

Transportation Consortium of South-Central States

Solving Emerging Transportation Resiliency, Sustainability, and Economic Challenges through the Use of Innovative Materials and Construction Methods: From Research to Implementation

# **Exploring Traffic Safety Problems and Challenges of Older Roads' Users in Louisiana: Causes and Countermeasures**

Project No. 20SALSU13

Lead University: Louisiana State University

Final Report October 2021

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#### 16. Abstract

It is well established that older pedestrians and drivers with 65 years and above are among the most vulnerable road users. As the number and proportion of older road users (as drivers and pedestrians) grows in many countries, as well as their share in pedestrians' and drivers' crashes and injuries, it behooves transportation researchers to further investigate the safety and mobility challenges of older road users. This study aims mainly to provide a comprehensive investigation of older pedestrians' and drivers' safety challenges. To this end, a three-fold research approach is designed to thoroughly examine older road users' safety challenges as pedestrians and drivers. First, crash data analysis identified significant risk factors causing/leading older drivers' to be involved in vehicle crashes. Second, a driving simulator experiment was performed to further investigate the identified risky conditions from the crash data analysis and literature review. Third, a self-reported survey was conducted across the country to address pedestrians' safety challenges, needs, and attitudes toward different pedestrian crossing facilities (i.e., signalized intersections, unsignalized intersections, midblock cross walks with and without flashing lights, and roundabouts). The results of this study provide a better understanding regarding older drivers' and pedestrian' needs and challenges that should be accommodated to improve their safety and mobility.

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# TABLE OF CONTENTS

TECHNICAL DOCUMENTATION PAGEii
TABLE OF CONTENTS iv
LIST OF FIGURES v
LIST OF TABLES vii
ACRONYMS, ABBREVIATIONS, AND SYMBOLS viii
1. INTRODUCTION
2. OBJECTIVES
3. LITERATURE REVIEW
4. METHODOLOGY 17
5. ANALYSIS AND FINDINGS
6. CONCLUSIONS
REFERENCES

# LIST OF FIGURES

Figure 1: Share of old age population in the total U.S. population
Figure 2: Overall research approach and tasks
Figure 3: Proportion of missing values in the dataset
Figure 4: Distribution of older drivers at fault by age and gender
Figure 5: Distribution of crash severity (0: No Injury, 1: Injury/Fatality) by drivers' age
Figure 6: Yearly and hourly distribution of senior crashes in Louisiana from 2014-2018
Figure 7: Analytical procedure used in this research
Figure 8: Logistic Regression Model
Figure 9: Interaction plots
Figure 10: ANOVA test comparing logistic regressions with and without interaction terms 27
Figure 11: Multicollinearity Assumption using VIF
Figure 12: Binned Residuals to test Heteroscedasticity of residuals
Figure 13. Senior drivers' hot spot location across Louisiana
Figure 14. Distribution of senior crashes at signalized intersections in Louisiana
Figure 15. Distribution of senior crashes at unsignalized intersections in Louisiana
Figure 16. Distribution of senior crashes at no-control locations in Louisiana
Figure 17. A. Baton Rouge area crashes
Figure 18. A. New Orleans crashes
Figure 19. A. Lafayette crashes
Figure 20. A. Shreveport crashes
Figure 21: Participants' opinion about the reasons that might causing them to be involved in pedestrian accident while crossing a road
Figure 22: Responses to "I walk less to compensate for my declining abilities to cross a street" statement
Figure 23: Responses to "I walk or drive with another person to compensate for my declining abilities" statement
Figure 24: Responses to "I avoid complex intersections and traffic for driving and walking" statement
Figure 25: Responses to "I select very large gaps in traffic to cross a road" statement
Figure 26: Self assessment of walking capability as a pedestrian
Figure 27: : Self assessment crossing capability at road crossings as a pedestrian
Figure 28: Health/medical conditions that negatively impacts their ability to walk or drive 45
Figure 29: Walking frequency at signalized intersections before and during the pandemic 47

Figure 30:	Walking frequency at unsignalized intersections before and during the pandemic $48$
-	Walking frequency at midblock crosswalks with flashing light before and during the ic
-	Walking frequency at midblock crosswalks without flashing light before and during the ic
Figure 33:	Walking frequency at roundabouts before and during the pandemic
Figure 34:	Driving simulator participants
Figure 35:	Approaching Speed at four intersections
Figure 36:	Maximum deceleration rates at four intersections
Figure 37:	Waiting time at four intersections
Figure 387	Furn duration at four intersections.    59
Figure 39:	Maximum acceleration at four intersections
Figure 40.	ANOVA results for approaching speed variable
Figure 41:	QQ-plot for checking normality assumption of approaching speed variable
Figure 42:	Post-hoc analysis for approaching speed variable
Figure 43:	ANOVA results for maximum deceleration variable
Figure 44:	QQ-plot for checking normality assumption of maximum deceleration variable 62
Figure 45:	Post-hoc analysis for maximum deceleration variable
Figure 46:	ANOVA results for waiting time variable
Figure 47:	QQ-plot for checking normality assumption of waiting time variable
Figure 48:	Post-hoc analysis for waiting time variable
Figure 49:	ANOVA results of average turning speed variable
Figure 50:	QQ-plot for checking normality assumption of average turning speed variable 64
Figure 51:	Post-hoc analysis for average turning speed variable
Figure 52:	ANOVA results of turn duration variable
Figure 53:	QQ-plot for checking normality assumption of turn duration variable
Figure 54:	ANOVA results of maximum acceleration rate variable
Figure 55:	QQ-plot for checking normality assumption of maximum acceleration rate variable. 66
Figure 56:	Post-hoc analysis for the main effect of maximum acceleration rate variable
Figure 57:	Post-hoc analysis for the interaction effect of maximum acceleration rate variable 67

# LIST OF TABLES

Table 1: Independent variables used in the analysis and their coding	. 24
Table 2: Survey participants by age and gender.	.37
Table 3: State share from older Americans' population and the survey respondents	. 38
Table 4: Survey respondents' demographics	. 39
Table 5: older pedestrians' walking or road crossing challenges.	40
Table 6: Prior Involvements in Traffic Collisions.	46
Table 7: Reasons for involvements in traffic collisions/ falls	46
Table 8: Pedestrians' challenges and needs at signalized intersections	48
Table 9: Pedestrians' challenges and needs at unsignalized intersections	. 49
Table 10: Pedestrians' challenges and needs at midblock crosswalks with flashing light	50
Table 11: Pedestrians' challenges and needs at midblock crosswalks with flashing light	. 52
Table 12: Pedestrians' challenges and needs roundabouts.	. 53
Table 13: Survey participants and response rates.	. 54
Table 14: Definitions of the driving simulator variables used in this study	57
Table 15: Summerized driving simulator variables across different intersection complexities	. 60

# ACRONYMS, ABBREVIATIONS, AND SYMBOLS

AIC	Akaike Information Criterion
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
CAV	Connected and Automated Vehicle
EB	Empirical Bayes
XGBoost	Extreme Gradient Boosting
НСА	Hierarchical Cluster Analysis
HIGA	Hybrid Intelligent Genetic Algorithm
AFT	Lognormal Accelerated Failure Time
МСМС	Markov Chain Monte Carlo
MLR	Multinomial Logistic Regression
NDS	Naturalistic Driving Study
PCA	Principal Component Analysis
RLVW	Red-light Violation Warning
ROR	Run-off-road
SP	Self-potential
SHAP	Shapley Additive Explanations
VR	Virtual Reality
LDWS	Lane-departure Warning System
LKAS	Lane-keeping Assist System
RDAS	Road Departure Assist System
LCA	Lane Centering Assist System
LaDOTD	Louisiana Department of Transportation and Development

#### **EXECUTIVE SUMMARY**

Statistics published by the U.S. Department of Transportation, National Highway Traffic Safety administration indicated that there were 6,784 people age 65 and older killed in traffic crashes in the United States in 2017, representing 18 percent of all traffic fatalities. Although the population of people 65 and older increased by 31 percent from 2008 to 2017, traffic crash fatalities in that age group increased by 22 percent over this period (1).

These figures can be explained due to several mobility and traffic safety challenges encountered by older adults while using roads as pedestrians or drivers. For example, prior research indicates that older pedestrians exhibit declining walking skills (e.g., decreased walking speed, reduced stability while walking, and less efficient wayfinding strategies), and a greater tendency to engage in unsafe crossing behaviors. Particularly, older adults tend to begin crossing when safe crossing gaps are available in the near lane, but not the far lane (2).

Another recent Canadian study by Gargoum et al. indicated that the design of road infrastructure could have an impact on the risk of traffic collisions for older adults. The findings of this study revealed that available sight distances fell below the stopping sight distance requirements for drivers with limited abilities (e.g., older drivers), particularly in poor driving conditions. Accordingly, it was recommended that changes in the design guidelines for future roadways should reflect the aging driving population (3).

However, little is known about the effect of different types of roadway crossing, geometry and traffic control devices on the safety of older roads' users. In addition, there is a lack of a solid understanding of older road users' preferences and needs while crossing different types of pedestrian crossings.

As the proportion of older adults continues to increase in USA and elsewhere, it is vital to understand the challenges faced by older roads' users (drivers and pedestrians), and suggest effective countermeasures to improve their safety and maintain their mobility and independence into later life stages. Therefore, the main objectives of this research are to:

- 1. Identify the circumstances and precipitating factors contributing to older roads users' crashes including driver, vehicle and road/environment factors.
- 2. Identify hotspot locations of crashes involving older road users (drivers/pedestrians).
- 3. Examine the effects of changes in the roadways design and traffic control devices on the drivers' behaviors and safety of aging population using driving simulator.
- 4. Provide a better understanding regarding older pedestrians' preferences and needs to cross different types of pedestrian crossings safely. This will also include examining older pedestrians' awareness of their declining abilities and their effects on safety and mobility.

## **1. INTRODUCTION**

Older road users (65 years and older) are at higher risk to be involved in motor vehicle and pedestrians related collisions. Indeed, older pedestrians and cyclists represent the largest group of vulnerable road users. In 2017, there were 6,784 people age 65 and older killed in traffic crashes in the United States, 18 percent of all traffic fatalities. Although the population of people 65 and older increased by 31 percent from 2008 to 2017, traffic crash fatalities in that age group increased by 22 percent over this period (1).

There are many contributing factors affecting traffic safety challenges of older roads' users. For example, Tournier et al. indicates that older pedestrians exhibit declining walking skills (e.g., decreased walking speed, reduced stability while walking, and less efficient wayfinding strategies), and a greater tendency to engage in unsafe crossing behaviors (2). Particularly, older adults tend to begin crossing when safe crossing gaps are available in the near lane, but not the far lane. Older drivers are also at higher risk to be involved in traffic crashes due to several factors including failure to yield to oncoming vehicles (3), reflecting difficulties in the evaluation and estimation of distance and speed of oncoming vehicles (4).

In addition, Gargoum et al. indicated that the design of road infrastructure can also have an impact on the risk of traffic collisions for older adults. The findings of this study revealed that available sight distances fell below stopping sight distance requirements for drivers with limited abilities (e.g., older drivers) in poor driving conditions in 20% of the length of the tested highway segments. Accordingly, it was recommended that changes in the design guidelines for future roadways should reflect the aging driving population (5).

It is worth mentioning that there are several types of at-grade pedestrian crossings in USA (i.e., signalized intersections, four-way stops intersections, mid-block, roundabouts etc.) and signal phasing for pedestrians (i.e., dedicated phase for pedestrian, flashing beacon). However, little is known about the effect of these crossing types on the safety of older pedestrians. In addition, there is a lack of better understanding of older pedestrians' preferences and needs to continue walking and crossing these different types of pedestrian crossings safely.

In recent years, the aging population of the United States has come into focus as a cause for concern. Indeed, statistics showed that the proportion of Americans aged 65 years and older has significantly increased from 8% in 1950 to 17% in 2020 (as shown in Figure 1). According to demographic projections, this proportion will continue to increase to approximately 22% of the total population in 2050 (6). As the proportion of older adults continues to increase, it is vital to understand the challenges faced by older roads' users (drivers and pedestrians) and suggest effective countermeasures to improve their safety and maintain their mobility and independence into later life stages.

Therefore, this research aims at examining traffic safety problems, challenges of older roads' users in Louisiana and thoroughly determining the causes, possible countermeasures and actionable plans to improve their safety.

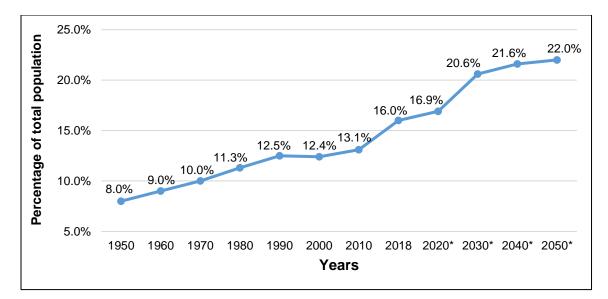


Figure 1: Share of old age population (65 years and older) in the total U.S. population from 1950 to 2050 (US Census Bureau, 2016).

## **2. OBJECTIVES**

The main objectives of this proposed study are to:

- 1. Identify the circumstances and precipitating factors contributing to older roads users' crashes including driver, vehicle and road/environment factors.
- 2. Determine hotspot locations of crashes involving older road users (drivers/pedestrians).
- 3. Examine the effects of changes in the roadways design and traffic control devices on the drivers' behaviors and safety of aging population.
- 4. Provide a better understanding regarding older pedestrians' preferences and needs to cross different types of pedestrian crossings safely. This will also include examining older pedestrians' awareness of their declining abilities and their effects on safety and mobility in Louisiana.

To better achieve the objectives of this research, three different methods were employed: (1) collecting and analyzing a sample of crash dataset of older adults in Louisiana, (2) designing and conducting a self-reported survey study among a sample of older road users, and (3) developing a driving simulator experiment among a sample of older adults' drivers. Figure 2 illustrates the research approach and tasks. The scope of work and corresponding detailed tasks is also described below.

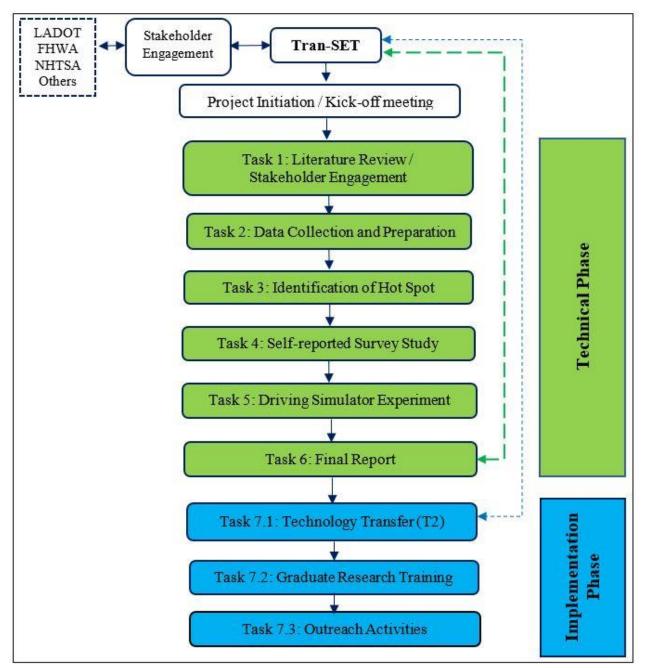


Figure 2: Overall research approach and tasks.

### **3. LITERATURE REVIEW**

This section provides an overview of prior studies addressing older road uses' safety and mobility challenges and findings in three sections. First section includes studies that investigated risk factors using crash data and spatial statistics. Second section reviews the most recent studies addressing older pedestrian crossing challenges. The last section discusses the most recent studies that observed older drivers' behavior using driving simulator experiment.

#### 3.1. Crash Data

Donorfio et al. studied how older drivers rationalize and manage with changes in their psychological and physical functioning as it relates to self-regulation and driving (7). Driving selfregulation is more than just a set of actions; it is a complex mix of behaviors and attitudes, involving significant psychological and social processes as well as vehicle characteristics. They conducted a countrywide survey of drivers with 50 years and above. With 3,824 valid replies, response rate was about 53%. Their findings showed that the structure of one's household played a significant impact in defining one's transportation alternatives and how serious they were about imposing self-control habits. They also recognized that the value of driving is in sustaining independence, emotions of self-worth, and a sense of connection to life and society. The survey results showed that self-regulation was defined by senior drivers as much more than behavioral changes because of decreasing health and ability. Self-regulation decisions were influenced by the makeup of the household. Those who lived in a two-person home, for example, were more inclined to allow their spouse drive or even share driving duties, whereas less self-regulation in driving was observed among those who lived alone. Senior drivers' self-regulatory educational programs should incorporate not just behavioral aspects of self-regulation, but also psychological issues that are as important. Legislators drafting policy initiatives should evaluate what transportation choices are available to the elderly. There were a few limitations in this study. Although a nationally representative sample of senior drivers with 50 years and above was collected, it was obtained from a research panel in "consumer market" sector; as a result, the opinions stated may differ from those of those who are unwilling to participate in such a panel. Second, every single one of the participants was a licensed driver at the time. Future study should focus on senior drivers who have recently stopped driving, whether for personal or professional reasons. Third, because all data is self-reported, it is possible that it is incomplete or incorrect due to self-assessment and memory. Finally, the qualitative analysis was headed by the first author. As a result, if someone else led the analysis and educated the senior analysts, the results may be different.

Amiri et al. studied the severity of run-off-road (ROR) collisions in which senior drivers, aged 65 or older, collide with a stationary object by comparing psychological and physical characteristics of older and younger drivers (8). Senior drivers are more susceptible to injuries in ROR crashes as a result of their psychological and physical differences. This research uses the California collision data from the Highway Safety Information System database to apply two types of Artificial Intelligence techniques. Although the developed Artificial Neural Network (ANN) over-performs the Hybrid Intelligent Genetic Algorithm (HIGA) in terms of overall prediction accuracy, the hybrid method was better at predicting high-severity accidents because it was trained using the Genetic Algorithm. In conclusion, the findings show that the "light condition" was the most significant predictor in determining the severity of fixed object crashes among senior drivers. The next significant variables found to be "the presence of the right and left shoulders". After these factors, the most relevant variables in the generated ANN were Average Annual Daily Traffic,

number of cars involved in the collision, age, the quality of road surface, and gender, respectively.

Rezapour et al. studied the effects of various environmental and traffic barrier design on the barrier-collision severity in two-lane highways (9). A mixed binary logistic regression model was used to predict crash severity, with some factors fixed and others unpredictable. The findings indicate that the main effect of "traffic barrier height, offset, and shoulder width" were not significant, but their interactions were statistically significant in the collision severity prediction model. The severity of these collisions were further influenced by factors such as "rollover, side slope height, alcohol participation, road surface conditions, and posted speed limits". In this study, random parameters were determined to be the best model for the impacts of "gender, truck traffic count, and time of day".

Darban Khales et al. developed "a random-parameter ordered probit model" using 2015-2016 collision database from New Mexico Department of Transportation to better understand the crash severity of teenage and older drivers (10). Two different sets of models were developed for the aforesaid age groups and were evaluated using likelihood ratio. The models were then compared to a single system that included both ages. In addition, they compared the random-parameter to a fixed-parameter ordered probit for both age groups. For both cases the findings were improved when the probit was arranged by separate random parameters. The results show that gender, age, vehicle type, lighting condition, weather, speeding, alcohol or drugs use, seatbelt use, and driver inattention were all significant for both age groups in terms of predicting drivers' injury severity. Driver inattention played a significant role in the older driver model. Marginal effects were used to assess the influence of accident factors on injury severity. The findings show that the influence of contributing variables on the severity of driving injuries varied significantly between teenage and older drivers.

Eboli and Forciniti examined data from two-vehicle traffic crashes in Italy in 2016. They also looked into different elements that impact traffic collisions, such as vehicle, driver, road, and environmental risk factors, which are evaluated using logistic regression models (11). They evaluated the impact of external environment, road, vehicle characteristics, driver's characteristics, and specific situations that contribute to traffic accidents. In addition, the combination of traffic circumstances causing the collision (e.g., a car in each combination traveled normally, while the other car performed an improper action such as being distracted, not maintaining a safe distance, speeding, etc.) was considered. The findings demonstrate that the variables that have a major impact on collision severity vary based on the combination that lead to the incident. The results of the presented models may be used to characterize different types of collisions and determine which aspects should be evaluated and improved in order to lower the severity of traffic collisions and improve the safety. The problem of unobserved heterogeneity is a limitation of the current study.

