Attribution Theory and Collisions at Intersections

Final Report

by

Judith L. Mwakalonge, South Carolina State University
Gurcan Comert, Benedict College
Samia Akter, South Carolina State University
Saidi Siuhi, South Carolina State University

Contact information
Judith L. Mwakalonge, Ph.D.
134 Engineering and Computer Science Complex, SCSU
300 College Street NE, Orangeburg, SC 29117
Phone: (803) 536-8321; *E-mail:* jmwakalo@scsu.edu

March 2021

Center for Connected Multimodal Mobility (C^2M^2)

200 Lowry Hall, Clemson University
Clemson, SC 29634

DISCLAIMER

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated in the interest of information exchange. The report is funded, partially or entirely, by the Center for Connected Multimodal Mobility (C^2M^2) (Tier 1 University Transportation Center) Grant, which is headquartered at Clemson University, Clemson, South Carolina, USA, from the U.S. Department of Transportation's University Transportation Centers Program. However, the U.S. Government assumes no liability for the contents or use thereof.

ACKNOWLEDGMENT

The project is funded by the Center for Connected Multimodal Mobility (C^2M^2) (Tier 1 University Transportation Center) Grant, from the U.S. Department of Transportation's University Transportation Centers Program and administered by the Transportation Program of the South Carolina State University (SCSU) and Benedict College (BC).

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Attribution Theory and Collisions at Intersections		5. Report Date 03/10/2021 6. Performing Organization Code
7. Author(s) Judith L. Mwakalonge, Ph.D.; ORCID: https://orcid.org/0000-0002-7497-6829; Gurcan Comert, Ph.D.; ORCID: https://orcid.org/0000-0002-2373-5013; Samia Akter; ORCID: https://orcid.org/0000-0002-0920-4929 Saidi Siuhi; ORCID: https://orcid.org/0000-0001-8409-9287		8. Performing Organization Report No.
9. Performing Organization Name and Address South Carolina State University 300 College Street NE, Orangeburg, SC 29115		10. Work Unit No. 11. Contract or Grant No. 69A3551747117
12. Sponsoring Agency Name and Address Center for Connected Multimodal Mobility (C2M2) Clemson University 200 Lowry Hall, Clemson Clemson, SC 29634		13. Type of Report and Period Covered Final Report (August 2019 - March 2021) 14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

Attribution theory refers to the psychological phenomenon where one person tries to perceive others' cognitive behavior by ascribing their own emotions, opinions, and desires. For instance, while passing at an intersection, a driver expects that the maneuver of other drivers coming from the opposite direction or conflicting movements would be like their own. When expected behaviors do not match the opposite or conflicting movement driver's future behaviors, a collision is likely to occur. This research investigated the application of attribution theory to assume the opposing drivers' cognitive behavior and performance at a highway intersection. This phenomenon was evaluated by utilizing the second Strategic Highway Research Program (SHRP-2) and National Highway Traffic Safety Administration (NHTSA) data sources. From the data analysis, it was observed that drivers aged 25-34 years were involved in the highest number of fatal accidents from 2009-2018 in the USA. Besides, it was found that younger drivers (aged 20-years old or less) contributed fewer fatal collisions (44,404 crashes) than elderly drivers (aged 65-years old or more, 62,572 crashes). The impact of the attribution theory and driver age in highway intersection-related collisions were examined from simulation models. From simulations, it was observed that there was a high possibility of collisions when an elderly driver was turning left. In this research, the combination of an elderly driver turning left, and the younger driver going straight resulted in the highest number of collisions compared to other groups. The key findings confirm elderly and younger drivers have different driving behavior that could be ascribed to their attribution. These results can assist transportation agencies to develop training and design strategies to better accommodate elderly drivers due to their declined physical and cognitive abilities and improve drivers' education programs for younger drivers.

17. Keywords	18. Distribution Statement		
Attribution Theory; Driver Behavior; SHRP-2; Intersection crashes; Driving Behavior Simulation;	This report or any part of this report is restricted to publish until prior permission from the authors.		
19. Security Classification (of this report)	**20. Security Classification (of this page)**	**21. No. of Pages**	**22. Price**
Unclassified	Unclassified	43	NA

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

EXECUTIVE SUMMARY

Attribution theory refers to the psychological phenomenon where one person tries to perceive others' cognitive behavior by ascribing their own emotions, opinions, and desires. For instance, while passing at an intersection, a driver expects that the maneuvering of other drivers coming from the opposite or conflicting movement directions would be like their own. When expected drivers' behaviors do not match the opposite or conflicting movement drivers' future behaviors, a collision is likely to occur. This research investigated the application of the attribution theory to predict the opposing drivers' cognitive behaviors and performance at highway intersections. This investigation was evaluated by utilizing the Transportation Research Board (TRB), Second Strategic Highway Research Program (SHRP-2), and National Highway Traffic Safety Administration (NHTSA) data sources. From the analysis of the fatal road crash data, it was observed that the driver's age group of 25-34 years old was the most common victim. Middle-aged people died more in road accidents than younger and elderly people. The most frequent fatal accidents occurred in the USA in July. Drivers aged 21-25 years were involved in the highest number of fatal accidents in the USA. From the comparison of the younger and elderly drivers, it was found that the younger driver contributed fewer fatal collisions than the elderly driver. It was demonstrated that the number of crashes at the intersection, which involved at least one younger and one elderly driver, was significant. From the simulation of the younger and elderly drivers, it was observed that there is a high possibility of collisions when elderly drivers turn left at an intersection. Rear-end and lane-changing crash types were the most observed from the simulation. The key findings confirm elderly and younger drivers have different driving behaviors that could be ascribed to their attribution. These results can assist transportation agencies in developing training and design strategies to better accommodate elderly drivers due to their declined physical and cognitive abilities.

CHAPTER 1

Introduction

1.1 Attribution Theory

The term attribution refers to the perception or inference of cause, and attribution theory defines the processes that a driver infers the behavior of other drivers based on how they would react to his surroundings (Kelley, 1967). People search for causal descriptions of their experiences. They often predict the perceptions of others based upon their perceptions. Sometimes these perceptions are right, and sometimes not. The prevailing ideas of many attribution theories are that people explain behavior concerning their causes, and these explanations play a significant role in determining reactions to the behavior. For instance, an automobile driver (D) is seldom alone at a highway intersection. If another vehicle, even only one, approaches the intersection, then the driver 'D' will try to guess the future driving behavior of the driver of other cars (O) and will estimate the possible maneuvers. The driver (D) may assume that the other driver (O) will do what D would do in whatever situation, like, if D needs to slow down, then D would expect the other driver (O) would also slow down.

Attribution is affected by information, beliefs, and motivation (Sahar, 2014). For information, the consequences of actions are compared with the effects of other actions taken by actors. In terms of beliefs, actors always think about what other actors will do in a similar circumstance. Moreover, finally, attribution is also affected by the actor's motivation. This occurs because the effect on the perceiver's welfare becomes a focal impact to which the other effects are integrated, and thereby the number of unrelated (noncommon) effects is abated. Thus, the perceiver's motivation, provoked by the action's consequences for him, is thought to affect the processing of information about the action.

1.2 The Importance of the Attribution Theory

Judgments of causal responsibility are an essential facet of attributions (Sahar, 2014). Perceptions of responsibility play a vital role in influencing policy attitudes. Let us consider two drivers, one young (Y) and another adult (A), who are approaching an intersection where A is turning left while Y is going straight at an approaching intersection. Since A is old, she/he will slow down and expect the driver going through (Y) would slow down. On the other hand, Y assumes that the turning driver (A) will accelerate after turning left to clear the way for Y. Therefore, Y will not slow down and move at the usual speed. This situation will possibly yield a collision where Y strikes A from the rear or side. The phenomena that one tries to understand other's behavior by attributing it to their own emotions, opinions, and desires are referred to as attribution theory. This theory for driving at the intersection is crucial to perceive the reasons and mechanisms of road accidents.

The perception of elderly drivers varies from younger drivers, requiring different mobility strategies to accommodate older drivers (Eberhard, 1996). The scenarios of the collisions entailed by an older driver are being more prominently featured in the present(Eberhard, 1996). In most cases, driving behavior controls the crash frequency, fatality, and injury rates on the highway. It is perceived that the risky-driving behavior yielded by younger drivers under age 25 years contributes to higher crash and injury rates (Eby & Molnar, 1998). Several factors affect the risk-taking behavior of drivers. Among them, risk perception and attribution are critical. Each year, many younger drivers are involved in road accidents due to the risky driving behaviors caused by incorrect perceptions and attributions (Summala, 1987).

1.3 Highway Accidents at Intersection

Motor vehicle crashes were ranked as the second leading cause of death of American people in 2015 (NHTSA, 2018). Unintentional injury, including motor vehicle crashes, was the number one cause of death in 2017. It is considered as the number one cause of death of younger people from ages 8 to 24 years and takes place in the top 10 causes of death in the USA for a decade. Approximately 33,561 people died in roadway crashes in 2012 in the USA, where 26% were intersection-related (NHTSA, 2013). From the latest NHTSA database update, in 2018, about 33,654 people died in road accidents, and 8,245 people (25%) died due to intersection-related crashes (NHTSA, 2019). An improved traffic safety system is required to abate the accidents at the highway intersections. In urban city or town areas, crashes at or near an intersection are higher than roadway mid-section-related crashes (Mamun et al., 2015). Vehicles are dynamic agents, and a considerable number of these agents are entailed in intersection crashes. The driving behavior at the intersection is not like driving on a roadway section without an intersection. Therefore, it is essential to study the drivers' behavior at intersection-related collisions and observe the impact of attributions in those collisions.

1.4 Research Goals and Objectives

The goals of this study are:

- ✓ To investigate the application of the attribution theory by conducting a comprehensive literature review.
- ✓ To examine the impact of driving performance in traffic safety by utilizing the SHRP-2 databases.
- ✓ To determine the role of driving behavior in the highway crashes at an intersection using the NHTSA database.
- ✓ To identify the application of the attribution theory in improving driving behavior models in traffic microscopic simulation software.
- ✓ Finally, explore the impacts of a roadway design on the cognitive behavior of automated vehicles at intersections.

CHAPTER 2

Literature Review

Several research works have been conducted on the perception of causation and the significances of such perception. Most of these research works have focused on the perceived causes of other persons' behavior. The related works about applying the attribution theory to traffic engineering are broken up and described in the following sections.

2.1 Attribution Theory- General Perspective

Heider (1958) proposed a psychological concept about attribution theory, where the author defined the mechanism of attribution as "Naïve sense" or "Common sense." According to that theory, humans try to comprehend other people's behavior by combining all those people's information until getting a complete picture. The main obstacle in this process is expected behavior. The study investigated the supportive thoughts to build a conceptual framework suitable to some of the attribution problems. The general concept of attribution theory proposed by Heider was later formalized and expanded upon by some other psychologists in the 1970s to apply this theory in practical life (Kelley & Michela, 1980). Some psychologists used the attribution theory to understand the casualty of any incidence (Shaver, 1983). Weiner et al. (1976) studied Social learning theory and attribution theory noting that they make opposing forecasts concerning the effect of causal factors on achievement expectancy. They explained that social learning theory states that expectancy is guided by the locus of control (i.e., the level of control that people believe they have within the outcome of events (Rotter, 1966)) of causal factors. On the other hand, attribution theory defines the stability of causal factors (i.e., consistency between the factor and the outcome (Weiner et al., 1976)) that influences expectancy. The research examined the number of favorable outcomes and weighed their causal attributions and the possibility of success. Contrary to the previous studies, it is applied to any subjective experimental design and inaugurated an innovative idea of judging attribution, which disjointed the locus of control and strength of the causality. The findings of the study powerfully strengthened the attributional situation ,whereas, opposing the social learning theory. The importance of the research and attribution theory for practical research and hypothesizing in the locus of control was conferred.

Weiner (1985) offered a theory of motivation and emotion wherein causal ascriptions perform a prominent role. It is acknowledged that a few governing causal perceptions prevail in achievement-related contexts. Locus, stability, and controllability are three common properties of the perceived causes of success and failure, where intentionality and globality are other possible causal structures. Motivated behavior is influenced by expectancy and affect. As a result, the theory is associated with the organization of thinking and the dynamics of feeling and action. The exploration of the motivational chapter concerning achievement strivings has been suggested, and several experimental pieces of evidence are investigated from the theoretical viewpoint in the study. Some other research observed that a large number of variables usually influence social perception and attribution towards other people (Marks & Miller, 1987). Besides, no single clarification can interpret the series of psychological data about attribution.

2.2 Attribution Theory on Mobility and Traffic Safety

Díaz (2002) proposed a theory about planned behavior and developed a simple model for driving behavior based on that theory. The most straightforward diagram of the proposed model is shown in Figure 1. According to the study, pedestrians' attitudes towards traffic rule violations and errors were investigated from collected field data. From the mean and standard deviation of violations and errors, it was observed that young people (2.76) had more intention to violate rules and to make errors than adult people (2.14), and males (2.78) were more than females (2.31). Further, young males were more vulnerable to involvement in accidents than females. Some other psychological driving models are available, like Wiedemann's (1974) model, which is used in VISSIM, a micro-simulation software (PTV, 2011).

