at curves to reduce the impact and to decrease fatalities (also recommended by Whitworth et al., 2004).

4.4.5. Non-Junctions

Results from the analysis also establish that non-junction areas have the highest frequencies of fatalities. Therefore, it is recommended that traffic control devices such as yield or stop signs should be installed at non-junctions. Also, traffic light systems at junctions should be installed if warranted. Stop signs or traffic lights can be installed if the intersection satisfies warrants or the minimum criteria that must be met before such a device can be installed. Moreover, extra lanes could be added to cope up with growing population because at non-junctions merging and diverging maneuvers always occur, thus these traffic conflicts could result in fatalities. Therefore, extra lanes can help to reduce fatalities by distributing the vehicles load evenly and reduce congestion (Anthony Downs et al., 2004). Moreover, safety awareness campaigns such as encouraging speed control, and enforcement on speeding could be introduced to reduce fatalities at non-junctions because this could be attributed to the fact that drivers tend to drive at (or above) the speed limit at non-junctions which can increase fatalities at non-junctions. Also, having 90-degree intersections instead of non-junctions could help for reducing fatalities, because in these intersections sight distance is not a problem which could make it a safest design for reducing fatalities. Moreover, the assurance of marking stop lines at non-junctions could play an important part to reduce fatalities (Kirolos Haleem et al., 2010). Moreover, installation of traffic control devices, and additional lanes could be expensive, therefore it is recommended that “Stop” and “Yield” signs could be installed. Furthermore, roundabouts could be considered when there is a large number of fatalities or congestion at a particular non-junction. Roundabouts contribute to reduce fatalities since they are fundamentally simpler and safer than choosing a coincident gap in two streams of traffic as it will be the case on a regular intersection. Moreover, in the event of a crash, the injury consequences will be less severe at roundabouts because of the greatly reduced impact speeds and more favourable collision angles experienced under this form of intersection control (Jennifer Oxley et al., 2006 Bhagwant N. Persaud et al., 2000).

4.4.6. Roadway Lighting

In addition, results indicate that for lighting conditions the majority of fatalities occurred during dark light conditions, with over 60% fatalities. Therefore, the best way to minimize these crashes is to provide proper lighting on streets especially on curves. Providing lighting is expensive due to the large infrastructure investment and maintenance costs. To reduce these expenses lighting should only be used when required, new equipment and technology can be implemented to customize lighting according to traffic, road, and weather conditions at any given time and place. This is known as adaptive lighting (Chen & Chen, 2011). Adaptive lighting permits the road luminaries to turn off when none or a small number of vehicles are using the roadway; and also lighting may then be turned on when needed. This could be achieved by sensors that will sense vehicles approaching and leaving a particular section of roadway and turn on and off traffic lights accordingly. This would ensure there are savings in the amount of consumed energy by lighting while at the same time providing the safety level that lighting offers to drivers, hence reducing crash fatalities. According to the FHWA (2018), adaptive lighting is permitted by current guidelines on road lighting. However, it is recommended that in selecting a suitable adaptive lighting level, various issues have to be considered such as the potential for conflict and the road classification (for complete recommended light-level selection methodology refer to IESNA, 2005). This study recognizes the need for adaptive roadway lighting to reduce crashes hence fatalities.

Firstly, it is recommended that adaptive road lighting should be installed on all freeways, limited-access roads, and expressways to aid drivers to remain on the roadway (prevent road departures) and to detect fixed objects like traffic control devices and lighting poles (which have been identified as major concerns for fatalities in this study) beyond and within the vehicle headlamps range. Secondly, regular street lighting to be installed on the local, collector, and major roads. The key aim of street lighting is to aid drivers to identify parked cars, cyclists, pedestrians, and other obstacles. This will assist drivers in visual observations both adjacent to and on the roadway (Chen & Chen et al., 2011).

4.4.7. Weekends

The number of driver fatality counts is higher on weekends compare to weekdays, because people tend to drive carelessly and under the influence of alcohol (Walz and Daniels et al., 2011). Several steps should be taken to address the concerns related to driving on weekends. Some of these steps include: police should test roadside drivers for BAC above the legal limits especially on weekends and if found under the influence while driving, then heavy penalties should be charged including licence cancellation and criminal record, which are already in practice in Canada, Australia, Denmark, France and Germany (Richard J. Lundman et al., 1998). Also, demerit points should be higher when found drunk driving. Another step would be to encourage drivers not to drive home when they are intoxicated, but to use other means of transport such as taxis and buses. Furthermore, new programs could be initiated where an on-call driver is available to take people home when they are drunk avoiding the possibility of driving when intoxicated. These programs could also be extended to, pick up and drop off between home and a bar at affordable rates which will reduce drunk driving (Ruth A. Shults et al., 2001). Public awareness regarding this issue should also be increased through radio, television, social media and newspapers. New education programs could be launched to give an insight about the consequences of impaired driving, especially to drivers which were found drunk before (Hadland et al., 2016).