Palumbo et al. studied age-related diseases, and how they might be linked to driving decrease or cessation, as well as increased collision risk (12). Their main goals was to interpret populationbased rates of senior driver licensing as well as collision and movement violation rates per driver. During the years 2010–2014, they looked at individual's driver license, traffic citations and collisions using New Jersey statewide data associated with senior drivers (65 years and over) and a control group drivers with 35–54 years old. Poisson regression was developed rate ratios (RR) were obtained for collisions and moving infractions. The findings show that a valid driver's license was held by 86% and 71% of senior males and females, respectively. With substantial variations by gender, senior drivers had 27% lower crash rates and 40% higher fatal crash rates per-driver compared to the middle-aged drivers. Older drivers had 72% fewer moving violations than middleaged drivers. Most of the seniors had a driver's license, however there was a considerable variance by age and gender. When compared to middle-aged drivers, older drivers had a greater risk of fatal collisions but a lower rate of moving infractions. Future study is needed to determine the extent to which senior individuals drive and to discover ways to minimize the risk of collisions and injuries that arise from them. The three main limitations are: driver exposure, reliability of self-reported exposures, and deaths to license holders may not always be reported.

Fraade et al. examined the risk of vehicle collisions among senior licensed drivers who were diagnosed with dementia. For this retrospective cohort research, data were obtained from a health maintenance group called Group Health (GH) in Washington State (13). 29,730 GH members aged 65–79, with a valid driver's license, and lived in the State during 1999 to 2009 were eligible to be included in this study. Police reported collision and licensure data were connected to participant health records. They utilized a "Cox proportional hazards model with robust standard errors" to estimate the collision risk of senior drivers diagnosed with dementia compared to a control group consisting of senior drivers without dementia. The research also accounts for recurring crashes, age, gender, depression, history of alcohol abuse, medicines, and comorbidities and were all factored into a multivariable model. The results show that before or during the research, about 6% of the participants were diagnosed with dementia. The accident rate, according to the police, was 14.7 per 1000 driver-years. When comparing senior drivers with dementia to the control group, the adjusted hazard ratio of a collision was 0.56. On-the-road and simulator studies revealed that older individuals with dementia had diminished driving skills and capacities. The decreased accident risk shown in this study might be due to preventive measures such as limiting driving among senior individuals with dementia. It is suggested that future studies investigate the influence of driving risk reduction methods at the time of dementia diagnosis on collision risk reduction. Some of the limitations include lack of information about vision issues and diminished driving exposure.

Guo et al. investigated the impact of age on the likelihood of an accident caused by driver distraction (14). For the "Second Strategic Highway Research Program Naturalistic Driving Study", 3542 volunteer drivers were recruited for up to three years and their driving data including behavior and performance were gathered constantly using multiple sensors and cameras on site. The videos were used to identify secondary task involvement at the start of collisions and during regular driving periods. The prevalence of secondary tasks as well as crash odds ratios were estimated using a case-cohort methodology for four age groups of 16-20, 21-29, 30-64, and 65-98 years old. The study only included serious collisions that resulted in property damage or were of a greater severity. In conclusion, distraction which was induced by the secondary task represented a constantly larger risk for 16-30 and 65-98 years old drivers compared with middle-age drivers, despite the fact that older drivers were far less frequently engaged in secondary tasks than younger drivers. Drivers of all ages were influenced by secondary tasks with significant visual-manual demand (being on a mobile phone). Only particular age groups were at an elevated risk from specific secondary duties, such as operating in-vehicle equipment and talking/singing. Secondarytask involvement had a greater negative influence on teen, young adult, and elderly drivers than on middle-aged drivers. Drivers of all ages are affected by visual-manual distractions, although young drivers may be more affected by cognitive distraction. The visual-manual activities associated with these technologies significantly enhance danger for all drivers, hence vehicle design requirements and policies should be broadened to include drivers of all ages.

Stutts et al. examined the elements that increase the probability of a motorist being involved in a sleep-related collision (15). In the case study, 312 drivers were classified as sleeping at the time of the incident on police records in recent North Carolina collision dataset, while 155 drivers were reported as weary. 529 drivers who had been in recent collisions but had not been classified as sleepy or exhausted, and 407 drivers who had not been in recent collisions served as controls. The case study also consisted of a brief phone interview with the drivers. The results show that drivers with night shifts, multiple jobs, and other atypical work patterns were more common to get in sleep-related incidents. These drivers slept for less hours on average, had not only lower sleep quality, but also felt sleepier throughout the day. In addition, these drivers were used to driving late at night, and found to have more driving incidents due to drowsiness. In comparison with the drivers with no sleep-related collisions, they had been awake and driving for longer periods of time, had slept less hours and had higher chance of taking soporific drugs the night before the collision.

Chevalier et al. tried to understand if a decrease in speeding is a part of the self-restrictive driving behavior shown in older drivers with impaired visual and cognitive function (16). Over the course of a year, driving data of 182 participants with 75-94 years old were obtained. Driving speed was calculated using GPS location as well as speed limit information was obtained from a service provider database. "Driving 1 km/h or more, with a 3% tolerance, above a single speed restriction, and averaged over 30 seconds", was considered as a speed occurrence. Almost all of the participants (99%) took part in speed events. Although 16% to 31% of subjects had a significant reduction in visual or cognitive functions over the course of the year, these decreases were not linked to a change in speed events. Findings of this study show that speeding tended to be more common in the younger age groups, but less so among the oldest drivers, who had a 7 percent lower rate of speed incidents per year older. During a 12-month monitoring period, senior drivers with poor function had less speed occurrences. The weekly distance travelled fell by around 0.45 km over the course of the year. Reduced function was not significant in predicting the speed incidents' involvement when distance traveled was taken into consideration, indicating that senior drivers with lower functional abilities may be able to reduce speed occurrences by limiting distance traveled. These findings are critical in formulating legislation to address the speeding behavior of an aging population of drivers in order to minimize the number of collisions and fatalities. One of the limitation of this study is the exclusion of personality factor on speed incidents, however, personality quantification and measurement is not easily doable.

Senior drivers are susceptible to vehicle crash involvement while making a left turn movement at signalized intersections. Zafian et al. utilized SHRP2 NDS (Naturalistic Driving Study) data as well as NDS pre-screening/questionnaire data to analyze infrastructures as well as other factors causing older drivers to be involved in left turn collisions at signalized intersections (17). The NDS data includes intersection related crashes as well as near-crash events for two drivers' age groups of 65 years and above and 30 to 49 years old. Using video scoring of trips, more information was obtained regarding the trip conditions and intersections. In order to identify the most significant risk factors, regression models and machine learning algorithms were developed. In conclusion, a relatively small proportion of crashes were due to making a left turn at signalized intersections. The factors that are statistically significant determinants of collision risk for elderly drivers were more closely linked to cognitive and health issues rather than a design or an infrastructure issue. They concluded that research based solely on SHRP2 NDS data will not yield conclusive results or suggestions for infrastructure upgrades to help improve the safety of senior drivers making left turn movements at signalized intersections. Future study should continue to investigate the impact

of infrastructure in the collision risk for older drivers making left turns at signalized crossings. There should also be prospective approaches for gathering comprehensive older drivers' collision data on a larger scale. Based on the findings of this study, future research should also look into the physiological, cognitive, and behavioral aspects that affect older drivers' safety during junction left-turns.

To understand why senior drivers, aged 65 and over, had higher rates of crash-related deaths than middle-aged drivers, and were notably over-represented in incidents involving left turn movements at signalized intersections in the New England area, Knodler et al. used data from the "SHRP2 (second Strategic Highway Research Program) naturalistic driving study (NDS)" to examine the suitability of this dataset for investigating such research questions (18). To this end, NDS data was prepared to include collisions or near-crash incidents at signalized intersections with a driver aged 65 or above. Also, it included a sample of random baseline trips which were non-eventful. According to their findings, most senior driver collisions were found to be minor collisions with 70% of crashes were either leaving the roadway or hitting a curb. The majority of the statistically significant factors influencing older drivers' involvement in a vehicle-collision were connected to their health, as well as cognitive and visual issues that influenced their ability to watch incoming traffic and determine whether there is a sufficient space to perform the left turn. The study mentions that training programs for senior drivers with the purpose of improving their navigation at signalized junctions and left turn movements have been useful in assisting them in adjusting to their age-related restrictions. The minimal number of crashes in the dataset restricted the study's conclusions as well as the statistical significance of the findings. Because a limited number of trips, events, and collisions were included in this study, some of the findings may not be completely generalizable, and certain results may be biased by the small sample size.

Chiou and Chiang conduct a case study over a five-year period of collision data from Taiwan's Freeway No. 1 (2004 2008) to illustrate the applicability of a suggested methodology (19). Evaluating multi-period accident severity and frequency data, this study offers a novel "multinomial generalized Poisson model with error components and spatiotemporal dependency (ST-EMGP)". By providing a spatiotemporal function, the suggested model not only represents collision severity and frequency simultaneously, but also accounts for spatiotemporal dependence (i.e. temporal and geographical dependency). Using Akaike information criterion (AIC), and log likelihood test, the ST-EMGP model consistently outperforms the models that do not incorporate spatiotemporal dependency. The calculated ST-EMGP model demonstrates that temporal and spatial dependencies exist and are related. When time dependency is disregarded, spatial dependence may exaggerate its effect size but understate its impact range. Based on the regression outcomes, temporal effects were found to be greater in crash frequency and were mostly influenced by traffic factors; spatial effects were larger in severe crash severity levels and were primarily influenced by geometric configuration. The suggested model can elucidate the origins of spatiotemporal dependency, along with their consequences for collision severity and frequency. Future research can gather more panel collision data to look into the impact of ETC systems on crash severity and frequency, as well as use an improved segmentation approach that models a highway network as interchanges and segments, which improved the homogeneity of study spatial units.

Barua et al. analyzed the incorporation of spatial correlation using random parameters collision count-data models (20). They utilized three years of crash data gathered from Richmond and Vancouver cities in British Columbia, Canada, and three alternative modeling formulations to

evaluate the impact of spatial correlation in random parameter models. They also used a Markov Chain Monte Carlo (MCMC) simulation to estimate the proposed models in a Full Bayesian (FB) environment. All the models were similar according to the chi-square statistics and Deviance Information Criteria values. The finding show that, according to the parameter estimates, there was several traffic and road geometry variables that had a substantial impact on collision rates. Only 38.3% of the overall variability in the Richmond dataset was explained by geographical correlation including both spatial correlation and heterogeneous effects (Model C), indicating that heterogeneous effects and site variation likely captured the majority of the differences. The effects of geographical correlation were considerably evident in the Vancouver sample, with a high proportion of total variability (83.8%) explained by spatial correlation under Model C. It was also found that when the sample size was limited, the results of model estimation revealed that using spatial correlation increased the precision of parameter estimations marginally. However, not significant changes were observed in parameter estimations, and goodness of fit did not increase, indicating that the random parameters model with both spatial correlation and heterogeneous effects was not superior to other models tested based on the present datasets. As a result, more research with diverse datasets is required to have a better understanding of the additional benefits of include spatial correlation in a random parameters model. The main limitation was the sample size condition. To understand the additional benefits of integrating spatial correlation in random parameters mode, more study utilizing other datasets is necessary.

#### **3.2. Pedestrian Challenges and Perceptions**

Doulabi et al. analyzed data from surveys of 1001 older adults (65+) living in South Ontario, Canada by using high-dimensional data reduction techniques of factor analysis and structural equation modeling (21). They identified significant contribute factors leading senior drivers' to be involved in pedestrian incidents. Pedestrian incidents refer to both pedestrian-vehicle collision (being nearly struck or struck on a crosswalk) as well as fall incidents while crossing. The combined response variable of pedestrian incident is one of the min contribution of this research to the literature which allowed a more detailed investigation of pedestrian risk factors at crosswalks. In conclusion the findings demonstrated that the amount of difficulty in walking, crossing appraisal skill, and fear of falling all increased older persons' vulnerability to pedestrian incidents. Levels of risk-taking crossing behavior and pedestrian confidence, on the other hand, were not found to be among the major determinants. It was also shown that pedestrian accidents. Transportation authorities may utilize this data to prioritize their plans, policies, and initiatives aimed at improving the mobility and safety of senior pedestrians. Future research is suggested to determine the most effective ways for addressing the walking challenges of senior pedestrians.

Guo et al. thoroughly investigated factors leading to elder pedestrian incidents (22). Traditional modeling techniques such as logistic models were suspected to cause modeling errors because of the independence assumptions. To avoid this, Extreme Gradient Boosting (XGBoost) was utilized to simulate the classification issue of crash severity of senior pedestrians using Colorado crash data. Shapley Additive Explanations (SHAP) was used to understand the XGBoost model output and assess each feature's relevance to different levels of crash severity of senior pedestrians. Their results revealed that the most significant elements determining the probability of the three severity levels are driver characteristics, older pedestrian characteristics, and vehicle movement. The data includes the coordinates of the pedestrian collision site, which may be combined with other environmental elements in future study. Future research is suggested to consider the influence of

environmental factors such as economic characteristics of the area.

Casado-Sanz et al. examined how age affects the severity of pedestrian-vehicle collisions based on the road characteristics (23). Logistic regression was used to analyze incidents involving one car and one elderly pedestrian on Spanish crosstown routes during 2006-2015. This study concludes that Spain has witnessed a dramatic increase in traffic accidents in recent years, particularly on rural crosstown routes, and older population should be considered as a possible risk factor. Future studies were suggested to investigate the impact of physical severance index or other territorial factors related with pedestrian mobility on crosstown highways in more details.

Baker et al. investigated risk factors associated with older pedestrians' injuries and fatalities in Massachusetts (24). Findings show that driver inattention, failure to give right of way, and visibility difficulties were the most common causes of collisions. Their findings also showed that pedestrians over the age of 65 have been most frequently hit typically at crosswalks of junctions. They determined that the time of day (rush hour), the season (winter), and community factors (a higher percentage of racial minority residents, higher rates of disabilities, a lack of dementia-friendly community efforts, and a higher number of cultural amenities) have all been found to contribute in senior pedestrian collisions. To enhance senior pedestrians' safety, communities identified in this study require immediate attention from aging services, health, and transportation authorities. There were limitations found relating to data sources, their hierarchical approach to reporting geographic units, reporting inconsistencies in the greater Boston crash data, not taking a closer look at the range of non-fatal injuries in older pedestrians, and not having distinct codes for pedestrian mobility modes (walking, running, and cycling) at the moment of the collision. All these limitations should be addressed for future research.

Das et al. looked to design effective countermeasures to identify factors related to senior pedestrian incidents (25). Using data mining technique of Empirical Bayes (EB), they looked at three years of senior pedestrian fatalities from the 2014-16 US "Fatality Analysis Reporting System". The data showed pedestrians with 65 years and over account for around 20% of all pedestrian deaths in 2015 (1,002 out of 5,376). The findings revealed several patterns and risk factors for senior pedestrians, including segment-related crashes at night for male pedestrians with 65-69 years old, and backing vehicle-related crashes for female pedestrians with 79years and over. In addition, poor street lighting and crossing an expressway at night were other hazardous conditions to older pedestrians.

Tournier et al. examined older adults' difficulties with the key factors of pedestrian activity including walking, navigation, obstacle negotiation, and road crossing (26). Compared to younger pedestrians, senior pedestrians had slower walking speeds, less stable balance, ineffective navigation methods, and a higher number of dangerous road crossing behaviors as compared to younger pedestrians. These issues are connected to changes in sensory, physical, cognitive, and self-perception skills as people get older. Physical frailty as well as attention and visual impairments had a significant detrimental influence on the safety and mobility of older pedestrians, but the functions of self-regulation and self-evaluation have been still hardly recognized. All these factors must be considered not just when devising effective safety measures for senior pedestrians, but also when planning roadways and automobiles. Further study should address the impact of functional losses, particularly older people's knowledge of their diminishing skills and their effects on safety and mobility in more details.

Wilmut and Purcell investigated factors affecting older pedestrians' vulnerability on a road (27).

They considered all peer-reviewed articles with data on healthy senior individuals and some component of roadside behavior or road crossing. A total of 142 articles published up to 2020 were reviewed, with only 60 meeting the requirements for inclusion. Crossing at a recognized crossing site, crossing without a designated crossing location, and views or actions were among the articles identified. Their study results indicated that road crossing in older adults was influenced by a variety of individual (walking time, attitudes, time-to-arrival judgment, perceived behavioral control, cognitive ability, and waiting endurance), environmental (time of day, road layout, and weather), and task (vehicle speed, vehicle size, and traffic volume) constraints. It is necessary to make sure that authorized crossing places are accessible by allowing enough time to cross and allowing for nonrestrictive waiting times. Their study also showed that crossings that are signalized, need to be simplified and visibility must be improved. Where there was not a designated crossing point, a lower speed restriction is required, as well as the installation of pedestrian islands to create "stop" areas. Where there is no designated crossing location, educational-based initiatives may also assist the safety of older individuals.

Pulvirenti et al. studied how elderly pedestrians perceive pedestrian pathways considering their age-related losses in perceptual and physical skills, as well as their road-user experiences (28). Underlying this objective was to identify significant difficulties that senior pedestrians encounter on their daily walks. To this end, they collected and evaluated the major elements that impact senior pedestrians' perceptions of pedestrian routes. They also determined how these views dependent on human factors for different pedestrian profiles. Gender, road user experience, and age-related issues (hearing, vision, and mobility problems) were considered. The results of this study show that the seniors' opinions on important concerns of pedestrian pathways they frequently travel are strongly influenced by their gender, their experience as road users, and eye problems that impair proper perception regarding the road environment. This is critical for determining interventions and might assist traffic planners, engineers, and decision-makers in considering contributing variables when designing countermeasures. By having a larger and more representative sample of senior pedestrians, other significant concerns and profiles of vulnerable senior pedestrians might be uncovered. Furthermore, the restrictions connected with the individual survey sites were one of the limitations of this study.

Kim investigated the relation between senior pedestrian safety and their physical conditions at the junction level (29). He believes that senior pedestrians are highly vulnerable road related injury or death in case of pedestrian-vehicle collisions. This is due to a combination of factors, including increasing fragility as well as concerns like response time and street confidence. He used a multinomial logistic regression (MLR) modeling technique to identify the relevant variables that are unique to senior pedestrian collisions. The findings from his study showed that features like a raised median, 3-way junction, street tree, park, and recreational land uses help senior pedestrians feel safer. The model he used suggests that bus stops increase the probability of senior pedestrians' involvement in collisions, whereas junctions with crosswalks or colored crosswalks add to the safety of younger walkers but not to the safety of senior pedestrians. The findings of this study assist to enhance the present road system intended for vehicles and road users who are healthy and young, by providing insight into transportation initiatives such as Complete Streets and Vision Zero. This study was unable to incorporate the volume data in the normalization procedure due to a lack of data about pedestrians' traffic volume in the study region. This paper also did not include vehicle speed data into the analysis for the same reason. Before making a broad generalization that a decorative crossing helps to pedestrian safety, further research is needed to study the dynamics between road users and ornamental crosswalks, including walkers and vehicles.

Wei et al. investigated how the senior pedestrians choose which street crossing facility to use (30). The study included three different types of footbridges with different convenience levels. The safety of the crossing, on the other hand, was directly related to the length of time remained on the pedestrian green light. In addition, an adaptive self-potential (SP) survey was created to gather choice data from seniors with 60 years and over, and a multilevel logistic regression model was developed. Their findings revealed that safety and convenience had a substantial impact on facility selection behavior. The elderly's decision-making behavior in making trade-off decisions between safety and convenience was investigated further using multilevel logistic regression analysis. It is suggested that future research incorporate more parameters in the study. Future studies are also suggested to consider the time spent waiting for a traffic light as well as the distance between the footbridge and the intended crossing point. Because weather and traffic volume influence pedestrian behavior, the related variables should be included in the future SP surveys. To better understand the differences in behavior among different age groups, more data on middle-aged and young people should be collected in future studies.

Lobjois et al. were interested to see if traffic flow influenced the behavior and decisions of senior and younger pedestrians when crossing the street (31). They tested whether crossing decisions and the mean duration gap were affected by the pedestrians' position in the traffic stream in an interactive street-crossing challenge. The findings in the study showed that pedestrians, regardless of age, preferred a shorter time gap when choosing the second traffic interval over the first. It was found that traffic-related behaviors were not resulted in an elevated decision risk, contrary to earlier ideas. Their data also revealed that when the second interval was chosen over the first, the transition threshold from rejecting to tolerating temporal gaps was lower. By comparing distances between pedestrians, this increase in task constraints may assist both senior and younger pedestrians to make action choices more correctly and be more sensitive to traffic situations.

Lord et al. investigated the views of senior pedestrians on the quality and dangers of traffic crossings in Montreal, Canada (32). The research was developed based on the direct observations and questionnaires in order to gain a better knowledge of the link between older people's characteristics, crossing behaviors, and perceptions. They also looked at how individuals move through space is influenced by their knowledge of their surrounds, as well as their capacity to adapt to changes. Five old pedestrians' profiles were created in both urban and suburban settings. A questionnaire was used to assess a group of 181 senior pedestrians (aged 65 to 93, with an average age of 74). In addition to answering closed-ended questions, participants were asked to rate 17 environmental factors and risk behaviors on a scale of one to ten. The data were categorized into 6 categories using hierarchical cluster analysis (HCA) as well as principal component analysis (PCA) to establish and distinguish seven senior profiles. Logistic regression modeling technique was used to assess the likelihood of adopting various crossing behaviors. In conclusion, the research show that physical ability, age, and roadways' spatial arrangement were significant factors of road safety, illustrating the intricacy of the interaction between individuals and their settings. These profiles were investigated based on respondents' socioeconomic level and crossing behaviors. The findings show that the senior pedestrians have a larger range of risk perceptions in terms of crossing behaviors and kind of signalization at junctions. Even among seniors, risk perceptions differed considerably, which may have influenced their actions. While some of the observed behaviors matched respondents' expectations, the findings of this study imply that they only have a minor influence.

