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Aging Road User Survey and Crash Analysis to Identify Issues and Applicable Improvement Strategies for Kansas Conditions

Sunanda Dissanayake, Ph.D., P.E., F.ASCE
Sameera Koththigoda

Kansas State University Transportation Center

Kansas Department of Transportation

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The percentage of the United States population aged 65 years or older is increasing rapidly. Statistics show this age group was 14.9 percent of the population in 2015 and is expected to be 20.7 to 21.4 percent for the years 2030–2050. Kansas has similar statewide trends with its aging population. Therefore, identifying issues, concerns, and factors associated with highway safety of older drivers in Kansas is necessary and useful. The Kansas Crash Analysis and Reporting System (KCARS) database maintained by the Kansas Department of Transportation was used in this study to identify older-driver crash characteristics, compare older drivers with all drivers, and develop crash severity models.

According to KCARS data, older drivers were involved in more than one in five fatalities in Kansas from 2010 to 2014. When compared with all drivers, older drivers were overly represented in fatal and incapacitating injuries. The percentage of older-driver fatal injuries was more than twice that of all drivers. Older drivers were involved more often in crashes at four-way intersections, on straight and level roads, in daylight hours, and at stop or yield signs.

Due to the high severities of older-driver crashes, an in-depth crash severity analysis was carried out for the older drivers involved in crashes. Three separate binary logistic regression models were developed for single-vehicle crashes where only the older driver was present (Model A), single-vehicle crashes involving an older driver with at least one passenger (Model B), and multi-vehicle crashes involving at least one older driver (Model C). From the crash severity analysis, it was found that left turns were significant in changing the crash severity for Model A, though it was not significant in Model B. For Model B, none of the passenger attributes were significant, though it was originally developed to identify passenger attributes. Gender of the older driver was not significant in any of the models. For all models, variables such as safety equipment use, crash location, weather conditions, driver ejected or trapped, and light conditions distinguished crash severity. Furthermore, for Model A, variables such as day of the week, speed, accident class, and maneuver, were associated with crash severity. Accident class, surface type, and vehicle type changed crash severity in Model B. Number of vehicles, speed, collision type, maneuver, and two-lane roads were significant in Model C.

A road-user survey was also conducted to identify habits, needs, and concerns of Kansas' aging road users, since it was not advisable to conclude safety factors solely on crash data. The probability of occurrence was calculated by taking the weighted average of answers to a question. Contingency table analysis was carried out to identify relationships among variables. For older drivers, seatbelt use as a driver had the highest probability of occurrence. Driving in heavy traffic, merging into traffic, moving away from traffic, and judging gaps were dependent on age group. Findings of this research gave understanding of older-driver crashes and associated factors. Since more than 85 percent of crash contributory causes were related to drivers, driver awareness programs, driver licensing restrictions, providing public transportation, and law enforcement can be considered as potential countermeasures. Accordingly, results of this study could be used to enhance older-driver safety and awareness programs.

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Prepared by

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Sameera Koththigoda

Kansas State University Transportation Center

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PREFACE

The Kansas Department of Transportation's (KDOT) Kansas Transportation Research and New-Developments (K-TRAN) Research Program funded this research project. It is an ongoing, cooperative and comprehensive research program addressing transportation needs of the state of Kansas utilizing academic and research resources from KDOT, Kansas State University and the University of Kansas. Transportation professionals in KDOT and the universities jointly develop the projects included in the research program.

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Abstract

The percentage of the United States population aged 65 years or older is increasing rapidly. Statistics show this age group was 14.9 percent of the population in 2015 and is expected to be 20.7 to 21.4 percent for the years 2030–2050. Kansas has similar statewide trends with its aging population. Therefore, identifying issues, concerns, and factors associated with highway safety of older drivers in Kansas is necessary and useful. The Kansas Crash Analysis and Reporting System (KCARS) database maintained by the Kansas Department of Transportation was used in this study to identify older-driver crash characteristics, compare older drivers with all drivers, and develop crash severity models.

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Acknowledgements

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Furthermore, the authors would like to thank survey participants, pastors of churches, administrators of senior citizen centers, administrators of Area Agency on Aging and others, who contributed to make the survey a success.

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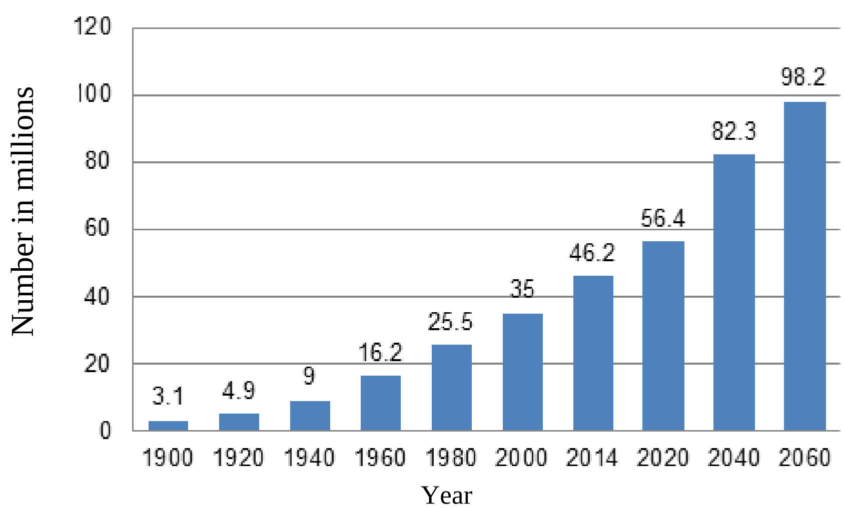
Chapter 1: Introduction

1.1 Background

The percentage of the United States population aged 65 years or older is increasing rapidly. According to the United States Census Bureau, the older population numbered 46.2 million in 2014, an increase of 10 million or 28 percent since 2004 (United States Census Bureau, 2016). Statistics also show that the older population accounted for 14.9 percent in 2015 and is expected to be 20.7 to 21.4 percent for the years 2030–2050. This means one in five Americans is expected to be 65 years or older by 2030 (He, Goodkind, & Kowal, 2016). By 2020, estimates have shown that more than 40 million Americans will be licensed older drivers (Kansas Traffic Safety Resource Office, n.d.). As shown in Figure 1.1, the older population will continue to grow rapidly in the future as the baby boom generation, those born from 1946 to 1964, begin to turn 65 years old. Kansas has indicated similar statewide trends on its aging population. U.S. Census Bureau population estimates show that 14.6 percent of Kansans were 65 years or older in 2015, and that number is expected to be 20.17 percent in 2030 (United States Census Bureau, 2016).



Source: Administration on Aging (2015)
Figure 1.1: Number of Persons 65 Years or Older in the United States (1900–2060)

In the U.S., most people rely on automobiles for daily transportation needs, meaning the U.S. is a primarily vehicular-based society. Transportation activity is an important component of the daily lives of the aging population because it allows them to maintain their independence and mobility. Suburbanization of the U.S. has caused driving to become the primary transportation option for older adults (Barr, 2002). Although public transportation systems exist in Kansas, especially in urban areas, they are lacking in many rural areas (Bull, Krout, Rathbone-McCuan, & Shreffler, 2001). Therefore, most people, including older drivers, tend to prefer using their own automobiles.

Table 1.1 shows the comparison between elderly (65+ years) to all ages involved in crashes in Kansas. As shown in Table 1.1, an increasing trend of number of elderly involved in crashes can be observed in Kansas during the past 5 years, while there is a decrease in the total number of people involved in crashes. Furthermore, most elderly are involved in crashes as occupants and only 292 pedestrians aged 65+ years were involved in crashes from 2010 to 2014. However, percentages of elderly occupants and elderly pedestrians involved in crashes have both increased gradually from 2010 to 2014, showing an alarming trend.

Table 1.1: Number of People Involved in Crashes in Kansas: Elderly vs. All Ages

Age category		**2010**	**2011**	**2012**	**2013**	**2014**
All ages	Occupants	137,451	134,451	131,455	131,998	130,694
	Pedestrians	876	952	1,072	976	958
	Total	138,327	135,403	132,527	132,974	131,652
Elderly	Occupants	10,448	10,662	10,877	11,217	11,470
	Pedestrians	46	53	65	58	70
	Total	10,494	10,715	10,942	11,275	11,540
% of elderly occupants involved in crashes		7.60	7.93	8.27	8.50	8.78
% of elderly pedestrians involved in crashes		5.25	5.57	6.06	5.94	7.31

Injury severity is typically categorized into three groups such as fatalities, injuries, and no injuries. Table 1.2 shows injury severity of older drivers versus drivers of all ages yearly from 2010 to 2014 and total for the 5-year time-period. People who were involved, but were not drivers are not included in these numbers.

Table 1.2: Comparison of Number of Drivers Involved in Crashes Based on Injury Severity: Older Drivers vs. All Drivers

Age category	Year					Total from 2010 to 2014
	2010	2011	2012	2013	2014	
Fatalities						
All drivers	305	281	282	250	283	1,401
Drivers aged 65+	63	53	60	62	59	297
% of drivers 65+	20.66	18.86	21.28	24.80	20.85	21.20
Injuries						
All drivers	12,806	12,728	13,115	12,438	12,229	63,316
Drivers aged 65+	1,125	1,123	1,244	1,290	1,267	6,049
% of drivers 65+	8.78	8.82	9.49	10.37	10.36	9.55
No injuries						
All drivers	76,862	76,675	74,624	75,919	75,735	379,815
Drivers aged 65+	6,784	7,121	7,268	7,513	7,815	36,501
% of drivers 65+	8.83	9.29	9.74	9.90	10.32	9.61

As shown in Table 1.4, among all fatalities, the percentage of older driver fatalities were greater than 20 percent for most of the years from 2010 to 2014, with an average of 21.2 percent. This means that older drivers were involved in more than one in five fatalities, though the elderly population in Kansas was only 14.6 percent of the total population in 2015 (United States Census Bureau, 2016). In contrast, 5-year average injury and no-injury rates of older drivers were 9.55 percent and 9.61 percent, respectively. Considering the data presented in Table 1.4, it is evident that older drivers experience higher injury severity when they are involved in crashes. Accordingly, in the Kansas Strategic Highway Safety Plan (KSHSP), older drivers were identified as a key area for improving safety in the state of Kansas (KDOT, 2015). In the KSHSP, particular attention has been paid to improving the quality of life for the traveling public by identifying problems and implementing effective educational and enforcement programs. Accordingly, KSHSP also identifying older drivers as a focus area shows the importance of highway safety issues faced by the elderly population in Kansas.

1.2 Problem Statement

The increasing elderly population has resulted in greater numbers of drivers aged 65 years or older in Kansas. The natural aging process results in slower perception reaction times and physical difficulties such as deterioration of strength, vision, and hearing. Older drivers have an increased risk on the roadway because they also maximize the risk to other road users due to deterioration of physical and mental capabilities (Dellinger, Kresnow, White, & Sehgal, 2004; Trieu, Park, & McFadden, 2014). When driving capabilities are reduced, drivers may be more prone to being involved in motor vehicle crashes. Although the number of crashes involving older drivers is less than the average because they have less driving exposure, such as driving distance and trips taken, crash rates of older drivers are higher when considering crashes per mile driven (Lyman, Ferguson, Braver, & Williams, 2002). Moreover, older drivers are more likely to experience fatal or incapacitating injuries when involved in crashes due to fragility. Even though many studies have been conducted throughout the United States about highway safety issues of older drivers, few studies have investigated older-driver-related issues in Kansas.

When making efforts to identify measures to improve highway safety and mobility related issues of elderly, it is important to understand various characteristics and situations surrounding the topic and this study was designed to serve that purpose.

1.3 Objectives

The main objective of this research was to identify issues, concerns, and barriers related to travel and highway safety for the elderly in Kansas, and then to suggest suitable improvement strategies that match Kansas conditions. This objective has been achieved by summarizing general crash data, comparing older-driver crash characteristics with all drivers, and analyzing results of three separate crash severity models. Direct opinions of the elderly were also gathered by conducting a road user survey in which habits, needs, and concerns of Kansas' aging road users were identified and analyzed.

1.4 Outline of the Report

This report includes five chapters. Chapter 2 focuses on previous studies about older-driver safety and includes studies related to factors affecting older-driver crashes, statistical methodologies, and road user surveys. Chapter 3 discusses the methodology used in the analysis and presents data used in the study. Chapter 4 presents results from general and statistical analysis of both crash data and road user survey data, and then identifies countermeasure ideas. Summary of research findings and conclusions are presented in Chapter 5.

Chapter 2: Literature Review

Highway safety of older drivers has been an issue for many decades in the United States. A number of past studies have been conducted to investigate older-driver safety. Previous researchers have used different kinds of statistical modeling techniques to identify injury or crash severities of older drivers, and different age groups such as young and middle age have also been studied to identify factors affecting their crashes. This chapter summarizes important previous studies in relation to older drivers and analysis conducted in this study.

2.1 Older-Driver-Related Studies

This section summarizes important older-driver-related studies in Kansas, the United States, and around the world, which provided insight into older-driver safety issues and concerns.

Rallabandi (2009) investigated the relationship of fatal crash involvement for 65 years and older drivers in the United States, considering driver, vehicle, environmental, and roadway factors. A Chi-square test and odds ratio were used to find the correlation between driver age and the selected variables. The double-pair comparison method was used to analyze the fatality risk for older occupants of passenger cars. The Fatality Analysis Reporting System (FARS) and National Household Travel Survey (NHTS) data were used for analysis by considering data from 1997 to 2006. Among other results, it was found that older drivers had more crash risk in rural areas than urban areas, with increased fatality risk in rural areas.

Dissanayake and Perera (2009) investigated safety concerns and characteristics of older drivers involved in crashes in Kansas. A detailed analysis was carried out for young, middle-aged, and older-driver groups involved in crashes, where the older-driver group was compared with other age groups. A separate, older-driver behavior survey was conducted to investigate the level of exposure to various traffic conditions. From the crash severity analysis using logistic regression, it was identified that injury severity of older drivers in rural areas was higher than for those in urban areas. Furthermore, the majority of older drivers were found to have difficulties with left turns at intersections and preferred to avoid roads with higher traffic. Most common factors contributing to increased crash severity of older drivers included driving in the wrong direction, speeding, and failing to comply with the traffic signs and signals.

Research in the Netherlands found an association between crash involvement and annual distance driven, and determined whether a relationship exists between age of the driver and crash involvement (Langford, Methorst, & Hakamies-Blomqvist, 2006). Two survey questionnaires were used to identify that independent of age, drivers who traveled fewer than 3,000 km per year usually had more crashes per kilometer, compared to drivers who traveled greater than 14,000 km per year.

A survey-based study, which was part of a major research project titled Safe Mobility for Older Drivers, was carried out jointly by Sweden and France to identify health issues including frequent diagnostics which affected vision, hearing, cognitive capacity, and physical function (Henriksson, Levin, Willstrand, & Peters, 2014). A random sample of 3,000 older people was assessed in this study. Driving habits and use of a car such as frequency, distance driven, and other available modes of transport were identified for older drivers. Difficult or dangerous traffic situations, avoidance strategies adopted for such situations, type of car used, and equipment used such as advanced driver assistance systems and their frequency of use were investigated. It was found that gender differences, such as women stopping driving at a lower age and driving less frequently than men do, were still existent in the older driver age group. This study confirmed that health status was not the only reason for somebody to stop driving; being less confident was also a considerable factor.

Another study analyzed risk factors for motor vehicle fatalities and injuries among young (35–54 years) and older (65+ years) drivers using Fatality Analysis Reporting System (FARS) data (Awadzi, Classen, Hall, Duncan, & Garvan, 2008). Person, vehicle, and environmental variables were used as explanatory variables at 95 percent confidence level. Multinomial logistic regression modeling was conducted to obtain odds ratios. Variables such as principal impact, number of occupants, and previous motor vehicle convictions were found to be statistically significant for injury severity. Front and rear-end, and angle-side impact crashes were identified as posing significant risks to older drivers. However, previous motor vehicle convictions were associated with reduced risk of injury when older driver involved crashes were considered. Driving during daylight hours and angle-side impact crashes were associated with fatalities among older drivers.

Another study that was carried out in Kentucky identified factors affecting older-driver safety with and without passengers and for single- and multi-vehicle crashes, using a quasi-induced exposure methodology (Hing, Stamatiadis, & Aultman-Hall, 2003). This study identified relative crash involvement ratios to measure crash-causing tendencies of older drivers. Logistic regression was used as a statistical methodology to test statistical significance of independent variables such as vehicle occupant gender mix, driver age, time of the day, road curvature, and number of lanes. According to this study, drivers aged 75 years or older were much more likely to cause single-vehicle crashes than drivers aged 65–74 years.

Tefft (2008) conducted a study to determine risks that drivers of different ages pose to themselves and to others on the road. Driver responsibility was weighed using driver-related contributory factors. At the age of 25, drivers' risk to themselves and others decreases. This trend was found to decline gradually until approximately 65 to 70 years old, and then again, risk increased around 70 years of age. A higher increase in driver risk was identified after approximately age 75. Drivers aged 85 years and older had the highest fatality rates compared to all other age groups.

Cheung and McCartt (2011) pointed out that older driver fatal crash involvement rates per licensed driver declined substantially in the United States during 1997–2006 and declined much faster than the rate for middle-age drivers. They wanted to investigate whether the decline of fatal crashes by older drivers continued to nonfatal crashes, and whether the decline in fatal crash risk reflected lower likelihood of crashing or an improvement in survivability of the crashes that occur. Using data obtained from the Fatality Analysis Reporting System (FARS), passenger vehicle crash involvement per 100,000 licensed older drivers was compared with that of middle-aged drivers, who were aged 35–54 years. In this research, 70 years and older drivers were considered as older drivers. This group was further divided into three subgroups of drivers aged 70–74, 75–79, and 80 years and older. The comparison group (middle-aged group) was selected because it excluded ages for which age-related impairments are a significant issue. To identify trends, the analysis of covariance (ANCOVA) method was performed using national fatal crash involvement rates. Odds of a crash-involved driver sustaining a fatal injury were computed for each of the years. Logistic regression was used to analyze the annual crash rate of change during the period for older drivers and for the comparison age group. Results showed that older-driver fatal crash involvement rates declined faster than that of middle-aged drivers, who experienced a greater-than-expected improvement in survivability once involved in crashes.

2.2 Crash Modeling Approaches

Past researchers have used various statistical modeling techniques to analyze crash data. This section summarizes relevant studies that provided insight into various statistical modeling approaches used in crash data analysis.

Logistic regression seems to be a commonly used modeling technique in safety studies. Dissanayake and Kotikalapudi (2012) investigated characteristics and contributory causes related to large truck crashes. Crash data from the Fatality Analysis Reporting System (FARS) database were examined during the first part of the study. Truck crashes of all severity levels were analyzed in the second phase to identify characteristics contributing to an increase in severity of truck crashes. Pearson's correlation coefficient was used to find correlated variables. Statistical methodologies such as cross-classification analysis and severity models using logistic regression with a confidence level of 95 percent were used to analyze the crash data. Model fit statistics such as the Akaike Information Criterion, Schwarz Criterion, and the value of twice the negative of log likelihood were used to select the best model. Variables such as road surface (type, character, and condition), accident class, collision type, driver and environment-related contributory causes, traffic control type, truck maneuver, crash location, speed limit, light, weather conditions, time of day, functional class, lane class, and average annual daily traffic (AADT) distinguished the crash severity of large truck crashes, whereas age and sex of drivers were found to be insignificant in crash severity models.

Liu and Dissanayake (2009) investigated characteristics of crashes reported on gravel roads in Kansas, where statistical analysis of police-reported crash data from Kansas over a 10-year time period was carried out. Logistic regression modeling was applied to evaluate the impact of speed limits considering 29 explanatory variables: driver, road, environment, and collision types. Goodness-of-fit tests were used to compare the models. Safety equipment usage, driver ejection, alcohol involvement, and speed limit were found to be significant in the model. The magnitude of such contributing effects was estimated by computing the odds ratios.

Donnelly-Swift and Kelly (2015) conducted a study in Ireland using generalized linear regression models to identify factors associated with injury severity of single and multi-vehicle crashes. The researchers developed three logistic regression models for single-vehicle driver-only crashes, a single-vehicle driver with passengers, and multi-vehicle collisions. According to the study, fatal or serious injury single-vehicle collisions and multi-vehicle collisions decreased during hours of darkness and wet pavement conditions, potentially due to careful driving under adverse conditions. Furthermore, single-vehicle crashes involving male drivers increased the likelihood of serious injury, and single-vehicle ‘driver with passengers’ crashes involving drivers under the age of 25 years also increased the likelihood of serious injury.

Morgan and Mannering (2011) conducted a study in Indiana that identified effects of age, gender, and road surface conditions on driver injury severities for single-vehicle crashes. Three categories of road surface conditions were used to divide crashes into groups such as dry, wet, and snow/ice. Effects of age, gender, and other factors on injury severities were also analyzed using mixed logit analysis. Results showed the likelihood of severe injuries increased on wet or snow/ice surfaces and for females of all ages and older males.

Out of these statistical modeling techniques, logistic regression modeling was chosen to model crash severity of older-driver-involved crashes in this study since it is the most widely used and more simple methodology.

2.3 Road User Survey

Surveys have commonly been used in the literature to identify safety issues of various road user groups. This section briefly summarizes the literature about road user surveys, which studied driver behavior or characteristics. The survey questionnaire that was prepared in this study was developed based on the understanding from these studies, even though some of these surveys were not necessarily on older drivers.

Hassan and Abdel-Aty (2011) conducted a questionnaire survey among 566 drivers in central Florida to understand how to improve drivers’ behavior under reduced visibility conditions.

The intention of the questionnaire survey was to examine drivers' satisfaction with variable speed limits, changeable message signs, and instructions in different visibility and traffic conditions, on two types of roadways such as freeways and two-lane roads. Explanatory factor analysis and structural equation modeling approaches were used as statistical analysis techniques. Variable speed limit (VSL) and changeable message signs (CMS) were the two most important factors that positively changed drivers' compliance. Warning messages displayed on VSL/CMS and human factors were the other important factors.

Berning, Compton, & Wochinger (2015) conducted a survey about alcohol and drug use by drivers in the U.S. between 2013 and 2014, which was a voluntary and anonymous study. The purpose of this survey was to collect data on drug use by drivers and to examine the trends of drug use at national level. Statistical sampling techniques were used to identify sites with similar characteristics. Results showed a large decrease of alcohol-positive drivers, from 35.9 percent in 1973 to 8.3 percent in 2013–2014. Also, results showed that during weekday daytime hours, 1.1 percent of drivers were alcohol positive, and during weekend nighttime hours, 8.3 percent of drivers were alcohol positive.

McCartt, Ribner, Pack, & Hammer (1996) conducted a telephone survey of New York State licensed drivers to identify factors affecting drowsy driving. Multiple regression analysis was used as the statistical methodology for analyzing the collected data. Explanatory variables such as younger drivers, more education, being a male, fewer hours of sleep at night, greater frequency of trouble staying awake during the day, work patterns, and driving patterns increased the rate of drowsy driving. Furthermore, results showed that an alarmingly high 22.6 percent of respondents had fallen asleep behind the wheel even though they did not end up having a crash. Out of reported crashes due to drowsy driving, 82.5 percent involved crashes when drivers were alone, and 60 percent of crashes occurred between 11:00 p.m. and 7:00 a.m. Forty percent of drowsy driving crashes took place on a highway or expressway.

Ruangkanchanasetr, Plitponkarnpim, Hetrakul, & Kongsakon (2005) conducted a study in Bangkok, Thailand, to identify youth risk behavior. Survey questionnaires were collected from 2,311 adolescents in eight schools, 13 communities, and two juvenile home institutions. Mean age of adolescents was 15.5 years and 59 percent of respondents were females. Gender, parental marital status, socioeconomic status, family relationship, parental drug addiction, peer group, loneliness, self-esteem, and school performance were the risk factors of interest in this study. Chi-square test and multiple logistic regression were used to categorize items in univariate analysis and to identify risk factors, respectively. An odds ratio with a 95 percent confidence level was used to determine the intensity of related risk factors of each health risk behavior. Crashes were associated with risk behaviors such as riding with drivers who had consumed alcohol, driving after consuming alcohol, rarely or never having worn a seat belt, and not wearing a helmet while bicycling and motorcycling among others.

Parker, McDonald, Rabbitt, & Sutcliffe (2000) conducted a driver behavior questionnaire in Manchester, United Kingdom, as a part of a survey of 1,989 drivers aged 50 years or older. Three main types of driver behavior, such as errors, lapses, and violations, were identified in this study. Twenty-four driver behaviors were investigated by indicating how often they occurred with a scale of 1: never, 2: hardly ever, 3: occasionally, 4: quite often, 5: frequently, and 6: nearly all the time. Research results identified that error factor and lapse factor were associated with involvement in an active accident, where lapse factor was also related to high scores of passive crash involvement.

Campos et al. (2013) conducted a roadside survey in Brazil to identify alcohol consumption, drinking, and driving. A questionnaire survey and breathalyzer data were used to determine the prevalence of drinking and driving. Also, a questionnaire survey was used to examine socio-demographic characteristics and drivers' behavior, attitude about driving, and alcohol consumption, where the data were collected at high-volume public roads in Brazil. A logistic regression modeling was used to identify relationships among socio-demographic characteristics, attitudes, driving behavior, and alcohol consumption of drivers. Drivers who thought drinking and driving was an offense were two-thirds more likely to have done so. Also, analysis based on the modeling showed that those who were regular alcohol users were found to be three times more likely to drink and drive.

