TN TDOT Department of Transportation

U.S. Department of Transportation
Federal Highway Administration

Addressing Traffic Safety to Reduce Pedestrian Injuries and Fatalities in Tennessee

Research Final Report from The University of Tennessee and Vanderbilt University | Christopher Cherry, Candace Brakewood, Saurav Parajuli, Oliver Stover, Hiba Baroud | August 31, 2022

Sponsored by Tennessee Department of Transportation Long Range Planning Research Office & Federal Highway Administration

THE UNIVERSITY OF TENNESSEE KNOXVILLE

VANDERBILT UNIVERSITY

DISCLAIMER

This research was funded through the State Planning and Research (SPR) Program by the Tennessee Department of Transportation and the Federal Highway Administration under ***RES #2021-11: Addressing Traffic Safety to Reduce Pedestrian Injuries and Fatalities in Tennessee.***

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
RES2021-11		

4. Title and Subtitle	5. Report Date
Addressing Traffic Safety to Reduce Pedestrian Injuries and Fatalities in Tennessee	August 2022
	6. Performing Organization Code
7. Author(s) Christopher R. Cherry, Candace Brakewood, Saurav Parajuli, Hiba Baroud, Oliver Stover	8. Performing Organization Report No.
9. Performing Organization Name and Address University of Tennessee 1331 Circle Park Drive, Knoxville, TN 37916	10. Work Unit No. (TRAIS)
	11. Contract or Grant No.
12. Sponsoring Agency Name and Address Tennessee Department of Transportation 505 Deaderick Street, Suite 900 Nashville, TN 37243	13. Type of Report and Period Covered Final Report: September 2020 – May 2022
	14. Sponsoring Agency Code

15. Supplementary Notes
Conducted in cooperation with the U.S. Department of Transportation, Federal Highway Administration.

16. Abstract

Pedestrian safety in the US has worsened significantly during the last decade. Media and safety advocates speculate on different scenarios responsible for the decline. Past studies attempted to explore the nationwide trends but have failed to answer whether pedestrian crashes are getting more severe. This study advances the investigation of declining pedestrian safety at the state levels, starting with investigating pedestrian death trends in Tennessee. It collected all reported pedestrian crashes from Tennessee Police crash data with their injury outcomes from 2009 to 2019. With more than doubled pedestrian deaths, Tennessee is exceeding the national trend of declining pedestrian safety. However, pedestrian involvement in traffic crashes only increased by 26 percent over the same time period, suggesting that pedestrian crashes becoming more severe may have precipitated the increase. A breakdown of trends relating to different covariates against fatality, involvement, and fatality rate trends identified the drivers of the increase in severity, with speeds and road designs being the most critical ones. The study also utilized spatial visualizations, multivariate modeling, and distance analyses to understand the severity increase over time. It also provides a decision framework for model validation, quantitative risk assessment, risk quantification, and countermeasure evaluation. Using this framework, decision makers can optimize their resources via a linear program to select the countermeasures that most effectively mitigate risk to pedestrians. Finally, the study recommends cities reduce design speeds to 35 mph or lower, to increase safe pedestrian crossing opportunities, and install more pedestrian-scale lighting infrastructure on urban arterials to reverse the ongoing pedestrian safety crisis.

17. Key Words	18. Distribution Statement
PEDESTRIAN SAFETY, PEDESTRIAN FATALITY RATES, DISTANCE-BASED ANALYSIS, QUANTITATIVE RISK ASSESSMENT	No restriction. This document is available to the public from the sponsoring agency at the website http://www.tn.gov/.

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	71	

Executive Summary

Pedestrian safety has declined significantly during the last decade. According to the Fatality Analysis Reporting System (FARS) database, pedestrian deaths on roads in the United States (US) increased by 51 percent from 2009 – 2019. This increase is unique to the US, as the pedestrian fatality trend in other developed countries is either constant or has declined over similar periods. Tennessee also exhibits a similar but worse trend, with a 117 percent increase in pedestrian deaths from 2009 - 2019. However, the fact that pedestrian exposure to traffic crashes has risen only by 26 percent highlights the problem of the rising severity of pedestrian crashes.

Pedestrian safety studies addressing the current US pedestrian fatality trends often stumble on the question: Are pedestrian crashes getting more severe? Studies and media sources often tend to speculate and link the increase in fatalities with growing vehicle size, lack of pedestrian facilities, alcohol or drug impairment, speeding, and so on. Some studies correlate the increasing vehicle size with the increasing fatalities, thus implying a rising severity of pedestrian crashes. One lack among these studies is that they solely depend on the fatality data and not overall pedestrian involvement in traffic crashes. A few studies include pedestrian involvement but use secondary data sources for the analyses. Moreover, there is a severe lack of state-specific pedestrian safety studies to dissect the ongoing pedestrian crisis in the country. In the context of pedestrian safety in Tennessee, this research sets out to answer the causes of increasing pedestrian deaths over the last decade. The scope of this study was to explore all contributing factors that cause severe outcomes in urban pedestrian crashes in Tennessee and piece them together to provide insight into what aspects have contributed to crash severity increases over the years. This study followed the principles of the Safe Systems Approach and utilized an interdisciplinary approach to assess risks and provide countermeasures for the pedestrian safety situation.

This study utilized Tennessee Integrated Traffic Analysis Network (TITAN) database, which contains critical information about all police recorded crashes in Tennessee, including pedestrian crashes. TITAN also records the injury outcome spectrum on the KABCO scale, facilitating the exposure and fatality information. This research further supplemented TITAN data by linking the socio-economic data from the US Census and determining pedestrians' home location coordinates after geocoding the pedestrians' address information included with the TITAN database. The data helped determine the critical variables associated with the severity increase, with the help of a frequency table and after performing trend analyses on total pedestrian involvement in crashes, total pedestrian fatality, and pedestrian fatality rate (PFR). The study also incorporated injury severity modeling using simple binomial logistic regressions to compare the severity disparity among variables in two time periods. The study compared the groups with the help of average discrete changes (ADC) for both periods and their difference to determine if the change was statistically significant. Other methods include home-based approaches and spatial visualization to enhance the findings from trend analyses. It also provides a tool to reduce pedestrian risks, which helps determine an optimal set of countermeasures in terms of budget and efficacy.