4.4.8. Vehicle Type

Results from the analysis also indicate that cars (sedans) have the maximum number of fatalities. In consequence, it is recommended that the overall structure of sedans should be made stronger so that passengers may avoid fatal injuries during the crash (Levine et al., 1999, and Bédard et al., 2002). In addition, new technologies (blind- spot indication, airbags for each passenger, auto-driver) could be implemented to reduce possibilities of collisions. In this sense, there is not enough data on recent technologies to determine if they are safer or not.

4.4.9. Collector and Minor Arterial Roads

This research also indicate that collector and minor arterial roadways have the highest number of fatality counts compare to interstate or local roads. It is recommended that designers balance the safety and traffic conflicts, rather than simply designing roadways (Najm et al., 2007). Fixed objects such as lighting poles and electric poles present on collector and minor arterial roads are hazards to vehicle and a possible reason for the higher fatality risk for drivers. As such, these poles should be redesigning and relocated to points where it is less likely to be struck (TAC 2017). Additionally, impact severity could be reduced by using an appropriate breakaway device (J.W.H van petegem et al., 2014). Furthermore, collector and arterial roads also have higher number of fatalities due to speeding (Lu Meng et al., 2006). It is recommended that traffic calming devices such as speed bumps and raised pedestrian crossings should be introduced to reduce the effect of a crash. Another approach recommended to reduce fatalities is to introduce the shared space concept. Shared space is an urban design approach that minimises the segregation between modes of road users. This is accomplished by removing surface markings, traffic signs, and traffic lights (Auttapone Karndacharuk et al., 2014). The authors suggest that by making unclear who has the right of way, drivers will reduce their speeds which will reduce the severity level of any collision in case they happened. Furthermore, vehicle speeds could be restricted by street design by using different methods such as horizontal curves, location of bollards and open parking spaces.

CHAPTER 5: SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

This chapter contains a summary of this research as well as conclusions, recommendations for additional research, and the limitations of the study.

5.1. Summary

Approximately 106 people die every day in the United States stated according to NHTSA (2016). Driver, vehicle, and crash characteristics are explored to obtain an insight of variables which independently cause fatalities in an effort to determine measures to reduce the number of driver fatalities and to implement vision zero. This research consists of three different analyses and a section about countermeasures. The first two analyses use univariate and multivariate logistic regressions to find the odds ratio for driver fatalities for driver, vehicle, and crash characteristics. The third analysis use Poisson regression to find total driver fatality counts using coefficients and incidence rate ratios (IRR). Lastly, countermeasures are considered based on the results from the analyses.

For the first analysis, Bédard et al., (2002) work was replicated using data from 1975 to1998. For the second analysis, two sections were considered. In the first section, Bédard et al., (2002) work was updated considering data from 1975 to 2015. Results revealed that odds of driver fatalities involved in collisions with fixed objects increase with increasing age, thus supporting past studies (Bédard et al., 2002, Clarke et al., 2010b and, Zhang et al., 2013). These studies indicate that there is a positive association between fatal injuries and age after controlling for other variables such as gender, restraint use, BAC, impact direction, vehicle speed, and vehicle weight and length, as well as model year. In addition, results showed that crash involvement was higher for young adults (>20 years) and old age drivers (< 80+ years) when compare with middle age drivers 40-49 years old. Nonetheless, fatality risk for the older driver is higher due to vulnerabilities which are age-related, such as more fragile bones, diabetes, heart disease, and other disorders that may make it more difficult to recover from injuries (Clarke, Ward, Bartle & Truman 2010b).

Furthermore, female drivers have higher odds of driver fatalities but male drivers have higher involvement. Data also showed that females of age 30-64 years are at higher risk as compared to younger and older females. The possible explanation is that females may have a more vulnerable body structure as compare to males (Abdel-Sty and Abdelwahab., 2004). In addition, male drivers have higher driver fatality counts which could indicate that male drivers drive more aggressively than female drivers (Hennessy et al., 2001). Moreover, findings on BAC levels revealed more driver fatalities at higher BAC concentrations. In this sense, the highest fatality risk was recorded for BAC levels of 0.30+ at 320 % and 329% in the first and second analyses respectively, which was three times more than for BAC level "0". There are two key reasons that may explained these results, firstly alcohol is a depressant which slows down brain activity and impacts the body's responses, and secondly under the influence of alcohol body is more vulnerable to injury or fatality in a crash compared to sober drivers (Patricia F. Waller et al., 1986). Also, these results were expected since alcohol has been blamed for worsening the effects of trauma once a crash has occurred indicated by (Stübig et al., 2012, Caetano & Clark et al., 2000, and Hadland et al., 2016).

In the second section for the second analysis, additional variables were added in the process.

Dupont et al., (2010) & Wang et al., (2017) suggested that geometric variables such as roadway alignment, roadway conditions, roadway type, and roadway function, among others, are linked with driver fatalities. Therefore, this research added the key environmental and roadway factors from literature review to the list of variables to be evaluated in the analysis.

