Analysis of risk factors associated with fatal intersection crashes involving older drivers in the Midwest

by

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B.S., Umm Al-Qura University, Saudi Arabia, 2010
M.S., University of Dayton, Ohio, 2017

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Civil Engineering
Carl R. Ice College of Engineering

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Abstract

Motor vehicles are the primary source of transportation in the United States. While this is true for any age group, the older population tend to rely more heavily on automobiles because of easy access and availability, compared to public transportation even when it is available. Older drivers aged 65 years and older are more vulnerable to fatal crashes due to cognitive impairments and frailty. When older drivers are involved in crashes, they sustain higher injury severities compared to younger drivers. One location where older driver experience higher crash risk is intersection, due to the complexity of the situation involving multiple tasks and movements. The objectives of this study were to determine risk factors associated with intersection-related crashes involving older drivers in the Midwestern states and to provide countermeasure ideas to improve safety. Five-year fatal crash data from 2014 to 2018 from the Fatality Analysis Reporting System (FARS) database were utilized, and statistical analysis was carried out to identify characteristics of fatal crashes involving older drivers and risk factors associated with intersection crashes among this age group.

Three separate binary logistic regression models were developed to identify statistically significant predictor variables. First model represents older drivers who are involved in fatal single-vehicle crashes. Second model represents fatal multi-vehicle crashes involving at least one older driver, whereas the third model represents fatal single-vehicle crashes involving drivers younger than 65 years for comparison purposes. The dependent variable is whether a fatal crash occurs at an intersection location or not. Many independent variables that include various crash, driver, vehicle, and environmental factors were considered. By considering a 95 percent confidence level, odds ratios were estimated and used to identify relative risk factors of fatal intersection crashes.

Analysis showed that controlled intersections, two-way undivided highways, and roads with posted speed limits less than 55 mph increased the risk of fatal single-vehicle and multi-vehicle crashes for older drivers. Fatal single-vehicle crashes were especially prevalent for these drivers. Factors such as urban roadways, driver age older than 75 years, nighttime driving, and speeding increased the risk of single-vehicle fatal intersection crashes, while turning movements and intersecting paths, straight and level roadways, two-lanes highway, and violation of roadway rules increased the risk of multi-vehicle fatal intersection crashes for older drivers. Single-vehicle fatal intersection crash analysis also showed that controlled intersections, two-way undivided highways, roads with posted speed limits less than 55 mph, urban roadways, speeding, nighttime driving, and fixed objects increased the risk of intersection-related fatal single-vehicle crashes, especially for older drivers. However, factors such as straight and level roadways, impaired driving, driver obesity, and the operation of recreation vehicles, buses, or motorcycles increased the risk of single-vehicle fatal intersection crashes for drivers in other age categories.

Based on model results, countermeasure ideas to improve the safety of older drivers at intersections as well as other road users were identified. Among suggested ideas, improving intersections designs to accommodate older driver needs is recommended, such as implementing roundabouts when it is appropriate, reach minimum of 75-degree skew angel at intersection, providing protected left turn signals, flashing yellow arrow, restricted crossing U-turn, median U-turn, using rumble stripes along the side of roadway and median, providing transverse rumble strips (TRS) at intersections, improving roadway lighting, signs and markings at intersections and interchanges, implementing roadway diet, enhancing roadway signs and retroreflective delineation, providing cable, guardrail, or concrete barriers, implementing continuous raised-curb medians, enhancing lane drop marking on interchanges, providing acceleration and deceleration lane for merging and diverging locations, providing fixed or portable changeable message signs, enhancing high friction surface treatments on risk prone locations, increasing contrast markings on concrete pavement. Beside the engineering countermeasures, using newer vehicles that equipped with many safety features is advisable to enhance older and other drivers' safety. In addition, older driver license renewal may be modified to be required yearly to overcome early signs of fatigue or cognitive decline to reduce fatal crash risks and enhance safety. Therefore, the results and suggested countermeasures can provide guidance to improve safety of older drivers and other road users.

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Three separate binary logistic regression models were developed to identify statistically significant predictor variables. First model represents older drivers who are involved in fatal single-vehicle crashes. Second model represents fatal multi-vehicle crashes involving at least one older driver, whereas the third model represents fatal single-vehicle crashes involving drivers younger than 65 years for comparison purposes. The dependent variable is whether a fatal crash occurs at an intersection location or not. Many independent variables that include various crash, driver, vehicle, and environmental factors were considered. By considering a 95 percent confidence level, odds ratios were estimated and used to identify relative risk factors of fatal intersection crashes.

Analysis showed that controlled intersections, two-way undivided highways, and roads with posted speed limits less than 55 mph increased the risk of fatal single-vehicle and multi-vehicle crashes for older drivers. Fatal single-vehicle crashes were especially prevalent for these drivers. Factors such as urban roadways, driver age older than 75 years, nighttime driving, and speeding increased the risk of single-vehicle fatal intersection crashes, while turning movements and intersecting paths, straight and level roadways, two-lanes highway, and violation of roadway rules increased the risk of multi-vehicle fatal intersection crashes for older drivers. Single-vehicle fatal intersection crash analysis also showed that controlled intersections, two-way undivided highways, roads with posted speed limits less than 55 mph, urban roadways, speeding, nighttime driving, and fixed objects increased the risk of intersection-related fatal single-vehicle crashes, especially for older drivers. However, factors such as straight and level roadways, impaired driving, driver obesity, and the operation of recreation vehicles, buses, or motorcycles increased the risk of single-vehicle fatal intersection crashes for drivers in other age categories.

Based on model results, countermeasure ideas to improve the safety of older drivers at intersections as well as other road users were identified. Among suggested ideas, improving intersections designs to accommodate older driver needs is recommended, such as implementing roundabouts when it is appropriate, reach minimum of 75-degree skew angel at intersection, providing protected left turn signals, flashing yellow arrow, restricted crossing U-turn, median U-turn, using rumble stripes along the side of roadway and median, providing transverse rumble strips (TRS) at intersections, improving roadway lighting, signs and markings at intersections and interchanges, implementing roadway diet, enhancing roadway signs and retroreflective delineation, providing cable, guardrail, or concrete barriers, implementing continuous raised-curb medians, enhancing lane drop marking on interchanges, providing acceleration and deceleration lane for merging and diverging locations, providing fixed or portable changeable message signs, enhancing high friction surface treatments on risk prone locations, increasing contrast markings on concrete pavement. Beside the engineering countermeasures, using newer vehicles that equipped with many safety features is advisable to enhance older and other drivers' safety. In addition, older driver license renewal may be modified to be required yearly to overcome early signs of fatigue or cognitive decline to reduce fatal crash risks and enhance safety. Therefore, the results and suggested countermeasures can provide guidance to improve safety of older drivers and other road users.

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Abbreviations

AIC:	Akaike Information Criterion
AUC:	Area Under the Curve
CIR:	Crash Involvement Ratio
DF:	Degree of Freedom
FARS:	Fatality Analysis Reporting System
HL:	Hosmer and Lemeshow
IIHS:	Insurance Institute for Highway Safety
FHWA:	Federal Highway Administration
MLE:	Maximum Likelihood Estimate
MLM:	Maximum Likelihood Method
MUTCD:	Manual on Uniform Traffic Control Devices
MV:	Multiple Vehicle
NHTSA:	National Highway Traffic Safety Administration
OR:	Odds Ratio
OD:	Older Driver
PDO:	Property Damage Only
ROC:	Receiver Operating Characteristics
SAS:	Statistical Analysis Software
SC:	Schwarz Criterion
SPSS:	Statistical Package for the Social Sciences
SV:	Single Vehicle
USCB:	United States Census Bureau
USDOT:	United States Department of Transportation

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Chapter 1 - Introduction

1.1 Background

The population aged 65 years and older in the United States is growing rapidly. According to the United States Census Bureau (2020), this age demographic accounted for 56 million people, or 16.9% of the total population, in 2020, compared to 13.1%, or 40.3 million people, in 2010. The percentage is expected to rise to 20.6% by 2030 and to 22.1% by 2050 (USCB, 2019). Figure 1.1 shows the increasing population trend from 1950 to 2050 in the United States, especially for people 65 years and older. In 2019, the number of licensed drivers in the United States was 227 million, with older drivers (aged 65 years and older) accounting for approximately 19% of the total number of licensed drivers (USDOT, 2019). In the Midwest, the number of older population has reached 11 million, which is about 15% of the total population (Census Bureau, 2019; FHWA, 2019). The increasing older population means increasing numbers of older licensed drivers in the coming years.

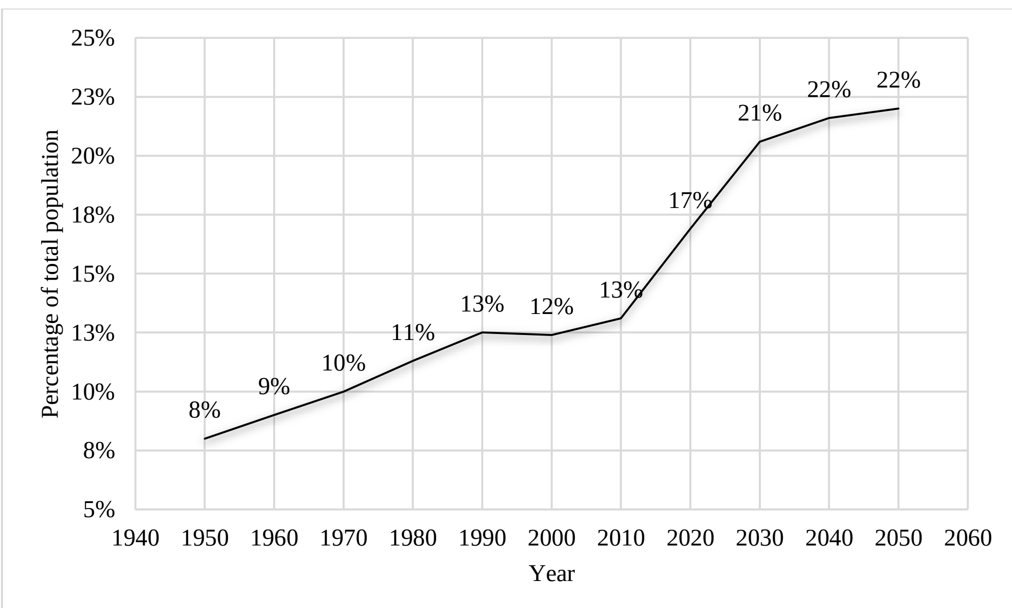

Figure 1.1 Percentage of Population 65 Years and Older in the United States (1950–2050)

Source: U.S. Census Bureau, ChildStats.gov, 2019

Motor vehicles are the primary source of transportation in the United States. The older population, ages 65 years and older, tend to rely heavily on automobiles due to ease of access compared to public transportation and the opportunity for independence and an active lifestyle (Rahman et al., 2020). However, drivers in this age range are more vulnerable to fatal crashes due to cognitive impairments and frailty, and they sustain more severe injuries in vehicle crashes compared to younger drivers. Table 1.1 compares fatal crashes for all age groups in the United States from 2014 to 2018. According to the Fatality Analysis Reporting System (FARS), the number of vehicle occupants aged 65 years and older who were involved in fatal crashes increased by 4% from 2014 to 2018. In contrast, younger age groups (less than 65 years old) increased by only 2% for total fatal crashes in the same period. As shown in Table 1.1, the increasing trend of fatal injuries among older drivers presents a serious safety issue that must be addressed.

Table 1.1 Fatal Crashes by Age Group

Occupants	2014	2015	2016	2017	2018	Total
All Ages	65,608	72,500	76,511	75,964	73,392	363,975
Older People Age > 65 years	7,968	8,914	9,609	9,756	9,725	45,972
Percentage of Older Occupants	12.1%	12.3%	12.6%	12.8%	13.3%	12.6%

Although the number of crashes involving older drivers is less than crashes involving younger age groups, older drivers sustain higher injury severities and more fatalities. Figure 1.2 shows fatal crashes by driver age from 2014 to 2018 for 100 million miles traveled. As shown in the figure, the fatality rate increased gradually when drivers reached the age of 50, and more than 70% of drivers involved in fatal crashes in 2018 were older than 70 years (IIHS, 2018). According to the National Highway Traffic Safety Administration (NHTSA), more than 7,214 people aged

65 years and older sustained fatal injuries in 2018 due to motor vehicle crashes. Since 1975, the rate of older people involved in fatal crashes increased by 32% in the United States.

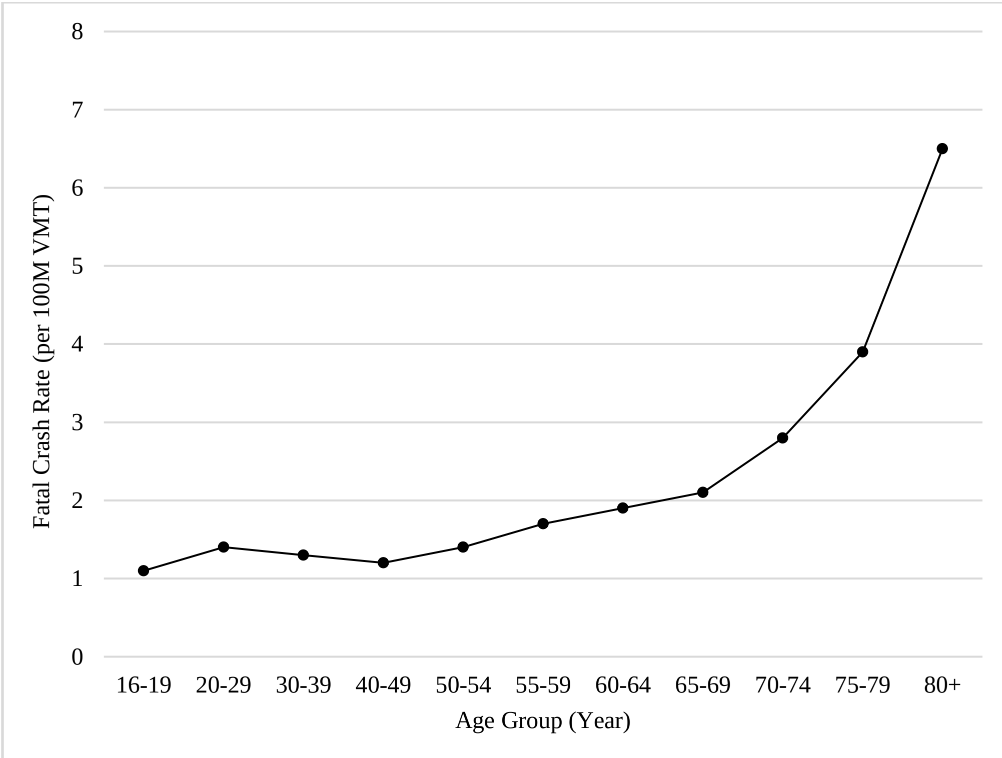

Figure 1.2 Passenger Vehicle Fatal Crash Involvement by Age Group (2014–2018)
Source: Insurance Institute for Highway Safety (IIHS), 2018

The percentage of fatalities among older drivers is considered the highest among all the age groups for all crash types. Of the four types of fatal crashes (multi-vehicle intersection crashes, single-vehicle intersection crashes, multi-vehicle non-intersection crashes, and single-vehicle non-intersection crashes), older drivers have the highest crash risks in multi-vehicle intersection crashes (IIHS, 2018). As shown in Figure 1.3, the percentage of involvement in fatal multi-vehicle crashes at intersections was noticeably elevated for drivers aged 65 years and older in 2018.

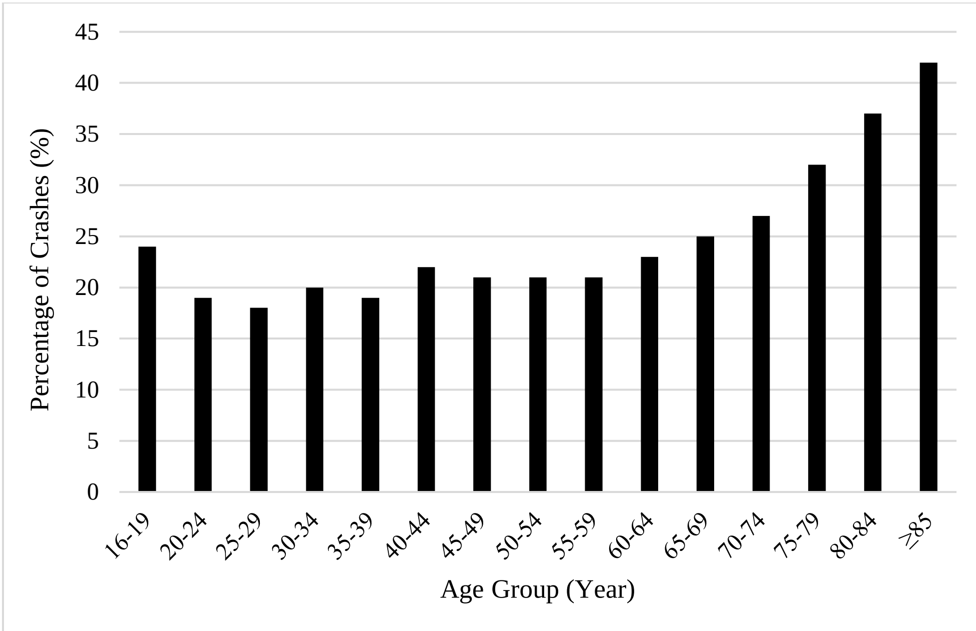

Figure 1.3 Multiple-Vehicle Intersection Crashes by Age Group in the United States, 2018

Source: Insurance Institute for Highway Safety (IIHS), 2018

A study by Sifrit et al. (2010) showed that intersection control plays an important role in reducing the severity of older driver crashes at intersections. Intersections controlled by traffic signals were the safest for older drivers, while intersections controlled by flashing signals was the riskiest. The highest number of fatalities among older drivers occurred at signalized intersections when turning left without a protected left turning signal. Thus, intersection locations are considered as risky among older drivers, particularly without traffic control signals.

1.2 Problem Statement

An increasing population of people aged 65 years and older in the United States means the number of older drivers has also increased. Unfortunately, however, older drivers may experience lack of attention, visual impairment, and restrictions in neck movement, which could lead to vehicle crashes, especially fatal crashes, due to natural aging issues that reduce mobility and perception reaction times (Rahman et al., 2020). Because older drivers often sustain higher crash injury severity compared to other age groups, increasing roadway safety criteria for older drivers is imperative.

Table 1.2 compares FARS data for fatal, injury, and no-injury crash severity by driver age group from 2014 to 2018 in the United States. As shown in the table, drivers aged 65 years and older were involved in more than 18% of fatal crashes, or one in five fatal crashes. The average injury rate for older drivers was 11%, or 7,093 injury crashes, but only approximately 10% of older drivers who survived crashes with no injuries were classified as property damage only (PDO). This increasing percentage of crashes involving older drivers also resulted in a 9.3% increase in fatalities among these drivers (i.e., 3,564 to 4,298) and an 11.5% increase (i.e., 1,217 to 1,533) in injuries over the study period.

Table 1.2 Driver Injury Severity by Age Group

Injury Severity	Drivers	2014	2015	2016	2017	2018	Total
Fatal	All drivers	20,778	22,339	23,696	23,738	22,904	113,455
	Older drivers	3,564	3,891	4,242	4,272	4,298	20,267
	% of Older	17%	17%	18%	18%	19%	18%
Injury	All drivers	11,071	12,397	13,223	13,291	12,817	62,799
	Older drivers	1,217	1,345	1,468	1,530	1,533	7,093
	% of Older	11%	11%	11%	12%	12%	11%
PDO	All drivers	11,865	13,299	13,759	14,187	14,221	67,331
	Older drivers	1,175	1,306	1,409	1,464	1,461	6,815
	% of Older	10%	10%	10%	10%	10%	10%

Table 1.3 compares the fatality-to-injury ratio among all drivers. As shown in the table, the ratio among older drivers is 2.85, compared to 1.67 for other drivers, and 59% of crashes involving older drivers were fatal, compared to 45% of crashes for other drivers. These results show the high probability of fatality for older drivers in vehicle crashes, thereby highlighting the critical need for improved driver safety.

Table 1.3 Fatality to Injury Ratio by Age Group in the United States (2014-2018)

Age Categories	Fatality	Injury	No Injury	Total	F/I
Older drivers ≥ 65 yrs.	20,267 (59%)	7,093 (21%)	6,815 (20%)	34,175	2.85
Other drivers < 65 yrs.	93,188 (45%)	55,706 (27%)	60,516 (29%)	209,410	1.67

1.3 Objectives of the Study

The primary objectives of this research are to identify the characteristics and nature of older-driver fatal crashes at intersections in the Midwest and suggest suitable countermeasures for improving the safety situation. More specific tasks completed in achieving the key objectives are to:

- Compare the U.S. regions regarding older driver fatal single-vehicle crash statistics.
- Analyze vehicle, road, driver, and environmental characteristics that are associated with older driver crashes at intersections.
- Identify factors associated with fatal intersection-related crashes involving older driver single-vehicle and multi-vehicle crashes.
- Identify factors associated with intersection-related crashes involving drivers younger than 65 years of age in single-vehicle crashes.
- Compare the factors associated with intersection-related crashes involving older driver single and multi-vehicle crashes.
- Compare the factors associated with intersection-related crashes involving older and other drivers in single-vehicle crashes.
- Identify favorable countermeasures according to the findings of the study that best suit to improve the safety of older drivers at intersections.

1.4 Organization of the Dissertation

This dissertation consists of five chapters. Chapter 1 contains an introduction, background about the aging population and impacts on driver safety, and study objectives. A detailed literature review on older driver crashes and safety, data analysis, and countermeasures are provided in Chapter 2. Chapter 3 explains the data of the study and the methodology used to analyze the data, Chapter 4 presents the result of the study, related discussion, and countermeasure ideas according to the study findings. Chapter 5 presents research summary, conclusions, recommendations, study limitations, and future research.

Chapter 2 - Literature Review

Many previous studies have investigated safety-related concerns for older drivers in the United States. The studies have identified driver, roadway, environmental, and vehicle-related factors associated with crash severity and analyzed crash risks for various age groups. This chapter summarizes previous studies, reviews the methodology used to analyze data, and identifies potential countermeasures to reduce crash severity for drivers aged 65 years and older.

2.1 General Studies

Bedard et al. (2002) utilized FARS data to determine factors that contribute to fatal injuries of single-vehicle crashes with fixed objects. They used multivariate logistic regression to determine the relationship between fatal injuries and driver age. The study specifically focused on the relationship between driver fatality and seating position of passengers, with consideration of driver, vehicle, roadway, and environmental characteristics. The multivariate logistic regression model was developed by eliminating non-significant factors using the backward selection technique. Results showed that a high probability of fatal-injury crashes were associated with driving under the influence of alcohol, female drivers, driver's side of the vehicle, and speeding. Seat belt usage was shown to reduce injury levels. The study recommended increasing seat belt usage and reducing speed limits to minimize fatal injuries in crashes.

Kahane (2013) utilized FARS data to study the impact of age and gender on crash injury severity and evaluate vehicle technologies and their role in reducing crash severity. The study used logistic regression, pair comparison, and backward selection to remove non-significant factors from the model. Although fatal injuries of drivers and all vehicle occupants were considered, the primary goal of the study was to assess injury severity of right-front-seat passengers in correlation with vehicle age. The study used two dependent variables: fatal or non-fatal injury for driver and right-front-seat passengers. Results showed that females were 17% more likely to be involved in fatal crashes than males, but seat belt usage was more beneficial for female drivers. Airbag technology, especially side airbags, was shown to significantly benefit all age groups, and a comparison of vehicles from the 1960s to vehicles from the 1990s showed that improved safety technologies reduced the risk of fatal injury by approximately 50%.

A study by Dissanayake (2004) utilized the Florida Traffic Crash database to identify factors that affect crash severity for older drivers (65 years and older) and younger drivers (16–25 years old) in single-vehicle crashes using unique models for each age group. A binary logistic regression model was used to analyze the data using statistical analysis software (SAS), and five levels of injury severity, which are fatal, incapacitating, non-incapacitating, possible, proparty damage only (KABCO), were used to compare every two sets for drivers in the two age groups. Four models for each age group were developed according to the injury severity level. Results showed that speed and use of restraining devices were the most influential factors for crash severity at all levels for both younger and older drivers in single-vehicle crashes. Older drivers experienced greatest crash severity with front-impact crashes, while younger drivers experienced highest crash severity upon crash ejection and driving on grade or curved roadways.

Farmer (2019) utilized the Poisson model to analyze 25 years of FARS data (1993–2017) from each state to determine the effects of increased speed limits on traffic fatalities. This study was an update to a previous study by Farmer in 2017. Throughout the study period, five states increased the speed limit from 55 to 65 mph, and 41 states increased their maximum speed limit to 70 mph. Only three states (Alaska, Massachusetts, and Vermont) did not change their maximum speed limits. Results showed that each 5 mph increase in speed limit was associated with an 8.5% increase in fatality rates on interstates and freeways and a 2.8% increase on other roadways, meaning no change in speed limit would have prevented 36,760 vehicle fatalities. The study urged authorities to consider the negative impacts of crashes and fatalities when increasing the speed limit to reduce travel time.

Friedman et al. (2009) investigated the effects of increasing the maximum speed limit on driver fatalities. The study analyzed FARS data from 1995 to 2005 on rural interstates throughout the United States using a mixed-regression model and Poisson distribution. Data analysis began in 1995 because most states increased the speed limit after the National Maximum Speed Limit law was cancelled in 1995. A total of 388,399 fatalities and 930,865 injuries were recorded after the speed limit increased on rural interstates. Results showed that fatalities decreased in states that did not change the maximum speed limit, while fatalities increased in states that increased the maximum speed limit. Urban interstates had the highest increases in fatalities, with a total of 12,545 fatalities during the study period, due to increasing maximum speed limits. The study recommended lowering speed limits and improving enforcement to reduce crash fatalities.

Stutts et al. (2009) utilized FARS and General Estimates System (GES) data from 2002–2006 to investigate crash-related driving behavior of drivers aged 60–69 years, 70–79 years, and drivers older than 80 years. Induced exposure analysis was used to compare the CIRs for at-fault and not-at-fault drivers within each age group. Data analysis focused on specific crash factors for older drivers and single-vehicle and two-vehicle crashes with different body types of vehicles. Study results showed that, although intersection crashes are dangerous for all age groups, especially with left turns, older drivers have a higher intersection-related crash risk, especially drivers 80 years and older. The study recommended countermeasures such as education, training, and self-regulation for drivers in this age group to reduce the risk of fatal crashes.