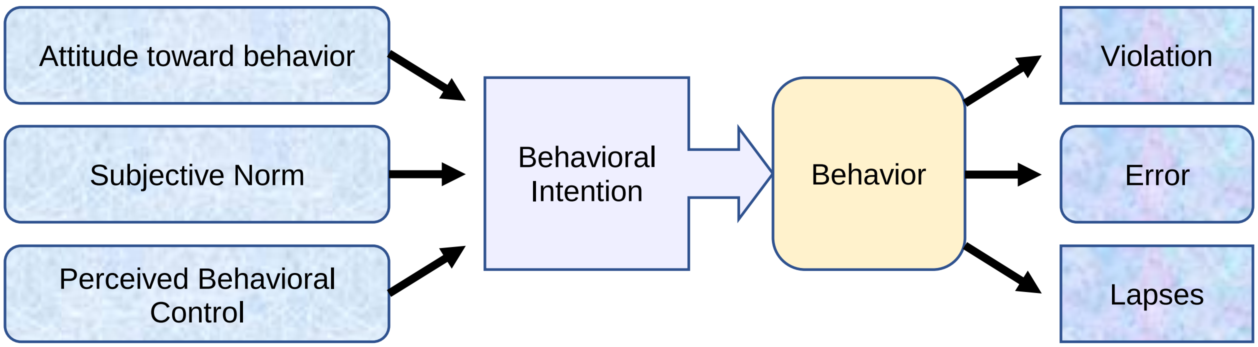


Figure 1 Díaz's sample model for planned driving behavior (Díaz, 2002)

Ho et al. (2000) investigated the impact of the relationship between the driver's external and internal attribution on roadway collisions. After analyzing 321 responses, they found that only 20% of drivers perceived that they were responsible for the accident, and the rest 80% did not. They observed that the driver group, who experienced excess psychological distress, ignored responsibility for the collision. Stewart (2005) proposed another theory named defensive attribution theory, highlighting how to use attribution to make driving safer. The author surveyed 321 drivers who survived road accidents and recorded the attribution ratings about the cause of collisions. It was observed that the drivers involved in severe crashes used the attribution rating of cause to others to make himself/herself safe and suggested to intervene attribution to avoid the collision. Smith and Martin (2007) proposed a framework to investigate drivers' attributed responsibility toward a road accident. Based on the attribution theory, they observed that intervening in drivers' attribution process from external factors (e.g., traffic) and other drivers to themselves could enhance traffic safety via driving more carefully. Some other research works focused on the impact of the attribution of responsibility, i.e., failure of safe driving on the collision's severity level (Eby & Molnar, 1998). They recommended incorporating a driver improvement program and adequate driver training to reduce the negative impact of attribution in roadway crashes.

Kotelnikova-Weiler et al. (2017) investigated the impact of the attribution methodologies on mobility. The authors used the attribution theory to evaluate the environmental impact of mobility and the corresponding economic analysis. They developed an analytical framework to incorporate the attribution strategies to estimate the local mobility implications in regional areas. The framework measured the contribution of individual trip-maker on the overall trips of the locality. The measured contribution was attributed to that individual, and information was presented through the bibliographical review of the attribution scheme.

2.3 Attribution and Perception Concept on Driving Behavior

Keskinen et al. (1998) studied the behavior of the elderly driver at a T-intersection and the governing factors for this age group's vulnerability versus others while passing an intersection. From a real-world experiment at a T-intersection, the research found that the head movements of elderly drivers were almost like the younger and mid-age groups. However, the pattern of the acceleration and deceleration habits, perception time, and gaps while turning was different among different age groups. They concluded that the elderly driver took more time while turning left or right than younger drivers. This maneuver denoted that the perception time of the older driver is high. They also observed that the more time taken by the elderly driver to pass an intersection yielded a higher possibility of collision.

Romoser and Fisher (2009) examined the cognitive declines of the elderly driver on side-to-side scanning while approaching an intersection. The researchers observed that older drivers performed fewer side-scanning while turning left or right than the middle-aged. They found that fewer scanning due to cognitive declines might lead to a higher possibility of accidents. The simulation and experimental data supported that the elderly drivers performed a decreased amount of scanning in an intersection while turning or passing. As a continuation of previous research, Romoser et al. (2013) compared the driving pattern between the younger and elderly drivers at a four-leg intersection. They examined the difficulties of scanning the surrounding hazards while approaching and passing an intersection. The study found that elderly drivers faced more hazardous situations due to the attention deficit, which might occur because of aging.

2.4 Safety Scenario of Senior Citizens

Eberhard (1996) investigated the safety perspective of the elderly driver and pedestrians' mobility by analyzing the NHTSA – FARS (Fatality Analysis Reporting System) database. The author found that older drivers were not potentially hazardous to others regarding the number of crashes per licensed driver. The research observed that the younger driver (age group of 16-20 years) had the highest crash and fatality rate, and the elder driver was lower than the younger group but higher than other driver age groups. Harré, Foster, and O'Neill (2005) investigated the impact of safety advertisements on young drivers (aged between 16 and 29 years) by assessing their driving attributes. From the first study of 314 samples, the researchers recorded the young driver's attributes like crash-risk optimism to their peers, their crash potentiality, and health safety concern. From the second study, 173 drivers were taken as an experimental group, and 193 drivers were taken as a control group. The advertisement "drinking and dangerous driving cause crash" was shown to the experimental group and "not to drive after drinking" to the control group. The driving attributes of the experimental and control groups were recorded in terms of the first study. The researchers observed that the experimental group showed more self-enhancement in driving ability than the control group.

Boot et al. (2014) investigated the way to enhance the safety of older drivers. The researchers observed that age-related changes increase crash risk and discomfort while driving and focused on some situations that are difficult to handle for aging drivers. The authors also illustrated how to create a better environment for older drivers and found that changing the roadway and better training strategies would be useful in ensuring all drivers' safety. Mamun et al. (2015) explored the age distribution of the roadway users involved in highway collisions for motorized and non-motorized modes in urban areas. They observed that the age group 20 to 35 years contributed about 41.67% of the total motorized accidents, where 22.22% was for road users ages 50 years or more. Mwakalonge et al. (2019) explored the age distribution of personal electric mobility vehicle (PEMV) users. They observed that younger users (age 20 years old or less) of scooters, electric carts, mopeds, and skateboards contributed about 65% of national injury in the USA related to these four PEMVs from 2006-2017. However, elderly road users (age 60-years old or more) contributed only 12%.

2.5 Simulation of Elderly and Distracted Driving Behavior

Like pedestrian, motor vehicle drivers can easily get distracted (Mamun & Mwakalonge, 2018). Vladisavljevic et al. (2007) developed a simulation model to mimic the unimpaired and distracted driver's traffic pattern. They integrated the mathematical model into VISSIM to modify the car-following behavior to generate distracted behavior among the drivers. They considered talking on a cellphone as the distracted driving behavior in the simulation. It was observed that proper calibration could help to create the real-world scenario of distracted driving. Zhou et al. (2015) investigated the gap acceptance behavior of the elderly driver on an unsignalized intersection while performing left-turn. The authors defined older drivers as 70 or more-year-old and younger drivers as 35 or less-year-old. From statistical analysis, they observed that the older drivers behaved differently from, the younger ones, and females were different from the males. From VISSIM simulations, micro-simulation software, the research found that the elderly drivers required more space while turning left and yielded more travel delays and the number of stops on the network.

Ulak et al. (2019) simulated the traffic performances and the safety measures for different age groups at a T-intersection in Florida. They considered three age groups, i.e., younger drivers (16-24 years old), mid-aged drivers (25-64 years old), and aging drivers (65 and more years old). They calibrated the model by modifying the car-following model parameters and driving behavior parameters to generate younger, mid-aged, and older drivers in VISSIM. The number of collisions was estimated using the Surrogate Safety Assessment Model (SSAM) tool developed by the Federal Highway Administration. The study concluded that the risk perception affected driving behavior, which significantly impacted traffic performance and safety. Arafat et al. (2020) provided a detailed guideline to calibrate microsimulation models for intersections by modifying the car-following model parameter in VISSIM. They observed that the average standstill distance parameter ranging from 3 feet to 6.56 feet performed well to replicate real-world mechanisms in passing intersections.

2.6 Estimating Conflicts from a Simulation Model

Gettman and Head (2003) developed the Surrogate Safety Assessment Model (SSAM) to estimate the collision among vehicles in a simulation model. The SSAM was prepared based on the trajectory path of a vehicle during simulations. Time-to-collision and post-encroachment time are two essential parameters to define the collision threshold in the SSAM software. Several research works have been performed by using the SSAM tool to evaluate the conflicts from the simulation. Kim et al. (2018) evaluate the SSAM tool's feasibility in estimating the collisions on a Two-way Left-turn lane from the simulation model. Based on findings using the SSAM, they proposed raised median to minimize collisions on a two-way left-turn lane. Besides the SSAM tool, the time-to-collision model can be used to estimate the number of collisions from simulation or video data (Namaki Araghi et al., 2008).

In this study, impacts of the driver age on highway collision have been investigated by using the SHRP-2 and NHTSA databases. The application of the attribution theory has been examined by traffic micro-simulation. This study will help to understand the role of driving behavior, and the application of attribution theory on highway crashes at the intersection.

CHAPTER 3

Methodology

Following the comprehensive literature review, this study explored the National Highway Traffic Safety Administration (NHTSA) and the Second Strategic Highway Research Program (SHRP 2) databases. The role of driving behavior in traffic safety and highway crashes was examined from the NHTSA and SHRP 2 databases. Then, traffic micro-simulation models were prepared to examine the conflict scenario at an intersection between younger and elderly drivers due to attribution. Synchro, VISSIM, and SSAM software were used in the simulation model preparation and attribution theory analysis. Figure 2 shows the illustration of the steps of the research approach of this study. The following sections will describe the research methodology.

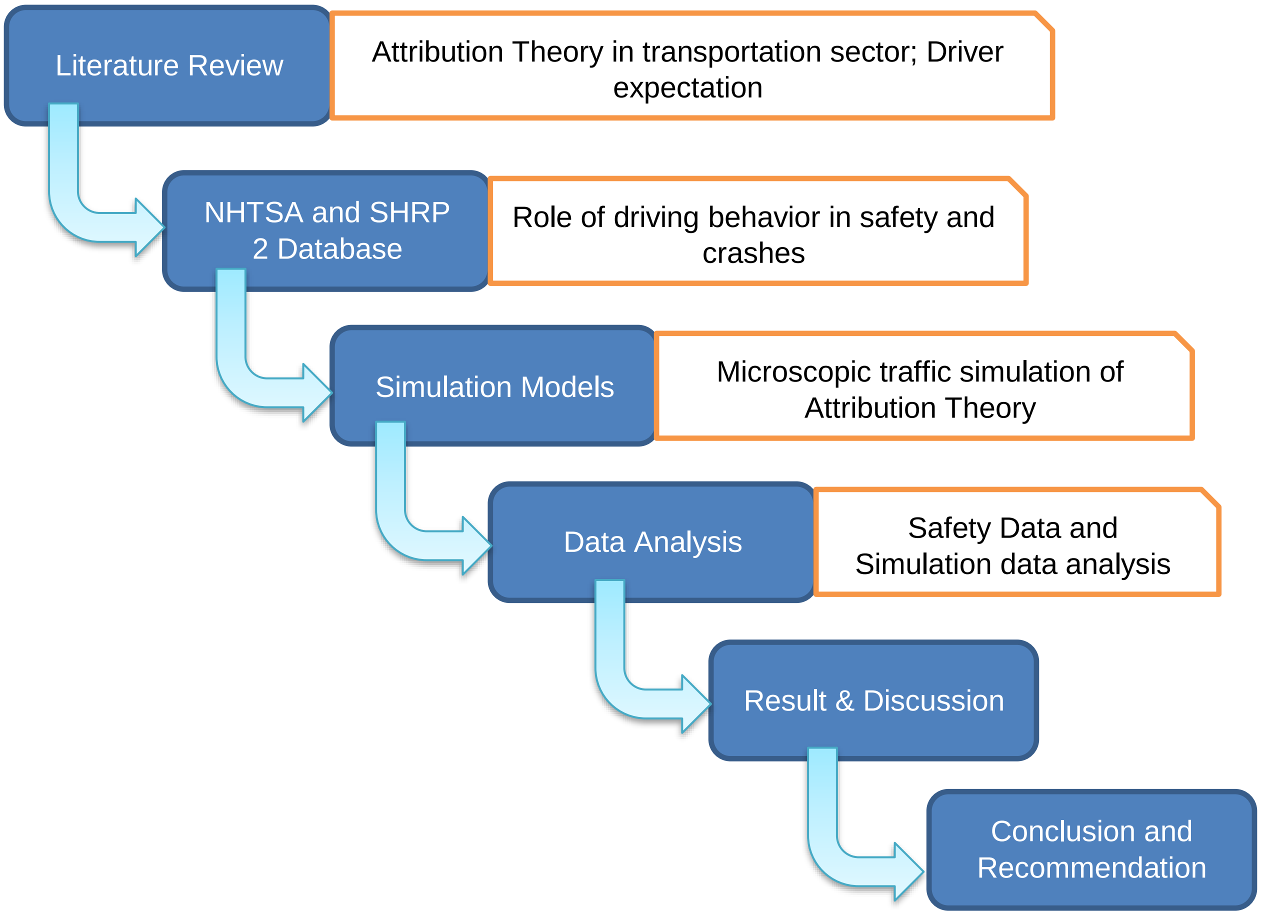


Figure 2 Research approach of this study

3.1 NHTSA FARS Database

The crash data used in this study was collected from the Fatality Analysis Reporting System (FARS) of the NHTSA. The data were extracted using the Fatality and Injury Reporting System Tool (FIRST) of the NHTSA database through a data query (NHTSA, 2019). These crash data were used to estimate the crash frequencies, fatalities, and injuries at intersections involving younger and elderly drivers. This study extracted and processed crash data from 2009-2018 for all states and the District of Columbia.

3.2 SHRP 2 NDS Databases

The Naturalistic Driving Study (NDS) data of TRB's second Strategic Highway Research Program (SHRP-2) was analyzed in this study. The SHRP 2 NDS data was collected from the Virginia Tech Transportation Institute through a data query (SHRP-2, 2020). The data contains the driving behavior data of approximately 3,400 drivers from the year 2010 to 2013 (Hankey et al., 2016). The data were recorded from Seattle, Washington; Tampa, Florida; Buffalo, New York; Durham, North Carolina; State College, Pennsylvania; and Bloomington, Indiana. This study used SHRP-2 data to describe the driver age distribution over fatal crashes and fatalities. Also, this database was compared with the crash data obtained from NHTSA FARS.