Chen, Donmez, Hoekstra-Atwood, & Marulanda (2016) conducted a survey in Canada to identify social and psychological factors of drivers who were often willingly involved in secondary tasks. A driver distraction questionnaire was conducted with a sample size of 578, including both genders where drivers over 18 years of age were surveyed. Ordinal logistic regression analyses and Spearman's rank correlations were conducted to identify which variables more or less affected distraction engagement. Results showed gender was insignificant in the models; however, drivers over the age of 60 years or more reported a lower level of distraction engagement than drivers between the ages of 26 and 39 years.

Survey studies have addressed different safety aspects by carrying out various types of statistical methodologies. Literature provided in this section provided an insight into some of the road user behavior-related surveys found in the literature.

Chapter 3: Data and Methodology

This chapter includes details of data used in this study, and the methodology utilized in crash and survey analyses.

3.1 Data

Data for crash analysis in this research were obtained from the Kansas Department of Transportation's (KDOT) Kansas Crash Analysis and Reporting System (KCARS) database. KCARS consists of a complete dataset containing information related to all the police reported crashes in Kansas, including all injury crashes and Property Damage Only (PDO) crashes of more than $1,000 in value (KDOT, 2014). The database also contains a limited dataset, which has geometric characteristics related to crashes occurring on the state highway system. KCARS database includes driver, vehicle, environment, and road-related characteristics of crashes. Due to lack of complete information or due to human error, the database may contain some missing values for some data elements. To maintain privacy, no personal information, such as names, addresses, or contact information of those involved in the crashes, are shared in the database.

The Kansas Motor Vehicle Accident Report Coding Manual was used to interpret the codes provided in the KCARS database (KDOT, 2014). Crash severities were identified as fatal, injury, or Property Damage Only (PDO), based on highest severity level of injury sustained by persons involved in the crash. In KCARS, a crash is considered fatal if an occupant dies within 30 days of the occurrence of the crash. Data related to crashes involving drivers aged 65 or over in Kansas, for six years from 2009 to 2014, were considered in this study. Data from 2010 to 2014 were used in the analysis, and 2009 data were utilized in the model validation.

Not all drivers or road users are involved in crashes, and hence it is not advisable to make conclusions on safety-related issues of older drivers solely based on crash data alone. Therefore, a road user behavior survey was also conducted in Kansas in order to gather direct opinions of older drivers and a control group. This survey was conducted throughout the state of Kansas so that a representative sample of older-driver respondents could be considered in making better conclusions.

3.2 Binary Logistic Regression Modeling

Crash severity models were developed in this study to identify factors affecting severity of older-driver-involved crashes. The logistic regression was chosen as the modeling technique since it is easy to interpret and very commonly used in highway safety-related research. Odds ratios were also used to determine factors that distinguish crash severity.

The odds can be defined as the ratio of the probability of occurrence of an event to that of its non-occurrence. For example, an event with 0.75 probability of occurrence has an odds ratio of 3, which is 0.75/(1-0.75). This odds ratio can be used to understand the influence of each of the independent variables on the severity of the crash. In this study, an event is referred to as a case where the dependent variable, which is crash severity, took a value of 1 (Agresti, 2007). In the database, crash severity was available at three levels, where it was re-categorized as injury and fatal in one category (event = 1) and PDO (non-event or event = 0) in another category for statistical analysis purposes. Odds are given by the following equation:

$$\alpha = Odds = \frac{P}{1-P}$$ **Equation 3.1**

Where:

P= probability that the crash severity takes value 1.

Transforming the probability into odds and taking its log value removes the bounded attributes of the dependent variable, and a logistic regression model is obtained by setting the logarithm of odds of the dependent variable to a linear function of the independent variables. In logistic regression function, the coefficient of an independent variable explains how that variable influences crash severity. The maximum likelihood method (MLM) was used to estimate the coefficients of independent variables in the models.

In this study, binary logistic regression models were developed, where the equation for k independent variables and i =1… n individual observations is given by:

$$\log\left(\frac{Pi}{1-Pi}\right)=\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_k x_k$$ **Equation 3.2**

Where:

Pi = probability that observed value =1,

β_0 = intercept parameter,

β = vector of slope parameters, and

$x = (x_1, x_2 \ldots x_k)$ a set of explanatory variables.

This logistic regression equation models a linear relationship between log odds of dependent and independent variables. An advantage of using the logit link function is that it can be easily interpreted. The log likelihood function can be written as:

$$\log L=\sum_i y_i \log\left(\frac{P_i}{1-P_i}\right)+\sum_i \log(1-P_i)$$ **Equation 3.3**

Where:

L = likelihood function,

y_i = n observed values (0 or 1) of dichotomous response variable, and

Pi = probability that y_i = 1.

The maximum likelihood method was used to estimate the parameters of the logistic regression function. Log likelihood function (Equation 3.3) can be maximized numerically to obtain the maximum likelihood.

3.2.1 Assessing Model Fit

Model fit of the logistic regression models was evaluated by Akaike's Information Criterion (AIC), Schwarz criterion (SC), and -2logL, which is a logarithm of likelihood function multiplied by -2 (Allison, 2012). The SAS 9.4 program was used for the statistical analysis in this study (SAS Institute Inc., 2013a). These model fit statistics are displayed for intercept only (no predictor variables) and a model that includes all specified predictors.

AIC is calculated as:

$$\text{AIC} = -2\log \text{L} + 2\text{k}$$ **Equation 3.4**

Where:

k = number of parameters including the intercept, and

L = likelihood function.

SC can be written as:

$$\text{SC} = -2\log \text{L} + \text{k} \log \text{n}$$ **Equation 3.5**

Where:

n = sample size.

Lower values of AIC and SC symbolize a more desirable model, meaning these two values can be used to compare the models (Allison, 2012). As a simple example, if two Models A and B have AIC values of 200 and 300 respectively, it means that Model A has better predictive capability than Model B. Values of three Chi-square statistics, such as likelihood ratio, score, and Wald test, provide the results of testing global null hypothesis BETA = 0. These three statistics test the same null hypothesis on whether all explanatory variables have coefficients of 0 (Dissanayake & Lu, 2002). The degree of freedom (DoF) for each Chi-square statistic is in accordance with a number of coefficients of explanatory variables. Moreover, characteristics of the logistic regression models were ascertained using the percentage of concordant, discordant, and tied observations. The connection between predicted probabilities and observed responses were identified using Somer's D, Goodman and Kruskal's gamma, and Kendall's Tau-a and c statistics, as mentioned in the following sections.

Intensity and direction of the association between pairs of variables were identified using Somer's D, where values range from 0.0 (all pairs disagree) to 1.0 (all pairs agree; Allison, 2012).

Somer's D can be defined as follows:

$$\textit{Somer's D} = \frac{C - D}{C + D + T}$$ **Equation 3.6**

Where:

C = number of concordant pairs,

D = number of discordant pairs, and

T = number of ties.

The Goodman-Kruskal Gamma indicates good association among variables in the model. Gamma values range from 0.0 (no association) to 1.0 (perfect association), and can be defined as follows (Allison, 2012):

$$Gamma = \frac{C - D}{C + D}$$ **Equation 3.7**

Kendall's Tau-a value shows the difference between numbers of possible paired observations and number of paired observations with different responses. It can be defined as (Allison, 2012):

$$Tau - a = \frac{C-D}{N}$$ **Equation 3.8**

Where:

N = total number of pairs.

c value is another measure of rank correlation of ordinal variables that ranges from 0 (no association) to 1 (perfect association), and can be defined as (Allison, 2012):

$$c = 0.5(1 + Somer's D)$$ **Equation 3.9**

These statistics can be used to identify a better fitting model in this study.

3.2.2 Multicollinearity

Data extracted from the KCARS database were suitably redefined using Microsoft Excel to take binary values of either 0 or 1, which were then data imported into SAS version 9.4 for analysis (SAS Institute Inc., 2013a). All independent variables were checked for linear dependencies using a correlation matrix. In this study, the PROC CORR statement available in SAS version 9.4 (SAS Institute Inc., 2013b) was used to develop Pearson's correlation matrix.

The accuracy of a model is lower with the presence of correlated variables. The magnitude of Pearson's correlation coefficient determines the extent of the relationship. Previous literature shows that values of 0.5 to 0.7 are considered as cutoff values of multicollinearity. Therefore, 0.6 was chosen as the cutoff value in this study, and variable pairs having a correlation coefficient of 0.6 or more were not considered together in the same model to minimize the effect of multicollinearity. The correlated variable pair with the highest magnitude of correlation coefficient was considered first. Each of the two variables was alternatively used in developing the model, while keeping everything else the same, and goodness fit statistics of the two models were compared. The variable that resulted in a better model was retained while the other was discarded, and then the procedure for the collinearity was repeated for the pair of variables having the next magnitude for Pearson's correlation coefficient. This procedure was continued until no pair of variables were retained in the model with a correlation coefficient of 0.6 or greater. This process is expected to mitigate the effect of multicollinearity of independent variables.

3.3 Likert Scale

Likert scale is a rating system used in questionnaires to quantify people's attitudes or opinions (Jamieson & Rogers, 2013). This method assigns different weights to each answer selected. Responses typically include "Never," "Very rarely," "Sometimes," "Most of the time," and "Always." Weights can be assigned as Never = 0, Very rarely = 25, Sometimes = 50, Most of the time = 75, and Always = 100. Then the weighted average can be calculated for each question in the survey. For example:

Frequency	Weight
a	0
b	25
c	50
d	75
e	100

$$\text{Weighted average} = (a*0+b*25+c*50+d*75+e*100)/ (a +b +c +d +e) \qquad \textbf{Equation 3.10}$$

This number, weighted average, represents the likelihood of occurrence of a particular question/concern in the survey. Then the likelihood of occurrence can be cited as a priority listing.

Using this method, a set of qualitative responses can be turned into a quantitative system and rankings could be developed.

3.4 Cross-Classification Analysis

Two age groups were identified for the self-reported road user survey questionnaire, such as older-driver group and reference group. Cross-classification analysis was performed to check the association of various factors on the older-driver group and the reference group. This test is used to identify the relationship between a pair of variables, one of them being age group of drivers, older vs. reference. The analysis related to the hypothesis testing, where the null hypothesis: H_0 and alternate hypothesis: H_1 are formulated as follows:

H_0: Variable considered is independent of the age group.

H_1: Variable considered is not independent of the age group.

If the null hypothesis is true, it means that there is no association between the variable under consideration and the age group of drivers. In the cross-classification analysis, variables were subdivided into several categories and arranged in rows. In this case, the columns contain the two age groups, older-driver group and reference group. Levels of variables were combined to obtain reasonably large frequencies for analysis because smaller values create smaller expected frequencies, which might lead to inaccurate results (Howell, n.d.). If there are 'n' rows and 'm' columns in the matrix, then the Degree of Freedom (DoF) is defined as follows (Dixon & Massey, 1951):

$$Degree\ of\ freedom = (n-1) * (m-1)$$ **Equation 3.11**

In a contingency table, entries are recorded as the observed frequencies 'O_{ij}' where i and j express the row and column numbers, respectively. Expected values for any cell in the matrix 'E_{ij}' are calculated as shown in Equation 3.12 (Dixon & Massey, 1951).

$$E_{ij} = \frac{(Row\ Total)*(Column\ Total)}{Sample\ Size}$$ **Equation 3.12**

After that, the Chi-square statistic ($\chi 2$) was computed as follows (Dixon & Massey, 1951):

$$\chi 2 = \sum_{i=1}^{i=k} \frac{\left(O_{ij} - E_{ij}\right)^2}{E_{ij}}$$ **Equation 3.13**

Where:

k = the number of cells in the contingency table, which is m x n.

Using the DoF obtained from Equation 3.11, the Chi-square value for a confidence interval of 95 percent can be determined from the standardized Chi-square distribution table. This critical Chi-square value is compared with the calculated Chi-square value estimated using Equation 3.13. The null hypothesis can be rejected if the calculated Chi-square value is greater than the critical Chi-Square value, which means a relationship exists between the variable considered and the two age groups, i.e., older drivers and the reference group. Also, if the calculated Chi-square value is less than the critical Chi-square value, then the null hypothesis cannot be rejected, which means the two variables are independent of each other. This test provides an understanding about the relationship between two variables, even though more advanced analysis is needed for deeper understanding.

Chapter 4: Results and Discussion

This chapter summarizes general crash characteristics of older drivers, compares older-driver crash characteristics with those of all drivers, and presents results from crash severity models and the road user survey.

4.1 General Crash Characteristics

In this section, data extracted from the Kansas Crash Analysis and Reporting System (KCARS) database related to older drivers involved in crashes during the 5-year time period from 2010 to 2014 are presented in summary tables.

4.1.1 Fatality Rates by Age Group

Kansas crash data showed that the elderly were involved in about 20 percent of fatal crashes and about 10 percent of all crashes, indicating that older drivers have higher risk of fatal crashes compared to other age groups. Figure 4.1 presents motor vehicle fatality rates by age group in Kansas from 2010 to 2014. The elderly had a very high fatality rate compared to all other age categories, indicating the critical nature of their highway safety-related issues.

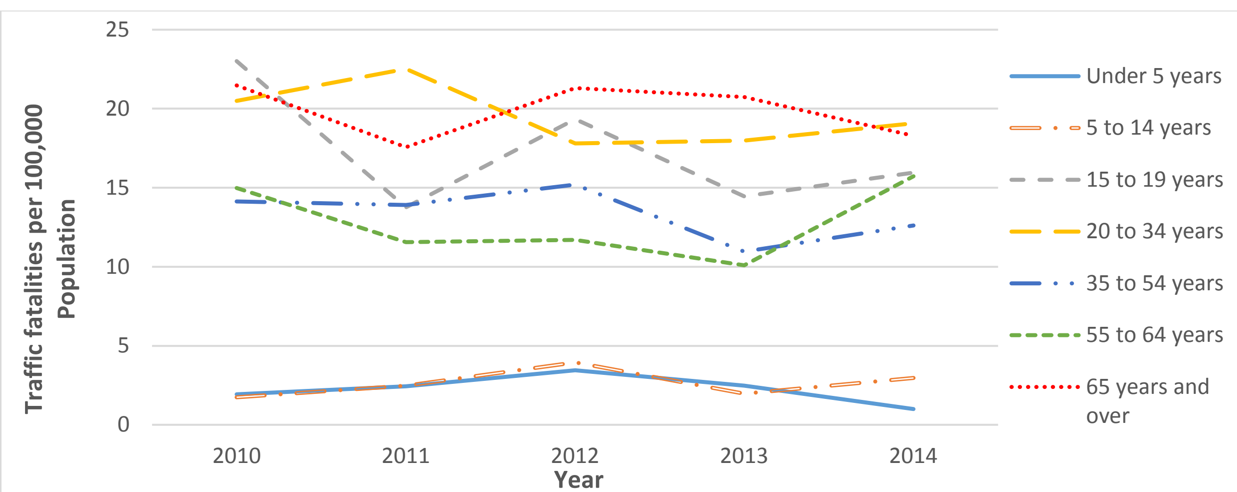


Figure 4.1: Motor Vehicle Fatality Rates by Age Group in Kansas, 2010 to 2014

4.1.2 Older-Driver Crash Characteristics

In order to get an understanding about general characteristics, older-driver crash data were studied and distributions based on various categories were summarized. Older drivers involved in crashes based on KDOT Districts are presented in Table 4.1. It is important to note the frequency of older drivers involved in crashes is much higher in District One, followed by District Five, which are more populated districts, than others.

Table 4.1: Number of Older Drivers Involved in Crashes Based on KDOT Districts (Combined Data from 2010 to 2014)

District	Older-driver injury severity			Total *	% of older-driver-involved crashes
	Fatalities	Injuries	No injuries		
1. Northeast Kansas	82	2,663	16,267	19,249	44.40
2. North Central Kansas	50	476	3,043	3,631	8.38
3. Northwest Kansas	18	203	1,777	2,025	4.67
4. Southeast Kansas	44	548	3,454	4,102	9.46
5. South Central Kansas	80	1,955	10,465	12,599	29.06
6. Southwest Kansas	23	204	1,495	1,745	4.03
Total	297	6,049	36,501	43,351	100.00

* Includes all unknown values

However, when considering the most critical KDOT District in terms of older-driver safety, population needs to be taken into consideration. Accordingly, rates were calculated as shown in Table 4.2 by considering total population in each district, since that controls for the demographics. Even though the majority of older drivers involved in crashes were in Northeast Kansas, older-driver crash involvement rate per 1,000 population was 2.85, which is lower than the overall Kansas rate of 2.99. Northwest Kansas was the most critical KDOT District for older-driver safety when considering older-driver crash involvement rate per 1,000 population. Other than KDOT Districts One and Six, all other districts' older-driver crash involvement rate per 1,000 population was higher than the average state rate, identifying those as more critical districts.

Table 4.2: Older Driver Crash Involvement Rate per 1,000 Population by KDOT District

District	*Total population in 2014	Older-driver crash involvement rate per 1,000 population	Older-driver safety risk rank 1- highest risk
1. Northeast Kansas	1,350,707	2.85	5
2. North Central Kansas	214,755	3.38	2
3. Northwest Kansas	96,962	4.18	1
4. Southeast Kansas	268,088	3.06	4
5. South Central Kansas	820,705	3.07	3
6. Southwest Kansas	152,754	2.28	6
Total	2,903,971	2.99	-

*Source: KU Institute for Policy & Social Research (2015)

Table 4.3 presents older-driver crash characteristics for combined crash data from 2010 to 2014 in Kansas, by older driver age sub-group. Older drivers experienced 297 fatal injuries within the 5-year time period under consideration. This group represents drivers who are older than 65 years, involved in crashes, and suffered fatal injuries as the result of those crashes. Also, 2,890 incapacitating and non-incapacitating injuries during the same time period were found. When considering the day of the week, Friday was the highest frequency of crashes involving older drivers, with Sunday being the lowest. Older drivers were involved in intersection or intersection-related crashes more often than any other crash location. Most older drivers were involved in crashes between 30 mph and 50 mph speed limits, where they are more likely to drive. Older drivers' exposure to higher speed limits may be less as they may be using more local roads during daytime for day-to-day activities. Also, they have been involved in more crashes during daytime hours from 3 p.m. to 6 p.m. Cars, followed by pickup trucks, were the most common vehicle types older drivers used at the time of crashes. Out of all older-driver crashes, 57.3 percent involved older male drivers. Also, older drivers were found to be involved in crashes mostly on dry surface conditions and asphalt surfaces. All these findings seem to be in accordance with what is generally expected regarding the situation.

Table 4.3: Crash Characteristics of Older Drivers Involved in Crashes by Age Subgroup (Combined Data from 2010 to 2014)

Characteristics	Older-driver age group (yrs.)			Total (%)
	65-74	75-84	85+	
Injury severity				
Fatal injury	132	109	56	297(0.7)
Incapacitating injury	298	165	60	523(1.2)
Non-incapacitating injury	1,350	758	259	2,367(5.5)
Possible injury	1,876	968	315	3,159(7.3)
No injury	22,090	10,961	3,450	36,501(84.2)
Total*	26,023	13,128	4,200	43,351(100.0)
Day of the week				
Monday	3,882	1,984	636	6,502(15.0)
Tuesday	4,143	2,111	640	6,894(15.9)
Wednesday	4,078	2,113	676	6,867(15.8)
Thursday	4,152	2,119	702	6,973(16.1)
Friday	4,472	2,234	709	7,415**(17.1)**
Saturday	3,141	1,514	456	5,111(11.8)
Sunday	2,154	1,041	381	3,576(8.2)
Total*	26,023	13,128	4,200	43,351(100.0)
Accident location				
Non-intersection	10,130	4,530	1,254	15,914(36.7)
Intersection/ intersection related	10,947	6,068	2,152	19,167**(44.2)**
Access to parking lot or driveway	2054	1234	452	3740(8.6)
Other	2,892	1,296	342	4,530(10.4)
Total*	26,023	13,128	4,200	43,351(100.0)
Speed limit				
Speed <30 mph	7,814	4,634	1,763	14,211(32.8)
30mph=< Speed <=50 mph	9,597	4,966	1,706	16,269**(37.5)**
Speed> 50 mph	8,135	3,256	655	12,046(27.8)
Total*	26,023	13,128	4,200	43,351(100.0)
Time of day				
09:00 – 12:00	4,886	3,103	1,107	9,096(21.0)
12:00 – 15:00	6,008	3,454	1,234	10,696(24.7)
15:00 – 18:00	6,822	3,276	1,067	11,165**(25.8)**
18:00 – 21:00	3,394	1,402	349	5,145(11.9)
Other	4,913	1,893	443	7,249(16.7)
Total*	26,023	13,128	4,200	43,351(100.0)

*Total includes unknown values. Note: Bold values represent the highest percentage.

Table 4.3: Crash Characteristics of Older Drivers Involved in Crashes by Age Subgroup (Combined Data from 2010 to 2014) (Continued)

Characteristics	Older-driver age group (yrs.)			Total (%)
	65–74	75–84	85+	
Gender				
Male	15,180	7,359	2,283	24,822**(57.3)**
Female	10,810	5,756	1,906	18,472(42.6)
Total*	26,023	13,128	4,200	43,351(100.0)
Vehicle body type				
Automobile	12,984	7,584	2,714	23,282**(53.7)**
Pickup truck <10, 001 lb.	5,011	2,246	617	7,874(18.2)
Sport utility vehicle	4,277	1,700	472	6,449(14.9)
Van	1,966	996	244	3,206(7.4)
Other vehicle	1,681	559	132	2,372(5.5)
Total*	25,919	13,085	4,179	43,351(100.0)
Surface conditions				
Dry	22,125	11,419	3,714	37,258(**85.9**)
Wet	2,507	1,212	367	4,086(9.4)
Snow	653	228	47	928(2.1)
Ice	494	175	39	708(1.6)
Other	244	94	33	371(0.9)
Total*	26,023	13,128	4,200	43,351(100.0)
Surface type				
Concrete	6,949	3,505	1,114	11,568(26.7)
Asphalt	18,000	9,050	2,905	29,955**(69.1)**
Gravel	571	274	60	905(2.1)
Other	503	299	121	923(2.1)
Total*	26,023	13,128	4,200	43,351(100.0)

*Total includes unknown values. Note: Bold values represent the highest percentage.

When considering older-driver safety, it is interesting to identify who is more at fault—the older driver or the other driver. In this study, two-vehicle crashes were used to identify the drivers who are not at fault. By considering the combined dataset from 2010 to 2014, the number of two-vehicle crashes where at least one older driver was involved was 23,495. Out of these crashes, in 2,466 cases, both drivers were older drivers, and 21,029 crashes involved one older driver and another non-older driver. Then, crashes with "no driver contributory circumstances" reported were counted to determine who is not at fault, because several driver-contributory circumstances were reported in many of the two-vehicle crashes. Among these crashes with no contributory circumstances recorded, older drivers had 5,824 cases of "no driver contributory circumstances," and drivers younger than 65 had 5,222 such cases. Therefore, it appears older drivers were more "not at fault" than other non-older drivers when considering two-vehicle crashes, even though this is not really a very scientific way of analyzing the situation.

4.1.3 Comparison of Older Drivers with All Drivers

In this section, characteristics of older drivers involved in crashes based on driver, environmental, roadway, and vehicle categories are compared with those of all drivers, by considering 5-year combined crash data from 2010 to 2014. Table 4.4 provides characteristics of older drivers and all drivers involved in crashes, which is a summary of tables provided in Appendix A. Older drivers were overly represented in fatal injuries and incapacitating injuries, which are more severe injuries. The percentage of older-driver fatal injuries was more than twice that of all drivers, confirming that crashes involving older drivers are more severe. When compared with all drivers, older drivers were involved in intersection crashes more often, though this was not the case with intersection-related crashes. Also, older drivers had higher crash involvement at four-way intersections and roundabouts than all drivers in general. At three-leg intersections, however both groups had an almost identical percentage of crash involvement. When compared with all drivers, older drivers were involved in crashes more often when stop signs were present, for which the most difference was seen. Older drivers were involved in crashes more frequently at traffic signals or yield signs than all drivers as well, indicating safety challenges faced by older drivers at intersections of many types.

Table 4.4: Characteristics of Older Drivers and All Drivers Involved in Crashes; Part 1 (Combined Data from 2010 to 2014)

Categories		Older drivers	All drivers	% of older drivers	% of all drivers
Injury severity*	Fatal injuries	297	1401	**0.69**	0.31
	Incapacitating injuries	523	5119	**1.22**	1.15
	Non-incapacitating injuries	2,367	24,398	5.52	5.48
	Possible injuries	3,159	34,173	7.37	7.68
	No injuries	36,501	379,815	85.19	85.37
	Unknown	504	22,256	-	-
	Total	43,351	467,162	-	-
Accident location	Non-intersection	15,914	175,409	36.71	39.34
	Intersection	12,927	105,301	**29.82**	23.62
	Intersection-related	6,240	67,957	14.39	15.24
	Other locations	6,026	64,114	13.90	14.38
	Off roadway	2,149	32,152	4.96	7.21
	Other and unknown	95	890	0.22	0.20
	Total	43,351	445,823	100.00	100.00
Intersection type	Four-way intersection	15,391	135,995	**70.36**	64.33
	T-intersection	3,523	35,654	16.10	16.87
	Part of an interchange	2,187	32,293	10.00	15.28
	Roundabout	165	1,345	**0.75**	0.64
	Other intersection types	610	6,115	2.79	2.89
	Total	21,876	211,402	100.00	100.00
Traffic Control device present	Traffic signal	4,930	48,293	**18.49**	17.11
	Stop sign	4,678	39,546	**17.55**	14.01
	Yield sign	335	3,190	**1.26**	1.13
	Some other traffic control device	11,182	130,958	41.95	46.41
	None	5,533	60,195	20.76	21.33
	Total	26,658	282,182	100.00	100.00

Note: Bold values indicate categories where older drivers are overly represented. *Since there are more unknown injury severities in the all driver group, “Unknown” category was ignored when calculating the percentages.