Cicchino et al. (2015) investigated fatalities among older (more than 70 years old) and younger (35–55 years old) drivers based on vehicle miles traveled (VMT). Decomposition methodology was used to obtain data from U.S. national databases from 1995 to 1998 and 2005 to 2008. Study results showed a 70% higher increase in crashes among older drivers compared to younger drivers. The study suggested that factors such as changing driver habits, improving roadway design, and enhanced vehicle technologies such as airbags could increase driver safety and reduce crash fatalities for older drivers.

Khattak et al. (2002) investigated factors (i.e., driver, vehicle, roadway, and environment) that increase injury severity for older drivers in vehicle crashes, and they estimated significant factors according to levels of injury severity. Using crash data from 1990 to 1999 in Iowa, the study utilized the injury severity level (KABCO) to organize and prepare the data and applied the ordered probit model according to the order of the injury severity level. Results showed that driver age and gender as well as driving under the influence of alcohol most significantly affected injury severity. In addition, crashes that occurred in rural areas or on curved roadways also resulted in increased injury severity. Recommendations from the study included reassessing the 1996 decision to increase the speed limit on many highways in Iowa, strengthening driving laws related to alcohol consumption and seat belt usage, and implementing warning signs or rumble strips on curved roadways. The study concluded that further research should compare crash injury severity for older and younger drivers and determine crash causation.

Dissanayake and Lu (2001) used police crash reports from 1994 to 1996 in Florida to study injury severity differences among older drivers involved in single-vehicle, fixed-object crashes. They developed two models using binary logistic regression to analyze injury severity and crash severity. The study considered five levels of injury severity ranging from no injury to fatality.

Crash severity was measured by the most severe injury sustained by a vehicle occupant or non-occupant as a result of the crash. Study results showed that travel speed, restraint device usage, point of impact, alcohol consumption, driving in rural and on curved roadways, and driver health conditions were the factors that most significantly impacted older drivers involved in single-vehicle, fixed-object crashes.

Cox and Cicchino (2021) used FARS data from 1997 to 2018 to evaluate current trends of vehicle crashes involving older drivers to compare the previous decline with the recent increase in crash fatalities in the United States. Analysis of covariance was used to explore crash involvement rates among older drivers. Study results showed that, although the VMT percentage decreased, the CIR and number of fatalities increased among older drivers, potentially due to the rising speed limits. The study recommended converting four-way intersections to roundabouts and improving vehicle safety features to enhance driving safety for older drivers especially. The study also advised older drivers to operate newer vehicles with modern safety equipment for increased protection in fatal crashes.

2.2 Intersection Safety Related Studies

Dukic et al. (2012) investigated driver eye movement at intersections to understand driving behavior of drivers 35–55 years old and drivers 75 years and older. Drivers from the two groups wore an eye tracker during the virtual exam to measure eye movement at four types of intersections. Results showed that the older drivers tended to navigate for turning left or right when approaching the intersection, while the younger drivers demonstrated higher speeds when entering the intersections. The only difference in driving behavior for the two age groups was observed at stop signs, where the younger drivers more readily utilized the rearview mirror. In addition, the younger drivers look around at the intersection more frequently before passing through. Most drivers from both age groups looked straight ahead when approaching complex four-way intersections. However, results also showed that the older drivers paid more attention to intersection road markings than oncoming vehicles, while the younger drivers were aware of potential dangers overall. The study recommended implementation of a support system for visualization that could improve the safety of older drivers at intersections.

Lombardi et al. (2017) used FARS data from 2011 to 2014 to study driver age and fatal intersection crashes in the United States. A total of 28% of the 120,809 fatal crashes during the study period occurred at intersections. The researchers utilized a multivariate Poisson logistic regression model to analyze the data and induced exposure analysis to calculate crash involvement ratios (CIRs). The study considered two age groups: drivers younger than 65 years old and drivers aged 65 years and older. The older drivers demonstrated a 56% at-fault rate for fatal intersection crashes, while younger drivers were at fault in 38% of the crashes. Factors associated with crashes were lane changing, yielding the right of way, changing speed, and alcohol involvement. The study recommended increasing the requirements to obtain a driver's license, implementing training for driver permits, and creating a system for monitoring road user safety to reduce crash severity.

Choi (2010) investigated crash factors such as weather conditions, gender, age, and traffic control type for approximately 790,000 intersection-related crashes in the United States. The study utilized a generalized logit model, descriptive analysis, and configural frequency analysis to study data obtained from the National Motor Vehicle Crash Causation Survey (NMVCCS) from 2005 to 2007. The generalized logit model was used to identify crash factors, and descriptive analysis was used to identify the characteristics of intersection crashes and crash factors. Although most intersection crashes were due to obstacles to the view when turning left or right, lack of full driving attention, disobeying the road rules, and misjudging the gap at intersections with a curve were also prevalent factors. Results showed that drivers younger than 25 years old and drivers older than 55 years old are at increased risk of involvement in intersections crashes. The findings of this study could be used to improve intersection design and to evaluate and develop collision avoidance technologies, including the Cooperative Intersection Collision Avoidance System (CICAS).

Choi et al. (2017) investigated driving behavior among older drivers in channelized and un-channelized intersections and identified risk factors associated with intersection-related turning behavior. The study utilized crash data from police reports from 2012 to 2014 in Seoul, South Korea. The data included factors related to location, time, weather conditions, crash and vehicle type, age, and gender. Study results showed that a majority of crashes among older drivers occurred on non-channelized intersections and involved turning movements. Countermeasure suggestions included improving current intersection designs to accommodate turning movements of older drivers, such as protecting left-turning movement to reduce crash frequency. Providing education and training programs and enhancing vehicle technologies for side and mid mirrors could also increase the safety of older drivers at intersections.

Braitman et al. (2007) investigated factors related to intersection crashes for drivers older than 70 years, with a comparison group of drivers aged 35–54 years, to identify factors that lead to at-fault crashes for older drivers. Data were obtained via in-depth telephone interviews with at-fault drivers and police crash reports from 2003 to 2004 in Connecticut. Study results showed that failure to yield at intersections, especially when turning left at stop signs, was the most prevalent contributing factor for crashes involving older drivers. Reasons for failing to yield included the inability of older drivers to see other vehicles in the intersection and misjudging the gap and time to proceed through the intersection. Distraction was the predominant factor for drivers from the younger age group. The study suggested converting intersections to roundabouts to reduce points of conflict, providing protected left turns to help older drivers proceed safely at intersections, and utilizing crash avoidance technologies to enhance driver safety and minimize fatal crash risks.

2.3 Older Driver Safety Research in Other Countries

A study by Oxley et al. (2006) focused on how intersection design improves the safety of older drivers in Australasia (Australia, New Zealand, and surrounding islands). The study identified several intersection design issues, specifically “black-spot” sites with an increased number of crashes, and recommended beneficial changes. Sixty-two locations were selected for the study period of 1994–1998, with over 400 crashes involving older drivers. Results showed that a majority of crashes involving older drivers occurred at intersections, with 65% of the intersections controlled by stop signs and 35% controlled by traffic signals. In addition, contributing factors such as selecting inappropriate gab when turning through the intersection, intersection complexity, traffic volume with high speeds, limited sight distance, and violation of traffic signs and signals were identified. The most high-risk factor was gap selection, and the intersection design that associated with 76% and 23% of the crashes, respectively. The primary issue of intersection crashes was the use of a separate signal to control each turn-lane movement. The study suggested the use of intersection roundabouts to reduce conflict points and decrease severe crashes.

Chen et al. (2012) utilized ten years of data (2000–2009) to investigate factors that contributed to the severity of intersection crashes in Victoria, Australia. The study focused on drivers and vulnerable road users, such as pedestrians and bicyclists. A logistic regression analysis was utilized to examine approximately 12,000 crashes. Factors such as gender, driver age, speed limit, traffic control type, seat belt usage, and time of day were primarily associated with intersection crashes. Most crashes occurred after midnight to early morning in high-speed zones greater than 80 km/hr without traffic control. According to study results, older drivers have an increased risk of involvement in fatal intersection crashes. The study recommended that risk factors should be identified and minimized at intersections to reduce the number of fatal crashes.

Thompson et al. (2018) compared crash involvement trends for drivers aged 65 years and older and drivers younger than 65 in Australia to evaluate the trend of fatal crashes (increasing or decreasing) for older drivers. Crash data were obtained from several transportation agencies in Australia from 2004 to 2013. Study results showed that the number of fatal crashes for older drivers remained steady throughout the study period, with only a slight increase for drivers who were older than 85 years. Similarly, the number of fatal crashes remained steady (with a slight decrease) for younger drivers. Suggested safety countermeasures for older drivers included operating newer cars with safety assistance and warning systems, providing education programs, altering vehicle crash test protocols to account for the needs of older drivers, and improving intersection safety, such as reducing uncontrolled turns on traffic lights and reducing speed limits at intersections.

Elliott et al. (1995) used data from 1990 to 1992 from Australia's Federal Office of Road Safety (FORS) database to evaluate risk factors associated with older drivers. Study results showed that older drivers were overrepresented in multi-vehicle crashes, crashes that occur during daylight hours of weekdays, and crashes that occur on complex intersections, as well as crashes when vehicles are traveling at reduced speeds and when drivers fail to yield the right of way. However, older drivers were underrepresented in crashes involving speeding and loss of control, alcohol use, and crashes during nighttime hours. Countermeasures such as educating and training older drivers to encourage self-regulation and license testing, including driving, knowledge, and health tests, and improving road and vehicle design to accommodate older drivers were suggested.

Chen et al. (2012) analyzed severity factors associated with intersection crashes. The study, which used logistic regression to analyze crash data from 2000 to 2009 in Victoria, Australia, specified the dependent variable to be the severity of intersection crashes and to be binary as a fatal or non-fatal crash. Independent variables such as driver age and gender, speed limit, type of traffic control, time of day, seat belt usage, crash type, and weather condition were utilized. The odds ratio was used to predict the risk of fatal intersection crashes to non-fatal intersection crashes, and SPSS software was used for the correlation process for logistic regression. The variables, which were reclassified from continuous to categorical for analysis, were selected using univariate analysis with a p-value < 0.25. The significance level of 0.05 for α value and a Wald chi-square test value were also considered. Study results showed that risk factors such as crash type, speed zone, traffic control, driver age and gender, seat belt usage, and time of day significantly impacted the severity of intersection crashes. The study concluded that male drivers (65 years and older) have a higher risk of involvement in fatal intersection crashes.

2.4 Data Analysis Related Studies

Lambardi et al. (2017) compared intersection and non-intersection crashes for two age groups (younger than 65 years old and 65 years and older). An age group consisting of drivers aged 20–24 years old was a reference group in the study. The multivariate logistic regression model was utilized to estimate the risk of fatal crashes at intersections, and the maximum likelihood method was used to analyze the crash data. Variables such as time of day, day of the week, type of road, type of trafficway, road alignment, weather conditions, lighting conditions, and driver fault were considered. Due to the high number of missing values, variables such as travel speed at the time of crash were neglected in the study.

In the same study, induced exposure analysis was used to estimate CIRs for two-vehicle crashes with at-fault or not-at-fault drivers. FARS data was used to identify driver-related factors such as failure to yield or careless driving, and then the CIRs and 95% confidence level were calculated for intersection crashes for specific age groups. When the CIR had a value greater than 1, the age group was at a high risk for intersection crashes; a value less than 1 meant the age group was at a low risk for intersection crashes. In the same study, the Multivariate Poisson regression model was used to compare different driver ages in fatal intersection crashes. Two age groups were considered, younger than 65 years and 65 years and older with respect of gender. The model was utilized to compare the two age groups concerning factors associated with intersection crashes that covered time of day, day of the week, type of road, type of traffic way, road alignment, weather conditions, lighting conditions, and driver at fault.

A study by Choi (2010) used data from the National Motor Vehicle Crash Causation Survey "NMVCCS" (2005–2007) to analyze factors associated with crashes at intersections. The study coded critical pre-crash events (e. g., turning left or right or crossing over) as the response variable and considered critical-reason factors such as driver gender and age, the presence of a traffic control device, critical pre-crash events, and weather conditions. The generalized logit model, which accounted for single variables and interaction effects, and cross-tabulation were used to determine frequency differences between observed and expected values, and the Wald chi-square and p-values were utilized to identify significant factors in the model. Results showed that critical reason with crash factors and their two-factor interaction effects had significant association. The study also compared driver characteristics and other interaction variables in the model using configural frequency analysis (CFA), which tests the Z-statistic. The study found that factors such as illegal maneuvering, inattention, obstructed view, misjudgment of gap while turning at intersections, and speeding were primary reasons for crash occurrence. These findings could be used to improve collision avoidance technologies and intersection design.

Wu et. al (2014) investigated injury severity for single-vehicle and multi-vehicle crashes on rural two-lane highways in New Mexico. The study claimed that, because most previous studies investigated injury severity on rural highways by analyzing single-vehicle and multi-vehicle crashes together, individual modeling of each crash type would beneficially reveal unique contributing factors for crash outcomes. The study used a total of 10,355 vehicle crash records, with single-vehicle crashes accounting for 47% of crashes and multi-vehicle crashes accounting for 53% of crashes. A mixed logit model was developed to analyze each crash type separately, and the study distinguished each model finding separately before comparing both. For single-vehicle crashes, variables such as crashes involving fixed objects, driving on dry and loose materials, driving a van, overtaking action, and driving under the influence of alcohol increased injury severity among drivers on rural highways. For multi-vehicle crashes, variables such as driving a motorcycle or truck, dark or dusty conditions, snowy conditions, driving under the influence of alcohol, and driver age of 65 years or older increased injury severity for crashes on rural highways. The study recommended using more flexible pavement materials to reduce crash severity. In addition, because overturn crashes often result in fatal injuries, the study urged the consideration of related factors such as roadway geometry, speed limit, driver behavior, and environmental factors and countermeasures to increase the visibility of warning signs and improve roadway lighting systems at night to reduce injury severity.

Dissanayake and Ratnayake (2006) investigated the factors that lead to high severe crashes in rural areas in Kansas. The study aimed to identify risk factors that increase the severity of rural highway crashes and determine suitable countermeasures to reduce the risk of those crashes. The study used an ordered probit model to analyze data from the Kansas Accident Reporting System (KARS) database from 1993 to 2002, and a sample dataset of 93,145 records was used to analyze the crash data. The response variable in the study was crash severity with five levels, meaning it was an ordinal response variable. Study results showed that excessive speed, lack of seat belt usage, and driving under the influence of alcohol increased the severity of rural crashes in Kansas. At-fault driving or driver age older than 55 years old also significantly increased the severity in single-vehicle crashes. Crashes occurring on curved roadways or at intersections tended to be more severe in rural areas, and vehicle maneuvering to avoid crashes was shown to increase injury severity. However, an emergency response time of less than 5 minutes was shown to reduce injury severity of rural crashes. The study concluded that Kansas should implement stricter seat belt laws in Kansas, and countermeasures should be identified to reduce the number of severe crashes and enhance driver safety in rural areas in Kansas.

Geedipally and Lord (2010) utilized Poisson and Poisson-gamma models to analyze single-vehicle and multi-vehicle crash data individually and collectively from the Texas Department of Transportation (TxDOT) for 1,552 undivided four-lane highway segments from 1997 to 2001. The study analysis used the scale (KABCO) of crash severity levels (i. e., fatal injury, injury type A or B or C, PDO). Study results showed that separate modeling of single-vehicle and multi-vehicle crashes provided a wider confidence interval than combined modeling. The study recommended further analysis using the same method for different highway types with consideration of the sample size to determine differences in the confidence intervals.

Padlo et al. (2005) evaluated data for younger (16–20 years old) and older (65 years and older) at-fault drivers in Connecticut from 1997 to 2001. The study evaluated crashes occurring at night, on various classes of roadways, and travel with several passengers. Single-vehicle and two-vehicle crashes were analyzed using the quasi-induced exposure analysis technique and logistic regression models. The study considered at least one vehicle to be at fault in two-vehicle crashes, and crashes that involved only single vehicles were assumed to be at fault. A total of 392,655 crashes were studied, of which 67% were two-vehicle crashes and 20% were single-vehicle crashes. Study results showed that both age groups were at increased risk of crashes at night and on freeways. Passengers with younger drivers increased the crash risk, while older drivers had higher crash risk when traveling alone. The study recommended increasing the length of licensure education and training for younger drivers. Further research should study the presence of passengers with older drivers and considering road type and light conditions.

Preusser et al. (1997) used FARS and GES data from 9,548 fatal crashes from 1994 and 1995 in the United States to compare fatal intersection crash risks for older drivers (65 years and older) and younger drivers (40–49 years old). The study aimed to quantify crash risk for older drivers at intersections while controlling for factors such as frailty. Induced exposure analysis identified risk factors among older drivers, but the study only considered crashes that identified at-fault older drivers for single-vehicle and multi-vehicle crashes. Study results showed that approximately 50% of intersection crashes were run red traffic light, and older drivers were overrepresented in crashes at intersections when turning left. The study suggested countermeasures such as protected left-turn signals and four-way stop sign signals at non-signalized intersections to minimize crash risks for older drivers.

2.5 Countermeasure Related Studies

The NHTSA has suggested the following countermeasures to reduce or prevent crashes involving older drivers: educating and training to evaluate driving ability and limitations; improving driving skills and reviewing roadway signs; closely monitoring medical conditions and treatments that could affect driving behavior; implementing license renewal laws for older drivers in conjunction with family members, physicians, and law enforcement for those who have difficulty driving; and using newer vehicle technology or vehicle adjustment to enhance overall driving safety (Richard et al., 2018). This section reviews countermeasures from previous studies that help prevent or reduce crashes involving older drivers. The countermeasures are broadly categorized as training, educating, and communicating with older drivers; licensing programs and law enforcement; utilizing newer vehicle technology to enhance driver safety; and designing roadways to accommodate older drivers.

2.5.1 Training, educating, and communicating with older drivers

Gaspar et al. (2012) examined how training interventions, specifically a commercial computer-based cognitive training program, could improve older drivers' driving performances. A total of 40 older drivers were divided into two test groups: one group used a driving simulator, while a control group played card games. The experiment was conducted in a driving simulator lab to examine participants in 14 aspects of cognition, including field of view, visual scanning, and working memory. The participants were assessed before and after training according to previously determined performance measurements. Results from the statistical method of analysis of variance showed that the simulation training program did not improve older drivers' driving performances. The study recommended that further improvement would be obtained using a training program that focuses on driving context rather than basic cognitive tasks.

Owsley et al. (2003) investigated how older drivers could benefit from an educational intervention that promotes self-regulation. A total of 365 older drivers in Birmingham, Alabama, were selected according to targeted age, driving status, and driving exposure and divided into the usual care control group (45%) and the usual care plus educational intervention group (55%).

Analysis results using t-tests and the chi-square test showed that educational intervention improve the driving knowledge of older drivers, although the educational curriculum did not change attitudes about general driving safety issues. Self-regulation, a relatively low-cost prevention measure, was shown to successfully enhance the safety of older drivers. To reduce crash risks for older drivers, the study recommended convincing visually impaired older drivers to reduce their driving exposure.

Dickerson et al. (2019) investigated three countermeasures (screening and evaluation, education and training interventions, and in-vehicle technology) to enhance the safety and mobility of older drivers. As a starting point for widespread intervention, the study recommended increasing the regularity of evaluation of older drivers by health care professionals. Education and training should follow evaluation to help improve driver knowledge and driving behavior, but no evidence suggested a change in crash risk among older drivers. The advanced technologies in today's vehicles were primarily shown to enhance the safety of older drivers, although some of the sophisticated technologies distracted older drivers. Resulting concerns of in-vehicle technologies included the extended time older adults require to learn new technology, as well as lack of previous studies that have included older drivers when testing new vehicle technology. Because future technology may include autonomous vehicles that will require close driver attention, this study questioned whether older drivers will be able to safely operate autonomous vehicles.

Fausto et al. (2020) utilized a systematic review and meta-analysis to study interventions that increase the safety of older drivers. Randomized control trials consisting of drivers 50 years of age and older were used to detect the effectiveness of each intervention. The systematic review included 26 previous studies for the meta-analysis. Study results showed that physical and visual-perceptual training exercises decreased at-fault crashes of older drivers by 30%. Educational training, however, did not effectively reduce the crash rate among older drivers, as proven by previous studies that have asserted that self-regulation does not reduce crash risk and could increase risk in some cases (Ross et al., 2009). Education was shown to increase knowledge of the risk but did not improve driving safety. Overall, this study found that combined training approaches, such as education and visual-perceptual training or education and physical training, could effectively improve the driving performance of older drivers. However, more studies are recommended to evaluate combined interventions. The study recommended that occupational therapists and driving rehabilitation specialists apply interventions that benefit all road users.

Gaines et al. (2011) used a survey to compare the short-term effects of the CarFit program for older drivers to self-reported driving. Participants completed a survey before and six months after applying to the CarFit program. Statistical analysis results showed that participants found the CarFit program useful and would recommend it to a friend. The CarFit program also showed promise for improving driving safety among older adults, including self-regulation, or letting drivers resign from driving for their own safety. The study advised continuation of the program to enhance the performance and safety of more drivers.

2.5.2 Licensing programs and law enforcement

Fraade-Blanar et al. (2018) examined crash risk factors associated with older drivers with cognitive impairment. The study utilized data from the Adult Changes in Thought (ACT) and Washington state crash reports from 2002 to 2015. A total of 2,615 was gathered for older drivers with active driver’s licenses. A negative binomial mixed-effects model was used to analyze the data by considering the association between the crash risk and level of cognition. Results showed that 13% of older drivers had at least one crash, with an average of seven years, and a 1-unit decrease in cognitive ability screening was observed, which correlated with increases in CIRs. The study concluded that decreased performance in cognitive screening could be a sign of a risk factor for a fatal crash. However, further studies are needed to examine driving behavior, especially for drivers with lower cognitive ability.

Snyder & Ganzini (2009) investigated a driver's license law in Oregon that requires a physician’s report of impaired drivers. A total of 1,664 physicians’ reports from 2003 to 2006 were examined, and the study utilized logistic regression to determine whether the driver failed to regain driving privileges. Study results indicated that cognitive impairments were seven times more common than functional impairments among older drivers. In fact, drivers older than 80 years of age were six times less likely to reobtain their driver's license, and more than half of the older drivers were reported to have chronic or progressive cognitive impairments. The study concluded that further studies are needed to determine if the driver’s license law successfully decreases the numbers of fatal and injury crashes.

Meuser et al. (2009) used data from 2001 to 2005 to investigate a voluntary reporting law in Missouri that requires each driver to have a physician evaluation before renewing their driver’s license. The report highlighted an issue with older drivers since frail, and medical difficulties were reported that included dementia and cognitive impairment. The report was combined and shared by police report 30%, license office staff 27%, physicians 20%, family members 16%, and others 7%. Of the approximate 4100 drivers over the age of 50 years old who were studied, only 144 (3.5%) passed the testing requirement and maintained a current driver’s license, potentially as a result of factors such as accurate self-awareness, pressure from a family member, or impairment. The study concluded that, although this Missouri law helps enhance the safety of older drivers, further assessment via on-road testing is needed to predict at-fault crash rates for older drivers.

2.5.3 Utilizing Newer Vehicles or Device Technology

Although mobile technology solutions could beneficially reduce the risk of vehicle crashes involving older drivers, these drivers must become familiar with the technology. A study by Stamatiadis and Kirk (2020) attempted to determine the safest route that could be used by older drivers using the automated route finding on mobile technology. They used the ArcGIS Network Analyst to develop a scoring route based on decreased intersection exposure, including minimizing left turns. Study results showed that mobile technology easily identifies the safest route and differentiates between safest routes and quickest routes based on travel time. The study concluded that use of this mobile technology could enhance driver safety and mitigate risks associated with fatal crashes involving older drivers.

Motamedi & Wang (2017) studied challenges related to in-vehicle technologies and older drivers. A total of 250 older drivers in Rhode Island completed two questionnaires: one to reveal the challenges drivers face when using in-vehicle technologies and a second questionnaire to assess the acceptance of in-vehicle technologies. The study developed a four-dimensional model to evaluate the usefulness, ease of use, safety, and anxiety related to these technologies. In addition, the Technology Acceptance Model (TAM) and Car Technology Acceptance Model were developed to analyze the questionnaire data and examine perceived-use behavior. The questionnaire focused on weather conditions, night driving, high-speed roads, changing lanes, heavy traffic, and intersections, while corresponding in-vehicle technologies were automatic windshield wipers (AWW), night vision cameras, adaptive cruise control (ACC), lane departure warning (LDW) systems, side view assist (SVA) system, and automated pedestrian detecting (APD) systems. Study results revealed that the SVA system, which reveals blind spots, draws attention to approaching vehicles, and offers an early warning system to mitigate crash risk, was the most-accepted vehicle technology among study participants.

Eby et al. (2020) investigated perceptions and learning methods among older drivers when using advanced driver assistance systems (ADASs). Data from the AAA Longitudinal Research on Aging Drivers (AAA LongROAD) for 2,990 participants (aged 65–79 years old) was collected from five health care locations, and a total of 15 in-vehicle technologies were investigated. Drivers were questioned regarding recognition and acceptance of these technologies. Descriptive data analysis results from the chi-square test showed that older drivers are aware of the presence of in-vehicle technologies, and most participants learned how to use technologies independently (Villavicencio & Kelley-Baker, 2020). The study revealed that people with high income tend to have newer cars with advanced technologies, such as forward collision warning systems, blind-spot warning, and fatigue/drowsy driver alert.

2.5.4 Roadway Design Improvement

Due to increased crash involvement of older drivers per VMT, Cicchino and McCartt (2015) investigated driver errors that result in serious injury. Data from the NHTSA (NMVCCS) for 620 crashes were considered, consisting of 647 drivers aged 70 and older. Driver errors for older drivers (>70) and middle-aged drivers (35–54) were compared. Results showed that 97% of crashes involving older drivers were a result of driver errors, such as inadequate surveillance, misjudgment of a gap between vehicles, and failure to see clearly. Approximately two-thirds of driver errors for older drivers occurred at intersections when turning left. Therefore, the study recommended countermeasures such as roundabouts and protected left-turn signals that would decrease left turns conflict in intersections. In addition, the study advised intersection design to be changed to a diverging diamond design to resolve crash factors of inadequate surveillance and speeding. Future communication technologies between vehicles and vehicles to infrastructure could also mitigate driving errors for older drivers.

Monyo et al. (2021) utilized crash data from 2016 to 2018 in Florida to analyze driver errors, or at-fault driving, of older drivers at interchanges. The study developed two models (latent class clustering and penalized logistic regression) to analyze environment, roadway, driver, and traffic factors that cause driver errors. A total of 895 interchange-related crashes were identified at five interchange types: diamond, full cloverleaf, partial cloverleaf, trumpet, and direct connect. Study results showed that decision errors accounted for 53% of crashes, while recognition errors accounted for 46% of crashes involving older drivers. Primary contributing factors were driver age, dark conditions, distractions, ramp terminals, speed limits, average daily traffic, and rural areas. The study recommended that roadway lighting be enhanced to reduce crash errors for older drivers on interchanges. Education and enforcement training for older drivers was also recommended to reduce crashes due to decision errors, and treatment was recommended on trumpet and direct connect interchanges to avoid recognition errors among older drivers.