Dommes et al. evaluated the effectiveness of a training program for senior pedestrians including

educational and behavioral treatments to see if and how age-related disparities might be decreased at crosswalks after the training (33). A simulated street-crossing task was used to examine twenty seniors on their street-crossing behavior before, immediately after, and six months after training. To establish a baseline, 20 younger individuals completed the identical simulated activity. The training resulted in considerable short- and long-term advantages, owing to a shift in choice criteria among the seniors toward more cautious judgements. When compared to the younger group, the older individuals significantly improved their conduct, with no significant changes in the mean safety-related markers. The capacity of the older participants to account for the speed of the incoming vehicle, on the other hand, did not increase. Older individuals, in contrast to younger ones, were shown to make more risky judgments as the speed of vehicles increased, placing them at greater danger at high speeds. The data might indicate age-related cognitive and perceptual issues problems that are beyond the scope of behavioral or educational instruction. The current findings highlight the importance of speed as a danger factor for senior pedestrians, which should be addressed by appropriate speed reduction strategies such as road narrowing and speed ramps. There were limitations in this study, but despite them, the results are compelling enough to warrant further investigation into senior pedestrian training.

Cugnet et al. evaluated the usefulness of a vibrotactile device and examined the behavior of older pedestrians while wearing a wristband, which were meant to assist them in making safer streetcrossing decisions (34). Seventeen younger individuals (years 20-45) and forty older adults (ages 60-80) completed a street crossing task in a simulated environment. The scenario consisted of a two-way traffic and participants completed the crossing task with and without a vibrotactile wristband giving warning messages. The findings show that when participants wore the wristband, the percentage of judgments that resulted in collisions with oncoming automobiles decreased considerably. When the wristband was worn, there were fewer crashes in the far lane and when cars approached quickly, which was especially beneficial to extremely senior ladies. However, collisions did not go away, and replies that followed the wristband guidance increased to just 51.6 percent on average for all subjects. Despite this, all participants found the wristband to be useful and simple to use. Furthermore, future purchase and usage intention of such devices were higher among senior individuals. These discoveries might be useful in the development of technologies that allow automobiles, infrastructures, and people to communicate. There are several limitations that must be considered. This research presented a gap-acceptance simulation, which is different from the real-life. In addition, sample size was relatively small and participants subjectively rated the wristband on a questionnaire.

#### 3.3. Driving Simulation Studies

With the purpose of enhancing the South Korean driver licensing system, Hwang et al. studied the relation between visual acuities and driving performance (*35*). They conducted two distinct studies: static and dynamic visual acuity testing, as well as virtual reality (VR)-based driving performance assessments. To assess the driving performance, a driving simulator experiment was designed and developed based on driving behaviors in a variety of experimental settings, such as nighttime and daylight driving on a rural highway, as well as unexpected event circumstances. They discovered statistically strong evidence that poor vision hinders driving performance, and that driving behaviors varied considerably between groups with various vision skills, particularly dynamic vision. Using the standard deviation of speed, driving behavior were found to be strongly affected by visual acuities, particularly dynamic visual acuity which was especially noticeable in curving road segments during the daytime trial. These findings indicated that driving ability of

participants with reduced dynamic visual acuity were poor and dangerous. This proved that dynamic visual acuity levels are important and can be used to accurately predict drivers' performance. These findings imply that a test of dynamic visual acuity should be included in the South Korean driver licensing system to promote better and safer driving. Some of the limitations include the lack of enough sample to analyze the patterns in diminishing visual acuity. It should be noticed that driving in virtual environment is also not the same as driving on actual roads. This research demonstrates how dynamic visual acuity may be used to predict driving ability; however, more research is needed to demonstrate that dynamic visual acuity is a valid screening component that does not alter quickly in response to external situations or conditions.

Banerjee et al. studied drivers' braking behavior when the green light changes abruptly from yellow in a simulated driving environment (36). To this end, a red-light violation warning (RLVW) system was developed using connected and automated vehicle (CAV) technology. 93 individuals from various socioeconomic backgrounds drove a virtual network of downtown Baltimore. Distractions and head movements were observed using an eye tracking device. This study employed a "Lognormal accelerated failure time (AFT) distribution model" to determine speed reduction durations from the time the green traffic light changes to yellow until a minimal speed was attained. In the presence of an RLVW system, speed reduction durations were substantially greater at the red light meaning a longer length of time were taken to make a complete stop. The jerk study shows that the RLVW system causes an extremely dangerous motion at the start of the warning. However, without the RLVW system, a very unpleasant positive jerk happens closer to the signal due to abrupt acceleration, since the participants may have slowed down much at first. The system was able to draw the attention of the drivers, as most of them saw the displayed warning, according to gaze analysis. According to the findings, the presence of an RLVW system provides sufficient time for the vehicle to adjust their initial approach speed in order to stop properly at the signal, preventing potential junction collisions, and notifies the driver about traffic light changes.

Schneider et al. investigated how older drivers could enhance their scanning for possible danger in cars when approaching stop-controlled junctions, as well as secondary looks when circumstances hide potential threat vehicles (37). They employed micro-scenarios to teach senior drivers how to use secondary glances, lowering the risk of participant withdrawal due to simulator sickness. Furthermore, driver immersion levels ranged from low to medium across different training platforms. A total of 91 people aged 67 to 86 were randomly allocated to one of five groups. Among these, three groups received active secondary look instruction on a driving simulator. To be more specific, one group had training on a low immersion simulator and the other two received training on medium immersion simulators. PowerPoint presentation was used to train the fourth group, while the last group received no training. All participants were examined while wearing head-mounted cameras in their personal automobiles, following the training session. Their findings revealed that the 82% of medium immersion group had secondary glances which was the largest percentage among all groups. While 42% of the control group had secondary glances which was the lowest percentage compared to other groups. The findings showed that training programs utilizing micro-scenarios in medium and low immersion simulators can improve the rate of secondary glances without causing significant simulator sickness dropout rates. Older driver training programs based on simulators have been shown to increase the frequency of secondary glances taken by senior drivers for up to two years after the training. However, the necessity for a full-scale driving simulator, as well as participant dropout rates from training programs due to simulator sickness, continue to limit the usefulness of these options.

#### 3.4. Gaps in Previous Studies

Considering the aforementioned studies (section 3.1), it is clear that numerous studies have been conducted to develop crash severity prediction models. However, these models were mainly developed based on a dataset from a specific state and therefore the results cannot be generalized to other states. One possible explanation is that crash risk factors are expected to be sensitive to socio-cultural and demographic factors. Another limitation with prior study is that no holistic research methodology was employed in the literature that simultaneously identify risk factors using the crash data analysis and test them using a driving simulator to validate the results.

Crash data analysis allows researchers to identify the risk factors and participating conditions leading or causing drivers to be involved in vehicle collisions. However, no further understanding of their actual behavior can be found using the crash data analysis. In fact, the effect of confounding variables may be misleading in these conditions. Therefore, validating the results from crash data analysis using data from another geographical location with similar socio-cultural and demographic characteristics or using a driving simulator experiment is one of the main gaps identified in the literature.

In terms of pedestrian studies, there is very limited research on the preferences, needs, attitudes, and perceptions of senior pedestrians toward different pedestrian crossing facilities (such as signalized intersections, unsignalized intersections, roundabouts, and so on). The existing body of literature is mainly focused on pedestrian challenges and their crossing decisions and behaviors. Therefore, more research is needed to address seniors' needs and preferences to cross a wide range of pedestrian crossing facilities.

Several driving simulator studies have been conducted to test different driving scenarios which are not feasible in real life, however, the majority of these research studies were conducted for younger drivers compared to senior drivers. Due to the lower response rate among senior drivers due to simulator sickness, many researchers are reluctant to focus on senior drivers. However, more simulator studies are needed to identify drivers' risk factor under the challenging conditions identified by crash data analysis. The current study strives to contribute to the literature by addressing these gaps.

## 4. METHODOLOGY

### 4.1. Literature review and Stakeholder Engagement

This task was started by conducting a kick-off meeting with Tran-SET and project's committee to introduce the project objectives, initial research plan and obtain their feedback. During this task, an in-depth literature review was conducted to identify the most relevant recent studies to the scope of the proposed research that include:

- The circumstances and precipitating factors contributing to older roads users' crashes including driver, vehicle and road/environment factors.
- Recent analytical techniques related to the identifications of crash Hot-Spot locations.
- The effects of changes in the roadways design and traffic control devices on the drivers' behaviors and safety of aging population.
- Older pedestrians' preferences and needs to cross different types of pedestrian crossings safely.
- Preferences and challenges of disabled persons as roads' users.
- Older road users' awareness of their declining abilities and their effects on safety and mobility in Louisiana.

This task encompassed a wide-variety of engagement activities with relevant stakeholders as explained in step 5 of section 7 "Project-Specific T2 Plan".

## 4.2. Data

In this task, a sample of traffic collisions data that occurred in Louisiana was collected from Louisiana Department of Transportation and Development (LADOTD). Traffic collisions dataset contains valuable information regarding crash location, road type, weather and lighting conditions, type of traffic control, road surface condition, crash severity, vehicle type, and driving behavior.

The data were prepared and coded before the analysis. During this task, descriptive distributions and two-way analysis have been conducted to better understand the data and associations between all variables in the dataset.

## 4.3. Identification of Hot Spot Locations

This task included a wide variety of statistical methods to better analysis the crash dataset. First, collision prediction models were developed using state of art statistical techniques in order to study the association between the frequency and severity of traffic collisions involving older adults and a set of covariates (traffic attributes, road characteristics, built environment, etc.).

Hot spot locations were then identified to provide insights regarding the potential remedies needed to improve safety of older road users. A hotspot is defined as a location that has higher crash frequency than expected, given the underlying risk factors. Risk factors can be related to road design, road surface conditions, weather conditions, traffic control devices, and human or other related factors.

## 4.4. Self-reported Survey

In this task, a self-reported survey instrument was designed and conducted out among a sample of older road users. The survey includes the following sections.

- Demographic characteristics and health status of the participants,
- Older road users' awareness of their declining abilities and their effects on safety and mobility,
- The circumstances and precipitating factors contributing to older roads users' crash involvement,
- Older pedestrians' preferences and needs to cross different types of pedestrian crossings safely.

The design, development, test, and implementation of the survey followed a design-thinking and user-centered approach. Considering literature review and the objectives of this study, the survey design was conducted. Survey design and a pilot of the survey have been tested with an elite sample of older roads users, who have been requested to comment on the initial survey questions to ensure clarity and completeness. The final questionnaire form was distributed among a sample of older pedestrians across the country after the Institutional Review Board (IRB) approval was approved.

#### 4.5. Driving Simulator Experiment

To gain a better understanding regarding the effects of changes in roadways design and traffic control devices on older drivers' behaviors and safety, a driving simulator experiment was conducted using LSU driving simulator.

During this task, multiple scenarios containing different configuration of roads geometric design, various traffic signal timings and types, different traffic signs contents and sizes were examined. A sample of older drivers in Louisiana was invited to participate in the driving simulator experiment. Accordingly, their driving behaviors to these scenarios was carefully recorded and analyzed.

The stages to design and implement the driving simulation experiment included: (1) develop simulation scenarios, (2) identify the minimum numbers of scenarios to be tested using a factorial design, (3) Recruit participants, (4) train participants on how to use the driving simulator and explain the purpose of the study and their role, (5) conduct the driving scenarios and collect data, (6) calibrate and validate the collected data and (7) finally analysis the data and provide results, conclusions and recommendations.

To better identify the minimum number of scenarios that shall be tested, a factorial design was employed. A factorial design is one involving two or more factors in a single experiment. Such designs are classified by the number of levels of each factor and the number of factors. So, a 2x2 factorial will have two levels or two factors and a 2x3 factorial will have three factors each at two levels.

Typically, in our driving simulator experiment, there are many factors such as gender, age, physical condition (e.g., walking ability, vision problems, etc.), driving status, roads features which can influence the outcome of the experiment. Therefore, factorial designs are efficient and provide extra information (the interactions between the factors), which cannot be obtained when using single factor designs.

Regarding calibration and validation, following the literature, we conducted the required testing to validate our simulator. This includes (1) intrinsic validation and (2) validation by objective. According to intrinsic validation, the simulator is valid if, for example, the accelerations caused by the simulator corresponds to the ones caused by the same operation in the actual world. Validation by objective, means to verify the relevance of the tool for a particular usage.

It is worth mentioning that LSU driving Simulator, a full-sized passenger car (Ford Fusion) combined with a series of cameras, projectors and screens to provide a high-fidelity virtual environment that offers a high degree of driving realism. It provides a one degree of freedom motion simulation to make a driver experience similar driving efforts as in an instrumented vehicle. Its open architecture software tools allow for data collection during simulation experiments, and creation of new networks and virtually an infinite number of simulation scenarios. Vehicle simulation makes it possible for inexpensive alternatives and sometimes impossible (unethical or safety implications) field tests to be undertaken in the lab.

To meet the requirements of the Institutional Review Board (IRB) and obtain their approval to conduct experiments on human subjects, the research team explained to participants the objectives of this research, their role in the experiment, how to participate, how the collected driving behaviors will be kept anonymous. They were informed also that their participation in this study is voluntary and were given a consent form to sign upon their approval to participate in this study.

Descriptive analysis and two-way analysis were used as a preliminary step to analysis the collected datasets (crash data, survey and driving simulator). Then, considering the literature review conducted in task 1 of this project. Suitable multivariate techniques were identified that can be used to analysis each dataset based on the nature of dependent and independent variables and the correlations between them.

#### 5. ANALYSIS AND FINDINGS

#### 5.1. Results

#### 5.1.1. Crash severity Prediction Models

#### Data

The crash data used in the analysis of this study includes a total of 957 crashes involving older adults (+65 years). Figure 3 shows the proportion of missing values with empty cells (which were labeled as NA by the analyst). Five variables (i.e., pavement width, pavement type, median width, urban area, and road's functional class) were identified with the highest level of missing values (i.e., about 28%). Due to relatively small sample size, it was decided to remove these five independent variables instead of removing 28% of the data (268 observations).

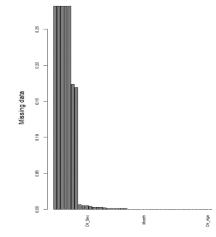


Figure 3: Proportion of missing values in the dataset.

Afterwards, observations with one percent missing values in the dataset were identified (30 observations) and were removed from the data. Therefore, in total, 30 observations were removed and 37 columns of data were remained with no missing values.

Since the data included many levels for some variables with low frequencies, the levels were modified by the research team to avoid model overfitting and other related issues. Also, at this stage many other variables were found to be irrelevant based on the literature review, so they were excluded from the model.

#### **Descriptive Statistics**

R software was used to conduct the analysis and all variables were dummified. The dataset used in this study included information on 957 traffic crashes that occurred in Louisiana involving older drivers. After data preparing and removing the missing values, a total of 927 traffic crashes were remained with no missing value on 21 independent variables. Figure 4 illustrates the distribution of at fault older drivers by age and gender which shows that the number of collisions decreases as the age increases. This might be explained due to drivers' exposure as drivers aged 65-75 years drive more compared to those aged more than 75 years. Also, in 60 % of the crashes, male drivers were at fault, while 40 % of crashes were due to female drivers' fault.

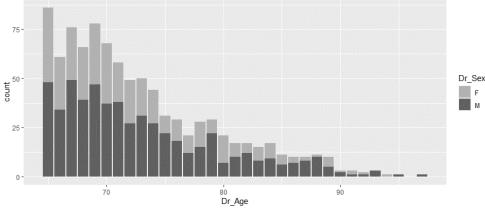


Figure 4: Distribution of older drivers at fault by age and gender.

The response variable of this study is crash severity which includes 674 observations with "No Injury/property damage only", 249 observations with Injury", and only 6 observations with "Fatalities". Considering very few observations in fatalities category, the response variable was combined into a binary response variable with two levels of "Fatalities/Injury" and "No Injury". As shown in Figure 5, the general trend is that crash severity increases as drivers' age increases.

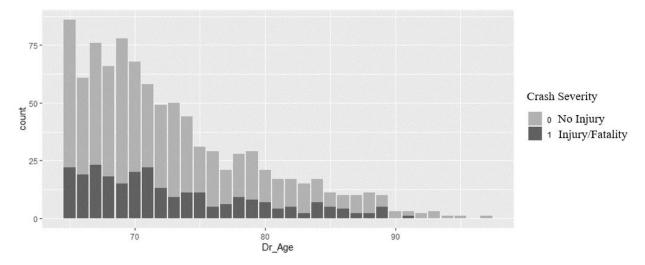


Figure 5: Distribution of crash severity (0: No Injury, 1: Injury/Fatality) by drivers' age.

About 68 % of crashes were at roads with unlimited access to roadway, 12 % had partial control (limited access to roadway), and 19 % of crashes happened in roads with full control access with ramp entrance & exit. The majority of crashes were reported to be on straight-level roads (85%). Although 36% of crashes occurred at normal road condition, about 58 % of them happened on a road under construction. It is worth mentioned that 80 % of collisions were on two-way roads in which 48 % and 32 % of them were on roads without and with a physical separation, respectively. More than half of the collisions (53 %) were on roads with speed limit ranging from 35 to 45 miles per hour (mph), however, 11 % and 10 % of crashes happened under 60 and 25 mph speed limit, respectively. Moreover, one third of crashes were found to be occurred at intersections (including signalized, roundabouts, stop-controlled intersections, etc.).

In terms of lighting condition, the majority of crashes were reported during daylight (83 %) possibly due to the fact that older drivers tend to avoid driving at nighttime, followed by 12 % under dark condition. Moreover, 62 % of crashes occurred at business areas (38 % in continuous business areas and 24 % in mixed business and residential areas).

Considering drivers' factors, about 30 % of drivers were in normal condition, while 53 % of them were inattentive. In 23 % of cases, the driver failed to yield, 23 % of crashes were due to drivers' careless operation, and 10 % of them were due to following a car too closely.

As shown in Figure 6, monthly fluctuations of crashes are similar in recent years, with relatively lower crash rates in the middle of those years compared to the beginning and end of the years. Also, hourly distribution of crashes show that older drivers' crashes mainly occurred between morning and evening peak periods.

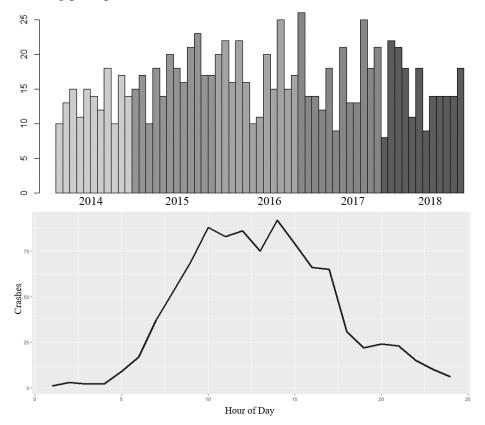


Figure 6: Yearly and hourly distribution of senior crashes in Louisiana from 2014-2018.

#### Generalized Linear Model- Logistic Regression

Figure 7 shows the analytical procedure used in this research. First logistic regression was performed using all independent variables. Then variable selection was done using stepwise regression. In the next step, the interaction effect between all the significant variables were studied. Similarly, stepwise regression was performed to identify best model possible. At the end, ANOVA analysis was performed to select the best model between the one with and without interaction term.

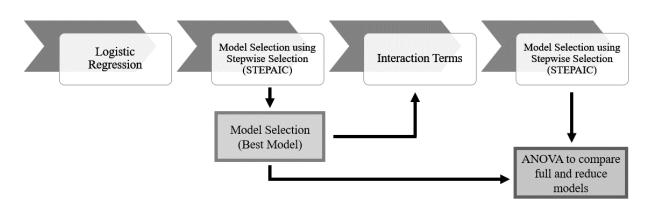


Figure 7: Analytical procedure used in this research.

To identify the effect of each explanatory variable on the response variable: crash severity of older adults (binary variable: Fatalities/Injury and No Injury), logistic regression analysis was performed. Significant factors' coefficients and associated standard error, significant variables were identified. Stepwise selection was then performed to select the best model with the least Akaike Information Criterion (AIC) value. The AIC is commonly used in stepwise procedure and other statistical methods as an estimate of prediction error and model quality for a given data (38).