3.3 Simulation Model for Attribution Theory

In this study, the potentiality of roadway collisions due to attribution behavior was investigated. A four-leg uncontrolled, unsignalized intersection was prepared in VISSIM, as shown in Figure 3. The number of conflicts around the collision-prone area (red circle) was estimated for different driving behavior. Details are given in the following sections.

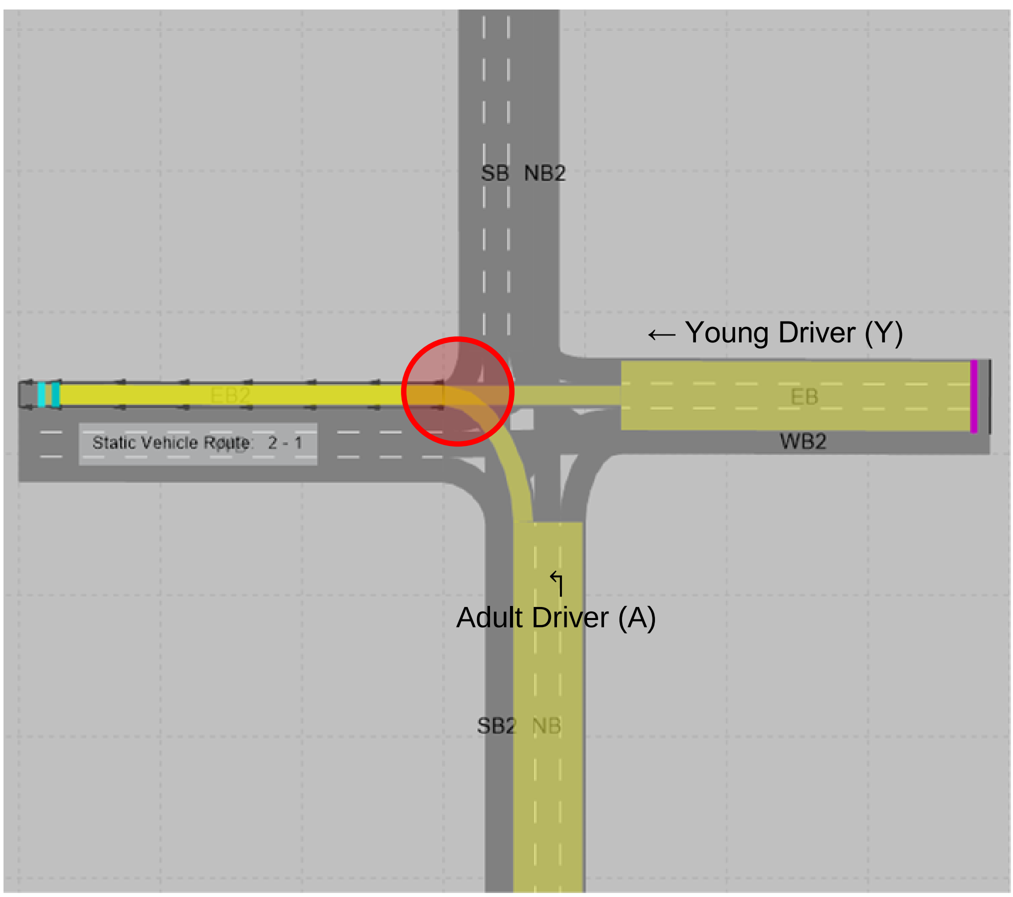


Figure 3 Application of attribution theory on intersection collision

3.3.1 Modification of Driving Behavior Parameters to Comply Attribution Theory

In VISSIM software, there are several types of parameters that can be adjusted to generate desirable driving behavior (Aghabayk et al., 2013; Arafat, Nafis, et al., 2020; PTV AG, 2020). In this research, the following parameters, car-following model parameters, lane changing parameters, and driver error parameters were modified to develop an elderly driver and a younger driving behavior besides the default behavior. The urban driving behavior has been considered for this study as it is assumed that the intersection is located in urban areas. This study has followed the parameter changing mechanism of the Florida Department of Transportation (FDOT) (2014) and Ulak et al. (2019) for defining driving behaviors of the elderly and younger drivers. Table 1 shows the modifications of the driving behavior parameters as described in detail below.

3.3.1.1 Following Parameters

The names of the parameters under urban road following groups are shown in Figure 4. A brief description of modified parameters with proposed values for elderly drivers and younger drivers is described as follows.

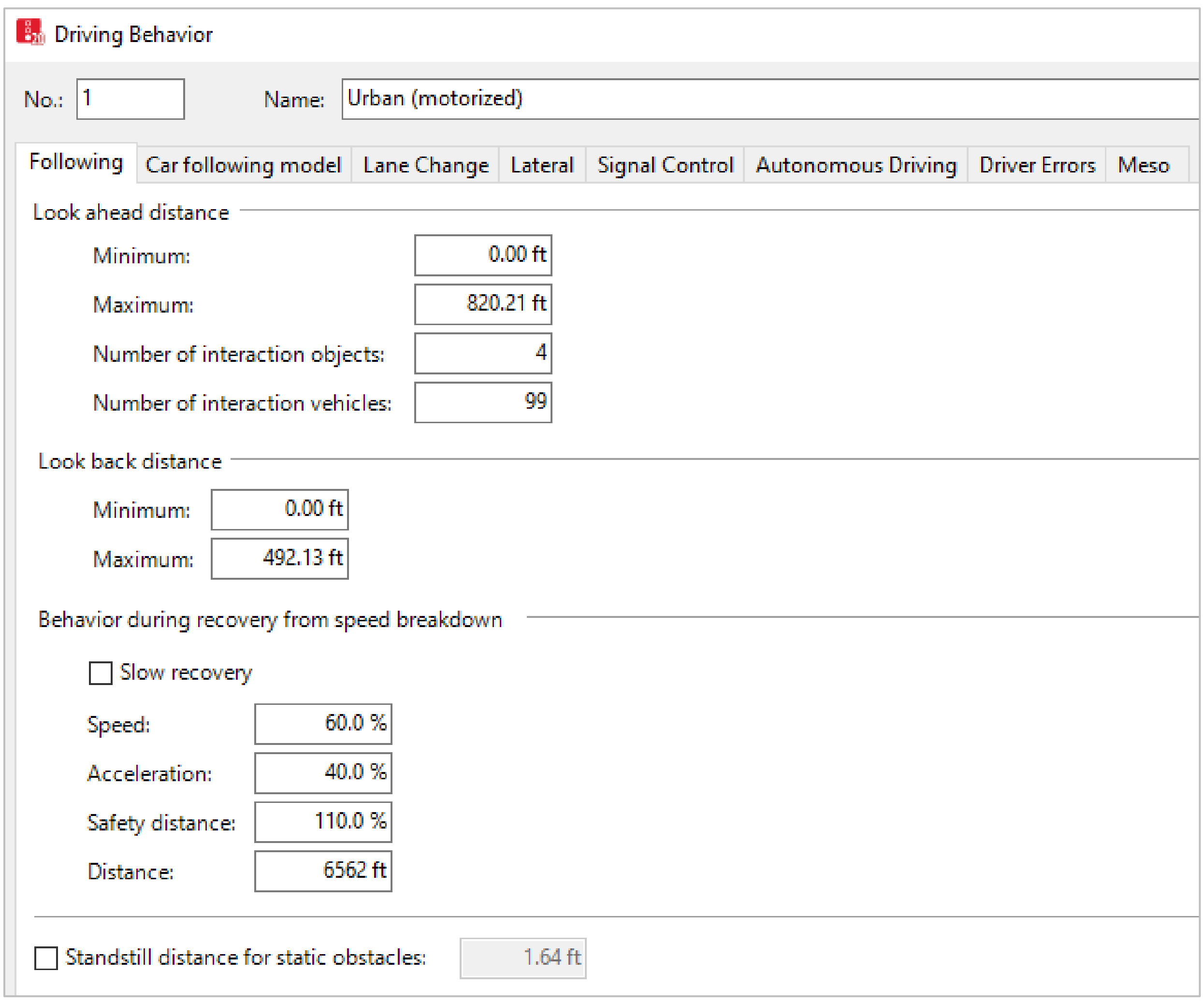


Figure 4 Driving behavior parameters for urban route

- ***Look Ahead Distance:*** the maximum and minimum distances a driver can see in a forward direction to respond to other vehicles and obstacles (PTV AG, 2020). The standard range is 0.00-820.21 ft. It should be higher for the younger driver and should be lower for the older driver. This study considered the maximum value for elderly drivers as 200 ft and younger drivers as 300 ft (Ulak et al., 2019).

- ***Look Back Distance:*** the minimum and maximum distance that a driver can see backward to react to other vehicles behind it (PTV AG, 2020). The range is 0.00 ft. to 492.13 ft. It should be higher for the younger driver and lower for an older driver, as per the previous study that the older driver usually does not scan the surrounding correctly (Pollatsek et al., 2012). The maximum value was considered 150 ft. for elderly drivers and 100 ft for younger drivers (Ulak et al., 2019).

- ***Behavior during Recovery from Speed Breakdown:*** after a speed breakdown, an older driver will think the surrounding driver will behave like him/her and perform slow-speed recovery (Ulak et al., 2019). However, the younger driver will think from their point of view and will drive aggressively. Therefore, "slow recovery" should be tick marked for the older driver.

- ***Standstill Distance for Static Obstacles:*** defines the standstill distance for static obstacles, including signal heads, stop signs, bus stops, priority rules, and conflict areas (PTV AG, 2020). The minimum distance is 1 inch, and the default is 1.64 ft. This distance should be higher for older drivers and smaller for younger drivers (Ulak et al., 2019). In this paper, for elderly drivers, the value was considered 2 ft and 1 ft for younger drivers.

3.3.1.2 Car Following Model Parameters

The VISSIM 2020 has three types of car-following models: no interaction model, Wiedemann 74 model, and Wiedemann 99 model (PTV AG, 2020). The no interaction model is suitable for simulating pedestrian flows, as in this model, there is no interaction among vehicles. Wiedemann 74 model is recommended for urban traffic with merging regions, and Wiedemann 99 model is for freeway traffic, where there is no merging (PTV AG, 2020). Therefore, in this study, Wiedemann's 74 models have been considered in the driving behavior generation. As shown in Figure 5, the Wiedemann 74 model has three parameters. The brief descriptions with modified values are provided as follows.

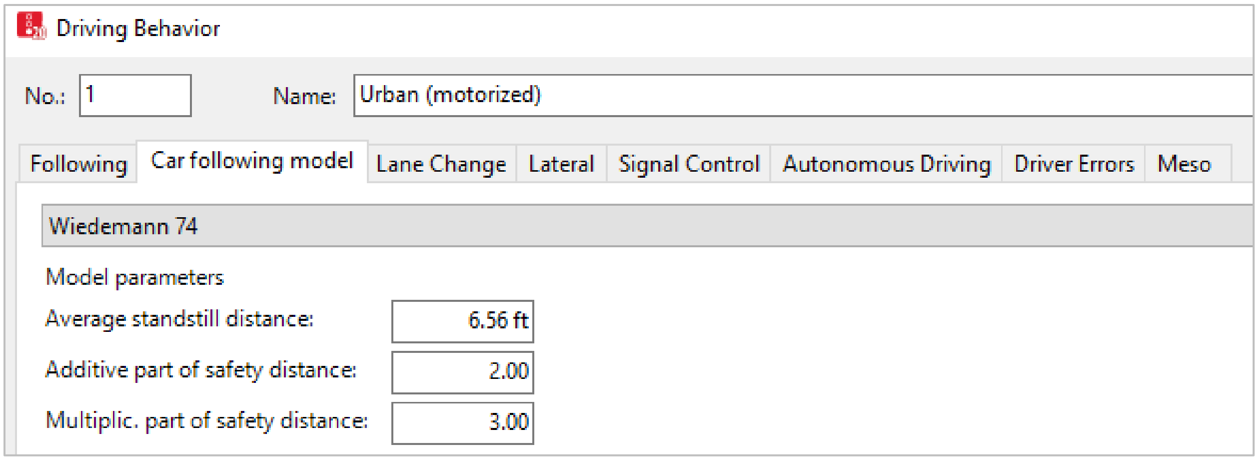


Figure 5 Driving behavior parameters for Wiedemann 74 model

- ***Average standstill distance:*** this factor defines the distance between two stationary vehicles, whose default value is 6.56 feet (2 m) (PTV AG, 2020). The FDOT Systems Planning Office (2014) recommends that this parameter be more than 3.28 ft. This study used the average standstill distance as 6.56 ft. for elderly drivers and 4.92 ft. for younger (Ulak et al., 2019).

- ***Additive part of safety distance:*** adjusts the time requirement in the safety distance estimation (PTV AG, 2020). The FDOT Systems Planning Office (2014) recommended value should be 1 to 3.5 ft. In this paper, the additive part's modified values used were 1.5 ft for young drivers and 3.5 ft for older drivers (Ulak et al., 2019).

- ***Multiplicative part of safety distance:*** it is another coefficient of the desired safety distance, regulating the safety distance distribution (PTV AG, 2020), the higher the value, the higher the standard deviation. This factor’s default value is 3 ft, and the FDOT Systems Planning Office (2014) recommendation is 2 to 4.5 ft. This study used 2.5 ft for younger drivers and 4.5 ft for elderly drivers (Ulak et al., 2019).

3.3.1.3 Lane Change Parameters

Several parameters can be modified to emulate lane-changing behavior, as shown in Figure 6. The adjusted parameters with supporting references are mentioned as follows.