According to Part 2 of Table 4.4, older drivers had higher crash involvement at straight and level roads than all drivers. Angle-side impact crashes were also more common among older drivers when compared with all drivers; however, older drivers were less involved in rear end crashes. Older drivers were involved in crashes during daylight conditions more often than all drivers, which may be because older drivers might be trying to reduce nighttime driving, if possible. Older drivers were more involved in crashes on rural roads than urban roads when compared with all drivers. It is worth exploring in future studies whether lack of transit services in rural areas is playing a role in this scenario.

Table 4.4: Characteristics of Older Drivers and All Drivers Involved in Crashes; Part 2 (Combined Data from 2010 to 2014)

Categories		Older drivers	All drivers	% of older drivers	% of all drivers
Road character	Straight and level	33,337	329,957	**76.9**	74.01
	Straight on grade/slope	6,796	74,361	15.68	16.68
	Curved and level	1,350	16,869	3.11	3.78
	Other road characters	1,868	24,637	4.31	5.53
	Total	43,351	445,823	100.00	100.00
First harmful event (FHE)	Rear end	10,224	136,676	23.58	30.66
	Angle-side impact	15,290	121,458	**35.27**	27.24
	All the other FHE	17,837	187,977	41.15	42.16
	Total	43,351	445,823	100.00	100.00
Light conditions	Daylight	34,779	311,171	**80.23**	69.8
	Non-daylight conditions	8,572	134,652	19.77	30.2
	Total	43,351	445,823	100.00	100.00
State road Category	Rural	7,253	66,908	**51.87**	42.91
	Urban	6,731	89,005	48.13	57.09
	Total	13,984	155,913	100.00	100.00

Note: Bold values indicate categories where older drivers are overly represented.

Table 4.5 presents a comparison of older drivers and all drivers involved in crashes based on driver contributing circumstances (CC). Driver CCs such as inattention in a general sense, failure to yield the right of way, improper lane change, and disregarding traffic signs/signals or markings were more common for older drivers than all drivers. Even though it is surprising to find out that disregarding traffic signs, signals, and markings and red-light running are more common among older drivers than among the general population, it could very well be because older drivers have longer perception reaction times and are slower to respond rather than intentionally violating or driving aggressively.

Furthermore, driver CCs such as making improper turns, improper backing, red light running (including disregarded traffic signal), being ill or having a medical condition, improper passing, wrong side or wrong way, improper or no turn signal, impeding or being too slow for traffic, and improper parking had higher percentages for older drivers than all drivers. Percentages of “no driver contributing circumstance evident” of all drivers were very slightly higher than the older-driver group. Therefore, older drivers were more likely to be ‘not at fault’ than all drivers. However, it is also seen that older drivers are less likely to follow too closely, speed/drive too fast for conditions, or even be distracted than other drivers.

Table 4.6 represents other non-driver-related contributory circumstances (CC) for older drivers and all drivers, which are categorized under roadway-related, pedestrian, environment-related, and vehicle-related CC. It is important to note that all these CC occur much less frequently than driver CC. Standing or moving water, debris or obstruction, and road construction or maintenance were the most frequent roadway-related contributory circumstances for older drivers involved in crashes, which were more common than those for all drivers. However, icy or slushy conditions, and snow accumulation or snow-packed conditions were less common roadway-related CC for older drivers, perhaps because older drivers avoided such conditions, if possible. Compared to other CCs, the number of pedestrian-related CCs is much less for the older-driver group as well as for the all-driver group, since the number of pedestrian crashes in Kansas is smaller. When compared with all pedestrians, older pedestrians were involved in crashes more often due to inattention, failing to yield the right of way, disregarding traffic control signs/signals/officer, and improper crossing, which seem to be somewhat surprising. When compared with all drivers, older drivers have considerable safety problems due to glare from sun, headlights, or other lights when considering environment-related CCs. Also, hitting an animal contributed to more older-driver crashes than all drivers. Pedestrian CCs followed by vehicle-related contributory circumstances had the least CCs recorded for older-driver crashes. Older drivers had more crashes from cargo falling and brake issues of vehicles than all drivers, even though the difference is very small.

Table 4.5: Older Drivers and All Drivers Involved in Crashes Based on Driver Contributing Circumstances (Combined Data from 2010 to 2014)

Driver contributing circumstances	**Older drivers**	**All drivers**	**% of Older drivers**	**% of All drivers**
Inattention (general sense)	11,556	115,653	**21.72**	20.42
No driver contributing circumstance evident	9,479	101,495	17.82	17.92
Failed to yield the right of way	8,665	69,290	**16.29**	12.23
Followed too closely	3,706	54,026	6.97	9.54
Unknown	3,385	28,499	6.36	5.03
Improper lane change	1,863	16,302	**3.50**	2.88
Disregarded traffic signs, signals, or markings	1,839	14,818	**3.46**	2.62
Too fast for conditions	1,773	37,378	3.33	6.60
Made improper turn	1,571	11,733	**2.95**	2.07
Improper backing	1,542	10,619	**2.90**	1.88
Red light running (disregarded traffic signal)	1,541	11,865	**2.90**	2.10
Other distraction in or on vehicle	823	11,442	1.55	2.02
Avoidance or evasive action	702	10,401	1.32	1.84
Ill or medical condition	654	3,165	**1.23**	0.56
Under the influence of alcohol	487	15,964	0.92	2.82
Fell asleep or fatigued	444	5,061	0.83	0.89
Other driver CC	369	3,510	0.69	0.62
Improper passing	356	3,375	**0.67**	0.60
Wrong side or wrong way	348	3,569	**0.65**	0.63
Over correction / over steering	345	5,945	0.65	1.05
An item or action not in or on vehicle	340	4,419	0.64	0.78
Reckless / careless driving	336	7,353	0.63	1.30
Mobile phone	185	4,080	0.35	0.72
Exceeded posted speed limit	161	3,782	0.30	0.67
Under the influence of medication	111	1,815	0.21	0.32
Did not comply with license restrictions	103	1,961	0.19	0.35
Improper or no turn signal	90	859	**0.17**	0.15
Impeding or too slow for traffic	88	828	**0.17**	0.15
Other electronic devices	85	1,728	0.16	0.31
Emotional: angry, depressed, upset, impatient, etc.	76	1,513	0.14	0.27
Aggressive / antagonistic driving	68	1,803	0.13	0.32
Improper parking	66	540	**0.12**	0.10
Under the influence of illegal drugs	39	1,551	0.07	0.27
Grand total	53,196	566,342	100.00	100.00

Note: Bold values indicate the driver CCs, where older drivers are overly represented.

Table 4.6: Older Drivers and All Drivers Involved in Crashes Based on Road, Pedestrian, Environment, and Vehicle Related Contributing Circumstances (Combined Data from 2010 to 2014)

Age category	Older drivers	All drivers	% of older drivers	% of all drivers
Road-related contributory circumstances				
Standing or moving water	612	9,749	**27.01**	26.96
Icy or slushy	536	10,398	23.65	28.75
Snow accumulation or snow packed conditions	373	7,200	16.46	19.91
Debris or obstruction	166	2,054	**7.33**	5.68
Road construction or maintenance	147	1,352	**6.49**	3.74
Other CCs	375	5,414	16.55	14.97
Grand total	2,266	36,167	100.00	100.00
Pedestrian-related contributory circumstances				
Inattention (general sense)	56	372	**17.50**	13.55
Failed to yield the right of way	45	328	**14.06**	11.94
Disregarded traffic control signs, signals, officer	28	236	**8.75**	8.59
Improper crossing	58	390	**18.13**	14.20
Other CCs	133	1,420	41.56	51.71
Grand total	320	2,746	100.00	100.00
Environment-related contributory circumstances				
Animal: domestic or wild	3,577	39,707	**67.16**	62.89
Rain, mist, or drizzle	482	7,278	9.05	11.53
Falling or blowing snow	242	5,246	4.54	8.31
Glare from sun, head/other lights	372	3,041	**6.98**	4.82
Other CCs	653	7,861	12.00	12.00
Grand total	5,326	63,133	100.00	100.00
Vehicle-related contributory circumstances				
Brake issues	205	2754	**20.81**	20.18
Tires	149	2688	15.13	19.70
Cargo falling	108	1378	**10.96**	10.10
Other	523	6824	53.10	50.01
Grand total	985	13644	100.00	100.00

Note: Bold values indicate CCs where older drivers are overly represented.

4.2 Crash Severity Modeling

In the Kansas Crash Analysis and Reporting System (KCARS) database, all crash-related variables are recorded in sub files. Environmental and roadway conditions are contained in the accident sub file, characteristics of occupants and other road users are included in the occupants sub file, and vehicle-related variables are listed in the vehicle sub file. The common variable accident key can be used to combine and merge different sub files included in the KCARS database so that more details about related variables can be obtained.

Crash severity is identified as the most severe personal injury severity experienced by an occupant or non-occupant involved in a crash. Therefore, factors that distinguish severity of a crash are essential to understand older-driver safety factors because the effect of one factor can be greater than the other, while some other factors are not relevant at all. Since those critically important factors can only be identified by crash severity modeling, this study developed three separate crash severity models to identify factors associated with older-driver crashes. Binary logistic regression was chosen to model crash severity where it was the response variable. This section summarizes factors affecting older-driver crashes for single-vehicle crashes involving an older driver only (Model A), single-vehicle crashes involving an older driver with at least one passenger (Model B) to identify attributes of passengers seated in the front seat, and multi-vehicle crashes involving at least one older driver (Model C).

4.2.1 Single-Vehicle Crash Severity Models (Models A and B)

The dataset used in modeling single-vehicle crashes where only an older driver was present (Model A) had a sample size of 7,229 involving drivers aged 65 years or older. Combined data from 2010 to 2014 were used in the modeling, and crash data for the year 2009 was allocated for model validation in each model. After studying the literature, explanatory variables were selected and then those variables were redefined to binary form of 1 or 0. Selected explanatory variables for modeling severity of single-vehicle crashes involving older drivers are given in Table 4.7. Thirty-six explanatory variables were checked for linear correlation using a PROC CORR statement available in SAS, because presence of correlated variables in a model reduces the accuracy (SAS Institute Inc., 2013b). Pearson's correlation coefficients were generated in a correlation matrix in order to understand the strength of relationships between corresponding variables. A correlation coefficient of 0.6 was chosen as the cutoff value to minimize the effect of collinearity, because previous studies used coefficients from 0.5 to 0.7 (Mukaka, 2012; Oh, Kang, Kim, & Kim, 2005).

Correlation matrices that were developed for modeling single-vehicle older-driver involved crashes are shown in Appendix B.

Another model was developed for single-vehicle crashes involving an older driver with at least one passenger (Model B). For Model B, variable PASSE was added where the driver was with a front seat passenger, PASSE = 1 (frequency = 2,267), otherwise 0 (frequency = 447). Two additional variables were added to identify the gender of the front seat passenger (SPASSGEN) and the age of the passenger (SPASSAGE) to identify whether the front seat passenger was older than 65 years or not. Otherwise, all variables and definitions in Table 4.7 are similar to variables used in Model B. Correlated variable pairs were removed in both models by considering each variable separately in the model, and then running the model. After that, model fit statistics were used to identify the variable to be retained in the model as described in Section 3.2.1. Table 4.8 shows the variables retained among correlated pairs for Models A and B.

Table 4.7: Explanatory Variables for Modeling Severity of Single-Vehicle Crashes Involving Older Drivers Only

Label	Explanation	Crash frequency (7,229)	
		"1"	"0"
ACCCLS2	If crash involved an animal = 1, otherwise 0	2,702	5,527
ACCCLS3	If crash involved a fixed object = 1, otherwise 0	2,270	4,959
ACCCLS4	If crash involved a legally parked vehicle = 1, otherwise 0	1,478	5,751
AIRB	If air bag deployed = 1, otherwise 0	294	6,935
CURLVEL	If on curved and level road = 1, otherwise 0	381	6,848
DRAGE1	If driver age 65 to 74 = 1, otherwise 0	4,659	2,570
DRAGE2	If driver age 75 to 84 = 1, otherwise 0	1,963	5,266
GEN	If driver is male = 1, otherwise 0	4,370	2,859
HSPEED	If speed is greater than or equal 40 mph = 1, otherwise 0	4,655	2,574
INTERR	If intersection/intersection-related = 1, otherwise 0	360	6,869
LANEM	If crash happened on multilane road = 1, otherwise 0	1,656	5,573
LANETWO	If crash happened on two-lane road = 1, otherwise 0	5,491	1,738
LIGHT1	If crash occurred in daylight = 1, otherwise 0	4,169	3,060
LIGHT2	If crash happened in dark (street light on) = 1, otherwise 0	587	6,642
LIGHT3	If crash happened in dark (no street light) = 1, otherwise 0	1,843	5,386
LTURN	If maneuver was left turn = 1, otherwise 0	177	7,052
NEJECT	If driver not ejected or trapped = 1, otherwise 0	6,900	329
NINTER	If non-intersection on roadway = 1, otherwise 0	4,937	2,292
OFFRD	If crash occurred off roadway = 1, otherwise 0	1,303	5,926
SEATB	If seat belt used = 1, otherwise 0	6,292	937
STLVEL	If straight and level road = 1, otherwise 0	5,213	2,016
STRAIG	If maneuver was straight/following road = 1, otherwise 0	5,329	1,900
SURFACE1	If asphalt surface = 1, otherwise 0	5,245	1,984
SURFACE2	If concrete surface = 1, otherwise 0	1,249	5,980
SURFACE3	If gravel/brick = 1, otherwise 0	444	6,785
TIME1	If 5:00 a.m.–9:00 a.m. = 1, otherwise 0	1,266	5,963
TIME2	If 9:00 a.m.–1:00 p.m. = 1, otherwise 0	1,615	5,614
TIME3	If 1:00 p.m.–5:00 p.m. = 1, otherwise 0	1,536	5,693
TIME4	If 5:00 p.m.–9:00 p.m. = 1, otherwise 0	1,779	5,450
VALID	If driver has valid license = 1, otherwise 0	7,064	165
VEH1	If automobile = 1, otherwise 0	3,470	3,759
VEH2	If SUV = 1, otherwise 0	874	6,355
WEATHER1	If no adverse conditions = 1, otherwise 0	6,343	886
WEATHER2	If rain = 1, otherwise 0	370	6,589
WEATHER3	If snow = 1, otherwise 0	193	7,036
WEEKE	If weekends = 1, otherwise 0	1,751	5,478

Table 4.8: Variables Retained Among Correlated Pairs for Model A and B

Correlated variable pair		Pearson's correlation coefficient	Variable retained
Model A			
LANEM	LANETWO	-0.969	LANETWO
DRAGE2	DRAGE1	-0.822	DRAGE1
OFFRD	NINTER	-0.688	OFFRD
LIGHT3	LIGHT1	-0.683	LIGHT1
ACCCLS4	HSPEED	-0.644	HSPEED
WEATHER2	WEATHER1	-0.621	WEATHER1
Model B			
DRAGE1	DRAGE2	-0.904	DRAGE1
LANETWO	LANEM	-0.901	LANETWO
SURFACE1	SURFACE2	-0.849	SURFACE1
LIGHT1	LIGHT3	-0.746	LIGHT1
NINTER	OFFRD	-0.708	OFFRD
ACCCLS2	ACCCLS3	-0.660	ACCCLS2
NINTER	ACCCLS2	0.622	ACCCLS2
HSPEED	ACCCLS4	-0.621	ACCCLS4

After eliminating the correlated variables, Model A and Model B were left with a set of 30 and 32 potential variables, respectively. Three variable selection methods, the backward elimination method, the forward selection method, and the stepwise selection method, were used to identify variables significant enough to remain in the models. Coefficient estimates and *p*-values of all considered variables were obtained by applying the PROC LOGISTIC procedure in SAS (SAS Institute Inc., 2013c), without using any selection method. A level of significance of 0.05 (*p*-value = 0.05) was chosen for modeling and no variable with a *p*-value greater than 0.05 remained in the models. Maximum likelihood estimates and odds ratios of logistic regression models are provided for Model A and Model B in Tables 4.9 and 4.10, respectively.

Table 4.9: Maximum Likelihood Estimates and Odds Ratios for Model A

Label	Coefficient estimate(β)	Standard error	*p*-value	Odds ratio	95% Wald confidence limits	
Intercept	**0.2372**	**0.227**	**0.296**	***N/A**	***N/A**	***N/A**
ACCCLS2	**-2.0301**	**0.157**	**<.0001**	**0.131**	**0.097**	**0.179**
ACCCLS3	**0.7742**	**0.093**	**<.0001**	**2.169**	**1.806**	**2.604**
AIRB	**2.0388**	**0.155**	**<.0001**	**7.681**	**5.668**	**10.409**
CURLEVEL	0.2225	0.154	0.148	1.249	0.924	1.689
DRAGE1	-0.1105	0.081	0.174	0.895	0.764	1.050
GEN	-0.0431	0.087	0.620	0.958	0.808	1.136
HSPEED	**0.9593**	**0.091**	**<.0001**	**2.610**	**2.183**	**3.120**
INTERR	**0.6895**	**0.155**	**<.0001**	**1.993**	**1.471**	**2.700**
LANETWO	0.0834	0.090	0.351	1.087	0.912	1.296
LIGHT1	**0.4027**	**0.094**	**<.0001**	**1.496**	**1.245**	**1.798**
LIGHT2	-0.1233	0.178	0.489	0.884	0.623	1.254
LTURN	**-0.5176**	**0.244**	**0.034**	**0.596**	**0.369**	**0.962**
NEJECT	**-2.3024**	**0.162**	**<.0001**	**0.100**	**0.073**	**0.137**
OFFRD	**0.3866**	**0.094**	**<.0001**	**1.472**	**1.224**	**1.770**
SEATB	**-1.554**	**0.096**	**<.0001**	**0.211**	**0.175**	**0.255**
STLEVEL	**-0.2248**	**0.082**	**0.006**	**0.799**	**0.681**	**0.937**
STRAIG	**0.4491**	**0.094**	**<.0001**	**1.567**	**1.305**	**1.882**
SURFACE1	0.0629	0.086	0.467	1.065	0.899	1.261
SURFACE2	0.1355	0.100	0.175	1.145	0.941	1.393
SURFACE3	0.0111	0.154	0.942	1.011	0.748	1.366
TIME1	-0.1621	0.175	0.354	0.850	0.604	1.198
TIME2	-0.3238	0.188	0.084	0.723	0.501	1.045
TIME3	-0.1533	0.186	0.408	0.858	0.596	1.234
TIME4	-0.1712	0.158	0.279	0.843	0.618	1.149
VALID	-0.4439	0.228	0.051	0.642	0.411	1.002
VEH1	-0.1125	0.092	0.220	0.894	0.747	1.069
VEH2	-0.0107	0.135	0.937	0.989	0.760	1.288
WEATHER1	**0.4017**	**0.120**	**0.001**	**1.494**	**1.181**	**1.891**
WEATHER3	**-0.7347**	**0.254**	**0.004**	**0.480**	**0.292**	**0.789**
WEEKE	**0.2605**	**0.088**	**0.003**	**1.298**	**1.093**	**1.540**

Note: *N/A = not applicable. Bold color indicates significant variables at 0.05 level.

Using the data provided in the Table 4.9, the following summary can be identified regarding Model A.

Variables that cause crash severity increase	Variables that cause crash severity decrease
Crash involved a fixed object	Crash involved an animal
Air bag deployed	Maneuver was left turn
Speed is greater than or equal to 40 mph	Driver not ejected or trapped
Intersection/intersection-related	Seat belt used
Crash occurred in daylight	Straight and level road
Maneuver was straight/following road	Snow conditions
No adverse conditions	
Crash occurred on off roadway	
On weekends	

The logistic regression equation for the Model A can be written as:

$$\ln\left(\frac{P}{1-P}\right) = 0.2372 - 2.0301 * \text{ACCCLS2} + 0.7742 * \text{ACCCLS3} + 2.0388 * \text{AIRB} + 0.9593 * \text{HSPEED} + 0.6895 * \text{INTERR} + 0.4027 * \text{LIGHT1} - 0.5176 * \text{LTURN} - 2.3024 * \text{NEJECT} + 0.3866 * \text{OFFRD} - 1.554 * \text{SEATB} - 0.2248 * \text{STLEVEL} + 0.4491 * \text{STRAIG} + 0.4017 * \text{WEATHER1} - 0.7347 * \text{WEATHER3} + 0.2605 * \text{WEEKE}$$

Equation 4.1

From Equations 3.1 and 3.2, the equation for Model A can be modified as follows.

$$\alpha = e^{\beta_o + \beta_1 X_1 + \beta_2 X_2 + \ldots . \beta_n X_n} = \exp\left(0.2372 - 2.0301 * \text{ACCCLS2} + 0.7742 * \text{ACCCLS3} + 2.0388 * \text{AIRB} + 0.9593 * \text{HSPEED} + 0.6895 * \text{INTERR} + 0.4027 * \text{LIGHT1} - 0.5176 * \text{LTURN} - 2.3024 * \text{NEJECT} + 0.3866 * \text{OFFRD} - 1.554 * \text{SEATB} - 0.2248 * \text{STLEVEL} + 0.4491 * \text{STRAIG} + 0.4017 * \text{WEATHER1} - 0.7347 * \text{WEATHER3} + 0.2605 * \text{WEEKE}\right)$$

Equation 4.2

Table 4.10: Maximum Likelihood Estimates and Odds Ratios for Model B

Label	Coefficient estimate(β)	Standard error	*p*-value	Odds ratio	95% Wald confidence limits	
Intercept	**2.284**	**0.539**	**<.0001**	*N/A	*N/A	*N/A
ACCCLS2	**-1.969**	**0.207**	**<.0001**	**0.140**	**0.093**	**0.209**
ACCCLS4	**-1.506**	**0.331**	**<.0001**	**0.222**	**0.116**	**0.424**
AIRB	**1.916**	**0.246**	**<.0001**	**6.797**	**4.198**	**11.005**
CURLEVEL	-0.239	0.336	0.477	0.788	0.408	1.520
DRAGE1	-0.261	0.153	0.089	0.771	0.571	1.041
GEN	-0.159	0.175	0.364	0.853	0.605	1.203
INTERR	-0.050	0.365	0.891	0.951	0.465	1.946
LANETWO	0.178	0.159	0.265	1.194	0.874	1.632
LIGHT1	**0.350**	**0.170**	**0.039**	**1.420**	**1.017**	**1.981**
LIGHT2	0.111	0.326	0.734	1.117	0.590	2.118
LTURN	-0.910	0.629	0.148	0.403	0.117	1.383
NEJECT	**-3.042**	**0.461**	**<.0001**	**0.048**	**0.019**	**0.118**
OFFRD	**0.735**	**0.172**	**<.0001**	**2.085**	**1.487**	**2.923**
PASSE	-0.286	0.200	0.153	0.751	0.507	1.112
SEATB	**-1.105**	**0.245**	**<.0001**	**0.331**	**0.205**	**0.535**
SPASSAGE	0.039	0.155	0.802	1.040	0.767	1.410
SPASSGEN	0.120	0.172	0.486	1.127	0.805	1.578
STLEVEL	0.068	0.166	0.682	1.070	0.774	1.480
STRAIG	-0.052	0.194	0.790	0.950	0.649	1.389
SURFACE1	**-0.306**	**0.153**	**0.045**	**0.736**	**0.545**	**0.994**
SURFACE3	0.334	0.366	0.362	1.397	0.681	2.865
TIME1	0.273	0.323	0.397	1.314	0.698	2.473
TIME2	0.045	0.349	0.898	1.046	0.527	2.074
TIME3	0.289	0.343	0.398	1.336	0.682	2.614
TIME4	0.001	0.243	0.996	1.001	0.622	1.613
VALID	-0.265	0.447	0.553	0.767	0.319	1.843
VEH1	**0.313**	**0.142**	**0.028**	**1.368**	**1.035**	**1.806**
VEH2	-0.077	0.229	0.736	0.925	0.590	1.451
WEATHER1	**0.417**	**0.191**	**0.029**	**1.517**	**1.043**	**2.205**
WEATHER2	-0.368	0.426	0.387	0.692	0.301	1.594
WEATHER3	0.089	0.392	0.821	1.093	0.507	2.354
WEEKE	-0.061	0.153	0.691	0.941	0.697	1.270

Note: *N/A = not applicable. Bold color indicates significant variables at the 0.05 level.

Using data provided in Table 4.10, the following summary can be identified regarding Model B.