Figure 8 shows the best model developed to predict crash severity among senor drivers in Louisiana. Table 1 shows the list of the variables found to be significant in the predictive model. The model findings shown in Figure 8 indicated that road geometry/separation, prior movement, lane departure, and gender were the significant variables affecting crash severity at 95 % confidence level. Also, alignment, crash location, and driver condition variables were found to be significant at 90 % confidence level. In addition, three interactions of alignment\*lane departure, high type\*gender, and location type\*driver condition were found to be significant.

Coefficients:					
	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-1.49846	0.42325	-3.540	0.000400	***
ALIGNMENTB	-0.14249	0.28079	-0.507	0.611832	
lane_departure1	1.00610	0.23481	4.285	1.83e-05	***
HWY_TYPE1	-0.26889	0.32819	-0.819	0.412621	
ALIGNMENTB lane_departure1 HWY_TYPE1 Dr_SexM ROAD_TYPEB ROAD_TYPEC	0.57363	0.21301	2.693	0.007082	**
ROAD_TYPEB	0.42579	0.36455	1.168	0.242804	
ROAD_TYPEC	0.38789	0.37102	1.045	0.295812	
ROAD_TYPED	0.99628	0.41260	2.415	0.015750	×
location_type1	0.53823	0.32615	1.650	0.098895	
DR_COND1	0.05105 0.92515	0.25534		0.841526	
DR_COND2	0.92515	0.36368	2.544	0.010964	×
PRIOR_MOVEMENT1	-1.30788	0.31199	-4.192	2.76e-05	***
PRIOR_MOVEMENT2	-0.94017	0.30384	-3.094	0.001973	**
PRIOR_MOVEMENT3	-2.05675	0.55531	-3.704	0.000212	***
PRIOR_MOVEMENT4	-0.60980	0.22875	-2.666	0.007680	**
ALIGNMENTB: lane_departure1	-1.58830	0.66819	-2.377	0.017453	×
HWY_TYPE1:Dr_SexM	-0.80461	0.42159	-1.909	0.056326	
location_type1:DR_COND1	-0.07045	0.40931	-0.172	0.863344	
location_type1:DR_COND2	-1.34059	0.69980	-1.916	0.055407	
Signif. codes: 0 '***' 0.	001'**'(	0.01 '*' 0.0	)5 '.' 0	.1''1	
(Dispersion parameter for	binomial 1	family taker	n to be 1	1)	
will devidence and 74	740				
Null deviance: 879.74					
Residual deviance: 782.92	on /22 (	degrees of f	reedom		
AIC: 820.92					

Figure 8: Logistic Regression Model.

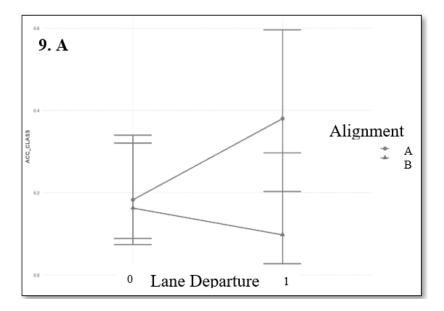
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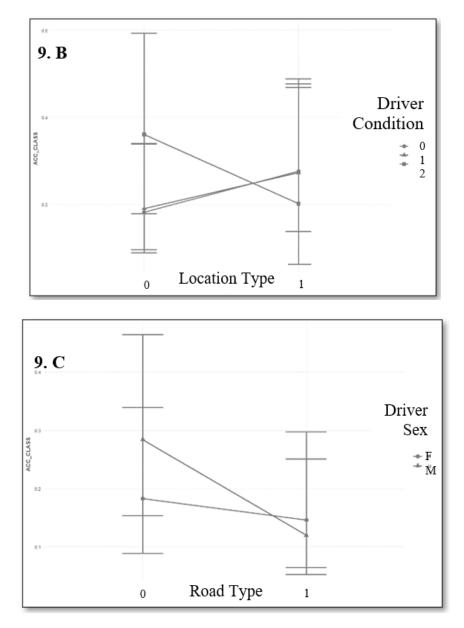
Table 1: Independent variables used in the analysis and their coding	g.
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Coding	Description
location_type1	Intersection (signalized and unsignalized)
location_type 0	Others
ROAD_TYPEA	One-Way Road
ROAD_TYPEB	Two-Way Road with No Physical Separation
ROAD_TYPEC	Two-Way Road with A Physical Separation
ROAD_TYPED	Two-Way Road with A Physical Barrier
AlignmentA	Straight-Level
AlignmentB	Others
HWY_TYPE0	Interstate/Highway
HWY_TYPE1	Others
Prior_Movement0	Proceeding Straight Ahead

Prior_Movement1	Changing Lanes On Multi-Lane Road
Prior_Movement2	Making Left Turn
Prior_Movement3	Making Right Turn
Prior_Movement4	Others
Lane_departure0	Not likely a Lane or Roadway Departure
Lane_departure1	Likely a Lane or Roadway Departure
DR_COND0	Normal
DR_COND 1	Inattentive
DR_COND 2	Others
Dr_SexM	Male
Dr_SexF	Female

By looking at the following interaction plots, alignment\*lane departure plot shows that crashes that were not due to lane departure were not affected by the road alignment considerably. However, there were more severe crashes when the lane departure happened on a straight level road (Figure 9.A). The highway type\*gender interaction plot shows that male had much higher chance of severe crashes on interstate/highway road type, while female had more probability of severe crashes on other road types (Figure 9.B). Location type\*driver condition interaction plot shows that normal condition and inattentive/distracted drivers had more severe crashes at intersections compared to other places, while less severe crashes were at intersections due to ill/fatigue/drug/alcohol condition of drivers (Figure 9.C).





**Figure 9: Interaction plots.** 

Afterwards, ANOVA test was conducted to see whether there is a significant difference between the model with and without interaction terms. According to Figure 10, there is a significant difference between the two models given 0.0078 P-value. Therefore, full model (i.e., model with interaction term) has better performance than its counterpart. This can also be concluded by its lower AIC value of 820.9 compared to 826.7 for the model without interaction term.

Analysis of Deviance Table Model 1: ACC\_CLASS ~ ALIGNMENT + HWY\_TYPE + ROAD\_TYPE + PRIOR\_MOVEMENT + lane\_departure + location\_type + Dr\_Sex + DR\_COND Model 2: ACC\_CLASS ~ ALIGNMENT + lane\_departure + HWY\_TYPE + Dr\_Sex + ROAD\_TYPE + location\_type + DR\_COND + PRIOR\_MOVEMENT + ALIGNMENT:lane\_ departure + HWY\_TYPE:Dr\_Sex + location\_type:DR\_COND Resid. Df Resid. Dev Df Deviance Pr(>Chi) 1 796.75 726 2 782.92 4 722 13.828 0.007864 \*\* 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1 Signif. codes:

Figure 10: ANOVA test comparing logistic regressions with and without interaction terms.

To test the prediction performance, the model was tested on the test set (20% of the data) and 0.27 misclassification error rate was obtained. It was found that the error rate of the test set was very close to the error obtained from the training set (0.26). This implies that the model has a good prediction accuracy on the trained data as well as unseen data.

In the next step, the assumptions of logistic regression were tested on the interaction model. Variance inflation factor (VIF) was used as a measure of multicollinearity. According to Figure 11, all the values are below 5 and there is no evidence of multicollinearity among the significant variables. Figure 12 shows Binned Residual plot was used. It is expected that a reasonable model contains the majority of observations within its  $\pm 2SE$  band. Although the residuals increase as the expected value increases, it is not very severe and therefore there is no strong evidence of heteroscedasticity of the residuals.

<pre>&gt; vif(logitMod4)</pre>	
ALIGNMENTB	lane_departure1
1.3019	1.2806
HWY_TYPE1	Dr_SexM
2.5384	1.3733
ROAD_TYPEB	ROAD_TYPEC
4.3148	3.9785
ROAD_TYPED	location_type1
2.5798	3.1203
DR_COND1	DR_COND2
2.0797	1.7430
PRIOR_MOVEMENT1	PRIOR_MOVEMENT2
1.1090	1.1717
PRIOR_MOVEMENT3	PRIOR_MOVEMENT4
1.0614	1.1593
ALIGNMENTB: lane_departure1	HWY_TYPE1:Dr_SexM
1.3161	2.6145
location_type1:DR_COND1	location_type1:DR_COND2
3.3473	1.6321

Figure 11: Multicollinearity Assumption using VIF.

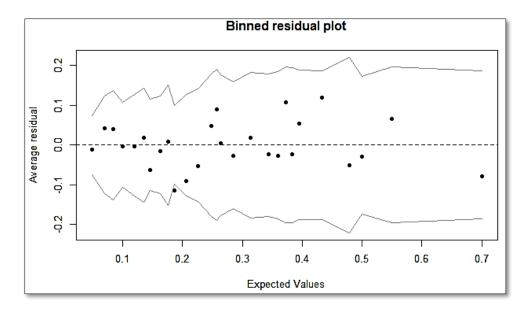


Figure 12: Binned Residuals to test Heteroscedasticity of residuals.

The model for older driver crash severity shows that four groups of variables were significant in predicting the two levels of crash severity (i.e., no injury and injury/fatality). The first group is related to the road infrastructure (crash location, road type, road alignment, and road geometry/separation). The second group refers to drivers characteristics (driver condition, and gender). The third contributing group found to include prior movement that driver performed which led to a vehicle collision as well as lane departure. The last group is the interactions of the above groups of variables including alignment\*lane departure, highway type\*gender, and location type\*driver condition.

Intersections including signalized and unsignalized were more prone to fatal/injury crashes compared to crashes that occur at other locations such as on-ramp or off-ramp, shoulder, turn-lane, and median of roads. More severe crashes were on straight level roads compared to curve or elevated road. One possible reason might be older drivers are more cautious while driving on non-straight roads leading to less number as well as less severe crashes. Interstates and highways had much severe crashes compared to lower roads' classifications, and as shown in the interaction plot, male drivers were more susceptible to fatal/injury crashes on highways and interstates compared to females. Two way roads were found to have more severe crashes compared to one way road, however, the level of severity was at its highest when a two way road had a physical barrier. After that, two way road without and with a physical separation, were more prone to fatal/injury crashes, respectively. This suggests that the separation of two way roads lowers crash severity of older drivers.

In terms of driver maneuvers, crashes that occur while an older driver is doing a lane departure contributes to a more severe collision, especially on straight roads segments. The probability of fatality/injury found to increase while collision occurred when at fault older drivers were proceeding straight ahead, however, the chance of no injury increases when crash occurred during a right or left turn or even changing lanes on a multilane road by at fault older driver.

Inattentive and distracted older drivers were much more probable to be involved in fatal/injury crashes. Male older drivers had more chance to cause fatal/injury crashes especially at interstates

and highways.

# 5.1.2. Hot Spot Locations

After geo-coding the crash data into ArcGIS software, about 17% of the data showed to have inaccurate coordinates. The rest were shown in the Figure 13 representing the spatial distribution of crashes in Louisiana. Figures 14, 15, and 16 show the intersection crashes which are signalized (Red Signal On, Yellow Signal On, Green Signal On, Green Turn Arrow On, Right Turn on Red, Light Phase Unknown, Flashing Yellow, and Flashing Red), unsignalized (stop/yield) control, and no-control across the state. Accordingly, 16.7 %, 11.8 %, and 28 % of crashes belonged to the aforesaid traffic-controlled intersections, respectively. In terms of shares of each urban areas within the state from total senior crashes, New Orleans has the highest share by having 19.9% of crashes. After that, Lafayette includes 13.5% of all senior crashes. Baton Rouge and Shreveport each consists of 10% of total senior crashes in Louisiana. Slidell (4.9%), Lake Charles (4%), Monroe (3.3%), Alexandria (3.2%), and Covington (3%) include small share of senior crashes. The rest of 20 % of crashes are spread across rural areas.

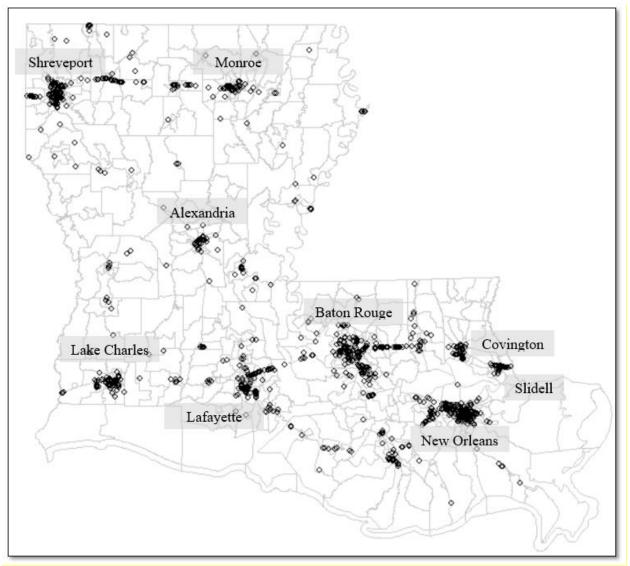


Figure 13. Senior drivers' hot spot location across Louisiana.

As shown in Figure 14, New Orleans (23%), Baton Rouge (21.6%), and Shreveport (11%) have the highest number of senior crashes at signalized intersections. These locations are known to have higher population density, land use diversity, and transportation network intensity compared to other urban areas in Louisiana. Almost every urban area within the state includes signalized intersection crashes, however, number of crashes at signalized intersections increase as population density, land use diversity, and transportation network intensity increase.

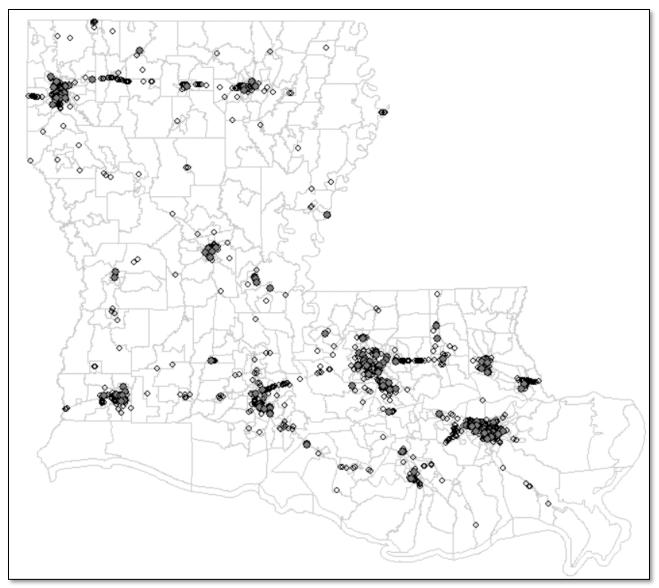


Figure 14. Distribution of senior crashes at signalized intersections in Louisiana.

As shown in Figure 15, crashes occurred at unsignalized intersections are more frequent in urbanized areas with high population and land use diversity such as New Orleans (22%) and Lafayette (21%). Baton Rouge (13%) has the highest unsignalized intersection crashes in Louisiana afterwards.

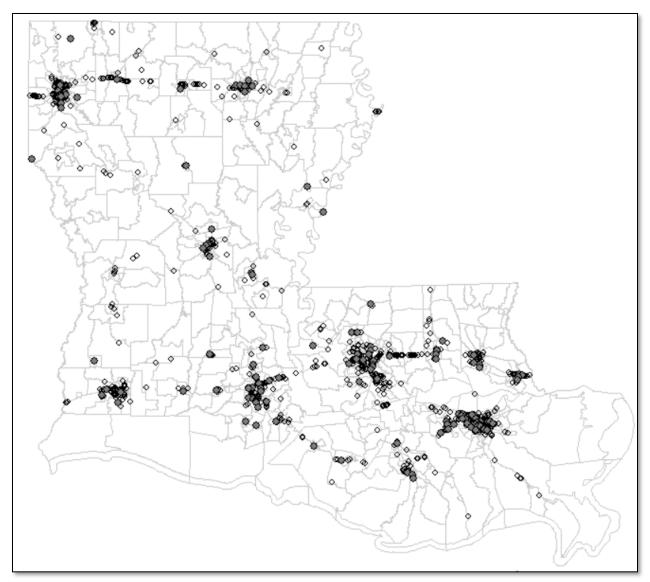


Figure 15. Distribution of senior crashes at unsignalized intersections in Louisiana.

According to Figure 16, share of no-control crashes are still higher in urban areas compared to rural areas. New Orleans (28.6%), Shreveport (10.5%), and Baton Rouge (9.5%) have the highest no-control crashes as well, follwoed by other urban areas.

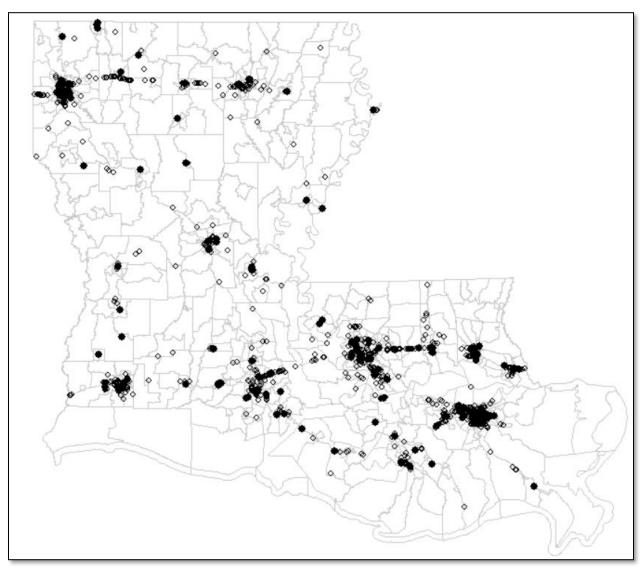


Figure 16. Distribution of senior crashes at no-control locations in Louisiana.

In this section, crashes at signalized and unsignalized intersections as well as no-control locations are investigated in more details across Baton Rouge, New Orleans, Lafayette, and Shreveport as these places were found to have more crashes compared to other locations within the state. This closer look at such places allows better understanding of the crash characteristics distributed across locations with more frequent crashes and provides beneficial insights regarding senior challenges by transportation facility in Louisiana.

Figure 17 shows signalized and unsignalized intersection crashes as well as crashes at no-control locations in Baton Rouge area. Jones Creek Rd is one of the links with the most number of crashes, especially from where it intersects to Tiger Bend Rd and Coursey Blvd (shown with a circle in

Figure 17). Although all three types of signalized, unsignalized intersections, and no-control crashes exist in this section of Jones Creek Rd, the majority of crashes were found to be no injury crashes. Another susceptible location to senior drivers found to be Sullivan Rd, especially from where it intersects to Hooper Rd and Greenwell Springs Rd and the crashes are spread around the T-intersection with the Wax Rd (shown with an ellipse in Figure 17). The majority of the crashes are at signalized intersections and have no-injury class of crash severity.

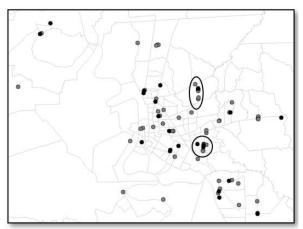


Figure 17. Baton Rouge area crashes at signalized intersections and unsignalized intersections (gray), and nocontrol locations (black).

Figure 18 demonstrates signalized and unsignalized intersection crashes as well as crashes at nocontrol locations in New Orleans area. There are several roads with intense concentration of senior crashes. Louisiana Ave, especially from where it intersects to Constance St and Robertson St, is one of the main hot spot locations in New Orleans (shown with an ellipse in Figure 18). French Quarter is another hot spot location that many no-control crashes occurred (shown with a circle in Figure 18). The share of no/injury and injury/severity is almost equal in this area. W St Bernard Hwy has also hosted many crashes specially the portion of this road where intersects to Lebeau St and Buffon St. A diverse mix of signalized, unsignalized intersection crashes as well as no-control crashes with mainly no injury and some injury/fatality can be observed in this road (shown with a dashed ellipse in Figure 18). William Blvd between 11<sup>th</sup> and 40<sup>th</sup> St is another hot spot location which includes signalized and unsignalized intersection crashes as well as no-control crashes and were mainly of no injury class of crash severity (shown with rectangular in Figure 18).

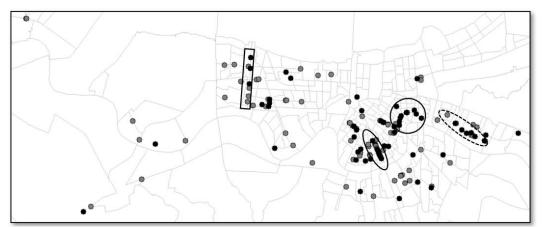


Figure 18. New Orleans crashes at signalized intersections and unsignalized intersections (grey), and no-

#### control locations (black).

Figure 19 depicts signalized and unsignalized intersection crashes as well as crashes at no-control locations in Lafayette area. There main road with intense concentration of senior crashes is Verot School Rd especially the section where it intersects with Beadle Rd and Millcreek Rd. The intersection of Ambassador Caffery Pkwy and Verot School Rd is one the most common crash location for senior drivers. Kaliste Saloom Rd from where it intersects with Miguel Dr and E Broussard Rd is another place with concentrated senior crashes (shown in Figure 19). According to the figure, the majority of crashes are at unsignalized intersection, also signalized intersection and no-control crashes exist. They were of no injury class of crash severity.