Chapter 3 - Data and Methodology

This chapter describes the data and methodology utilized in this dissertation research. The first section discusses the source of data related to crashes involving older drivers at intersections in the midwestern United States, including details regarding data preparation, and it describes the variables used in this study. The second section explains the methodology used to analyze the data.

3.1 Source of Data

This study obtained traffic crash data from the FARS database of the NHTSA. Since 1975, FARS has compiled crash data for all 50 United States as well as the District of Columbia and Puerto Rico. FARS data is obtained from police crash reports, death certificates, state vehicle registration files, medical examiner reports, state drivers' licensing files, state highway departments, emergency medical service reports, vital statistics, and other state records for crashes that occur on public roadways and crashes that result in fatal injuries for a motorist or non-motorist within 30 days of the crash (NCSA, 2019). This study focused on 12 midwestern states (Ohio, Michigan, Indiana, Illinois, Wisconsin, Minnesota, Iowa, Missouri, Kansas, Nebraska, South Dakota, and North Dakota) because the data sample size for a state such as Kansas is low compared to the total data size of the Midwest and the total area of the midwestern states is similar in size to the western or eastern United States. The population of the midwestern states is 21% of the total population of the United States, with 47.4 million licensed drivers, or 21% of total licensed drivers in the United States in 2018 (US Census, 2017; USDOT, 2018).

The FARS database is organized into main data files related to vehicle, person, and accident, with crash data compiled by calendar year. Other data files such as CEVENT include harmful and non-harmful events in a crash, DISTRACT identifies each driver distraction, DRIMPAIR identifies each driver impairment, DRUGS identifies each specimen tested and the corresponding drug result, MANEUVER identifies objects the driver attempted to avoid on the roadway, VIOLATION identifies each violation committed by drivers, and VISION identifies each visual obstruction on the roadway. These data files are used in conjunction with the three main files: ACCIDENTS (crash data), PERSON (motorist and non-motorist data), and VEHICLE (in-transport motor vehicle, driver, and pre-crash data). Each file has a key variable, or ST_CASE, that locates the crash case number in all files. Because these files contain records of all crashes throughout the United States, the ST_CASE variable advantageously compiles all the files for analysis.

The following describes more about the three main data file. The ACCIDENTS record file contains information related to crash occurrences, including crash characteristics and environmental conditions. The data file includes crash location, type of intersection, weather condition, light condition, time and day of crash, type of crash, and other variables. Similarly, the PERSON file contains information related to all persons involved in a crash, whether in vehicles in motion or not in motion, including age and gender of the person, injury severity, drinking and drug use, person type (driver, passenger), and other variables. The VEHICLE file contains information related to vehicles involved in the crash, including vehicle type, make and model, accident type, and other variables.

3.1.1 Creating and Merging Data File

To retain only data of interest in one data record, this study merged the ACCIDENT, PERSON, and VEHICLE data files. As mentioned, the files were organized according to a unique crash record, ST_CASE, and calendar year. For the first criterion of the study, the ACCIDENT data file was refined to keep only single-vehicle crashes; data associated with multi-vehicle crashes were removed at this stage. In order to match the research goals, the second criterion kept only records related to drivers 65 years and older and removed all records related to other drivers in the PERSON file. The third criterion considered only “driver” as the person type in the PERSON file. Then the two files (ACCIDENT and PERSON) were merged into a single file using a single-to-many merging technique in SPSS statistical software. The new data file was then merged into the VEHICLE data file using the same procedure, and the other data files were merged similarly to obtain the final dataset. Similar process was followed to create other two data records; one for older driver who involve in multi-vehicle crashes, and one for other drivers who involve in single-vehicle crashes. Figure 3.1 illustrates the file merging process.

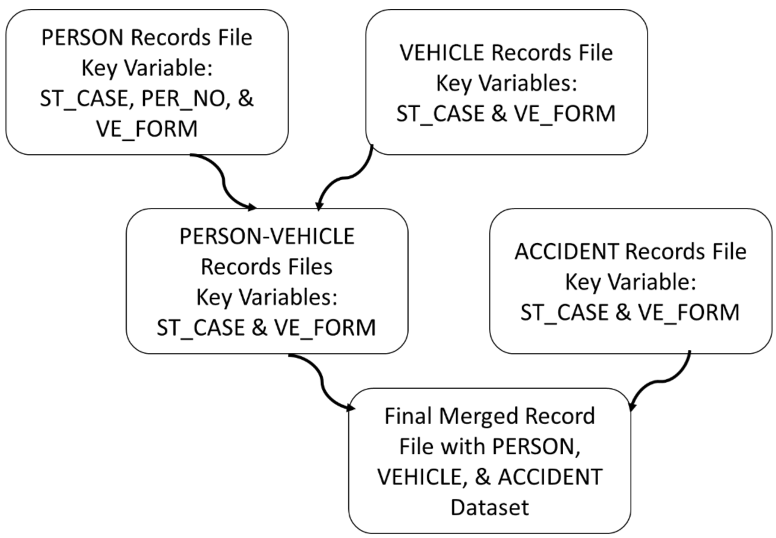

Figure 3.1 Merging Accident, Person, and Vehicle Record Files

3.1.2 FARS Data Elements

A primary study objective was to analyze FARS data for fatal crashes involving older drivers at intersections in the midwestern United States. According to the research objectives, variables related to the study were highlighted to focus on issues related to the safety of older drivers. Specific elements of each data file are described below.

As mentioned, the ACCIDENT data file contains variables related to weather condition, light condition, type of intersection, type of roadway, day and time of crash occurrence, and crash location (city, county, and state) (FARS, 2019).

Weather Condition: The FARS database categorizes weather conditions at the time of a crash as clear, cloudy, rain, sleet, snow, fog, wind, dust, not reported, and unknown. To simplify data analysis, however, this study consolidated multiple categories of weather conditions, resulting in clear, cloudy, and adverse weather conditions.

Light Condition: The FARS database classifies light conditions as daylight, dark (no light), dark (with light), dawn, dusk, unknown, and not reported. The light condition at the time of a crash is crucial because it could be a cause of the crash. This study reduced the current classifications of light condition to be only daytime and dark conditions to simplify the analysis.

Type of Intersection: The FARS database categorizes the type of intersection as a four-way intersection, T-intersection, Y-intersection, traffic circle, roundabout, intersection not related, not reported, or unknown. This variable is essential to the study because the crash occurrence as intersection related or intersection not related is the dependent variable of the research. This variable was considered binary instead of multiple categories and reclassified as intersection-related or non-intersection-related crashes.

Type of Roadway: The FARS database categorizes type of roadway as rural, urban, not reported, and unknown. For analysis purposes in this study, the type of roadway was not reclassified.

The PERSON file contains variables related to age, gender, person type, injury severity, in-vehicle seating position, alcohol use, and drug use. This data file is most essential to this research because the study focuses on older drivers. Therefore, age groups were specified accordingly to match the focus group, the person type was specified as “driver,” and injury severity was specified as “fatal injury severity” to achieve the objective of the study (FARS, 2019).

Age & Gender: The FARS database categorizes age as a continuous variable, but this study classified age groups, thereby reclassifying the variable to be a categorical variable. The cutoff age was 65 years old to distinguish between older and other drivers in fatal crashes, and the gender was a binary variable with two categories (male and female).

Person Type & Seat Position: The FARS database classifies person type as driver, passenger, pedestrian, or bicyclist. The seat position variable is also associated with person type. Using one of the two variables was sufficient to achieve the goals of this research. To simplify data analysis and meet study criteria, only “driver” was used as the person type.

Injury Severity: The FARS database defines the injury severity of a person involved in a crash according to a the following five-point scale (KABCO):

- Fatal Injury (K) defines an injury that occurs within 30 days of a crash and results in death.
- Suspected Serious Injury (A) defines an injury other than a fatal injury that has a significant negative impact on a person, such as losing an organ or being unable to walk.
- Suspected Minor Injury (B) defines any injury other than a fatal or serious injury that does not have a life-threatening effect on the person involved in the crash.
- Possible Injury (C) defines any injury other than previously mentioned injuries that cannot be observed but may be felt by the person involved in the crash.
- No Injury (O) means no injury was mentioned or could be seen on the person involved in the crash rather could be property damage only.

The VEHICLE data file has variables related to vehicles involved in crashes, such as body type, make and model of vehicle, year of vehicle, pre-crash event, manner of collision, vehicle speed before the crash, and accident type (FARS, 2019).

Body Type: The FARS database defines body type as the vehicle's classification according to the size, shape, and number of doors. This variable includes 2-door and 4-door sedans, wagon vehicles, limousines, utility vehicles, vans and pickups of various sizes, trucks of various weights, motorcycles, and buses. For simplification of analysis, multicategories of body type were combined into two categories.

Manner of Collision: The FARS database defines the manner of collision as when two vehicles in transport are involved in a fatal crash. The subcategories include rear-ended, head-on, rear-to-rear, angle, sideswipe same, or opposite direction.

Accident Type: The FARS database categorically defines accident type as the way a vehicle was involved in the crash, including single-vehicle crashes (drive off-road, loss control, avoiding collision with others) and multi-vehicle crashes (rear-end, forward-impact, sideswipe, head-on). To simplify analysis, this variable was reclassified to a categorical format.

Speed of Vehicle: The FARS database identifies the speed of a vehicle when a crash occurs. However, this variable was dropped due to many missing values in the database. Instead, the posted speed limit at the crash location was considered. This variable, which is classified in 5-mph increments, was simplified to a categorical format for analysis.

Harmful Event: The FARS database associates severe injury with the manner of collision, including overturning, fire, gas leak, animal, railway train, or a fixed object such as a building, wall, embankment, or tree.

3.1.3 Data Used in the Study

Five years of data (2014–2018) were obtained from the FARS database. This dataset was screened according to the age group for older drivers (65 years and older), and then the data were sorted according to single-vehicle crashes, so the final data file included only older drivers who were involved in single-vehicle crashes as the first dataset. The second dataset was prepared which included older drivers involved in multi-vehicle crashes. The last dataset was gathered for only drivers other than older who were involved in single-vehicle crashes. Table 3.1, which compares driver injury severity by age group in the Midwest, shows that older drivers were involved in more than 18%, or 1 in 5, fatal crashes over the data period. The average percentage of injury for older drivers was 12%, with 1,553 injury crashes. Although older drivers were involved in approximately 10% of non-injury, PDO-only crashes, they sustained high injury severity and death in fatal crashes.

Table 3.1 Comparison of Driver Injury Severity by Age Group in the Midwest

Injury Severity	Drivers	2014	2015	2016	2017	2018	Total
Fatal	All Ages	4,351	4,634	4,921	4,966	4,739	23,611
	Older Ages	847	916	994	945	915	4,617
	% of Older	19%	20%	20%	19%	19%	20%
Injury	All Ages	2,380	2,524	2,732	2,721	2,672	13,029
	Older Ages	275	286	340	327	325	1,553
	% of Older	12%	11%	12%	12%	12%	12%
PDO	All Ages	2,134	2,410	2,405	2,530	2,449	11,928
	Older Ages	203	220	252	261	268	1204
	% of Older	10%	9%	10%	10%	11%	10%

According to the dataset, 4,617 older drivers sustained fatal injuries in crashes over the data period, but only 1,553 injuries occurred, meaning that 63% of crashes were fatal for older drivers, while 21% of crashes caused sustained injuries. Although previous studies have investigated the safety of older drivers, no study has focused on the Midwestern region of the

United States, which has a rural roadway percentage of 80% compared to 20% urban roadways. Table 3.2 compares fatality-to-injury crash ratios for older and other drivers. As shown in the table, the percentage of fatality-to-injury ratio among older drivers was 2.97 compared to 1.65 for other drivers, highlighting the high probability of fatal injuries for older drivers involved in vehicle crashes.

Table 3.2 Fatality-to-Injury Crash Ratio for All Drivers in the Midwestern States (2014–2018)

Age Categories	Fatality	Injury	No Injury	Total	F/I
Older Driver > 65	4,617 (63%)	1,553 (21%)	1,204 (16%)	7,374	2.97
Younger Driver < 65	18,994 (46%)	11,476 (28%)	10,724 (26%)	41,194	1.65

Overall, data preparation for this research was extensive, especially since several data files had to be combined with case numbers. Only 1,496 cases from the FARS data related to single-vehicle fatal crashes for older drivers (65 years and older) in the Midwestern region of the United States. An additional set of data comprised of 2,203 cases was prepared for older drivers who were involved in multi-vehicle fatal crashes, and a dataset consisting of 9,486 cases was compiled for drivers younger than 65 years old who were involved in fatal single-vehicle crashes in the Midwest. Upon completing the data preparation, the next step was to determine the preferred statistical methodology for data analysis.

3.2 Methodology

Variables related to vehicle, driver, environment, and crash were tested to determine the most significant factors for fatal single-vehicle and multi-vehicle crashes involving older drivers. Intersection association was the response variable to model. Because the dependent variable has two outcomes (intersection or non-intersection), the binary logistic regression was utilized to estimate factors related to these crashes.

3.2.1 Logistic Regression Model

The logistic regression model is generally used to model the relationship between dependent variables and independent variables, known as a binary categorical response, that could be nominal or ordinal response variables. A successful response has a value of 1, but failure shows a zero value (Agresti, 2018). In the current study, the probability of success also had two outcomes: intersection crash = 1 and non-intersection crash = 0. Logistic regression is typically associated with the odds ratio, which is the probability of occurrence to non-occurrence for an event. The occurrence of an event in this study meant the dependent variable had a value of 1, meaning it was an intersection-related crash. The following equation describes the odds ratio:

$$Odds = \frac{P}{1-p} \tag{3.1}$$

where P is the probability that the fatal crash occurs at an intersection.

Probability is usually constraint, and to remove this restriction; it needs to be transformed into a linear function. Using logarithm and transforming the probability to odds removes the restriction of the response variable. The logistic model is created by applying the logarithm of the odds of the response variable to a linear function of the dependent variables (Agresti, 2018). The logistic regression model has an equation form as follows:

$$logit\ (p) = log\left(\frac{P}{1-P}\right) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k \tag{3.2}$$

Where:

p = probability for ($Y = 1$), fatal crash involving an older driver at an intersection,

α = model constant term (intercept).

β_k = regression coefficient for a predictor variable, x_k,

x_k = predictor variable k

Regression coefficients of independent variables influence the dependent variable, or crash location, regardless of whether or not the crash occurs at an intersection. To estimate the regression coefficient of the independent variables, the maximum likelihood method (MLM) was utilized in the model. The logistic regression model links the log odds of the response variable with the explanatory variables, so the logit link function interprets the relationship. Equation 3.3 manipulates the logistic regression equation by taking the exponential of the response variable's regression coefficient to solve the probability (i.e., p in the logit model in equation 3.2).

$$P = \frac{exp(\alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k)}{1 + exp(\alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k)} \tag{3.3}$$

3.2.1.1 Multicollinearity

As mentioned in section 3.1, the data were imported into SPSS for further analysis. The variables were categorized in binary form with values of 0 or 1, and all explanatory variables were checked for linear dependencies using the correlation matrix in SPSS. Multicollinearity means that two or more explanatory variables are highly linearly related (Allison, 2012). Correlate procedure analysis in SPSS was used to develop Pearson's correlation matrix, which determined the extent of the relationship. Strong correlation among pairs of variables typically reduces the accuracy of the model (Mela et al., 2002). Previous studies used values of 0.5–0.7 as the cutoff values of collinearity (Booth et al., 1994; Swinscow, 2002). This study utilized a cutoff value of 0.6 to locate correlated pairs among independent variables. Any pairs with a value greater than 0.6 were selected for further analysis, and a pair of variables with the highest correlation coefficient was considered first. Each variable in the pair was entered into the model, and the goodness-of-fit value was checked. The variable with a lower Akaike information criterion (AIC) value was kept in the model. The collinearity process was repeated for each pair of variables until no variables were retained in the model with a correlation coefficient greater than 0.6. This procedure beneficially impacted the model accuracy and the subsequent final result.

This study utilized the logistic regression model after reviewing previous studies regarding the suitable model format to analyze crash database. The variables were tested for independency before running the model, and a multicollinearity check was conducted to remove correlated pairs that could weaken the model. The logistic regression results were verified to determine if the model fit the data well by using the goodness-of-fit test. Due to its ease of use for organizing, recoding, and writing variable descriptions, SPSS statistical software was used to prepare the data for analysis, while SAS was used to develop the logistic regression model. Although SAS is a sophisticated software that can perform extensive and complicated statistical functions, it struggles to sort/split data and does not allow easy copying and pasting of charts and tables. Also, SAS requires coding knowledge from the user and time-consuming data processing.

3.2.1.2 Variable Screening Methods

When collecting data for analysis, many independent variables are potential predictors for dependent variables, meaning the decision of which set of variables to include in the regression model is crucial. This study utilized three common variable screening methods (stepwise selection, forward selection, and backward elimination) to select significant variables to stay in the model (Mendenhall & Sincich, 2020).

Stepwise selection begins when a dependent variable and a set of independent variables are entered into the SAS software. The statistical software fits all possible one-variable models, and then the variable is selected according to the smallest and significant p-value ($< \alpha$). Then the software fits all possible two-variable models, including the variable selected in the first step, and selects the variable with the smallest and significant p-value ($< \alpha$). If no variables are significant, then the model selected in the previous step is the final model. Although this method is similar to forward selection, stepwise selection adds or removes independent variables one at a time. For example, stepwise selection either removes the least significant variable or adds the most significant variable (Mendenhall & Sincich, 2020).

The forward selection screening method begins when a dependent variable and a set of independent variables are entered into the SAS software. The statistical software fits all possible one-variable models, and then the variable is selected according to the smallest and significant p-value ($< \alpha$). The software then fits all possible two-variable models, including the variable selected in the first step, and selects the variable with the smallest and significant p-value ($< \alpha$). If no variable is significant, then the selected model from the previous step is the final model (Mendenhall & Sincich, 2020).

Backward elimination begins when a dependent variable and a set of independent variables are entered into the SAS software. The statistical software fits all possible variables into the regression model and then eliminates the variable with the largest and non-significant p-value ($> \alpha$). Then the software fits the model with remaining variables and deletes the variable with the largest p-value ($> \alpha$). If all variables are significant, then this model is the final model (Mendenhall & Sincich, 2020).

3.2.1.3 Assessing Model Fit

This study used AIC, Schwarz criterion (SC), -2 Log L, and R^2 to estimate the logistic regression model fit (Allison, 2012). SAS 9.4 software was utilized to obtain the model fit values (SAS Institute Inc., 2013). AIC is typically used to compare models. Low AIC values indicate a desirable model.

$$AIC = 2\,k - 2\,\log L \tag{3.4}$$

where k is the number of parameters in the model (including intercept) and L is the likelihood function. Also, SC considers another criterion to compare models and select a model with a low SC value is preferred.

$$SC = k \log n - 2 \log L \tag{3.5}$$

where n is the sample size. Finally, -2 Log L, which refers to the maximum value of the algorithm of likelihood function multiplied by -2, is typically used to compare two models, with the lower value indicating a better model.

R-squared, or R^2, is the coefficient of determination that measures the variation between data and its closeness to the fitted regression line. The range of the value is from zero to 1 or occasionally 0–100%. A higher value indicates that the model fits the data well. R^2 can also be used to compare two models as follows (Allision, 2012):

$$R^2 = 1 - \frac{Unexplained\ Variation}{Total\ Variation} \tag{3.6}$$

As mentioned, AIC and SC values are essential for comparing multiple models, with lower values indicating model with better model fit (Allision, 2012). However, another logistic regression method for checking model fit is testing chi-square values, or the global null hypothesis BETA = 0, which contains three chi-square values (likelihood ratio, score, and Wald test). Chi-square is associated with the degree of freedom, which is related to the variation among explanatory variables. P-value plays a vital role in accepting or rejecting the null hypothesis in the chi-square table (Allision, 2012). Other outcome statistics can also validate the model using the percentage of concordant, discordant, tied observations, Somers' D, Goodman and Kruskal's gamma, Kendall's Tau-a, and the C-statistic. The following are descriptions about the parameters mentioned above:

Of the parameters mentioned, concordant produces a percentage based on a pair of variables with different observed responses. Concordant means that a variable with a low ordered response value has a lower predicted mean compared to a variable with a high ordered response value. The higher concordant value indicates a better model. Conversely, discordant means that a variable with a high ordered response has a lower predicted mean compared to a variable with a low ordered response with a higher predicted mean value. A low discordant value indicates a better model. The percent tied parameter is present if a pair of variables with different response values have the same predicted value.

For other terms mentioned above, pairs is the number of possible ways to pair different variables. As shown in equation 3.7 (Allision, 2012), the Somers' D value identifies the direction and intensity of the relationship between pairs of variables, with a value range between 0.0 (all pairs disagree) to 1.0 (all pairs agree).

$$\text{Somers' } D = \frac{C-D}{C+D+T} \tag{3.7}$$

Where,

C = number of concordant pairs,
D = number of discordant pairs, and
T = number of ties

Similarly, Goodman and Kruskal's gamma (equation 3.8) shows the association between model variables, with a gamma value range between 0.0 (no association) to 1.0 (perfect association) (Allision, 2012).

$$\text{Gamma} = \frac{C-D}{C+D} \tag{3.8}$$

As shown in equation 3.9, Kendall's Tau-a value shows the difference between pairs of independent variables and differences between pairs of independent variables with various responses (Allision, 2012).

$$Tau\text{-}a = \frac{C-D}{N} \tag{3.9}$$

where N is the total number of pairs. Finally, the C-statistic, or the concordance statistic, measures the goodness-of-fit for binary outcomes. This value is also equal to the area under the receiver operating characteristic (ROC) curve. A value equal to or below 0.5 indicates a poor model, a value over 0.7 indicates a good model, and a value over 0.8 indicates a strong model. The C-statistic has the following equation (Allison, 2012):

$$C = 0.5 * (1 + Somers'\ D) \tag{3.10}$$

The Hosmer-Lemeshow (HL) test can also test goodness-of-fit for a logistic model, but it is only applicable for a binary response model. The HL generates a predicted probability for all explanatory variables, and then the variables are grouped into ten equal groups (equation 3.11). The test then compares the expected and the predicted probabilities of creating the p-value (Allison, 2012).

$$G^2_{HL} = \sum_{j=1}^{10} \frac{(o_j - E_j)^2}{E_j(1 - E_j/n_j)} \sim X^2 \tag{3.11}$$

Where:

X^2 = chi-squared,
n_j = number of observations in the j^{th} group,
O_j = number of observed cases in the j^{th} group,
E_j = number of expected cases in the j^{th} group.

Model accuracy can also be estimated by measuring the area under the ROC curve. This tool plots the false positive rate on the x-axis and the true positive rate on the y-axis and indicates the relationship between sensitivity (true positive rate) and specificity (true negative rate). In terms of accuracy, the value range is 0.5–1.0. The vast area under the curve indicates an accurate model, with a value closer to 1.0.

3.2.2 Quasi-Induced Exposure Analysis

Preusser et al. (1997), Reinfurt et al. (2000), and Stutts et al. (2009) previously utilized quasi-induced exposure (QIE), which defines a ratio that indicates the risk factor of over or under involvement in fatal crashes. QIE also calculates the crash involvement ratio (CIR) that account for at-fault or not-at-fault as shown in equation 3.12. A value greater than 1.0 indicates overinvolvement in fatal crashes for an age group, while a value less than 1.0 shows under involvement in fatal crashes (Lombardi et al., 2017).

$$CIR = (Driver\ at\ fault/Driver\ not\ at\ fault)\ in\ each\ age\ group \qquad (3.12)$$

This study used QIE analysis in a multi-vehicle crash model to find risk factors for each age group. Because a majority of multi-vehicle crashes involved only two vehicles, this study defined a multi-vehicle crash as "two vehicles involved in one crash." At-fault driving was determined using the contributing factor and/or moving violation variables from the FARS data. In the multi-vehicle crashes, at least one driver was deemed at-fault due to one or more contributing factors or moving violations; crashes in which both drivers were at fault or not at fault were excluded from the analysis. Common factors related to the multi-vehicle crashes were failure to stay in a driving lane, failure to yield right-of-way, and careless driving. Appendix B shows the factors used to identify at-fault driving in fatal multi-vehicle crashes.

3.2.3 Model Validation

Model validation is usually applied to check the accuracy and the performance of the model to see if the model actually achieves its intended purposes, and to check how the model predicts future outcomes. Two main ways to validate a model are by bringing a new data sample and running statistical analysis, then comparing the model performance, which is called external validation, and another way is by internally validating the model performance. External validation tends to assess the generalizability of modeling to similar related population, while internal validation aims to measure optimism in model performance. There are several ways to validate the data internally, which include data splitting, iterated data splitting, jackknife technique, and bootstrapping. This study was focused on internal validation by using the data splitting technique. Data splitting is a technique that includes splitting the data into training data and validating data, and usually the data is split between 70% for training, and 30% for validating. The training data model assesses how well the model fits the given data in which it was developed, whereas the validating data model evaluates the model's validity as it tries to predict an independent sample. The process of model validation starts by splitting the data into training and validation, then applying the statistical model on the original, training, and validating data. Next, computations of performance measures on all samples are checked and compared, which include measures of discrimination (C Statistics), and measures of calibration (Hosmer and Lemeshow test). Then, a result draws by explaining the difference in models' performance (Giancristofaro & Salmaso, 2003; Harrell *et al.*, 1996; Picard and Berk, 1990).

Chapter 4 - Results and Discussion

Five years of data from 2014 to 2018 were obtained from the Fatality Analysis Reporting System (FARS) database. The objective of the study was to identify factors associated with older driver (>65) fatal crashes at the intersection, and comparing that with factors associated with other driver (<65) fatal crashes at the intersection in the Midwest region. Single and multi-vehicle crashes were taken into consideration for older driver. For other driver, only single-vehicle crashes were considered for comparison purposes. Comparisons were made for other regions in the US (Northeast, South, and West) with the Midwest region regarding older driver fatal single-vehicle crashes statistics. Characteristics related to vehicle, driver, road, and environment were taken into account. This chapter also describes the logistic regression models result that were developed for this study, as well as model fit and accuracy results. The risk factors associated with intersection-related fatal crashes for older and other drivers were explained, and countermeasure ideas were discussed at the end of this chapter.