Variables that cause crash severity increase	Variables that cause crash severity decrease
Air bag deployed	Crash involved an animal
Crash occurred in daylight	Crash involved a legally parked vehicle
Crash occurred on off roadway	Driver not ejected or trapped
Automobile	Seat belt used
No adverse conditions	Asphalt surface

The logistic regression equation for the Model B can be written as:

$$\ln\left(\frac{P}{1-P}\right) = 2.2842 - 1.1050 * \text{SEATB} + 1.9164 * \text{AIRB} + 0.7347 * \text{OFFRD} - 0.3063 * \text{SURFACE1} + 0.4165 * \text{WEATHER1} + 0.3130 * \text{VEH1} + 0.3503 * \text{LIGHT1} - 1.9687 * \text{ACCCLS2} - 1.5062 * \text{ACCCLS4} - 3.0422 * \text{NEJECT}$$

Equation 4.3

From Equations 3.1 and 3.2, the equation for Model B can be modified as:

$$\alpha = e^{\beta_o+\beta_1 X_1+\beta_2 X_2+.....\beta_n X_n} = \exp(2.2842 \ -1.1050*\text{SEATB} \ +1.9164*\text{AIRB} \ + \ 0.7347*\text{OFFRD} \ - 0.3063*\text{SURFACE1} \ + \ 0.4165*\text{WEATHER1} \ +0.3130*\text{VEH1} \ +0.3503*\text{LIGHT1} \ - 1.9687*\text{ACCCLS2} - 1.5062*\text{ACCCLS4} - 3.0422*\text{NEJECT})$$

Equation 4.4

Lower AIC and SC values were used to identify a desirable model from the described crash severity models. The stepwise selection method was chosen for both models to assess the model fit. For both models, significant *p*-values (<0.05) for the likelihood ratio, score, and Wald statistic indicated that at least one of the regression coefficients was non-zero. Then, accuracy of a model can be identified using an association of predicted probabilities and observed responses, which are shown in Table 4.11. Model A and Model B had c values of 0.872 and 0.850, respectively, which was an indication that both models had a good model fit (Hosmer & Lemeshow, 1989).

Table 4.11: Association of Predicted Probabilities and Observed Responses for Single-Vehicle Crashes

Measure	Model A	Model B
Percent concordant	87	83.7
Percent discordant	12.6	13.8
Percent tied	0.5	2.5
Pairs	7,614,720	723,096
Somer's D	0.744	0.699
Gamma	0.748	0.717
Tau-a	0.217	0.161
c	0.872	0.850

4.2.1.1 Accuracy of Model A and Model B

If the association of predicted probabilities and observed responses was calculated using the same dataset, results can be biased. To eliminate this bias, the validation dataset should be different from the dataset used for modeling. Therefore, year 2009 crash data were used to validate the models using classification tables, as the predictive power of the developed logistic regression model can be assessed by doing so.

In these severity models, response variable y has values of 1 or 0 in a binary outcome. Let p_i be the predicted probability that $y_i = 1$ for individual i. Actual predictions of crash severity (y) = 1 or not can be obtained from predicted probabilities using a cut-off value of p_i, where the natural cut-off value is 0.5 (Allison, 2012). After that, $p_i \geq 0.5$, y_i can be predicted as 1, and when $p_i \leq 0.5$, y_i can be predicted as 0.

The year 2009 data was extracted from the KCARS database and modified to the binary format. By substituting values (1 and 0) in Equations 4.2 and 4.4, probability of occurrence (P) was calculated. If the calculated P value > 0.5, then it was considered as an event and value 1 was assigned. Otherwise it was considered as a non-event and value 0 was assigned. Then the calculated (predicted) value was then compared with the observed value for all of the single vehicle crashes that involved older drivers.

The classification table for Model A had a total of 1,310 crashes, which included 252 fatal or injury crashes (events) and 1,058 PDO crashes (non-events). Model A, from Equation 4.2, correctly predicted 107 as events and 1,003 as non-events, using the probability cut point of 0.5.

Based on 2009 data, there were a total of 526 single-vehicle crashes that involved an older driver with at least one passenger, which were used to validate the model. The classification table for Models A and B is shown in Table 4.12. Accuracy of a model can be defined as shown in Equation 4.5.

$$\text{Accuracy} = \frac{(\text{TRUE POS} + \text{TRUE NEG})}{\text{Sample Size}}$$ **Equation 4.5**

Where:

TRUE POS = events of dependent variable predicted as events, and

TRUE NEG = non-events of dependent variable predicted as non-events.

Therefore,

Accuracy of Model A = (107+1,003)/1,310 = 0.847 or 84.7%.

Accuracy of Model B = (19+446)/ (67+459) = 0.884 or 88.4%

Table 4.12: Classification Table for Model A and Model B

Observed value	Predicted value		Total
	P_i>= 0.5	P_i< 0.5	
Model A			
Y_i =1	107	145	252
Y_i=0	55	1,003	1,058
		Total	1,310
Model B			
Y_i =1	19	48	67
Y_i=0	13	446	459
		Total	526

Events and non-events in Models A and B are not evenly distributed and in both these cases, events are much less than non-events. Therefore, another measure, sensitivity (true positive rate) can also be used to predict accuracy. It is the proportion of events of dependent variables successfully predicted as events. Sensitivity of a model can be defined as shown in Equation 4.6.

$$\text{Sensitivity} = \frac{\text{TRUE POS}}{(\text{TRUE POS} + \text{FALSE NEG})} \qquad \textbf{Equation 4.6}$$

Where:

TRUE POS = events of dependent variable predicted as events, and

FALSE NEG = events of dependent variable predicted as non-events.

Sensitivity of Model A= 107/252 = 0.424, or 42.4 percent

Sensitivity of Model B= 19/67= 0.284, or 28.4 percent

For non-events, specificity (true negative rate) is used to predict accuracy. It is the proportion of dependent variables successfully predicted as non-events. Specificity of a model can be defined as shown in Equation 4.7.

$$\text{Specificity} = \frac{\text{TRUE NEG}}{(\text{TRUE NEG} + \text{FALSE POS})} \qquad \textbf{Equation 4.7}$$

Where:

TRUE NEG = non-events of dependent variables predicted as non-events, and

FALSE POS = non-events of dependent variables predicted as events.

Specificity of Model A=1003/1,058 = 0.948, or 94.8 percent

Specificity of Model B=446/459 =0.972 or 97.2 percent

Model A has an accuracy of 84.7 percent, sensitivity of 42.4 percent, and specificity of 94.8 percent. Also, Model B has an accuracy of 88.4 percent, the sensitivity of 28.4 percent, and specificity of 97.2 percent. Therefore, both models show reasonable accuracies.

4.2.2 Multi-Vehicle Crashes Involving at least One Older-Driver (Model C)

The multi-vehicle crashes from 2010 to 2014 involving at least one older driver were considered for the Model C. Crash data for the year 2009 was allocated for model validation in this case as well. Once the explanatory variables were sorted out, those variables were redefined to binary format of 1 or 0. Selected explanatory variables for multi-vehicle crashes involving older drivers are listed in Table 4.13. Explanatory variables were checked for linear correlation using a PROC CORR statement available in SAS (SAS Institute Inc., 2013b). Pearson’s correlation coefficients were generated in a correlation matrix to understand the intensity of relationships between corresponding variables. The correlation coefficient of 0.6 was chosen as the cutoff value, as in previous models.

Correlated variable pairs were removed in the model by adding each variable separately into the model and then running the model. After that, model fit statistics were used to identify the variable to be retained in the model. Table 4.14 shows the variables retained among correlated pairs.

The maximum likelihood method (MLM) was used for estimating coefficients of the independent variables in the crash severity model. MLM generates relevant model fit statistics such as the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and the value of twice the negative of log likelihood (-2 log L), both for the intercept only and the fitted model. These model fit statistics can be used in making comparisons among a set of models obtained by different variable selection methods, with smaller values representing a better model.

Table 4.13: Multi-Vehicle Crash Severity Model Variable Definitions

Variable	Explanation	Crash Frequency	
		"1"	**"0"**
TRAUNIT	If number of vehicles equals 2 = 1, otherwise = 0	3,850	8,186
MOLDDR	If older driver/s is/are male = 1, otherwise 0	6,960	5,076
FEMOLDDR	If older driver/s is/are female = 1, otherwise 0	4,608	7,428
MIXOLDDR	If both gender older drivers involved in the crash =1, otherwise 0	468	11,568
VALID	If older driver has valid license=1, otherwise 0	11,982	54
SEATB	If seat belt used=1, otherwise 0	11,510	526
AIRB	If air bag deployed=1, otherwise 0	501	11,535
WEEKE	If week ends=1, otherwise 0	2,853	9,183
MORNIN	If 5:00 a.m. – 9:00 a.m. =1, otherwise 0	763	11,273
DAYT	If 9:00 a.m. – 1:00 p.m. =1, otherwise 0	3,642	8,394
AFNOON	If 1:00 p.m. – 5:00 p.m. =1, otherwise 0	4,730	7,306
EVENIN	If 5:00 p.m. – 9:00 p.m. =1, otherwise 0	2,514	9,522
NINTER	If non-intersection on roadway=1, otherwise 0	3,190	8,846
INTERR	If intersection/intersection related on roadway=1, otherwise 0	6,684	5,352
ASPH	If asphalt surface=1, otherwise 0	8,130	3,906
CON	If concrete surface=1, otherwise 0	3,653	8,383
NADVERS	If no adverse conditions =1, otherwise 0	10,672	1,364
RAIN	If rain=1, otherwise 0	871	11,165
SNOW	If snow =1, otherwise 0	224	11,812
STLVEL	If straight and level road =1, otherwise 0	9,386	2,650
CURLVEL	If curved and level road = 1, otherwise 0	324	11,712
HSPEED	If speed is 40 mph or above =1, otherwise=0	6,038	5,998
AUTO	If automobile =1, otherwise 0	9,720	2,316
SUV	If SUV= 1, otherwise=0	3,806	8,230
REND	If rear-end collision = 1, otherwise=0	3,976	8,060
ANGLE	If angle collision = 1, otherwise=0	5,455	6,581
DAYLIGHT	If crash happens in daylight = 1, otherwise 0	10,428	1,608
DARKSTON	If crash happens in dark (streetlights on) =1 otherwise 0	981	11,055
DRAGE1	If vehicle driver age 65 to 74 =1, otherwise 0	7,296	4,740
DRAGE2	If vehicle driver age 75 to 84 = 1, otherwise 0	4,000	8,036
STRAIG	If crash happens when straight/following road = 1 otherwise = 0	10,159	1,877
LTURN	If crash happens when left turn = 1, otherwise =0	2,910	9,126
NEJECT	If driver not ejected or trapped= 1, otherwise = 0	11,829	207
TWOLN	If crash happens on two-lane road = 1, otherwise=0	4,030	8,006
MLANE	If crash happens on multi-lane road = 1, otherwise=0	7,654	4,382
PASSAGE	If passenger age>65 =1, otherwise=0	4,836	7,200
PASSGEN	If passenger is male=1, otherwise=0	4,776	7,260

Table 4.14: Variables Retained Among Correlated Pairs in Model C

Correlated variable pair		Pearson's correlation coefficient	Variable retained
MOLDDR	MIXOLDDR	0.999	MOLDDR
FEMOLDDR	MIXOLDDR	0.999	FEMOLDDR
ASPH	CON	-0.952	CON
TWOLN	MLANE	-0.938	TWOLN
NADVERS	RAIN	-0.781	NADVERS
DAYLIGHT	DARKSTON	-0.759	DAYLIGHT
DRAGE1	DRAGE2	-0.749	DRAGE1
NINTER	INTERR	-0.671	INTERR
REND	ANGLE	-0.639	REND

After eliminating the correlated variables, the model development was left with a set of 29 variables. A stepwise selection method was performed to select the variables, which were significant enough to stay in the model (Dissanayake & Kotikalapudi, 2012). The PROC LOGISTIC statement, available in SAS version 9.4, was used to develop models using the selection method. A p-value of 0.05 was chosen as the level of significance, and any variable having a p-value greater than 0.05 did not stay in the model. Maximum likelihood estimates and the odds ratio for Model C are shown in Table 4.15.

The logistic regression equation for Model C can be mathematically written as:

$$\ln\left(\frac{\mathrm{P}}{1-\mathrm{P}}\right) = 0.652 - 0.746 * \mathrm{TRAUNIT} - 0.365 * \mathrm{SEATB} + 1.889 * \mathrm{AIRB} + 0.475 * \mathrm{INTERR} - 0.435 * \mathrm{SNOW} + 0.372 * \mathrm{HSPEED} + 0.263 * \mathrm{REND} - 0.122 * \mathrm{DAYLIGHT} + 0.802 * \mathrm{STRAIG} + 0.165 * \mathrm{LTURN} - 1.748 * \mathrm{NEJECT} + 0.119 * \mathrm{TWOLN}$$

Equation 4.8

Table 4.15: Maximum Likelihood Estimates and Odds Ratio for Model C

Parameter	Estimate (β)	Standard error	p-value	Odds ratio	95% Wald confidence limits	
INTERCEPT	**0.652**	**0.216**	**0.003**	**N/A**	**N/A**	**N/A**
MOLDDR	0.004	0.11	0.97	1.004	0.809	1.246
FEMOLDDR	0.051	0.112	0.652	1.052	0.844	1.311
TRAUNIT	**-0.746**	**0.061**	**<.0001**	**0.474**	**0.42**	**0.535**
VALID	-0.252	0.303	0.405	0.777	0.429	1.407
SEATB	**-0.365**	**0.098**	**<.0001**	**0.694**	**0.573**	**0.842**
AIRB	**1.889**	**0.111**	**<.0001**	**6.613**	**5.315**	**8.227**
WEEKE	-0.031	0.049	0.528	0.97	0.881	1.067
INTERR	**0.475**	**0.043**	**<.0001**	**1.607**	**1.478**	**1.748**
MORNIN	-0.371	0.153	0.016	0.69	0.511	0.932
DAYT	-0.289	0.14	0.039	0.749	0.569	0.985
AFNOON	-0.244	0.138	0.077	0.783	0.598	1.027
EVENIN	-0.252	0.127	0.048	0.777	0.606	0.997
CON	0.061	0.046	0.184	1.062	0.972	1.162
NADVERS	-0.021	0.07	0.767	0.979	0.853	1.124
SNOW	**-0.435**	**0.166**	**0.009**	**0.647**	**0.468**	**0.896**
STLEVEL	-0.047	0.053	0.372	0.954	0.86	1.058
CURLEVEL	-0.051	0.139	0.712	0.95	0.724	1.247
HSPEED	**0.372**	**0.043**	**<.0001**	**1.451**	**1.333**	**1.578**
AUTO	-0.033	0.056	0.553	0.967	0.866	1.08
SUV	-0.058	0.047	0.221	0.944	0.86	1.035
REND	**0.263**	**0.05**	**<.0001**	**1.301**	**1.181**	**1.434**
DAYLIGHT	**-0.122**	**0.06**	**0.04**	**0.885**	**0.788**	**0.995**
DRAGE1	-0.027	0.043	0.533	0.973	0.894	1.06
STRAIG	**0.802**	**0.066**	**<.0001**	**2.23**	**1.961**	**2.536**
LTURN	**0.165**	**0.053**	**0.002**	**1.179**	**1.064**	**1.307**
NEJECT	**-1.748**	**0.173**	**<.0001**	**0.174**	**0.124**	**0.244**
TWOLN	**0.119**	**0.046**	**0.009**	**1.126**	**1.03**	**1.232**
PASSAGE	-0.017	0.044	0.692	0.983	0.902	1.071
PASSGEN	-0.087	0.043	0.045	0.917	0.842	0.998

*N/A = not applicable. Note: Bold color indicates the significant variables at 0.05 level.

Equation 4.8 can be written as:

$$P/(1-P) = e^{\beta_o+\beta_1 X_1+\beta_2 X_2+.....\beta_n X_n}$$
$$= e\,\hat{}(0.652 - 0.746 * \text{TRAUNIT} - 0.365 * \text{SEATB} + 1.889 * \text{AIRB} + 0.475 * \text{INTERR} - 0.435 * \text{SNOW} + 0.372 * \text{HSPEED} + 0.263 * \text{REND} - 0.122 * \text{DAYLIGHT} + 0.802 * \text{STRAIG} + 0.165 * \text{LTURN} - 1.748 * \text{NEJECT} + 0.119 * \text{TWOLN})$$

Equation 4.9

According to the Model C results:

Variables that cause crash severity increase	Variables that cause crash severity decrease
Airbag deployment	Number of vehicles greater than two
Intersection/intersection-related	Seat belts used
Speed is 40 mph or above	Snow conditions
Rear-end collision	Crash happens in daylight
Crash happens on straight/following road	Driver not ejected or trapped
Maneuver was left turn	
Crash happens on two-lane road	

The positive sign of the coefficient (β) indicates the variable increases the possibility of causing a more severe crash, whereas the negative sign of the coefficient indicates that the variable reduces the probability of having a more severe crash. For example, the variable AIRB has a positive coefficient and indicates that air bag deployment has 6.613 higher odds of causing more severe crashes as compared to cases where it did not happen. The variable SEATB has a negative coefficient, which indicates that the seat belt use has 0.694 of higher odds of causing a less severe crash as compared to other safety equipment use. Associations of predicted probabilities and observed responses are shown in the Table 4.16. Model C has a c value of 0.68, which is a good indication of a good model fit.

Table 4.16: Association of Predicted Probabilities and Observed Responses of Model C

Percent concordant	67.1	Somers' D	0.359
Percent discordant	31.2	Gamma	0.366
Percent tied	1.7	Tau-a	0.156
Pairs	31,516,100	c	0.68

4.2.2.1 Accuracy of Model C

Crash data from 2009 were used to validate the multiple vehicle crash severity involving at least one older driver (Model C). The same procedure described in Section 4.2.1.1 was used to validate Model C. The logistic regression equation for Model C is given in Equation 4.8.

By substituting values of the variables for each crash in the above equation, probability (P) was calculated. If the calculated probability > 0.5, then it is considered as an event and value 1 was assigned; otherwise, it is considered as a nonevent and value 0 was assigned. Then the calculated or predicted value was compared with the observed value. Table 4.17 presents a classification table for Model C.

Table 4.17: Classification Table for Model C

Observed value	Predicted value		Total
	P_i>= 0.5	P_i< 0.5	
Y_i =1	139	590	729
Y_i=0	99	1,479	1,578

From Equation 4.6,

Sensitivity =139/729= 0.19 = 19 percent.

From Equation 4.7,

Specificity = 1479/1578 =0.94 = 94 percent.

From Equation 4.5,

Accuracy = (139+1479)/ (729+1578) =0.70 =70 percent.

Model C has a sensitivity of 19 percent, specificity of 94 percent, and an accuracy of 70 percent. This model can be used to predict non-events accurately, but events can be predicted marginally since fatal and injury crashes are typically more difficult to be modeled.

4.3 Road User Survey

A survey was conducted throughout the state of Kansas so that direct opinions of older drivers could be gathered. Figure 4.2 shows the Kansas zip codes map where surveys were conducted and survey forms were collected from. Two primary methods were used to collect survey responses: a mail-back survey, and an online survey using Qualtrics software. Mail-back survey responses were collected mainly from senior citizen centers, area agencies on aging, and churches. A list of places where the survey was conducted is shown in Appendix C. The analysis and results of the road user survey are discussed in this section, where the preliminary analysis of likelihood of occurrence and percentages were first calculated. Then, the contingency table analysis was carried out to understand the relationships among key variables.

The survey form used is provided in Appendix D. The survey form consists of three parts:

Part 1: Background information about the respondent

Part 2: Information about the respondent's health as related to health

Part 3: Information about mobility and driving activities of the respondent

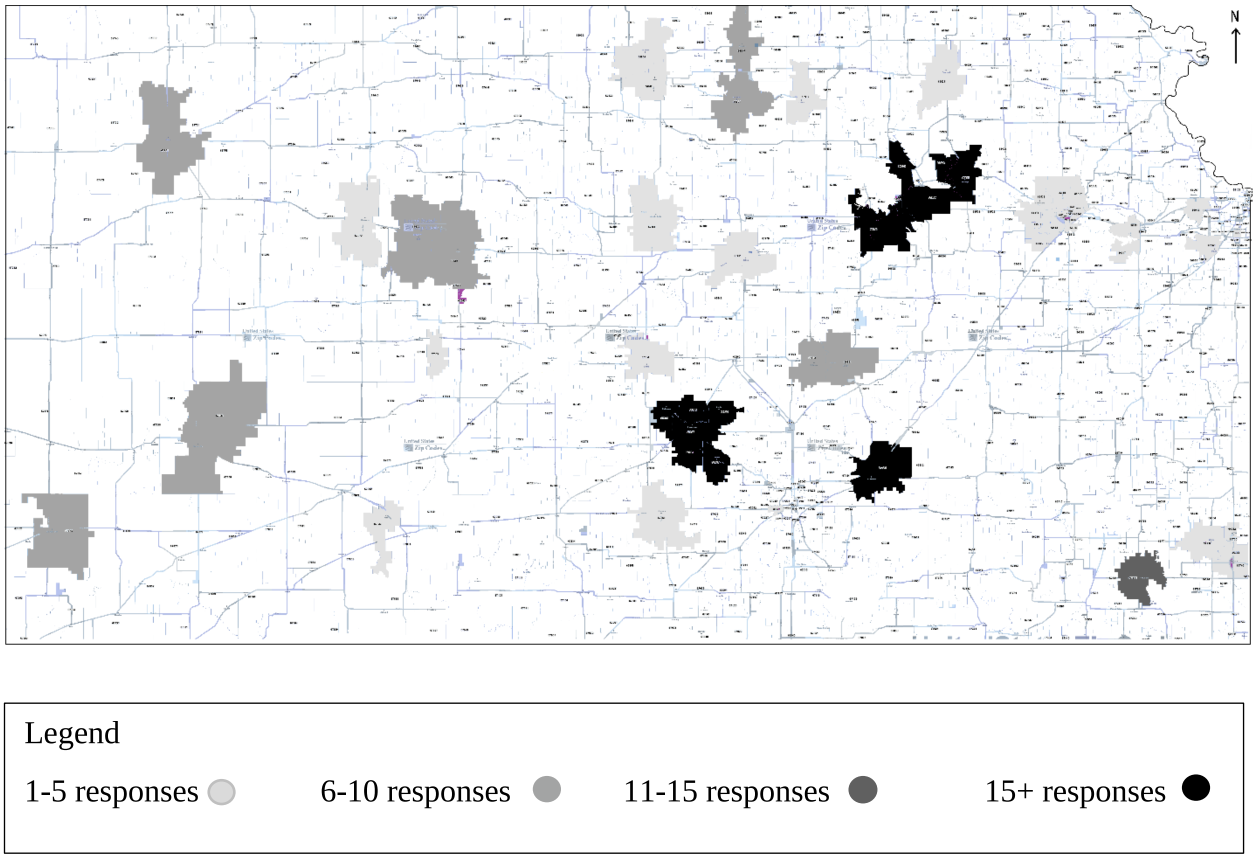


Figure 4.2: Kansas Zip Codes Map of Survey Responses

4.3.1 Descriptive Statistics

A total of 541 survey responses were collected, out of which 164 forms were in the 55–64 year old age range, which is considered as the reference age group to the older driver group. As the first step of the analysis, simple percentages were calculated for the older driver group (65+ age range) and the reference group for every question to get an idea about the overall situation.

Questions 1 to 8 of the survey gathered background information of the drivers, including age, gender, zip code of the residence, marital status, level of education, use of a mobile phone, internet usage, and household income category. Table 4.18 shows the distribution of survey responses for those general background type questions, where a reasonable representation by both age groups (older driver vs. reference group) could be seen. Out of all the valid responses, older males were 25.8 percent and females were 70.3 percent. However, reference group distribution was 42.68 percent to 56.71 percent among males and females. Percentage of respondents who live as singles in the older-driver group is much higher than the corresponding percentage in the reference group. In the older-driver group, the single respondents were 45.09 percent and for reference group, it was 29.27 percent. Use of mobile phones in the car was higher in the reference group and its use as the primary phone was significantly higher than the older-driver group. Nearly 28 percent of the older-driver group and 50.48 percent of reference group drivers used a mobile phone as their primary phone. More than half of the older-driver group had a high school-level education, and the reference group had more formal education than older driver group. Internet usage and income level of the reference group were also greater than those of the older-driver group. A possible reason for this situation was that more respondents in the reference-age group were still working, but most of the older-driver respondents were retired and/or out of the workforce.

Table 4.18: Summary of Responses on Background Information by Respondents

Question	Frequency	Percentage %	Frequency	Percentage %
	Older-driver group		Reference group	
Q: What is your age group?				
55–59 years	NA	NA	81	49.39
60–64 years	NA	NA	83	50.61
65–69 years	66	17.51		
70–74 years	83	22.02		
75–79 years	83	22.02		
80–84 years	70	18.57		
85+ years	75	19.89		
TOTAL	377	100.00	164	100.00
Q: What is your gender?				
Male	97	25.80	70	42.68
Female	264	70.21	93	56.71
No response	15	3.99	1	0.61
TOTAL	377	100.00	164	100.00
Q: What is your marital status?				
Single	170	45.09	48	29.27
Married	172	45.62	115	70.12
No response or other	35	9.28	1	0.61
TOTAL	377	100.00	164	100.00
Q: What is your highest level of education?				
Elementary school	11	2.92	0	0.00
High school	199	52.79	65	39.63
College degree	83	22.02	56	34.15
Graduate degree	48	12.73	38	23.17
No response	36	9.55	5	3.05
TOTAL	377	100.00	164	100.00
Q: How do you use a mobile phone?				
I use it in my car.	63	14.22	32	15.38
It is my primary phone	124	27.99	105	50.48
I use it away from home	190	42.89	67	32.21
I don’t own one	49	11.06	2	0.96
No response	17	3.84	2	0.96
TOTAL	443	100.00	208	100.00
Q: How often do you use the internet?				
Daily	140	37.14	107	65.24
Three to four days/week	34	9.02	31	18.90
Weekly	21	5.57	9	5.49
Maybe a couple times/ month	21	5.57	8	4.88
I don't use the internet.	122	32.36	3	1.83
Unknown	39	10.34	6	3.66
TOTAL	377	100.00	164	100.00
Q: How much is your annual household income?				
Less than $9,999	17	4.51	2	1.22
$10,000–$19,999	72	19.10	16	9.76
$19,999–$29,999	45	11.94	11	6.71
$30,000–$39,999	26	6.90	22	13.41
$40,000–$49,999	30	7.96	11	6.71
More than $50,000	51	13.53	36	21.95
Prefer not to answer	90	23.87	63	38.41
Unknown	46	12.20	3	1.83
TOTAL	377	100.00	164	100.00

Table 4.19 provides a summary of responses for health-related information in the survey questionnaire. Older-driver respondents rated their health at the good or very good level. They rated their hearing as not as good as their vision. Altogether, the responses confirmed that the reference group had better health conditions as they were younger than the older-driver respondents.