Findings

Results show a significant overall increase in pedestrian crash severity in Tennessee from 2009 to 2019 concerning fatal outcomes. Severe injury and other injury outcomes did not exhibit a significant trend. Urban area crashes showed a consistent and significant increase in severity over the years, unlike rural area crashes, where the crashes are naturally more severe. Furthermore, urban crashes make up the overwhelming majority of total pedestrian exposure and deaths, narrowing the scope of this study to urban areas in the state. The frequency table indicates a disproportionate fatality and involvement associated with elderly pedestrians, males, impaired pedestrians, impaired drivers, and pedestrians not in the crosswalk. Roads with higher speeds, multiple lanes, and straight maneuvers also report a higher proportion of fatalities than the involvement. Nighttime crashes with lighted and unlighted conditions also have a notable disparity in severity outcomes. In the case of vehicles, heavy vehicles and front-end collisions have the highest fatality rate compared to the other vehicle types and collision types, respectively. The pedestrian fatality rate visualizations helped to find the critical variables associated with the severity increase, with the visualization of fatality and involvement trend validating in terms of severity and magnitude. The increase in PFR is positive and significant for the pedestrian of the age group 51 – 65, male pedestrians, and pedestrians living far from homes. PFR is also positive and significant for female drivers and impaired drivers. There is a significant rise in PFR for non-intersection locations, multi-lane roads, and roads with a posted speed limit of 35 mph and higher in non-residential locations but not in parking lots and private roads or property. The fatality rate is also high on weekends, and nighttime crashes with a significant increasing trend over time. The PFR increase is also significantly associated with straight maneuver and non-hit-and-run crashes, but we cannot see a significant trend associated with vehicle types. Spatial visualization of non-residential crashes shows that they cluster around the major urban arterials. Despite high overall crash severity for commercial or freight vehicles, no significant trend is associated with the increase in severity. The binary logistic regression models reveal the critical attributes of a fatal outcome, such as pedestrian crashes involving heavy vehicles, impairment, dark-lighting conditions, elderly pedestrians, high-speed roads, and census characteristics such as high-income and walkable neighborhoods. Although the ADC associated with most of these variables was significant in determining the probability of outcomes, the difference in ADC between the two models is largely insignificant. Although statistically insignificant, we can see substantial increases in ADC in pedestrian and driver impairment, adult pedestrians, dark conditions, hit-and-runs, high-speed roads, high-income census blocks, and walkable neighborhoods. We also performed home-based distance analyses. Pedestrians involved in non-residential crashes live farther than the pedestrian involved in residential crashes. A trend-visualization of median pedestrian home-to-crash distances shows a significant trend of pedestrians getting struck farther from their homes over the years.

Recommendations

This report includes an interdisciplinary application of risk-based decision tools. Mitigation efforts have focused on hyper-local surgical interventions to mitigate risk at high-risk locations (known as hot spots). We have proposed a decision framework to identify crash hot spots, identify, and evaluate countermeasures, and select the most effective ones. However, these frameworks only capture the impact on the number and not the consequence of crashes. This study expands on these decision frameworks to include model validation, quantitative risk assessment (by considering both the number and consequence of crashes), and explicit inclusion of crash outcomes in risk quantification and countermeasure evaluation. This approach allows for national, state, and city decision-making – rather than focusing efforts on individual, location-based decisions. Using this proposed framework, decision makers can optimize their resources to select the countermeasures that most effectively mitigate risk to pedestrians.

Even though the report points out several crash attributes associated with the increasing severity, we established that road design aspects disproportionately drive the increase. Speculative claims about the explosion of sport utility vehicles (SUVs) and trucks, the boom of e-commerce with commercial vehicles and delivery trucks encroaching the residential areas, and the increase in aging demographics driving the pedestrian severity remain largely untrue for Tennessee. This study recommends six core recommendations:

1) Adopt a Safe Systems approach that holistically evaluates pedestrian safety
2) Reform TDOT standard designs and drawings to mandate pedestrian friendly designs
3) Reduce speed limits to a maximum of 35 mph in urban commercial corridors
4) Implement quick-build traffic calming interventions on high-speed urban streets
5) Focus on improving mid-block crossings with proven interventions
6) Work with transit agencies to ensure transit corridors are safe for pedestrians

Table of Contents

List of Tables

List of Figures

Chapter 1 Introduction

Traffic crashes are one of the primary causes of injury-related deaths in the United States (US) (*1*). Usually, drivers, passengers, and non-motorized road users are the victims of traffic crashes, among which pedestrians are the most exposed and vulnerable users of the road. Traffic crash data and fatality trends from the last decade show a pedestrian safety crisis underway in the US. According to the Fatality Analysis Reporting System (FARS) dataset, although US pedestrian fatality numbers constantly dropped from 1979 until 2009, from 2009 to 2019, the country has seen an unprecedented fatality increase of 51 percent (*2*). The US pedestrian safety situation has worsened compared to traffic crash deaths involving other road users. While total lives lost in traffic crashes have increased slightly, the share of pedestrian deaths per traffic death rose from 12 percent in 2009 to 17 percent in 2019 (*2; 3*) and has increased since. The US has had a comparatively poor performance in pedestrian safety over the years compared to other developed countries, whose pedestrian fatalities have continued to decline, while pedestrian safety in the US worsened significantly in the last decade (*4*). For instance, the pedestrian fatality trends were flat for Australia and the United Kingdom (*5; 6*). On the contrary, the European Union saw a gradual decrease in pedestrian deaths from 2010 to 2018, with an overall 19 percent decline (*7*).

Unsurprisingly, most US states contributed to the rise, with the state of Tennessee being no exception. Pedestrian fatalities doubled in Tennessee from 72 in 2009 to 156 in 2019 (*8*). Part of this increase is because crashes have become more severe. According to the Traffic Safety Facts: Pedestrians from 2009 – 2019 provided by the National Highway Traffic Safety Administration (NHTSA), there was a slight increase in the total number of injured pedestrians in the US, unlike the fatality numbers showing a clear increasing trend. The growing likelihood of being involved in fatal pedestrian crashes can be observed even more distinctly in the case of Tennessee. Pedestrians involved in traffic crashes increased 26 percent between 2009 and 2019, from 1687 to 2126, a comparatively small figure from the 117 percent rise in pedestrian fatalities in Tennessee over the same period (*8*). Figure 1.1 shows the overall pedestrian injury and fatality growth over the past 13 years. Compared to USA's 51 percent, the increase in Tennessee also suggests that it has become one of the weaker performers in terms of pedestrian safety over the same period.