Results indicate that straight roadways have 9% lower fatality risks than curved roadways which could be possible due to the higher number of straight segments than curved segments, which also supports the findings by Hummer et al., (2010). These authors stated that curve crashes have more than three times the fatality crash rate compare to straight roads.

Also, dry roadway conditions have 7% lower fatalities when compare to not dry roadway conditions (Andrey and Yagar et al., 1993). This may be likely due to the fact that not dry conditions are less compared to dry conditions.

Moreover, fatality risk increases by 70% during rainy conditions rather than normal conditions also supported by Andrey and Yagar et al., (1993). Eisenberg and Warner, (2005) stated that first day of rain can be proved fatal especially for older people. This could explain that the differences in driver detection and reaction times are affected due to deteriorated weather conditions (Andrey et al., 2003).

Additionally, weekends have 3.7% higher fatality risk than weekdays, possibly because people tend to drive carelessly and under the influence of alcohol, which supports findings by several researchers (Brorsson et al., 1993, Lenne, Triggs, & Redman; 1999, Walz and Daniels; 2011, Hadland et al., 2016, and Ackaahand Adonteng; 2011). Moreover, asphalt or concrete have 9.4% higher fatality risk than brick, gravel, or dirt pavements. This could be explained by the fact that most of the pavements are paved, and VMT are higher on paved

roadways which could be the cause for higher driver fatalities. Previous research (Saplioglu et al. 2013, and Cairney & Bennet; 2008), suggest that fatal crashes occur on paved roadway conditions.
Moreover, the road function variable recorded local roads to have the highest fatality risk at 116.4%, and the relation to junction variable established driveway/ alley to have the highest risk at 180.1%. This may explain the fact that driveways/ alley could have congested space and vision obstruction which could result in driver fatalities (Lu Meng et al., 2006). In regard to relation to junction, lane departures have been established the most common crash types explained by Mehler et al., 2014. this can be due to speeding (Garber & Garber et al., 1990). In relation to the direction of impact, driver side impacts have the highest driver fatality odds similar to past studies (Wang et al., 2017, Samaha & Elliott et al., 2003; and Bédard et al., 2002). Drive side impacts pose higher risk of driver fatalities probably because the sides of vehicles have a limited ability to crumple and absorb energy in collision compare to front and rear end (Elisa R. Braver et al., 2004).
Moreover, results from restraint usage established that usage of seatbelts considerably reduces fatality rates supporting findings by Høye (2016). Three-point belts were established as the safest with a reduction of approximately 16% chances of fatalities. Evans et al., (1993) proposed that at least 15% of fatal injuries could be avoided with seatbelts. Furthermore, airbags have been established to reduce fatalities supporting the findings of Crandall, Olson, and Sklar (2001). Airbags aim at preventing serious injuries from impacts of the driver's head or upper body against the steering wheel or other parts of the interior of the vehicle in collisions (Høye et al., 2010). Høye also established that airbags reduce fatalities when used with seat belts.

In addition, vehicle speed revealed that speeds of 112kph+ have the highest risk of a fatality at 246.4%, supported by Bédard et al., (2002). Generally, fatality risk increase with higher speeds which could be due to the distance required to stop the vehicle increase at higher speeds and enormous energy is absorbed by driver's body at the time of crash when the speed is higher (Elvik et al., 2013). Furthermore, increasing vehicle model age by 5 years resulted in 1.05 increase to fatality odds supporting the findings by Bédard et al., (2002), while a 25cm wheelbase increment decreased fatality risk by 7.4%. In this sense, increasing vehicle age has been linked to deteriorating of parts, and also older vehicles tend to be poorly maintained and more vulnerable to mechanical failures. Older vehicles will reduce the safety of passengers due to their inefficiency to bear the effect of the crash according to Lécuyer and Chouinard (2006). Results also suggest that newer vehicles are safer.

The third analysis evaluated driver fatality counts. Coefficients and IRRs were calculated. IRRs are simply the exponential of coefficients, which shows the incidence rate. Data used are from 1982 to 2014. Results indicate that straight roads had 57.26% of the fatality counts for the roadway alignment variable similar to previous findings from multivariate analysis. These results also support the findings by Hummer et al., (2010), Glennon et al., (1985), and Stimpson et al; (1987). One possible reason for this is the greater number of straight sections compared to curved sections. Moreover, dry conditions have the highest driver fatality counts, 77.88%, for roadway conditions contradicting with the results by other researchers (Morgan and Mannering; 2001, Eisenberg; 2004, and Andrey and Yagar; 1993). It is likely possible that dry conditions are higher compared to not dry conditions which could explain that there are more driver fatalities on dry roadways. Results are also similar to findings from second analysis. Moreover, results on lighting conditions suggest that the majority of crashes occurred in darkness or in cloudy weather conditions, which supported similar observations from previous studies (Anarkooli & Hosseinlou, 2016; Khorashadi et al., 2005; Chen & Chen, 2011). Results indicate that dark condition has a fatality count of 60.82% more than day light conditions. Moreover, this conflicted with the suggestion by Xie et al., (2012) and Pahukula et al., (2015) that darkness reduces fatality proportions for drivers. Moreover, paved roadways account for 94.47% of all pavement type related driver fatalities. Results are also similar to findings from the second analysis. As mentioned earlier this could be due to more paved surfaces than unpaved surfaces. Furthermore, collectors contribute to the highest number of fatal crashes for drivers, which is supported Garber & Garber et al., (1990). Main reasons may be attributed to congestion and speeding, similar to previous multivariate analysis findings. Moreover, non-junctions have the highest number of driver fatality counts for the junction variable, which agrees with findings from previous second analysis. This is possibly because at non-junctions drivers are speeding, and dark light conditions persist (Garber & Graham et al., 1990, and Kirolos Haleem et al., 2015). In addition, findings indicate that weekends (65%) have a greater proportion of driver fatality counts than weekdays, which supports previous multivariate analysis findings as well as from Lenne, Triggs, and Redman; (1999). A possible reason is that on weekends, drivers seems to engage in drunk-driving and more risk-taking behaviour (Walz and Daniels., 2011).