Table 4.19: Summary of Responses on Health Information by Respondents

Question	Frequency	Percentage	Frequency	Percentage
	Older driver-group		Reference group	
Q: How do you rate your current health?				
1(Very poor)	3	0.80	0	0.00
2	5	1.33	4	2.44
3	82	21.75	17	10.37
4	192	50.93	52	31.71
5(very good)	91	24.14	91	55.49
Unknown	4	1.06	0	0.00
TOTAL	377	100.00	164	100.00
Q: How do you rate your vision? (Corrected with glasses or contact lenses if needed.)				
1(Very poor)	3	0.80	2	1.22
2	13	3.45	6	3.66
3	67	17.77	15	9.15
4	174	46.15	73	44.51
5(very good)	114	30.24	68	41.46
Unknown	6	1.59	0	0.00
TOTAL	377	100.00	164	100.00
Q: How do you rate your hearing? (Corrected with hearing aids if needed.)				
1(Very poor)	8	2.12	1	0.61
2	26	6.90	3	1.83
3	84	22.28	15	9.15
4	161	42.71	43	26.22
5(very good)	94	24.93	101	61.59
Unknown	4	1.06	1	0.61
TOTAL	377	100.00	164	100.00

Summary of responses for the mobility and driving behavior-related questions in the survey form are provided in Table 4.20. Most of the older-driver respondents were currently driving, and most of them have more than 50 years of driving experience. Both older drivers and reference-group drivers tend to use cars, SUVs, or pickup trucks, and most of the vehicles were less than 15 years of age.

Table 4.20: Responses on Mobility and Driving Behavior of Drivers in Kansas; Part 1

Question	Frequency	Percentage	Frequency	Percentage
	Older-driver group		Reference group	
Q: Do you currently drive?				
Yes	364	96.55	161	98.17
No	11	2.92	3	1.83
Unknown	2	0.53	0	0.00
TOTAL	377	100.00	164	100.00
Q: How long have you been driving?				
0–10 years	0	0.00	0	0.00
11–20 years	0	0.00	0	0.00
21–30 years	5	1.33	12	7.32
31–40 years	16	4.24	75	45.73
41–50 years	23	6.10	64	39.02
More than 50 years	321	85.15	10	6.10
Unknown	12	3.18	3	1.83
TOTAL	377	100.00	164	100.00
Q: What type of vehicle do you usually drive?				
(1) Car	237	54.36	89	49.44
(2) SUV	70	16.06	53	29.44
(3) Van	33	7.57	10	5.56
(4) Pick-up truck	55	12.61	22	12.22
(5) Other	10	2.29	3	1.67
Unknown	31	7.11	3	1.67
TOTAL	436	100.00	180	100.00
Q: How old is the vehicle you drive?				
0–5 years	130	34.48	61	37.20
6–10 years	109	28.91	58	35.37
11–15 years	84	22.28	35	21.34
16–20 years	28	7.43	6	3.66
21–25 years	9	2.39	0	0.00
More than 25 years	4	1.06	0	0.00
Unknown	13	3.45	4	2.44
TOTAL	377	100.00	164	100.00

Most older-driver respondents and reference-age-group drivers drove less than 500 miles per month. Also, 25.2 percent of older-driver respondents drove less than 100 miles per month, which was almost twice that of the reference group drivers' percentage. Compared to reference-group drivers, older-driver respondents indicated that intersections were more complicated in comparison to driving on other roadways. Roundabouts followed by no-control intersections were the most difficult places for older-driver respondents. Stop sign- and yield sign-controlled locations were also difficult for them. Also, as shown in Table 4.4, older drivers were overly represented in crashes at roundabouts, stop signs, and yield signs, according to Kansas crash data.

Approximately 85 percent of both groups responded that they hadn't had any traffic violation during the past 5 years, and speeding was the main violation of both groups, when present.

Table 4.20: Responses on Mobility and Driving Behavior of Drivers in Kansas; Part 2

Question	Frequency	Percentage	Frequency	Percentage
	Older-driver group		Reference group	
Q: Approximately how many miles do you drive per month?				
0–100 miles	95	25.20	21	12.80
101–200 miles	93	24.67	58	35.37
201–500 miles	84	22.28	49	29.88
501–1,000 miles	45	11.94	14	8.54
1,001–2,000 miles	20	5.31	12	7.32
More than 2,000 miles	11	2.92	6	3.66
Unknown	29	7.69	4	2.44
TOTAL	377	100.00	164	100.00
Q: Do you have any difficulties at intersections compared to driving on other roadways?				
Yes	72	19.10	17	10.37
No	287	76.13	142	86.59
Unknown	18	4.77	5	3.05
TOTAL	377	100.00	164	100.00
Q: If yes, what locations are more difficult?				
(1) Stop lights/ traffic lights	7	8.33	8	38.10
(2) Roundabouts	33	39.29	9	42.86
(3) STOP sign-controlled	10	11.90	0	0.00
(4) No control	17	20.24	3	14.29
(5) YIELD sign-controlled	11	13.10	1	4.76
Unknown	6	7.14	0	0.00
TOTAL	84	100.00	21	100.00
Q: Have you received any traffic violation(s) during the past five years?				
None	320	84.88	140	85.37
Speeding	22	5.84	15	9.15
Driving too slow	0	0.00	0	0.00
DUI	0	0.00	1	0.61
Reckless driving	4	1.06	0	0.00
Expired tags/ license	2	0.53	0	0.00
Equipment violations	2	0.53	0	0.00
Improper turns	3	0.80	0	0.00
Other	5	1.33	3	1.83
Unknown	19	5.04	5	3.05
TOTAL	377	100.00	164	100.00

Most older-driver respondents didn’t attend any driver awareness programs and most were unaware of the CarFit program. In this program, older drivers can have information on minor adjustments of their automobiles, which offers an opportunity to check how well their personal vehicles fit them. Also, materials regarding road safety are provided to older drivers during the program. KDOT is already conducting these CarFit programs statewide, but older drivers’ awareness of the CarFit program was very low regardless of the urban or rural nature of the zip code. Older drivers’ awareness was categorized as urban-rural by nature of the zip code. According to the United States Census Bureau, it identifies two types of urban areas: urbanized areas (UAs) of 50,000 or more people, and urban clusters (UCs) of at least 2,500 and less than 50,000 people. All populations not included within an urban area can be identified as rural. In most of the zip codes where the survey was conducted, driver awareness of CarFit was less than the 33.33 percent, even though it is important to point out these are based on stated responses. These data are presented in Appendix E. Also, a contingency table analysis was conducted in order to identify the relationship between CarFit awareness and urban or rural nature of the zip code. Results showed those two variables were independent of each other.

Most older-driver respondents never tried to find public transportation in their area. Around 11 percent of older-driver respondents didn’t know how to find information on public transportation. Nearly half of the reference-group drivers also never tried to find information on public transportation, which is understandable because almost everyone in this group are working and normally functioning adults.

Only 33 percent of older-driver respondents have access to public transportation within walking distance, and they tend to quit driving mainly when they feel unsafe or when a doctor advises it. However, they were more willing to quit driving when they themselves felt unsafe, or when their vision got poor. Interventions by family members were not very high among the possible reasons compared to that of medical professionals. Most older-driver respondents have no plans for when they can no longer safely drive. Some even mentioned “die” as an option. Some older-driver respondents have plans such as staying close to children or going to a retirement/ nursing home. More older-driver respondents than reference-group respondents responded that Kansas roads are safe.

Table 4.20: Responses Given for Mobility and Driving Behavior of Drivers in Kansas; Part 3

Question	Frequency	Percentage	Frequency	Percentage
	Older-driver group		Reference group	
Q: Have you participated in any driving awareness programs?				
Yes	108	28.65	28	17.07
No	257	68.17	132	80.49
Unknown	12	3.18	4	2.44
TOTAL	**377**	**100.00**	**164**	**100.00**
Q: Are you aware of any driver awareness programs such as CarFit?				
Yes	102	27.06	48	29.27
No	247	65.52	113	68.90
Unknown	28	7.43	3	1.83
TOTAL	**377**	**100.00**	**164**	**100.00**
Q: On average, how often do you drive?				
About once a month	3	0.80	0	0.00
Two to three times/month	5	1.33	1	0.61
Four to five times/month	11	2.92	3	1.83
Eight to 20 times/month	74	19.63	29	17.68
More than 20 times/ month	260	68.97	125	76.22
I don’t drive.	9	2.39	2	1.22
Unknown	15	3.98	4	2.44
TOTAL	**377**	**100.00**	**164**	**100.00**
Q: What is your most common trip purpose?				
(1) Grocery shopping	185	31.04	63	26.47
(2) To see a doctor	99	16.61	18	7.56
(3) To visit relatives/ children	80	13.42	31	13.03
(4) Other	172	28.86	118	49.58
Unknown	60	10.07	8	3.36
TOTAL	**596**	**100.00**	**238**	**100.00**
Q: Do you know how to find information about public transportation in your area?				
No	41	10.88	22	13.41
I have never tried.	168	44.56	79	48.17
Yes	144	38.20	59	35.98
Unknown	24	6.37	4	2.44
TOTAL	**377**	**100.00**	**164**	**100.00**

Table 4.20: Responses Given for Mobility and Driving Behavior of Drivers in Kansas; Part 4

Question	Frequency	Percentage	Frequency	Percentage
	Older-driver group		Reference group	
Q: Do you have access to a bus (public transportation) within walking distance of your residence?				
Yes	125	33.16	34	20.73
No	170	45.09	83	50.61
Don't know	68	18.04	44	26.83
Unknown	14	3.71	3	1.83
TOTAL	**377**	**100.00**	**164**	**100.00**
Q: Would (or did) you quit driving for any of these reasons:				
(1) When my doctor advises	144	20.75	66	20.12
(2) When my adult children interfere	75	10.81	24	7.32
(3) When my vision gets poor	124	17.87	68	20.73
(4) When my spouse advises	44	6.34	30	9.15
(5) When I feel unsafe	228	32.85	120	36.59
(6) Other	7	1.01	3	0.91
Unknown	72	10.37	17	5.18
TOTAL	**694**	**100.00**	**328**	**100.00**
Q: What are your plans when you can no longer safely drive? (Please specify)	NA	NA	NA	NA
Q: Do you consider Kansas roads safe?				
Yes	255	67.64	89	54.27
No	37	9.81	26	15.85
No opinion	66	17.51	45	27.44
Unknown	19	5.04	4	2.44
TOTAL	**377**	**100.00**	**164**	**100.00**
Q: In your opinion, what are the primary dangers on Kansas roads?				
(1) Speeding	174	23.29	68	22.97
(2) Road rage	67	8.97	16	5.41
(3) Distracted drivers	256	34.27	126	42.57
(4) Drivers under influence	111	14.86	46	15.54
(5) Construction zones	69	9.24	30	10.14
(6) Other	26	3.48	10	3.38
Unknown	44	5.89	0	0.00
TOTAL	**747**	**100.00**	**296**	**100.00**

NA – Open ended question

4.3.2 Comparison between Driving Behavior of Older-Driver Group and Reference Group

The last part of the survey asked for information about mobility and driving conditions related to respondents. Driving situations and conditions that are important are highlighted in this section.

Table 4.21 represents road-use behavior of older drivers and reference-group drivers. As described in the methodology in Section 3.3, likelihood of occurrence (score) of road use behavior was calculated. For older-driver respondents, seatbelt use as a driver had the highest score, which means a 93.95 likelihood of occurrence they will wear seat belts as drivers. In this case, the reference group showed a higher rank than older drivers. The reference group showed a higher score than the older-driver group as passengers, too. Most of the time, older drivers and reference-age-group drivers drive alone. The score value of the reference group for driving alone was higher than for the older-driver group. Driving in adverse weather conditions, such as wind or rain, had an almost identical score for older drivers and for the reference group. However, in snowy weather conditions, older drivers had a lesser score than the reference group. This result tallies with crash severity modeling, which showed in snowy conditions older drivers had less crash severity because they drive less in snowy weather conditions. Older drivers had a score of 52.65 for driving while using over-the-counter medicines, which is not a good condition. However, the reference group has a lesser chance of driving while using over-the-counter medicines, as it can be expected. Driving in heavy traffic, and driving against the sun or with the sun behind, is much harder on older drivers than the reference group.

Table 4.21: Road Use Behavior of Older Drivers (OD) and Reference Group (RG) Drivers; Part 1

Behavior		Never	Very rarely	Sometimes	Most of the time	Always	Total*	Score
How often do you wear the seat belt while driving?	Frequency of OD	2	5	11	39	290	377	94.0
	% of OD	0.5	1.3	2.9	10.3	76.9	100.0	
	Frequency of RG	2	3	2	7	141	164	95.5
	% of RG	1.2	1.8	1.2	4.3	86.0	100.0	
How often do you wear the seat belt as a passenger?	Frequency of OD	7	5	11	49	275	377	91.8
	% of OD	1.9	1.3	2.9	13.0	72.9	100.0	
	Frequency of RG	1	2	3	11	137	164	95.6
	% of RG	0.6	1.2	1.8	6.7	83.5	100.0	
Do you think medical professionals should report their patients who are mentally or physically impaired?	Frequency of OD	23	15	64	45	158	377	74.6
	% of OD	6.1	4.0	17.0	11.9	41.9	100.0	
	Frequency of RG	6	10	48	23	34	164	64.3
	% of RG	3.7	6.1	29.3	14.0	20.7	100.0	
How often do you drive alone?	Frequency of OD	10	14	80	174	51	377	68.4
	% of OD	2.7	3.7	21.2	46.2	13.5	100.0	
	Frequency of RG	2	1	40	95	14	164	69.4
	% of RG	1.2	0.6	24.4	57.9	8.5	100.0	
How often do you drive in windy weather conditions?	Frequency of OD	5	35	156	81	54	376	60.9
	% of OD	1.3	9.3	41.4	21.5	14.3	100.0	
	Frequency of RG	0	6	97	30	19	164	60.2
	% of RG	0.0	3.7	59.2	18.3	11.6	100.0	
How often do you drive in rainy weather conditions?	Frequency of OD	12	61	174	49	39	377	53.1
	% of OD	3.2	16.2	46.2	13.0	10.3	100.0	
	Frequency of RG	2	11	106	16	16	164	55.5
	% of RG	1.2	6.7	64.6	9.8	9.8	100.0	
How often do you drive when on prescription or over-the-counter medicine?	Frequency of OD	76	40	57	56	85	377	52.7
	% of OD	20.2	10.6	15.1	14.9	22.6	100.0	
	Frequency of RG	23	23	38	9	28	164	49.2
	% of RG	14.0	14.0	23.2	5.5	17.1	100.0	
Do you think reports by medical professionals should be anonymous?	Frequency of OD	73	30	63	47	80	377	52.7
	% of OD	19.4	8.0	16.7	12.5	21.2	100.0	
	Frequency of RG	28	7	34	12	39	164	55.6
	% of RG	17.1	4.3	20.7	7.3	23.8	100.0	
Driving in heavy traffic	Frequency of OD	31	55	148	45	39	377	50.5
	% of OD	8.2	14.6	39.3	11.9	10.3	100.0	
	Frequency of RG	59	25	53	7	5	164	28.9
	% of RG	36.0	15.2	32.3	4.3	3.1	100.0	
Driving against the sun or sun behind you	Frequency of OD	33	64	142	44	28	377	47.6
	% of OD	8.8	17.0	37.7	11.7	7.4	100.0	
	Frequency of RG	53	23	46	26	2	164	33.5
	% of RG	32.3	14.0	28.1	15.9	1.2	100.0	
How often do you drive in snowy weather conditions?	Frequency of OD	26	87	157	35	32	377	47.0
	% of OD	6.9	23.1	41.6	9.3	8.5	100.0	
	Frequency of RG	2	11	109	22	9	164	54.1
	% of RG	1.2	6.7	66.5	13.4	5.5	100.0	

*Total includes “unknown” and “does not apply” values.

Merging into traffic was harder for older-driver respondents, and was much easier for the reference group. When compared with nighttime driving and driving on freeways, the reference group had the higher score than the older-driver-respondent group. This may be because they are more active than older drivers and more likely to be engaged in driving under such conditions. The score for overtaking was higher for older-driver respondents than the reference group, which means overtaking is more difficult for older-driver respondents. Moving away from the traffic is much easier than merging into traffic for older-driver respondents as well as for reference group. Judging gaps when merging or turning, followed by lane changing, were the most-difficult tasks for older-driver respondents. Driving with passengers was more difficult for the older-driver group than the reference group. Making left turns at unsignalized intersections was harder than making left turns without a green arrow, followed by a left turn with a green arrow, for both groups. Detecting traffic signs or signals was more difficult for the older-driver group than the reference group. Making right turns was much easier than making left turns even with a green arrow, which was the least difficult option for both groups. Yielding or stopping was much harder for the older-driver respondents than the reference group. Difficulty in yielding or stopping increased crashes at intersections for the older-driver group. Results of the survey matched with the data extracted from the KCARS database, which also showed that older drivers have more difficulties at intersections.

Table 4.21: Road Use Behavior of Older Drivers (OD) and Reference Group (RG) Drivers; Part 2

Behavior		Never	Very rarely	Sometimes	Most of the time	Always	Total*	Score
Merging into traffic is more difficult?	Frequency of OD	49	67	139	37	31	377	44.9
	% of OD	13.0	17.8	36.9	9.8	8.2	100.0	
	Frequency of RG	62	33	44	9	1	164	25.5
	% of RG	37.8	20.1	26.8	5.5	0.6	100.0	
How often do you drive at night compared to daytime?	Frequency of OD	24	86	176	26	14	377	43.9
	% of OD	6.4	22.8	46.7	6.9	3.7	100.0	
	Frequency of RG	3	14	107	17	10	164	52.8
	% of RG	1.8	8.5	65.2	10.4	6.1	100.0	
How frequently do you drive on freeways/interstates/turnpikes?	Frequency of OD	37	81	158	37	13	377	42.9
	% of OD	9.8	21.5	41.9	9.8	3.5	100.0	
	Frequency of RG	2	11	101	27	7	163	54.4
	% of RG	1.2	6.7	61.6	16.5	4.3	100.0	

Table 4.21: Road Use Behavior of Older Drivers (OD) and Reference Group (RG) Drivers; Part 2 (Continued)

Behavior that has become more difficult?		Never	Very rarely	Sometimes	Most of the time	Always	Total*	Score
Overtaking/passing on roads with one lane in each direction	Frequency of OD	68	91	110	17	20	377	36.1
	% of OD	18.0	24.1	29.2	4.5	5.3	100.0	
	Frequency of RG	75	24	49	1	1	164	21.5
	% of RG	45.7	14.6	29.9	0.6	0.6	100.0	
Moving away from the traffic	Frequency of OD	70	101	96	20	19	377	35.1
	% of OD	18.6	26.8	25.5	5.3	5.0	100.0	
	Frequency of RG	75	32	38	1	1	164	19.6
	% of RG	45.7	19.5	23.2	0.6	0.6	100.0	
Judging gaps when merging or making a turn	Frequency of OD	69	105	93	21	17	377	34.6
	% of OD	18.3	27.9	24.7	5.6	4.5	100.0	
	Frequency of RG	72	26	47	2	1	164	22.0
	% of RG	43.9	15.9	28.7	1.2	0.6	100.0	
Lane changing	Frequency of OD	74	98	105	23	12	377	34.1
	% of OD	19.6	26.0	27.9	6.1	3.2	100.0	
	Frequency of RG	70	31	44	3	1	164	22.2
	% of RG	42.7	18.9	26.8	1.8	0.6	100.0	
Have you felt unsafe as a passenger?	Frequency of OD	77	129	83	15	13	377	30.9
	% of OD	20.4	34.2	22.0	4.0	3.5	100.0	
	Frequency of RG	34	71	46	0	0	164	27.0
	% of RG	20.7	43.3	28.1	0.0	0.0	100.0	
Driving with passengers	Frequency of OD	89	99	95	16	9	377	30.3
	% of OD	23.6	26.3	25.2	4.2	2.4	100.0	
	Frequency of RG	79	28	38	3	0	164	19.1
	% of RG	48.2	17.1	23.2	1.8	0.0	100.0	
Making left turns at un-signalized intersections	Frequency of OD	94	102	81	17	13	377	29.9
	% of OD	24.9	27.1	21.5	4.5	3.5	100.0	
	Frequency of RG	82	30	35	2	0	164	17.8
	% of RG	50.0	18.3	21.3	1.2	0.0	100.0	
Detecting traffic signs/signals	Frequency of OD	100	98	76	14	15	377	29.0
	% of OD	26.5	26.0	20.2	3.7	4.0	100.0	
	Frequency of RG	80	30	37	0	1	164	18.2
	% of RG	48.8	18.3	22.6	0.0	0.6	100.0	
Making left turns at traffic signals without a green arrow	Frequency of OD	103	104	80	14	9	377	27.6
	% of OD	27.3	27.6	21.2	3.7	2.4	100.0	
	Frequency of RG	85	29	35	0	0	164	16.6
	% of RG	51.8	17.7	21.3	0.0	0.0	100.0	
Making left turns at traffic signals with a green arrow	Frequency of OD	130	89	53	14	18	377	25.4
	% of OD	34.5	23.6	14.1	3.7	4.8	100.0	
	Frequency of RG	90	24	33	0	1	164	15.9
	% of RG	54.9	14.6	20.1	0.0	0.6	100.0	
Making right turns	Frequency of OD	133	98	47	14	18	377	24.7
	% of OD	35.3	26.0	12.5	3.7	4.8	100.0	
	Frequency of RG	91	26	29	2	0	164	15.2
	% of RG	55.5	15.9	17.7	1.2	0.0	100.0	

Table 4.21: Road Use Behavior of Older Drivers (OD) and Reference Group (RG) Drivers; Part 2 (Continued)

Behavior		Never	Very rarely	Sometimes	Most of the time	Always	Total*	Score
Yielding or stopping	Frequency of OD	131	99	45	14	18	377	24.7
	% of OD	34.8	26.3	11.9	3.7	4.8	100.0	
	Frequency of RG	93	25	30	0	1	164	14.9
	% of RG	56.7	15.2	18.3	0.0	0.6	100.0	
How often do you make sudden stops or slow down on the road without any real necessity?	Frequency of OD	170	116	22	6	3	377	15.0
	% of OD	45.1	30.8	5.8	1.6	0.8	100.0	
	Frequency of RG	70	55	21	2	0	164	17.4
	% of RG	42.7	33.5	12.8	1.2	0.0	100.0	
Have you ever reported someone as an unsafe driver?	Frequency of OD	265	36	16	4	5	377	7.7
	% of OD	70.3	9.6	4.2	1.1	1.3	100.0	
	Frequency of RG	112	11	16	2	1	164	9.3
	% of RG	68.3	6.7	9.8	1.2	0.6	100.0	
How often do you drive after consuming alcohol?	Frequency of OD	261	30	5	1	0	377	3.6
	% of OD	69.2	8.0	1.3	0.3	0.0	100.0	
	Frequency of RG	103	24	16	1	1	164	10.9
	% of RG	62.8	14.6	9.8	0.6	0.6	100.0	

*Total includes “unknown” and “does not apply” values.

4.3.3 Contingency Table Analysis Results

Contingency table analysis was performed with a level of confidence of 0.95 to identify the relationship between a variable and an age group. The null hypothesis (H_o) was established. The degree of freedom can be calculated using Equation 3.11, and in this case, for all scenarios it is equal to 1. The Chi-square value for 0.95 confidence level and degree of freedom of 1 is 3.841. Observed frequencies of survey responses are given in Table 4.22. For the less frequent category, the sum of “Never,” “Very rarely,” and “Sometimes” of survey responses were used. The more frequent category included the sum of “Most of the time” and “Always” subcategories.

Table 4.22: Observed Frequencies for Survey Responses on Question Regarding Seatbelt Usage While Driving

Question		Older-driver group	Reference group	Total
How often do you wear the seat belt while driving?	Less frequent	18	7	25
	More frequent	329	148	477
	Total	347	155	502

As described in the methodology Section 3.4 and Equation 3.12, expected frequencies of survey responses were calculated.