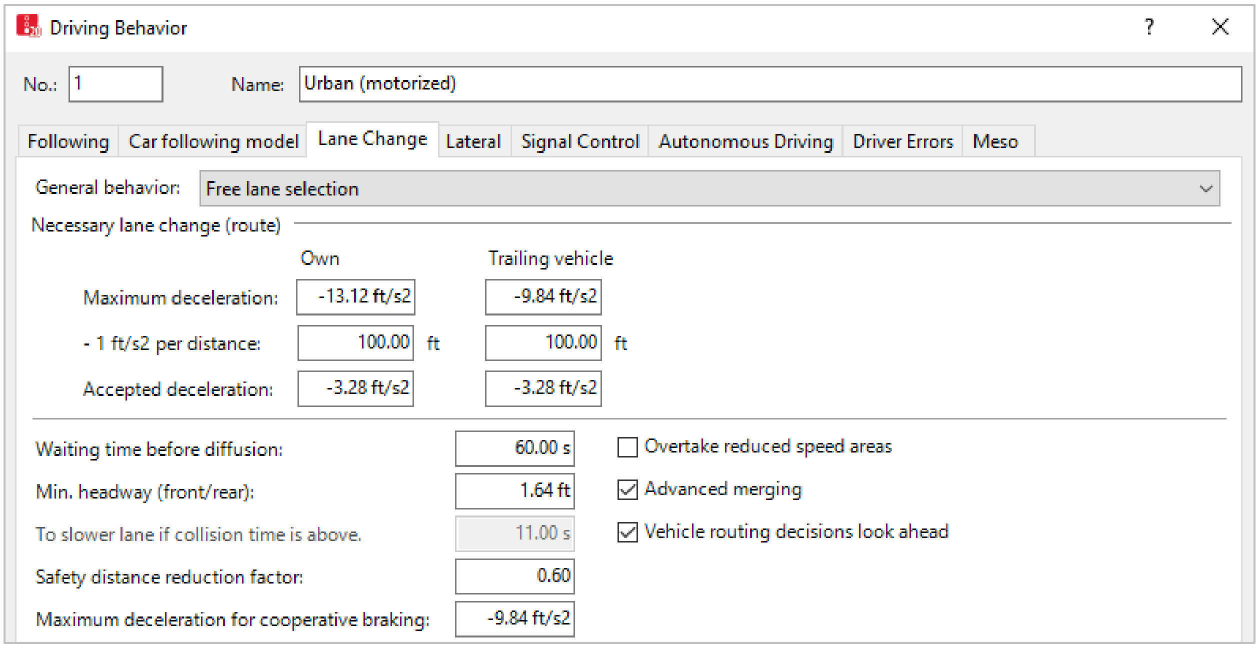


Figure 6 Driving behavior parameters for lane change

- ***Maximum deceleration (ft/s^2) (own and trailing vehicle):*** it denotes the lane changing and trailing vehicle's maximum deceleration. The default values are -13.12 ft/s^2 for own and -9.84 ft/s^2 for trailing vehicle (PTV AG, 2020). FDOT Systems Planning Office (2014) recommendation is lower than -12 ft/s^2 for own vehicle and lower than -8 ft/s^2 for trailing vehicle. In this study, for younger drivers, the values were -12 ft/s^2 and -8 ft/s^2, and for elderly drivers, -8 ft/s^2 and -6 ft/s^2 for the own and trailing vehicle, respectively (Ulak et al., 2019).

- ***-1 ft/s2 per distance:*** it regulates the standard distance to decelerate the vehicle speed at a rate of -1 ft/s^2. The default value is 100 ft for both own and trailing vehicles (PTV AG, 2020). FDOT Systems Planning Office (2014) recommendation is greater than 100 ft for own vehicles and 50 ft for trailing vehicles. This study considered 60 ft for younger drivers and 100 ft for an elderly driver for both own and trailing vehicles (Ulak et al., 2019).

- ***Accepted deceleration (own and trailing):*** it denotes the lane changing and trailing vehicle's accepted deceleration. The default value is -3.28 ft/s^2 for both own and trailing vehicles (PTV AG, 2020). FDOT Systems Planning Office (2014) recommendation is lower than - 2.5 ft/s^2 for own vehicle and lower than -1.5 ft/s^2 for trailing vehicles. In this study, for younger drivers, the values were -2.5 ft/s^2 and -1.5 ft/s^2, and for elderly drivers, -1.5 ft/s^2 and -1 ft/s^2 for the own and trailing vehicle, respectively (Ulak et al., 2019).

- ***Minimum headway (front/rear):*** it defines the minimum clear distance between two vehicles on both the front and rear sides while changing lanes. The default value is 1.64 ft (PTV AG, 2020), and FDOT Systems Planning Office (2014) and the FDOT Systems Planning Office (2014) recommendation is 1.5 to 6 ft. This study considered 2.5 ft for younger drivers and 6 ft for elderly drivers (Ulak et al., 2019).

- ***Safety distance reduction factor:*** it is another coefficient of the desired safety distance, regulating the safety distance distribution (PTV AG, 2020). the higher the value, the higher the standard deviation. This factor's default value is 3 ft, and the FDOT Systems Planning Office (2014) recommendation is 2 to 4.5 ft. This study used 2.5 ft for younger drivers and 4.5 ft for elderly drivers (Ulak et al., 2019).

- ***Maximum deceleration for cooperative braking:*** *maximum deceleration for cooperative braking:* It defines the maximum value of the deceleration during braking while changing lanes. The default value is -9.84 ft/s^2 (PTV AG, 2020). FDOT Systems Planning Office (2014) recommendation is -32.2 ft/s^2 to -3 ft/s^2 This study considered -19.32 ft/s^2 for the younger driver and -6 ft/s^2 for the elderly driver (Ulak et al., 2019).

3.3.1.4 Driver Errors Parameters

Lastly, in this study, the parameters have been adjusted for the temporary lack of attention during the following vehicles. Brief descriptions of the modified parameters are mentioned as follows.

- ***Probability of temporary lack of attention during the following:*** the default probability is 0.00%. As per a previous study, 25% probability has been considered for younger drivers and 20% for elderly drivers (Ulak et al., 2019).

- ***Duration of temporary lack of attention during the following:*** the default duration is 0 seconds. As per the previous study, the duration has been used as 2 seconds for younger and 1.5 seconds for elderly drivers (Ulak et al., 2019).

In summary, the modified parameters are mentioned in Table 1.

Table 1 Modified Driving Parameters

Parameters	Default Value	Younger Driver	Elderly Driver
Following Parameters			
Look Ahead Distance (ft.)	820.21	300	200
Look Back Distance (ft.)	492.13	150	100
Behavior during Recovery from Speed Breakdown	No-tick	No-tick	Tick marked
Standstill Distance for Static Obstacles (ft.)	1.64	1	2
Car Following Model Parameters (Wiedemann 74)			
Average standstill distance (ft.)	6.56	4.92	6.56
Additive part of the safety distance	2	1.5	3.5
Multiplicative part of the safety distance	3	2.5	4.5
Lane Change Parameters			
Maximum deceleration (ft/s^2) (own / trailing vehicle)	– 13.12 / – 9.84	– 12 / – 8	– 8 / – 6
– 1 ft/s^2 per distance (ft.)	100	60	100
Accepted deceleration (own / trailing) (ft/s^2)	– 3.28	– 2.5 / – 1.5	– 1.5 / – 1
Minimum headway (front/rear) (ft.)	1.64	2.5	6.0
Safety distance reduction factor	0.6	0.5	0.9
Maximum deceleration for cooperative braking (ft./s^2)	– 9.84	– 19.32	– 6
Driver Errors Parameters			

Parameters	Default Value	Younger Driver	Elderly Driver
Probability of temporary lack of attention during the following (%)	0.00	25	20
Duration of temporary lack of attention during the following (seconds)	0.00	2.0	1.5

3.3.2 Estimation of Traffic Volume by Synchro

This research considered the level of service (LOS) A to investigate the applicability of the Attribution Theory in predicting driving behaviors at an unsignalized intersection. First, one symmetric intersection was coded in Synchro simulation software, and unsignalized conditions were adopted. The LOS of that intersection was measured in terms of intersection capacity utilization (ICU). Several vehicle inputs were conducted in Synchro, started from a higher volume, and then reduced gradually to achieve the LOS A criteria. The traffic movement shown in Figure 7 has an ICU value of 53.5%, which satisfies the LOS A criteria of 55% (Husch & Albeck, 2003). Estimated through movements are 250 vehicles/hour (vph) each; the left turns are 125 vph, and the right turns are 50 vph. In this research, field traffic volume data was not used. Therefore, Synchro was used to measure the traffic volumes for different directions at an unsignalized intersection to create a microsimulation model in the VISSIM for investigating drivers' attribution.

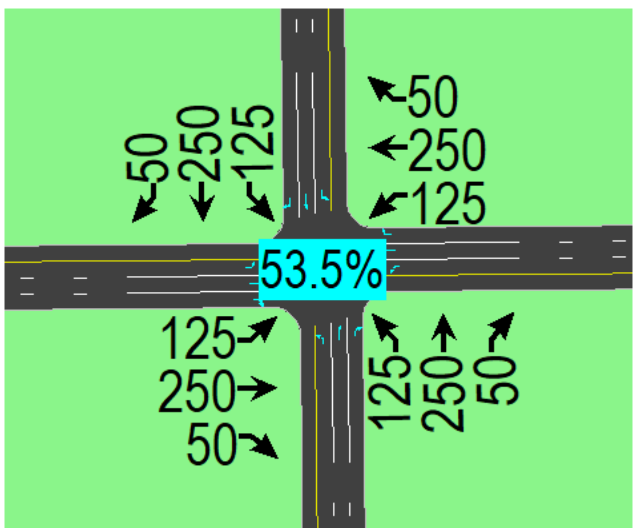


Figure 7 Traffic flow estimation for LOS A from Synchro software

3.3.3 Model Preparation in VISSIM

Based on the traffic estimation from Synchro, a model was prepared in the VISSIM (see Figure 3) with similar physical properties from the Synchro. Two driving behaviors replicating an elderly driving behavior and younger driving behavior were generated as per the parameters mentioned in Table 1. Then, trajectory files were exported during simulation in the VISSIM for further analysis. Seven scenarios were considered in this study, which is mentioned in Table 2. For each scenario, 10 simulations were performed with varying random seeds, starting from 42, and an average value for each measure of effectiveness was used for analysis. Multiple runs were undertaken in order to capture traffic stochastic nature of traffic behavior. Please note that the study does not include elderly-elderly and young-young scenarios which will be considered in a future study.

Table 2 Scenarios of Mixing Different Drivers in the VISSIM

Scenario SL	Scenario Name	Left Turning Driving Behavior	Going Straight Driving Behavior
1	Base	Default	Default
2	Elderly Left	Elderly	Default
3	Elderly Straight	Default	Elderly
4	Young Left	Young	Default
5	Young Straight	Default	Young
6	Elderly Left – Young Straight	Elderly	Young
7	Young Left – Elderly Straight	Young	Elderly

3.3.4 Traffic Conflict Estimation by the SSAM

Traffic conflicts can be estimated in several methods, including using crash modification factors (CMFs) from CMF Clearinghouse, vehicle trajectories, or deep learning approach (Arafat, Iqbal, et al., 2020; Hadi et al., 2019; Saha et al., 2020). The vehicle trajectories obtained from the VISSIM simulations were imported into the Surrogate Safety Assessment Model (SSAM) to estimate traffic conflicts. Time-to-collision (TTC) and post-encroachment time (PET) are two parameters used in the SSAM to estimate traffic conflict. This research used 1.5 seconds for TTC and 5 seconds for PET as recommended by Gettman and Head (2003). The total number of traffic conflicts in the intersection with collision types was generated and used to examine driving behaviors between older and younger drivers.

CHAPTER 4

Data Analysis

4.1 NHTSA Traffic Safety Data Analysis

4.1.1 Vehicle Traffic Fatality by Age Group of Victims

Table 3 represents the total number of vehicle fatalities by different age groups from 2009–2010 extracted from the NHTSA crash data. It was found that the highest number of fatalities (61,121) occurred in the age group 25–34 years for the past ten years (2009-2018). The reason might be that this age group is regarded as younger people; hence, they may generate a maximum number of trips versus other age groups because of their mobility for jobs, recreation, and other purposes. Apart from this age group, the second-highest number of crashes occurred among the ages 45-54. Statistics also indicate that, as a big picture, the most vulnerable age group is between 25-64 years (40k+ crash).

Table 3 Total Vehicle Traffic Fatality by Age Group From 2009-2018

Age Group	Crash Date (Year)										
	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Total
<5	430	403	358	406	393	339	379	400	404	344	3856
5-9	381	353	344	349	344	352	354	384	321	331	3513
10-15	734	675	638	617	588	564	612	659	622	521	6230
16-20	3945	3445	3420	3244	2977	3008	3147	3225	3129	2883	32423
21-24	3301	3340	3296	3453	3331	3297	3464	3629	3345	3204	33660
25-34	5695	5551	5518	5936	5757	5824	6344	6941	6822	6733	61121
35-44	4838	4546	4340	4564	4398	4237	4707	5021	5096	4989	46736
45-54	5413	5092	5099	5226	4966	4914	5304	5360	5370	5136	51880
55-64	3780	4024	3991	4330	4368	4402	4856	5222	5386	5380	45739
65-74	2377	2396	2542	2712	2755	2750	3140	3450	3295	3513	28930
>74	2927	3128	2881	2895	2961	2976	3097	3396	3560	3394	31215
Unknown	62	46	52	50	55	81	80	119	123	132	800
Total	33883	32999	32479	33782	32893	32744	35484	37806	37473	36560	346103

The motor vehicle-related fatalities by different age groups are shown in Figure 8. It was observed that the number of accidents for each group is growing over time. Ages between 25-34 years had the highest numbers of fatality incidences, which was increasing over time.