4.1 Statistical Comparisons of Fatal Crashes

Fatal crash statistics based on region is presented for older and other drivers which account for 51 states excluding Puerto Rico and Virgin Islands. The U.S. Census Bureau classifies the United States into four main regions: Northeast, South, West, and Midwest (Figure 4.1). This study focused on fatal crashes involving older drivers in the Midwest region. It would be interesting to see how older driver fatal crashes compare across different regions in the US.

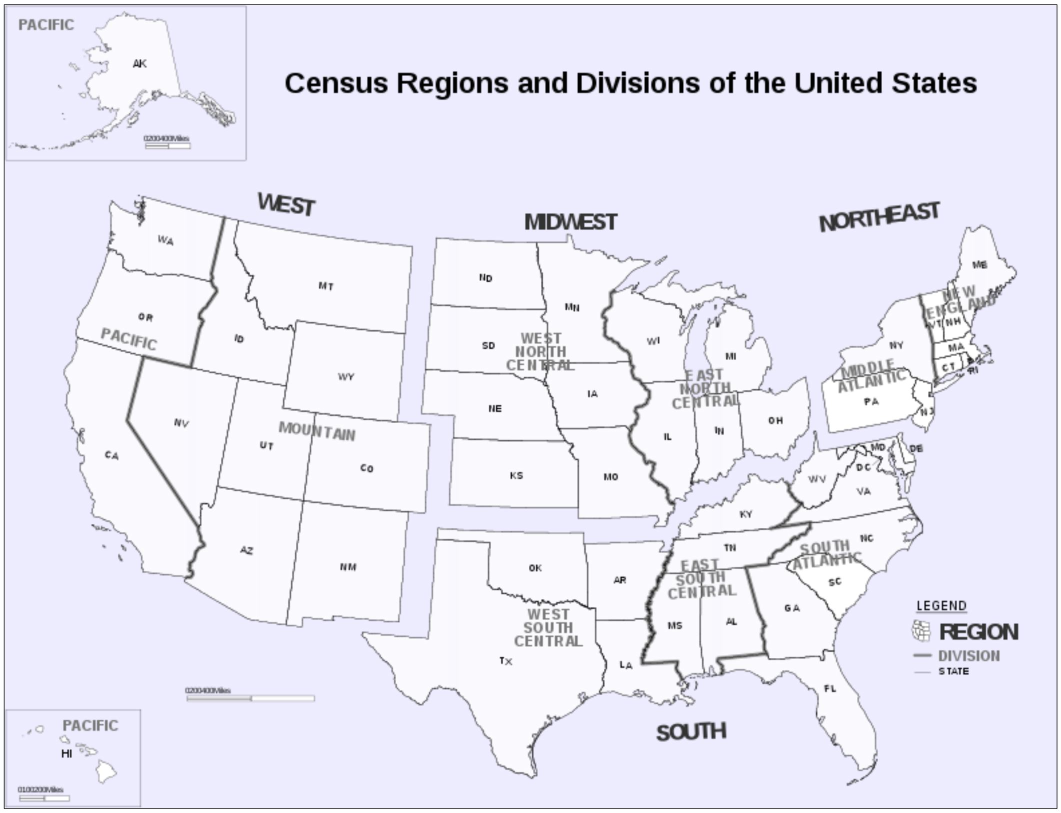

Figure 4.1 United States Regions

Source: United States Census Bureau Regions and Divisions, 2000

Figure 4.2 compares crashes and fatalities among all regions for all age groups over the range of studied FARS data (2014–2018). As shown in the figure, the highest number of crashes and fatalities occurred in the South, potentially due to the high number of states in this region, and the least number of crashes occurred in the Northeast. Although the Midwest and West regions showed similar results for driver fatalities, the West region is more populated than the Midwest, meaning the Midwest had more crash fatalities per capita than other regions. In fact, the Midwest region had the highest percentage of fatalities to total crashes (62%) even though it had significantly less crashes overall than the South region. Therefore, the risk of involvement in fatal crashes is higher in the Midwest than in other regions in the United States.

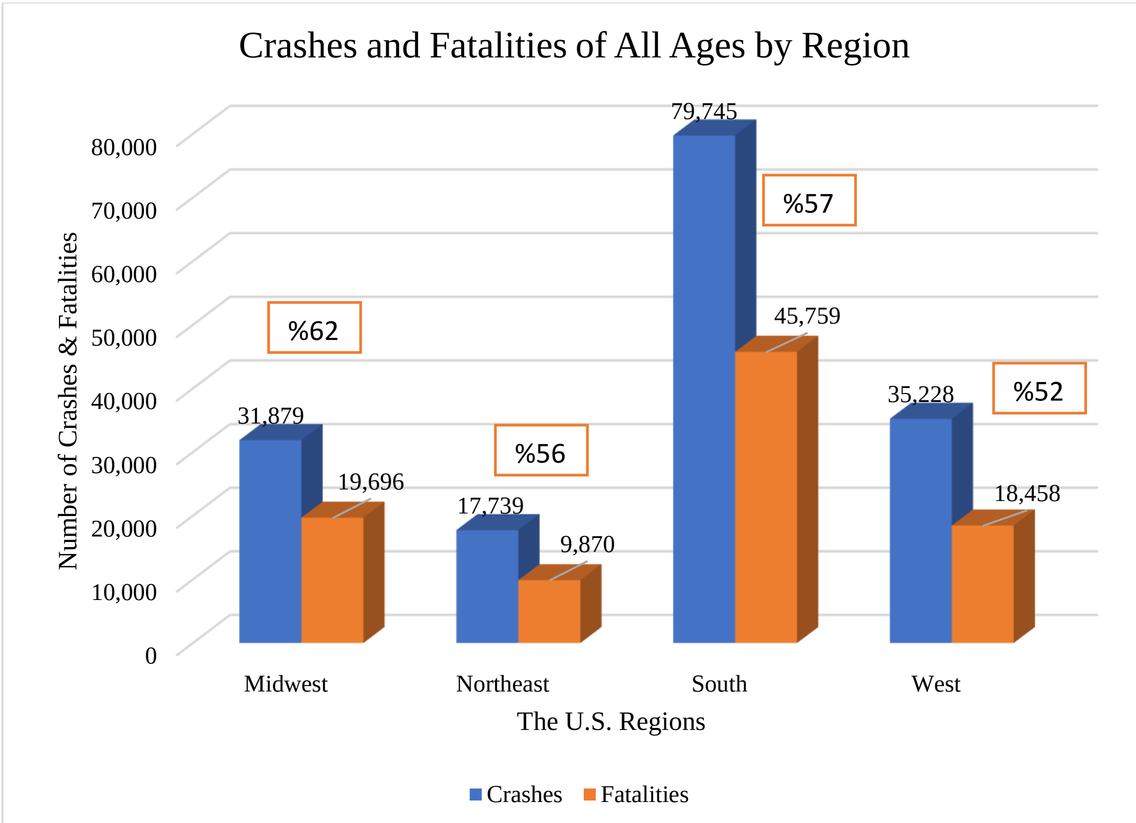

Figure 4.2 Crashes and Fatalities of All Ages Based on Regions (2014-2018)

As another regional comparison, Table 4.1 includes the numbers of fatal single-vehicle and multi-vehicle crashes by age group and region from 2014 to 2018. As shown in the table and demonstrated in Figure 4.2, the Midwest had the highest percentage of fatal crashes (62%) overall. The Northeast and West regions showed a similar trend for fatal crashes involving older drivers, and the Midwest and South regions showed a similar trend as well, although the Midwest had the most fatal multi-vehicle crashes involving older drivers. As shown in the table, the highest number of fatal single-vehicle crashes for other drivers was in the Northeast region. All regions showed similar trends for fatal multi-vehicle crashes. The three highest percentage of older driver fatal single-vehicle crashes belong to; California, Texas, and Florida, which consider the most populated states in the US. Overall, older drivers were more often involved in fatal multi-vehicle crashes, while other drivers were more represented in fatal single-vehicle crashes. Additional details about crash fatalities in each state are provided in Appendix C.

Table 4.1 Fatal Crash Comparisons by Age Group and Region (2014–2018)

Region	Older Drivers (≥65 yrs.)			Other Drivers (<65 yrs.)			Total
	Single Vehicle	Multi Vehicle	Total	Single Vehicle	Multiple Vehicle	Total	
Northeast	941	1,430	2,371	4,999	2,500	7,499	9,870
	40%	60%		67%	33%		
South	3,454	6,227	9,681	23,457	12,621	36,078	45,759
	36%	64%		65%	35%		
West	1,435	2,155	3,590	9,206	5,662	14,868	18,458
	40%	60%		62%	38%		
Midwest	1,575	3,047	4,622	9,696	5,378	15,074	19,696
	34%	66%		64%	36%		
Total	7,405	12,859	20,264	47,358	26,161	73,519	93,783

4.2 Characteristics of Fatal Single-Vehicle Crashes Based on Age Group

This section highlights vehicle, crash, road, driver, and environment factors related to fatal single-vehicle crashes for older (65 years and older) and other (less than 65 years old) drivers. The FARS data accounted for 1,496 single-vehicle crashes involving older drivers and 9,486 single-vehicle crashes involving other drivers over the data study period (2014–2018). This study divided the older drivers into two groups for analysis: drivers aged 65–74 years old and drivers older than 75. The group with drivers aged 65–74 years old showed a 58% involvement percentage in total fatal crashes, since drivers older than 75 limit their driving. Other drivers were also divided into two age groups: drivers aged 31–64 years old and drivers younger than 31. The group with drivers aged 31–64 had 60% involvement percentage in total fatal crashes. This study reduced the variables into a binary category, and many variables were proportionated due to unknown data.

4.2.1 Driver and Environmental Characteristics

Table 4.2 shows variables related to driver and environmental characteristics of older and other drivers in fatal single-vehicle crashes. As shown in the table, male drivers were overrepresented in fatal crashes compared to female drivers for both age groups. Alcohol was less likely to be a factor among older drivers in fatal crashes. However, drug use was involved in one-third of the fatal single-vehicle crashes involving other drivers. In terms of driving under the influence (DUI) of alcohol, older drivers were less likely to drive drunk, while approximately 50% of fatal crashes with other drivers involved alcohol. More than half of fatal crashes for both age groups occurred during summer and fall seasons, and two-thirds of older drivers were more likely to be involved in crashes on weekdays during the day, while fatal crashes for other drivers were more prevalent at night during weekends. Most fatal crashes occurred during clear or cloudy conditions for both age groups. There was similar trend in both age groups except of elevated trend among other drivers when DUI.

Table 4.2 Driver and Environmental Characteristics in Fatal Single-Vehicle Crashes Based on Age Group

Driver and Environmental Characteristics	Older Drivers (≥65 yrs.)		Other Driver (<65 yrs.)	
	Number	Percentage	Number	Percentage
Driver Gender				
Male	1,170	78%	7,677	81%
Female	326	22%	1,809	19%
Driver Height				
Normal Height (35-70 inches)	969	65%	5,515	58%
Excessive Height (71-85 inches)	527	35%	3,971	42%
Driver Weight				
Normal Weight (85-200 pounds)	969	65%	6,553	69%
Overweight (201- 450 pounds)	527	35%	2,933	31%
Total	1,496	100%	9,486	100%
Drug Use				
No	1,347	90%	5,941	63%
Yes	149	10%	3,545	37%

Table 4.2 Driver and Environmental Characteristics in Fatal Single-Vehicle Crashes Based on Age Group (Continued)

Driver and Environmental Characteristics	Older Drivers (≥65 yrs.)		Other Drivers (<65 yrs.)	
	Number	Percentage	Number	Percentage
Driving Under Influence				
No	1,346	90%	4,847	51%
Yes	150	10%	4,639	49%
Month				
July-December	836	56%	5,327	56%
January-June	660	44%	4,159	44%
Day of the Week				
Weekdays	1,050	70%	5,680	60%
Weekend	446	30%	3,806	40%
Light Condition				
Daytime	1,147	77%	3,951	42%
Dark	349	23%	5,535	58%
Weather Condition				
Clear/Cloudy	1,319	88%	8,368	88%
Rain/Snow/Other	177	12%	1,118	12%

4.2.2 Crash and Vehicle Characteristics

Table 4.3 shows variables pertaining to crash and vehicle characteristics of older and other drivers in fatal single-vehicle crashes. As shown in the table, fatal crashes involving fixed objects demonstrated a similar trend between older and other drivers, and most drivers of all ages were going straight immediately prior to a crash. Run-off-road crashes accounted for 62% of fatal crashes involving older drivers, but other drivers had more run-off-road fatal crashes overall. Speeding was less likely to be a factor for older drivers, but other drivers were twice as likely to be involved in fatal single-vehicle speed-related crashes. Both age groups were less likely to be involved in fatal single-vehicle crashes while driving recreational vehicles (RVs), buses, or motorcycles, and most crashes occurred while driving vehicles newer than 2000.

Table 4.3 Crash and Vehicle Characteristics in Fatal Single-Vehicle Crashes Based on Age Group

Crash and Vehicle Characteristics	Older Drivers (≥65 yrs.)		Other Drivers (<65 yrs.)	
	Number	Percentage	Number	Percentage
Harmful Event				
Fixed Object	1,248	83%	7,107	75%
Rollover	248	17%	2,379	25%
Pre-Crash Event				
Going Straight	1,065	71%	6,118	64%
Negotiating a Curve	431	29%	3,368	36%
Crash Type				
Off Road	926	62%	8,031	85%
Other (Animal, Collision Avoidance)	570	38%	1,455	15%
Speed Related				
No	1,167	78%	5,137	54%
Yes	329	22%	4,349	46%
Total	1,496	100%	9,486	100%
Vehicle Body Type				
Automobile/SUV/Van/Pickup Truck/Light & Heavy Truck	1,230	82%	7,469	79%
Other (RV, Bus, Motorcycle, Golf cart)	266	18%	2,017	21%
Total	1,496	100%	9,486	100%
Vehicle Model Year				
1999 and Newer	1,238	83%	7,750	82%
Older than 1999	258	17%	1,736	18%
Total	1,496	100%	9,486	100%

4.2.3 Roadway Characteristics

Table 4.4 shows variables related to roadway characteristics of fatal single-vehicle crashes for older and other drivers. As shown in the table, most fatal crashes among the two age groups occurred on two-way undivided highways, primarily two-lane trafficways. The study data showed that two-thirds of fatal single-vehicle crashes for all drivers occurred on rural roadways since a majority of roads in the Midwest are rural and this study focused on fatal crashes in the Midwestern region. In addition, two-thirds of fatal crashes occurred on minor, collector, or local roadways; only 30% of crashes occurred on interstate highways or freeways. Over 60% of fatal crashes for both age groups occurred on level roadways, but only 20% and 18% of fatal crashes involving older and other drivers, respectively, occurred on wet roadways. Notably, less than 10% of fatal single-vehicle crashes were intersection related, and fatal crashes for both age groups occurred on roadways with posted speed limits greater than 55 mph. Overall, both age groups demonstrated similar trends related to roadway characteristics, even though the number of fatal single-vehicle crashes was higher for other drivers than older drivers.

Table 4.4 Roadway Characteristics in Fatal Single-Vehicle Crashes Based on Age Group

Roadway Characteristics	Older Drivers (≥65 yrs.)		Other Drivers (<65 yrs.)	
	Number	Percentage	Number	Percentage
Traffic Way Type				
Two-Way Undivided	1,197	80%	7,460	79%
Two-Way Divided	299	20%	2,026	21%
Number of Lane				
Two Lanes (Each Direction)	1,299	87%	8,183	86%
Other	197	13%	1,303	14%
Roadway Type				
Rural	1,030	69%	6,219	66%
Urban	466	31%	3,267	34%
Roadway System				
Minor Arterial/Collector/Local	1,026	69%	6,897	73%
Interstate/Principal Arterial (Expressways, Freeways, Other)	470	31%	2,589	27%
Roadway Profile				
Level	991	66%	5,971	63%
Grade (Hillcrest, Sag, Uphill, Downhill)	505	34%	3,515	37%
Roadway Surface Condition				
Dry	1,203	80%	7,746	82%
Wet	293	20%	1,740	18%
Roadway Alignment				
Straight	1,013	68%	5,869	62%
Curve	483	32%	3,617	38%
Type of Intersection				
Intersection Not Related	1,371	92%	8,751	92%
Intersection Related	125	8%	735	8%

4.3 Characteristics of Older Drivers Based on Fatal Crash Types

This section highlights vehicle, crash, road, driver, and environment factors related to fatal single-vehicle and multi-vehicle crashes for older drivers. According to the data, older drivers were involved in 1,496 single-vehicle crashes and 2,203 multi-vehicle crashes from 2014 to 2018. Fatal Multi-vehicle crashes had at least one at-fault driver, while crashes that had both driver at fault or not at-fault were excluded. Variables related to fatal-crash factors were reduced into a binary category, and many variables were proportionated due to unknown data.

4.3.1 Driver and Environmental Characteristics

Table 4.5 shows variables related to driver and environmental characteristics for older drivers in single-vehicle and multi-vehicle fatal crashes. As shown in the table, female drivers were overrepresented in fatal multi-vehicle crashes, while male drivers were overrepresented in fatal single-vehicle crashes. In terms of driver height, normal height was observed in both type of crashes, but there was slight increase of taller drivers observed in fatal multi-vehicle crashes. One-third of drivers in fatal single-vehicle crashes and half of drivers in fatal multi-vehicle crashes were over-weight. Alcohol and drug were not a prevalent factor among older drivers in fatal crashes. Notably, more than half of all fatal crashes for older drivers occurred during summer and fall seasons, and two-thirds of all fatal crashes involving older drivers occurred on weekdays during the day with clear or cloudy conditions. Since older drivers may avoid driving during the weekend. It could be the reason that older drivers may avoid driving during the night or adverse weather conditions. Overall, the characteristic trends were similar for older drivers in fatal single-vehicle and multi-vehicle crashes.

Table 4.5 Driver and Environmental Characteristics in Fatal Crashes Involving Older Drivers Based on Crash Type

Driver and Environmental Characteristics	Single-Vehicle		Multi-Vehicle	
	Number	Percentage	Number	Percentage
Driver Gender				
Male	1,170	78%	1,051	48%
Female	326	22%	1,152	52%
Driver Height				
Normal Height (35in-70in)	969	65%	1,028	47%
Excessive Height (71in-85in)	527	35%	1,175	53%
Driver Weight				
Normal Weight (85Ib - 200Ib)	969	65%	1,119	51%
Overweight (201Ib - 450Ib)	527	35%	1,084	49%
Drug Use				
No	1,347	90%	2,015	91%
Yes	149	10%	188	9%
Driving Under Influence				
No	1,346	90%	2,014	91%
Yes	150	10%	189	9%
Month				
July-December	836	56%	1,238	56%
January-June	660	44%	965	44%
Day of the Week				
Weekdays	1,050	70%	1,713	78%
Weekend	446	30%	490	22%
Light Condition				
Daytime	1,147	77%	1,804	82%
Dark	349	23%	399	18%
Weather Condition				
Clear/Cloudy	1,319	88%	1,976	90%
Rain/Snow/Other	177	12%	227	10%

4.3.2 Crash and Vehicle Characteristics

Fatal single-vehicle and multi-vehicle crashes typically have distinct collision scenarios. Table 4.6 compares crash and vehicle characteristics for fatal single-vehicle and multi-vehicle crashes involving older drivers. As shown in the table, single-vehicle crashes were overrepresented in fixed-object collisions and fatal multi-vehicle crashes were overrepresented in angle and sideswipe collisions, meaning that single-vehicle crashes were typically due to running off the road and then hitting a fixed object, while multi-vehicle crashes involved turning movements and intersecting paths. Two-thirds of single-vehicle crashes and approximately 50% of multi-vehicle crashes occurred while going straight, but speeding was not typically a factor in crashes involving older drivers. Although older drivers were less likely to be involved in fatal single-vehicle crashes while driving RVs, buses, or motorcycles, almost half of fatal multi-vehicle crashes involved automobiles, heavy trucks, RVs, and buses. Most crashes occurred while driving vehicles newer than 2000. Overall, fatal single-vehicle and multi-vehicle crashes had similar characteristics, with the exception of the manner of collision.

Table 4.6 Crash and Vehicle Characteristics in Fatal Crashes Involving Older Drivers Based on Crash Type

Crash and Vehicle Characteristics	Single-Vehicle		Multi-Vehicle	
	Number	Percentage	Number	Percentage
Manner of Collison				
Fixed Object / Angle , Sideswipe	1,248	83%	1,465	67%
Rollover / Front to Rear, Front to Front	248	17%	738	33%
Crash Type				
Off Road / Turning Movement, Intersecting Path	926	62%	1,376	62%
Other (Animal, Collision Avoidance, parked vehicle) / Same & Opposite Direction (Head on, Rear end, Sideswipe, Angle)	570	38%	827	38%
Pre-Crash Event				
Going Straight	1,065	71%	1,120	51%
Negotiating a Curve	431	29%	1,083	49%
Speed Related				
No	1,167	78%	1,926	87%
Yes	329	22%	277	13%

Table 4.6 Crash and Vehicle Characteristics in Fatal Crashes Involving Older Drivers Based on Crash Type (Continued)

Crash and Vehicle Characteristics	Single-Vehicle		Multi-Vehicle	
	Number	Percentage	Number	Percentage
Vehicle Body Type				
Automobile/SUV/Van/Pick up/Light & Heavy Truck	1,230	82%	1,226	56%
Other(RV, Bus, Motorcycle, Golf car)	266	18%	977	44%
Vehicle Model Year				
1999 and Newer	1,238	83%	1,623	74%
Older than 1999	258	17%	580	26%

4.3.3 Roadway Characteristics

Table 4.7 shows variables related to roadway characteristics of fatal single-vehicle and multi-vehicle crashes involving older drivers. Both crash types occurred most often on two-way undivided rural highways with two lanes in each direction. Two-thirds of fatal single-vehicle crashes occurred on minor, collector, or local roadways, while multi-vehicle crashes were most prevalent on interstate and collector roadways. The table also shows that most crashes occurred on level roads with dry surface conditions. As expected, fatal multi-vehicle crashes were often intersection related due to increased crash exposure because of conflict in movement direction at intersections compare to fatal single-vehicle crashes. In addition, older drivers were involved in both fatal crash types on roadways with posted speed limits greater than 55 mph. Overall, the roadway characteristics showed similar trends for fatal single-vehicle and multi-vehicle crashes for older drivers.

Table 4.7 Roadway Characteristics in Fatal Crashes Involving Older Drivers Based on Crash Type

Roadway Characteristics	Single-Vehicle		Multi-Vehicle	
	Number	Percentage	Number	Percentage
Traffic-Way Type				
Two-Way Undivided	1,197	80%	1,711	78%
Two-Way Divided	299	20%	492	22%
Number of Lanes				
Two Lanes	1,299	87%	1,685	76%
Other	197	13%	518	24%
Roadway Type				
Rural	1,030	69%	1,334	61%
Urban	466	31%	869	39%
Roadway System				
Minor Arterial/Collector/Local	1,026	69%	1,152	52%
Interstate/Principal Arterial (Expressways, Freeways, Other)	470	31%	1,051	48%
Roadway Profile				
Level	991	66%	1,576	72%
Grade(Crest, Sag, Uphill, Downhill)	505	34%	627	28%
Roadway Surface Condition				
Dry	1,203	80%	1,834	83%
Wet	293	20%	369	17%
Roadway Alignment				
Straight	1,013	68%	1,924	87%
Curve	483	32%	279	13%
Type of Intersection				
Intersection Not Related	1,371	92%	945	43%
Intersection Related	125	8%	1,258	57%
Posted Speed Limit				
Greater than 55 mph	980	66%	1,414	64%
Less than 55 mph	516	34%	789	36%

4.4 Crash Involvement Ratio for Fatal Multi-Vehicle Crashes

As mentioned on previous chapter, this study utilized the CIR method in the fatal multi-vehicle crash model to identify risk factors for each age group. Because a majority of the multi-vehicle crashes involved only two vehicles, a multi-vehicle crash was defined as “two vehicles involved in one crash.” At-fault driver was determined using at least one of two variables (contributing factor and/or moving violation) from the FARS data. Crashes in which both drivers were at fault or not at fault were excluded from the analysis. Common driving-related factors included failure to stay in lane, failure to yield right-of-way, and careless driving. A complete list of these factors is given in Appendix B.

Figure 4.3 illustrates the CIR in fatal multi-vehicle crashes based on age group. As shown in the figure, the CIR value was lowest for drivers aged 55–64 years old, with a sharp increase in CIR for drivers older than 65. For drivers 85 years of age and older, the CIR was four times higher than younger drivers. The lowest CIR trend was for the group aged 45–64 years old. Both younger driver group aged (15-24) and older drivers (65 and older) showed increased risk of involvement in at-fault multi-vehicle crashes because older drivers suffer from age factors such as frailty and cognitive impairment and younger drivers struggle with driving inexperience.

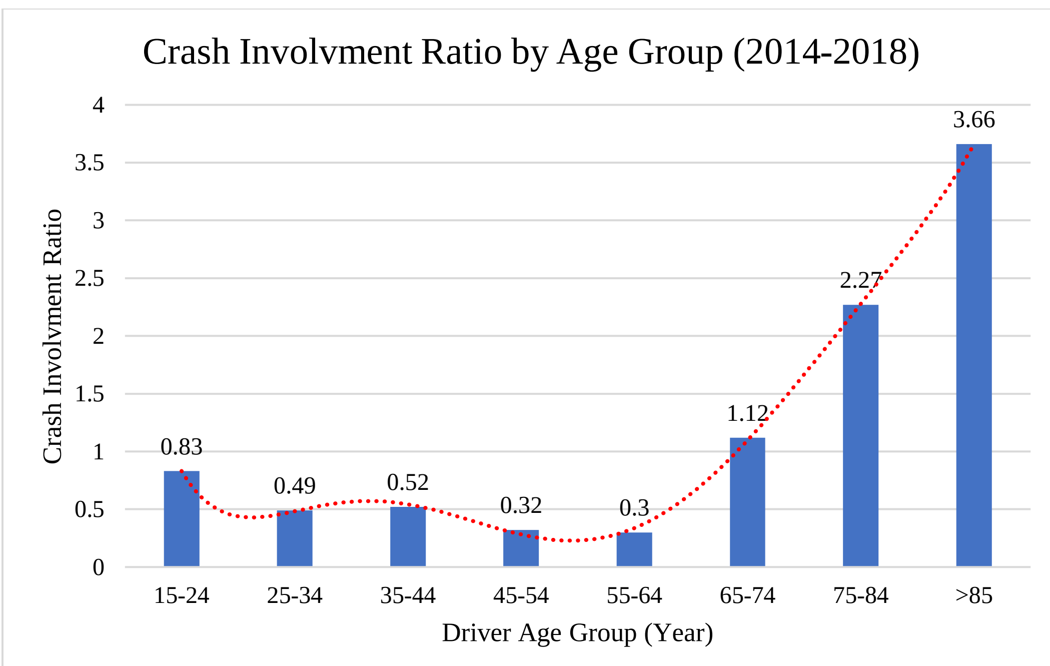

Figure 4.3 CIR for Multi-Vehicle Crashes Based on Age Group

4.5 Results of Fatal Crash Models

As previously described, a binary logistic regression model was developed to analyze fatal crashes involving older drivers at intersections in the Midwest from 2014 to 2018. The binary response variable was intersection type, labeled as intersection or non-intersection. Non-intersection crashes presented a value of zero, and intersection-related crashes had a value of 1.