In regards to vehicle type, passenger cars (sedans) have 50 % more driver fatality counts compare to vans supporting findings from previous studies (Bédard et al., 2012, Classen et al., 2007, and Awadzi et al., 2008). Furthermore, older adults and younger drivers have the highest number of driver fatality counts supporting findings by Bédard et al., (2002), and Brorsson et al. (1993). A possible reason is that younger drivers drive carelessly and at high speeds on the other hand older drivers may have a vulnerable body structure due to age and fragile bones (Clarke, Ward, Bartle & Truman 2010b, Lombardi et al., 2017). Additionally, male drivers have higher fatality counts with 70.77% of all fatalities. As mentioned in the previous updated and replicated analyses, male drivers are more involved in crashes compared to females and probably drive carelessly and at higher speeds than females (Clarke, Ward, Bartle & Truman 2010b, Lombardi et al., 2017).

In reference to countermeasures, it is suggested that new learning programs should be implemented in the system to reduce the fatalities of older and younger drivers which is also supported by Michael A. Morrisey et al., (2005). Furthermore, roads should be provided with proper adaptive lighting, reflecting signs, proper road markings and should be free from fixed objects on the side. Also, recommendations suggest that there should be enough lighting on the curves, so that drivers have lower difficulty to drive at night-time (Chen & Chen et al., 2011). There should be enough reflective signs present on the roadway, and road markings should be proper and clear. Moreover, companies and policymakers could consider making vehicles stronger and moving fixed objects far away from a roadway, which could help to increase the amount of time available for a vehicle to decelerate before hitting a fixed object, which proportionally should decrease the severity of the crash (TAC 2017). In reference to vehicle type, the overall structure of sedans could be improved so that crashes involving passengers can lower the possibility of fatal injuries (Levine et al., 1999, and Bédard et al., 2002). Also, roadside barriers could be installed wherever the fixed objects like a mountain or boulder are present which cannot be moved and where safe distance is not achieved at curves in order to reduce the impact of a crash and to decrease the odds of fatalities (Whitworth et al., 2004). Furthermore, it is recommended a mandatory waiting period of ≥3 months before the intermediate phase (new drivers), a nighttime driving restriction, and either ≥30 hours of supervised driving or a passenger restriction could be used to reduce fatalities, and which can help to gain driving experience, and avoid risky situations probably due to improper lighting (Li-Hui Chen et al., 2006). Additionally, impact severity could be reduced by using an appropriate breakaway device such as crash cushions/impact attenuators in front of fixed objects (J.W.H van petegem et al., 2014). Also, frangible poles could be used instead or fixed poles. A frangible pole is one that will yield or break when impacted by a vehicle.

5.2. Conclusions

- Fatalities increase with age for both replicated and updated analyses, but crash involvement appears to decrease with age.
- Younger drivers and older drivers have high fatality risk and driver fatality counts.
- Females have higher fatality odds than males in replicated and updated analyses, but male drivers have higher counts of fatalities as well as more involvement in crashes.
- Results also reveal more fatalities at higher BAC concentrations for both replicated and updated analyses: BACs of ≥0.30 indicate three times greater odds of a fatality than in sober drivers.
- Three-point belts were established as the safest with a reduction of approximately 16% chances of fatalities.
- Driver side crashes have the highest fatality odds.
- In both replicated and updated results, the fatality risks increased with increasing speeds.
- The analyses also indicate that older models of vehicles increase the odds of fatality, and an increase in wheelbase by 25 cm reduces the odds of driver fatalities
- Curved roadways have higher fatality risk compare to straight roads.
- Weekends have higher driver fatality risk than weekdays.
- Minor arterials and collector roads have the highest fatality risk for drivers.
- Non- junctions have the highest fatality counts.
- Driver fatalities increase when the light conditions are dark.

In regards to countermeasures, the following are proposed according to results from the analyses and literature review:

- Provide driver simulators and on-road driving evaluations training programs with individual feedback of on-road driving performance to older adult drivers (Dennis P. McCarthy 2005).