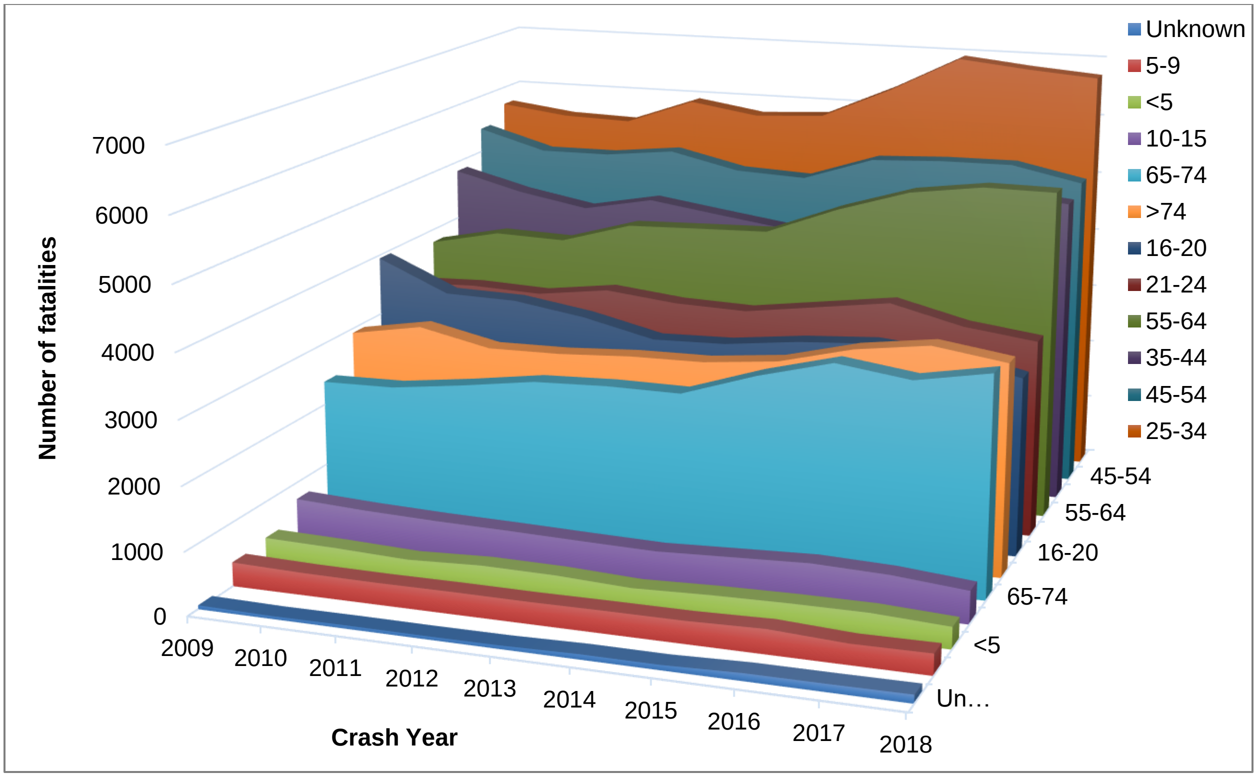


Figure 8 Number of traffic fatalities for different age group by year

A clear demonstration of the total highway fatality for 2009-2018 by age groups is presented in Figure 9. The age groups of 25-34 years old and 45-54 years old are the first and second critical groups in motor vehicle crashes, respectively.

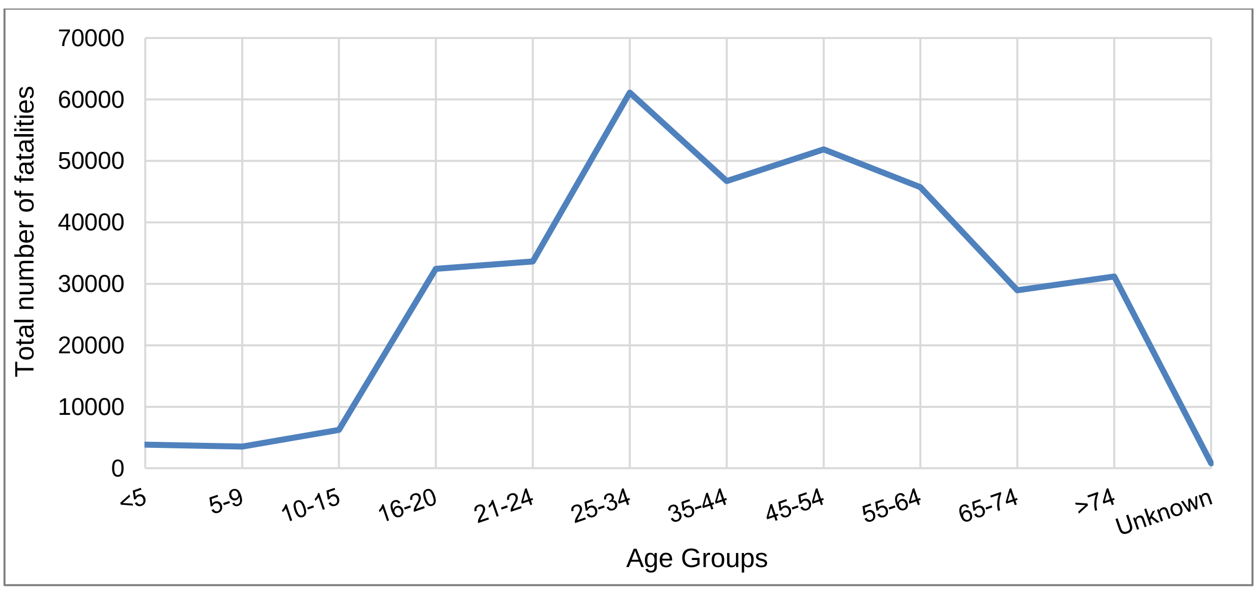


Figure 9 Total number of the fatalities by different age groups for the past ten years

The monthly distribution of the fatalities on highway accidents with age groups is shown in Table 4. It was observed that the maximum fatal crashes occurred in May for ages less than five years and in June for the age group 5-9 years. The highest fatality for 10-15, 16-20, and 35-44 years old was observed in July. August was the vulnerable time for 21-24, 25-34, and 45-54 years old. However, for the age groups of 55-64, 65-74, and over 74 years old, the peak crash fatalities occurred in September, October, and December, respectively.

Table 4 Number of Fatalities by Month and Age Groups

Age Groups	Crash Date (Month)												
	Jan	Feb	Mar	April	May	June	July	August	Sept	Oct	Nov	Dec	Total
<5	241	277	316	338	404	354	373	340	318	317	299	279	3856
5-9	245	223	296	305	328	362	353	351	264	258	243	285	3513
10-15	408	368	471	499	547	659	663	582	494	550	521	468	6230
16-20	2274	2057	2534	2607	2885	2981	3078	3035	2703	2963	2762	2544	32423
21-24	2412	2248	2695	2607	3029	2928	3125	3132	2908	3035	2888	2653	33660
25-34	4311	4064	4834	4938	5410	5312	5591	5703	5445	5544	5078	4891	61121
35-44	3529	3117	3511	3794	4109	4087	4366	4310	4160	4209	3861	3683	46736
45-54	3908	3392	3926	3974	4527	4669	4773	4859	4689	4791	4280	4092	51880
55-64	3247	3020	3361	3569	3857	4015	4187	4204	4346	4246	3816	3871	45739
65-74	2070	1932	2164	2204	2390	2498	2578	2557	2607	2687	2580	2663	28930
>74	2552	2046	2361	2374	2573	2551	2580	2546	2706	2968	2970	2988	31215
Unknown	51	62	67	56	58	60	49	80	73	82	73	89	800
Total	25248	22806	26536	27265	30117	30476	31716	31699	30713	31650	29371	28506	346103

The number of fatalities for different age groups by month is depicted in Figure 10. From the figure, a higher number of fatalities were observed during the summertime for all age groups. Furthermore, for all age groups, the highest number of fatal crashes occurred in July. People usually go camping or engage in outdoor activities in the summertime; therefore, this could be attributed to the fact that the highest number of fatalities occur in July.

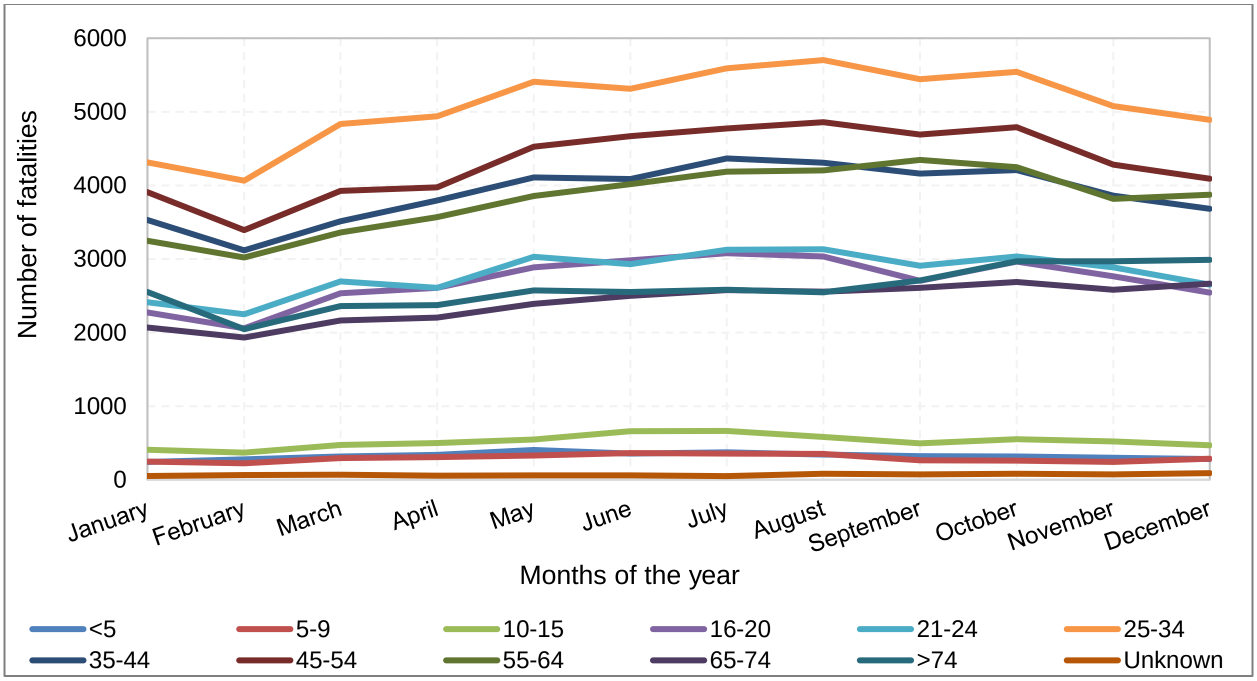


Figure 10 Number of the fatalities for different age groups by months

4.1.2 Vehicle Traffic Fatality at Intersection by Age Group of the Driver

The age distribution of the driver involved in fatal accidents is mentioned in Table 5. Like the age distribution of victims, the driver of the age group 25-34 years old is mostly entailed into a fatal crash. The reason for this might be that this age group participated in a higher percentage of driving than others. It was observed that the younger age groups (less 20 and 21-24) contributed to a smaller number of fatal accidents. The middle age groups (25-54) were involved in a considerable number of fatal crashes. However, the elder age groups (55-64 and over 65 years) were in the middle between the younger and mid-aged groups.

Table 5 Age of Drivers Involved in Fatal Accidents at Intersection

Year	Driver's age group							
	15-20	21-24	25-34	35-44	45-54	55-64	65-74	75+
2009	1,343	1,148	2,171	2,104	2,008	1,510	848	1,068
2010	1,273	1,173	2,199	1,953	2,033	1,588	948	1,175
2011	1,110	1,128	2,191	1,832	1,947	1,602	917	1,079
2012	1,104	1,185	2,391	1,926	2,067	1,624	1,062	1,065
2013	1,070	1,147	2,254	1,888	1,995	1,680	1,068	1,098
2014	1,098	1,176	2,383	1,880	2,012	1,677	1,002	1,118
2015	1,266	1,333	2,645	2,079	2,149	1,898	1,210	1,225
2016	1,293	1,445	2,886	2,250	2,215	2,058	1,362	1,347
2017	1,298	1,359	3,097	2,272	2,242	2,092	1,366	1,376
2018	1,242	1,304	2,920	2,286	2,153	2,012	1,355	1,303
Total	12,097	12,398	25,137	20,470	20,821	17,741	11,138	11,854