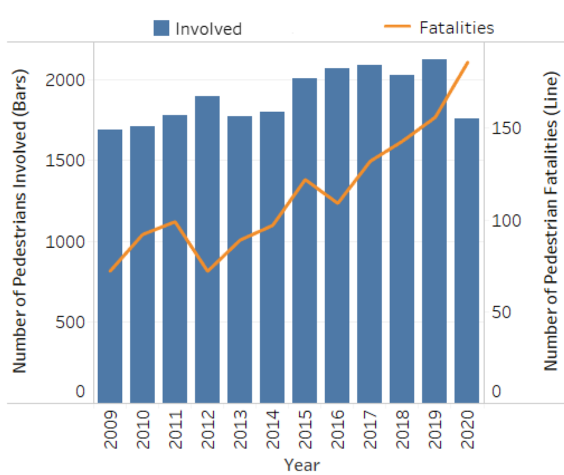


Figure 1.1 Pedestrian Crash Trend in Tennessee

There is a lot of speculation regarding the rise in pedestrian fatalities. Safety advocates often point to the rise in vehicle size, suburbanization of poverty, speed, lack of pedestrian facilities, intoxication, driver distraction, and other factors. Similarly, others point to the pedestrian's role, including distraction, intoxication, lack of attention to traffic control devices, and so on (*9*). To date, very little research has been conducted that tackles each of these factors to identify if they are part of the causal chain that results in a pedestrian being struck and killed or severely injured by a car (*10*).

Walking is a fundamental mode of transportation and an integral part of life. Even the most car-dependent individuals become pedestrians at times of the day while walking to vehicles. However, the population relying on walking, by choice or not, and those not having access to cars are more affected by a hazardous pedestrian safety environment. Besides contributing to unwanted injuries and inflicting an economic cost at the individual and national level, such a burden of injury and death can call to question the equity in the transportation system. As vulnerable road users, pedestrians always bear a disproportionate burden of injury than other road users; that is, they are nearly always harmed more than other participants in a crash (*11*). In most cases, the most harm from the pedestrian safety challenges faced in the city is borne disproportionately by lower income or minority populations.

With a focus on the gravity of pedestrian safety issues in the US, especially in Tennessee, this study aims to assess the contributors to declining pedestrian safety in Tennessee. Fundamentally, what has happened in Tennessee to cause severe crashes to more than double in a decade, with no evidence of a coming decline? Then, what can the Tennessee Department of Transportation (TDOT) and other state partners do to stem this growth in pedestrian harm? This research, pinning itself to the Safe Systems Approach, seeks to create a complete picture of the growth in pedestrian crashes happening in Tennessee and identify the pedestrian crash types and the temporal trend followed by each type. This study aims to supplement traditional crash analysis with more nuanced system data, where available, to understand factors contributing to crashes. To that end, another goal of this study is to use the home-based approach to understand the causes and identify the hotspots of pedestrian crashes, focusing primarily on the severe and fatal ones. The home-based approach relies on understanding the home location of the crash victim, the socioeconomic and situational factors that contribute to crashes, and the burden of crashes in different neighborhoods. It is beneficial in aiming to understand geographic factors associated with crashes, like whether the crash victim was near or far from home. Finally, this report aims to implement a quantitative decision framework for selecting countermeasures to the pedestrian safety problem.

1.1. Definitions

For clarity of presentation, below are the definitions for some of the terms used in the report, which can have ambiguous meanings.

- **Safe Systems Approach:** An approach adopted by the Federal Highway Administration (FHWA) to reduce death and serious injuries through design that accommodates human mistakes and injury tolerances. It works by building and reinforcing multiple layers of protection to both prevent crashes from happening in the first place and minimize the harm caused to those involved when crashes do occur.

- **Pedestrian Crash:** Traffic crashes involving at least one pedestrian and one vehicle. It excludes falls or pedestrian injuries generated by collisions with non-vehicle devices (e.g., bicycles, farm equipment, etc.).
- **Severe Injury:** Pedestrian crash outcomes with the pedestrian sustaining incapacitating (serious) injury.
- **Fatal Injury:** Pedestrian crash outcomes resulting in pedestrian death.
- **Pedestrian Involved:** Pedestrians engaged in pedestrian crashes with or without injuries.
- **Urban areas:** City areas as defined by the Tennessee Integrated Traffic Analysis Network (TITAN) database. Seventy-five percent of Tennessee's urban pedestrian crash locations lie within the Metropolitan Statistical Area of four major cities (Nashville, Memphis, Knoxville, and Chattanooga).
- **Pedestrian Fatality Rate (PFR):** Pedestrian deaths per 100 pedestrians involved.
- **Pedestrian Home to Crash Distance (PHCD):** Geodesic distance of the pedestrian from the crash location to their home.
- **Pedestrian position:** Position of the pedestrian at the time of the crash concerning the roadway, crosswalks, or elsewhere. In case the pedestrian is on the roadway, the police officer notes if there are no crosswalks in the vicinity of the existing one or if it is reasonably far, based on their judgments. In that situation, the officer classifies the pedestrian position as "on the roadway – crosswalk not available."
- **First Impact**: First Impact determines whether the vehicle directly hit the pedestrian and, if yes, the hitting surface of the vehicle. Front End exclusively means front end impacts. Right Side includes the right corner near the headlight and the right side near-front, center, and near-rear. Left Side includes the left corner near the headlight and the left side near-front, center, and near-rear. Rear End includes the rear end, rear-left, and rear-right corners near backlights.

1.2. Organization of the Report

The report is organized into five additional sections. Chapter 2 is the literature review section, which briefly outlines the past studies relevant to the scope of this project. Chapter 3 describes the data sources and delineates multiple approaches to fulfill this report's objectives. In Chapter 4, the report presents the results of the analyses while illustrating them with visualizations. Chapter 5 is an interdisciplinary application of risk-based decision tools that help meet this report's final objective. Chapter 6 provides conclusions and recommendations pertinent to the issues discussed in this report and future research needs/ opportunities.

Chapter 2 Literature Review

Traffic safety boasts years of research using sophisticated tools, but pedestrian safety analysis has sometimes lagged because of fewer robust datasets or exposure variables. Researchers have recently developed a more advanced understanding of motor vehicle crash dynamics with pedestrians and the causative factors. This section of the report reviews past studies to understand the critical aspects of pedestrian safety, including the factors significantly influencing the outcomes of traffic crashes involving pedestrians. It also attempts to identify gaps in the literature about pedestrian safety and the US pedestrian fatality trend. For better organization, this section has four sub-sections.