- Introduce, driving learning programs for drivers emphasizing the safety benefits of the proper use of seatbelts and the importance of the airbag in the vehicle.
- A mandatory waiting period of ≥3 months before the intermediate phase (new drivers), a nighttime driving restriction, and either ≥30 hours of supervised driving or a passenger restriction could help to reduce fatalities which is already implemented in countries such as, Canada, USA, and London (Li-Hui Chen et al., 2006).
- Roadside barriers should be installed wherever fixed objects like a mountain or boulder are present which cannot be moved and where safe distance is not achieved at curves to reduce the impact and to decrease fatalities (Whitworth et al., 2004).
- Installation of adaptive roadway lighting at all freeways, limited-access roads, and expressways to aid drivers to remain on the roadway (prevent road departures) which help to detect fixed objects like traffic control devices and lighting poles.
- Implementation of new education programs about the consequences of impaired driving, especially to drivers which were found drunk before (Hadland et al., 2016).
- Recommendations, that the overall structure of sedans should be made stronger (Levine et al., 1999, and Bédard et al., 2002).
- Redesign or relocate fixed objects such as lighting poles and electric poles to minimize or avoid the impact of vehicle in case of a crash, respectively. (TAC 2017).

5.3. Limitations and Recommendations

- The data used in the research came from FARS and are limited to fatal crashes. It is recommended that a database including all severity levels for crashes should be considered for evaluating.
- Another limitation concerns the selection of variables. Only certain variables were included in the study as mentioned in the methodology because there were not enough data and information available for all the variables in FARS. Another database with sufficient variable information should be used.
- This study does not consider all types of crashes and hence limited to single vehicle crashes only. Further studies will be required to determine whether current findings also apply to other crash situations or not (multivehicle crashes)

- Cohorts of different vehicles and years for each data year should be evaluated to get an insight of trends. Cohorts will provide a detailed information, which can help to predict changes made in vehicles with passage of time.

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APPENDIX A: FIXED OBJECTS WITH ATTRIBUTE CODES FROM FARS MANUAL (1975-2015) USED IN THE ANALYSIS

Table A.1: Attribute codes for fixed objects.

1	Boulder (17)
2	Building (19)
3	Impact Attenuator/crash cushion (20)
4	Bridge pier/ abutment (21)
5	Bridge Rail (23)
6	Guard Rail Face (24)
7	Concrete traffic barrier (25)
8	Other traffic barriers (26)
9	Utility poll (30)
10	Other post, Other poll (31)
11	Culvert (32)
12	Curb (33)
13	Ditch (34)
14	Embankment (35)
15	Embankment – rock, stone or concrete (36)
16	Embankment – material type unknown (37)
17	Fence (38)
18	Wall (39)
19	Fire hydrant (40)
20	Shrubbery (41)
21	Tree (standing only) (42)
22	Other fixed object (43)
23	Traffic signal support (46)
24	Collision with snow bank (48)
25	Bridge overhead structure (50)
26	Guard rail end (52)
27	Mailbox (53)
28	Cable barrier (57)
29	Ground (58)
30	Traffic sign support (59)

APPENDIX B: FIXED OBJECTS WITH ATTRIBUTE CODES FROM FARS MANUAL (1975-2015) USED FOR THE ADDITIONAL VARIABLES ANALYSIS

Table B.1: Attribute codes for light conditions.

1	(1) Daylight
2	(2) Dark, not-lighted
3	(3) Dark but lighted
4	(4) Dawn
5	(5) Dusk
6	(6) Dawn or dusk, dark unknown lighting
7	(7) Other

Table B.2: Attribute codes for weather and pavement conditions.

	Dry Conditions
1	(0) No adverse atmosphere conditions
2	(1) Clear, normal
	Not Dry Conditions
3	(2) Rain
4	(3) Sleet, Hail
5	(4) Snow or blowing snow
6	(6) Fog, smoke, smog
7	(7) Blowing sand, soil, dirt
7	(8) Other: smog, smoke, blowing sand or dust
8	(10) Cloudy
9	(11) Blowing snow
10	(12) Frezzing rain

APPENDIX C: ADJUSTED ODDS RATIO CURVES FROM REPLICATED ANALYSIS (1975-1998)