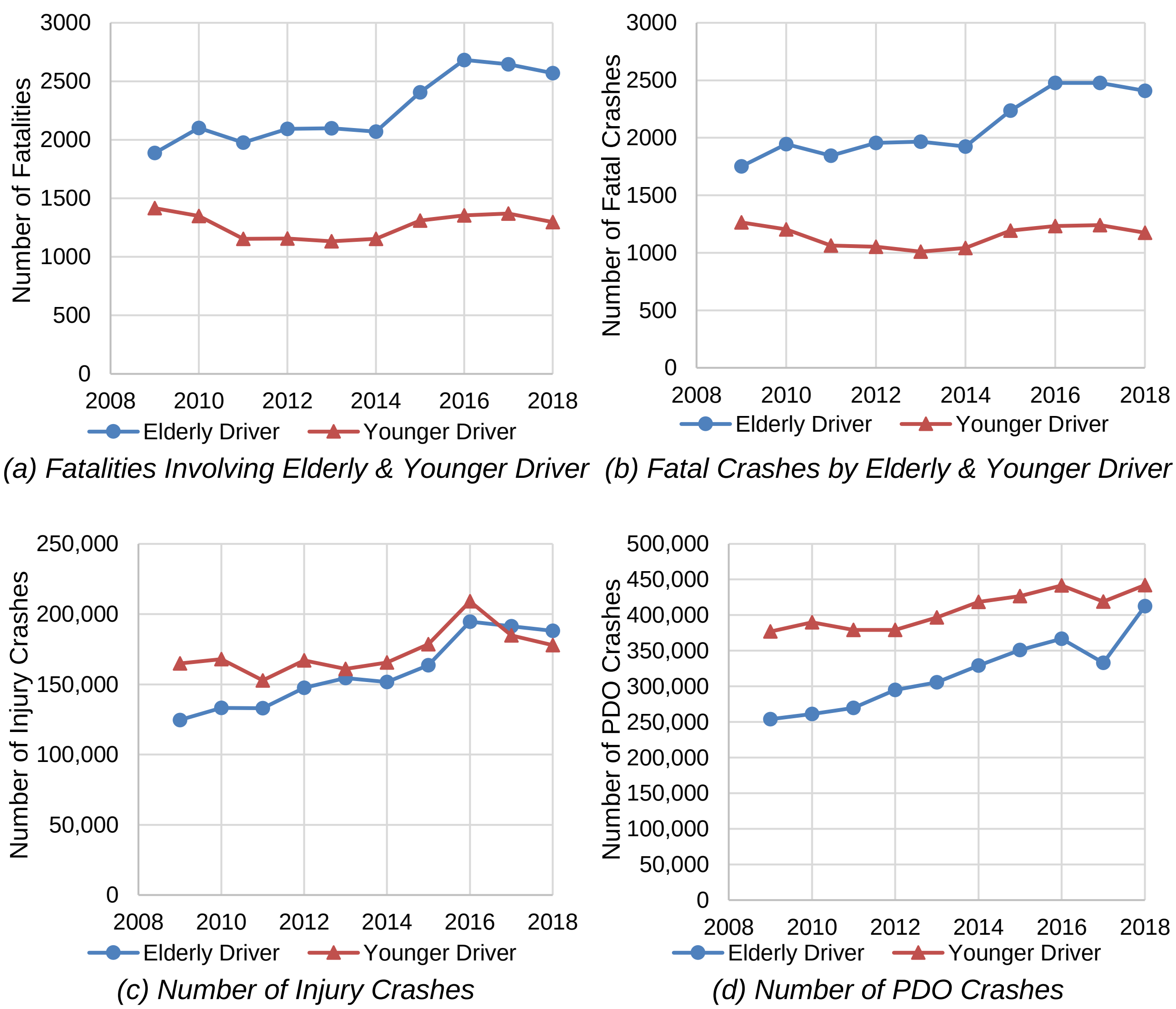
4.1.3 Vehicle Traffic Fatalities Involving At least One Younger and One Elder Driver

In this research, the driver of age 20 years or lower is considered younger, and 65 years or more is considered elderly drivers. Table 6 shows intersection-related collisions that involve one younger and one elderly driver. It was observed that about 2,236 people died in intersection crashes from 2009-2018, involving younger and elderly drivers.

Table 6 Intersection Fatal Crashes Involving of at least One Young and One Older Driver

		fatality			Fatal crash			Injury crash			PDO		
		Involved Younger Driver?											
Crash Year	Involved Older Driver?	Yes	No	Total	Yes	No	Total	Yes	No	Total	Yes	No	Total
2009	Yes	220	1,667	1,887	200	1,551	1,751	15,441	109,198	124,639	31,675	222,277	253,952
	No	1,196	4,478	5,674	1,064	4,167	5,231	149,548	425,318	574,867	345,267	904,880	1,250,147
	Total	1,416	6,145	7,561	1,264	5,718	6,982	164,989	534,516	699,506	376,942	1,127,157	1,504,099
2010	Yes	224	1,877	2,101	210	1,735	1,945	15,630	117,584	133,214	34,533	226,526	261,059
	No	1,124	4,430	5,554	993	4,135	5,128	152,201	448,151	600,352	355,452	908,584	1,264,037
	Total	1,348	6,307	7,655	1,203	5,870	7,073	167,831	565,735	733,565	389,985	1,135,110	1,525,095
2011	Yes	188	1,788	1,976	178	1,667	1,845	15,897	117,192	133,089	34,726	234,863	269,588
	No	966	4,311	5,277	885	4,078	4,963	136,906	448,701	585,607	344,310	936,918	1,281,229
	Total	1,154	6,099	7,253	1,063	5,745	6,808	152,803	565,893	718,697	379,036	1,171,781	1,550,817
2012	Yes	193	1,900	2,093	175	1,781	1,956	19,708	127,761	147,470	31,042	263,752	294,794
	No	963	4,706	5,669	878	4,382	5,260	147,361	468,057	615,418	348,072	987,145	1,335,217
	Total	1,156	6,606	7,762	1,053	6,163	7,216	167,069	595,818	762,888	379,114	1,250,897	1,630,011
2013	Yes	219	1,881	2,100	198	1,769	1,967	17,840	136,650	154,490	40,885	264,665	305,550
	No	914	4,524	5,438	812	4,226	5,038	143,049	445,936	588,985	355,887	968,757	1,324,644
	Total	1,133	6,405	7,538	1,010	5,995	7,005	160,889	582,586	743,475	396,772	1,233,422	1,630,194
2014	Yes	205	1,864	2,069	192	1,733	1,925	19,308	132,402	151,710	41,780	287,253	329,032
	No	948	4,625	5,573	851	4,322	5,173	146,135	471,626	617,761	376,752	1,108,631	1,485,382
	Total	1,153	6,489	7,642	1,043	6,055	7,098	165,443	604,029	769,472	418,531	1,395,883	1,814,415
2015	Yes	228	2,177	2,405	209	2,027	2,236	21,736	141,888	163,623	44,043	306,750	350,793
	No	1,082	5,058	6,140	984	4,706	5,690	156,766	485,070	641,836	382,455	1,131,618	1,514,073
	Total	1,310	7,235	8,545	1,193	6,733	7,926	178,501	626,958	805,459	426,498	1,438,368	1,864,866
2016	Yes	262	2,421	2,683	240	2,237	2,477	24,895	169,777	194,672	42,453	324,339	366,792
	No	1,092	5,429	6,521	992	5,076	6,068	184,165	638,753	822,919	399,038	1,144,062	1,543,100
	Total	1,354	7,850	9,204	1,232	7,313	8,545	209,060	808,530	1,017,590	441,490	1,468,401	1,909,892
2017	Yes	278	2,368	2,646	255	2,222	2,477	22,863	168,531	191,394	40,276	292,830	333,106
	No	1,091	5,470	6,561	987	5,130	6,117	162,047	539,983	702,030	378,719	1,080,042	1,458,761
	Total	1,369	7,838	9,207	1,242	7,352	8,594	184,910	708,515	893,424	418,995	1,372,872	1,791,867
2018	Yes	219	2,352	2,571	204	2,205	2,409	22,405	165,788	188,192	49,803	362,724	412,527
	No	1,077	5,327	6,404	971	4,981	5,952	155,517	571,102	726,619	392,335	1,215,798	1,608,133
	Total	1,296	7,679	8,975	1,175	7,186	8,361	177,922	736,890	914,811	442,138	1,578,522	2,020,660
Last Ten Years	Yes	2,236	20,295	22,531	2,061	18,927	20,988	195,722	1,386,771	1,582,493	391,216	2,785,977	3,177,193
	No	10,453	48,358	58,811	9,417	45,203	54,620	1,533,696	4,942,699	6,476,394	3,678,287	10,386,436	14,064,722
	Total	12,689	68,653	81,342	11,478	64,130	75,608	1,729,417	6,329,470	8,058,887	4,069,502	13,172,413	17,241,915

Figure 11 shows a comparison between the number of fatalities and crash types at an intersection by both younger and older drivers from 2009-2018. It was acknowledged that younger drivers were involved in fewer fatal accidents than elderly drivers. A possible explanation might be that the younger drivers are more attentive and require less perception than older drivers. Similarly, the number of fatalities decreased for the younger driver over the years. However, the death number increased gradually for the elderly driver. Also, the fatalities resulting in collisions by younger drivers were smaller than the elderly driver, as shown in Figure 11(a). However, younger drivers were involved in more injury, and property damage only (PDO) crashes than elderly drivers [Figure 11(c) and (d)]. A reason for this might be that younger drivers are involved in minor crashes while learning to drive or getting a driving license as they are inexperienced. The number of injury crashes involving elderly drivers has increased since 2017.



(a) Fatalities Involving Elderly & Younger Driver (b) Fatal Crashes by Elderly & Younger Driver

(c) Number of Injury Crashes (d) Number of PDO Crashes

Figure 11 Comparison of intersection crashes and fatalities by a younger and elderly driver

Figure 12 shows the number of fatalities and different crash types at intersections from 2009-2018 that involve at least one younger and one elderly driver. It was observed that about 2061 intersection-related fatal crashes occurred in the USA from 2009-2018, which were associated with both older and younger drivers. These crashes resulted in about 2,236 fatalities, having an upward trend from 2011 to 2017 [Figure 12 (a) and (b)]. The number of injury and PDO crashes involving younger and elderly drivers had an uptrend for the last ten years. These statistics denote that there might be a possibility of misinterpretation of the behavior among the younger and elderly drivers. Therefore, policymakers and planners should acknowledge the impact of the different drivers on traffic safety.

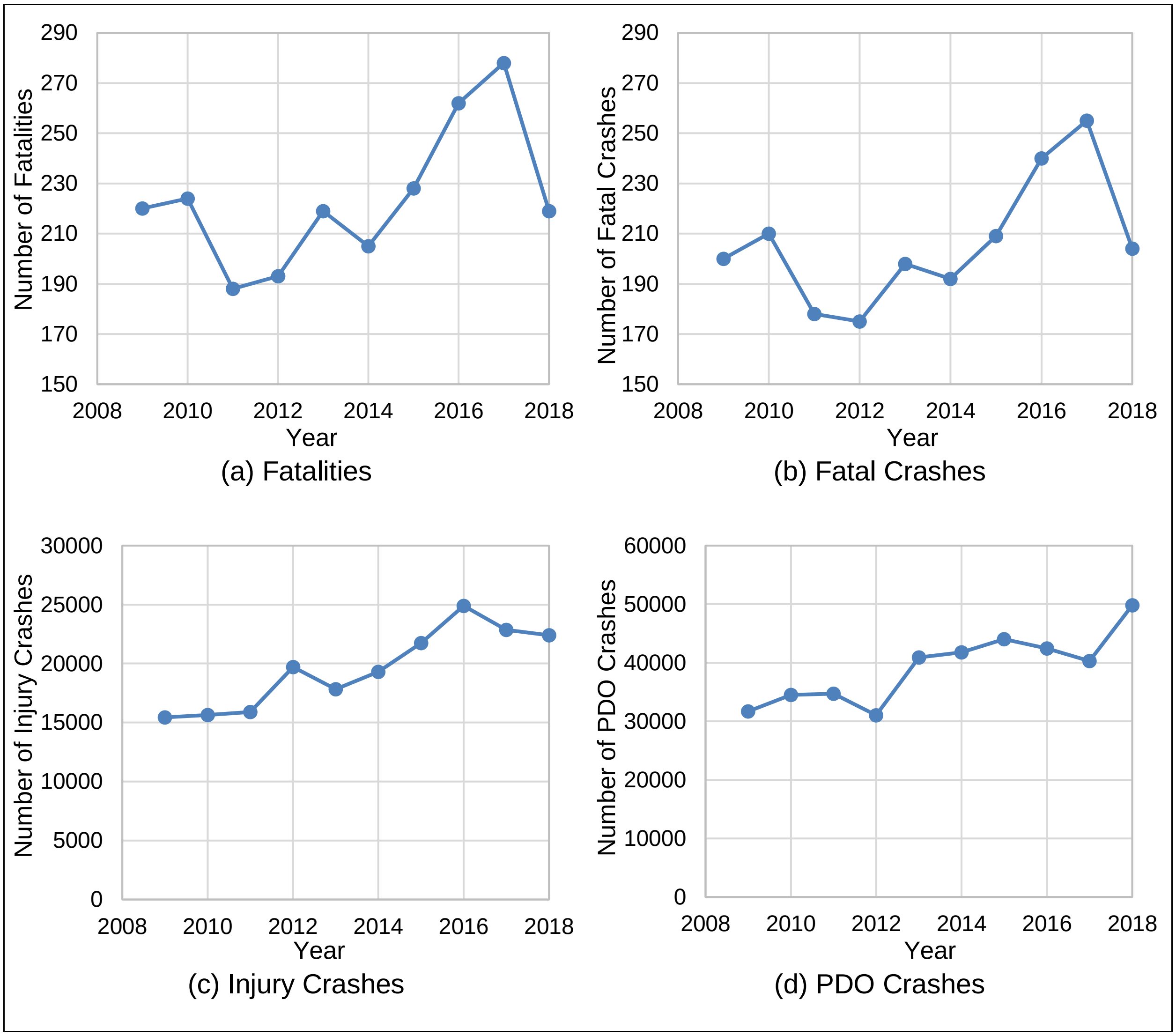


Figure 12 Intersection crashes and fatalities involving at least one younger and one elderly driver

4.2 Comparison Between NHTSA and SHRP-2 Database

A comparison between the NHTSA and SHRP-2 databases is given in Table 7. Here, the NHTSA data column indicates the percentage of total crashes contributed by a specific age group from 2009-2018. Similarly, the SHRP-2 data column indicates the percentage of total crashes from

2010-2013 contributed by a specific age group. From both databases, it was observed that the driver age group of 20-24 years old contributed to most of the intersection crashes.