4.5.1 Multicollinearity Analysis of Fatal Single-Vehicle Crashes for Older Driver

This study developed two separate models for fatal single-vehicle and multi-vehicle crashes, and 38 explanatory variables, or candidate variables, were considered for the fatal single-vehicle crash model. These candidate variables were identified according to previous studies (Sifrit et al., 2010; Lombardi et al., 2017; Dissanayake & Koththigoda, 2018). SAS version 9.4 was utilized to analyze the data and develop the model (SAS Institute Inc., 2013), and Pearson's correlation matrix was used to check the explanatory variables for multicollinearity to identify highly correlated pairs of variables. Appendix A, Table A.1 contains a full list of correlation matrices.

Table 4.8 shows variables retained among correlated pairs in the fatal single-vehicle crash model. For the selection criterion, a total of six correlated pairs were chosen among the explanatory variables with a value of 0.6 or higher. One of the two variables correlated to each other were removed, starting with a pair with the highest Pearson correlation coefficient value and retaining other pairs in the model. Then each variable was input into the model to determine the outcome of the model fit value. The model with the lowest AIC value was retained. Consequently, variables such as Pre-Crash Event1, Accident Type, Light Condition, Drinking, Roadway Surface Condition, and Roadway System were removed. Although other variables such as Speed Related, Posted Speed Limit, Type of Intersection, and Traffic Control usually have a relationship, they were not sufficiently correlated in this analysis.

Table 4.8 Variables Retained among Correlated Pairs

Variable 1	AIC	Variable 2	AIC	Pearson's Correlations Coefficient	Variable Retained
Roadway Alignment	586.2	Pre-Crash Event1	587.8	0.915	Roadway Alignment
Accident Type	596.2	Pre-Crash Event2	585.2	0.663	Pre-Crash Event2
Light Condition	585.2	Hour	583.6	0.658	Hour
Drinking	582.9	Drunk Driver	582.1	0.650	Drunk Driver
Roadway Surface Condition	585.9	Weather	582.2	0.648	Weather
Roadway System	590.3	Trafficway Type	580.4	0.605	Trafficway Type

4.5.2 Model Results of Fatal Single-Vehicle Crashes for Older Drivers

After screening the data for multicollinearity, the final model development had 32 unique variables. Stepwise selection, backward elimination, and forward selection were utilized to identify significant variables in the model. Any variable with a p-value greater than 0.05 was insignificant and not retained. The PROC LOGISTIC procedure in SAS (SAS Institute Inc., 2013) was applied to obtain p-value and coefficient estimates corresponding to each variable. Because results of all three screening methods were identical, this study utilized the stepwise selection method to identify significant variables in the model.

Table 4.9 shows results of the maximum likelihood estimates (MLEs) and odds ratios of the logistic regression model for single-vehicle fatal intersection-related crashes involving older drivers. The model identified the following eight statistically significant explanatory variables ($p \leq 0.05$) that could increase the risk of older drivers' involvement in fatal single-vehicle crashes at intersections: if the trafficway type is two-way undivided, if the land use is urban, if the intersection is with control, if the time is between 8:00 p.m. and 8:00 a.m., if the age of the driver is 75+ years old, if the posted speed limit is less than 55 mph, if the pre-crash event is speeding, and if the most harmful event is a rollover or hitting trees.

Table 4.9 Analysis of Maximum Likelihood Estimate and Odds Ratio

Parameter	Coefficient Estimate (β)	Standard Error	Wald Chi-Square	Pr > Chi Sq	Odds Ratio	95% Wald Confidence Limits for Odds Ratio	
Intercept	-1.1116	0.4492	6.1223	0.0133	N/A*	N/A*	N/A*
VTRAFCON	1.6248	0.1325	150.4421	<.0001	25.782	15.34	43.34
VSPD_LIM	0.5615	0.1399	16.1001	<.0001	3.074	1.776	5.320
P_CRASH2	0.5268	0.1200	19.2629	<.0001	2.868	1.792	4.591
VTRAFWAY	0.6227	0.1894	10.8113	0.0010	3.474	1.654	7.298
M_HARM	-0.3812	0.1238	9.4842	0.0021	0.467	0.287	0.758
AGE	0.2806	0.1197	5.4990	0.0190	1.753	1.097	2.802
RUR_URB	0.3237	0.1402	5.3275	0.0210	1.911	1.103	3.311
HOUR	-0.2695	0.1293	4.3401	0.0372	0.583	0.351	0.969

N/A*: Not Applicable

Table 4.10 presents the significant variables revealed by the stepwise selection method at a p-value of 0.05. As shown in the table, the odds of fatal intersection crashes on controlled intersections was 25.7 times higher than on intersections without control. In addition, the variable VTRAFWAY (trafficway type) shows a positive coefficient estimate (β), meaning that a two-way undivided trafficway has 3.47 times higher odds of fatal intersection crashes for older drivers compared to a two-way divided trafficway. Similarly, the variable VSPD_LIM (posted speed limit) shows a positive coefficient estimate, meaning that the odds of intersection fatal crashes with a posted speed less than 55 mph are 3.07 times higher among older drivers. A positive coefficient estimate for the P_CRASH2 (pre-crash event) variable means that older drivers have 2.86 times higher odds of being involved in fatal intersection crashes when speeding. Likewise, the positive coefficient for the variable RUR-URB (rural-urban road type) means that urban roadways have 1.91 times higher odds of fatal intersection crashes for older drivers than rural roadways. Notably, the odds of fatal intersection crashes were shown to be 1.75 times higher for drivers aged 75+ years old. The occurrence of fatal intersection crashes primarily during daytime hours (9:00 a.m.–7:00 p.m.) means a lower fatality rate with odds of 0.5; the most harmful event (rollover or hitting trees) had a low odds ratio of 0.467.

Table 4.10 Significant Variables in Fatal Single-Vehicle Crashes Involving Older Drivers

Parameter	Effect	Coefficient Estimate (β)	Odds Ratio
Traffic Control Type (VTRAFCON)	Other VS No Control	1.62	25.77
Trafficway Type (VTRAFWAY)	Two-way undivided VS Two-way divided	0.62	3.47
Posted Speed Limit (VSPD_LIM)	Less than 55 mph VS 55 mph and greater	0.56	3.07
Pre-Crash Event2 (P_CRASH2)	Speeding VS Off the Edge of the Road (R/L)	0.53	2.86
Roadway Location (RUR_URB)	Urban VS Rural	0.32	1.91
Driver Age (AGE)	75+ VS 65-74	0.28	1.75
Time of the Day (HOUR)	9am-7pm VS 8pm-8am	-0.27	0.58
Most Harmful Event (M_HARM)	Rollover Or Hitting Tree VS Other(fire, immersion, building, ditch)	-0.38	0.47

4.5.2.1 Model Accuracy of Fatal Single-Vehicle Crashes for Older Drivers

Table 4.11 presents an overview of the model fit statistics for the best-fitting logistic regression model. The model for fatal single-vehicle crashes involving older drivers was applied twice without a screening method and once with a screening method to compare model accuracy. A small value of all models fit statistics is preferred. In this process, screening method by stepwise selection performed better. In terms of R^2, the higher the value is better, even though there was a slight decrease in the value of R^2 with stepwise procedure as shown in Table 4.11.

Table 4.11 Model Fit Statistics

Criterion	Logistic Regression	Stepwise Logistic Regression
	Intercept and Covariates	Intercept and Covariates
AIC	582.49	555.41
SC	747.12	603.21
-2 Log L	520.49	537.41
R^2	0.203	0.194

Table 4.12 shows additional goodness-of-fit measurements obtained from the logistic regression modeling using SAS version 9.4. The three selection methods were identical for goodness-of-fit test results.

Table 4.12 Associations of Predicted Probabilities and Observed Responses

Percent Concordant	88.6	Somers' D	0.780
Percent Discordant	10.7	Gamma	0.785
Percent Tied	0.7	Tau-a	0.119
Pairs	171,375	c	0.890

Based on definitions described in section 3.2.1.3, the following list describes the identified values of the model fit statistics for the logistic regression model:

Percent concordant: In this case, the model found that 89.3% of pairs were concordant, indicating a strong model since the value is greater than 80%.

Percent discordant: The output showed that 10.7% of pairs were discordant. The lower value indicates a preferred model.

Percent tied: The model found that 0.7% of variables were tied.

Pairs: The total number of pairs (concordant, discordant, tied) was 171,375.

Somers' D: The model had a Somers' D value of 0.78, which is close to 1, meaning that the model produced more matched pairs than unmatched pairs.

Gamma: The model had a gamma value of 0.785, indicating a decent association between variables in the model.

Tau-a: The model produced a value of 0.119 for Kendall's Tau-a.

C-value: The model had a c-value of 0.89, which indicates a robust predictive model.

ROC: The model output showed a value of 0.8887, which indicates an accurate model. Figure 4.4 illustrates the ROC curve for the model.

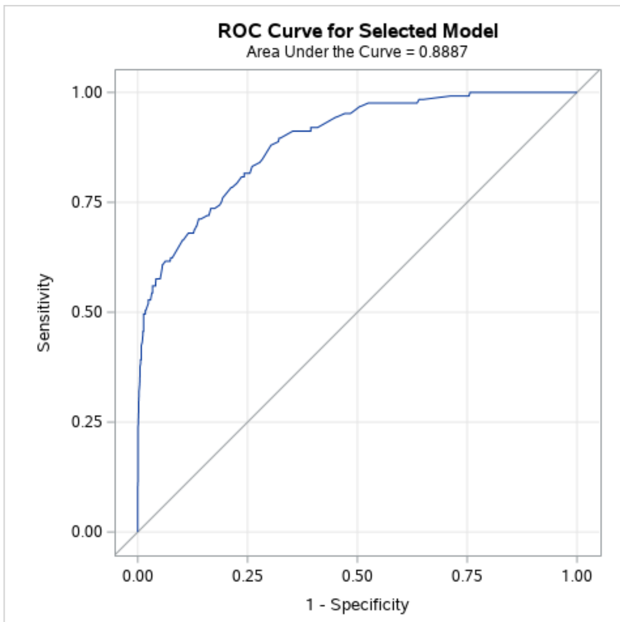

Figure 4.4 ROC Curve for the Logistic Regression Model

HL test: In general, a model is considered a good fit if the p-value is greater than 0.05. The results indicate that the model adequately fit the data since the p-value was 0.212.

Table 4.13 summarizes variables that were shown to increase or decrease intersection-related fatal crash probabilities for older drivers compared to non-intersection crashes.

Table 4.13 Variables Status in Fatal Single-Vehicle Crashes Involving Older Driver

Variables that increase fatal crash probability for older drivers at intersections	- Controlled Intersection - Two-way Undivided Highway - Posted Speed Limit Less than 55 mph - Speeding as Pre-crash Event - Urban Roadway Location - Driver Age 75+ years
Variables that decrease fatal crash probability for older drivers at intersections	- Rollover or Hitting Tree Crash Event - Daytime Hours

According to Table 4.13 and equations 3.1 and 3.2, the logistic regression equation to represent the scenario was written as follows:

$$ln\left(\frac{P}{1-P}\right) = -1.6638 + 0.6227(VTRAFWAY) + 0.3237(RUR\_URB) + 1.6248(VTRAFCON) - 0.2695(HOUR) + 0.2806(AGE) + 0.5615(VSPD\_LIM) + 0.5268(P\_CRASH2) - 0.3812(M\_HARM) \quad (4.1)$$

Where:

P = probability for the dependent variable (*Y* = 1 for intersection or 0 for non-intersection), fatal crash involving an older driver at an intersection,

VTRAFWAY = trafficway type (two-way undivided = 0, two-way divided = 1),

RUR_URB = road location type (rural = 0, urban = 1),

VTRAFCON = traffic control type (no control = 0, other = 1),

HOUR = time of crash (9:00 a.m.–7:00 p.m. = 0, 8:00 p.m.–8:00 a.m. = 1),

AGE = age of driver (65–74 = 0, 75+ = 1),

VSPD_LIM = posted speed limit (55+ mph = 0, less than 55 mph = 1),

P_CRASH2 = pre-crash event (off roadway = 0, speeding = 1), and

M_HARM = most harmful event (rollover or hitting tree = 0, other = 1).

The odds ratio was obtained as follows:

$$P/(1-P) = exp\ [-1.6638 + 0.6227(VTRAFWAY) + 0.3237(RUR\_URB) + 1.6248(VTRAFCON) – 0.2695(HOUR) + 0.2806(AGE) + 0.5615(VSPD\_LIM) + 0.5268(P\_CRASH2) – 0.3812(M\_HARM)] \qquad (4.2)$$

The results of equation 4.2 could then be applied to the following equation to obtain the probability of risk factors in older driver fatal single-vehicle crashes:

$$P = \frac{exp(\alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k)}{1 + exp(\alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k)} \qquad (4.3)$$

where P is the probability that the crash occurs at an intersection (Y = 1), given the independent variables. For example, when P (Crash location = Intersection) ≥ 0.5, the crash occurred at an intersection. However, when P (Crash location = Intersection) < 0.5, the crash occurred at a non-intersection location. In terms of a binary variable, the probability of intersection and non-intersection location sums up to 1.

The logistic regression model accurately identified eight statistically significant predictor variables out of 32 explanatory variables tested. Based on the sign of coefficients, variables such as trafficway type, roadway system, traffic control system, driver age, posted speed limit, and pre-crash event tended to increase the probability of fatal crashes, while the variables that tended to decrease the probability of fatal crashes include the most harmful event and time of the day.

4.5.3 Multicollinearity Analysis of Fatal Multi-Vehicle Crashes for Older Drivers

This study considered 37 explanatory variables, or candidate variables, for a fatal multi-vehicle crash model. Table 4.14 shows the variables retained in the model among the correlated pairs. A total of four correlated pairs were chosen from the explanatory variables, with a value of 0.6 or more as the selection criteria. A full list of the correlation matrix is provided in Appendix A, Table A.2. One of the two correlated variable pairs was removed, starting with the pair with the highest Pearson correlation coefficient value and retaining the other pairs in the model. Then each variable was entered into the model to determine the outcome of the model fit value. The model with a lower AIC value was retained in the model, meaning the Accident Type 2, Manner of Collision, Drunk Driver, and Weather variables were removed by this process. Although other variables such as Speed Related, Posted Speed Limit, Type of Intersection, Traffic Control, Light Condition, and Hour typically have a relationship, they were not sufficiently correlated in this analysis.

Table 4.14 Variables Retained among Correlated Pairs

Variable 1	AIC	Variable 2	AIC	Correlation Value	Retained Variable
Accident Type 1	1452.58	Accident Type 2	1454.57	0.991	Accident Type 1
Accident Type 1	1450.68	Manner of Collision	1691.13	0.752	Accident Type 1
Drinking	1448.83	Drunk Driver	1452.46	0.707	Drinking
Roadway Surface Condition	1447.94	Weather	1450.57	0.663	Roadway Surface Condition

4.5.4 Model Results of Fatal Multi-Vehicle Crashes for Older Drivers

After screening the data for multicollinearity, 32 unique variables were identified for the model. Stepwise selection, backward elimination, and forward selection were utilized to identify significant variables in the model. Any variable with a p-value greater than 0.05 was insignificant and eliminated from the model. The PROC LOGISTIC procedure in SAS (SAS Institute Inc., 2013) was applied to obtain p-value and coefficient estimates corresponding to each variable., the stepwise selection method was applied to identify significant variables in the model, since the three screening methods were matched. Table 4.15 shows the results of MLEs and odds ratios of the logistic regression model developed for multi-vehicle fatal intersection crashes involving older drivers. The model identified the following eight statistically significant explanatory variables with a $p \leq 0.05$: if the accident type is head-on, rear-end, sideswipe, or angle; if the intersection is without control; if roadway alignment is curved; if number of lanes is more than two; if trafficway type is two-way divided; if driving under influence of alcohol; if violation is committed; and if pre-crash event is changing lane, crossing lane, defective vehicle, or turning movement.

Table 4.15 Analysis of Maximum Likelihood Estimates and Odd Ratios

Parameter	Coefficient Estimate (β)	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio	95% Wald Confidence Limits	
Intercept	0.750	0.291	6.602	0.0102	N/A*	N/A*	N/A*
AccType1	1.589	0.102	239.305	<.0001	24.005	16.048	35.907
VTRAFCON	1.188	0.083	201.085	<.0001	10.782	7.762	14.978
VALIGN	0.454	0.122	13.798	0.0002	2.484	1.537	4.014
VNUM_LAN	0.313	0.093	11.329	0.0008	1.872	1.299	2.697
VTRAFWAY	0.291	0.090	10.491	0.0012	1.793	1.259	2.552
Drinking	-0.309	0.136	5.131	0.0235	0.539	0.316	0.92
Violation	0.206	0.092	4.965	0.0259	1.51	1.051	2.171
PreCrash2	0.208	0.1	4.358	0.0368	1.518	1.026	2.247

N/A*: Not Applicable

Table 4.16 shows significant variables (p-value of 0.05) in the model as a result of the stepwise selection method. As shown in the table, the variable Accident Type1 (AccType1) has a positive coefficient estimate, meaning older drivers are 22.11 times more likely to be involved in fatal crashes due to turning movements and intersecting paths at intersections. Similarly, the odds of fatal intersection crashes on controlled intersections were shown to be 11.18 times higher than uncontrolled intersections. Older drivers were 2.68 and 1.79 times more likely to be involved in fatal crashes on straight-alignment and two-lanes roadways, respectively. The positive coefficient estimate (β) for the variable Trafficway Type (VTRAFWAY) means that, compared to a two-way divided trafficway, a two-way undivided trafficway is 1.725 times more likely to be a factor in a fatal intersection crash for older drivers. The Violation parameter increased the likelihood of involvement in fatal multi-vehicle crashes at intersections by 1.56, and positive coefficient estimates for the P_CRASH2 (pre-crash event) variable showed that older drivers are 1.5 times more likely to be involved in fatal intersection crashes when other vehicles encroach into their driving lane. The table also shows that the odds of fatal intersection crashes among older drivers were 1.42 higher on level roadways than roadways with a grade. The positive coefficient estimate for the variable VSPD_LIM (posted speed limit) means that fatal crashes are 1.39 times more likely to occur among older drivers if the roadway has a posted speed less than 55 mph.

Table 4.16 Significant Variables in Fatal Multi-Vehicle Crashes Involving Older Drivers

Parameter	Effect	Coefficient Estimate (β)	Odds Ratio
Accident Type (AccType1)	Turning Movements, Intersecting Paths, Other (Backing) VS Same & Opposite Direction (Head on, Rear end, Sideswipe, Angle)	1.548	22.113
Traffic Control Type (VTRAFCON)	Other VS No Control	1.207	11.186
Roadway Alignment (VALIGN)	Straight VS Curve	0.493	2.683
Number of Lanes (VNUM_LAN)	Two Lanes VS Other	0.293	1.796
Traffic Way Type (VTRAFWAY)	Two-way undivided VS Two way divided	0.273	1.725
Violation	Yes VS No	0.224	1.566
Pre-Crash Event2 (PreCrash2)	Another vehicle approaching into lane VS Changing or Crossing lane, Defective vehicle, Turning movement	0.203	1.501
Roadway Profile (VPROFILE)	Level VS Grade (hillcrest, sag, uphill, downhill)	0.177	1.425
Posted Speed Limit (VSPD_LIM)	Less than 55 mph VS 55 mph and greater	0.165	1.39
Driving Under the Influence (Drinking)	Yes VS No	-0.376	0.472

4.5.4.1 Model Accuracy of Fatal Multi-Vehicle Crashes for Older Drivers

Table 4.17 presents an overview of the model fit statistics for the best-fitting logistic regression model. The stepwise selection method yielded the model fit statistics values. The model for fatal multi-vehicle crashes involving older drivers was applied twice without a screening method and once with screening method to compare the models. As the results show, the stepwise selection method was preferred because it yielded smaller values. In terms of R^2, the higher the value is better, even though there was a slight decrease in the value of R^2 with stepwise procedure.

Table 4.17 Model Fit Statistics Comparison Based on Screening Methods

Criterion	Logistic Regression	Stepwise Logistic Regression
	Intercept and Covariates	Intercept and Covariates
AIC	1447.942	1429.494
SC	1635.962	1492.167
-2 Log L	1381.942	1407.494
R^2	0.522	0.517

Table 4.19 presents additional goodness-of-fit measurements from the logistic regression modeling using SAS version 9.4. The three selection methods had identical results from the goodness-of-fit test.

Table 4.18 Association of Predicted Probabilities and Observed Responses

Percent Concordant	93.2	Somers' D	0.868
Percent Discordant	6.4	Gamma	0.872
Percent Tied	0.4	Tau-a	0.425
Pairs	1,188,810	c	0.934

Based on definitions described in section 3.2.1.3, the following list describes identified values of the model fit statistics for the logistic regression model:

Percent concordant: The model found that 93.2% of pairs were concordant, indicating a strong model since the value is greater than 80%.

Percent discordant: The output shows that 6.4% of pairs were discordant. The lower value indicates a preferred model.

Percent tied: The model found that 0.4% of variables were tied.

Pairs: The total number of distinct pairs (concordant, discordant, tied) was 1,188,810.

Somers' D: The model had a Somers' D value of 0.868, meaning the model produced more matched pairs than unmatched pairs.

Gamma: The model had a gamma value of 0.872, indicating good association between model variables.

Tau-a: The model produced a value of 0.425 for Kendall's Tau-a.

C-value: The model had a c-value of 0.934, which indicates a robust predictive model.

ROC: The model output showed a value of 0.9340, which indicates an accurate model. Figure 4.5 illustrates the ROC curve for the model.

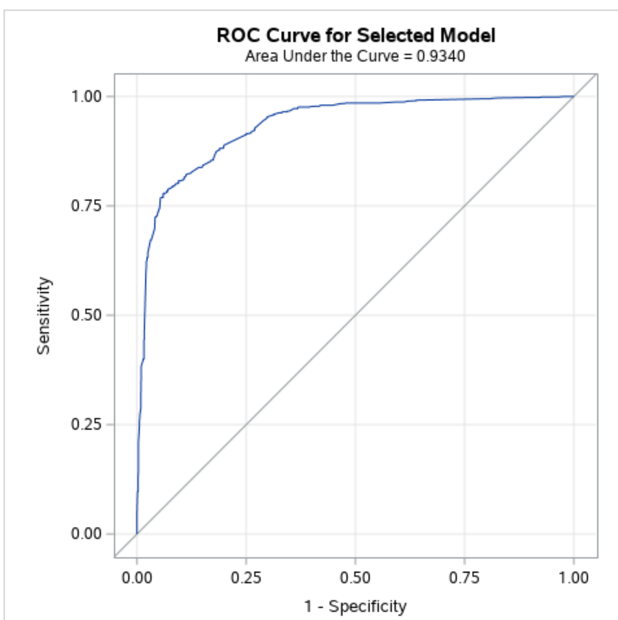

Figure 4.5 The ROC Curve for the Logistic Regression Model

HL test: In general, a model is considered a good fit if the p-value is greater than 0.05. Results from the stepwise selection method show that the model adequately fit the data since the p-value was 0.5295.

Table 4.19 summarizes variables that increased or decreased multi-vehicle fatal intersection-related crashes for older drivers. The table was created according to sign of the coefficient estimate (β).

Table 4.19 Variables in Fatal Multi-Vehicle Crashes Involving Older Drivers

Variables that increase fatal crash probability for older drivers at intersections	- Turning Movements, Intersecting Paths - Controlled intersection - Straight Roadway Alignment - Two lanes roadway - Two-way Undivided Highway - Committed violation - Lane Encroachment of Another Vehicle - Level roadway profile - Posted speed limit less than 55 mph
Variables that decrease fatal crash probability for older drivers at intersections	- Driving Under the Influence of Alcohol

According to Table 4.19 and equations 3.1 and 3.2, the logistic regression equation to represent the scenario was written as follows:

$$ln\left(\frac{P}{1-P}\right) = 0.4263 + 1.5481(AccType1) + 1.2073(VTRAFCON) + 0.4934(VALIGN) + 0.2929(VNUM\_LAN) + 0.2726(VTRAFWAY) + 0.2243(Violation) + 0.2032(PreCrash2) + 0.1770(VPROFILE) + 0.1647(VSPD\_LIM) - 0.3759(Drinking) \quad (4.4)$$

Where:

P = probability for the dependent variable (*Y* = 1 for intersection or 0 for non-intersection), fatal crash involving an older driver at an intersection,

AccType1 = accident type (same and opposite direction = 0, turning movement = 1),

VTRAFCON = traffic control type (no control = 0, other = 1),

VALIGN = roadway alignment (curve = 0, straight = 1),

VNUM_LAN = number of roadway lanes (more than two lanes = 0, two lanes = 1),

VTRAFWAY = trafficway type (two-way divided = 0, two-way undivided = 1),

Violation = roadway violation (no = 0, yes = 1),

PreCrash2 = pre-crash event (changing or crossing lanes = 0, vehicle approaching into lane = 1),

VPROFILE = roadway profile (grade = 0, level = 1),

VSPD_LIM = posted speed limit (55 mph and higher = 0, less than 55 mph = 1), and

DRINKING = (no = 0, yes = 1).

The results of equation 4.5 could then be applied to the following equation to obtain the probability:

$$P/(1-P) = exp\ [0.4263 + 1.5481(AccType1) + 1.2073(VTRAFCON) + 0.4934(VALIGN) + 0.2929(VNUM\_LAN) + 0.2726(VTRAFWAY) + 0.2243(Violation) + 0.2032(PreCrash2) + 0.1770(VPROFILE) + 0.1647(VSPD\_LIM) - 0.3759(Drinking)] \quad (4.5)$$

and it could be applied to the following equation to obtain the probability:

$$P = \frac{exp(\alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k)}{1 + exp(\alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k)} \quad (4.6)$$

where P is the probability that the crash occurs at an intersection ($Y = 1$), given the independent variables. For example, when P (Crash location = Intersection) ≥ 0.5, the crash occurred at an intersection. However, when P (Crash location = Intersection) < 0.5, the crash occurred at a non-intersection location. In terms of a binary variable, the probability of intersection and non-intersection location sums up to 1.