Table 4.23: Expected Frequencies for Survey Responses on Question Regarding Seatbelt Usage While Driving

Question		Older-driver group	Reference group	Total
How often do you wear the seat belt while driving?	Less frequent	17.28	7.72	25
	More frequent	329.72	147.28	477
	Total	347	155	502

For the question, "How often do you wear the seat belt while driving?" in the survey, Null hypotheses H_o is:

H_o = Wearing seat belt while driving and age group are independent of each other.

H_1 = H_o is not true.

$$\chi^2_{est} = \frac{(18-17.28)^2}{17.28} + \frac{(7-7.72)^2}{7.72} + \frac{(329-329.72)^2}{329.72} + \frac{(148-147.28)^2}{147.28}$$ **Equation 4.6**

$$\chi^2_{est} = 0.102$$

$$(\chi^2_{est} = 0.102) < (\chi^2_{critical} = 3.841)$$

Therefore, the null hypothesis of independence is not rejected (Dixon & Massey, 1951). Age group and seat belt usage as a driver are independent of each other or there is no difference based on the age category. The rest of the results are included in Table 4.24.

The driving on freeways/interstates/turnpikes variable has a relationship with the age group variable, which means driving on freeways depends on the age group. Conditions such as driving in heavy traffic, merging into traffic, moving away from the traffic, judging gaps when merging or making a turn, overtaking/passing on roads with one lane in each direction, lane changing, driving against the sun or sun behind you, and driving with passengers were dependent of the age group. When comparing older-driver respondents with the reference age group, most of these conditions were difficult for older-driver respondents. According to general crash data presented in Table 4.3 and comparisons with all age groups in Table 4.4, older drivers were not good at maneuvering intersections. This is confirmed furthermore from results of the contingency table analysis, as making left turns at traffic signals without a green arrow and making left turns at un-signalized intersections were related to age group. Driving after consuming alcohol was related to the age group as well. According to KCARS data, alcohol-related, older-driver crash frequency is much less when compared with all-age drivers.

For the question regarding CarFit awareness, the contingency table analysis was performed with a level of confidence of 0.95, as described in methodology Section 3.4. In this analysis, a zip code is considered as urban if the population of that particular zip code is 50 percent or greater in urban areas (ProximityOne, 2016). At least 50 percent of the responders were aware of the CarFit program which was considered as "Aware" category. More detailed tables regarding CarFit awareness and contingency table analysis are included in Appendix E. According to the results, CarFit awareness and urban/rural nature of the zip code are independent of each other.

Table 4.24: Contingency Table Analysis Results

Variable compared with age group	χ^2_{est} **value**	**Result** Variable pair is independent = Yes Variable pair is dependent = No
Drive at night compared to day time	2.691	Yes
Drive in rainy weather conditions	1.443	Yes
Drive in snowy weather conditions	0.010	Yes
Drive in windy weather conditions	3.228	Yes
Drive alone	0.540	Yes
Drive on freeways/ interstates/ turnpikes	4.070	No
Drive when on prescription or over-the-counter medicine	7.415	No
Think medical professionals should report their patients who are mentally or physically impaired	13.780	No
Reports by medical professionals should be anonymous	0.025	Yes
Driving in heavy traffic	37.705	No
Merging into traffic	31.982	No
Moving away from traffic	11.972	No
Judging gaps when merging or making a turn	46.291	No
Overtaking/passing on roads with one lane in each direction	8.076	No
Lane changing	6.689	No
Driving against the sun or sun behind you	16.374	No
Driving with passengers	5.547	No
Detecting traffic signs/signals	3.701	Yes
Making left turns at traffic signals without a green arrow	4.537	No
Making left turns at traffic signals with a green arrow	1.277	Yes
Making left turns at un-signalized intersections	5.868	No
Making right turns	1.130	Yes
Yielding or stopping	1.015	Yes
Reported someone as an unsafe driver	3.788	No
Make sudden stops or slow down on road without any real necessity	3.263	Yes
Drive after consuming alcohol	20.497	No
Felt unsafe as a passenger	0.951	Yes

Note: Bold color indicates variables related with the age group.

4.4 Countermeasure Ideas

Countermeasures for improving older driver safety and hence mobility of the aging population can be identified based on crash analysis and survey study. The following general countermeasure ideas were obtained from the literature review and provided to reduce older drivers' crash risk on Kansas roadways.

- Older-driver education/awareness programs
- Older-driver licensing programs
- Discuss safety practices
- Roadway improvements
  - Clear zones and dedicated left-turn signals at intersections
  - Median barriers, rumble strips, paved shoulders
  - Street lighting
    - Intersections with overhead lighting
    - Complete interchange lighting
- Traffic calming measures
- Law enforcement

Older-driver education programs can be taken as the most prioritized option of the countermeasures for several reasons. First, these programs can be used as a facilitator of older drivers' decisions about when to stop driving and increase their knowledge of other transportation options (NHTSA, 2014). From the survey, it is clear that older-drivers' knowledge about available public transportation options is low. Less than half of older drivers were aware of at least how to find information about public transportation and one-third of them had access to public transportation within walking distance of their residence. Therefore, driver education programs can be used as an opportunity to provide information about public transportation, and other regional services such as ATA bus service in Manhattan and Rcat service. Secondly, driver awareness programs can be used to address specifically identified problems such as the CarFit program, which helps older drivers adjust their vehicles to the best fit for them.

Older-driver licensing can be taken as the next prioritized option to control risk on the road. In Kansas, both vision and written tests are required to be taken by drivers aged 65 and older, but the road test is not necessary for all older drivers (DMV.com, n.d.). However, the literature showed that drivers over 75 years of age had drastically decreasing physical fitness and were involved in more crashes (Stutts, Martell, & Staplin, 2009). Therefore, a 4-year license renewal time can be reduced for drivers aged 75 years or older. In addition to a vision test, legislative steps can be taken to require older drivers to be evaluated for muscle strength, flexibility and range of motion, coordination and reaction time, judgment and decision-making skills, and ability to drive with adaptive equipment.

Some safety practices such as seat belt use as a driver or passenger, avoiding alcohol consumption or illegal drug use when driving, safety driving tips, and a refresher course on road rules can be discussed, and then maintained or improved by addressing those in senior centers, area agencies on aging, or at gatherings of older drivers. Driver awareness programs, CarFit program, child passenger safety programs, and Area Agency on Aging (AAA) driver improvement programs can be used to introduce safety practices effectively.

To improve the safety of older drivers, several improvements can be made on roadways as well. According to the KCARS database, from 2010 to 2014, older drivers were involved in 29.82 percent (Appendix A) of crashes at intersections, which is a considerable percentage. Therefore, improvements can be made at intersections to reduce crashes by providing more clear zones on nearby sections and additional overhead lighting (Staplin, Lococo, Byington, & Harkey, 2001). Survey results showed that older-driver respondents had difficulties when merging into traffic and moving away from traffic. Therefore, more complete interchange lighting could be proposed (Staplin et al., 2001). Furthermore, KCARS data showed 76.9 percent (Appendix A) of older drivers are involved in crashes on straight and level roads, as Kansas has a flat terrain. Rumble strips, median barriers, and paved shoulders can help to reduce the number of crashes or reduce crash severity. The percentage of crashes of older drivers in daylight condition was 80.23 percent, as per the KCARS database, and survey results showed that older drivers tend to drive at night 43.87 percent of the time. Better street lighting conditions improve visibility at night. Also, conflicts or misjudgments of older drivers can be reduced by placing better road markings and signs. According to the crash analysis, left turns are a significant factor in single-vehicle, older-driver-only crashes, where they mostly hit nearby fixed objects; however, with at least one passenger, left turns were not significant. Also, survey results showed a 27.58 likelihood of occurrence of older drivers having difficulties in turning left without a green arrow signal. Therefore, dedicated left-turn signals are more appropriate for older-driver safety enhancement.

In order to improve older-pedestrians' safety, speed of vehicles can be reduced using traffic calming methods in areas of high senior citizen populations. European countries such as the Netherlands and Germany have a number of projects in position to improve the transportation infrastructure used by pedestrians (Pucher & Dijkstra, 2000). These have already been tested and can be adapted here in the United States. Traffic calming methods such as reducing speed in residential areas to 20 mph, roundabouts, road narrowing, speed bumps and humps, and raised intersections can be easily implemented. Furthermore, to provide a wider field of vision at intersections, regulations can be established for vehicles to park a minimal distance from the intersection. To simplify road crossings for older pedestrians or slower-moving pedestrians, refuge islands can be installed. Also, increased lighting at intersections will help both drivers and pedestrians. Also, vehicle-free zones or pedestrian malls can be introduced in downtown areas to improve the safety of pedestrians.

Finally, law enforcement plays a significant role in improving the safety of all drivers, including older drivers. Enforcement of seat belt usage may help increase seat belt usage of both drivers and occupants. Also, drivers with impairments can be identified and introduce them to licensing agencies.

Chapter 5: Summary and Conclusions

5.1 Summary and Conclusions

Transportation activity is a major component of the daily lives of the aging population because it allows this group to maintain their independence and mobility. One in five U.S. citizens is expected to be elderly by 2030. An increase in elderly population increases elderly drivers as well. Kansas has shown similar statewide trends in aging, making it important to identify which factors distinguish crash severity of older drivers from other drivers.

This study identified issues, concerns, and barriers about safety aspects of the elderly in Kansas by conducting a statewide survey and crash data analysis. Crash data were obtained from the Kansas Department of Transportation (KDOT) for 2009 to 2014. A questionnaire survey was distributed throughout the state, and a total of 541 survey responses were collected utilizing various methods.

5.1.1 Crash Characteristics of Older Drivers Involved in Crashes

General crash characteristics of older drivers were summarized. KDOT District One (Northeast Kansas) had the highest share of elderly related crashes, but when considering the older-driver crash involvement rate per 1,000 population, it had a rate below the average state rate. Other than KDOT Districts One and Six, older drivers' crash involvement rate per 1,000 population is higher in other districts than Kansas' average rate. Summarized crash data showed that the highest percentage of older drivers were involved in crashes on Fridays and the fewest on Sundays. Most older-driver-related crashes occurred in daytime without any adverse weather conditions. The highest percentage of crashes occurred between 3 and 6 p.m. Intersection or intersection-related crashes were a factor in 44.2 percent of all crashes. Older male drivers experienced higher crash involvement than their female counterparts.

Older-driver crash characteristics were then compared with all drivers (including older drivers). Fatal, incapacitating, and non-incapacitating injury percentages were higher in older drivers than all drivers. When compared with all drivers, older drivers were involved in four-way intersection crashes more often. In T-intersections, older drivers and all drivers had an almost identical percentage of crashes. Older drivers were found to be involved in crashes more often when a stop sign was present, as well as at a traffic signal or yield sign, than all drivers. Angle-side impact crashes were more common with older drivers when compared with all drivers. Furthermore, driver inattention, failure to yield the right of way, and improper lane changing were the most driver-contributing circumstances to a crash of older drivers, when compared with all drivers. Standing or moving water, followed by icy or slushy conditions, had the highest percentages of road-related contributing circumstances for older drivers. Crash with a domestic or wild animal was the highest environment-related contributory circumstance for older drivers compared with all drivers. Problems with vehicle brakes and cargos were the highest vehicle-related contributory circumstances represented more by older drivers than by all drivers.

5.1.2 Crash Severity Modeling

Statistical analysis was carried out using crash data obtained from KDOT. Three separate crash severity models were developed using binary logistic regression methods for single-vehicle crashes where only older driver is present (Model A), an older driver with at least one passenger present (Model B), and multi-vehicle crashes with at least one older driver involved (Model C). A 95 percent confidence level was used in each model. According to the analysis results, left turns were significant in single-vehicle crashes with only an older driver present, but were not significant in single-vehicle crashes involving an older driver with at least one passenger, meaning older drivers may be safer with passengers. No adverse weather conditions were significant and increased the severity of the accident in single-vehicle crashes but not in multi-vehicle crashes. From the analysis, daylight conditions were shown to be a factor that increased crash severity for single-vehicle crashes but were not significant in multi-vehicle crashes. In all three cases, air bag deployment was an indicator for a severe crash. Meanwhile, intersection-related crashes ended up with severe crash severities for single-vehicle crashes where only an older driver was present, and for multi-vehicle crashes. The weekend was a significant factor for increasing crash severity in single-vehicle crashes where only an older driver was present.

5.1.3 Road User Survey

Likelihood of occurrence and percentages were calculated for the preliminary analysis of the survey. Then the contingency table analysis was carried out to identify relationships between variables. Two age groups had been designated as the elderly age group (65+ years) and reference age group (55 to 64 years). In the survey, questions were asked regarding demographics, information about road users' health, and information about mobility and driving. Most of the older-driver-age-group respondents and all of the reference-group respondents had high school-level educations. Both age groups used mobile phones in the car with the same tendency; however, for the reference group, it was the primary phone for half of them. One-third of older-driver respondents didn't use the internet and one-third knew how to find information about public transportation. One-third of older-driver respondents and one-fifth of reference-group respondents had the access to a bus (public transportation) within walking distance from their residence. As expected, most older-driver respondents had no plan in place for when they could no longer safely drive and considered Kansas roads safe. Both groups rated distracted drivers, followed by speeding and drivers under the influence as primary dangers on Kansas roads.

For older-driver respondents, seatbelt use as a driver had the highest likelihood of occurrence (Score). In this case, the reference group showed a higher score than elderly drivers. Scores of driving alone were similar among older-driver respondents and the reference age group. When driving in adverse weather conditions such as snowy weather, the reference group had higher scores than older-driver respondents. Driving in heavy traffic, and driving against the sun or with the sun behind them was much harder for older drivers than the reference group. Merging into traffic was much harder for older-driver respondents than the reference group. The contingency table analysis was used to identify dependency between a particular variable and age group. Driving in heavy traffic, merging into traffic, moving away from traffic, and judging traffic gaps were dependent with age group. Making left turns at un-signalized intersections and at traffic signals without a green arrow were dependent with the age group, while making left turns at traffic signals with a green arrow was independent of the age group. The variables which depend on the age group should be treated carefully to lessen the effect on older drivers.

More attention can be provided for the conditions where the older drivers overly represented. The model results show which factors contribute either increasing or decreasing crash severity significantly. Road user survey provides insight into opinions of older road users. This study contributes to the road safety by addressing older driver safety.

5.2 Study Limitations

The multi-vehicle crash-severity model had a lesser accuracy than single-vehicle crash-severity models. This may be due to unforeseen factors such as a multi-vehicle crash creating a more complicated situation than a single-vehicle crash. Furthermore, a higher number of survey responses would be more efficient for a better in-depth analysis.

5.3 Future Studies

This study can be extended to further improve safety aspects by addressing driver contributory circumstances (CC), more of a factor than any other CCs. Also, from all analysis techniques, it was shown that older-drivers experienced the highest number of crashes at intersections. Therefore, these types of crashes could be analyzed separately in more depth.

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Appendix A: Summary Tables

Table A.1: Older Drivers and All Drivers (Including Older Drivers) Involved in Crashes Based on Accident Location

Year	Age in years	Accident Location						Total
		On roadway				Off roadway	Other and unknown	
		Non-intersection	Intersection +	Intersection-related +	other locations	Off roadway		
2014	65+	2,903	2,592	1,517	1,499	654	35	9,200
	All	28,678	19,887	15,027	14,671	9,516	203	87,982
	% of 65+	31.55	28.17	16.49	16.29	7.11	0.38	100
	% of All	32.60	22.60	17.08	16.68	10.82	0.23	100
2013	65+	3,279	2,548	1,310	1,264	510	11	8,922
	All	34,360	20,773	13,385	12,398	7,188	167	88,271
	% of 65+	36.75	28.56	14.68	14.17	5.72	0.12	100
	% of All	38.93	23.53	15.16	14.05	8.14	0.19	100
2012	65+	3,263	2,696	1,134	1,154	378	16	8,641
	All	35,866	21,192	12,792	12,073	5,746	177	87,846
	% of 65+	37.76	31.20	13.12	13.35	4.37	0.19	100
	% of All	40.83	24.12	14.56	13.74	6.54	0.20	100
2011	65+	3,239	2,507	1,225	1,099	351	20	8,441
	All	36,581	21,248	13,887	13,433	5,249	146	90,544
	% of 65+	38.37	29.70	14.51	13.02	4.16	0.24	100
	% of All	40.40	23.47	15.34	14.84	5.80	0.16	100
2010	65+	3,230	2,584	1,054	1,010	256	13	8,147
	All	39,924	22,201	12,866	11,539	4,453	197	91,180
	% of 65+	39.65	31.72	12.94	12.40	3.14	0.16	100
	% of All	43.79	24.35	14.11	12.66	4.88	0.22	100
2010 to 2014	65+	15,914	12,927	6,240	6,026	2,149	95	43,351
	All	175,409	105,301	67,957	64,114	32,152	890	445,823
	% of 65+	36.71	29.82	14.39	13.90	4.96	0.22	100
	% of All	39.34	23.62	15.24	14.38	7.21	0.20	100

Table A.2: Older Drivers and All Drivers (Including Older Drivers) Involved in Crashes Based on Intersection Type

Year	Age in years	Intersection type				Total
		Four-way intersection	T-intersection	Part of an interchange	Other intersection types	
2014	65+	3,342	710	553	135	4,740
	All	27,661	6,991	7,161	1,241	43,054
	% of 65+	70.51	14.98	11.67	2.85	100.00
	% of All	64.25	16.24	16.63	2.88	100.00
2013	65+	3,158	672	463	128	4,421
	All	26,990	6,984	6,110	1,256	41,340
	% of 65+	71.43	15.20	10.47	2.90	100.00
	% of All	65.29	16.89	14.78	3.04	100.00
2012	65+	3,060	708	440	148	4,356
	All	26,658	6,921	6,291	1,376	41,246
	% of 65+	70.25	16.25	10.10	3.40	100.00
	% of All	64.63	16.78	15.25	3.34	100.00
2011	65+	2,979	698	382	145	4,215
	All	27,544	7,110	7,153	1,514	43,321
	% of 65+	70.68	16.56	9.06	3.44	100.00
	% of All	63.58	16.41	16.51	3.49	100.00
2010	65+	2,852	735	349	208	4,144
	All	27,142	7,648	5,578	2,073	42,441
	% of 65+	68.82	17.74	8.42	5.02	100.00
	% of All	63.95	18.02	13.14	4.88	100.00
2010 to 2014	65+	15,391	3,523	2,187	764	21,876
	All	135,995	35,654	32,293	7,460	211,402
	% of 65+	**70.36**	16.10	10.00	3.49	100.00
	% of All	64.33	16.87	15.28	3.53	100.00

Table A.3: Older Drivers and All Drivers (Including Older Drivers) Involved in Number of Crashes Based on Traffic Control Device Present

Year	Age Category	None	Another Traffic Control Device	Yield sign	Stop sign	Traffic Signal	Total
2014	Older drivers	1,145	2,440	60	958	1,112	5,715
	All drivers	11,477	26,429	590	7,850	9,820	56,166
	% of Older drivers	20.03	42.69	1.05	16.76	19.46	100.00
	% of all drivers	20.43	47.06	1.05	13.98	17.48	100.00
2013	Older drivers	1,072	2,382	65	918	1,068	5,505
	All drivers	11,536	26,751	568	7,672	9,734	56,261
	% of Older drivers	19.47	43.27	1.18	16.68	19.40	100.00
	% of all drivers	20.50	47.55	1.01	13.64	17.30	100.00
2012	Older drivers	1,123	2,182	79	963	961	5,308
	All drivers	12,102	25,571	693	7,858	9,644	55,868
	% of Older drivers	21.16	41.11	1.49	18.14	18.10	100.00
	% of all drivers	21.66	45.77	1.24	14.07	17.26	100.00
2011	Older drivers	1,173	2,150	65	919	926	5,233
	All drivers	12,645	26,274	695	8,025	9,630	57,269
	% of Older drivers	22.42	41.09	1.24	17.56	17.70	100.00
	% of all drivers	22.08	45.88	1.21	14.01	16.82	100.00
2010	Older drivers	1,020	2,028	66	920	863	4,897
	All drivers	12,435	25,933	644	8,141	9,465	56,618
	% of Older drivers	20.83	41.41	1.35	18.79	17.62	100.00
	% of all drivers	21.96	45.80	1.14	14.38	16.72	100.00
2010 to 2014	Older drivers	5,533	11,182	335	4,678	4,930	26,658
	All drivers	60,195	130,958	3,190	39,546	48,293	282,182
	% of Older drivers	20.76	41.95	1.26	17.55	18.49	100.00
	% of all drivers	21.33	46.41	1.13	14.01	17.11	100.00

Table A.4: Older Drivers and All Drivers (Including Older Drivers) Involved in Crashes Based on Road Character

Year	Age in years	Road Character				Total
		Straight & Level	Straight on grade/slope	Curved & level	Other Road Characters	
2014	65+	7,102	1,420	316	362	9,200
	All	65,908	14,100	3,523	4,452	87,983
	% of 65+	77.20	15.43	3.43	3.93	100.00
	% of All	74.91	16.03	4.00	5.06	100.00
2013	65+	6,911	1,355	288	368	8,922
	All	65,503	14,758	3,381	4,629	88,271
	% of 65+	77.46	15.19	3.23	4.12	100.00
	% of All	74.21	16.72	3.83	5.24	100.00
2012	65+	6,668	1,381	252	340	8,641
	All	65,930	14,184	3,232	4,500	87,846
	% of 65+	77.17	15.98	2.92	3.93	100.00
	% of All	75.05	16.15	3.68	5.12	100.00
2011	65+	6,446	1,349	259	387	8,441
	All	66,322	15,516	3,391	5,315	90,544
	% of 65+	76.37	15.98	3.07	4.58	100.00
	% of All	73.25	17.14	3.75	5.87	100.00
2010	65+	6,210	1,291	235	411	8,147
	All	66,294	15,803	3,342	5,741	91,180
	% of 65+	76.22	15.85	2.88	5.04	100.00
	% of All	72.71	17.33	3.67	6.30	100.00
2010 to 2014	65+	33,337	6,796	1,350	1,868	43,351
	All	329,957	74,361	16,869	24,637	445,823
	% of 65+	**76.90**	15.68	3.11	4.31	100.00
	% of All	74.01	16.68	3.78	5.53	100.00

Table A.5: Older Drivers and All Drivers (Including Older Drivers) Involved in Crashes Based on First Harmful Event

Year	Age in years	First Harmful Event (FHE)			Total
		Rear end	Angle-side impact	All the other FHE	
2014	65+	2,182	3,146	3,872	9,200
	All	26,640	24,001	37,341	87,982
	% of 65+	23.72	34.20	42.09	100.00
	% of All	30.28	27.28	42.44	100.00
2013	65+	2,082	3,116	3,724	8,922
	All	26,434	24,190	37,647	88,271
	% of 65+	23.34	34.92	41.74	100.00
	% of All	29.95	27.40	42.65	100.00
2012	65+	2,097	3,097	3,447	8,641
	All	27,323	23,662	36,861	87,846
	% of 65+	24.27	35.84	39.89	100.00
	% of All	31.10	26.94	41.96	100.00
2011	65+	1,956	2,932	3,553	8,441
	All	27,845	24,603	38,096	90,544
	% of 65+	23.17	34.74	42.09	100.00
	% of All	30.75	27.17	42.07	100.00
2010	65+	1,907	2,999	3,241	8,147
	All	28,328	24,820	38,032	91,180
	% of 65+	23.41	36.81	39.78	100.00
	% of All	31.07	27.22	41.71	100.00
2010 to 2014	65+	10,224	15,290	17,837	43,351
	All	136,676	121,458	187,977	445,823
	% of 65+	23.58	**35.27**	41.15	100.00
	% of All	30.66	27.24	42.16	100.00

Table A.6: Older Drivers and All Drivers (Including Older Drivers) Involved in Crashes Based on Speed Limit

Year	Age in years	Speed Limit (mph)			Total
		Speed Limit<= 40 mph	Speed Limit>40 mph	Unknown	
2014	65+	5,607	3,471	122	9,200
	All	48,303	38,687	992	87,982
	% 65+	60.95	37.73	1.33	100.00
	% All	54.90	43.97	1.13	100.00
2013	65+	5,556	3,291	75	8,922
	All	49,355	38,247	669	88,271
	% 65+	62.27	36.89	0.84	100.00
	% All	55.91	43.33	0.76	100.00
2012	65+	5,412	3,115	114	8,641
	All	49,780	36,977	1,089	87,846
	% 65+	62.63	36.05	1.32	100.00
	% All	56.67	42.09	1.24	100.00
2011	65+	5,137	3,085	219	8,441
	All	49,257	38,889	2,398	90,544
	% 65+	60.86	36.55	2.59	100.00
	% All	54.40	42.95	2.65	100.00
2010	65+	4,955	2,897	295	8,147
	All	49,172	39,013	2,995	91,180
	% 65+	60.82	35.56	3.62	100.00
	% All	53.93	42.79	3.28	100.00
2010 to 2014	65+	26,667	15,859	825	43,351
	All	245,867	191,813	8,143	445,823
	% 65+	**61.51**	36.58	1.90	100.00
	% All	55.15	43.02	1.83	100.00

Table A.7: Older Drivers and All Drivers (Including Older Drivers) Involved in Crashes Based on Light Condition