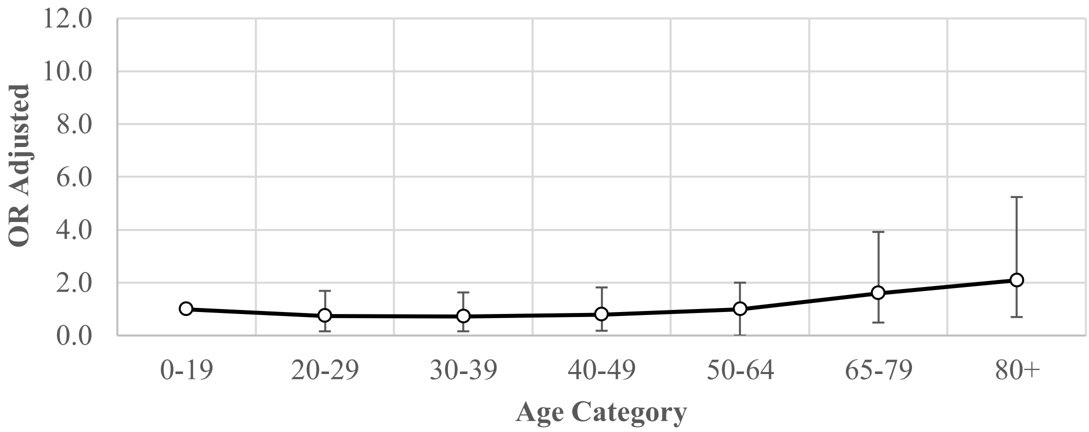

Figure C.1: Replicated analysis OR for age category.

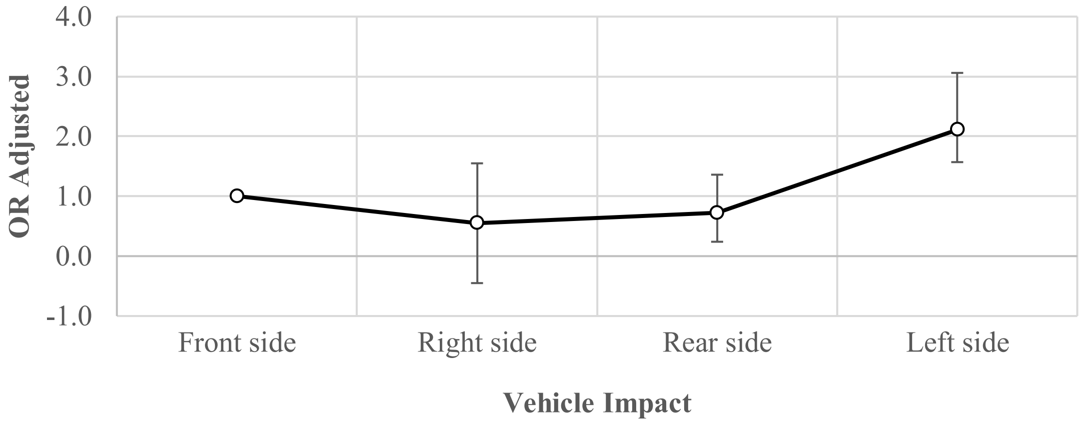

Figure C.2: Replicated analysis adjusted OR for vehicle impact.

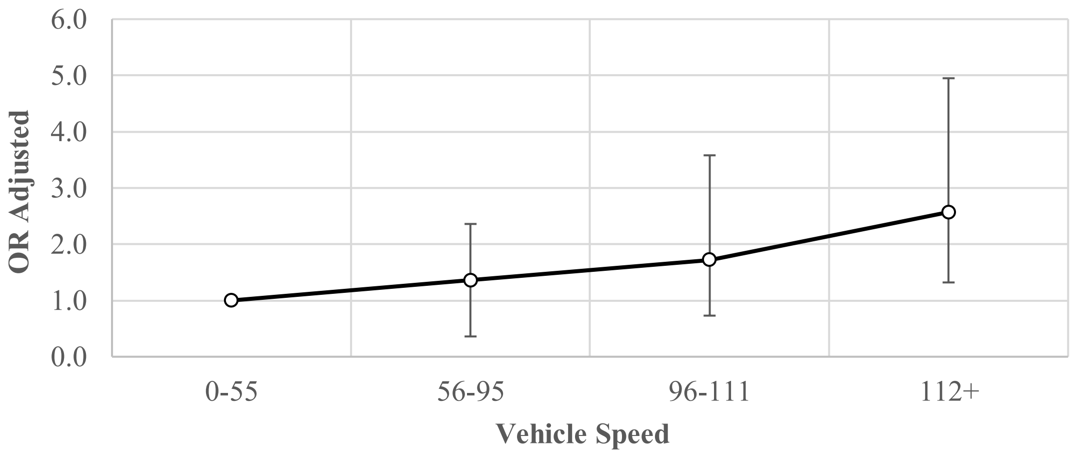

Figure C.3: Replicated analysis adjusted OR for vehicle impact.