2.1 Attributes of a Severe Outcome

Studies have identified that severe outcomes in pedestrian crashes are associated with diverse variables. Studies often attribute serious or fatal injury in pedestrian crashes to these features: pedestrian and driver characteristics such as age, sex, height, alcohol and drugs influence, the color of clothing; crash environment; and situational characteristics such as land use, geometric design, presence of sidewalks, weather, time of day, lighting conditions, intersections, crossing-width, crossing infrastructure; and vehicle characteristics such as vehicle type, vehicle model, vehicle weight and size, presence of protection mechanism, and autonomous braking (*12-14*).

Safety research often identifies elderly pedestrians, children, and pedestrians under the influence of alcohol or drugs as the most vulnerable pedestrian groups. Elderly pedestrians are often over-represented in traffic crashes and are likely to sustain fatal injuries during a traffic crash (*15-19*). Kröyer (2015) illustrated that the risk of dying increases dramatically as pedestrians are over 75 (*20*). Alcohol-intoxicated pedestrians have a substantial chance of severe injury (*21; 22*) and quicker death (*23*). For children under 14, pedestrian crashes were among the top ten injury-related deaths in the US in 2019 (*1*). Researchers associate the cause behind this vulnerability with the declining, underdeveloped, and impaired cognitive and perceptual abilities of the elderly, children, and pedestrians under the influence of alcohol, respectively (*24-27*).

Aside from the most vulnerable pedestrians, studies also reveal that pedestrian fatalities are skewed towards minorities, including African Americans and other people of color, and low-income households (*28; 29*). After analyzing the FARS pedestrian fatality data from 2012 to 2017, Sanders and Schneider (2022) have found that Black and Native Americans disproportionately contributed to pedestrian fatality (*30*). Roll and McNeil (2022) hint at the past negligence in the land use development of minority neighborhoods being the cause of the current imbalance, as it precipitates increased traffic exposure and deficient infrastructure (*28*). A pair of studies have also suggested a prevalent racial bias in pedestrian safety as drivers yield more for White pedestrians than Black pedestrians (*31; 32*). The situation is even more difficult in the case of the homeless population. A study in Clark County in Nevada, from 2008 to 2011, found that the homeless population was almost 22 times more at risk than other residents (*33*). Another vulnerable pedestrian group is pedestrians who walk near their homes (*34-36*). Lee et al. (2015) highlighted that half of the pedestrians were involved in traffic crashes at zip code locations of their residential addresses (*34*).

Studies also looked at pedestrian and driving behaviors during traffic crashes and assessed what kind of behaviors produced severe or fatal outcomes. Like walking under the influence (*37*), many studies agree that driving under the influence of alcohol or drugs is linked to causing more severe injury to pedestrians (*38-41*). Studies also concur that distracted driving is another risk factor for pedestrians, especially in an unfavorable built environment. Lym and Chen (2021) have reported greater odds of striking a pedestrian severely while driving while distracted in work zones, curves, and when speeding (*42*). Khan and Habib (2022) found that distracted driving on linear roads with communication devices causes severe pedestrian injuries. Some studies claim that pedestrian crossing behavior also makes a difference in the injury outcome, as pedestrians are likely to sustain a more severe injury during midblock crossings than crossing at a signalized intersection (*43*) or intersections in general (*40*).

The kinetic energy transfer from the motor vehicle to the body of a pedestrian is the reason behind severe outcomes (*44*). One of the most often cited infographics points to the chance of fatal injury as a speed function (Figure 2.1).

Figure 2.1 Role of Speed in Pedestrian Crashes, reprinted from Vision Zero action strategy (45)

In the literature, the vehicle speed is portrayed as the most prominent determinant of a pedestrian crash outcome as it governs the kinetic energy transfer during the impact from the vehicle to the pedestrian in the second-order (1/2*mass*velocity^2) (*44; 46*). Hussain et al. (2019) maintain that although the average speed of vehicles running on a road is correlated with the posted speed limit, actual impact speed during a crash dictates the risk of pedestrian fatality. That study utilized a meta-analysis to predict the pedestrian fatality risk from impact speed during the crash by reviewing 20 other studies. The results of the study suggest that on average, with a 1 km/h speed increase during impact, the probability of fatal outcome increases by 11 percent, with chances of death of 5 percent, 10 percent, 50 percent, 75 percent, and 90 percent at the impact speeds of 30 km/h, 37 km/h, 59 km/h, 69 km/h and 80 km/h (*47*). Nevertheless, studies have widely used posted speed limits as a representation of speed in their pedestrian injury severity models and consistently observed higher posted speed limits significantly producing severe injuries than the lower ones (*20; 37; 40; 48*). Safe Speeds is one of the core strategies associated with the Safe Systems Approach.

Those speed-only relationships tend to ignore vehicle mass. To the extent of the authors' knowledge, very few studies have looked at the direct relationship between the kinetic energy values and crash outcomes in pedestrians. Injury severity studies concerning motorized vehicle crashes involving pedestrians often highlight the role of the vehicle weight, another component of the kinetic energy, but in terms of vehicle size or vehicle type. Many studies associate increasing vehicle size with more severe outcomes in pedestrian crashes. Researchers often segregate cars and larger personal vehicles like sport utility vehicles (SUVs), pickups, vans, etc., into separate categories to compare the injury severity. The results mostly point to larger vehicles responsible for causing severe outcomes (*15; 20; 40*). Modern vehicles are fitted with pedestrian detection system with autonomous emergency braking technology and evasive steering, which could reduce the kinetic energy transfer before impact by hard braking, or completely avoiding the imminent crash (*13*). Research has shown that vehicles with this technology could potentially lower the crash involvement of pedestrians by 60 to 70 percent (*49*).

Similarly, studies have also focused on the impacts of the built environment on the crash outcomes, including variables such as functional classification of the road, road width/ number of lanes, and intersection characteristics. Studies have characterized severe injury outcomes with the urban arterials, which are wide roads with attributes like higher speed limits (*41*) and roads lacking pedestrian crossing infrastructure roads. Upon scrutinizing the literature, these attributes again boil down to speed and vehicle size. Simply put, this kind of road encourages speeding and facilitates large vehicle operation, compared to a heavily traffic-calmed road in a dense downtown neighborhood of a city (*41; 50*). Ewing et al. (2003) identify wide and long streets as the features of suburban roads and suggest urban sprawl contributes to pedestrian deaths in traffic crashes (*51*).