The logistic regression model accurately identified 10 statistically significant predictor variables out of 32 explanatory variables tested. The predictors that increase fatal multi-vehicle crashes for older drivers at intersections include if the accident type is in the same or opposite direction (head-on, rear end, sideswipe, angle), if the traffic control type is intersection with no control device, if trafficway alignment is curved roadway, if the number of roadway lanes is more than two lanes, if trafficway type is two-way divided, if roadway violation is committed, if the pre-crash event is changing or crossing lanes, if the vehicle is defective, if turning movement is required, if roadway profile is grade (hillcrest, sag, uphill, downhill), and if the posted speed limit is higher than 55 mph. Based on the sign of coefficients, variables such as accident type, traffic control type, trafficway alignment, number of roadway lanes, trafficway type, roadway violation, pre-crash event, roadway profile, posted speed limit tend to increase the probability of fatal crashes, while the variable that tends to decrease fatal crashes is DUI.

4.5.6 Multicollinearity Analysis of Fatal Single-Vehicle Crashes for Other Drivers

This study considered 34 explanatory variables, or candidate variables, for fatal single-vehicle crash model for other drivers. Table 4.20 shows the variables retained in the model among the correlated pairs. A total of four correlated pairs was chosen from the explanatory variables, with a value of 0.6 or more as the selection criteria. A full list of the correlation matrix is provided in Appendix A, Table A.3. One of the two correlated variable pairs was removed, starting with the pair with the highest Pearson correlation coefficient value and retaining the other pairs in the model. Then each variable was entered into the model to determine the outcome of the model fit value. The model with a lower AIC value was retained in the model, meaning the roadway alignment (VALIGN), time of crash (HOUR), roadway system (FUNC_SYS), and roadway surface condition (VSURCOND) variables were removed. Although other variables such as Speed

Related, Posted Speed Limit, Type of Intersection, and Traffic Control typically have a relationship, they were not sufficiently correlated in this analysis.

Table 4.20 Variables Retained among Correlated Pairs

Variable 1	AIC	Variable 2	AIC	Pearson's Correlations Coefficient	Variable Retained
VALIGN	3884.47	P_CRASH1	3865.66	0.846	P_CRASH1
LGT_COND	3864.04	HOUR	3867.59	0.746	LGT_COND
FUNC_SYS	3872.65	VTRAFWAY	3864.67	0.671	VTRAFWAY
VSURCOND	3863.58	WEATHER1	3862.98	0.669	WEATHER1

4.5.7 Model Results of Fatal Single-Vehicle Crashes for Other Drivers

After screening the data for multicollinearity, 30 unique variables were identified for the model. Stepwise selection, backward elimination, and forward selection were utilized to identify significant variables in the model, and any variable with a p-value greater than 0.05 was insignificant and eliminated from the model. The PROC LOGISTIC procedure in SAS (SAS Institute Inc., 2013) was applied to obtain p-value and coefficient estimates corresponding to each variable. Table 4.23 shows the results of MLEs and odds ratios of the logistic regression model developed for single-vehicle fatal intersection crashes involving younger drivers. The model identified the following 15 statistically significant explanatory variables with a $p \leq 0.05$: if intersection is controlled; if vehicle type is RV, bus, motorcycle, or golf cart; if the pre-crash event is going straight; if roadway location is urban; if roadway profile is level; if trafficway type is two-way undivided; if posted speed limit is less than 55 mph; if speed is related; if DUI; if light condition is dark; and if drug result is detected and positive.

Table 4.21 Analysis of MLEs and Odds Ratio

Parameter	Coefficient Estimate (β)	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio	95% Confidence Limits	
Intercept	-1.8238	0.1417	165.7044	<.0001	NA	NA	NA
VTRAFCON	1.5172	0.0496	937.2887	<.0001	20.789	17.119	25.247
BODY_TYP	-0.3595	0.0576	38.9635	<.0001	0.487	0.389	0.611
P_CRASH1	-0.322	0.0518	38.6131	<.0001	0.525	0.429	0.643
RUR_URB	0.2947	0.0563	27.4124	<.0001	1.803	1.446	2.248
VPROFILE	0.2193	0.0485	20.4423	<.0001	1.55	1.282	1.875
VTRAFWAY	0.3037	0.0709	18.3505	<.0001	1.836	1.39	2.424
VSPD_LIM	0.2177	0.0517	17.7109	<.0001	1.546	1.262	1.893
SPEEDREL	0.1551	0.048	10.4478	0.0012	1.364	1.13	1.646
DR_DRINK	0.1152	0.0495	5.4102	0.02	1.259	1.037	1.529
LGT_COND	-0.1092	0.0504	4.7001	0.0302	0.804	0.66	0.979
DRUGS	-0.1064	0.0516	4.2439	0.0394	0.808	0.66	0.99
DRUGRES1	0.1072	0.0558	3.6903	0.0547	1.239	0.996	1.542

The backward elimination method produced the best-fit model according to model fit statistics, so it was chosen to present the results for fatal single-vehicle crashes involving younger drivers (Table 4.22). As shown in the table, the variable traffic control type (VTRAFCON) has a positive coefficient estimate, meaning that other drivers are 20.78 times more likely to be involved in fatal single-vehicle crashes at controlled intersections. Similarly, the odds of fatal intersection crashes on urban roadway intersections are 1.86 times higher than rural roadway intersections, and younger drivers are 1.62 times more likely to be involved in fatal crashes on two-way undivided highways. The table also shows that the odds of younger drivers being involved in fatal single-vehicle crashes increases 1.58 times on roadways with posted speed limits less than 55 mph. The variable roadway profile (VPROFILE) has a positive coefficient estimate (β), meaning that younger drivers are 1.52 times more likely to be involved in fatal intersection crashes on level roadways than roadways with a grade. The positive coefficient estimates for the variables drug result (DRUGRES1) and DUI (DR_DRINK) show that younger drivers are 1.25 times more likely to be involved in fatal intersection crashes when using drugs or drinking. Overweight (201–450 lbs) younger drivers are 1.22 times more likely to be involved in fatal single-vehicle crashes at intersections. Finally, the results show that the odds of younger drivers being involved in intersection crashes decrease if the crashes occur during the day, on roadway boundaries or when negotiating curves with the most harmful event being rollover or hitting an animal, or when driving a sedan, SUV, pickup, or light or heavy truck.

Table 4.22 The significant variables in Fatal Single-Vehicle Crashes for Other Driver

Parameter	Effect	Coefficient Estimate (β)	Odds Ratio
VTRAFCON	Other vs No Control	3.0348	20.797
RUR_URB	Urban vs Rural	0.6203	1.859
VTRAFWAY	Two-Way Undivided vs Two-way Divided	0.4862	1.626
VSPD_LIM	Less than 55 mph vs 55 mph and Greater	0.4601	1.584
VPROFILE	Level vs Grade (Hillcrest, Sag, Uphill, Downhill)	0.4228	1.526
SPEEDREL	Yes vs No	0.2724	1.313
DRUGRES1	Positive vs Negative	0.2226	1.249
DR_DRINK	Yes vs No	0.2204	1.247
DrWeight	Overweight (201 – 450 pounds) vs Normal Weight (85 – 200 pounds)	0.1988	1.22
LGT_COND	Daylight vs Dark	-0.2174	0.805
DRUGS	Yes vs No	-0.2236	0.8
M_HARM	Other (Rollover, Fire, Animal) vs Fixed Object (Tree, Building, Street Object)	-0.2628	0.769
REL_ROAD	Other (On Roadway, Median, Gore, Separator) vs On Roadside	-0.4731	0.623
BODY_TYP	Sedan/SUV/Pick up/Light & heavy truck vs Other (RV, Bus, Motorcycle, Golf Cart)	-0.641	0.527
P_CRASH1	Negotiating a Curve vs Going Straight	-0.6585	0.518

4.5.7.1 Model Accuracy of Fatal Single-Vehicle Crashes for Other Drivers

An overview of the model fit statistics for the best fitting logistic regression model is presented in Table 4.23. This model was applied three times using the three screening methods to identify which model perform better. The results from forward and stepwise selection were the same, but the backward elimination gives better outcome. A lower value of all models fit statistics considers better when compare between models. As the results show, the backward elimination method was preferred because it yielded smaller values and there was a slight increase in the value of R^2, which is preferred.

Table 4.23 Model Fit Statistics Comparison

Criterion	Forward Selection	Backward Elimination	Stepwise Selection
AIC	3849.69	3846.88	3849.69
SC	3949.89	3961.40	3949.89
-2 Log L	3821.69	3814.88	3821.69
R^2	0.1326	0.1332	0.1326

Table 4.24 shows additional goodness-of-fit measurements from the logistic regression modeling using SAS version 9.4. The three selection methods had identical results from the goodness-of-fit test.

Table 4.24 Association of Predicted Probabilities and Observed Responses

Percent Concordant	81.4	Somers' D	0.629
Percent Discordant	18.5	Gamma	0.629
Percent Tied	0	Tau-a	0.09
Pairs	6,431,985	c	0.814

Based on definitions described in section 3.2.1.3, the following list describes identified values of the model fit statistics for the logistic regression model:

Percent concordant: The model found that 81.4% of pairs were concordant, indicating a strong model since the value is greater than 80%.

Percent discordant: The output shows that 18.5% of pairs were discordant. The lower value indicates a better model.

Percent tied: The model found that 0% of the variables were tied.

Pairs: The total number of pairs (concordant, discordant, tied) was 6,431,985.

Somers' D: The model had a Somers' D value of 0.629, which is close to 1, meaning the model produced more matched pairs than unmatched pairs.

Gamma: The model had a gamma value of 0.629, indicating a decent association between model variables.

Tau-a: The model produced a value of 0.09 for Kendall's Tau-a.

C-value: The model had a c-value of 0.814, which indicates a robust predictive model.

ROC: The output showed a ROC value of 0.8144, which indicates an accurate model. Figure 4.6 illustrates the ROC curve for the model.

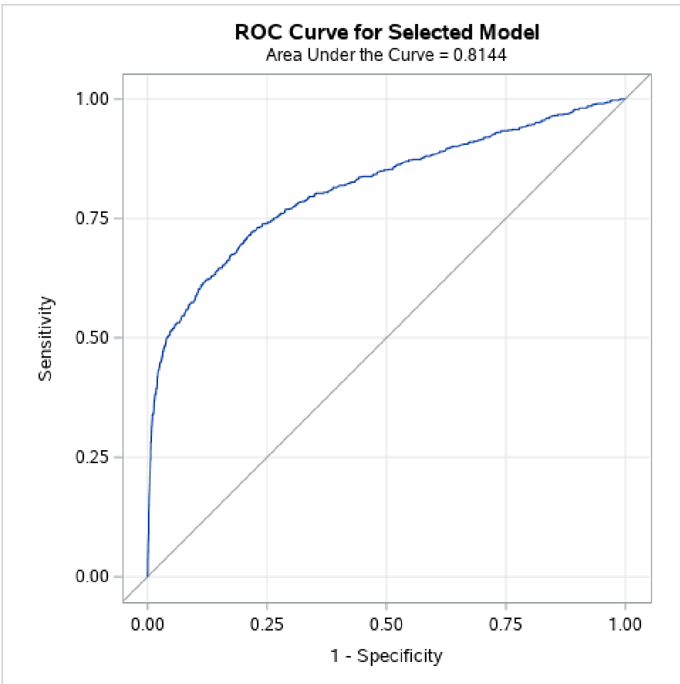

Figure 4.6 ROC Curve for the Logistic Regression Model

HL test: In general, a model is considered a good fit if the p-value is greater than 0.05. Results of the backward elimination selection method showed that the model produce p-value of 0.0052.

From the logistic regression model result, the following summary can be identified. Table 4.25 shows variables that tend to increase/decrease other driver fatal crashes at intersections in the Midwestern States, in comparison to non-intersection crashes.

Table 4.25 Variables Status in Other Driver Fatal Single-Vehicle Crashes

Variables that increase fatal crash probability for other drivers at intersections	- Controlled Intersection - Urban Roadway - Two-Way Undivided Highway - Posted Speed Limit Less Than 55 Mph - Level Profile Roadway - Speeding - Positive Drug Result - Driving Under Influence (Dui) - Overweight Driver
Variables that decrease fatal crash probability for other drivers at intersections	- Daytime Driving - Rollover Crash, Or Hitting an Animal - Crash within Roadway Boundary - Vehicle Type (Sedan, Pickup, SUV, Light or Heavy Truck)

According to Table 4.28 and equations 3.1 and 3.2, the logistic regression equation to represent the scenario was written as follows:

$$ln\left(\frac{P}{1-P}\right) = -3.6945 + 3.0348(VTRAFCON) + 0.6203(RUR\_URB) + 0.4862(VTRAFWAY) + 0.4601(VSPD\_LIM) + 0.4228(VPROFILE) + 0.2724(SPEEDREL) + 0.2226(DRUGRES1) + 0.2204(DR\_DRINK) + 0.1988(DrWeight) - 0.2174(LGT\_COND) - 0.2236(DRUGS) - 0.2628(M\_HARM) - 0.4731(REL\_ROAD) - 0.6410(BODY\_TYP) - 0.6585(P\_CRASH1) \quad (4.7)$$

Where:

P = probability for the dependent variable (*Y*=1 for intersection or 0 for non-intersection), fatal crash involving a younger driver is at an intersection,

VTRAFCON = traffic control type (no control = 0, other = 1),

RUR_URB = roadway location (rural = 0, urban = 1),

VTRAFWAY = trafficway type (two-way divided = 0, two-way undivided = 1),

VSPD_LIM = posted speed limit (55 mph or higher = 0, less than 55 mph = 1),

VPROFILE = roadway profile (level = 0, grade = 1),

SPEEDREL = speeding (no = 0, yes = 1),

DRUGRES1 = drug result (negative = 0, positive = 1),

DR_DRINK = DUI (no = 0, yes = 1),

DrWeight = driver weight (normal weight = 0, overweight = 1),

DRUGS = using drugs (no = 0, yes = 1),

M_HARM = most harmful event (fixed object = 0, other = 1),

REL_ROAD = roadway related (on roadside = 0, other = 1),

BODY_TYP = vehicle body type (sedan/SUV/pickup/light or heavy truck = 0, other (RV/bus/motorcycle/golf cart) = 1), and

P_CRASH1 = pre-crash event (going straight = 0, negotiating a curve = 1).

The odds ratio was obtained as follows:

$$P/(1-P) = exp\,[-3.6945 + 3.0348(VTRAFCON) + 0.6203(RUR\_URB) + 0.4862(VTRAFWAY) + 0.4601(VSPD\_LIM) + 0.4228(VPROFILE) + 0.2724(SPEEDREL) + 0.2226(DRUGRES1) + 0.2204(DR\_DRINK) + 0.1988(DrWeight) - 0.2174(LGT\_COND) - 0.2236(DRUGS) - 0.2628(M\_HARM) - 0.4731(REL\_ROAD) - 0.6410(BODY\_TYP) - 0.6585(P\_CRASH1)] \qquad (4.8)$$

The results of equation 4.8 could then be applied to the following equation to obtain the probability:

$$P = \frac{\exp(\alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k)}{1 + \exp(\alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k)} \qquad (4.9)$$

where P is the probability that the crash occurs at an intersection ($Y = 1$), given the independent variables. For example, when P (Crash location = Intersection) ≥ 0.5, the crash occurred at an intersection. However, when P (Crash location = Intersection) < 0.5, the crash occurred at a non-intersection location. In terms of a binary variable, the probability of intersection and non-intersection location sums up to 1.

The logistic regression model accurately identified 15 statistically significant predictor variables out of 32 explanatory variables tested. The predictors that increase fatal single-vehicle crashes for other drivers at intersections include if the intersection is controlled; if vehicle type is RV, bus, motorcycle, or golf cart; if pre-crash event is going straight; if roadway location is urban; if roadway profile is level; if trafficway type is two-way undivided, if posted speed limit is less than 55 mph; if speed is related; if DUI is related; if light condition is dark; and if drug result is detected and positive.

4.6 Results of Model Validation

In this study, model validation was applied to all the three fatal crash models to check how the models predict what was observed in the research outcomes. The extent of model discriminations was computed by using the accuracy values of fatal intersection crashes. Table 4.26 presents the information regarding model discrimination comparisons. The model fitted on all three samples have excellent discrimination with low variation. The lowest value of C-statistic was 0.80 in the training model of other driver fatal single-vehicle crashes, while the highest value belonged to the validating model of older driver fatal multi-vehicle crashes with 0.94. Thus, all the three models discriminate very well when the data was split with low variability.

Table 4.26 Comparisons of Model Discrimination

Data Sample	Discrimination C-Statistics		
	OD SV Model	OD MV Model	Other Drivers SV Model
Original	0.894	0.936	0.814
Training	0.902	0.939	0.803
Validating	0.923	0.943	0.853

The Hosmer & Lemeshow test, which measures the goodness-of-fit test of a statistical model, was also used to calculate the extent of calibration. The Hosmer and Lemeshow method divides the data into equal groups, with 10 being the most common. With (n-2) degrees of freedom, the model has an asymptotic chi-squared distribution. Under the null hypothesis, the test has a chi-squared distribution with eight degrees of freedom. As a result, the chi-squared of the model with Alpha (α) 0.05 and 8 degrees of freedom (df) is 15.5; this suggests that the values of a model should not exceed this value. Table 4.27 shows that all three models are adequately calibrated, with the exception of the original model of other driver fatal single-vehicle crashes, which did not stand up well; however, after splitting the data, the model reveals that the null hypothesis has a fair calibration. As a result, model validation verifies that the model fits the data set in which it was created.

Table 4.27 Comparisons of Model Calibration

Data Sample	(Calibration) Hosmer & Lemeshow Test Comparision [Chi-Square]		
	OD SV Model	OD MV Model	Other Drivers SV Model
Original	5.54	6.82	32.73
Training	6.96	6.74	14.18
Validating	9.01	5.64	10.64
Target Point α (0.05), df (8)	15.5	15.5	15.5

4.7 Comparison of Risk Factors of Fatal Single-Vehicle and Multi-Vehicle Crashes for Older Drivers

Risk factors were compared for fatal single-vehicle and multi-vehicle crashes to see how the effect difference in two different scenarios. This study identified four significant risk factors for fatal single-vehicle and multi-vehicle crashes involving older drivers: traffic control type (controlled intersection), trafficway type (two-way undivided), posted speed limit (< 55 mph), and pre-crash event [speeding (SV)/another vehicle approaching into lane (MV)]. As shown in Figure 4.7, the effects of these risk factors for both crash types were not identical since all the factors trended strongly (doubled) towards increasing the likelihood of fatal single-vehicle crashes for older drivers in the Midwestern Region.

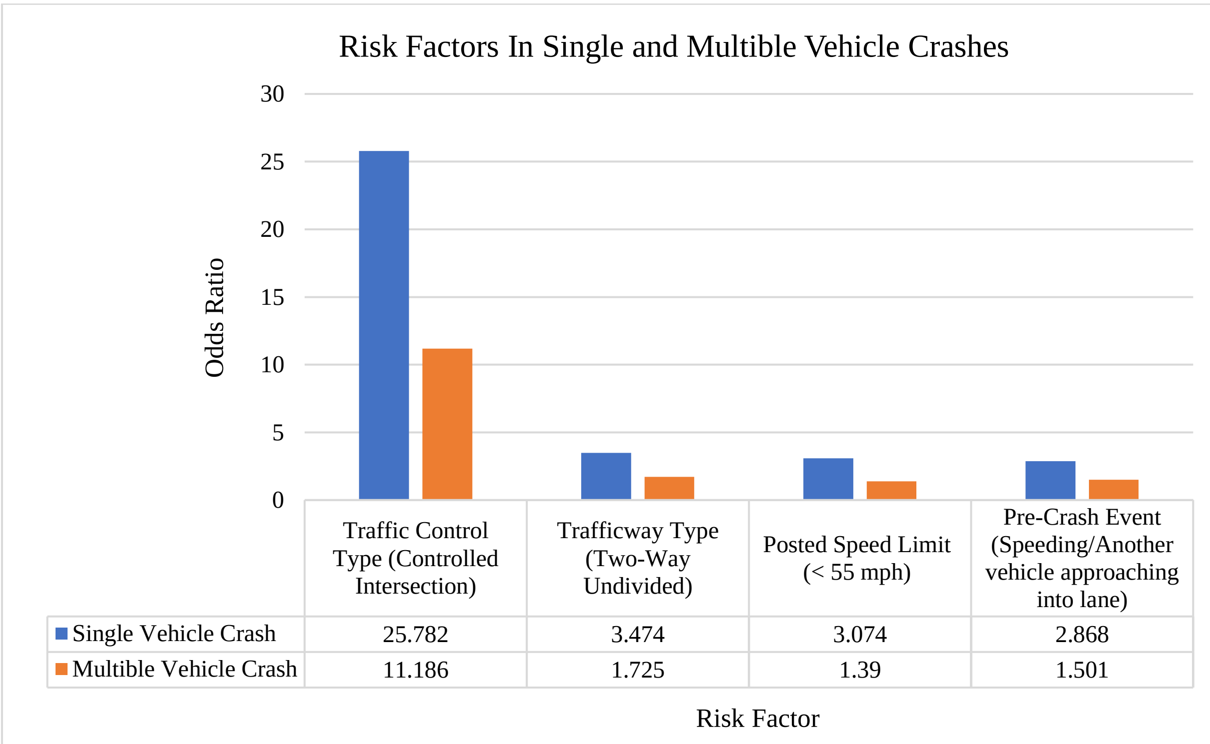

Figure 4.7 Comparison of Risk Factors in Fatal Single-Vehicle and Multi-Vehicle Crashes

Other risk factors were shown to increase the risk of involvement in single-vehicle but not multi-vehicle fatal intersection crashes and vice versa (Table 4.26). For example, roadway location (urban), driver age (75+), time of day (9:00 a.m.–7:00 p.m.), and most harmful event (fire, immersion, ditch) increased the odds of fatal single-vehicle crashes for older drivers, but accident type (turning movements, intersecting paths), straight roadway alignment, two-lane roadways, violations, level roadway profile, and DUI increased older-driver involvement in fatal multi-vehicle crashes. Overall, single-vehicle crashes for older drivers most often occur with harmful events of hitting a fixed object, such as a building or ditch, and fatal multi-vehicle crashes involving accident type turning movements or intersecting paths. Some factors could appear according to the way vehicle collide because single vehicle crash is different than multiple vehicle crash.

Table 4.28 Risk Factors Comparison of Older Drivers Fatal Crashes

Risk Factor	Odds Ratio
Single-Vehicle Crash	
Roadway Location (Urban)	1.911
Driver Age (75+)	1.753
Time of Day (9:00 a.m.-7:00 p.m.)	0.583
Most Harmful Event (Rollover, fixed object)	0.467
Multi-Vehicle Crash	
Accident Type (Turning Movements, Intersecting Paths)	22.113
Roadway Alignment (Straight)	2.683
Number of Lanes (Two in Each Direction)	1.796
Violation (Yes)	1.566
Roadway Profile (Level)	1.425
Driving Under The Influence (Yes)	0.472

4.8 Comparison of Risk Factors of Older and Other Drivers in Fatal Single-Vehicle Crashes

This study also compared risk factors for fatal single-vehicle crashes based on two age groups: older drivers (65 years and older) and other drivers (less than 65 years old). As illustrated in Figure 4.8, significant factors included traffic control type (controlled intersection), trafficway type (two-way undivided), posted speed limit (<55 mph), roadway location (urban), time of day (nighttime), and most harmful event (fixed object) for both age groups. As shown, all the factors more significantly increased fatal single-vehicle crashes for older drivers compared to other drivers. For example, an older driver involved in a single-vehicle rollover crash is more likely to die than a younger driver. Controlled intersections were shown to increase the involvement of fatal single-vehicle crashes for both age groups.

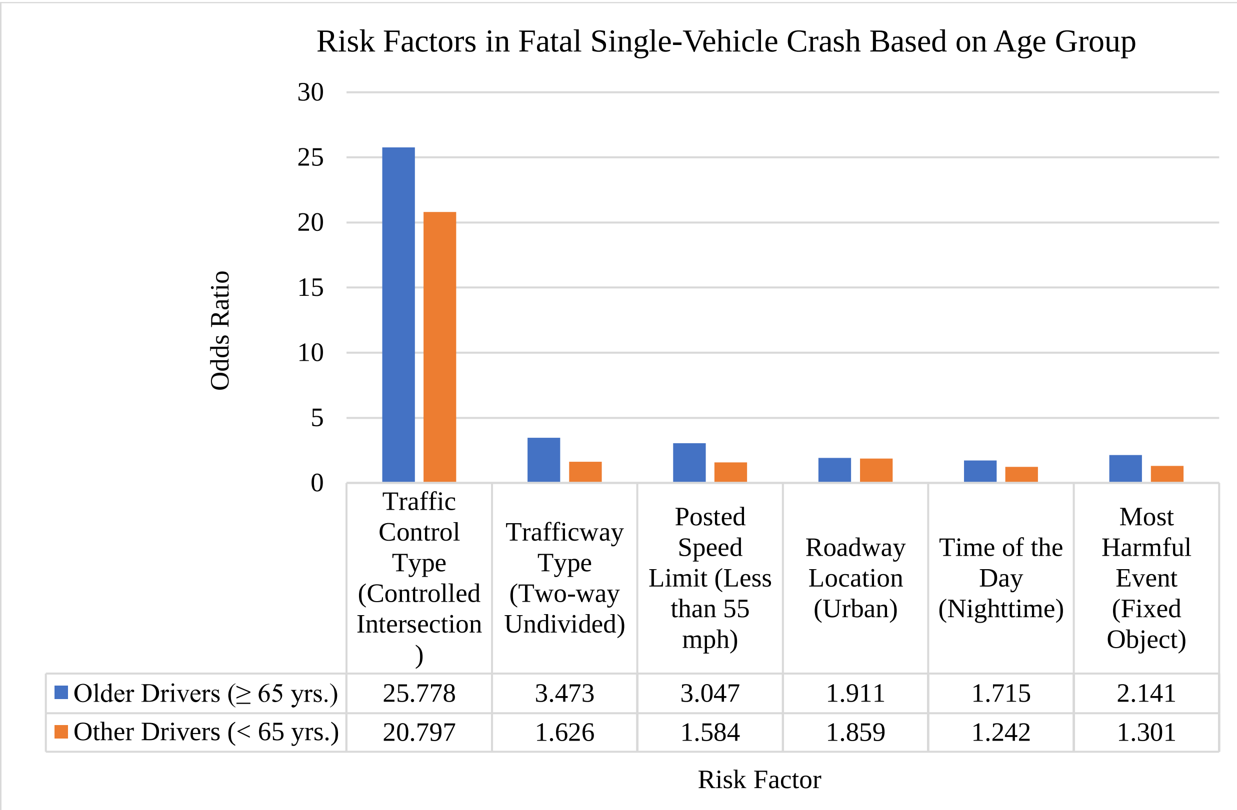

Figure 4.8 Comparison of Risk Factor in Fatal Single-Vehicle Crashes Based on Age Group

Other risk factors were shown to increase the risk of involvement in fatal single-vehicle intersection crashes for younger drivers but not older drivers and vice versa (Table 4.30). For example, roadway profile (level), speeding, positive drug result, DUI, being overweight, crash on roadside, vehicle type (RV, bus, motorcycle, golf cart), and going straight prior to the crash increased younger-driver involvement in fatal single-vehicle crashes at intersections. However, driver age older than 75 years and speeding increased older-driver involvement in fatal single-vehicle crashes at intersections. To highlight, other drivers have more risk factors of involvement in fatal single-vehicle crashes. Some factors could appear according to the age of the driver, as a younger driver has more enthusiastic when driving compare to an older driver who drives more carefully.