Table 7 Comparison between NHTSA and SHRP 2 Database

Driver Age Group	NHTSA (%)	SHRP-2 (%)
16-19	6.87	20.37
20-24	11.74	27.62
25-29	10.43	9.37
30-34	8.66	5.04
35-39	7.81	3.45
40-44	7.74	3.45
45-49	7.84	3.31
50-54	7.98	3.50
55-59	7.40	3.78
60-64	6.08	3.54
65-69	4.65	4.38
70-74	3.81	2.73
75-79	3.19	3.99
80-84	2.91	4.06
85-89	2.02	1.23
90-94	0.77	0.12
95-99	0.12	0.04
Total	100%	100%

A corresponding graph is shown in Figure 13. It is noted that both databases show a similar trend in the driver age distribution.

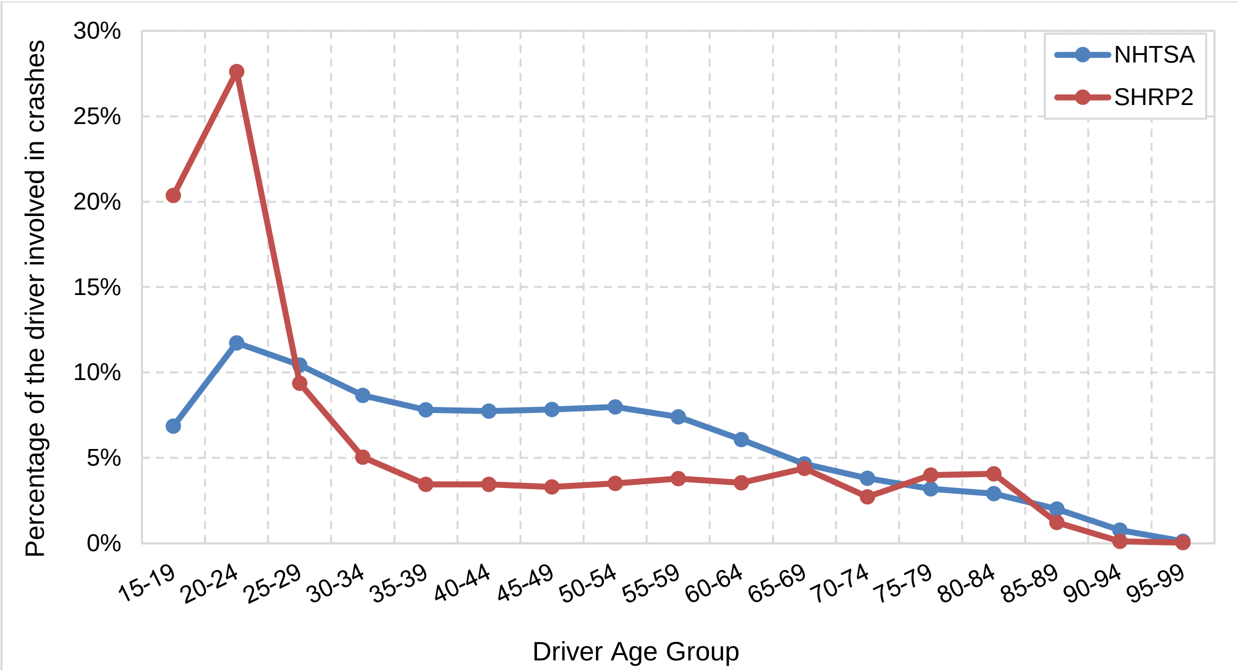


Figure 13 Comparison between NHTSA and SHRP 2 databases

4.3 Simulation Data Analysis

From simulations in the VISSIM microscopic traffic simulation, individual vehicle trajectory files were generated for the seven driving behavior scenarios presented earlier in this research. Those trajectory files were imported into the SSAM program to analyze different conflict types. The SSAM tool made by the FHWA has four categories of collisions, which are lane change (crashes occurred while changing a lane; merging & side-swipe collisions (included in this category), rear-end, crossing (right angle type crashes), and unclassified (all other types of crashes). The SSAM conflict analysis for the seven scenarios is presented in Tables 8-14.

Table 8: Scenario 1 – Base Case

Scenario	Sim_No	Unclassified	Crossing	Rear-end	Lane change	Total
1	All	0	0	1	10	11
1	1	0	0	0	2	2
1	2	0	0	0	4	4
1	4	0	0	0	1	1
1	6	0	0	0	1	1
1	7	0	0	1	0	1
1	8	0	0	0	2	2

Table 9: Scenario 2 – Elderly Driving Behavior on Left Turning

Scenario	Sim_No	Unclassified	Crossing	Rear-end	Lane change	Total
2	All	0	0	2	15	17
2	11	0	0	0	3	3
2	12	0	0	0	4	4
2	14	0	0	0	2	2
2	15	0	0	0	1	1
2	17	0	0	2	2	4
2	18	0	0	0	2	2
2	19	0	0	0	1	1

Table 10: Scenario 3 – Elderly Driving Behavior on Straight-Through

Scenario	Sim_No	Unclassified	Crossing	Rear-end	Lane change	Total
3	All	0	0	1	12	13
3	21	0	0	0	2	2
3	22	0	0	0	3	3
3	24	0	0	0	1	1
3	25	0	0	0	2	2
3	26	0	0	0	2	2
3	27	0	0	1	0	1
3	28	0	0	0	2	2

Table 11: Scenario 4 – Younger Driving Behavior on Left Turning

Scenario	Sim_No	Unclassified	Crossing	Rear-end	Lane change	Total
4	All	0	0	1	12	13
4	31	0	0	0	3	3
4	32	0	0	0	2	2
4	34	0	0	0	2	2
4	35	0	0	0	1	1
4	37	0	0	1	1	2
4	38	0	0	0	2	2
4	39	0	0	0	1	1

Table 12: Scenario 5 – Younger Driving Behavior on Straight-Through

Scenario	Sim_No	Unclassified	Crossing	Rear-end	Lane change	Total
5	All	0	0	2	11	13
5	41	0	0	0	2	2
5	42	0	0	0	4	4
5	44	0	0	0	1	1
5	46	0	0	0	1	1
5	47	0	0	1	1	2
5	48	0	0	1	2	3

Table 13: Scenario 6 – Elderly on Left Turn and Younger on Straight-Through

Scenario	Sim_No	Unclassified	Crossing	Rear-end	Lane change	Total
6	All	0	0	3	15	18
6	51	0	0	0	3	3
6	52	0	0	0	4	4
6	54	0	0	0	2	2
6	55	0	0	0	1	1
6	57	0	0	2	2	4
6	58	0	0	1	2	3
6	59	0	0	0	1	1

Table 14: Scenario 7 – Younger on Left Turn and Elderly on Straight-Through

Scenario	Sim_No	Unclassified	Crossing	Rear-end	Lane change	Total
7	All	0	0	1	14	15
7	61	0	0	0	3	3
7	62	0	0	0	3	3
7	64	0	0	0	2	2
7	65	0	0	0	2	2
7	66	0	0	0	1	1
7	67	0	0	1	0	1
7	68	0	0	0	2	2
7	69	0	0	0	1	1

Table 15 indicates the summary of the conflicts obtained from the simulations in the VISSIM for all scenarios. From the SSAM conflict analysis, unclassified and crossing type collisions did not appear at the intersection.

Table 15: Summary of all scenarios

Scenario	Unclassified	Crossing	Rear-end	Lane change	Total Conflict
1	0	0	1	10	11
2	0	0	2	15	17
3	0	0	1	12	13
4	0	0	1	12	13
5	0	0	2	11	13
6	0	0	3	15	18
7	0	0	1	14	15

Total estimated conflicts for all scenarios are graphically shown in Figure 14. It was observed that about 18 collisions occurred for scenario 6, i.e., Elderly driver turning left – Young driver going straight. Besides, 17 collisions occurred for scenario 2, i.e., Elderly drivers turning left and default drivers going straight. The high number of collisions indicates a substantial possibility of getting involved in a conflict when an elderly driver tends to turn left.

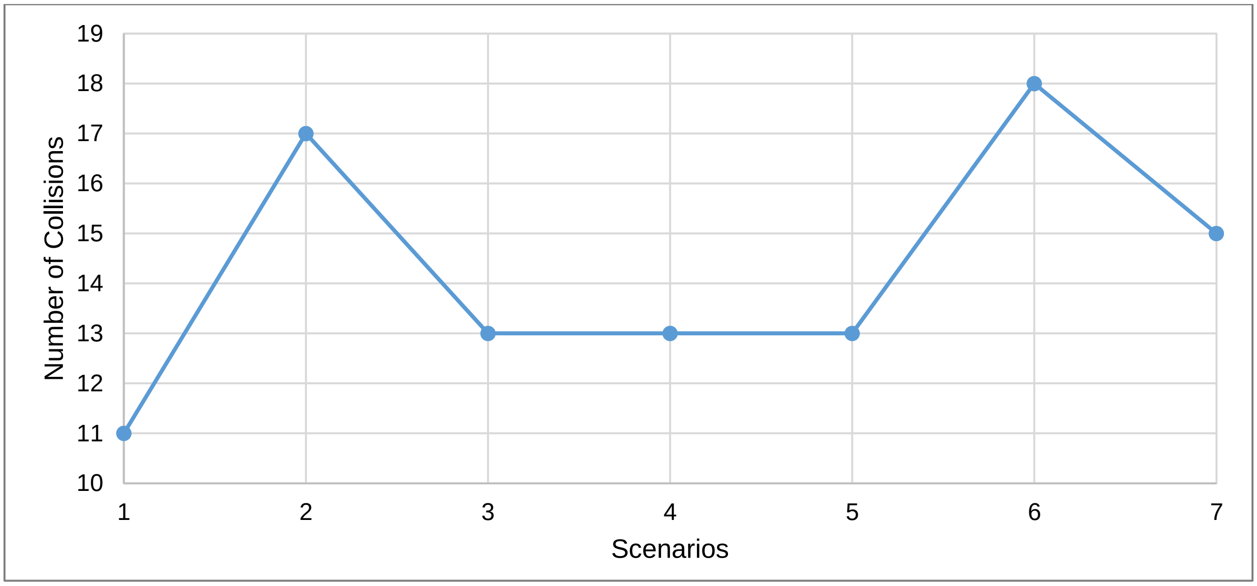


Figure 14: Total estimated conflicts for elderly and younger driver

Figure 15 shows different collision types observed in conflict analysis from the VISSIM and SSAM for all seven simulation scenarios. From the SSAM conflict analysis, it was observed that lane changing was the most common type of conflict at the intersection involving the different drivers. Unclassified and crossing type collisions did not appear at the intersection. Like the total crash number, lane-changing collisions were higher for scenarios 2 and 6 that involved the elderly driver turning left.

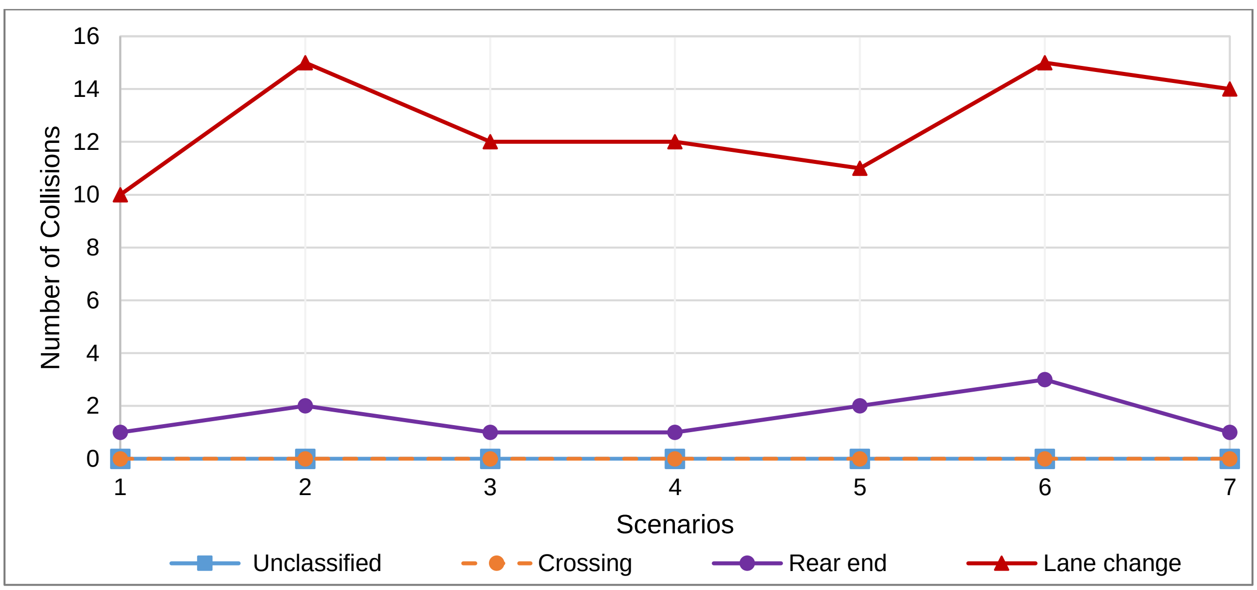


Figure 15: Different collision types observed in the SSAM analysis

CHAPTER 5
CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

This research applied attribution theory to predict driving behavior among younger and elderly drivers at unsignalized urban intersections. Furthermore, the research analyzed intersection-related fatalities that involved older and younger drivers. From the analysis, the following can be concluded:

(i) From the analysis of the fatal road crash data, it was observed that the age group of 25-34 years old was the most common victim. Middle-aged (25-54 years old) people died more in road accidents than younger (20 or fewer years old) and elderly people (65 or more).