Last, inclement weather conditions and nighttime walking/ driving negatively affect pedestrian injury outcomes. During harsh weather conditions, loss of visibility and road friction can cause slippery surfaces and amplify maneuver errors in drivers, increasing pedestrian injury severity (*52*). Also, a decrease in visibility during late-night walking or driving increases the reaction time of the drivers and pedestrians, affecting the injury severity in pedestrians (*48*).

2.2 Pedestrian Crash Typology

Although some pedestrian types are associated with a more severe outcome, a correlation exists between a combination of variables dictating the pedestrian fatality. For instance, Sanders and Schneider (2022) performed a multivariate analysis concerning race and observed that child pedestrians from Black and Hispanic backgrounds were more likely to get killed, while the same was valid for elderly Asian pedestrians (*30*). Other studies found that children and elderly pedestrians are also more exposed to serious safety hazards in parking lots and driveways (*53; 54*). Hezaveh and Cherry (2018) investigated pedestrian crashes in Tennessee involving pedestrians intoxicated with alcohol, with an elevated risk of severe outcomes observed more at night, among the middle-aged males, and during the weekends (*37*). Haule et al. (2019) found that aging pedestrians were more prone to close-to-home pedestrian crashes. More than 35 percent of crashes involving pedestrians above 65-year age occurred within 0.5 miles from their home, and 64 percent of the crashes occurred within 2 miles (*36*).

Only a few studies have created a typology to classify pedestrian crashes, rather than looking at the interaction between variables using manual classification or other clustering techniques.

Stutts, Hunter, and Pein (1996) created a crash typology of pedestrian crashes from 5000 police-reported pedestrian crashes from six states to identify the problems and suggest appropriate countermeasures. The study attributed more than 80 percent of pedestrian crashes to nine crash types based on the vehicle involved, drivers' and pedestrians' behaviors, locations, and circumstances. The study highlights that each crash type varied with the characteristics of the pedestrians and road environment (*55*). Preusser et al. (2002) identify eighteen different crash types and categorize them into seven categories for the 852 and 1234 pedestrian crashes data in Washington DC and Baltimore city, respectively (*56*). Fontaine and Gourlet (1997) analyzed the fatal pedestrian crashes in France between March 1990 and February 1991. The study classifies the crashes into four groups:

- Elderly pedestrians crossing the road in the daytime in urban areas
- Children playing in the urban streets in the daytime
- Pedestrians under alcohol influence walking at night in rural areas
- Other pedestrians in secondary crashes or during mode transfer

One of the study's findings is that children and the elderly are the most vulnerable groups among the pedestrians (*57*). The above studies agree that there were no significant relationships between the diverse types of pedestrian crashes, implying that developing a pedestrian typology could avoid redundant analyses on non-significant variables. Additionally, Sasidharan, Wu, and Menendez (2015) used a data mining technique for cluster analysis to investigate pedestrian crash severity to reduce heterogeneity in the pedestrian data. The study uses a latent cluster analysis to form seven homogeneous clusters of pedestrian crashes from a large dataset. The study concluded that one factor could significantly affect a cluster's crash outcome, while the same factor could have a negligible effect on the other (*58*).

Injuries are often underreported while working with the police data, especially for the pedestrians. A 1990 study in Orange County, California, reports at least 20 percent of underreporting for severity in the police data for pedestrians (*59*). Safety researchers recommend matching the police data with the hospital entries for a correct estimate of injuries and severity reporting (*60*). In a recent North Carolina study, Harmon et al. (2021) investigated police-reported pedestrian crashes from 2017 and linked the pedestrians injured by matching with their hospital (emergency department visit) data, which have comparatively more reliability in terms of injury reporting. The study discovered that although the police data labeled pedestrians as "not injured," the hospital had instances of pedestrian follow-ups, with some getting admitted days after the crash. The authors also discovered disparities regarding the treatment of injuries among men and women and Black and White pedestrians (*61*). Although severe and suspected injuries are subject to substantial underreporting, fatal injuries are almost captured perfectly by the police data (*60*).

2.3 Use of Home-Based Approaches

Haule et al. (2019) applied a newer approach of using actual addresses to precisely calculate distances by integrating GIS and Google application programming interface (API) services to gauge the relationship of residence proximity to crash locations in the case of elderly pedestrians. One key finding of this study was that aging pedestrians were more prone to close-to-home pedestrian crashes as more than 35 percent of these crashes involving pedestrians above 65-

year age occurred within 0.5 miles from their home, and 64 percent of the crashes occurred within 2 miles (*36*).

Hezaveh and Cherry (2019) developed a deeper application of home-based analysis by investigating the role of neighborhood characteristics of the pedestrian on the crash outcome that may have occurred in other areas. Specifically, this method can help understand some of the cultural or geographically correlated factors that influence traveler behavior and therefore aim to understand if methods can be developed to target those neighborhoods or socioeconomic groups. Similarly, this approach can assess the impact burden on different groups (*62*).

2.4 US Pedestrian Crash Trends

Most pedestrian safety studies are pertinent in depicting pedestrian crashes' nature and severity. Studies have also modeled the injury severity by considering the heterogeneities associated with time and space (*40; 63*). Although it is vital to understand the significant variables affecting pedestrian crashes with the help of these studies, they focus on the cross-sections of time and do not precisely present how each factor affecting the injury severity has progressed over time. For instance, although children are one of the most vulnerable pedestrians and are likely to die, even from a minor vehicle impact, children's deaths are not causing the rise in overall pedestrian fatalities. In truth, children's pedestrian fatalities have significantly decreased over time (*64*).

A few studies have investigated the longitudinal effects of the aforementioned factors over the years, directly or indirectly responsible for the sudden increase in pedestrian fatality trends. Trend analysis in the US from 1977 to 2016 reported a hundred percent increase in pedestrian fatalities are correlated with larger vehicles (SUVs, vans, and pickups), 26 percent growth on roads with posted speed limits of 35 mph and higher, and 41 percent increase on roadways with four or more lanes (*64*). Two pedestrian fatality trend analyses were done around a similar time, based on the FARS database, and have reported substantial growth in pedestrian deaths in traffic crashes involving SUVs, with a rise of around 80 percent. Besides, both studies identified a significant upward trend in pedestrian deaths in urban areas, arterials, and dark conditions (*10; 65*). A recent study looks back 20 years and explores the effects of pedestrian fatalities and larger vehicles. The study reports that replacing larger vehicles (SUVs, pickups, and minivans) with cars would prevent 8000 pedestrian fatalities from 2000 to 2019. Despite being one of the significant contributors, the study results suggest that larger vehicles are not solely behind the dramatic surge in the deaths of pedestrians in the last decade (*66*).