Table 4.29 Risk Factor Comparison for Fatal Single-Vehicle Crashes Based on Age Group

Risk Factor	Odds Ratio
Older Driver	
Pre-Crash Event2 (Speeding)	2.868
Driver Age (75+)	1.753
Other Driver	
Pre-Crash Event1 (Going Straight)	1.931
Vehicle Body Type (RV, Bus, Motorcycle, Golf Cart)	1.898
Roadway Related (On Roadside)	1.605
Roadway Profile (Level)	1.526
Speed Related (Yes)	1.313
Using Drug (No)	1.251
Drug Result (Positive)	1.249
Driving Under the Influence (Yes)	1.247
Driver Weight (Overweight) [201-450] pounds	1.221

The results of this study could provide insight to policymakers, engineers, and transportation companies to provide rational and effective interventions, countermeasures, and crash prevention strategies.

4.9 Results and Discussion

Results from this study confirmed that older drivers are more vulnerable to fatal crashes. Although the findings of this study can be compared to previous studies of intersection-related crashes involving older drivers, unlike the current study that utilized separate models to identify risk factors for older and other drivers, other studies combined age groups or considered a specific age, such as older than 65 and younger than 24, while ignoring other age groups. In addition, this study individually developed crash scenarios for fatal single-vehicle and multi-vehicle crashes instead of combining all crash scenarios into one model. This study also combined fatal crash data from the Midwest due to limited amounts of data and similarities among land nature and population in several Midwestern states in the United States.

A comparison of the current study results and studies by Bedard et al. (2002) and Dissanayake (2004), which analyzed single-vehicle crashes to identify contributing factors for older and younger drivers, showed that the studies investigated different parameters. However, the studies agreed that older driver, speeding, DUI for drivers younger than 65 years old, and a roadway with a curve or grade increase the odds of crash fatalities. However, other factors they identified, such as female drivers and restraint device usage, were not significant enough (95% confidence level) for the current study.

The current study can also be compared to a study by Lombardi et al. (2017) that utilized a national crash-fatality database (FARS) to analyze factors that contribute to intersection crashes for older drivers. Their findings showed that the CIR was highest for drivers older than 85 years of age, and they found that the odds of involvement in fatal intersection crashes increase with aging drivers. Their study highlighted factor differences between younger (<65 years) and older (65+ years) drivers in terms of lighting conditions, time of day, weather conditions, type of road, and number of lanes. These results were similar to findings from the current study, in which crashes involving older drivers occurred primarily during daylight hours and on weekdays, while crashes involving other drivers often occurred during nighttime hours and on weekends. Crashes at controlled intersections in rural areas and at-fault driving were significant factors for older drivers in the current study.

Farmer (2019) analyzed 25 years of data (1993–2017) to investigate the effect of increased speed limits on traffic fatalities. The study claimed that increased speed limit was associated with increased involvement in fatal crashes in the United States, highlighting the 8% increase in fatality rates since 20 states increased their maximum speed limits in 2011 and 2012. Similarly, Cox and Cicchino (2021) identified an increase in crash fatalities for older drivers as a result of increased speed limits, and a study by Dissanayake and Le (2001) found that factors such as travel speed, restraint device usage, point of impact, alcohol consumption, driving on rural and curved roadways, and driver health conditions most significantly impacted injury severity for older drivers involved in single-vehicle fixed-object crashes. The current study had similar findings, with speeding, alcohol use, and driving on urban and straight roadways as factors that increase involvement in fatal crashes for older drivers.

Kumfer et al. (2015) found that speeding, distracted driving, avoidance maneuvers, and alcohol consumption are significant factors that increase involvement in fatal single-vehicle crashes among several age groups. Similarly, the current study identified speeding and alcohol consumption as risk factors that increase the likelihood of involvement in fatal single-vehicle crashes. However, the two studies differ in terms of data analysis. While Kumfer et al. (2015) predicted risk factors in fatal single-vehicle and multi-vehicle crashes in one model, the current study utilized two separate models to determine risk factors for fatal single-vehicle and multi-vehicle crashes. Previous studies confirmed that utilization of separate models for predicting risk factors produces more robust findings.

The results from a study by Dissanayake and Koththigoda (2018) investigated crash severity among older drivers to identify issues and suitable countermeasures in the state of Kansas. The study found that fatal injuries for older drivers occurs most often at four-way intersections, on straight or level roadways, at controlled intersections, and during daytime hours. Their study results also revealed that factors such as crash location, light condition, speed, vehicle type, and collision type were associated with fatal single-vehicle crashes involving older drivers. Similarly, the current study found that driver age (older driver), speeding, and crash location increased the likelihood of fatal single-vehicle crashes at intersections. However, in contrast to the findings by Dissanayake and Koththigoda (2018), the current study did not find the risk factors of seat belt usage, weather condition, and day of the week to be significant enough.

4.10 Identification of Countermeasures

According to the findings of this study, countermeasure ideas for older drivers' crashes focus on the three EEE's (Engineering, Education, and Enforcement) which discussed on the literature reviews section of this study. The main countermeasures are roadway design, vehicle design, education and training, and licensing program, (Elliott et al., 1995, Richard et al., 2018). These elements were shown promising improvement in the safety of older drivers and all road users. The following section will discuss these countermeasures in detail.

Findings of the current study revealed that the risk factor of controlled intersection for older drivers caused a crash probability of 0.96. According to the FARS database, older drivers were involved in 57% of intersection-related crashes in the Midwest from 2014 to 2018. Furthermore, as drivers age they struggle to navigate complex driving situations, such as intersections and uncontrolled left turns (Stutts et al., 2009). A survey-based study in Kansas showed that older drivers had difficulty turning left at uncontrolled intersections due to the many processing tasks required in a short period of time, such as speed of oncoming vehicles and judging the gap to cross at intersections. However, other study results have shown that older drivers are more confident when making protected left turns or right turns at intersections controlled with a traffic light on (Dissanayake & Perera, 2011). As a result, improving roadway design would help to accommodate older driver needs and enhance their safety.

As a countermeasure for multi-vehicle intersection crashes revealed as a significant factor in this study, controlled and uncontrolled intersections could be converted to roundabouts when appropriate to improve the safety of all road users (Brilon, 2016; Qin et al., 2013; Braitman et al., 2007; Oxley et al., 2006; Jacque art, 1998). Roundabouts reduce the number of conflict points from 32 to only 8 (Rodegerdts, 2010), and they have been shown to significantly reduce severe injury crashes (Persaud et al., 2001; Elvik, 2003; Lord et al., 2007). Beneficial features of roundabouts include lower vehicle speeds, decreased left-turn conflicts, and clarification of right of way, and enhancing traffic calming, which a four-way intersection lacks (Stone et al., 2002).

Studies have shown that when older drivers became familiar with a new roundabout design, the level of public support one year after installation increased from 35% to 70% (Retting et al., 2007; Hu et al., 2014). However, preemptive roundabout driving training for older drivers by community campaign is recommended. In addition, one-lane roundabouts with one circulating lane are recommended to prevent unintentional lane change inside the circulating lane (Brewer, 2014). The central island of a roundabout should have retroreflective marking and luminance as well as advance warning signs and directional signs to enhance conspicuity and legibility for older drivers. Roundabouts must be designed to accommodate the needs of older drivers (Brewer, 2014).

Another suggestion for increased intersection safety for older drivers is utilization of protected left-turn signals, a cost-effective countermeasure that would decrease the prevalence of fatal crashes that occur on unprotected left-turn lanes (Braitman et al. 2007; Cicchino & McCartt, 2015; Bagdade, 2004). The addition of a flashing yellow arrow (FYA) has also shown promising results for reducing conflict at intersections when turning left without a protected left-turn signal (Noyce et al., 2007). FYAs at intersections remind older drivers to wait for an appropriate gap to turn left, thereby eliminating right-of-way conflicts at controlled intersections (Brewer et al., 2014).

Crash occurrences at urban intersections was a significant factor in the current study. Intersection countermeasures in urban areas, such as restricted crossing U-turn (RCUT) and median U-turn (MUT), have shown promise for resolving intersection conflicts. A Missouri study found that converting conventional four-way intersections to RCUT reduced severe injury and fatal crashes by 54% (Edara et al., 2013). Another study found that using an MUT at intersections could reduce intersection-related crashes by 30% (Reid et al., 2014). These two solutions could decrease left-turn conflicts at intersections with significant traffic movement, such as urban intersections, by 50% compared to conventional four-way intersections (Brewer et al., 2014). Improved intersection design should also consider reducing required head movements for older drivers or redesigning skewed intersection with angles of 75^{o} or greater (Brewer et al., 2014). If a skewed intersection cannot be redesigned, right turn on red should be prohibited and a protected left turn should be applied to prevent common errors for older drivers, such as misjudging gap and speed for upcoming traffic to turn safely (Phillips et al., 2006; Staplin et al., 2001; Brewer et al., 2014).

In order to improve safety of older driver on urban area, introduce some of traffic calming devices are advisable. Traffic calming methods could be applied on residential area to reduce speed such as traffic circles, mini-roundabouts, and roundabouts, raised intersections, road narrowing, speed humps, speed cushion, and speed table. These calming devices could enhance the safety of not only older drivers but also non-motorist such as pedestrian and cyclists. Several studies approved that traffic calming devices where reduce vehicle speed as well as the severity of injury among drivers and pedestrians in urban area (Distefano & Leonarde, 2019; Hu, & Cicchino, 2020).

Providing portable or fixed changeable message signs to warn drivers that running over the speed limit is another countermeasure to minimize risk among road users (Brewer et al, 2014).

The current study also found crashes occurring at night and crashes involving fixed object were significant risk factors. Because older drivers experience decreased visual acuity when driving at night, especially in locations that lack street lighting, this study and other previous studies have recommended increasing intersection lighting at intersections known to produce severe crashes (Monyo et al., 2021; Obeidat & Rys, 2016; Staplin et al., 2001). A study of nighttime crashes and intersection lighting showed a reduction in severe crashes on illuminated signalized and unsignalized intersections. A cost-benefit analysis of installed lighting on intersections with a high rate of severe crashes showed a reduction in crashes and subsequent safety benefits that outweigh the associated costs of lighting installation (Li et al., 2020; Bhagavathula et al., 2019). Similarly, an analysis of rural interstation crashes in Illinois revealed a 30% reduction of nighttime crashes due to illumination at intersections (Wortman et al., 1972).

Due to risk factors associated with intersection crashes for older drivers, the study recommended implementing adequate intersection sight distance (ISD) to reduce head movement and provide adequate perception reaction time through an intersection (Brewer et al., 2014). In addition, an offset left-turn lane to be applied at least 4 ft to the left of the opposing left-turn lane, or 5.5 ft if heavy trucks commonly use the intersection, to enhance the ISD for left-turning drivers, and signs and pavement markings at intersection should be enhanced to accommodate older drivers and to reduce intersection conflicts, such as wrong-way crashes. Providing warning intersection signs in-advance before reaching intersection would also benefit older drivers because their perception reaction time is longer (Brewer et al., 2014).

Because the relatively flat midwestern terrain could encourage speeding and unintentional lane changes, this study recommended improved roadway design that includes countermeasures such as delineations of edge lines and curbs that could help older drivers maintain correct lane position and reduce the number of fixed-object crashes. In addition, street signs should not be less than 12 inches for uppercase letter height and 9 inches for lowercase letter height for major intersections. Complex and busy intersections should also be equipped with prismatic retroreflective sheeting signs that increase conspicuity and legibility for older drivers. Acceleration and deceleration lane design should have parallel lanes to allow time for merging drivers into through-traffic stream, thereby decreasing sideswipe and rear-end crashes (Brewer et al., 2014).

Guardrails, cable barriers, or concrete barriers have also shown to be effective countermeasures to reduce crash severity for run-off-road and rollover crashes. An Indiana study demonstrated a 57% reduction of injury severity when a vehicle hit a cable barrier, asserting that, of the three barriers, a cable barrier is preferable to a guardrail, but a guardrail is preferable to a concrete barrier when road and traffic conditions allow (Zou et al., 2014).

The current study identified the following factors as increasing the probability of fatal single-vehicle crashes for older drivers: two-way undivided highways, straight roadway alignment, level roadway profile, run-off-road crashes, and speeding. Therefore, roadway countermeasures such as the utilization of centerlines and shoulder rumble strips are essential for alerting drivers when they leave their travel lane (Khan et al., 2015). A study of continues shoulder rumble strips in California and Illinois found an 18% reduction of run-off-road crashes on urban highways and a 21% reduction on rural freeways (Griffith, 1999). According to FHWA (2017), centerline rumble strips reduce head-on, opposite-direction, and sideswipe fatal and injury crashes by 55%. Also, shoulder rumble strips minimize single-vehicle run-off-road fatal and injury crashes up to 51% (Torbic, 2009).

Considering that speed was a risk factor identified in this study, a previous study showed that transverse rumble strips (TRS) on high-speed intersections positively impacted speed reduction and acted as a warning to reduce severe crashes at intersections, especially in rural areas (Yang et al., 2016). Speed enforcement is another effective way to control vehicle speed and enhance the safety of all road users. Since two-way undivided highway was a risk factor for all drivers in two different crash scenarios, a countermeasure for this type of roadway is the application of a roadway diet which converting a four-lane undivided roadway to a three-lane roadway, one lane on each direction with a center two-way left-turn lane (TWLTL) (Huang et al, 2002; Brewer et al., 2014). An Iowa study found that crash frequency per mile decreased by 25% and crash rate decreased by 18.8% after applying a road diet (Pawlovich et al., 2005).

Due to crashes occurred on undivided highway, providing continuous raised curb median could reduce the severity of crashes such as vehicle crossing to opposing lane. Improving lighting, signs and markings on interchanges is crucial to reduce wrong way crashes. Enhancing lane drop marking to distinguish between through lane and mandatory exit lane is advisable to improve visibility among older drivers. Increase contrast markings on concrete pavement also another task needs to be enhanced for older drivers need. To enhance pavement materials friction resistant, providing high friction surface treatments is crucial to enhance the safety especially on locations prone to frequent rain, snow, or ice, and on horizontal and vertical curve, as well as on intersection location due to frequent vehicle break activities, on and off-ramps, and on bridge decks (Brewer et al, 2014).

The current study also identified several significant risk factors related to speeding, aging, and violation that specifically impact the safety of older drivers and that could be remedied by newer vehicles equipped with a warning system (Choi et al., 2017). In-vehicle technologies that interact with the environment show promise for improving the safety of older drivers, such as adaptive cruise control (ACC) and intelligent speed adaption (ISA), which can maintain speed and detect and respond to other vehicles in the same lane to maintain a safe following distance. The vehicle warning system can also deduce the speed limit of the roadway and provide a warning or active control to prevent vehicle speeding (Venkatraman et al., 2021). These two collision avoidance technologies effectively reduced rear-end and frontal crashes by 38% and 45%, respectively (Hellman & Lindman, 2015).

Another countermeasure to prevent run-off-road crashes is a lane departure warning system (LDW) equipped in newer vehicles. A comparison of vehicles with and without the LDW system revealed a 24% reduction in severe injury crashes and a 86% reduction in fatal crashes, thereby proving the effectiveness of the LDW system for older drivers and all road users (Cicchino, 2018). Similarly, a blind spot warning (BSW) system helps prevent intended and unintended lane changes and warns drivers of vehicles in an adjacent lane, thereby preventing multi-vehicle crashes due to another vehicle approaching into a lane. Vehicles equipped with BSW showed a 14% reduction in crash involvement rates in lane-change crashes (Cicchino, 2018). Future technologies such as autonomous vehicle (AV) and vehicle-to-vehicle communication also show promise for enhancing the safety of older drivers and all road users (Friedrich, 2016).

According to crash fatality data for older drivers, driver age over 75 years old and roadway violations were significant factors for increased likelihood of involvement in fatal crashes. Therefore, enhanced education and training, specifically for older drivers, would update older drivers about road hazards, increase their knowledge of driving safety, and encourage use of public transportation instead of driving. Self-regulation, or the ability of older drivers to evaluate their own driving abilities and voluntarily cease driving if needed, is a successful, cost-effective countermeasure to enhance the safety of older drivers (Owsley et al., 2003).

However, the effectiveness of education and training to reduce fatal crashes among older drivers is still questionable since there is no clear evidence that this intervention helps prevent fatal crashes instead of only improving driving knowledge (Potts et al, 2004; Strategy D2; Richard, 2018). Comparatively, training approaches that combine education with visual-perceptual training and physical training have shown to effectively improve driving safety (Gaspar et al., 2012; Choi et al., 2017; Dickerson et al., 2019; Fausto et al., 2020). Driver awareness programs, such as the CarFit program, evaluate older drivers' abilities to drive independently and potentially enhance their driving performance. Continuation of the program would benefit future drivers by improving their driving knowledge and safety (Stav, 2010; Gaines et al., 2011; McConomy et al., 2018).

The current study found that older drivers were overrepresented in fatal single-vehicle and multi-vehicle crashes at controlled intersections and that driver age of 75 years and older and roadway violations were significant risk factors for fatal crashes. Therefore, licensing programs that emphasize driving, knowledge, and health tests could be mandatory and implemented annually for all drivers over 65 years of age to evaluate driving performance. A survey-based study in Kansas showed that older drivers are at high risk for fatal crashes at intersections due to the increased likelihood of misjudging the gap and the speed of oncoming vehicles (Dissanayake & Perera, 2011). These findings highlight age-related issues associated with eye movement and vision, decision making, and neck flexibility. Many states have outdated drivers' licensing guidelines, meaning agencies do not include all medical recommendations for older drivers (Richard et al., 2018).

Furthermore, although most midwestern states require drivers' license renewal on an average of every four years (Graham et al., 2020; Stutts & Wilkins, 2009), a previous study found that older drivers had drastically decreasing physical fitness that caused over-involvement in more fatal crashes (Stutts et al., 2009). As a result, an annual drivers' license renewal policy for older drivers may be implemented to identify early signs of fatigue or cognitive decline, thereby decreasing crash severity and enhancing driver safety. A survey of older driver referral to licensing agency found that the highest percentage of referral comes from law enforcement and medical physicians (Stutts, 2005). A Missouri study highlighted a voluntary reporting law that has significantly decreased crash involvement for older drivers who have been voluntary reported by family members, physicians, or law enforcement officers (Meuser et al., 2009).

Cooperation between licensing agencies and law enforcement is crucial for reporting events that are only seen by police officers who observe drivers at traffic lights or stop signs (Richard et al., 2018). A noteworthy restricted driving license program for older drivers in Iowa, Kansas, and Minnesota has shown promise for decreasing crashes for this age group, but this program requires older driver or family member initiatively reporting (AAAFTS, 2009b). The licensing program that includes screening, testing, referral, and license restriction consider to be the most effectiveness countermeasures among older driver (Snyder & Ganzini, 2009, Meuser et al., 2015, AAAFTS, 2009a, AAAFTS, 2009b, Langford & Koppel, 2011, Stutts & Wilkins, 2012). Table 4.28 summarizes proven and promising countermeasures related to each risk factor in this study.

Table 4.30 Countermeasure Ideas to Each Risk Factor

Risk Factor	Countermeasures
Controlled Intersection	Minimum Of 75-Degree Skew Angel
	Improve Intersection Sight Distance
	Offset Left Turn Lane
	Protected Left Turn Signal
	Roundabout
	Provide Flashing Yellow Arrow
	Restricted Crossing U-Turn (RCUT) Intersection
	Median U-Turn (MUT) Intersection
	Contrast Markings On Concrete Pavement
	High Friction Pavement Surface
	Transverse Rumble Strips (TRS)
	Lane Drop Marking
Two-Way Undivided Highway with Two Lanes in Each Direction	Road Diet
	Rumble Strips
	Continuous Raised Curb Medians
	Lane Drop Marking
	Contrast Markings On Concrete Pavement
Speeding	Traffic Calming Device
	Enforcement
	In-Vehicle Technology
	Transverse Rumble Strips
	Fixed Or Portable Changeable Message Signs
Another Vehicle Approaching into Lane	Rumble Strips
	Parallel Acceleration And Deceleration Lane Design
	Guardrail, Cable Barrier
	Continuous Raised Curb Medians
	Lane Drop Marking
Aging Driver/Violation	Education And Training
	Licensing
	Enforcement
Nighttime	Lighting
	Retroreflective Delineation
	Fixed Changeable Message Signs
	Lane Drop Marking

Table 4.30 Countermeasure Ideas to Each Risk Factor (Continued)

Risk Factor	Countermeasures
Rollover, Fixed Object	Rumble Strips
	Retroreflective Delineation
	Guardrail, Cable Barrier, Concrete Barrier Lane Drop Marking
Urban	Traffic Calming
	Delineations Of Edge Lines And Curbs
	Roundabout
	Restricted Crossing U-Turn (RCUT) Intersection
	Median U-Turn (MUT) Intersection
	Offset Left Turn Lane
	Protected Left Turn Signal
	Flashing Yellow Arrow
	Continuous Raised Curb Median
	Adequate Intersection Sight Distance (ISD)
Straight and Level Roadway	Rumble Strips
	In-Vehicle Technology
	Guardrail, Cable Barrier, Concrete Barrier

Chapter 5 - Summary, Conclusions, and Recommendations

5.1 Summary

As a result of natural aging process, older drivers may experience lack of attention, visual impairment, and neck movement issues, which could cause slower movement on the roadway and slower perception reaction time to respond to traffic problems eventually lead to crashes. One of the most challenging locations for older drivers to navigate is intersection. The percentage of fatalities among older drivers is considered the highest among all age groups in all crashes. The objective of this study was to determine factors associated with intersection-related crashes involving older drivers in the Midwestern states, and to provide countermeasure ideas to improve safety. This study examined five years (2014 to 2018) of fatal crash data from the Fatality Analysis Reporting System (FARS) database. A logistic regression analysis was used to identify the risk factors among older driver fatal intersection crashes.

Regional comparisons of fatal and injury crash statistics showed that the Midwest has the highest percentage of fatal-to-total crashes, with 62% of all crashes were fatal for drivers of all ages. Specifically, the midwestern region had the most fatal multi-vehicle crashes involving older drivers. Although the highest rate of fatalities for single-vehicle crashes involving other drivers was in the Northeast, a similar trend was observed for fatalities of other drivers in fatal multi-vehicle crashes for all regions in the United States. The three states with the highest percentages of fatal single-vehicle crashes involving older drivers were California, Texas, and Florida due to their high concentrations of older drivers. Overall, study results showed that older drivers are more likely to be involved in fatal multi-vehicle crashes, while other drivers are more prone to fatal single-vehicle crashes.

To determine the characteristics of older driver fatal single-vehicle and multi-vehicle crashes in the Midwest, vehicle, crash, driver, and environment characteristics were examined. In terms of crash characteristics, older drivers were less involved in fatal crashes while driving under the influence of alcohol or consuming drug, driving on the weekend, during dark condition, no adverse weather, speed unrelated, driving on two-way divided highways on urban areas, on level and straight roadways. Driving off roadway, hitting fixed objects, and being not related to intersections were associated with fatal single-vehicle crashes. At the same time, head-on, rear-end, sideswipe, angle, and intersection related crashes were associated with fatal multi-vehicle crashes. Male drivers were over-represented in fatal single-vehicle crashes, while female drivers were over-involved in fatal multi-vehicle crashes. Older drivers being aware of these factors would help to mitigate risks and enhance driving habits.

Another comparison was made between the characteristics of fatal single-vehicle crashes based on age groups (older Versus other) drivers in the Midwest. In terms of crash characteristics, older drivers were less-represented in fatal single-vehicle crashes that involve driving under the influence of alcohol, or illegal drugs, occurring during the evening and early morning hours. While speeding, going off roadway, driving at nighttime, driving under the influence of alcohol, or illegal drugs were factors that dominate on other drivers in fatal single-vehicle crashes. The two age groups shared similar characteristics, on gender, crash occurring on weekdays, having no adverse weather conditions, hitting fixed objects, driving a newer passenger vehicle, crashes occur on two-way undivided highways, rural areas, higher posted speed limits (greater than 55 mph), crashes occur on level roads, and straight alignment. Addressing these factors, which associated with fatal single-vehicle crashes, are crucial to minimize the severity and improve level of safety not only older drivers, but also all road users.

This study also identified several proven and promising countermeasures to support the needs of older drivers and enhance safety for all road users. Accommodating intersection design is essential for older drivers to avoid and reduce crash severity. Additional recommended intersection designs include redesigning intersections to reach minimum of 75-degree skew angel, improving intersection sight distance, adding offset left turn lane, adding protected left turn signal, providing flashing yellow arrow, implementing roundabout, providing restricted crossing U-turn, implementing median U-turn. Implementing road diet, providing rumble strips, enhancing roadway signs and retroreflective delineation along the roadways, providing lighting along the roadway and specially at intersection locations, providing cable barrier, or guardrail, implementing traffic calming device, providing continues raised curb medians, enhancing lane drop marking on interchange, implementing fixed or portable changeable message signs, improving frictions on pavement, increasing contrast markings on concrete pavement, and using in-vehicle technology equipped in newer vehicles are also effective countermeasures. Overall, these countermeasures would minimize crash severity for older drivers and all road users.

5.2 Conclusions

In order to analyze older driver fatal single-vehicle and multi-vehicle crashes, and other drivers fatal single-vehicle crashes, three separate models were developed using a binary logistic regression based on FARS data for the Midwestern states. In this study, model validation was checked to all the three crash models to verify how the models predict what was observed in the research outcomes. All the three models discriminated and calibrated very well when the data were split with low variability. As a result, model validation verifies that the model fits the data set in which it was developed.