(ii) From monthly distribution, it was observed that May was the critical period for road users age less than five years, June was for the age of 5-9, July was for the age of 10-20 and 35-44, August was for the age of 21-34 and 45-54 years, September was for 55-64 years, October was for 65-74 years, and December was for people ages over 74 years. The most frequent fatal accident occurred in the USA in July. People usually go camping or participate in outdoor activities in the summertime. Therefore, this might be a cause of the highest number of fatalities in July.

(iii) The driver, ages 25-34 years, was involved in the USA's highest number of fatal accidents. Middle-aged drivers usually need to drive more than younger and older people. Therefore, they have higher fatality rates than others.

(iv) From the comparison of the younger and elderly drivers, it was found that the younger driver (age 20 years or less) had lower fatal collisions than the elderly driver (age 65 or more). The governing reason might be that younger drivers have better perception and attentional demand than older drivers.

(v) The number of fatal accidents entailed by younger drivers decreases over the year, increasing for elderly drivers.

(vi) It was demonstrated that the number of crashes at the intersection, which involved at least one younger and one elderly driver, was significant. These types of collisions increased from 2011 and peaked in 2017 in the USA.

(vii) This study examined how different age groups affect driving attribution. Simulation models with younger and elderly drivers were developed to relate the driving attribution with the intersections' collisions. From simulations, it was observed that there is a high possibility of collisions when an elderly driver is turning left. In this study, the combination of an elderly driver turning left, and the younger driver going straight resulted in 18 collisions. In the case of elderly drivers turning left and default drivers going straight, 17 crashes were observed.

(viii) Rear-end and lane changing types of crashes were observed while simulating younger and elderly driver behavior at an intersection. So, it can be concluded that driving attribution is more likely to result in rear-end and lane-changing collisions at unsignalized intersections.

5.2 Recommendations and Future Scopes

The following are recommended from this study,

(i) The driving and safety patterns of younger and elderly drivers are not similar. The impact of the combination of the younger and elderly drivers should be considered in the traffic safety analysis.
(ii) This study observed that there might be an effect of attribution in the case of younger and elderly drivers while passing an intersection. This effect can be validated from real-world experiments.
(iii) This research investigated only crashes that occurred at an intersection. In the future, a similar study can be conducted for other sections of roadways.
(iv) The principal intention of this study is to propose an improvement in driver behavior. However, these improvements can be validated by conducting simulation tests and experiments and comparing them with the existing models.
(v) In the future, the impact of attribution theory on pedestrians can be investigated to enhance pedestrian safety and walkability.
(vi) This study does not include elderly-elderly and young-young scenarios which will be considered in a future study.

REFERENCES

Aghabayk, K., Sarvi, M., Young, W., & Kautzsch, L. (2013). A novel methodology for evolutionary calibration of VISSIM by multi-threading. *Australasian Transport Research Forum, ATRF 2013 - Proceedings*, 1–15.

Arafat, M., Iqbal, S., & Hadi, M. (2020). Utilizing an Analytical Hierarchy Process with Stochastic Return On Investment to Justify Connected Vehicle-Based Deployment Decisions. *Transportation Research Record: Journal of the Transportation Research Board*, *2674*(9), 462–472. https://doi.org/10.1177/0361198120929686

Arafat, M., Nafis, S. R., Sadeghvaziri, E., & Tousif, F. (2020). A data-driven approach to calibrate microsimulation models based on the degree of saturation at signalized intersections. *Transportation Research Interdisciplinary Perspectives*, *8*, 100231. https://doi.org/10.1016/j.trip.2020.100231

Boot, W. R., Stothart, C., & Charness, N. (2014). Improving the Safety of Aging Road Users: A Mini-Review. *Gerontology*, *60*(1), 90–96. https://doi.org/10.1159/000354212

Díaz, E. M. (2002). Theory of planned behavior and pedestrians' intentions to violate traffic regulations. *Transportation Research Part F: Traffic Psychology and Behaviour*, *5*(3), 169–175. https://doi.org/10.1016/S1369-8478(02)00015-3

Eberhard, J. W. (1996). Safe Mobility for Senior Citizens. *IATSS Research*, 29–37. https://trid.trb.org/view/481451

Eby, W. D., & Molnar, J. L. (1998). *Matching Traffic Safety Strategies To Youth Characteristics: a Literature Review of Cognitive Development*. University of Michigan Transportation Research Institute.

FDOT. (2014). *Traffic Analysis Handbook - A Reference for Planning and Operations*. Systems Planning Office, Florida Department of Transportation.

Gettman, D., & Head, L. (2003). Surrogate Safety Measures from Traffic Simulation Models. *Transportation Research Record: Journal of the Transportation Research Board*, *1840*(1), 104–115. https://doi.org/10.3141/1840-12

Hadi, M., Iqbal, M. S., Wang, T., Xiao, Y., Arafat, M., & Afreen, S. (2019). *Connected Vehicle Vehicle-to-Infrastructure Support of Active Traffic Management* (Florida International University - Lehman Center for Transportation Research (ed.)). State of Florida Department of Transportation. https://rosap.ntl.bts.gov/view/dot/49955

Hankey, J. M., Perez, M. A., & McClafferty, J. A. (2016). Description of the SHRP 2 Naturalistic Database and the Crash, Near-Crash, and Baseline Data Sets. In *Virginia Tech Transportation Institute*. http://hdl.handle.net/10919/70850

Harré, N., Foster, S., & O'Neill, M. (2005). Self-enhancement, crash-risk optimism, and the impact of safety advertisements on young drivers. *British Journal of Psychology*, *96*(2), 215–230. https://doi.org/10.1348/000712605X36019

Heider, F. (1958). The psychology of interpersonal relations. In *John Wiley & Sons Inc.* John Wiley & Sons Inc. https://doi.org/10.1037/10628-000

Ho, R., Davidson, G., Van Dyke, M., & Agar-Wilson, M. (2000). The Impact of Motor Vehicle Accidents on the Psychological Well-being of At-fault Drivers and Related Passengers. *Journal of Health Psychology*, *5*(1), 33–51. https://doi.org/10.1177/135910530000500108

Husch, D., & Albeck, J. (2003). *Intersection capacity utilization: Evaluation procedures for* *intersections and interchanges* (F. Buckholz & R. Aguilar (eds.); 1st ed.). Trafficware Corporation. https://www.trafficware.com/uploads/2/2/2/5/22256874/intersection_capacity_utilization_2003.pdf

Kelley, H. H. (1967). Attribution theory in social psychology. *Nebraska Symposium on Motivation*, *15*, 192–238. https://psycnet.apa.org/record/1968-13540-001

Kelley, H. H., & Michela, J. L. (1980). Attribution Theory and Research. *Annual Review of Psychology*, *31*(1), 457–501. https://doi.org/10.1146/annurev.ps.31.020180.002325

Keskinen, E., Ota, H., & Katila, A. (1998). Older drivers fail in intersections: Speed discrepancies between older and younger male drivers. *Accident Analysis & Prevention*, *30*(3), 323–330. https://doi.org/10.1016/S0001-4575(97)00113-9

Kim, K. M., Saito, M., Schultz, G. G., & Eggett, D. L. (2018). Evaluating Safety Impacts of Access Management Alternatives with the Surrogate Safety Assessment Model. *Transportation Research Record: Journal of the Transportation Research Board*, *2672*(17), 120–128. https://doi.org/10.1177/0361198118773505

Kotelnikova-Weiler, N., Leurent, F., & Poulhès, A. (2017). Attribution Methodologies for Mobility Impacts. *Transportation Research Procedia*, *26*, 131–143. https://doi.org/10.1016/j.trpro.2017.07.014

Mamun, M. M. H., Miah, M. M., & Islam, M. I. (2015). Present Condition of Road Traffic Accident: A Case Study of Rajshahi City, Bangladesh. *International Journal of Computer Applications*, *111*(7), 36–41. https://doi.org/10.5120/19554-1279

Mamun, M. M. H., & Mwakalonge, J. L. (2018). Theoretical Estimation of Pedestrian Uncertainty Arising from Distracted Walking. *6th Annual University Transportation Centers Conference for the Southeastern Region*, 21p. https://www.researchgate.net/publication/328527091_Theoretical_Estimation_of_Pedestrian_Uncertainty_Arising_from_Distracted_Walking

Marks, G., & Miller, N. (1987). Ten years of research on the false-consensus effect: An empirical and theoretical review. *Psychological Bulletin*, *102*(1), 72–90. https://doi.org/10.1037/0033-2909.102.1.72

Mwakalonge, J. L., Mamun, M. M. H., Hong, J.-D., & Chowdhury, M. (2019). Infrastructure and Policy Needs for Personal Electric Mobility Devices in a Connected Vehicle World. In *Center for Connected Multimodal Mobility*. Center for Connected Multimodal Mobility, Clemson University. https://doi.org/https://rosap.ntl.bts.gov/view/dot/53587

Namaki Araghi, bahar, Shahi, J., & Mehdizadeh, A. (2008). Estimation of Rear-End Potential Conflict using Time-To-Collision Model. *Proceedings of the First Annual International Symposium on Vehicular Computing Systems*, 15 p. https://doi.org/10.4108/ICST.ISVCS2008.3748

NHTSA. (2013). Traffic Safety Facts 2012. In *National Highway Traffic Safety Administration*. https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812032

NHTSA. (2018). Motor Vehicle Traffic Crashes as a Leading Cause of Death in the United States, 2015. In *National Highway Traffic Safety Administration*.

NHTSA. (2019). *Fatality and Injury Reporting System Tool (FIRST)*. Fatality Analysis Reporting System. https://cdan.dot.gov/query

Pollatsek, A., Romoser, M. R. E., & Fisher, D. L. (2012). Identifying and Remediating Failures of

Selective Attention in Older Drivers. *Current Directions in Psychological Science*, *21*(1), 3–7. https://doi.org/10.1177/0963721411429459

PTV. (2011). *VISSIM 5.30-05 User Manual* (5.30). PTV Group.

PTV AG. (2020). PTV Vissim 2020 User Manual. In *PTV Group* (2020th ed.). PTV Group.

Rotter, Julian B (1966). "Generalized expectancies for internal versus external control of reinforcement". Psychological Monographs: General and Applied. 80 (1): 1–28. doi:10.1037/h0092976. PMID 5340840. S2CID 15355866.

Romoser, M., & Fisher, D. L. (2009). Effects of Cognitive and Physical Decline on Older Drivers' Side-to-Side Scanning for Hazards While Executing Turns. *Proceedings of the 5th International Driving Symposium on Human Factors in Driver Assessment, Training, and Vehicle Design : Driving Assessment 2009*, 61–68. https://doi.org/10.17077/drivingassessment.1303

Romoser, M. R. E., Pollatsek, A., Fisher, D. L., & Williams, C. C. (2013). Comparing the glance patterns of older versus younger experienced drivers: Scanning for hazards while approaching and entering the intersection. *Transportation Research Part F: Traffic Psychology and Behaviour*, *16*, 104–116. https://doi.org/10.1016/j.trf.2012.08.004

Saha, R., Tariq, M. T., & Hadi, M. (2020). Deep Learning Approach for Predictive Analytics to Support Diversion during Freeway Incidents. *Transportation Research Record: Journal of the Transportation Research Board*, *2674*(6), 480–492. https://doi.org/10.1177/0361198120917673

Sahar, G. (2014). On the Importance of Attribution Theory in Political Psychology. *Social and Personality Psychology Compass*, *8*(5), 229–249. https://doi.org/10.1111/spc3.12102

Shaver, K. G. (1983). An Introduction to Attribution Processes. In *An Introduction to Attribution Processes* (1st ed.). Routledge. https://doi.org/10.4324/9781315536019

Smith, K., & Martin, J. W. (2007). A barrier to building a traffic safety culture in America: Understanding why drivers feel invulnerable and ambivalent when it comes to traffic safety. In J. P. Kissinger (Ed.), *Improving traffic safety culture in the United States: The journey forward* (pp. 201–212). AAA Foundation for Traffic Safety.

Stewart, A. E. (2005). Attributions of responsibility for motor vehicle crashes. *Accident Analysis & Prevention*, *37*(4), 681–688. https://doi.org/10.1016/j.aap.2005.03.010

Summala, H. (1987). Young Driver Accidents: Risk-Taking or Failure of Skills? *Alcohol, Drugs and Driving*, *3*(3), 79–91. https://trid.trb.org/view/364890

Ulak, M. B., Ozguven, E. E., Moses, R., Sando, T., Boot, W., AbdelRazig, Y., & Sobanjo, J. O. (2019). Assessment of traffic performance measures and safety based on driver age and experience: A microsimulation based analysis for an unsignalized T-intersection. *Journal of Traffic and Transportation Engineering (English Edition)*, *6*(5), 455–469. https://doi.org/10.1016/j.jtte.2018.05.004

Vladisavljevic, I., Martin, P. T., & Stevanovic, A. (2007). Integration of mathematical and physical simulation to calibrate car-following behaviour of unimpaired and impaired drivers. *World Review of Intermodal Transportation Research*, *1*(4), 403. https://doi.org/10.1504/WRITR.2007.017095

Weiner, B. (1985). An attributional theory of achievement motivation and emotion. *Psychological Review*, *92*(4), 548–573. https://doi.org/10.1037/0033-295X.92.4.548

Weiner, B., Nierenberg, R., & Goldstein, M. (1976). Social learning (locus of control) versus attributional (causal stability) interpretations of expectancy of success. *Journal of Personality*, *44*(1), 52–68. https://doi.org/10.1111/j.1467-6494.1976.tb00583.x

Zhou, H., Lownes, N. E., Ivan, J. N., Gårder, P. E., & Ravishanker, N. (2015). Left-Turn Gap Acceptance Behavior of Elderly Drivers at Unsignalized Intersections. *Journal of Transportation Safety & Security*, *7*(4), 324–344. https://doi.org/10.1080/19439962.2014.976689