Year	Age in years	Light Condition		Total
		Daylight	Non-daylight conditions	
2014	65+	7,309	1,891	9,200
	All	61,777	26,205	87,982
	% of 65+	79.45	20.55	100.00
	% of All	70.22	29.78	100.00
2013	65+	7,151	1,771	8,922
	All	62,058	26,213	88,271
	% of 65+	80.15	19.85	100.00
	% of All	70.30	29.70	100.00
2012	65+	6,991	1,650	8,641
	All	61,388	26,458	87,846
	% of 65+	80.90	19.10	100.00
	% of All	69.88	30.12	100.00
2011	65+	6,755	1,686	8,441
	All	63,244	27,300	90,544
	% of 65+	80.03	19.97	100.00
	% of All	69.85	30.15	100.00
2010	65+	6,573	1,574	8,147
	All	62,704	28,476	91,180
	% of 65+	80.68	19.32	100.00
	% of All	68.77	31.23	100.00
2010 to 2014	65+	34,779	8,572	43,351
	All	311,171	134,652	445,823
	% of 65+	**80.23**	19.77	100.00
	% of All	69.80	30.20	100.00

Table A.8: Older Drivers and All Drivers (Including Older Drivers) Involved in Crashes on State Roads Based on Urban Rural Nature

Year	Age category	Rural	Urban	Total
2014	65+	1,471	1,534	3,005
	All	12,838	18,279	31,117
	% of 65+	48.95	51.05	100.00
	% of All	41.26	58.74	100.00
2013	65+	1,470	1,371	2,841
	All	13,154	16,905	30,059
	% of 65+	51.74	48.26	100.00
	% of All	43.76	56.24	100.00
2012	65+	1,390	1,279	2,669
	All	12,916	16,607	29,523
	% of 65+	52.08	47.92	100.00
	% of All	43.75	56.25	100.00
2011	65+	1,511	1,264	2,775
	All	13,993	18,191	32,184
	% of 65+	54.45	45.55	100.00
	% of All	43.48	56.52	100.00
2010	65+	1,411	1,283	2,694
	All	14,007	19,023	33,030
	% of 65+	52.38	47.62	100.00
	% of All	42.41	57.59	100.00
2014 to 2010	65+	7,253	6,731	13,984
	All	66,908	89,005	155,913
	% of 65+	51.87	48.13	100.00
	% of All	42.91	57.09	100.00

Appendix B: Correlation Matrices

Table B.1: Correlation Matrix for Model A

	GEN	VALID	SUSP	SEATB	AIRB	WEEKE	NINTER	OFFRD	MORNIN	DAYT	AFNOON	EVENIN	INTERR	ASPH	CON	GRA	NADVER	RAIN	SNOW	STLEVEL
GEN	1.000																			
VALID	-0.014	1.000																		
SUSP	0.028	-0.436	1.000																	
SEATB	-0.110	0.068	-0.074	1.000																
AIRB	-0.043	-0.015	0.028	0.021	1.000															
WEEKE	0.012	-0.026	0.011	-0.021	0.005	1.000														
NINTER	-0.011	0.025	-0.008	0.091	-0.081	-0.001	1.000													
OFFRD	0.018	-0.022	0.018	-0.060	0.098	0.005	-0.688	1.000												
MORNIN	0.033	0.012	-0.014	0.047	-0.005	-0.028	0.071	-0.043	1.000											
DAYT	-0.034	-0.020	-0.006	-0.035	0.007	-0.011	-0.117	0.076	-0.247	1.000										
AFNOON	-0.022	-0.004	-0.004	-0.084	0.018	-0.010	-0.142	0.100	-0.239	-0.279	1.000									
EVENIN	-0.015	0.016	-0.014	0.059	-0.017	0.014	0.128	-0.092	-0.263	-0.306	-0.297	1.000								
INTERR	0.010	-0.008	-0.015	-0.057	-0.005	-0.008	-0.336	-0.107	0.003	0.004	0.029	-0.036	1.000							
ASPH	-0.001	0.003	0.017	0.008	-0.006	0.016	0.014	-0.014	-0.013	-0.007	-0.005	0.013	-0.021	1.000						
CON	-0.005	-0.008	0.024	0.005	-0.004	0.010	-0.068	-0.007	-0.013	0.047	0.021	-0.050	0.016	-0.002	1.000					
GRA	0.000	0.012	-0.008	-0.043	-0.009	0.003	0.022	0.014	-0.003	-0.012	-0.011	0.034	-0.008	0.027	-0.117	1.000				
NADVERS	-0.030	0.019	-0.013	-0.027	-0.017	0.018	0.146	-0.148	-0.028	-0.051	0.009	0.056	-0.044	0.016	-0.057	0.027	1.000			
RAIN	0.022	0.006	-0.006	0.030	0.025	-0.017	-0.058	0.030	0.020	0.031	-0.012	-0.028	0.036	0.003	0.016	-0.013	-0.621	1.000		
SNOW	0.022	-0.015	0.002	0.036	-0.004	-0.014	-0.094	0.096	0.014	0.049	-0.015	-0.033	0.029	-0.025	0.053	-0.021	-0.443	-0.038	1.000	
STLEVEL	-0.032	-0.002	0.000	0.038	-0.047	-0.039	0.099	-0.123	-0.024	0.005	-0.028	0.034	0.016	0.015	-0.005	-0.028	0.066	-0.022	-0.048	1.000
CURLEVEL	0.020	0.003	-0.006	-0.067	0.005	0.023	-0.104	0.115	-0.016	-0.017	0.047	-0.018	0.023	-0.021	0.023	0.006	-0.025	-0.001	0.022	-0.379
HSPEED	0.075	0.057	-0.029	0.103	0.058	0.019	0.066	0.117	0.132	-0.153	-0.175	0.112	-0.074	0.003	-0.058	0.097	-0.071	0.008	0.028	-0.084
AUTO	-0.306	0.021	-0.018	0.115	0.067	0.018	0.005	0.000	-0.007	0.001	0.002	-0.011	0.003	0.007	0.021	-0.060	0.015	0.013	-0.001	-0.014
SUV	-0.067	0.011	0.007	0.061	0.005	0.006	0.010	0.003	-0.009	-0.016	-0.031	0.048	-0.019	0.019	-0.013	0.030	-0.006	-0.011	0.018	0.000
DAYLIGHT	-0.047	-0.022	-0.002	-0.100	0.022	-0.021	-0.242	0.161	-0.087	0.447	0.420	-0.384	0.039	-0.024	0.058	-0.006	-0.023	0.013	0.024	-0.035
DARKSTON	0.024	-0.033	0.049	-0.009	0.000	-0.016	-0.013	-0.029	-0.045	-0.155	-0.151	0.136	0.053	0.001	0.091	-0.043	-0.036	0.025	0.048	0.008
DARKSTOFF	0.021	0.045	-0.020	0.093	-0.010	0.032	0.223	-0.120	-0.087	-0.307	-0.295	0.311	-0.076	0.023	-0.097	0.023	0.038	-0.022	-0.032	0.030
DRAGE1	0.054	-0.005	0.015	0.022	-0.023	-0.011	0.031	-0.008	0.056	-0.098	-0.080	0.067	-0.007	0.004	-0.008	-0.010	-0.011	-0.006	0.015	-0.042
DRAGE2	-0.037	0.010	-0.017	-0.013	0.027	0.014	-0.004	0.010	-0.030	0.078	0.032	-0.043	-0.010	0.004	-0.002	0.013	0.004	0.004	0.005	0.031
ACCCLS2	0.009	0.064	-0.043	0.193	-0.059	0.020	0.474	-0.350	0.174	-0.259	-0.306	0.234	-0.115	0.020	-0.129	0.021	0.155	-0.056	-0.108	0.079
ACCCLS3	-0.004	-0.006	0.031	-0.047	0.144	-0.005	-0.507	0.488	-0.057	0.118	0.149	-0.145	0.142	-0.016	0.088	0.026	-0.188	0.085	0.145	-0.146
ACCCLS4	-0.060	-0.056	0.018	-0.041	-0.070	-0.007	0.074	-0.199	-0.105	0.135	0.127	-0.072	-0.070	0.000	0.024	-0.096	0.073	-0.023	-0.037	0.124
STRAIG	0.032	0.041	-0.022	0.093	0.037	0.001	0.255	0.000	0.091	-0.148	-0.129	0.104	-0.154	0.007	-0.048	0.050	-0.009	-0.008	-0.010	-0.029
LTURN	-0.027	0.000	0.003	-0.029	0.004	-0.012	-0.161	-0.002	-0.024	0.005	0.047	-0.030	0.276	-0.010	0.017	-0.011	-0.020	0.008	0.024	0.051
NEJECT	-0.037	0.042	-0.045	0.289	-0.012	-0.016	0.117	-0.139	0.015	0.009	-0.072	0.038	-0.023	-0.006	-0.009	-0.046	0.026	0.012	0.016	0.054
TWOLN	-0.030	0.007	-0.006	-0.001	-0.064	0.013	0.182	-0.082	-0.001	-0.052	-0.035	0.085	-0.060	0.010	-0.251	0.061	0.107	-0.059	-0.069	0.086
MLANE	0.028	-0.009	0.008	0.004	0.068	-0.015	-0.170	0.079	-0.001	0.056	0.035	-0.087	0.048	-0.006	0.245	-0.055	-0.102	0.054	0.067	-0.082

Table B.1: Correlation Matrix for Model A (Continued)

	CURLEV	HSPEED	AUTO	SUV	DAYLIGHT	DARKST	DARKST(	DRAGE1	DRAGE2	ACCCLS2	ACCCLS3	ACCCLS	STRAIG	LTURN	NEJECT	TWOLN	MLANE
CURLEVEL	1.000																
HSPEED	0.007	1.000															
AUTO	0.000	-0.029	1.000														
SUV	-0.012	0.036	-0.356	1.000													
DAYLIGHT	0.033	-0.302	-0.013	-0.037	1.000												
DARKSTOI	0.016	-0.121	0.027	0.019	-0.347	1.000											
DARKSTOI	-0.029	0.348	-0.005	0.041	-0.683	-0.174	1.000										
DRAGE1	0.036	0.179	-0.164	0.071	-0.139	0.008	0.124	1.000									
DRAGE2	-0.024	-0.093	0.093	-0.035	0.085	-0.014	-0.067	-0.822	1.000								
ACCCLS2	-0.107	0.499	0.016	0.063	-0.532	-0.059	0.512	0.164	-0.087	1.000							
ACCCLS3	0.113	-0.030	0.058	-0.015	0.254	0.044	-0.249	-0.060	0.028	-0.523	1.000						
ACCCLS4	-0.058	-0.644	0.000	-0.022	0.241	0.048	-0.248	-0.149	0.082	-0.392	-0.343	1.000					
STRAIG	-0.048	0.453	0.033	0.026	-0.266	-0.008	0.246	0.075	-0.012	0.422	-0.089	-0.431	1.000				
LTURN	-0.033	-0.084	0.011	-0.023	0.060	0.025	-0.058	-0.026	-0.002	-0.109	0.142	-0.023	-0.265	1.000			
NEJECT	-0.067	-0.033	0.053	0.028	-0.069	0.004	0.061	-0.011	0.003	0.139	-0.064	0.063	0.001	0.013	1.000		
TWOLN	-0.006	-0.036	-0.045	0.011	-0.074	-0.092	0.124	-0.007	0.005	0.177	-0.237	0.113	0.030	-0.049	0.011	1.000	
MLANE	0.008	0.038	0.042	-0.011	0.073	0.085	-0.120	0.004	-0.002	-0.168	0.228	-0.107	-0.024	0.044	-0.009	-0.969	1.000

Table B.2: Correlation Matrix for Model B

	PASSE	GEN	VALID	SEATB	AIRB	WEEKE	MORNIN	DAYT	AFNOON	EVENIN	NIGHT	NINTER	INTERR	OFFRD	ASPH	CON	GRA	NADVERS	RAIN
PASSE	1.000																		
GEN	0.071	1.000																	
VALID	-0.032	-0.008	1.000																
SEATB	-0.004	-0.002	0.081	1.000															
AIRB	0.043	0.032	-0.023	0.031	1.000														
WEEKE	-0.015	0.042	0.018	-0.020	0.006	1.000													
MORNIN	-0.040	0.008	0.032	0.009	0.013	-0.033	1.000												
DAYT	0.032	-0.049	-0.026	-0.055	0.015	-0.018	-0.149	1.000											
AFNOON	0.007	-0.100	-0.015	-0.044	0.000	-0.037	-0.154	-0.181	1.000										
EVENIN	0.030	0.044	0.013	0.078	0.010	0.040	-0.267	-0.312	-0.324	1.000									
NIGHT	-0.037	0.073	-0.004	-0.011	-0.034	0.026	-0.191	-0.223	-0.231	-0.400	1.000								
NINTER	-0.010	0.076	0.047	0.074	-0.035	0.024	0.036	-0.192	-0.229	0.155	0.158	1.000							
INTERR	0.009	-0.009	-0.051	-0.078	-0.020	-0.017	0.019	0.034	0.045	-0.017	-0.064	-0.338	1.000						
OFFRD	0.017	-0.054	-0.044	-0.040	0.050	-0.015	-0.044	0.129	0.183	-0.119	-0.100	-0.708	-0.071	1.000					
ASPH	0.015	0.029	-0.014	0.026	0.005	0.005	0.013	-0.063	-0.036	0.067	-0.002	0.110	-0.017	-0.022	1.000				
CON	-0.017	-0.010	0.010	0.010	0.011	0.006	-0.021	0.053	0.035	-0.056	0.004	-0.102	0.018	0.016	-0.849	1.000			
GRA	0.002	-0.012	-0.006	-0.044	-0.009	-0.023	0.014	0.000	-0.027	-0.014	0.029	-0.020	0.013	0.011	-0.323	-0.087	1.000		
NADVERS	-0.016	-0.028	-0.011	0.055	0.021	-0.026	-0.047	-0.073	-0.034	0.057	0.063	0.209	-0.019	-0.223	0.053	-0.059	0.017	1.000	
RAIN	-0.007	-0.006	0.016	-0.054	-0.011	0.001	0.037	-0.019	0.036	-0.010	-0.032	-0.055	-0.009	0.041	0.007	0.004	-0.008	-0.571	1.000
SNOW	0.020	0.026	-0.010	-0.006	-0.004	0.018	0.011	0.113	-0.005	-0.046	-0.047	-0.202	0.032	0.230	-0.058	0.058	-0.018	-0.449	-0.036
STLEVEL	-0.018	0.009	-0.006	0.035	-0.060	-0.038	-0.004	-0.027	-0.050	0.026	0.039	0.138	-0.008	-0.123	0.014	-0.017	-0.010	0.079	-0.014
CURLEVEL	-0.042	-0.009	0.004	-0.044	0.022	0.007	0.018	0.009	0.027	-0.037	-0.001	-0.092	0.000	0.059	-0.014	0.023	-0.009	-0.021	0.023
HSPEED	0.026	0.104	0.072	0.144	0.035	0.038	0.025	-0.137	-0.202	0.123	0.134	0.231	-0.150	-0.021	0.062	-0.029	0.006	0.007	-0.022
AUTO	0.043	-0.122	0.015	0.088	0.031	0.023	-0.005	-0.031	-0.032	0.045	0.006	0.031	-0.029	0.000	0.007	0.019	-0.025	0.037	0.006
SUV	-0.033	-0.017	0.022	0.021	0.016	0.015	-0.007	-0.010	-0.026	0.008	0.028	0.017	0.001	-0.015	-0.018	0.028	-0.024	-0.001	0.028
DAYLIGHT	0.030	-0.117	-0.048	-0.084	0.007	-0.051	0.027	0.502	0.510	-0.410	-0.425	-0.352	0.075	0.266	-0.073	0.049	0.006	-0.080	0.032
DARKSTOI	0.024	0.038	-0.019	-0.005	-0.020	0.001	-0.051	-0.110	-0.114	0.098	0.120	-0.053	0.061	0.002	-0.031	0.060	-0.031	-0.061	0.046
DARKSTOI	-0.021	0.079	0.045	0.083	0.017	0.066	-0.164	-0.373	-0.389	0.315	0.422	0.328	-0.099	-0.217	0.090	-0.065	-0.016	0.100	-0.049
DRAGE1	-0.089	-0.024	-0.018	-0.002	-0.023	0.060	0.003	-0.079	-0.049	0.018	0.087	0.047	-0.013	-0.030	-0.017	0.024	-0.007	-0.001	-0.033
DRAGE2	0.073	0.021	0.036	0.007	0.016	-0.059	0.017	0.050	0.021	-0.007	-0.066	-0.010	0.004	0.011	0.027	-0.029	0.011	-0.010	0.043
ACCCLS2	-0.009	0.119	0.077	0.170	-0.035	0.052	0.052	-0.299	-0.365	0.273	0.221	0.622	-0.146	-0.504	0.144	-0.100	-0.033	0.252	-0.079
ACCCLS3	0.028	-0.078	-0.054	-0.098	0.095	-0.015	-0.039	0.212	0.245	-0.192	-0.145	-0.596	0.111	0.581	-0.115	0.105	0.025	-0.250	0.093
ACCCLS4	-0.047	-0.136	-0.046	-0.060	-0.039	-0.032	-0.003	0.106	0.148	-0.102	-0.100	-0.098	0.030	-0.060	-0.039	0.000	-0.010	0.038	-0.017
STRAIG	-0.006	0.112	0.044	0.096	0.007	0.039	0.033	-0.160	-0.192	0.127	0.133	0.309	-0.113	-0.093	0.079	-0.020	-0.027	0.006	0.016
LTURN	-0.021	-0.010	-0.033	-0.057	-0.008	-0.024	-0.009	-0.010	0.106	-0.029	-0.044	-0.096	0.184	-0.014	-0.045	0.040	0.017	0.012	-0.008
NEJECT	-0.014	0.043	0.034	0.143	-0.040	0.008	0.038	-0.035	-0.119	0.062	0.033	0.113	-0.042	-0.119	0.014	-0.023	-0.001	0.056	-0.016
TWOLN	-0.009	-0.010	-0.005	-0.003	-0.021	0.010	-0.018	-0.065	-0.093	0.119	0.013	0.228	-0.027	-0.148	0.203	-0.260	0.040	0.099	-0.072
MLANE	0.016	0.019	0.012	0.021	0.038	0.002	0.014	0.053	0.081	-0.109	0.000	-0.187	0.011	0.165	-0.170	0.262	-0.100	-0.101	0.070
SPASSAGE	0.150	0.049	0.026	0.052	0.024	-0.003	-0.057	0.020	0.005	0.047	-0.032	0.043	-0.029	-0.039	0.019	-0.004	-0.012	0.017	0.010
SPASSGEN	-0.111	-0.439	-0.016	-0.026	-0.012	-0.014	0.023	-0.015	0.069	-0.047	-0.009	-0.055	0.017	0.062	-0.041	0.020	0.043	-0.015	0.022

Table B.2: Correlation Matrix for Model B (Continued)

	SNOW	STLEVEL	CURLEVEL	HSPEED	AUTO	SUV	DAYLIGHT	DARKSTOI	DARKSTOI	DRAGE1	DRAGE2	ACCCLS2	ACCCLS3	ACCCLS4	STRAIG	LTURN	NEJECT	TWOLN	MLANE	SPASSAGE	SPASSGEN
SNOW	1.000																				
STLEVEL	-0.098	1.000																			
CURLEVEL	0.028	-0.355	1.000																		
HSPEED	-0.005	0.038	-0.058	1.000																	
AUTO	-0.036	0.035	-0.008	0.070	1.000																
SUV	-0.014	-0.022	0.015	0.005	-0.471	1.000															
DAYLIGHT	0.079	-0.070	0.058	-0.312	-0.050	-0.044	1.000														
DARKSTOI	0.066	-0.038	0.037	-0.088	-0.002	0.015	-0.213	1.000													
DARKSTOI	-0.096	0.077	-0.069	0.318	0.048	0.049	-0.746	-0.241	1.000												
DRAGE1	0.003	-0.015	0.003	0.069	-0.114	0.065	-0.107	0.019	0.088	1.000											
DRAGE2	0.003	0.004	0.002	-0.023	0.082	-0.053	0.062	-0.016	-0.053	-0.904	1.000										
ACCCLS2	-0.206	0.140	-0.102	0.472	0.074	0.050	-0.564	-0.059	0.510	0.081	-0.030	1.000									
ACCCLS3	0.221	-0.173	0.110	-0.183	0.023	-0.034	0.375	0.043	-0.341	-0.079	0.040	-0.660	1.000								
ACCCLS4	-0.029	0.041	-0.005	-0.621	-0.077	0.003	0.230	0.050	-0.228	-0.032	-0.005	-0.368	-0.137	1.000							
STRAIG	-0.059	0.034	-0.093	0.487	0.050	0.009	-0.292	-0.029	0.269	0.044	-0.014	0.444	-0.224	-0.459	1.000						
LTURN	0.001	0.024	0.039	-0.186	-0.021	-0.026	0.085	0.051	-0.097	-0.031	0.020	-0.136	0.144	0.059	-0.275	1.000					
NEJECT	0.010	0.052	-0.039	-0.001	0.054	-0.008	-0.121	0.009	0.094	0.026	-0.013	0.165	-0.093	0.023	0.044	-0.005	1.000				
TWOLN	-0.064	0.115	-0.046	-0.004	-0.013	0.006	-0.132	-0.090	0.139	-0.020	0.016	0.214	-0.218	0.082	0.055	-0.021	0.014	1.000			
MLANE	0.062	-0.080	0.023	0.071	0.012	0.016	0.108	0.090	-0.114	0.019	-0.007	-0.179	0.196	-0.111	-0.006	0.009	-0.029	-0.901	1.000		
SPASSAGE	-0.049	-0.015	0.039	0.065	0.118	-0.050	0.003	-0.014	0.023	-0.238	0.211	0.067	-0.031	-0.085	0.025	0.010	-0.004	-0.010	0.022	1.000	
SPASSGEN	0.004	-0.010	0.033	-0.017	-0.031	-0.011	0.049	-0.037	-0.029	0.070	-0.058	-0.088	0.092	0.008	-0.005	-0.023	-0.059	-0.018	0.017	-0.082	1.000

Table B.3: Correlation Matrix for Model C

	molddr	femolddr	mixolddr	traunit	valid	seatb	airb	weeke	ninter	interr	mornin	dayt	afnoon	evenin	asph	con	nadvers	rain
molddr	1.000																	
femolddr	1.000	1.000																
mixolddr	0.999	0.999	1.000															
traunit	0.005	0.011	-0.040	1.000														
valid	0.003	-0.001	-0.006	-0.014	1.000													
seatb	-0.048	0.034	0.037	-0.018	0.016	1.000												
airb	-0.023	0.010	0.033	-0.038	0.008	0.010	1.000											
weeke	0.025	-0.017	-0.023	0.041	-0.012	0.006	-0.002	1.000										
ninter	0.033	-0.034	0.001	-0.052	0.001	0.001	-0.019	0.011	1.000									
interr	-0.055	0.050	0.015	0.021	-0.005	-0.017	0.036	-0.007	-0.671	1.000								
mornin	0.026	-0.023	-0.008	0.000	0.002	-0.004	-0.001	-0.058	0.011	0.000	1.000							
dayt	-0.020	0.008	0.031	0.032	-0.002	0.009	0.004	0.052	0.002	-0.008	-0.171	1.000						
afnoon	-0.030	0.033	-0.006	-0.012	0.001	-0.009	-0.010	-0.029	-0.014	0.016	-0.209	-0.530	1.000					
evenin	0.028	-0.022	-0.017	-0.030	-0.002	0.007	-0.002	-0.018	0.002	-0.005	-0.134	-0.338	-0.413	1.000				
asph	-0.027	0.023	0.010	0.026	0.001	-0.015	0.038	0.009	-0.003	0.075	-0.014	-0.005	0.008	0.004	1.000			
con	0.020	-0.017	-0.007	-0.043	-0.004	0.030	-0.037	-0.012	-0.002	-0.077	0.010	0.003	-0.005	-0.003	-0.952	1.000		
nadvers	-0.037	0.033	0.011	0.015	0.003	0.001	-0.016	-0.001	-0.045	0.028	-0.052	0.003	0.040	-0.014	-0.012	0.013	1.000	
rain	0.005	-0.005	0.000	-0.024	0.000	0.019	-0.002	-0.012	0.002	0.003	0.033	-0.006	-0.018	0.010	0.021	-0.016	-0.781	1.000
snow	0.040	-0.031	-0.025	0.007	-0.009	-0.022	0.002	0.013	0.023	-0.007	0.032	0.020	-0.023	-0.019	-0.004	0.000	-0.385	-0.038
stlevel	-0.019	0.020	0.000	0.009	0.009	0.000	-0.015	0.014	-0.041	0.073	-0.026	0.007	0.006	0.002	-0.038	0.041	0.033	-0.016
curlevel	0.016	-0.009	-0.020	0.030	-0.004	0.018	-0.004	-0.006	0.021	-0.036	0.001	0.001	-0.008	0.002	-0.009	0.010	-0.009	0.003
hspeed	0.074	-0.070	-0.014	-0.101	0.018	0.023	0.080	0.022	0.085	-0.130	0.014	-0.032	-0.026	0.041	-0.084	0.094	-0.053	0.026
auto	-0.122	0.117	0.018	-0.092	-0.008	0.020	0.028	0.017	-0.037	0.042	-0.027	-0.033	0.014	0.034	0.016	0.004	0.009	0.009
suv	-0.024	0.028	-0.009	-0.136	0.011	0.028	0.002	0.002	0.011	-0.012	-0.014	0.012	-0.006	0.007	-0.010	0.016	0.009	-0.012
rend	0.017	-0.016	-0.004	-0.289	0.015	0.029	-0.050	-0.025	0.141	-0.096	-0.012	-0.046	0.029	0.029	-0.017	0.043	-0.044	0.064
angle	-0.029	0.033	-0.010	0.173	-0.006	-0.014	0.073	0.007	-0.353	0.297	0.013	0.022	-0.003	-0.023	0.014	-0.026	0.034	-0.028
daylight	-0.029	0.023	0.016	0.002	0.003	0.000	-0.018	-0.022	-0.014	0.008	-0.016	0.254	0.284	-0.426	-0.018	0.016	0.097	-0.054
darkston	0.012	-0.003	-0.024	-0.004	0.006	0.001	0.011	0.022	-0.035	0.033	-0.035	-0.196	-0.234	0.347	0.008	-0.002	-0.060	0.048
drage1	-0.031	-0.006	0.095	-0.033	-0.006	0.017	-0.023	0.001	0.036	-0.020	0.008	-0.040	-0.018	0.042	-0.007	0.003	-0.016	-0.001
drage2	-0.021	-0.012	0.084	0.005	0.000	-0.002	0.030	-0.008	-0.021	0.002	0.002	0.039	0.008	-0.041	-0.006	0.009	0.005	0.006
straig	-0.023	0.023	0.000	-0.054	0.005	0.011	0.051	-0.002	-0.011	0.035	0.008	-0.011	-0.008	0.019	-0.021	0.024	-0.006	0.012
lturn	-0.030	0.033	-0.005	0.118	-0.003	0.002	0.037	-0.003	-0.248	0.124	-0.012	-0.014	0.011	0.013	0.021	-0.009	0.040	-0.016
neject	-0.004	-0.006	0.027	0.014	0.020	0.134	-0.088	0.003	0.003	-0.017	-0.005	-0.007	0.007	0.008	-0.007	0.012	0.015	0.005
twoln	0.002	-0.006	0.012	0.131	-0.010	-0.050	0.014	0.019	0.019	0.049	0.033	0.011	-0.012	-0.015	0.104	-0.155	-0.007	-0.027
mlane	-0.002	0.008	-0.013	-0.139	0.014	0.051	-0.007	-0.022	-0.018	-0.031	-0.032	-0.017	0.013	0.018	-0.096	0.155	0.002	0.029
passage	0.112	-0.153	0.098	0.029	-0.013	0.034	0.017	0.013	0.009	-0.028	-0.021	0.039	-0.002	-0.018	0.001	0.006	0.004	-0.008
passgen	-0.169	0.177	-0.012	-0.038	0.006	0.001	-0.005	-0.039	-0.026	0.025	0.039	-0.014	-0.003	-0.005	0.014	-0.024	0.002	0.002