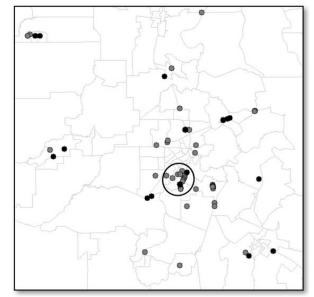


Figure 19. Lafayette crashes at signalized intersections and unsignalized intersections (grey), and no-control locations (black).

Figure 20 depicts signalized and unsignalized intersection crashes as well as crashes at no-control locations in Shreveport area. The intersection where E kings Hwy intersects with Shreveport Barksdale Hwy and Zeke Dr. is one of the locations with concentrated crashes (shown with a circle in Figure 20). These crashes were mainly of no injury class.

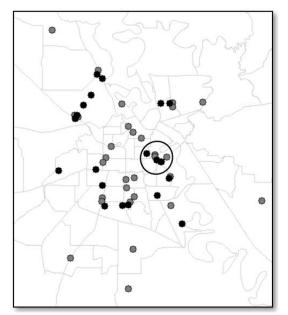


Figure 20. Shreveport crashes at signalized intersections and unsignalized intersections (grey), and no-control locations (black).

## 5.1.3. Pedestrian Survey

## **Survey Features**

The national pedestrians' survey in this study was administrated by Qualtrics Company. Qualtrics provides online data collection services from panels of general population which are representative of the target population (in this case older American pedestrians). Invitations to participate in this survey by Qualtrics through emails to collect complete responses while maintaining the privacy of the respondents, the survey included "Prefer not to answer" and "Not applicable" options wherever needed. This allowed us to require participants to complete each page of the survey before proceeding to the next page. To validate responses, multiple "soft launches" were run to verify that reasonableness of the initial responses. In addition, there were multiple questions randomly located throughout the survey that allowed us to check whether participants were consistent in their responses. Participants were also provided with incentives by Qualtrics ("may include cash, airline miles, gift cards, redeemable points, charitable donations, sweepstakes entrance, and vouchers") upon the survey completion.

As shown in Table 2, a total of 1000 older Americans (65 years or above) completed the pedestrian survey. It was found that the collected survey responses well represent the composition of older adults' population within the United States in terms of gender and age groups. According to the Table, 50.3% of participants were females, 37.4% were 65-69 years old, 29.8% were 70-74, 19.3% were 75-79, 10% were 80-84, 3.1% were 85-89 and 0.4% were 90 years old or over. One of the limitations of this study is underrepresentation of older adults with 85 years and which is most probably due to their smaller share of the population as well as lack of internet access. Future studies are suggested to consider multiple survey methods in addition to the online survey to avoid this issue.

Age by Gender	Male	Female	Proportion of survey respondents	Proportion of US older adults
65-69	164	210	37.4%	33%
70-74	145	153	29.8%	25%
75-79	115	78	19.3%	17%
80-84	57	43	10%	12%
85-89	15	16	3.1%	8%
90+	1	3	0.4%	5%
Proportion of survey respondents	49.7%	50.3%	100%	100%
Proportion of US older adults	49.2%	50.8%	100%	100%

 Table 2: Survey participants by age and gender.

In terms of place of residence, the survey sample is similar to the geographical distribution of older adults within the country. Share of each state in the survey was identified based on the proportion of older Americans living at that specific survey. Table 3 shows the State share from older Americans' population and the survey respondents which indicates that a well representative national survey responses were collected.

States	State share from older Americans' population	State share of the survey respondents	States	State share from older Americans' population	State share of the survey respondents
Alabama	16	15	New Jersey	28	27
Arizona	24	24	New York	62	62
California	108	108	North Carolina	32	31
Colorado	15	15	Ohio	39	39
Connecticut	12	12	Oklahoma	12	11
Florida	83	83	Oregon	14	14
Georgia	28	28	Pennsylvania	45	45
Illinois	39	39	South Carolina	17	17
Indiana	20	20	Tennessee	21	20
Kentucky	14	14	Texas	68	68
Louisiana	14	12	Virginia	25	25
Maryland	18	17	Washington	22	22
Massachusetts	22	23	Wisconsin	19	18
Michigan	33	33	Pooled Category	118	123
Minnesota	17	17	Tota1	100	100
Missouri	20	18	-	-	-

Table 3: State share from older Americans' population and the survey respondents.

#### **Demographics**

As shown in Table 4, 57% of respondents were married while and 30% of them were singles. In terms of education, half of the participants have college diploma or university degree while the other half have either high school diploma or apprenticeship/trades certificate or diploma. More than 80% of the participants were retired and only 14% of them were still in the work-force. When respondents were asked about their annual household income, only 4% preferred not to answer. Among those responded, household with 40-80 K, 20-40 K, and above 100 K annual household income had the largest share of the sample by nearly 36%, 25%, and 15% of the respondents. About 92% and 84% of the respondents claimed to have either 1 or 2 household members including themselves either one or two vehicles in their household. More than half and a quarter of the surveyed population were residing in suburban and rural areas, and only 18% of participants were living in urban areas. Nearly 77% of respondents were living in a house and 80% of them owned their place of residence.

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AHI Prefer not to answer         22         25         17         11         12         4         3         0         47           -         497         503         374         298         193         100         31         4         1000           Number of vehicles in household (VIH)         30         28         30         14         9         3         1         1         58           0         209         275         165         136         100         59         22         2         484           VIH 2         204         162         139         117         71         31         7         1         366           VIH 3+         54         38         40         31         13         7         1         0         92           -         497         503         374         298         193         100         31         4         1000           Number of adults in HH (AiHH)         455         470         342         275         179         94         31         4         925           1 to 2         0         0         0         0         0         1         1         0	AHI \$80Kto \$99,999	56	55	38	33	23	12		2	111
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	Home Ownershin-Rent									
	Home Ownership-Own	400	395	286	242	155	88	24	0	795

Table 4: Survey respondents' demographics

Not Applicable	6	9	5	4	3	2	1	0	15
Total	497	503	374	298	193	100	31	4	1000

#### **Pedestrian Challenges**

The first part of the survey addressed older pedestrians' walking and road crossing challenges related to their health condition as well as the effect of these challenges on their safety and mobility. As can be seen from Table 5, respondents were asked to report their walking, hearing, vision, and fear of falling issues.

#### Table 5: older pedestrians' walking or road crossing challenges

Statements	%Strongly Disagree	%Disagree	%Neutral	%Agree	%Strongly Agree
I often use a mobility aid device (such as walker, cane, wheelchair, or scooter) while walking on a street or a crosswalk	78.1	9.2	1.6	5.4	5.7
It is difficult for me to stay balanced while walking	64	15.8	9.1	8.7	2.4
My safety while crossing a street is negatively affected by my walking difficulties	63.2	14.9	8.6	10.7	2.6
I currently walk less than before due to my walking difficulties	55.6	16	6.5	14.4	7.5
I have difficulty hearing vehicles or people while walking on a street	69.1	19.3	5.1	5.3	1.2
It is hard for me to see and read road signs and markings at night	29.4	36.1	14.3	13.1	7.1
It is hard for me to distinguish fixed or moving objects even at night	29.7	38.6	14.3	12.1	5.3
My safety while crossing a street is negatively affected by my vision issues	59.2	22.2	9.1	7.3	2.2
I walk less as a pedestrian due to my vision impairment	67	22.3	6.3	3.6	0.8
I worry about falling while crossing a street	57.1	18.6	11	10.2	3.1
I worry about falling if I feel rushed while crossing a street	52.9	16.5	10.4	15.8	4.4
I walk less as a pedestrian because of my fear of falling	61.2	19.4	8.5	8.9	2
I have difficulty judging the speeds of oncoming vehicles	53.7	25.4	11.3	8.5	1.1
It is hard to judge when it is safe to cross when there is no signal	49.8	20.1	15.1	12.6	2.4
My safety while crossing a street is negatively affected by decline in my traffic judgement	59.2	22.9	10.6	5.7	1.6

According to Table 5, it was found that over 50% of the respondents strongly disagree that they have any walking, hearing, vision, and fear of falling issues that affects their safety and mobility while walking or crossing a street. In terms of walking difficulties, about 11% of the participants reported to often use mobility aid devices such as walker, cane, wheelchair, or scooter. They also reported to have difficulty to stay balanced while walking. About 9% of the respondents were neutral in terms of being balanced while walking, however, 7.5% of them disagree or strongly disagree to often use mobility aid devices. The rest of 1.6% were neutral to often use mobility aid devices. 78%, 13%, and 9% of the participants disagree/strongly disagree, agree/strongly agree, and neutral that their safety while crossing a street is negatively affected by their walking difficulties.

Although 13% of the participants agree/strongly agree that their safety while crossing a street is negatively affected by their walking difficulties, 22% of them agree/strongly agree that they currently walk less than before due to their walking difficulties. In contrast, 78% and 72% disagree/strongly disagree that their safety and mobility is negatively affected by their walking difficulties.

In terms of hearing issues, 88% disagree/strongly disagree to have any difficulty hearing vehicles or people while walking on a street. In terms of night-time vision issues, 65% and 68% of participants stated that they disagree/strongly disagree to have difficulties in seeing and reading road signs and markings and to distinguish fixed or moving objects, respectively. The rest of 35% and 32% of the above categories were neutral/agree/strongly agree to have the aforesaid night time vision problems. In response to the impact of the vision issues on the respondents' safety and mobility, 81% and 89% of the participants claimed that they disagree/strongly disagree to be negatively impacted, respectively.

Although 76% of participants claimed not being worried about falling while crossing a street, this number reduced to 69% when they felt being rushed while crossing a street. In general, 80% of the participants reported that they disagree/strongly disagree to walk less due to their fear of falling.

When participants were asked about their traffic judgements skills at crosswalks, 80% reported to not having any difficulty in judging the speeds of oncoming vehicles. However, 70% of them reported to be able to judge when it is safe to cross when there is no traffic signal. In addition, 82% of the respondents claimed that their safety while crossing a street is not negatively affected by any decline in their traffic judgement skills.

### Pedestrians' Awareness of their Declining Abilities

Figure 21 shows survey participants' opinion about the reasons that might causing them to be involved in pedestrian related crashes while crossing a road. Accordingly, 33% stated that decline in their personal abilities (such as walking, hearing, vision, judging abilities) or having a medical condition may cause them to be involved in pedestrian accident while crossing a road. In contrast, 34% reported that they disagree or strongly disagree with this statement. About 33% reported to be neutral. Figure 21 shows more details about the percentages of different agreement levels.

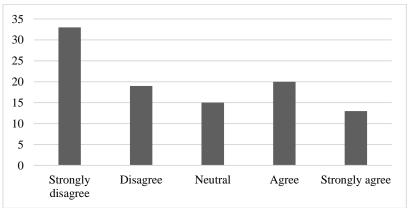


Figure 21: Participants' opinion about the reasons that might causing them to be involved in pedestrian accident while crossing a road (%).

When participants were asked to specify their level of agreement with "I walk less to compensate for my declining abilities to cross a street" statement regarding the actions they were currently applying to increase your safety as a road user, 15% claimed that they agree or strongly agree. About 11 % selected neutral. About 74% of the respondents disagree or strongly disagree to take such actions. Figure 22 shows more details about the percentages of different agreement levels.

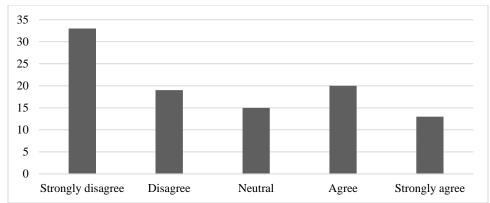


Figure 22: Responses to "I walk less to compensate for my declining abilities to cross a street" statement (%).

Participants were then asked to specify their level of agreement with "I walk or drive with another person to compensate for my declining abilities" statement regarding the actions they were currently applying to increase your safety as a road user. It was found that 9% of respondents agree or strongly agree. About 11 % were neutral. In addition, 80% of the respondents disagree or strongly disagree to take such actions. Figure 23 shows more details about the percentages of different agreement levels.

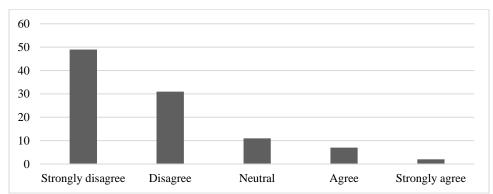


Figure 23: Responses to "I walk or drive with another person to compensate for my declining abilities" statement (%).

When participants were asked to specify their level of agreement with "I avoid complex intersections and traffic for driving and walking" statement regarding the actions they were currently applying to increase your safety as a road user, 21% of them reported that they agree or strongly agree. About 16 % were neutral. The rest of 63% of the respondents were disagreed or strongly disagreed to take such actions. Figure 24 shows more details about the percentages of different agreement levels.

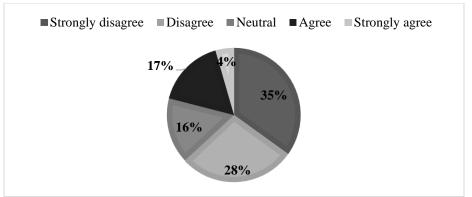


Figure 24: Responses to "I avoid complex intersections and traffic for driving and walking" statement.

When participants were asked to specify their level of agreement with "I select very large gaps in traffic to cross a road" statement regarding the actions they were currently applying to increase your safety as a road user, 24% were agreed or strongly agreed. About 38% were neutral. The rest of 38% of the respondents were disagreed or strongly disagreed to take such actions. Figure 25 shows more details about the percentages of different agreement levels.

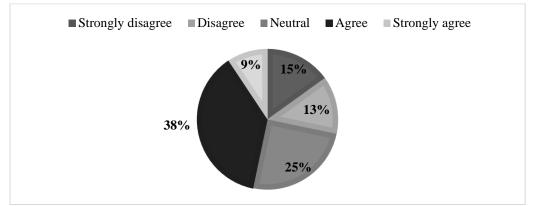


Figure 25: Responses to "I select very large gaps in traffic to cross a road" statement.

Participants were requested to assess their walking capability as a pedestrian. It was found that 85% evaluated themselves as good or very good. About 9% were neutral. The rest of 6% of the respondents scored themselves as bad or very bad. Figure 26 shows more details about the percentages of different agreement levels.

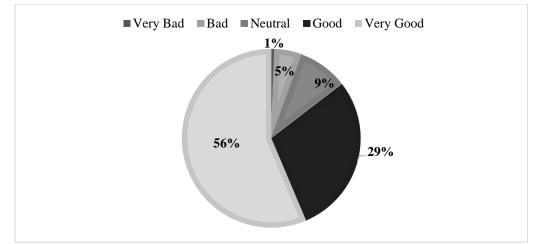


Figure 26: Self assessment of walking capability as a pedestrian.

When participants were asked to assess their crossing capability at road crossings as a pedestrian, 87% evaluated themselves as good or very good. About 9% were neutral. The rest of 4% of the respondents scored themselves as bad or very bad. Figure 27 shows more details about the percentages of different agreement levels.

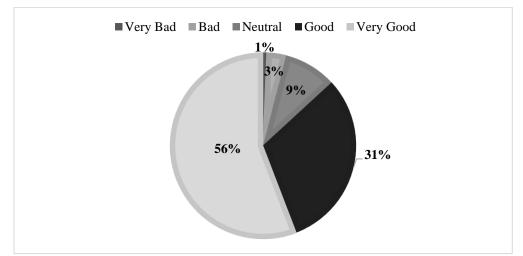


Figure 27: : Self assessment crossing capability at road crossings as a pedestrian.

When participants were asked whether they have any of the following condition that negatively impacts their ability to walk or drive, 77.5% reported not having any physical, medical, or disability conditions. However, the rest of participants (22.5%) reported that they have at least one of these limitations. Figure 28 shows more details about the percentages of different agreement levels.

- Physical limitation
- Physical limitation, Medical condition, Disability
- Medical condition
- Disability

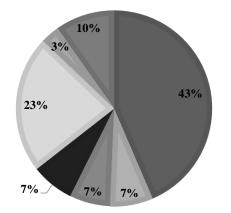


Figure 28: Health/medical conditions that negatively impacts their ability to walk or drive.

#### **Prior Involvements in Traffic Collisions**

As shown in Table 6, only 3% of the participants (i.e., 30 individuals) have been or nearly been involved in a pedestrian incident including pedestrian-vehicle collision and/or a fall incident. Males and females had nearly equal share of being involved in a pedestrian related incident. In addition, half of them were 65 to 70 years old and the other half were 70 to 85 years old. No participant with more than 85 years was involved in any pedestrian incidents. During the past five years, only 3 participants have been struck by a vehicle while walking or crossing a road, while 25 participants have nearly been struck by a vehicle at least one time. Moreover, 4 participants (2 male and 2 female) have fallen while walking or crossing a road.

- Phisical limitation, Medical condition
- Physical limitation, Disability
- Medical condition, Disability

#### **Table 6: Prior Involvements in Traffic Collisions**

V1: In the past 5 years, have you ever had an incident at a crosswalk? The incident can be being or nearly being involved in a collision as a pedestrian or even being fallen or nearly fallen on a crosswalk.

V2: In the past 5 years, how many times have you been struck by a vehicle while walking or crossing a road?

V3: In the past 5 years, how many times have you nearly been struck by a vehicle while walking or crossing a road?

Category	Male	Female	65-69	70-74	75-79	80-84	85-89	90+	Total
V1-Yes	16	14	14	4	5	7	0	0	30
V1-No	481	489	360	294	188	93	31	4	970
V2-0	15	12	13	4	5	5	0	0	27
V2-1	0	2	1	0	0	1	0	0	2
V2-2	1	0	0	0	0	1	0	0	1
V3-0	1	4	4	0	0	1	0	0	5
V3-1	7	3	3	2	3	2	0	0	10
V3-2	4	3	2	1	1	3	0	0	7
V3-3	1	0	0	0	0	1	0	0	1
V3-4+	3	4	5	1	1	0	0	0	7
V4-0	14	12	11	4	5	6	0	0	26
V4-1	0	2	2	0	0	0	0	0	2
V4-2	2	0	1	0	0	1	0	0	2

V4: In the past year, how many times have you fallen while walking or crossing a road?

Table 7 summarizes the results of possible reasons for involvements in vehicle-pedestrians collisions / falls. According to Table 7, the majority of pedestrian incidents were due to drivers' violation (70% of the pedestrian incidents or 22 out of 30 respondents). In 53% of cases, participants claimed that they saw the vehicle on time, but expected the driver to yield, stop, or go in another direction. Poor pedestrian marking and signage, crossing at a non-dedicated crossing, and unusual weather conditions were not major contributors in the reported collisions.

Table 7: Reasons for	r involvements in	traffic collisions/ falls.
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Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I did not see the vehicle before the collision	8	5	9	7	1
I did not see the vehicle in time to avoid being struck	9	5	11	4	1
I saw the vehicle on time, but failed to react quickly	7	9	9	4	1
I saw the vehicle on time, but misjudged the vehicle's speed	9	7	8	6	0
I saw the vehicle on time, but expected the driver to yield, stop, or go in another direction	4	4	6	11	5
The driver violated a traffic rule (such as driving above the speed limit and violating a traffic signal)	0	2	6	8	14
I was crossing at a non-dedicated crossing	17	5	6	2	0

The accident happened during unusual weather conditions	12	9	8	1	0
I was crossing at a dedicated crossing with poor pedestrian marking and signs	12	4	9	5	0

## Pedestrians' Attitude toward Different Crossing Facilities

### Signalized intersections

About 98% of the participants reported that they had walked on a crosswalk at a signalized intersection during the past two years. They were asked how frequently they have been crossing at signalized intersection before COVID-19 Pandemic (before March 2020) and during the COVID-19 Pandemic (after April 2020 till April 2021). Figure 29 shows their walking frequency pattern before and during the pandemic. Accordingly, daily, 2-4times a week, weekly, and 1-3 times per month categories show a reduction pattern, meaning those pedestrians who were actively walk before the pandemic reduced their walking activity. In contrast the frequency of walking patterns for monthly, 2-11 times per year, annually and less than once per year categories increase belongs to less than once per year category. This shows that senior pedestrians' activity level was affected by the pandemic.

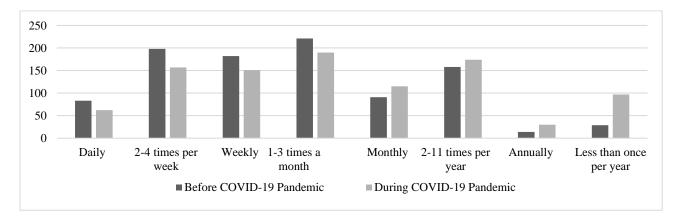


Figure 29: Walking frequency at signalized intersections before and during the pandemic

Eleven questions were designed to address senior pedestrians' challenges and needs at signalized intersections and are categorized in Table 8. Accordingly, more than 80% of the respondents either agree or strongly agree to feel safe while crossing at signalized intersections. Nearly 28% agree/strongly agree to not having enough crossing time at signalized intersections. About and 32% agree/strongly agree to get rushed in the presence of a pedestrian signal without countdown.