Studies such as Tefft et al. (2021) and Ferenchak and Abadi (2021) are some of the most recent investigations on the US pedestrian fatality trend using the FARS dataset (*10; 67*). Tefft et al. (2021) listed fatal pedestrian death counts for every year from 2009 - 2018 but only reported the percentage changes for 2009 and 2018. Despite not including the trend, the findings from this study corroborate the predecessors' findings, such as fatality increase on high-speed roads (urban non-freeway arterials), nighttime crashes, crashes involving SUVs and cars, and so on. Because the nighttime accounted for more than 85 percent of the increase in US pedestrian deaths, Ferenchak and Abadi (2021) decided to only look at nighttime pedestrian fatalities concerning variations among other variables such as infrastructure, human factors, vehicle characteristics, and situational factors. The study further attempted to answer whether the pedestrian fatality increase could be attributed to the increasing severity of the pedestrian crashes or not by looking at the ratio of pedestrian fatality to the pedestrian injured. The study was unable to answer that question (*67*).

The fundamental limitation of the above studies is that they only look at the fatality data provided by the FARS dataset but not the overall injuries. Ferenchak and Abadi (2021) and Hu and Cicchino (2018) attempted to incorporate the exposure data from the National Automotive Sampling System (NASS) and General Estimates System (GES), which itself is not the parent database for the FARS fatality data, but a sample dataset incorporating traffic crashes from all US states (*68*). Our study, although foundationally like Hu and Cicchino (2018) and Ferenchak and Abadi (2021), overcomes this limitation by examining a single base dataset for fatalities and pedestrians' involvement in Tennessee, and also incorporates other novel addition of home-based and distance approaches and census data merger at a disaggregate level.

Chapter 3 Methodology

To characterize the growth in pedestrian fatalities in Tennessee, we aim to dissect the police crash database (TITAN) and examine the types and causes of crashes over a 10+ year span of time. We exclude crashes that occur on interstate highways since most of those are related to work-zone crashes or crashes related to disabled vehicles, both out of the scope of this study. We also focus specifically on urban crashes for reasons described later. We begin with a high-level descriptive analysis of pedestrian fatality trends and their associated variables. We aim to maintain a strong focus on only those pedestrian crashes that result in severe injuries and fatalities and identify trends over time that could cumulatively account for the significant increase in fatalities.

3.1 Data

The core data for this report is the statewide police crash data, TITAN, from 2009 to 2020. We supplement this data with data from the US Census American Community Survey (2013 - 2019) to identify demographic trends over time. We also use geocoding to determine the coordinates from the pedestrian/drivers' home addresses.

3.1.1 Police Crash Data (TITAN)

Tennessee Integrated Traffic Analysis Network (TITAN) database system is managed by the Tennessee Department of Safety and Homeland Security. All traffic safety-related data, including traffic crashes occurring in Tennessee, are reported to the database system by law enforcement agencies. Before storing the information, it tests the data for completeness and accuracy and prepares it for future use. To maintain uniformity in crash records across the US, as required by the Department of Safety and Homeland Security, TITAN follows Model Minimum Uniform Crash Criteria (MMUCC) guidelines to record traffic crash details, including injury outcomes in the KABCO scale (*69*). The scale codes K for a fatal crash, A for incapacitating (serious) injury, B for non-incapacitating apparent injury (minor) injury, C for possible injury, and O for no injury (*70*).

The TITAN database has three key elements: person, crash, and vehicle datasets. The Person dataset includes information on all people involved in the crash, including pedestrians, drivers, and passengers. Specifically, the person dataset includes the person's age, gender, race, ethnicity, person's action during the crash, evidence of alcohol and drug presence, person's distraction, driving license status and expiration information, violations if present, and outcome of the crash in terms of severity levels experienced by the person. The Crash database includes crash details such as date, time, county, land use (urban and rural), coordinates, number of fatalities, number of injured, type of intersection if intersection related, lighting condition, manner of collision, type of road/ route, speeding indication, type of traffic way, and other details relevant to the police. The vehicle (Unit) database includes details on every vehicle involved in the crash, including the stopped vehicles with or without drivers and information about the built environment. The unit database includes information such as hit-and-runs indication, hazardous material indication, Gross Vehicle Weight Rating (GVWR), place of the first impact, the extent of damage in the vehicle, vehicle body size, type and color, type of maneuver (straight, backing, right-turn, left-turn and so on), driver presence indicator, license plate details, manufacturer's name and model, vehicle age and commercial vehicle indication. It also contains information about the posted speed limit, road alignment, road profile and surface type, condition of road surface, the number of travel lanes, travel direction, name of the street, sequence of events that occurred, and so on. We gained access to the TITAN dataset containing personal identification information, such as the driver's and pedestrian's home addresses and the owner's vehicle identification number (VIN). This portion of the dataset was essential to applying the Home-Based Approach to traffic safety.

In the Python Environment, we prepared the data by extracting pedestrians from the person dataset and then identified all crashes linked to those pedestrians as pedestrian crashes. We filtered out person, vehicle, and crash data unrelated to pedestrian crashes. Then, we linked each pedestrian entry with the corresponding crash and striking vehicle entries with the driver details. In the rare case of multiple vehicle-pedestrian crashes, we only linked the vehicle and driver information of the largest vehicle. However, while merging the vehicle data with the crash and pedestrian datasets, we prioritized the smaller vehicle if the police determine the smaller vehicle's fault or in the case where the large vehicle is not in operation.

We encountered some complications while using the TITAN data. Our main study period spans 11 years, from 2009 to 2019. During this period, the technology for data collection improved with the advent of smartphones and portable computers. From our experience, while using the TITAN data, we also notice data collection quality improvement. For instance, TITAN started to report the races of pedestrians extensively from around 2013, while the earlier data reported a sizable number of "unknown" entries for the race. The crash location coordinates and pedestrian address reporting also suffer similar problems. For a longitudinal analysis like this, these problems will affect the significance tests and may misrepresent the growth percentage. We overcame this by using pedestrian fatality rates (PFRs), the total fatality per pedestrian involved during pedestrian crashes. Assuming that missing data are random occurrences, taking such ratios normalizes the voids created by missing data as the existing data (fatality and detailed data) would act as a sample representing the population. The data also had missing addresses from September 30, 2019, onward, so we excluded those data from the home-based approach and census information analyses. Nevertheless, we have a relatively comprehensive series of digitized data spanning about a decade that we use for this study.