APPENDIX D: ADJUSTED ODDS RATIO CURVES FROM UPDATED ANALYSIS (1975-2015)

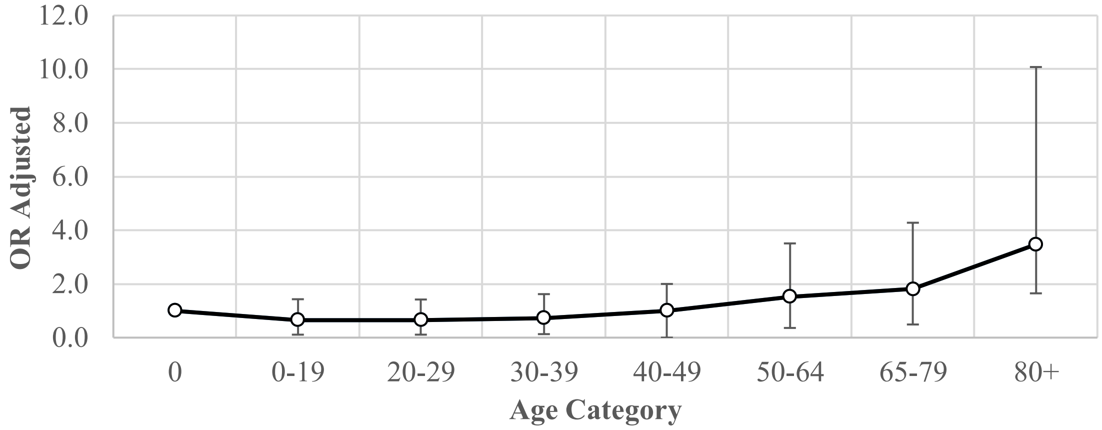

Figure D.1: Updated analysis adjusted OR for age category.

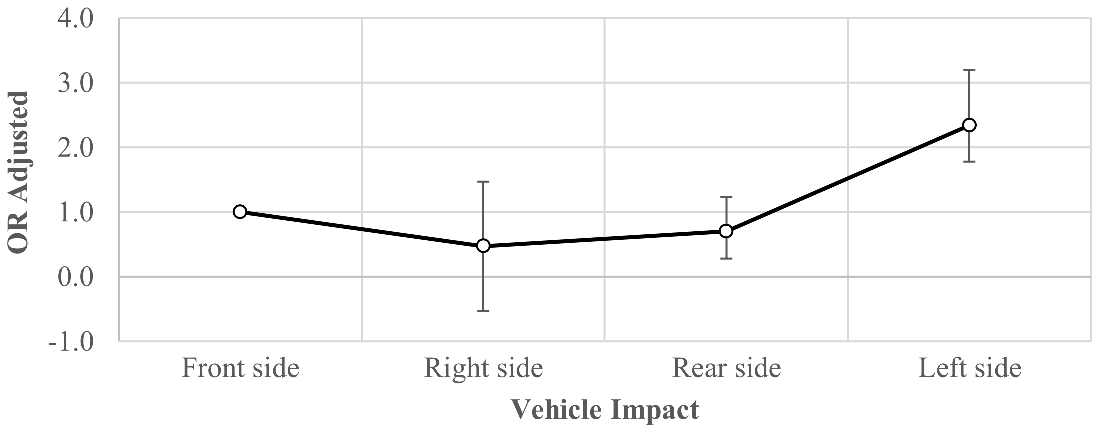

Figure D.2: Updated analysis adjusted OR for vehicle impact.

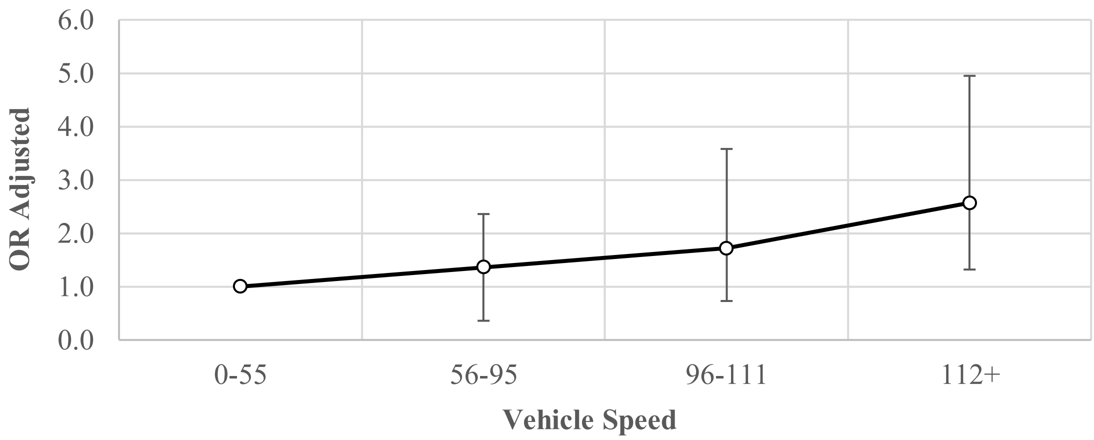

Figure D.3: Updated analysis adjusted OR for vehicle speed.