Table B.3: Correlation Matrix for Model C (Continued)

	snow	stlevel	curlevel	hspeed	auto	suv	rend	angle	daylight	darkston	drage1	drage2	straig	lturn	neject	twoln	mlane	passage	passgen
snow	1.000																		
stlevel	-0.016	1.000																	
curlevel	0.004	-0.313	1.000																
hspeed	0.011	-0.074	0.029	1.000															
auto	-0.019	0.005	-0.009	-0.020	1.000														
suv	0.023	-0.010	0.001	0.035	-0.271	1.000													
rend	-0.003	-0.070	-0.012	0.146	0.026	0.104	1.000												
angle	0.006	0.099	-0.045	-0.132	0.017	-0.057	-0.639	1.000											
daylight	-0.029	0.020	-0.010	-0.072	-0.023	-0.001	0.005	0.023	1.000										
darkston	0.011	-0.018	-0.008	0.017	0.038	0.004	0.003	0.000	-0.759	1.000									
drage1	0.028	-0.029	0.006	0.038	-0.066	0.061	0.086	-0.080	-0.045	0.044	1.000								
drage2	-0.020	0.019	-0.005	-0.015	0.039	-0.043	-0.049	0.049	0.046	-0.043	-0.749	1.000							
straig	-0.002	0.060	-0.036	-0.001	0.032	-0.015	-0.051	0.179	-0.017	0.013	-0.030	0.021	1.000						
lturn	-0.036	0.057	-0.024	0.007	0.022	-0.044	-0.342	0.386	-0.018	0.033	-0.047	0.019	-0.042	1.000					
neject	-0.001	0.015	-0.010	-0.019	0.013	0.001	0.044	-0.030	-0.001	0.016	0.024	-0.002	-0.023	0.003	1.000				
twoln	0.018	0.001	0.031	-0.191	-0.066	-0.041	-0.149	0.064	0.018	-0.071	0.001	0.008	-0.058	-0.073	-0.046	1.000			
mlane	-0.018	0.022	-0.046	0.208	0.070	0.041	0.150	-0.058	-0.023	0.071	-0.001	-0.008	0.071	0.086	0.047	-0.938	1.000		
passage	-0.013	-0.019	0.021	0.043	0.010	-0.004	0.008	-0.027	0.035	-0.036	-0.135	0.143	-0.007	-0.010	0.009	-0.015	0.015	1.000	
passgen	-0.010	0.003	0.003	0.005	-0.011	-0.010	-0.027	0.019	-0.014	0.018	0.020	-0.005	0.013	0.017	-0.002	0.010	-0.010	-0.125	1.000

Appendix C: Locations Where Survey was Conducted

Ms. Peggy Collingwood Stanton County Senior Service Center 205 E Weaver Ave. Johnson City, KS 67855	Ms. April Maddox Jayhawk Area Agency on Aging Case Management Program Manager 2910 SW Topeka Blvd. Topeka, Kansas
Trego County Senior Center 413 Russell Ave Wakeeney, KS 67672	Ms. Margorie Troy 310 Highland Dr. Parsons, KS 67357 620-421-7000
Ms. Barbara Jensen, Executive Director Senior Center of Finny County 907 North Tenth Garden City, Kansas 67846	P. O. 254 St. Francis, KS 67756
Ms. Rozen Tomlin Great Bend Senior Center 2005 Kansas Ave. Great Bend, KS 67530	Hays Senior Center 2450 E. 8th St. Hays, KS 67601
Ms. Brenda Moss Hillsboro Senior Center 212 N. Main St. Hillsboro, KS 67063	Ms. Kaila Deboer 165 Fike Park Street Colby, KS 67701
Ms. Jennifer Zimmermann El Dorado Senior Center 210 E. 2nd Ave. El Dorado, KS 67156	Southeast Kansas Area Agency on Aging PO Box J Chanute, KS 66720
Ms. Kari Kyle 431 S. Main St. Greensburg, KS 67054	Ms. Jody Getman Administrative Assistant Delos V. Smith Senior Center 101 West 1st Avenue Hutchinson, KS 67501

Locations where survey was conducted; continued

Ms. Diane Yunghans 607 Nemaha Seneca, KS 66538 785-336-3091	Paola Senior Center 121 W Wea St Paola, KS 66071
Topeka LULAC Senior Center 1502 NE Seward Ave Topeka, KS 66616 785-234-5809	East Topeka Senior Center 432 SE Norwood Street Topeka, KS 66607 785-232-7765
Nancy Mock, Director Greenwood County Council on Aging 209 North Oak Eureka, KS 67045	North Central-Flint Hills Area Agency on Aging, 401 Houston St, Manhattan, KS 66502
College Heights Baptist Church 2320 Anderson Ave, Manhattan, KS 66502	Trinity Presbyterian Church 1110 College Ave, Manhattan, KS 66502
Grace Baptist Church 2901 Dickens Ave, Manhattan, KS 66502	College Avenue United Methodist Church 1609 College Ave, Manhattan, KS 66502

Appendix D: Survey Form

Road User Survey

This survey asks for information about road user behaviors with the intention of improving safety. Your participation is completely voluntary and the research team is not collecting your personal information. Information collected will be used for research purposes only. If you do not wish to answer a question, or if a question does not apply to you, you may leave the answer blank.

BACKGROUND INFORMATION

1. What is your age group? ☐ 55 - 59 years ☐ 60 - 64 years ☐ 65 - 69 years ☐ 70- 74 years ☐ 75 - 79 years ☐ 80-84 years ☐ 85+ years	2. What is your Gender? ☐ Male ☐ Female 3. Your zip code is…? __ __ __ __ __
4. What is your marital status? ☐ Single ☐ Married	5. What is your highest level of education? ☐ Elementary school ☐ High school ☐ College degree ☐ graduate degree
6. How do you use a mobile phone? ☐ I use it in my car ☐ It is my primary phone ☐ I use it away from home ☐ I don't own one	7. How often do you use Internet? ☐ Daily ☐ 3-4 days/ week ☐ Weekly ☐ May be a couple times/ month ☐ I don't use internet.
8. How much is your annual household income? ☐ Less than- $ 9,999 ☐ $ 10,000 - $ 19,999 ☐ $19,999 -29,999 ☐ $ 30,000 - $ 39,999 ☐ $40,000 - $ 49,999 ☐ More than $50,000 ☐ Prefer not to answer	

INFORMATION ABOUT YOUR HEALTH

9. How do you rate your current health?						
	1	2	3	4	5	
Very poor	☐	☐	☐	☐	☐	very good
10. How do you rate your vision? (Corrected with glasses or contact lenses if needed.)						
	1	2	3	4	5	
Very poor	☐	☐	☐	☐	☐	very good
11. How do you rate your hearing? (Corrected with hearing aids if needed.)						
	1	2	3	4	5	
Very poor	☐	☐	☐	☐	☐	very good

INFORMATION ABOUT MOBILITY AND DRIVING

12. Do you currently drive?

☐ yes ☐ No

If 'No', please skip to question number 18.

13. How long have you been driving?

☐ 0 -10 years ☐ 11-20 years
☐ 21-30 years ☐ 31-40 years
☐ 41-50 years ☐ More than 50 yrs

14. What type of vehicle do you usually drive?

☐ Car ☐ SUV,
☐ Van ☐ Pick-up Truck
☐ Other (Please specify)…………………………

15. How old is the vehicle you drive?

☐ 0 -5 years ☐ 6- 10 years
☐ 11-15 years ☐ 16-20 years
☐ 21-25 years ☐ More than 25 yrs

16. Approximately how many miles do you drive per month?

☐ 0-100 miles ☐ 101 -200 miles ☐ 201-500 miles ☐ 501 -1000 miles
☐ 1001- 2000 miles ☐ More than 2000 miles

17. Do you have any difficulties at intersections compared to driving on other roadways?

☐ Yes ☐ No

If yes, what locations are more difficult? (You may select multiple answers.)

☐ Stop light/ traffic lights ☐ Roundabouts ☐ STOP sign controlled ☐ No control
☐ YIELD sign controlled

18. Have you received any traffic violation(s) during the past 5 years?

☐ None ☐ Speeding ☐ Driving too slow ☐ DUI ☐ Reckless driving
☐ Expired tags/ license ☐ Equipment violations ☐ Improper turns ☐ Other (specify)……….

19. Have you participated in any driving awareness programs?

☐ Yes ☐ No

20. Are you aware of any driver awareness programs such as CarFit?

☐ Yes ☐ No

21. On average how often do you drive?

☐ About once a month ☐ 2-3 times/month
☐ 4-5 times/month ☐ 8-20 times/month
☐ More than 20 times/ month ☐ I don't drive

22. What is your most common trip purpose?

☐ Grocery shopping ☐ To see a doctor
☐ To visit relatives/ children
☐ Other (please specify) …………………………

23. Do you know how to find information about public transportation in your area?

☐ No ☐ I have never tried ☐ Yes (please specify source) ………………………………………………
………

24. Do you have access to bus (public transport) within walking distance from your residence?

☐ Yes ☐ No ☐ Don't know

25. Would (or did) you quit driving for any of these reasons? (You may select multiple answers.)

☐ When my doctor advises ☐ When my adult children interfere ☐ When my vision gets poor

☐ When my spouse advises ☐ When I feel unsafe ☐ Other (Please specify) ....

26. What are your plans when you can no longer safely drive? (Please specify)

....

....

....

27. Do you consider Kansas roads as safe?

☐ Yes ☐ No ☐ No opinion

28. In your opinion what are the primary dangers on Kansas roads?

☐ speeding ☐ Road rage

☐ Distracted drivers ☐ Drivers under influence

☐ Construction zones

☐ Other (specify)...

Please check the box that best describes your situation.	Does not apply	Never	Very rarely	Sometimes	Most of the time	Always
29. How often do you wear the seat belt while driving?	☐	☐	☐	☐	☐	☐
30. How often do you wear the seat belt as a passenger?	☐	☐	☐	☐	☐	☐
31. Have you felt unsafe as a passenger?	☐	☐	☐	☐	☐	☐
32. Have you ever reported someone as an unsafe driver?	☐	☐	☐	☐	☐	☐
33. How often do you drive at night compared to day time?	☐	☐	☐	☐	☐	☐
34. How often do you drive on rainy weather conditions?	☐	☐	☐	☐	☐	☐
35. How often do you drive on snowy weather conditions?	☐	☐	☐	☐	☐	☐
36. How often do you drive on windy weather conditions?	☐	☐	☐	☐	☐	☐
37. How often do you drive alone?	☐	☐	☐	☐	☐	☐
38. How frequently do you drive on freeways/interstate/turnpike?	☐	☐	☐	☐	☐	☐
39. How often do you make sudden stops or slow down on road without . any real necessity?	☐	☐	☐	☐	☐	☐
40. How often do you drive after consuming alcohol?	☐	☐	☐	☐	☐	☐

41. How often do you drive when on prescription or over the counter medicine?	☐	☐	☐	☐	☐	☐
42. Do you think medical professionals should report their patients who are mentally or physically impaired?	☐	☐	☐	☐	☐	☐
43. Do you think reports by medical professionals should be anonymous?	☐	☐	☐	☐	☐	☐
44. **Are any of these driving situations more difficult today than when you were 40 years old?**						
Driving in heavy traffic	☐	☐	☐	☐	☐	☐
Merging into traffic	☐	☐	☐	☐	☐	☐
Moving away from the traffic	☐	☐	☐	☐	☐	☐
Judging gaps when merging or making a turn	☐	☐	☐	☐	☐	☐
Overtaking/passing on roads with one lane in each direction	☐	☐	☐	☐	☐	☐
Lane changing	☐	☐	☐	☐	☐	☐
Driving against the sun or sun behind you	☐	☐	☐	☐	☐	☐
Driving with passengers	☐	☐	☐	☐	☐	☐
Detecting traffic signs/signals	☐	☐	☐	☐	☐	☐
Making Left Turns at traffic signals without a green arrow	☐	☐	☐	☐	☐	☐
Making Left Turns at traffic signals with a green arrow	☐	☐	☐	☐	☐	☐
Making Left Turns at un-signalized intersections	☐	☐	☐	☐	☐	☐
Making Right Turns	☐	☐	☐	☐	☐	☐
Yielding or Stopping	☐	☐	☐	☐	☐	☐

45. Have you been involved in a crash during the last 10 years?

☐ Yes ☐ No

If yes, explain how severe it was. Who was at fault? Add any other information that you would like to share with the research team.

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THANK YOU!

Appendix E: CarFit Awareness of Older Drivers

Table E.1: CarFit Awareness of Survey Respondents with Zip Code

Zip code	CarFit Awareness %	Census 2010 total population	Population urban	Population rural	% Population urban	% Population rural
66402	Less than 33.33%	2,995	0	2,995	0.0	100.0
66441	In between 66.66% to 100%	26,746	24,703	2,043	92.4	7.6
66502	Less than 33.33%	43,850	40,727	3,123	92.9	7.1
66503	In between 33.33% to 66.66%	13,428	10,281	3,147	76.6	23.4
66517	Less than 33.33%	2,087	0	2,087	0.0	100.0
66535	Less than 33.33%	2,616	0	2,616	0.0	100.0
66547	In between 33.33% to 66.66%	7,617	4,418	3,199	58.0	42.0
66604	In between 33.33% to 66.66%	23,344	23,344	0	100.0	0.0
66605	In between 33.33% to 66.66%	19,919	19,830	89	99.5	0.5
66606	Less than 33.33%	11,284	11,279	5	100.0	0.0
66607	Less than 33.33%	10,498	10,288	210	98.0	2.0
66608	Less than 33.33%	5,991	5,977	14	99.8	0.2
66609	In between 33.33% to 66.66%	7,068	6,507	561	92.1	7.9
66610	Less than 33.33%	9,080	6,774	2,306	74.6	25.4
66611	Less than 33.33%	9,832	9,832	0	100.0	0.0
66614	Less than 33.33%	31,354	30,252	1,102	96.5	3.5
66615	Less than 33.33%	2,814	913	1,901	32.4	67.6
66616	Less than 33.33%	5,874	5,716	158	97.3	2.7
66617	Less than 33.33%	8,688	4,375	4,313	50.4	49.6
66618	In between 66.66% to 100%	9,402	5,738	3,664	61.0	39.0
66712	In between 66.66% to 100%	1,939	0	1,939	0.0	100.0
66743	Less than 33.33%	4,373	2,547	1,826	58.2	41.8
66762	In between 33.33% to 66.66%	24,786	20,146	4,640	81.3	18.7

Table E.1: CarFit Awareness of Survey Respondents with Zip Code (Continued)

66763	Less than 33.33%	3,369	2,772	597	82.3	17.7
66861	In between 66.66% to 100%	3,204	0	3,204	0.0	100.0
66901	In between 33.33% to 66.66%	6,605	5,340	1,265	80.8	19.2
66935	Less than 33.33%	2,563	0	2,563	0.0	100.0
66949	Less than 33.33%	668	0	668	0.0	100.0
66956	Less than 33.33%	1,157	0	1,157	0.0	100.0
67042	Less than 33.33%	17,969	14,724	3,245	81.9	18.1
67063	Less than 33.33%	3,942	2,815	1,127	71.4	28.6
67068	Less than 33.33%	4,354	2,978	1,376	68.4	31.6
67209	Less than 33.33%	13,654	13,654	0	100.0	0.0
67357	Less than 33.33%	13,006	10,298	2,708	79.2	20.8
67401	In between 33.33% to 66.66%	51,499	47,493	4,006	92.2	7.8
67410	In between 66.66% to 100%	10,141	7,054	3,087	69.6	30.4
67420	In between 33.33% to 66.66%	4,721	3,295	1,426	69.8	30.2
67470	Less than 33.33%	456	0	456	0.0	100.0
67501	In between 33.33% to 66.66%	27,212	22,980	4,232	84.5	15.6
67502	In between 33.33% to 66.66%	23,739	18,988	4,751	80.0	20.0
67505	Less than 33.33%	2,457	2,352	105	95.7	4.3
67522	Less than 33.33%	2,049	0	2,049	0.0	100.0
67543	Less than 33.33%	2,125	0	2,125	0.0	100.0
67553	In between 33.33% to 66.66%	114	0	114	0.0	100.0
67554	In between 33.33% to 66.66%	4,334	3,652	682	84.3	15.7
67561	Less than 33.33%	1,538	0	1,538	0.0	100.0
67579	Less than 33.33%	3,095	0	3,095	0.0	100.0
67601	In between 33.33% to 66.66%	23,797	21,180	2,617	89.0	11.0
67637	In between 66.66% to 100%	2,651	0	2,651	0.0	100.0

Table E.1: CarFit Awareness of Survey Respondents with Zip Code (Continued)

67672	In between 33.33% to 66.66%	2,359	0	2,359	0.0	100.0
67701	Less than 33.33%	6,502	5,463	1,039	84.0	16.0
67842	Less than 33.33%	427	0	427	0.0	100.0
67846	Less than 33.33%	33,696	29,942	3,754	88.9	11.1
67855	Less than 33.33%	1,976	0	1,976	0.0	100.0

In the following Figures E.1 and E.2, urban or rural zip codes were divided based on population percentage. If the urban population is greater than 50%, it is considered as an urban zip code and vice versa.

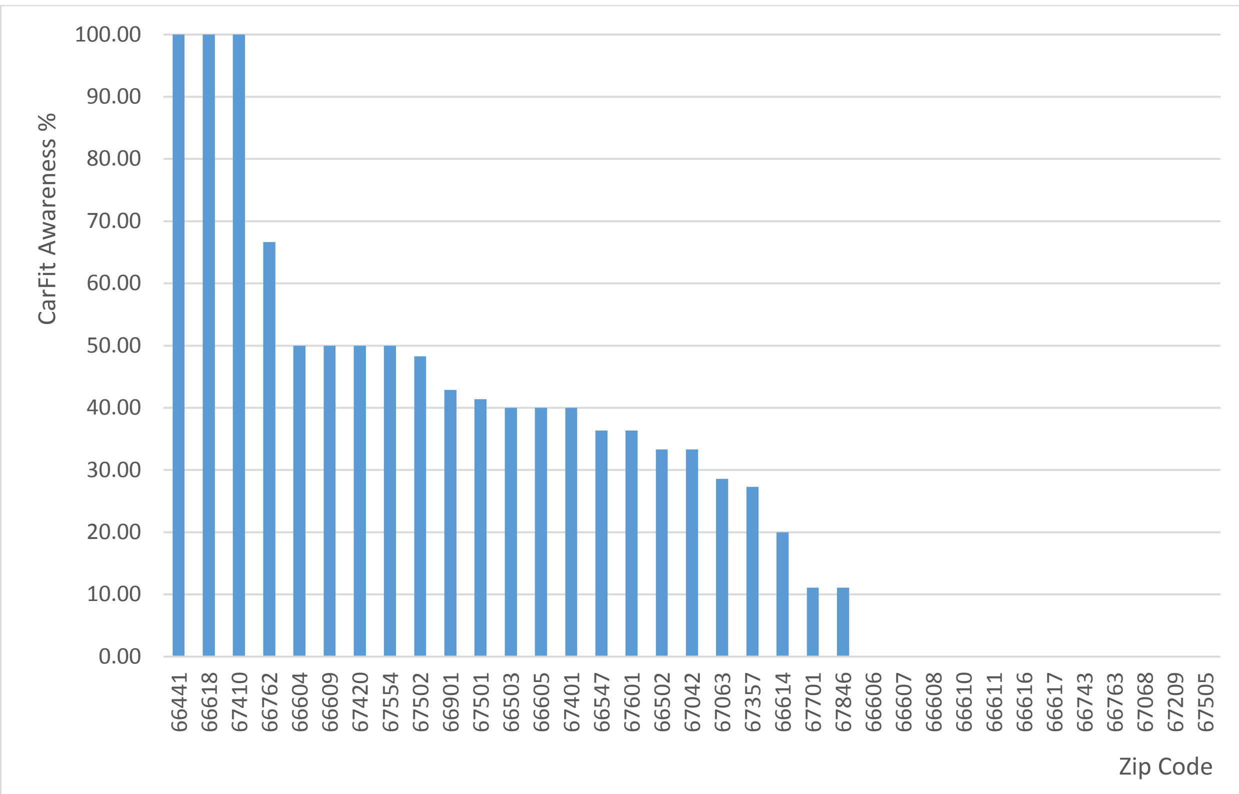

Figure E.1: CarFit Awareness % of Older Drivers in Urban Zip Codes

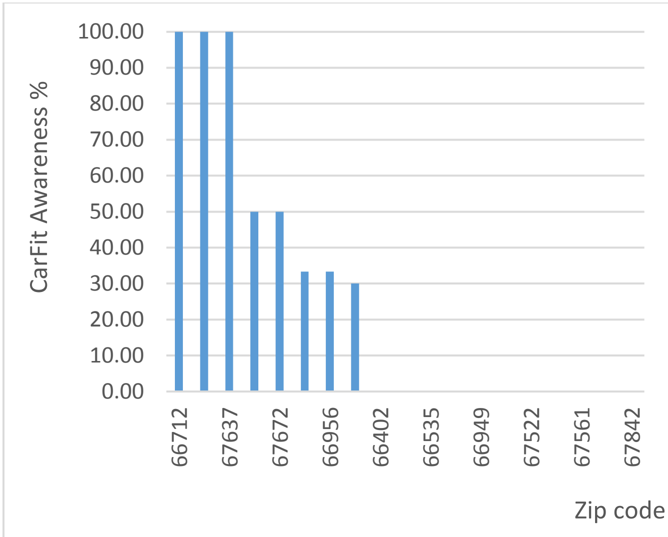

Figure E.2: CarFit Awareness % of Older Drivers in Rural Zip Codes

<u>Contingency analysis results of CarFit awareness</u>

Table E.2: Observed Frequencies for Survey Responses on Question Regarding CarFit Awareness

CarFit Awareness	No. of Urban Zip codes	No. of Rural Zip codes	Total
Aware	8	3	11
Not Aware	27	16	43
Total	35	19	54

Table E.3: Expected Frequencies for Survey Responses on Question Regarding CarFit Awareness

CarFit Awareness	No. of Urban Zip codes	No. of Rural Zip codes	Total
Aware	7.13	3.87	11
Not Aware	27.87	15.13	43
Total	35	19	54

For question regarding CarFit awareness in the survey, Null hypotheses Ho is,

H_o = CarFit awareness and Urban or Rural nature of the zip code are independent of each other.

$H_1 = H_0$ is not true

$$\chi^2_{est} = \frac{(8-7.13)^2}{7.13} + \frac{(3-3.87)^2}{3.87} + \frac{(27-27.87)^2}{27.87} + \frac{(16-15.13)^2}{15.13}$$

$$\chi^2_{est} = 0.386$$

If $\chi^2_{est} > \chi^2_{critical}$

$(\chi^2_{est} = 0.386) < (\chi^2_{critical} = 3.841)$

Null hypothesis of independence is rejected.

Therefore, null hypothesis of independence cannot be rejected. CarFit awareness and Urban or Rural nature of the zip code are independent variables.

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