Statements	%Strongly Disagree	%Disagree	%Neutral	%Agree	%Strongly Agree
I feel safe while crossing the road at signalized intersections	0.1	1.2	13.9	61.9	22.8
Pedestrian signal timings are often too short for me at signalized intersections to cross the intersection considering my walking speed	18.0	34.6	19.0	21.3	7.1
I feel rushed in the presence of a pedestrian signal without countdown	14.8	30.8	21.9	25.2	7.3
I prefer intersections that do not have right-turn on red to avoid conflict with pedestrians	6.8	15.5	35.8	30.6	11.4
I have a conflict with left turn vehicles on the pedestrian right of way at signalized intersections	10.1	23.7	38.0	23.2	5.0
Turning vehicles do not yield to pedestrians on the pedestrian green signal at intersections	5.5	13.5	26.8	41.9	12.2
I have a conflict with bicycles on my right of way at signalized intersections	15.3	29.6	30.6	19.8	4.7
I have difficulty to see and read traffic signals and signs easily	49.5	37.3	8.7	3.3	1.2
I have difficulty to interpret traffic signals and signs at large intersections	50.0	35.1	9.1	4.9	0.8
It is difficult to cross the road at intersections lacking a median/island in the middle of the road as a refuge	24.2	29.5	24.3	18.5	3.5
I avoid crossing at large, complex, and irregular intersections	16.5	20.6	24.2	27.5	11.3

#### Table 8: Pedestrians' challenges and needs at signalized intersections

### Unsignalized intersections (2-way and all-way stop control)

About 93% of the participants reported to walk on a crosswalk at an unsignalized intersection during the past two years. They were asked how frequently they have been crossing at signalized intersection before COVID-19 Pandemic (before March 2020) and during the COVID-19 Pandemic (after April 2020 till April 2021). Figure 30 shows their walking frequency pattern before and during the pandemic. Accordingly, daily to 1-3 times per month categories had a reduction in their frequencies, while an increase is observed for monthly to less than once per year categories. The largest decrease belongs to week 1 to 3 times a month, while the largest increase belongs was for less than once per year category. Similar to the intersections, senior drivers walk less at unsignalized intersections during the pandemic.

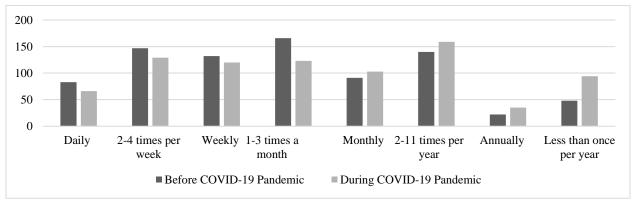


Figure 30: Walking frequency at unsignalized intersections before and during the pandemic

As shown in table 9, participants were asked to answer seven questions about their challenges and needs at unsignalized intersections. Accordingly, it was found that 67% and 74% indicated that they feel safe at 2-way and 4-way stop control intersections, respectively. About one third of the respondent reported that vehicles do not yield to pedestrian at 2-way and 4-way stop controlled intersections, while the other one third strongly disagree or disagree to this statement. The rest of participants were neutral to this statement. When they were asked about the lack proper pedestrian markings and signs at unsignalized intersections that they usually cross, 37% were in the favor of the statement, while 29% were opposed to this issue. About 47% of the respondents felt being pushed to walk faster at 2-way or 4-way stop control intersections, while 31% were disagreed or strongly disagreed to feel pressure to complete their crossing at these facilities. In addition, 43% preferred to have a curb extension in the roads with 2-way or 4-way stop control intersections to reduce crossing distance. Only 18% did not prefer the curb extension, and the rest of 38% were neutral toward it.

Statements	%Strongly Disagree	%Disagree	%Neutral	%Agree	%Strongly Agree
I feel safe crossing the road at intersections with 2-way stop control	0.6	6.1	26.2	54.4	12.7
I feel safe to cross the road at intersections with 4-way stop control	1.1	5.3	19.4	56.6	17.6
Vehicles do not yield to pedestrian at 2-way and 4-way stop controlled intersections	6.7	29.0	35.4	24.3	4.7
2-way and 4-way stop control intersections lack proper pedestrian markings and signs	5.9	23.5	33.1	32.7	4.8
I often feel pressure to walk faster at 2-way or 4-way stop control intersections	10.6	20.5	22.1	37.0	9.8
I prefer to have a curb extension in the roads with 2-way or 4-way stop control intersections to reduce crossing distance	7.0	11.2	38.2	34.5	9.0

Table 9: Pedestrians	' challenges and	needs at unsignalized	intersections
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#### Midblock crosswalks with flashing light

About 33% of the participants reported to walk on a crosswalk at a midblock crosswalk with flashing lights during the past two years. They were asked to report how frequently they have been crossing at a roundabout before COVID-19 Pandemic (before March 2020) and during the COVID-19 Pandemic (after April 2020 till April 2021). Figure 31 shows their walking frequency pattern before and during the pandemic at such crossing facilities. The results indicate that there is a reduction in all categories except for those walking monthly or 2-11 times per year. The largest decrease belongs to 1 to 3 times a month category, while the largest increase belongs was for less than once per year category. This result shows that senior Pedestrians has a noticeable decrease in crossing at midblock crosswalks with flashing light during the pandemic.

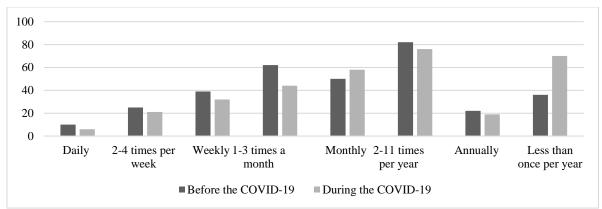


Figure 31: Walking frequency at midblock crosswalks with flashing light before and during the pandemic

As shown in Table 10, participants were requested to address their challenges and needs at midblock crosswalks with flashing light. About 68% of respondents stated that they feel safe to cross at midblock crosswalks with flashing light. About 31% and 43% were in the favor and oppose to the statement that they feel rushed while crossing the road at mid-block crosswalks with flashing lights. When they were asked whether vehicles yield to them at such crossing facilities, approximately equal percentages were in the favor, in oppose, and neutral to this statement. The same percentages were observed regarding their opinion about whether there are missing/inadequate mid-block crosswalks with flashing lights when they need those most. The last question was about difficulty of crossing the road at mid-block crosswalks with flashing lights without median/islands to allow crossing in two stages and the responses showed that 44% strongly disagree or disagree to it, while 29% agree or strongly agree with it.

Statements	%Strongly Disagree	%Disagree	%Neutral	%Agree	%Strongly Agree
I feel safe to cross the road at Mid-Block crosswalks with flashing lights	0	3.1	28.2	54.0	14.7
I feel rushed while crossing the road at mid-block crosswalks with flashing lights	11.3	31.6	26.4	28.5	2.1
Vehicles do not yield to pedestrians at mid-block crosswalks with flashing lights	8.0	28.5	35.0	23.9	4.6
I feel that there are missing/inadequate mid-block crosswalks with flashing lights when I need those most	9.8	23.0	37.1	25.2	4.9
It is difficult to cross the road at mid-block crosswalks with flashing lights without median/islands to allow crossing in two stages	13.5	30.7	27.0	26.1	2.8

Table 10: Pedestrians' challenges and needs at midblock crosswalks with flashing light

## Midblock crosswalks without flashing light

Nearly 42% of the participants reported to walk on a crosswalk at a midblock crosswalk without flashing lights during the past two years. They were asked about how frequently they have been crossing at a roundabout before COVID-19 Pandemic (before March 2020) and during the COVID-19 Pandemic (after April 2020 till April 2021). Figure 32 shows their walking frequency

pattern before and during the pandemic at such crossing facilities. The findings revealed that there was a reduction in all categories except for those walking monthly. The largest decrease belong to 1 to 3 times a month category, while the largest increase belongs was for less than once per year category. This shows senior pedestrians has a noticeable decrease in crossing at midblock crosswalks without flashing light during the pandemic.

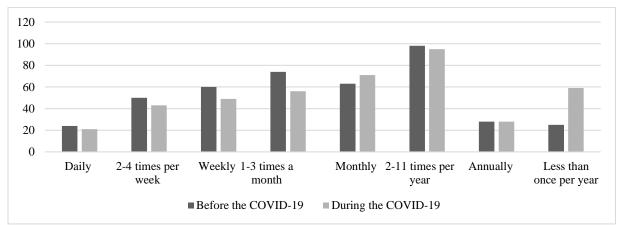


Figure 32: Walking frequency at midblock crosswalks without flashing light before and during the pandemic

Table 11 shows the ten questions that were asked to better understand senior pedestrians' challenges and needs at midblock crosswalks without flashing light. About 46.4% reported that they feel safe to cross at midblock crosswalks without flashing light. About 46% claimed that they feel rushed while crossing the road at mid-block crosswalks without flashing lights. Approximately 44% of participants claimed that vehicles yield with pedestrians at such crossing facilities agree/strongly agree. In response to the question that it is difficult for them to cross the road at Mid-Block crosswalks without flashing lights lacking median/island in the middle of the road to refuge, 40% of respondents reported that they agree/ strongly agree with this statement. About 60.5% of participants claimed that they agree/ strongly agree that these crossing facilities are not visible at night. In addition, 56.5% and 55% of the participants reported that Mid-Block crosswalks without flashing lights lack warning pedestrian signs and stop or yield sign, respectively. Moreover, 46% believe that such facilities lack pavement words/symbols to enhance pedestrian visibility. More than 66% of the respondents prefer to have a lower speed limit at Mid-Block crosswalks without flashing lights. Finally, 55% prefer to have a curb extension in the road at Mid-Block crosswalks without flashing lights to reduce the crossing distance.

Statements	%Strongly Disagree	%Disagree	%Neutral	%Agree	%Strongly Agree
I feel safe to cross the road at Mid-Block crosswalks without flashing lights	2.4	15.2	36.0	40.3	6.2
I feel rushed while crossing the road at mid-block crosswalks without flashing lights	7.8	22.3	23.7	39.8	6.4
Vehicles do not yield to pedestrians at mid-block crosswalks without flashing lights	5.9	20.6	29.6	38.2	5.7
It is difficult to cross the road at Mid-Block crosswalks without flashing lights lacking median/island in the middle of the road to refuge	7.3	25.4	27.3	32.0	8.1
Mid-Block crosswalks without flashing lights are not visible at night	3.1	12.3	24.2	44.1	16.4
Mid-Block crosswalks without flashing lights lack warning pedestrian signs	2.8	13.7	27.0	45.3	11.1
Mid-Block crosswalks without flashing lights lack stop or yield sign	3.1	12.1	30.1	42.9	11.8
I prefer to have a lower speed limit at Mid-Block crosswalks without flashing lights	2.1	8.8	22.3	45.7	21.1
Mid-Block crosswalks without flashing lights lack pavement words/symbols to enhance pedestrian visibility	3.1	15.2	35.5	38.4	7.8
I prefer to have a curb extension in the road at Mid-Block crosswalks without flashing lights to reduce the crossing distance	4.5	12.3	28.4	40.0	14.7

#### **Roundabouts**

Only 10% of the participants reported to walk on a crosswalk at a roundabout during the past two years. This small percentage can be attributed due to the less numbers of roundabouts in USA compared to other intersection types. Survey participants were asked regarding how frequently they have been crossing at a roundabout before COVID-19 Pandemic (before March 2020) and during the COVID-19 Pandemic (after April 2020 till April 2021). Figure 33 shows their walking frequency pattern before and during the pandemic at such crossing facilities. It was found that weekly to monthly as well as annually categories had a reduction during the pandemic, while other walking frequencies had an increase or constant frequencies during the pandemic. The largest reduction and increase of categories belong to monthly and less than once per year, respectively.

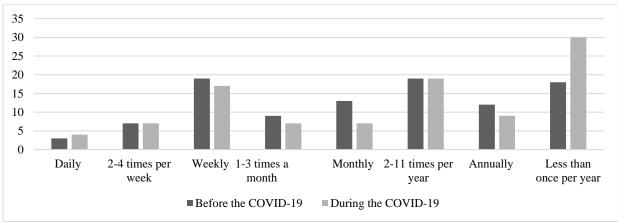


Figure 33: Walking frequency at roundabouts before and during the pandemic

As shown in Table 12, eight questions were provided to understand senior pedestrians' challenges and needs at roundabouts. About 40% of participants reported that they feel safe to cross at roundabouts. In addition, 49% of respondents claimed that drivers do not yield to pedestrians at roundabouts. When they were asked specifically about whether right-turn vehicles do not yield properly to crossing pedestrians at roundabouts, 46% of them stated that they agree/strongly agree. Only 19% of respondents claimed that it is easy to cross roundabouts without splitter islands (allowing to cross the road in two stages). While 48% stated that roundabouts have longer crossing distance compared to signalized intersections, which makes it inconvenient and unsafe for older adults. Moreover, 48% of the respondents repoerted that they are familiar with the operational rules of roundabouts. While 73% stated that pedestrians should have the right of way at roundabouts. About half of participants claimed that they avoid crossing the road on large roundabouts (with more than three lanes).

Statements	%Strongly Disagree	%Disagree	%Neutral	%Agree	%Strongly Agree
I feel safe to cross the road at roundabouts	2	26	32	31	9
Drivers do not yield to pedestrians at roundabouts	5	16	30	42	7
Right-turn vehicles do not yield properly to crossing pedestrians at roundabouts	6	13	35	40	6
It is difficult to cross roundabouts without splitter islands (allowing to cross the road in two stages)	5	14	36	40	5
Roundabouts have longer crossing distance compared to signalized intersections, which makes it inconvenient and unsafe for older adults	5	15	32	38	10
Pedestrians should have the right of way at roundabouts	2	2	23	51	22
I am not familiar with the operational rules of roundabouts, which makes it difficult and challenging for me to cross the road at roundabouts	17	31	25	23	4
I avoid crossing the road on large roundabouts (with more than three lanes)	6	16	29	37	12

 Table 12: Pedestrians' challenges and needs roundabouts

# 5.1.4. Driving Simulator Experiment

The objective of this section was to address the effect of roadways design and traffic control devices on the drivers' behaviors and safety of aging population. To this end, a 4.8-mile length network encompassing four four-leg intersections were designed to evaluate senior drivers' behaviors (e.g., left turn performance). The network was created based on a sample of Baton Rouge transportation networks including straight and curve roads, four-leg and T-intersections to resemble Baton Rouge network and provides a sense of familiarity in participants. Factorial design is used to identify the required number of scenarios to be tested. Therefore, two levels of traffic volume (low and high) and two levels of pedestrian crossing (with and without pedestrian crossing) were considered to evaluate senior drivers' behavior and performance under various intersection complexities. To test the impact of traffic control devices on senior drivers, permitted left turn signal was assigned to the four-leg intersections.

### **Participants**

A total of 30 senior drivers (14 male, 16 female) ranged in age from 65 to 77 years (mean of 70.57 and standard deviation of 3.6) participated in this study. Among these, 9 males and 6 females were able to complete the driving simulator experiment and the rest preferred to withdraw the experiment due to simulator sickness. After the initial analysis, one female participant was removed from the data, due to unrealistic driving behavior and outlier values. Table 13 and Figure 34 show the recruited and participated senior drivers' statistics and image, respectively.

	Participated	Completed	<b>Response Rate</b>
Male	14	9	64%
Female	16	5	32%

Table 13: Survey participants and response rates



**Figure 34: Driving simulator participants** 

## **Simulator Specifications**

This study used a full-size driving simulator located at the college of engineering at Louisiana State University. The simulator is high-fidelity and includes a full-cab vehicle (Ford) along with automatic transmission, adjustable seat, steering wheel, pedals, gear box, seat belt, and other components. The vehicle is capable to twist and move in three dimensions using its motion platform. A surround-sound system is also provided to support engine noise as well as surrounding environmental sounds.

Three CANON WUX450XT front-view projectors were used to create a large field view to participants. Drivers were receiving high-resolution footage which was created at 60 Hz frequency and high resolution of  $1920 \times 1200$  pixels. Another projector (OPTOMA TECHNOLOGY) was used for the rear-view with 60 Hz frequency and high resolution of  $1600 \times 1200$  pixels. To simulate the side view, two monitors were used with the same frequency and resolution. SimVista, SimeCreatorDX, and SimCreator software were used to develop the environment, scenarios, and to run the experiment, respectively.

# **Experimental design**

Participants first started with training and warm up session to get familiar to the vehicle. They drove about five to ten minutes in a network similar to what they will be driving for this experiment. After this session, they received a 15-minute rest and then those who were eligible to continue proceeded to the main experiment.

The experiment aimed to address the impact of intersection complexity and drivers' characteristics on drivers' behavior while making a left turn maneuvers at signalized intersections. Four types of intersection complexities were designed using two levels of traffic volume (low and high) and two levels of pedestrian crossing (with and without pedestrian crossing). "With pedestrian crossing" means pedestrians were given the right of way to cross at the same times that the subject vehicles are given the permitted left turn signal.

A two-way, two-lane (12 ft. lane width) road network including four intersections and a 45 mi/h speed limit was designed and developed. By approaching each intersection, drivers received a direction audio notifying them to make a left turn at the next intersections. Traffic signal was programmed to give the participants a permitted left turn signal as they are approaching. The oncoming traffic was generated randomly which were consistent within the traffic volume classes, but the number of vehicles were different between the two traffic volume classes. In total, the experiment took about 10 minutes.

At the end, participants who completed the experiment, were asked to fill a five-minute online questionnaire. The survey was developed using Qualtrics online survey platform to collect sociodemographic information, health condition, crash history over the past five years, as well as their stated driving preferences and behaviors.

# Data

This study includes two sets of data, survey data and driving simulator data. Survey data includes age, gender, health condition, education, driving experience (in terms of years), driving frequency, prior crash involvement and their stated preferences at different driving conditions.

The second part of data collected and analyzed in this study is driving simulator variables which are categorized into two classes of "pre-crossing" and "crossing" variables. "Pre-crossing"

variables are measures collected from the time drivers received direction audio to make a left turn at the next intersection to the time they actually took an action to make the turn. "Crossing" variables refers to the measures collected from the time participants initiated their left-turn movement to the time their signal was released automatically after making the turn. Driving simulator variables, their definition, and descriptive statistics are described in more details in the following sections.

## **Survey Descriptive Statistics**

Participants were asked about their health and medical conditions that may negatively impact their ability to drive. Seven percent of male participants reported to have vision problem especially at nighttime. In terms of marital status, 86% of participants were married, 7% of participants were single and the rest of 7% of the participants selected "Others". About 80% of participants had university degree, while the rest had college and high school diploma. In terms of employment status, 28% of the participants are still working, while the rest of them are retired. More than half of the participants (nearly 58%) reported to have more than \$100K household annual income, while the rest of them were equally distributed in "\$20-40K", "\$40-80K", and "Prefer not to answer" categories. 72%, 21%, 7% and of the participants reported to have two, one, and three vehicles in their household, respectively. In terms of household size, 78.5% and 21.5% reported to have 1-2 and 3-4 adults including themselves within their household. About 64%, 22%, and 14% participants have been living in suburban, rural and urban areas, respectively.

On average, participants had about 54 years of driving experience (standard deviation of 3.8). Nearly 29%, 43%, and 28% of the participants reported to drive 5-10K, 11-15K, and 16-20K miles per year. In terms of driving frequency, 21.5% of the drivers have been driving 2-4 times a week, while the rest of 78.5% have been driving on a daily basis. When participants asked to assess their driving capabilities, 64%, 29%, and 7% scored themselves as "Good", "Very Good", and "Neutral".

In terms of prior collisions senior participants had within the past 5 years, 65%, 14%, and 22% had 0, 1, and 2 collisions, respectively. Except for one of the drivers with one collision within the past 5 years, the others were at fault at least in one of the collisions and all collisions were property damage only (PDO). It should be noted that the driver with 2 collisions and being at fault for both of them evaluated his driving capability as "Neutral", while the rest considered their driving capabilities as "Good" or "Very Good".

## **Driving Simulator Descriptive Statistics**

As can be seen from the literature on this topic, driving simulator variables were collected at two stages of pre-crossing and crossing while intersection related studies are investigated (*38*). Table 14 shows the name and description of driving simulator variables used in this study. These variables allow us to study drivers' behavior before they made the turn as well as during the turning phase which is the main focus of this section.