APPENDIX E: ADJUSTED ODDS RATIO CURVES FROM UPDATED ANALYSIS WITH ADDITIONAL VARIABLES (1982-2014)

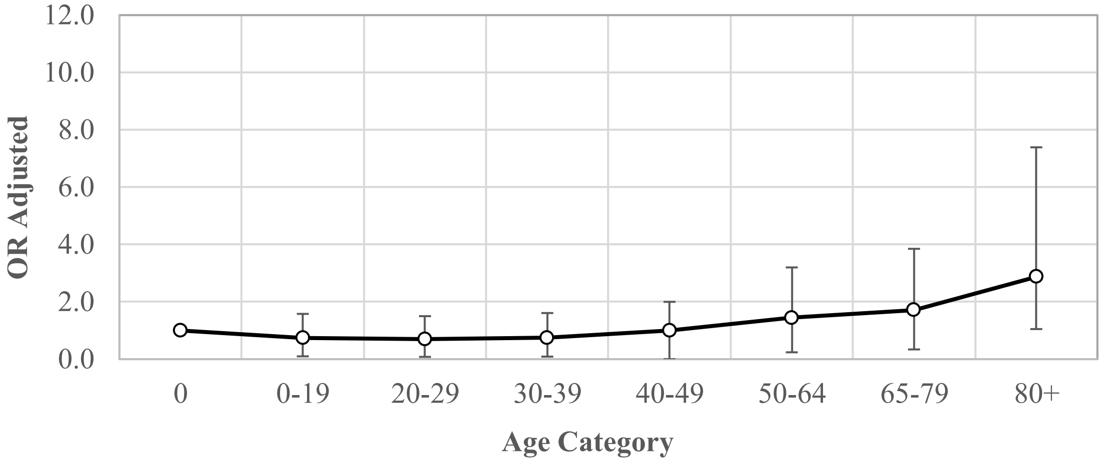

Figure E.1: Updated analysis adjusted OR for age category with additional variables.

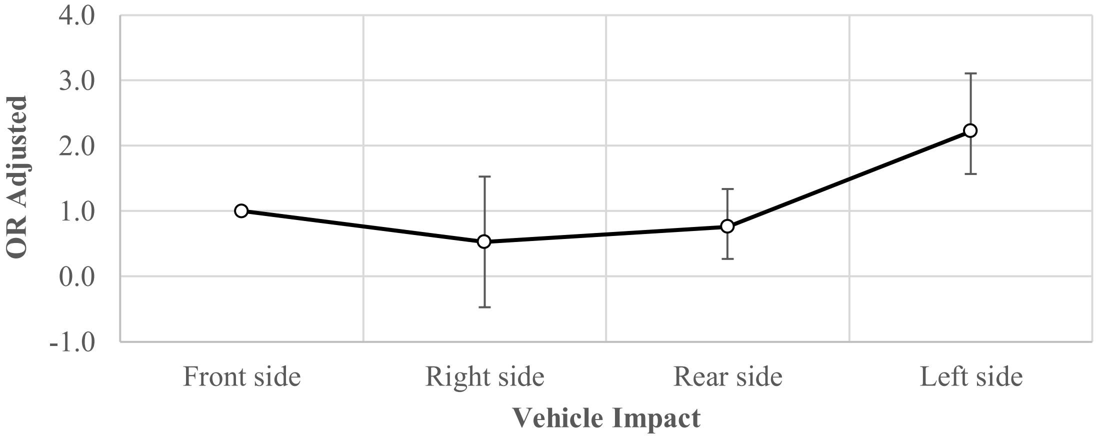

Figure E.2: Updated analysis adjusted OR for vehicle impact with additional variables.

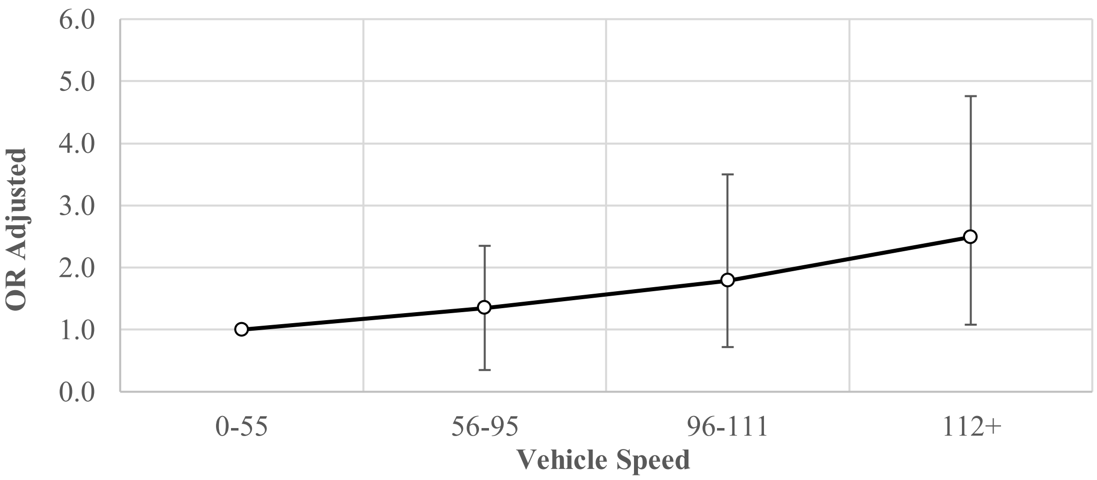

Figure E.3: Updated analysis adjusted OR for vehicle speed with additional variables.