3.1.2 Geocoding with Google API

TITAN also records the addresses of the people involved in the crashes. With access to their addresses, we can also determine the coordinates where the pedestrians and drivers reside using geocoding tools. We used Google API to convert locations in the "address" format to coordinates. Google API also enables users to geocode addresses and return details such as the type of the establishment, coordinates, and so on. We also calculated the pedestrian and driver home distance using Python's geodesic distance calculator function. Home distance is the Euclidean (crow-flies) distance between the home location of the pedestrian/ driver and the crash location.

3.1.3 Census Data

While the TITAN data contains a wide range of helpful information, the data is limited to what the police officer observed during the crash and does not encompass the socio-economic characteristics of the crash location. However, TITAN does record the crash location coordinates, enabling us to link the crash locations to their respective census block groups and supplement the socio-economic aspects of the crash location. Census block group data are the smallest unit of locations with information such as average race, income levels, median income, household car ownership, education levels, and so on in the neighborhood, provided by the American Community Survey. We tied this information to each pedestrian crash.

Thus, we not only had census information about the crash locations but also the socio-economic information of the home locations of pedestrians and drivers. We joined the census information with the census block groups using the TIGER Line Shapefiles from the US Census website with the help of ArcGIS Pro software. Then, we performed spatial join analysis in ArcGIS Pro to map the coordinates to their respective block groups. The American Community Survey only has census information on block groups from 2013 onwards, so we omitted the 2009-2012 data while performing census-related analyses.

3.2 Pedestrian Injury Trend Analysis

In this report, we conducted trend analysis, focusing on the fatal crashes and Pedestrian Fatality Rates (PFRs) using simple regression analyses and cross-tabulation tools. We first tabulated the data in a frequency table to identify the variables that contribute most to the fatal injuries. We then performed one-way Analysis of Variance (ANOVA) tests on the attributes within each variable. This helped us to determine whether the variables' trends are statistically significant or not. One-way ANOVA can sufficiently check the variations in the PFR or fatal crash counts for variables having two or more classifications. For instance, if we do the one-way ANOVA test on the age of pedestrians and it fails, that suggests no significant variation among the constituents of age. The total increase or decrease in the PFR is distributed uniformly amongst them.

Then, we utilized Microsoft Excel and Stata for the one-way ANOVA and basic regression models. These regressions helped us identify what variables are statistically correlated with the increasing trend in the severity of pedestrian crashes by looking at their respective p-values of the slope coefficient. We also visualized the significant trends with the Tableau software.

3.3 Pedestrian injury severity modeling

We estimated binary logistic regression models with fatal injury outcome as the dependent variable and diverse characteristics of pedestrian crashes such as pedestrian, driver, built environment, temporal, vehicle characteristics, and socio-economic variables as the independent variables. It helps to determine the variables contributing the most to pedestrian fatality. The binary logistic regression model is among the simplest and most easily interpretable type of discrete outcome models. It follows a random utility maximization framework and estimates factors contributing to a discrete outcome's changing probability. In our case, a discrete outcome is either a fatal or non-fatal crash outcome and can be predicted by independent variables correlated with that outcome (e.g., higher speeds). Multiple formulations can provide more robust outcome prediction, including ordered logistic regression and others we can explore in future work. It is essential to note that the model estimates the probability of severe injury, given that the individual has already encountered the crash. It does not estimate the probability of the individual's involvement in a crash since we do not have exposure data to estimate relative risk.

We also aimed to understand the severity of pedestrian crashes and how they have changed over time. For a more straightforward analysis, we broke the data into two groups for 2013 – 2015 and 2016 – 2019. We bifurcated the data into two-time segments in 2015/2016 because this is when the noticeable trend of increasing injury severity occurs. Due to the lack of census data, we do not include 2009 – 2012 data for the modeling process. Interaction variables are generally preferred in a model with few variables to assess before-aftereffects. However, we wanted to see the severity disparity associated with all variables in our model. At this point, it is more manageable to separately model two groups. That said, we were unable to compare the coefficients and log-odds ratio across the logistic regression models, unlike linear regression models, across these groups due to the possibility of unobserved heterogeneity (*71; 72*). Mood (2010) proposes probability change methods with the comparison of marginal effects to compare the variables across groups and models for logistic regression models (*71*). Based on the marginal effects, Mize et al. (2019) suggest calculating average discrete change (ADC) or discrete change at representative values (DCR) to compare two non-overlapping groups (*73*). We adopted calculating ADC and the group differences associated with ADCs in the case of our study as a tool to compare groups (time-points). We also followed the software and analysis guidelines Mize et al. (2019) provided for our calculations using Stata. Please refer to Mize et al. (2019) for more information on ADC and DCRs (*73*).

Chapter 4 Results and Discussion

This section of the report presents the results of descriptive statistics of the pedestrian crash, regression and trend analyses, and multivariate modeling.

4.1 Statewide crash characteristics

A total of 22,719 pedestrians in Tennessee were involved in 21,457 crashes from January 1, 2009, to December 31, 2020. From those crashes, 1,369 pedestrians were killed. Out of 22,719 pedestrians involved, we excluded 569 as they were struck on the interstate highways. We also excluded the data from the year 2020, being a potential outlier because of the COVID-19 pandemic. To observe the outlier effect of 2020, refer to Figure 1.1, where there is a significant rise in pedestrian fatalities but also a considerable decrease in total pedestrians involved (implying a spike in severity). Of the 20,445 pedestrians involved in crashes, 1,030 died. Total fatalities per year reduced to 64 in 2012 and have risen yearly since, more than doubled to 138 deaths in 2019 (and continued higher in 2020).

Pedestrian fatality rate (PFR) has been rising in Tennessee suggesting that pedestrian crashes are becoming more severe. Figure 4.1a shows that PFR has a statistically significant increasing pedestrian fatality rate trend with a regression coefficient of 0.218 (p-value = 0.011). The graph reveals an overall increase of 63 percent from 2009 to 2019. Whereas Figure 4.1b gives an overview of the overall composition of injury classes, including fatal, over the years in Tennessee. We can see that severe and fatal pedestrian crashes increased as a proportion of all crashes. This fact motivates us to explore and identify the factors driving the increase in pedestrian deaths.