Variable	Description
Approaching speed	The speed at the moment when drivers receive the left-turn audio
(mi/h)	direction at the next intersection
Maximum deceleration	The maximum deceleration value while drivers approached the
(m/s^2)	intersection
Waiting time (s)	The time duration that participants stopped at each intersection
Average turning speed	The average speed that drivers adopted while making the left turn
(mi/h)	
Turn duration (s)	The time duration that drivers started the left turn till the signal releases
Turn duration (s)	automatically
Maximum acceleration	The maximum acceleration value while drivers completed a left-turn
(m/s^2)	maneuver

Table 14: Definitions of the driving simulator variables used in this study

By looking at the simple statistics of the approaching speed, this variable has an average value of 34.54 mi/h and a standard deviation of 6.35. The maximum and minimum values were found to be 55.59 and 22.82 mi/h, respectively. This shows that some participants were driving above and below the speed limit (45 mi/h) as they approached the intersections. Figure 35 shows the boxplot of approaching speed across four different intersections. As shown in the Figure, the median approaching speed was at its highest while drivers approached the first intersection with low traffic volume and no pedestrian crossing. Also, lest variation is observed among the participants. By approaching to the second intersection with low traffic volume and pedestrian crossing, the median speed value decreased, while the variation in speed increased. Considering the third intersection with high traffic volume and pedestrian crossing, median speed remained constant approximately, however, less variation is observed compared to the previous intersection. The fourth intersection with high traffic volume and no pedestrian crossing, showed to have higher median speed as well as highest variation. Overall, the first and last intersections. In addition, no significant outlier was observed across all four intersections.

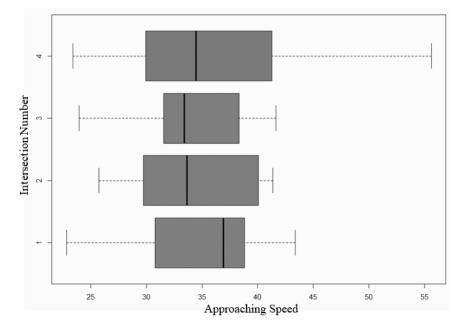


Figure 35: Approaching Speed at four intersections.

According to the simple statistics of the maximum deceleration, this variable has an average value of  $-0.01 \text{ m/s}^2$  and a standard deviation of 0.01. The maximum and minimum values were found to be -0.066 and  $-0.025 \text{ m/s}^2$ , respectively. Figure 36 shows the boxplot of maximum deceleration across four different intersections. As shown in the Figure, the first intersection (low traffic volume and no pedestrian crossing) contains two outliers that are very different with the rest of the data. After removing the outlier, the average, standard deviation, maximum and minimum values of deceleration rates are -0.01, -0.006, -0.002, and -0.025, respectively. Because all boxplots overlap and contain the median of the maximum decollation rates within their interquartile range, no significant difference of maximum deceleration rates is observed across all four intersections.

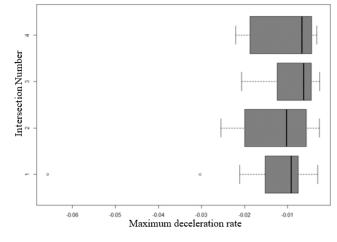


Figure 36: Maximum deceleration rates at four intersections.

Based on the simple statistics of the waiting time variable, this variable showed an average value of 3.98 seconds with a standard deviation of 4.09. The maximum and minimum values were found to be 16.33 and 0 seconds, respectively. Zero second waiting time was observed at the intersections with low traffic volumes that drivers slow down to get the desire gap and complete their turn maneuver and no stop (speed of 0 mi/h) was recorded. Figure 37 shows the boxplot of waiting time across four different intersections. According to the Figure, the median waiting time was at its highest while drivers approached the third and fourth intersections with high traffic volumes. Although the fourth intersection had slightly higher waiting time, the third intersection had higher variation. Comparing the first two intersections with low levels of traffic volume, drivers spent more time waiting at the second intersection (with pedestrian crossing) compared to the first intersection (without pedestrian crossing). By reviewing the videos of drivers' eye and head movements, it was found that drivers were scanning pedestrians' behavior to avoid pedestrian-vehicle conflict at the intersection.

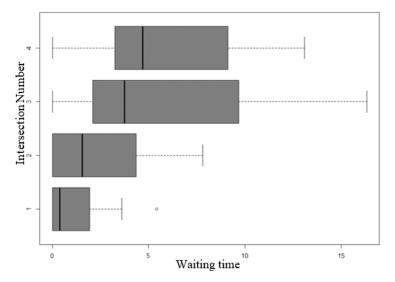
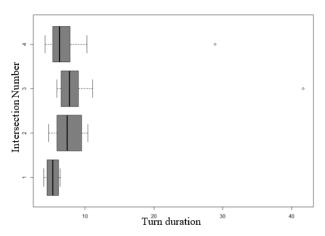


Figure 37: Waiting time at four intersections

Concerning the turn duration variable, this variable showed an average value of 3.98 seconds with a standard deviation of 4.09. The maximum and minimum values were found to be 16.33 and 0 seconds, respectively. According to Figure 38, there are some outliers at the third and fourth intersections with high level of traffic volume. This shows that some senior drivers were more cautious than the majority and behaved significantly different from others. The amount of variation was higher at the second intersection with low traffic volume and pedestrian crossing compared to its counterparts. This implies that when pedestrians were present and traffic volume was low, some senior drivers preferred to be more cautious toward pedestrians and allowed them to complete their crossing, in the expense of being exposed to the oncoming traffic for a longer time duration. One justification might be senior drivers felt more comfortable to prioritize pedestrians over completing their turn movement, due to low level of oncoming traffic.



**Figure 38Turn duration at four intersections** 

With respect to the maximum acceleration variable, an average value of  $0.08 \text{ m/s}^2$  with a standard deviation of 0.07 were obtained across the intersections. The maximum and minimum values were found to be 0.51 and 0.02 m/s<sup>2</sup>, respectively. According to Figure 39, some outliers were observed at three intersections which can be due to distinctive characteristics of the drivers. In addition, the

maximum acceleration value was found to have small variability except at the third intersection which has high level of traffic volume and pedestrian crossing. After that, the fourth intersection had higher variation followed by the second and first intersection. This implies the level of traffic volume and pedestrian crossing affected the maximum acceleration value while making the leftturn maneuvers.

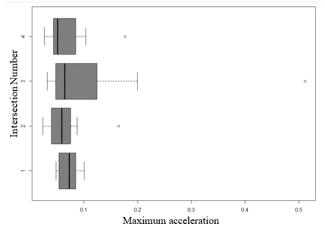


Figure 39: Maximum acceleration at four intersections

To better compare the aforesaid driving simulator variables' statistics, Table 15 provides mean and standard deviation values categorized into four levels of intersection complexity.

	Intersection	ı Complexity		Standard Deviation	
Variables	Traffic	Pedestrian	Mean		
	Condition	Crossing		Deviation	
A 1.	L	0	35.15	5.78	
Approaching	L	1	33.72	5.17	
speed (mi/hr)	Н	1	33.66	5.51	
(mi/ff)	Н	0	35.61	8.78	
NC .	L	0	-0.02	0.02	
Maximum deceleration	L	1	-0.01	0.01	
	Н	1	-0.01	0.01	
(m/s^2)	Н	0	-0.01	0.01	
	L	0	1.22	1.69	
W7-itin - time	L	1	2.71	2.83	
Waiting time	Н	1	5.96	4.85	
	Н	0	6.04	4.20	
	L	0	14.90	3.32	
Average turning	L	1	9.25	2.04	
speed (mi/h)	Н	1	8.96	2.58	
	Н	0	12.40	4.82	
	L	0	7.53	2.02	
True Areation	L	1	5.3	0.85	
Turn duration	Н	1	10.3	9.15	
	Н	0	8.13	6.18	
Maximum	L	0	0.07	0.02	
acceleration	L	1	0.06	0.04	
(m/s^2)	Н	1	0.11	0.12	

Table 15: Summerized driving simulator variables across different intersection complexities.

### **ANOVA Analysis**

In this section analysis of variance (ANOVA) is presented for pre-crossing and crossing variables. The reason to choose this analytical method is to identify differences in drivers' behaviors based on intersection complexity, age, gender, and health condition among the participants. Age variable was used as a factor variable with three levels of 1 (65-69), 2(70-74), and 3 (75-79).

According to Figure 40, ANOVA results showed that main effects of traffic volume had no significant on the approaching speed. It does make sense that pedestrian crossing at the intersection does not affect this variable, so it was not included in the analysis. However, age variable was found to be highly significant with an F-value of 7.6 and P-value of 0.0013. No interaction effect of age with other variables were found to be significant. It should be noted that gender and health showed no significant as well, so they were removed from the analysis.

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
Traffic	1	0.6	0.57	0.017	0.89561	
Age	2	502.4	251.20	7.607	0.00127	**
Residuals	52	1717.1	33.02			

Figure 40. ANOVA results for approaching speed variable

As can be seen from QQ-plot shown in Figure 41, the residuals are normal with few outliers at either end meaning the model meets the normality assumption.

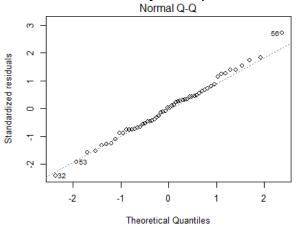


Figure 41: QQ-plot for checking normality assumption of approaching speed variable.

ANOVA results showed that there is a significant difference in approaching speed of the participants with different age groups but did not specify where the differences are. To do so, posthoc analysis was performed and is presented in Figure 42. The approaching speed of drivers with age classes of 2 (70-74) is significantly different with approaching of the first age group (65-69) and third age group (75-79). However, the approaching speed between the first and the third age groups were not significantly different from each other. The average approaching speed for first, second, and third age groups are 33, 40, and 32.7 mi/h, respectively. Therefore, those drivers with 70-74 years old had higher approaching speed than other participants who were younger or older than them.

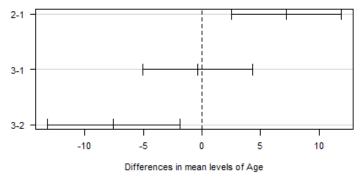


Figure 42: Post-hoc analysis for approaching speed variable

As shown in Figure 43, traffic volume (90% confidence level) and age (95% confidence level) were significant main effects in maximum deceleration rates drivers adopted when approaching the intersection. It does make sense pedestrian crossing at the intersection does not affect this variable and the analysis results confirmed so. Therefore, it is not included in the analysis. Traffic and age interaction were not significant.

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
Traffic	1 0	.000253	0.0002528	2.837	0.0981	
Age	2 0	.000772	0.0003860	4.331	0.0182	×
Residuals	52 0	.004634	0.0000891			

Figure 43: ANOVA results for maximum deceleration variable

As can be seen from the QQ-plot, residuals for this model are acceptable in terms of normality assumption as they are aggregated along the dashed line. Some outliers are also existing at either ends.

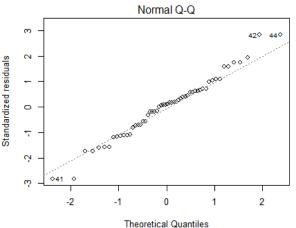


Figure 44: QQ-plot for checking normality assumption of maximum deceleration variable

As shown in Figure 45, post-hoc analysis for age variable depicts more significant difference among drivers with 70-74 years old with those with 65-69 years old. Although the difference among drivers with 70-74 years old is significant with drivers with 75-79 years old, the difference is much smaller compared to the previous pair. There was no significant difference in amximum deceleration rates among drivers with age groups 1 and 3.

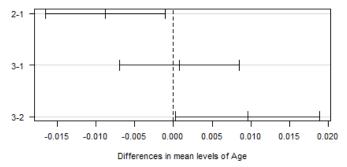


Figure 45: Post-hoc analysis for maximum deceleration variable

According to Figure 46, the main effects of traffic volume and health condition variables were highly significant at 95% confidence level on waiting time variable. No other variables showed to have a significant main or interaction effect.

Df Sum Sq Mean Sq F value Pr(>F) 22.536 1.71e-05 \*\*\* Traffic 1 228.0 228.02 Health 3 177.5 59.18 5.849 0.00164 \*\* 51 Residuals 516.0 10.12 Figure 46: ANOVA results for waiting time variable

According to Figure 47, the residuals are slightly right skewed, and some outliers can be observed at the right tail. However, the majority portion of the plot meets the normality assumption. This slight skewedness might be due to small sample size; therefore, it is suggested to collect more samples for future studies.

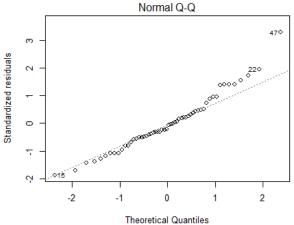


Figure 47: QQ-plot for checking normality assumption of waiting time variable

The left side image on Figure 48 shows that there is a significant difference in waiting time at intersections with low and high traffic volume as they do not include the zero value. In fact, waiting time was found to be 6 and 1.9 seconds at intersections with high and low traffic volumes, respectively. The right-side image in Figure 48 shows the most significant differences in waiting time belongs to drivers with heath condition level 1 (vision problem) had different waiting times compared to those with health condition levels 2 (no health issue) and 4 (medical condition). Moreover, drivers with health condition levels 2 (no health issue) had significant different waiting time with those with health condition levels 3 (vertigo).

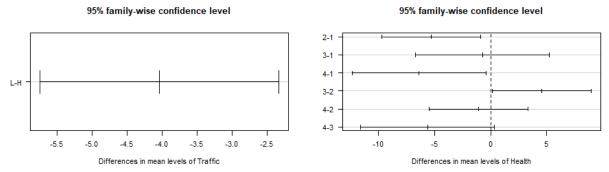


Figure 48: Post-hoc analysis for waiting time variable.

Figure 49 shows the main effects of pedestrian crossing, and age variables on the average turning speed that drivers adopted to complete their left-turn maneuvers. Main effect of pedestrian crossing was found to be highly significant at 95% confidence level, while the main effect of age was significant at 90% confidence level. No significant main or interaction effect were found with the level of traffic volume.

D	f	Sum Sq	Mean Sq	F value	Pr(>F)		
Ped	1	57.70	57.70	26.097	4.71e-06	***	
Age	2	11.03	5.52	2.495	0.0923		
Residuals 5	2	114.98	2.21				
Figure 49: ANOVA results of average turning speed variable.							

Based on Figure 50, the residuals for average turning speeds are slightly left skewed and some outliers were also identified. However, due to the small sample size those observations are kept in the analysis, and it is suggested to collect more observation for future research.

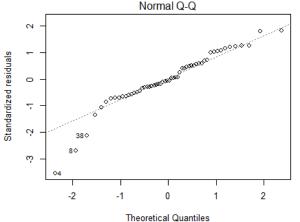


Figure 50: QQ-plot for checking normality assumption of average turning speed variable.

By looking at the 95% confidence level of pedestrian crossing variable on the average turning speed shown in the left side in Figure 51, it was found that there is significant difference as they do not include zero value. In fact, the average speed was 8.9 mi/h and 13.4 mi/h at intersections with and without pedestrian crossing, respectively. This show drivers adopted slower average speed when they saw a pedestrian crossing the road while making their left turns. As shown in the right-side image in Figure 51, no significant difference can be seen at 95% confidence level, but

at 90% confidence level, drivers with age group 1 (65-69) and 2 (70-74) had significant different mean turning speed. In fact, drivers with age group 1, had an average turn speed value of 1.5 mi/h, while their counterpart had a value of 13.2 mi/h.

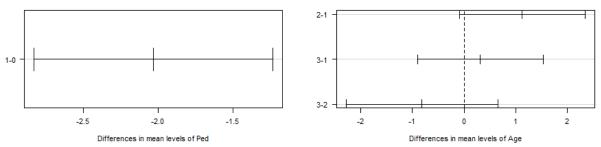


Figure 51: Post-hoc analysis for average turning speed variable

Based on Figure 52, turn duration variable were found to be affected by traffic volume at 90% confidence level. No other significant main effect and interaction terms, so the main two variables of traffic volume and pedestrian crossing were kept in the analysis. The average turn duration was 6.4 and 9.2 seconds for low and high traffic volumes, respectively.

Df Sum Sq Mean Sq F value Pr(>F) Traffic 1 109.4 109.45 3.518 0.0662 . Ped 1 67.6 67.64 2.174 0.1463 Residuals 53 1649.0 31.11

Figure 52: ANOVA results of turn duration variable

The QQ-plot in Figure 53 shows that turn duration residuals are normal and few outliers exists. Outliers are kept in the model due to the small sample size.

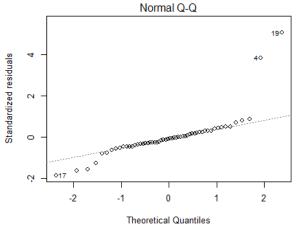


Figure 53: QQ-plot for checking normality assumption of turn duration variable

As shown in Figure 54, the result of maximum acceleration rate while making the left-turn movements shows that the main effects of traffic volume and health condition were significant at 90% and 95% confidence levels, respectively. All interactions between intersection complexity attributes (i.e., traffic volume and pedestrian crossing) with the health condition variable were significant at 95% confidence level. This shows that drivers' maximum acceleration rates while making the left-turn maneuver was highly affected by the intersection complexity and drivers'

health condition.

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
Traffic	1	0.00671	0.006705	2.840	0.098996	
Health	3	0.05997	0.019990	8.468	0.000149	***
Ped	1	0.00368	0.003680	1.559	0.218405	
Traffic:Health	3	0.04247	0.014157	5.997	0.001616	**
Health:Ped	3	0.04600	0.015335	6.496	0.000980	***
Residuals	44	0.10387	0.002361			
		• •				

Figure 54: ANOVA results of maximum acceleration rate variable

Similar to the previous variables, the residuals are nearly normal and few outliers can be detected based on Figure 55. However, all observations were kept in the analysis due to the small smple size.

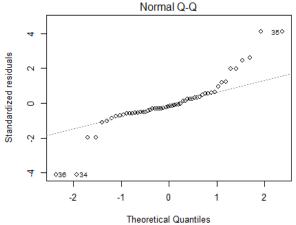


Figure 55: QQ-plot for checking normality assumption of maximum acceleration rate variable

Based on the 95% confidence level post hoc results shown in Figures 56 and 57, differences across different levels of the aforesaid significant main effects and interaction terms can be identified. Figure 56 shows the differences in mean levels of acceleration rates among participants with different health status. Accordingly, those who had health condition level 3 (vertigo) had different acceleration rate compared to those with levels 1 (vision problem), 2 (no health issue), and 4 (medical condition) of health condition. The average acceleration rate for these groups of health condition are  $0.19 \text{ m/s}^2$  (health condition level 3),  $0.087 \text{ m/s}^2$  (health condition level 1),  $0.065 \text{ m/s}^2$  (health condition level 2), and  $0.089 \text{ m/s}^2$  (health condition level 4), respectively. It should be noted that 78% of the participants reported to have health condition level 2, therefore small sample size in other levels of health condition which might affect the result.

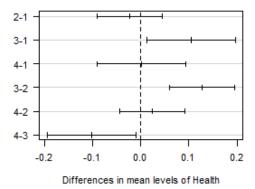


Figure 56: Post-hoc analysis for the main effect of maximum acceleration rate variable

As can be seen from the interaction plots in the left side image of Figure 57, the following traffic and health condition levels had significant different maximum acceleration rates. H:3-H:1, H:3-H:2, H:3-L:1, H:3-L:2, and L:4-H:3, where the letter refers to the traffic level (H: high, L: low traffic volume) and the digit refers to the health condition (1: vision problem, 2: no health issue, 3: vertigo, and 4: medical condition). According to the right side image of Figure 57 depicting health and pedestrian crossing interactions, the following pairs had a significant maximum acceleration rate while making the left-turn maneuvers. 3:1-1:0, 3:1-2:0, 3:1-3:0, 3:1-4:0, 3:1-1:1, 3:1-2:1, and 4:1-3:1 where the first digit refers to the health condition and the second one refers to the presence or absence of crossing pedestrians. These two interaction plots show that health variable plays an important role in maximum acceleration rates that senior drivers take in making the left turn, however, it is suggested that more samples to be collected to validate these results.

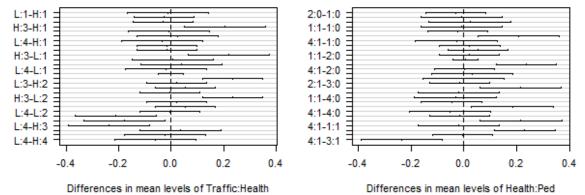


Figure 57: Post-hoc analysis for the interaction effect of maximum acceleration rate variable

### **5.2.** Discussion

#### 5.2.1. Crash severity Prediction Model

First, a sample of Louisiana crash data has been analyzed to identify significant risk factors causing older drivers' to be involved in traffic crashes. A high dimensional dataset was obtained from LA DOTD containing senior crashes from 2014 to 2018. Using statistical procedures and analyst judgment, a more manageable set of variables was included in the analysis. The variables included but not limited to drivers' characteristics, road features, maneuver information, and environmental factors. Variable selection (using STEPAIC) procedure was conducted to identify the most significant variables and avoid multicollinearity issue. After conducting several statistical methods using logistic regression and investigating the interaction terms, the results indicated that four groups of variables were significant in predicting the crash severity levels (i.e., no injury and injury/fatality). These factors were found to be 1) road infrastructure related factors (crash location, road type, road alignment, and road geometry/separation), 2) drivers' characteristics related factors (driver condition, and gender), 3) prior movement and lane departure, and 4) interactions of the above groups of variables (i.e., alignment\*lane departure, highway type\*gender, and location type\*driver condition).