The predictors that increase older driver fatal single-vehicle crashes at the intersections are; if the time of the day nighttime, if the pre-crash event is speeding, if land use is urban, if the driver age older than 75 years, if the intersection is controlled, if trafficway type is undivided, if the posted speed limit is less than 55 mph, and if the time of the day is between 8 pm to 8 am. These factors were shown to be risk factors to increase fatal crashes among older drivers at intersections.

From the older driver fatal multi-vehicle crash model, the results showed that older drivers were over-involved in fatal multi-vehicle crashes if accident type is turning movements, and intersecting paths at intersection, if intersection is controlled, if roadway alignment is straight, if trafficway type is two way undivided with two lanes on each direction, if violation is committed, if pre-crash event is another vehicle approaching into lane, if roadway profile is level, and if the posted speed limit is less than 55 mph.

In terms of other drivers' fatal single-vehicle crash model results, drivers younger than 65 years were most likely to be involved in fatal single-vehicle crashes; if intersection is controlled, if roadway location is urban, if trafficway type is two-way undivided, if posted speed limit is less than 55 mph, if roadway profile is level, if speed is related, if drug and drinking results are positive, if driver is overweight, if light condition is dark, if the most harmful event is fixed object, if vehicle body type is RV, bus, motorcycle, or golf cart, and if pre-crash event is going straight.

5.3 Recommendations

According to the findings of this study, countermeasures were recommended to enhance the safety of older drivers and other road users at intersections, including education, enforcement, and engineering to accommodate and enhance the needs of older drivers. Roadway design improvement as an engineering countermeasure is one of vital factors to enhance the safety of older drivers. Improving intersections design to accommodate necessity of older drivers is suggested such as implementing roundabouts when appropriate, reach minimum of 75-degree skew angel at intersection, protected left turn signal, offset left turn lane, flashing yellow arrow, restricted crossing U-turn, median U-turn, and transverse rumble strips (TRS) which show improvement of safety of not only older drivers but also all road users. Improving roadway lighting, signs and markings at intersection and interchanges is advisable to enhance the visibility of older drivers. Increasing the use of rumble stripes along the roadway as well as median, and implementing roadway diet, enhancing roadway signs and retroreflective delineation along the roadways, providing cable barrier, or guardrail, and traffic calming on residential areas are also recommended to minimize the severity of traffic crashes.

Implementing continuous raised-curb medians, land drop marking on interchanges, providing acceleration and deceleration lane for merging and diverging, fixed or portable changeable message signs, high friction surface treatments on risk prone locations, increasing contrast markings on concrete pavement are shown improvement of roadway safety overall. Using newer vehicles that are equipped with many safety features is advisable to enhance older and other drivers' safety. Beside the engineering countermeasures, educational and training campaign for older drivers to improve their driving performance is recommended. Older drivers' license renewal policy may be modified to overcome early signs of fatigue or cognitive decline and to be mandatory for all drivers over 65 years and to be implemented annually. The main findings of this study would benefit authorities, stockholders, law enforcement officers, and transportation agencies by increasing awareness of these risk factors to guide policy development and the application of effective interventions and crash prevention strategies.

5.4 Limitations

Although this study revealed the risk factors associated with older drivers at intersections in the Midwest, some limitations were identified during the research process. The FARS database has several methodological advantages over other sources of traffic fatality data, as mentioned, it also has limitations. For example, the FARS database relies on police reports, which could be prone to human error, underreporting, or miscoding. Also, some dataset variables have missing or unknown data records, meaning variables that were important to include in the study but had missing/unknown data were portioned accordingly for analysis, potentially leading to miscoding errors that drop significant variables or consider a variable to be unimportant in the model. This study was also limited because it used the FARS database, which only accounts for fatal crashes; as a result, other injury severities could not be modeled using this dataset. Nevertheless, the FARS database is the only source that combined several databases from all the fifty states in the US, and the availability of data for four decades which outweigh its downside. Addressing these limitations would improve the prediction ability of older driver fatal crash model.

5.5 Future Research

The logistic regression model as a methodology provided a reasonable approach to identify risk factors associated with fatal intersection-related crashes involving older drivers. Even though the logistic regression accurately handles binary outcomes, this study recommends that future research apply other statistical modeling to similar data for the same classification purposes to highlight undiscoverable independent factors that may not have been significant enough in the current study. Using an advanced discrete choice model, such as Mixed Logit Model, may reveal more details regarding confounding factors and random parameters to account for in the analysis process. Therefore, different contributing factors for single-vehicle and multi-vehicle crashes could be investigated to determine how risk factors vary for various crash scenarios.

The findings of this study may raise the awareness of crash-fatality trends for other regions in the United States; similar studies could be performed using data from other regions to compare. Consequently, nationwide interventions can be implemented to improve driving safety for older drivers throughout the country. The current study recommends further studies concentrate on injury severities of older drivers using the KABCO (fatal, incapacitating injury, non-incapacitating injury, possible injury, and no injury) scale from other dataset that account for several injury severities by using Ordered Logit Model.

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Appendix A - Correlation Matrix

Appendix A Table A.1

Pearson's correlation matrix for older driver single-vehicle fatal intersection crashes used in the study. The coefficient value of 0.6 and greater was selected among two pairs of variables to be tested for correlation. This value has been highlighted in the table with bold text.

	MONTH	DAY_WEEI	VTRAFWA	VNUM_LA	DSTATUS	RUR_URB	DRUGRES1	VTRAFCOI	DRUGS	DRINKING	SPEEDREL	DRUNK_D	SEX	VPROFILE	FUNC_SYS	TYP_INT	HARM_EV	VSURCON	LGT_CONI	WEATHER
MONTH	1.000																			
DAY_WEEI	0.038	1.000																		
VTRAFWA	-0.044	-0.001	1.000																	
VNUM_LA	-0.028	0.005	0.389	1.000																
DSTATUS	-0.015	-0.047	0.028	0.036	1.000															
RUR_URB	-0.068	0.054	0.274	0.421	0.072	1.000														
DRUGRES1	-0.006	-0.004	0.023	0.050	0.473	0.032	1.000													
VTRAFCOI	0.022	0.008	0.008	0.083	0.038	0.128	-0.049	1.000												
DRUGS	-0.001	0.032	0.046	0.003	-0.150	-0.007	0.044	0.042	1.000											
DRINKING	-0.022	0.026	0.000	-0.031	0.009	0.006	0.026	0.009	0.253	1.000										
SPEEDREL	-0.029	0.017	-0.011	-0.002	0.059	0.009	0.030	0.023	0.055	0.070	1.000									
DRUNK_D	0.015	0.051	-0.032	-0.013	0.171	-0.012	0.156	0.005	0.046	**0.650**	0.115	1.000								
SEX	-0.001	-0.047	-0.057	0.000	0.006	0.058	-0.007	0.018	-0.030	-0.079	-0.050	-0.120	1.000							
VPROFILE	0.048	0.032	-0.017	-0.036	0.040	-0.086	-0.014	0.025	0.036	-0.017	0.078	0.026	0.017	1.000						
FUNC_SYS	-0.040	-0.010	**0.605**	0.269	0.049	0.129	0.018	-0.039	0.001	-0.020	-0.036	-0.053	-0.029	-0.026	1.000					
TYP_INT	0.006	-0.001	-0.054	0.090	-0.002	0.178	-0.013	0.518	0.029	-0.004	0.020	0.014	0.051	0.009	-0.053	1.000				
HARM_EV	0.016	0.000	0.042	-0.051	0.034	-0.187	0.040	-0.058	0.002	0.019	0.024	0.022	-0.105	0.012	0.070	-0.076	1.000			
VSURCON	-0.067	-0.057	-0.002	-0.018	0.009	-0.045	-0.013	-0.052	0.010	-0.041	0.096	-0.028	-0.040	0.068	-0.015	-0.033	0.025	1.000		
LGT_CONI	0.019	-0.021	0.044	0.061	0.035	0.079	0.069	0.025	0.033	0.142	0.047	0.209	-0.038	-0.029	0.011	0.039	-0.033	0.102	1.000	
WEATHER	-0.037	-0.022	0.003	-0.045	-0.007	-0.023	-0.019	0.007	0.009	-0.026	0.090	-0.004	-0.013	0.023	-0.012	0.039	0.020	**0.648**	0.131	1.000

Appendix A Table A.1

Correlation Matrix (Continued)

	BODY_TYP	VPAVETYP	HOUR	AGE	VSPD_LIM	MOD_YEA	MDRMANAV	VALIGN	P_CRASH1	REL_ROAD	ACC_TYPE	P_CRASH2	DR_SF1	M_HARM	NUMOCCS	MDRDSTRD	DRIMPAIR	CF1	DrHeight	DrWeight
BODY_TYP	1.000																			
VPAVETYP	0.003	1.000																		
HOUR	-0.126	0.049	1.000																	
AGE	-0.162	-0.009	-0.087	1.000																
VSPD_LIM	-0.069	0.020	0.031	0.100	1.000															
MOD_YEAR	0.089	0.055	-0.033	-0.045	-0.048	1.000														
MDRMANA\	-0.018	-0.031	0.047	-0.002	0.036	-0.042	1.000													
VALIGN	0.176	-0.090	0.026	-0.073	-0.026	-0.012	-0.062	1.000												
P_CRASH1	0.187	-0.069	0.017	-0.084	-0.067	0.007	-0.075	**0.915**	1.000											
REL_ROAD	0.144	0.121	0.026	-0.086	-0.033	0.037	-0.051	-0.060	-0.046	1.000										
ACC_TYPE	0.096	0.080	0.022	0.015	-0.019	0.010	0.009	-0.053	-0.074	0.174	1.000									
P_CRASH2	0.155	0.082	-0.018	0.017	0.004	0.030	-0.024	-0.060	-0.065	0.161	**0.663**	1.000								
DR_SF1	-0.027	-0.035	-0.038	-0.006	0.017	-0.021	0.035	-0.017	-0.042	0.025	0.118	0.055	1.000							
M_HARM	0.056	0.029	0.023	0.011	0.127	-0.024	0.009	0.018	-0.017	0.058	0.041	0.046	0.001	1.000						
NUMOCCS	-0.069	0.014	-0.001	0.021	-0.069	-0.038	-0.031	-0.009	-0.019	0.069	0.033	0.021	0.035	-0.026	1.000					
MDRDSTRD	-0.047	0.052	0.049	0.048	-0.018	-0.016	0.165	-0.031	-0.021	-0.018	0.003	-0.023	-0.071	0.000	-0.061	1.000				
DRIMPAIR	-0.118	0.053	0.037	-0.058	0.007	0.035	0.022	0.027	0.061	-0.053	-0.120	-0.117	-0.119	-0.030	-0.024	0.090	1.000			
CF1	0.049	0.066	-0.018	0.027	-0.014	0.014	0.086	-0.016	-0.036	0.072	0.071	0.090	0.017	-0.001	0.018	0.073	-0.025	1.000		
DrHeight	0.067	0.037	0.022	-0.118	-0.011	0.041	0.002	0.000	0.007	0.062	-0.020	0.017	-0.028	0.000	0.012	-0.052	-0.004	-0.012	1.000	
DrWeight	0.049	0.044	0.016	-0.152	-0.043	0.015	-0.029	-0.027	-0.015	0.098	0.032	0.051	0.012	-0.017	0.041	-0.008	-0.028	0.025	0.373	1.000

Appendix A Table A.2

Pearson's correlation matrix for older driver multi-vehicle fatal intersection crashes used in the study. The coefficient value of 0.6 and greater was selected among two pairs of variables to be tested for correlation. This value has been highlighted in the table with bold text.

	MONTH	*HOUR*	*RUR_URB*	*FUNC_SYS*	*MannColl*	*AccType1*	*AccType2*	*BodyTyp*	*ModYear*	*ImpactDR*	*Gender*	*InjuryLevel*	*Dstatus*	*Drugs*	*DrugRes*	*DAY_WEEK*	LGT_CONI	WEATHER
MONTH	1.000																	
HOUR	0.014	1.000																
RUR_URB	0.031	0.017	1.000															
FUNC_SYS	-0.003	0.030	0.038	1.000														
MannColl	0.013	0.087	-0.038	0.000	1.000													
AccType1	0.066	0.100	-0.069	0.016	**0.753**	1.000												
AccType2	0.069	0.098	-0.071	0.010	**0.749**	**0.990**	1.000											
BodyTyp	-0.009	0.015	-0.113	-0.048	-0.028	-0.007	-0.009	1.000										
ModYear	-0.029	0.017	-0.002	-0.032	-0.033	-0.025	-0.027	0.116	1.000									
ImpactDR	-0.033	-0.077	-0.004	0.019	**-0.713**	-0.581	-0.585	0.000	0.033	1.000								
Gender	0.021	-0.091	0.023	-0.028	-0.079	-0.082	-0.076	-0.186	-0.056	0.050	1.000							
InjuryLevel	0.043	0.038	-0.050	0.021	0.202	0.183	0.183	-0.041	-0.022	-0.133	0.000	1.000						
Dstatus	0.068	-0.005	0.002	0.046	-0.128	-0.124	-0.126	0.031	-0.013	0.031	0.024	-0.110	1.000					
Drugs	-0.018	0.055	0.013	-0.035	0.069	0.062	0.062	0.012	0.046	-0.053	-0.037	0.038	-0.118	1.000				
DrugRes	-0.033	0.035	0.015	-0.051	0.122	0.135	0.135	-0.030	0.015	-0.087	0.001	0.144	-0.454	0.317	1.000			
DAY_WEEK	-0.054	0.015	-0.019	0.009	0.011	-0.002	-0.007	0.048	0.035	0.030	0.013	0.024	-0.004	0.040	-0.007	1.000		
LGT_COND	0.195	0.516	0.006	0.042	0.136	0.134	0.132	-0.019	-0.024	-0.097	-0.046	0.055	-0.005	0.012	0.011	0.001	1.000	
WEATHER	0.104	0.074	-0.026	-0.007	0.054	0.092	0.092	-0.008	-0.050	-0.021	0.004	0.022	0.024	-0.029	-0.019	-0.016	0.096	1.000

Appendix A Table A.2

Correlation Matrix (Continued)

	DrunkDr	*NumOccs*	*Age*	*Violation*	*Drinking*	*SpeedRel*	*VTRAFWAY*	*VNUM_LAN*	*VSPD_LIM*	*VALIGN*	*VPROFILE*	*VPAVETYP*	*VSURCOND*	*VTRAFCON*	*PreCrash1*	*PreCrash2*	*DrHeight*	*DrWeight*
DrunkDr	1.000																	
NumOccs	0.034	1.000																
Age	-0.025	0.008	1.000															
Violation	0.036	0.002	0.010	1.000														
Drinking	**0.708**	0.036	-0.023	0.195	1.000													
SpeedRel	0.075	0.010	-0.041	0.096	0.099	1.000												
VTRAFWAY	-0.007	-0.024	-0.020	-0.009	0.003	0.017	1.000											
VNUM_LAN	-0.027	-0.022	0.004	0.043	-0.002	-0.013	0.248	1.000										
VSPD_LIM	-0.046	-0.045	-0.006	0.061	-0.019	-0.023	-0.010	0.296	1.000									
VALIGN	0.026	0.002	-0.030	-0.074	0.020	0.037	0.048	0.014	0.034	1.000								
VPROFILE	0.017	0.013	0.009	-0.031	0.004	-0.036	0.005	0.039	-0.016	0.220	1.000							
VPAVETYP	-0.028	-0.022	0.001	-0.018	-0.029	0.010	0.161	0.135	-0.012	0.034	0.225	1.000						
VSURCOND	0.014	-0.008	-0.015	-0.062	0.023	0.057	0.043	0.064	0.010	0.151	0.097	0.051	1.000					
VTRAFCON	-0.070	0.046	-0.007	0.045	-0.052	-0.047	-0.050	0.073	0.126	-0.203	-0.015	0.082	-0.080	1.000				
PreCrash1	-0.044	-0.012	-0.020	0.080	-0.029	0.013	0.092	0.155	0.118	0.308	0.048	-0.026	0.035	-0.076	1.000			
PreCrash2	0.032	-0.028	-0.007	-0.010	0.028	0.033	0.205	0.036	-0.029	-0.053	-0.061	-0.031	-0.034	-0.120	-0.018	1.000		
DrHeight	-0.044	0.060	0.026	0.005	-0.027	-0.003	0.005	0.011	-0.002	-0.011	-0.015	0.003	0.024	0.043	0.003	-0.025	1.000	
DrWeight	0.044	-0.046	0.006	-0.012	0.032	0.035	0.009	-0.017	-0.048	0.027	0.019	0.010	-0.028	-0.033	-0.033	0.030	-0.315	1.000

Appendix A Table A.3

Pearson's correlation matrix for other driver single-vehicle fatal intersection crashes used in the study. The coefficient value of 0.6 and greater was selected among two pairs of variables to be tested for correlation. This value has been highlighted in the table with bold text.

	MONTH	*LGT_COND*	*HOUR*	*RUR_URB*	*FUNC_SYS*	*HARM_EV*	*MOD_YEAR*	*BODY_TYP*	*AGE*	*SEX*	*DR_DRINK*	*DSTATUS*	*DRUGS*	*DRUGRES1*	*SPEEDREL*	*DR_SF1*	*VTRAFWAY*
MONTH	1																
LGT_COND	-0.137	1.000															
HOUR	-0.026	**0.746**	1.000														
RUR_URB	0.000	-0.090	-0.085	1.000													
FUNC_SYS	0.006	0.009	-0.014	0.242	1.000												
HARM_EV	-0.043	0.075	0.085	-0.179	0.005	1.000											
MOD_YEAR	-0.028	0.025	0.025	-0.050	-0.044	0.044	1.000										
BODY_TYP	-0.259	0.109	0.121	0.033	-0.053	0.168	-0.035	1.000									
AGE	0.022	-0.129	-0.156	0.009	-0.054	-0.055	-0.024	-0.154	1.000								
SEX	0.053	0.072	0.052	-0.016	0.039	-0.002	-0.054	-0.191	0.056	1.000							
DR_DRINK	-0.023	-0.310	-0.261	0.030	-0.111	-0.048	0.005	-0.008	0.017	-0.094	1.000						
DSTATUS	0.008	-0.062	-0.054	0.114	0.021	-0.093	-0.008	-0.065	0.052	0.003	0.216	1.000					
DRUGS	-0.006	-0.028	-0.032	0.030	0.022	-0.058	0.015	-0.060	0.003	0.018	0.098	0.217	1.000				
DRUGRES1	-0.033	-0.036	-0.040	0.107	0.022	-0.083	0.033	-0.072	0.020	0.028	0.127	0.475	0.408	1.000			
SPEEDREL	0.004	-0.056	-0.045	0.070	-0.047	-0.070	-0.025	0.007	0.126	-0.059	0.089	0.089	0.057	0.053	1.000		
DR_SF1	-0.012	-0.009	0.003	0.021	-0.016	-0.016	0.011	-0.090	0.091	0.034	0.061	0.061	-0.025	0.081	0.011	1.000	
VTRAFWAY	0.003	0.013	-0.005	0.312	**0.670**	0.004	-0.052	-0.027	-0.036	0.027	-0.100	0.043	0.010	0.033	-0.020	-0.011	1.000

Appendix A Table A.3

Correlation Matrix (Continued)

	VNUM_LAN	*VSPD_LIM*	*VALIGN*	*VPROFILE*	*VPAVETYP*	*VTRAFCON*	*P_CRASH1*	*P_CRASH2*	*ACC_TYPE*	*DAY_WEEK*	*TYP_INT*	*REL_ROAD*	*VSURCOND*	*WEATHER1*	*NUMOCCS*	*M_HARM*
VNUM_LAN	1.000															
VSPD_LIM	0.106	1.000														
VALIGN	-0.017	0.026	1.000													
VPROFILE	0.008	0.012	0.141	1.000												
VPAVETYP	0.091	0.014	-0.099	0.025	1.000											
VTRAFCON	0.029	0.114	-0.022	0.000	-0.006	1.000										
P_CRASH1	0.002	0.019	**0.846**	0.106	-0.084	-0.029	1.000									
P_CRASH2	0.033	0.044	-0.031	0.031	0.069	0.034	-0.006	1.000								
ACC_TYPE	0.002	0.014	-0.082	-0.010	0.000	0.112	-0.067	0.266	1.000							
DAY_WEEK	-0.002	0.006	0.042	0.006	0.005	-0.004	0.039	0.016	0.004	1.000						
TYP_INT	0.050	0.144	-0.039	-0.048	0.005	0.436	-0.063	0.003	0.023	0.001	1.000					
REL_ROAD	0.115	-0.070	-0.107	0.001	0.072	0.100	-0.081	0.232	0.513	-0.011	-0.002	1.000				
VSURCOND	-0.004	-0.027	-0.054	0.009	0.011	-0.007	-0.039	0.103	-0.031	-0.025	-0.009	-0.021	1.000			
WEATHER1	-0.019	-0.036	-0.035	-0.008	-0.015	0.009	-0.023	0.047	-0.021	-0.002	-0.011	-0.009	**0.669**	1.000		
NUMOCCS	0.007	0.020	-0.004	0.029	0.026	-0.013	0.000	0.095	0.004	0.051	-0.006	0.003	0.024	0.006	1.000	
M_HARM	-0.111	-0.191	-0.034	0.022	0.076	-0.009	-0.008	0.097	0.167	-0.019	-0.070	0.216	-0.047	-0.029	0.050	1.000

Appendix B - FARS Related Factors, Moving Violation

Variables Determining Driver At-Fault

Rules of the Road – Traffic Sign & Signals	**Rules of the Road-Turning, Yielding, Signaling**
Fail to Stop for Red Signal	Turn in Violation of Traffic Control
Fail to Stop for Flashing Red	Improper Method & Position of Turn
Violation of Turn on Red	Fail to Signal for Turn or Stop
Fail to Obey Flashing Signal	Fail to Yield to Emergency Vehicle
Fail to Obey Signal Generally	Fail to Yield Generally
Violate RR Grade Crossing Device/Regulations	Enter Intersection When Space Insufficient
Fail to Obey Stop Sign	Turn, Yield, Signaling Violations Generally
Fail to Obey Yield Sign	**Reckless/Careless/Hit-And Run Offenses**
Fail to Obey Traffic Control Device Generally	Manslaughter or Homicide
Rules Of The Road – Lane Usage	Willful Reckless Driving
Unsafe or Prohibited Lane Change	Unsafe Reckless
Improper Use of Lane	Inattentive, Careless, Improper Driving
Certain Traffic to Use Right Lane	Fleeing or Eluding Police
Motorcycle Lane Violations	Fail to Obey Police
Lamp Violations	Hit-and-Run
Impairment Offenses	Fail to Give Aid
Driving While Intoxicated	Serious Violation Resulting in Death
Driving While Impaired	Use of Telecommunications Device
Driving under Influence	**Rules of the Road - Wrong Side, Passing & Following**
Drinking While Operating	Driving Wrong Way on One-Way Road
Illegal Possession of Alcohol or Drugs	Driving on Left, Wrong Side of Road Generally
Driving with Detectable Alcohol	Improper, Unsafe Passing
Impairment Violations Generally	Pass on Right (Drive off Pavement to Pass)
Speed-Related Offenses	Pass Stopped School Bus
Racing	Fail to Give Way When Overtaken
Speeding	Following Too Closely
Exceeding Special Speed Limit	Wrong Side, Passing, Following Violations Generally
Energy Speed (Exceeding 55 mph, Non-Pointable)	
Driving Too Slowly	
Speed-Related Violations Generally	

Appendix C - Fatality Distribution Based on Region and Crash Type

Appendix C Table C.1

Other Drivers Fatal Crashes in the US Regions (2014-2018)

Region	Fatal Crashes	2014	2015	2016	2017	2018	Total
Northeast	Single	1,015	1,046	1,034	973	931	4,999
	Multi	471	497	499	524	509	2,500
South	Single	4,623	4,667	4,939	4,758	4,470	23,457
	Multi	2,136	2,474	2,657	2,701	2,653	12,621
West	Single	1,737	1,814	1,930	1,912	1,813	9,206
	Multi	946	1,089	1,187	1,255	1,185	5,662
Midwest	Single	1,818	1,936	2,031	2,031	1,880	9,696
	Multi	962	1,060	1,103	1,109	1,144	5,378
Total		13,708	14,583	15,380	15,263	14,585	73,519

Appendix C Table C.2

Older Drivers Fatal Crashes in The US Regions (2014-2018)

Region	Fatal Crashes	2014	2015	2016	2017	2018	Total
Northeast	Single	191	184	189	180	197	941
	Multi	270	277	273	318	292	1,430
South	Single	621	638	716	761	718	3,454
	Multi	1,042	1,194	1,291	1,317	1,383	6,227
West	Single	264	281	319	287	284	1,435
	Multi	326	400	459	462	508	2,155
Midwest	Single	286	330	328	323	308	1,575
	Multi	561	587	667	624	608	3,047
Total		3,561	3,891	4,242	4,272	4,298	20,264

Appendix C Table C.3

Older Driver Fatal Single-Vehicle Crashes Based on State and Region (2014-2018)

South	**OD Population**	**SV Crash**	**West**	**OD Population**	**SV Crash**
Alabama	826,894	199	Alaska	87,011	12
Arkansas	511,827	149	Arizona	1,258,250	158
Delaware	181,086	14	California	5,669,025	509
Florida	4,358,071	453	Colorado	808,229	107
Georgia	1,460,409	318	Hawaii	260,967	21
Kentucky	730,626	200	Idaho	278,282	81
Louisiana	718,433	124	Montana	198,902	65
Maryland	931,136	79	Nevada	476,181	60
Mississippi	474,475	144	New Mexico	366,189	56
North Carolina	1,689,265	304	Oregon	738,691	121
Oklahoma	619,553	155	Utah	350,478	85
South Carolina	899,915	176	Washington	1,164,232	136
Tennessee	1,109,697	287	Wyoming	95,375	24
Texas	3,602,320	497	*Total*	*11,751,812*	*1,435*
Virginia	1,315,401	234	**Midwest**	**OD Population**	**SV Crash**
West Virginia	359,878	116	Illinois	1,992,961	204
Total	*19,788,986*	*3,449*	Indiana	1,055,021	159
Northeast	**OD Population**	**SV Crash**	Iowa	539,830	89
Connecticut	615,121	51	Kansas	462,241	116
Maine	275,999	59	Michigan	1,716,604	172
Massachusetts	1,139,100	99	Minnesota	889,802	91
New Hampshire	245,645	40	Missouri	1,033,964	261
New Jersey	1,438,527	122	Nebraska	303,666	42
New York	3,213,534	244	North Dakota	116,637	24
Pennsylvania	2,335,630	296	Ohio	1,995,022	241
Rhode Island	182,254	18	South Dakota	146,854	40
Vermont	121,207	15	Wisconsin	985,473	133
Total	*9,567,017*	*944*	*Total*	*11,238,075*	*1,572*