The first group of variables which were related to infrastructure reflect that road network plays a significant role in senior drivers' crash involvement. Crash locations were defined as signalized and unsignalized intersection versus other locations and the model shows that the odds of injury/fatality crashes increase at 90% significance level when senior drivers were at intersections compared to other locations. This is consistent with other researchers analyzing senior drivers' challenges using crash data analysis. Mayhew et al. also reported senior drivers are at higher risk of crash involvement at intersections compared to other locations and other age-groups (*39*). In addition, they found that intersection collisions were mainly because of senior drivers' failure to yield the right-of-way, traffic violation, or disregarding the traffic signal. This is also consistent with our finding which is reflected in the significant interaction between location type and driver condition. This interaction in fact shows that severe crashes (i.e., injury or fatality) at intersections were associated with inattentive and distracted senior drivers. The results indicate that illness, fatigue, drug, and alcohol condition of drivers had no significant association with senior susceptibility to traffic collisions, which might be due to their self-regulation to avoid driving at the risky conditions that they are aware of.

Drivers' gender was another significant contributing factor in senior drivers' crash involvement, which were categorized under the second significant group of variables in determining crash severity of senior drivers. The result of this research reveals that senior male drivers were more prone to severe crashes than female drivers in general. This is consistent with other researchers' fining such as Evans (40), Khattak et al. (41), and McGwin and Brown (42) who reported male senior drivers are more in danger of severe crashes and fatalities.

The third group of significant variables in senior drivers' crash severity prediction model was prior movement and lane departure. In fact, senior drivers who were doing a lane departure maneuver were involved in more severe crashes compared to their counterparts. This maneuver was led to severe crashes when senior drivers where on a straight level road. In fact, this implies that senior drivers committed less lane departure maneuver on other segments of roads such as curves and elevated segments of roads. Therefore, they are at elevated risk when driving at straight segments of roads.

#### 5.2.2. Hot Spot Locations

Spatial hot-spot analysis was performed also to identify locations of vehicle crashes concentrations involving older road users in Louisiana. The results show that senior drivers were more involved in traffic collisions in intra-urban trips (nearly 80%) rather than in inter-urban trips. The highest percentage of crashes by facility type were found to belong to no-control locations by including 28% of crashes. After that, the share of signalized and unsignalized intersections (yield or stop sign) intersections were noticeable by nearly 17 % and 12% of total crashes. New Orleans (23%), Baton Rouge (21.6%), and Shreveport (11%) have the highest number of senior crashes at signalized intersections. Regarding the crashes occurred at unsignalized intersections, New Orleans (22%), Lafayette (21%), and Baton Rouge (13%) had the highest share of unsignalized intersection crashes in Louisiana. In terms of no-control crashes, New Orleans (28.6%), Shreveport (10.5%), and Baton Rouge (9.5%) had the highest share of senior crahses. Therefore, New Orleans and Baton Rouge are the most suseptible urban areas in Louisiana in terms of senior drivers' crash involvement. In Nw Orleans, Louisiana Ave, French Quarter, W St Bernard Hwy, and William Blvd were found to be hot spot locations with the most frequent crashes. In Baton Rouge, Jones Creek Rd, and Sullivan Rd were the frequent locations of senior crashes. To alleviate senior drivers' crash involvement in these locations, we suggest improving roadway environment to meet senior drivers' need. This can be done through advancing warning signs at identified hot spot locations. Providing guidance signs in advance (including information about the location, route, roadside services, and directing them to nearby destinations) at hop spot locations especially at complex intersections can help senior drivers as well. Advance street name signs can be also effective in improving wayfinding of senior drivers. Another countermeasure is to increase the font size as well as letter height of traffic signs to be legible by senior drivers. In fact, FHWA Older Driver handbook suggests a 30% increase in letter height to accommodate senior drivers' need who suffer from visual acuity. The handbook provides detailed information of sign specifications to improve senior drivers' safety. Therefore, LA DOTD is strongly suggested to comply FHWA Older Driver handbook recommendations at least at identified hot pot location in New Orleans and Baton Rouge area to improve senior drivers' safety.

Another approach to reduce senior drivers' crash involvement at intersections is to provide all-red clearance interval at each signal phase. This allows senior drivers to have sufficient time to process the signal changes and decreases the processing demand on them. To further improve safety of senior drivers, providing protected left-turn phases at signalized intersection at identified hot spots is expected to improve the safety of senior drivers. To further improve the safety of intersections for left-turn maneuvers, offset left-turn lanes facilitate senior drivers' judgment of the traffic operation and result in safer stopping due to a better sight distance. In addition, channelization yields and medians are suggested to being raised instead of being painted because many seniors suffer from poor contrast sensitivity.

#### 5.2.3. Pedestrian Survey

Second, a national survey was conducted in this study to address safety challenges, behaviors, and preferences, needs, and attitudes toward different pedestrian crossing facilities (i.e., signalized intersections, unsignalized intersections, midblock cross walks with and without flashing lights, and roundabouts).

In terms of pedestrian challenges, it was found that 22% of senior pedestrians decreased their level of mobility due to their walking difficulties. However, half of them were often using a mobility

aid devices. This shows that either reluctance to use mobility aid devices or lack of access to such facilities among seniors is in the expense of their mobility level. Therefore, it is suggested that future research to investigate this issue among senior pedestrians to clarify whether the lack of using mobility aid devices among seniors (who can actually benefit from them) is due to their reluctance to use them or not having access to them. In both case, transportation authorizes can take precautions to increase the safety of senior pedestrians by improving their walking abilities. Training programs, self-regulatory strategies, promoting the use of mobility aid devices, introducing the new technologies and options available to senior pedestrians to improve their walking ability, and integrating such aid-devices in transportation facilities are expected to alleviate the issue.

Vision difficulties were found to be a challenge among senior pedestrians especially at night time, however, it did not resulted in lowering their mobility because of night time vision problems. One reason might be seniors usually avoid driving at nighttime due to multiple reasons. Although providing better lighting at crosswalks is an effective countermeasure to improve senior pedestrians' visibility at nighttime, the supply of them is contingent upon the demand that justifies them. Therefore, it is suggested that future studies to investigate the relation between Louisiana crashes of senior pedestrians and lighting condition at various crosswalks in Louisiana.

Fear of falling is another issue that affected seniors' performance at crosswalks especially when feeling rushed. To avoid this issue, it is suggested to provide sufficient crossing time at signalized intersections. Dynamic adjustment of traffic signals is another effective countermeasure that uses high-tech sensors to identify senior pedestrians' presence on roadside based on their physical feature, walking speed, and designated push buttons. Using V2I communication technologies, invehicle sensors will be able to alert drivers about the presence of senior pedestrians to adjust their speed and yield properly.

Another identified issue among senior pedestrians was their declining ability in judging when is safe to cross a road and in fact they claimed their safety is affected by this issue. To alleviate this issue, transportation authorities are suggested to provide sufficient dedicated signalized crossing at critical locations where the concentration of senior pedestrian is noticeable. Future research is expected to identify locations and crosswalks which have been using more frequently by senior pedestrians and investigate the extent to which dedicated signalized crossing can improve senior pedestrians.

The survey also provided information regarding senior pedestrians' awareness of their declining abilities and how it affected their pedestrian behavior. Despite participants claiming that their decline in their personal abilities (such as walking, hearing, vision, judging abilities) or having a medical condition may cause them to be involved in pedestrian accident while crossing a road, about 10% of them walk less or by a companion because of the declining ability. The most-frequent self-regulatory behaviors were found to be selecting larger gaps while crossing a road and avoiding large and complex intersections to cross. This in fact shows the necessity of equipping the transportation network for seniors' needs as the majority of them attempted to maintain their mobility in the expense of probably walking further to find appropriate crossing facilities that accommodate their needs as they refuse to cross large and complex crossing facilities. The lack of proper pedestrian crossing may decrease the mobility level of seniors especially those older or living in not pedestrian-friendly neighborhoods.

Prior traffic collisions data analysis revealed that older seniors with more than 85 years were not

involved in any pedestrian incidents during the past five years. This might be due to two potential reasons. First, older seniors were less active as a pedestrian and therefore have less crash involvement. Second, they maintained an acceptable level of pedestrian activity, however, they were more cautious to use crossing facilities. According to their answers to the survey questions regarding their level of activity at different crossing facilities during and before the pandemic, it seems that older seniors had in fact lower level of mobility which lowered their probability of being involved in pedestrian-vehicle collisions across different crossing facilities. In contrast, younger seniors (65 to 85 years old) showed highest level of mobility as well as highest level of pedestrian-vehicle crash involvement at crosswalks. These results are consistent with senior pedestrians' crash involvement at crosswalks across the Greater Golden Horseshoe, South Ontario, Canada (21). Similarly, younger Canadian seniors showed more susceptible to pedestrian crashes. One possible justification for lower crash rate among senior females can be females are generally more cautious in comparison with males. This finding is consistent with Doulabi et al. and Hong et al. who reported that male Canadians and Koreans were at higher risk of pedestrian crashes than females in Canada and Korea, respectively (43). Therefore, transportation authorities are suggested to provide senior pedestrians with training programs, to aware them regarding the elevated risk conditions (i.e., younger seniors who are male) to help them improve their crossing skills across different crossing facilities.

The results show that there was a decrease in senior pedestrians' road crossing frequencies by occurrence of the COVID-19 pandemic. Many seniors decreased their crossing and therefore walking frequencies. Many of those who were walking a crossing facility daily or at least 1 to 3 times a week experienced a reduction of annually up to monthly crossing frequency during the pandemic. This shows that the mobility of senior pedestrians were noticeably affected by the pandemic. It is suggested follow-up research to be conducted to address near-term and long-term changes in senior pedestrians' mobility due to the Pandemic.

The main issues regarding the unsignalized intersections were related to lack of proper pedestrian markings and signs, not being yielded by vehicles, and feeling to be pushed to walk faster. To alleviate senior pedestrians' challenges at unsignalized crossing, we suggest using oversized "Stop Ahead" and "Stop" signs on the stop and through approaches.

Senior pedestrians were mainly concerned about feeling rushed to cross and not being yielded by vehicles at mid-block crosswalks with and without flashing lights. In addition, they reported to mid-block crosswalks without flashing lights are not visible at night. Lack of warning pedestrian signs, stop or yield sign, and pavement words/symbols (to enhance pedestrian visibility) were another challenging issue of senior pedestrians at such facilities.

The main issues identified at roundabouts were that senior pedestrians were not yielded by drivers and lack of splitter islands (allowing to cross the road in two stages). Promoting public awareness programs are expected to be effective for drivers to support senior pedestrians in roundabouts. To adjust senior pedestrians' need at such crossing we suggest to provide splitter islands and proper pedestrian signage and marking specially at the locations were pedestrians may conflict with rightturn vehicles.

#### 5.2.4. Driving Simulator Experiment

In this study a high-fidelity driving simulator was used to investigate senior drivers' behaviors at signalized intersections while making a left-turn maneuver. Four different intersection complexities as well as drivers' characteristics were taken into account as potential risk factors. Two sets of driving simulator variables (pre-crossing and crossing) as well as self-reported data from an online survey were collected and analyzed in this research. The experiments results showed that pre-crossing variables were affected by drivers' characteristics, while crossing stage was affected by intersection complexity level, drivers' characteristics, and the interaction between them.

Based on the ANOVA results of the variables related to the pre-crossing stage, it was found that drivers' characteristics had a significant impact on drivers' pre-crossing behaviors. No significant impact of intersection complexity was observed on pre-crossing variables.

Approaching speed variable for senior drivers with 70-74 years old was significantly higher compared to those younger or older. Although drivers with 65-69 and 75+ years old were driving below the speed limit of 35 mi/h, 70–74-year-old drivers were driving above the speed limit (about 40 mi/h). Similarly, in terms of maximum deceleration rate that senior drivers took at signalized intersections, drivers with 70-74 years old were different compared to others. The difference driving behavior of senior drivers with 70-74 years old in pre-crossing variables.

Intersection waiting time was found to be affected by traffic volume and drivers' health condition. Senior drivers were more cautious and spend more time waiting at intersections with higher traffic volume, while at intersections with low traffic volume, the majority of participants adjust their speed to find a gap and accomplish their left-turn maneuver by minimizing their waiting time at those intersections. Senior drivers with vision problem and vertigo showed significantly different waiting times compared to those healthy or having medical condition. In fact, senior drivers suffering from these health conditions found to be more cautious and spend more time at the intersections to compensate for their health condition.

ANOVA results of the variables related to the crossing stage (i.e., the left-turn maneuver) were affected by intersection complexities as well as drivers' characteristics. Average turning speed was affected by presence of pedestrians on sidewalks as well as age of the drivers. In the presence of pedestrians, senior drivers reduced their turning speed by 66% to avoid pedestrian-vehicle collision, however, they spend more waiting time at the intersections to accommodate for their lower turning speed. More specifically, senior drivers with 65-69 years old showed very slow turning speed and longer waiting time compared those with 70-74 years old.

Similarly, maximum acceleration rate while making the left-turn maneuver was found to be a function of traffic volume as well as health condition. In addition, intersection complexity attributes showed to have significant interactions with the health condition variable. Vertigo was associated with significantly different acceleration rate compared to those drivers without having vertigo condition. Although the acceleration rate was expected to be lower in participants with vertigo condition, the data showed a igher acceleration rate was adopted. This issue might be due to small sample size and confounding factors, therefore, it is suggested to collect more samples in future studies to investigate the relation between vertigo and acceleration speed while making a left-turn manuvers among senior drivers.

As can be understood from the aforesaid findings, senior drivers' behavior and safety is mainly associated to their demographics as well as health condition. However, their behavior and safety is associated with the transortation network characteristics and intersection complexities (such as level of traffic volume and pedestrian crossing) as well as their demographics and health condition. In fact, the interacton between drivers' characteristics and intersection complexities emphasize the fact that senior drivers are at elevated risk, specially those with 70-74 years old and suffering from a health condition (such as vision problem and vertigo). In order to help senior drivers to have a safer left-turn manuvers, transportation authorities are suggested to use protected leftt-urn phase at large and complex intersections, especially at those hot spot locations with frequent senior crashes. Another critical locations are interscetions with crossing pedestrias and high level of traffic volume. This study observed that senior drivers lower they turning speed to avoid involving in pedestrian-vehicle crashes, but it is suspected the odds of vehicle-vehicle crashes increases if senior drivers are not able to finish their turn in the proper time. Lowering the speed limit or to use traffic calming techniques are another countermeasures that can help senior drivers to complete their leftturn manuvers at large and complex intersections. Lowering the speed limit will provide larger gaps for seniors to accomplish their left-turn manuver.

# 6. CONCLUSIONS

Older pedestrians and drivers with 65 years and above are among the most vulnerable road users. As the number and proportion of older adults grows in many countries, as well as their share of pedestrians' and drivers' crashes and injuries, it behooves transportation researchers to further investigate the safety and mobility challenges of older road users. The main objective of this study was to provide a comprehensive investigation of older pedestrians' and drivers' safety challenges, causes and countermeasures. To this end, a three-fold research approach was designed to thoroughly examine older road users' safety and mobility challenges. Accordingly effective data-driven results and discussion is provided in this research to improve the safety of senior road users.

First, a relatively large sample of Louisiana crash data has been analyzed to identify significant risk factors causing/leading older drivers' to be involved in vehicle crashes. The results indicated that four groups of variables were significant in predicting the crash severity levels (i.e., no injury and injury/fatality). These factors were found to be 1) road infrastructure related factors (crash location, road type, road alignment, and road geometry/separation), 2) drivers' characteristics related factors (driver condition, and gender), 3) prior movement and lane departure, and 4) interactions of the above groups of variables (i.e., alignment\*lane departure, highway type\*gender, and location type\*driver condition). In addition, intersections (signalized and unsignalized) and straight level roads (especially two-way roads) were more prone to severe crashes.

The finding of crash severity analysis provides transportation authorities with valuable insights regarding safety challenges of older road users. Training programs can be offered to the most susceptible older drivers (i.e., male drivers who commute on interstate and highways) to improve their safety specially on highways and interstates. Older drivers can be informed about the most challenging and risk taking maneuvers and road conditions in order to either attend training programs or use alternative routes to lessen the crash exposure and its severity level. The findings of this study can also shed light on needed technological advances to be implemented by car manufacturers to improve traffic safety of older road users. Vehicle-to-vehicle (V2V) communication, Vehicle-to-infrastructure (V2I) communication, lane departure warning (LDW) system, and blind spot warning mirrors (with red flashlights on mirrors) are examples of the

technological advances that can facilitate driving performance (specially lane departure) of older adults.

Based on the hotspot analysis, transportation authorities are suggested to improve roadway environment in Louisiana Ave, French Quarter, W St Bernard Hwy, and William Blvd in New Orleans. Jones Creek Rd, and Sullivan Rd in Baton Rouge area and other identified hot spot locations in this study. Advancing warning signs, guidance signs in advance including information about the location, route, roadside services, and directing them to nearby destinations, advance street name signs to improve wayfinding, better marking and signage by increasing the font size and letter height of traffic signs were the effective countermeasures suggested to improve the safety of senior drivers at the identified hot spot locations.

Second, a national survey was conducted to address a wide range of seniors' safety challenges and needs. To this end, a total of 1000 older Americans (65+ years and above) from all US states have participated in this study. The results of the survey also showed that senior pedestrians are aware of their declining abilities and tried to adopt self-regulatory behaviors to maintain their safety and mobility as a pedestrian. Selecting larger gaps while crossing a road and avoiding large and complex intersections were found to be the most-frequent self-regulatory behaviors, while no record of walking with a companion was found to be significant self-regulatory behavior. This in fact shows that seniors prefer to keep their independence as a pedestrian.

The impact of COVID-19 pandemic was noticeable on the mobility of the senior pedestrians. Many seniors decreased their crossing and therefore walking frequencies from daily or at least 1 to 3 times a week prior to the pandemic to annually up to monthly crossing frequency during the pandemic. In addition, signalized intersections and 4-way stop control intersections claimed to be safe by the majority of the participants. Mid-block crosswalks with flashing lights and 2-way stop control intersections were the second group of safe crossing facilities, while mid-block crosswalks without flashing lights and roundabouts were found to be the least safe crossing facilities by the seniors. Feeling being rushed and not being yielded properly were found to be one of the main issues across all the crossing facilities.

Third section included a driving simulator experiment as well as a survey questionnaire to explore drivers' behavior at identified risky conditions as well as their demographics and health conditions. Based on the literature and crash data analysis, performing a left-turn maneuver is one of the most challenging tasks for senior drivers in the presence of permitted left turn. Several driving simulator variables were collected and analyzed using ANOVA analysis to identify the differences of driving behavior among different age groups, health condition, and gender across four different intersection complexities with two levels of traffic volume and two levels of pedestrian crossing. Based on the results and findings of the driving simulator experiment pre-crossing variables were found to be associated with the drivers' characteristics, while crossing variables were not only associated with the intersection complexities (i.e., traffic volumes and pedestrian crossings), but also drivers' characteristics, and the interaction between intersection complexities and drivers' characteristics.

The level of traffic volume and drivers' health condition were affected the waiting time of the seniors at intersections in such a way that senior drivers were more cautious and waited for larger gaps when traffic level was high. However, they showed riskier behavior when the traffic volume was low by trying to not stop at the intersection via speed adjustments. Senior drivers with vision problem and vertigo showed significantly longer waiting times compared to others. Crossing

variables were affected by intersection complexities as well as drivers' characteristics. The presence of pedestrians on sidewalks as well as age affected average turning speed in such a way that senior drivers reduced their turning speed by 66% to yield to the pedestrians properly. Although senior drivers with 65-69 years old showed very slow turning speed and longer waiting time, drivers with 70-74 years old had shorter wait time and higher turning speed at the intersections with high traffic volume and pedestrian crossing.

The results of this this study shows that senior drivers' behaviors are affected by their demographics and health condition not only while conducting left-turn maneuvers at intersections, but also while driving on straight segements roads. Intersection complexities (such as level of traffic volume and pedestrian crossing) were major participating factors in drivers' behaviors of seniors while making a left-turn at intersections. Drivers with 70-74 years old and those suffering from a health condition (such as vision problem and vertigo) were at elevated risk at signalized intersection wih permitted left-turn signal phase. The use of protected leftt-urn phase at large and complex intersections(especially at those hot spot location with frequent senior crashes), lowering the speed limit or using traffic calming techniques, and providing alternative routs (i.e., safer routes instead of shorter routes) to seniors are effective counetrmeasures to improve senior drivers' behavior at these locations.

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