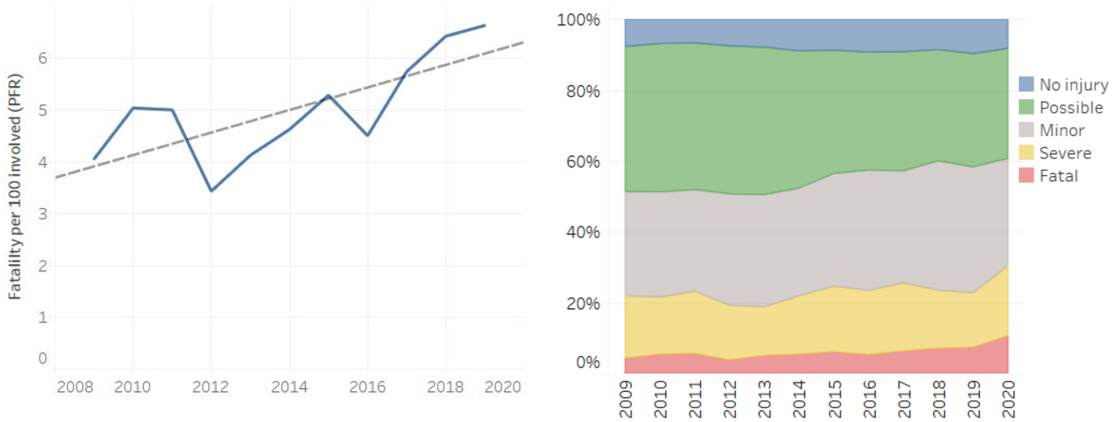


Figure 4.1 a) Pedestrian crash trend for fatal outcomes (per 100 involvement) b) Pedestrian crash composition for all types of injury outcomes

4.1.1 Urban and Rural Crashes

A total of 18,766 pedestrians were involved in crashes in urban Tennessee, with 811 pedestrian fatalities, and 1,679 were involved in rural Tennessee, where 219 pedestrians died, as illustrated by Figure 4.2. First, we divided the dataset into two groups according to the crash location setting: urban pedestrian crashes and rural pedestrian crashes. As illustrated in Figure 4.2, rural pedestrian crashes make up less than 10 percent of Tennessee's total pedestrian crashes. They contribute to about twenty percent of the total fatalities and are getting more severe over the years. Still, they are a relatively small proportion of total crashes distributed over large areas. The bulk of the increase in pedestrian crashes statewide occurred in urban areas. Of the 74 additional fatalities that have occurred in 2020, compared to 2012, 61 (82 percent) have occurred in urban areas. Moreover, upon breaking down the Figure 4.1a into urban and rural fatal crashes, we also observed that urban pedestrian crashes are the reason for a consistent and significant overall increase in pedestrian fatalities. PFR trend for urban crashes increased by 58 percent from 2009 – 2019 (coef. = 0.193, p-value = 0.008), while the increase was not significant for rural crashes (p-value = 0.111). Thus, we aimed to investigate the larger number of crashes causing significant and steady increases in pedestrian crashes in urban areas.

For the remainder of this report, we aimed to assess the factors contributing to the annual growth in urban pedestrian crashes.

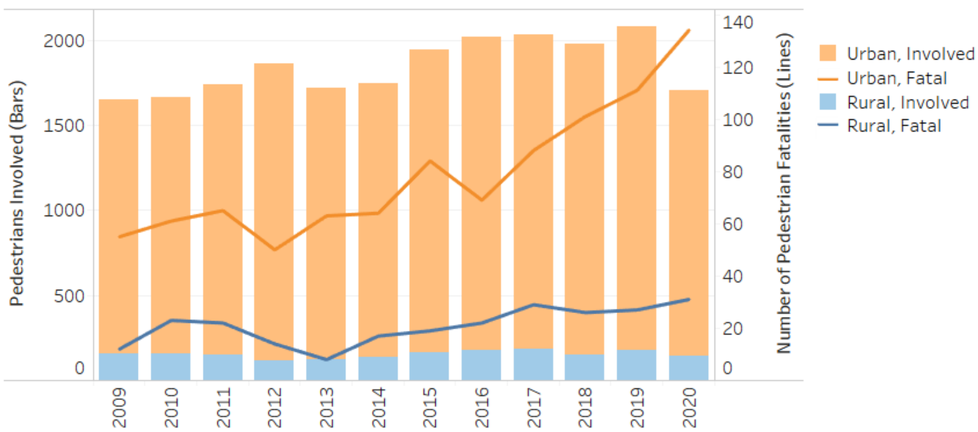


Figure 4.2 Pedestrian Crash and Fatality Trends in Urban and Rural Tennessee

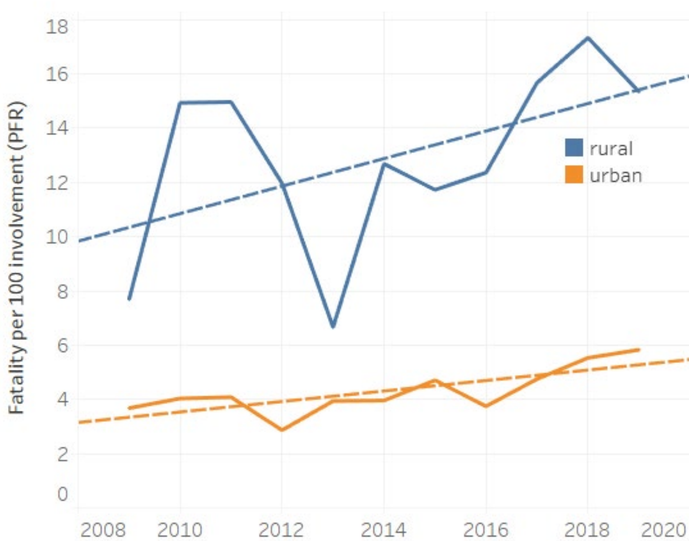


Figure 4.3 Pedestrian crash trend for fatal outcomes for urban and rural areas

4.1.2 Descriptive statistics

Table 1 is a frequency table of fatal pedestrian crashes and the total involved crashes for each variable from 2009 to 2019. We divide the variables into four significant groups: pedestrian characteristics, driver characteristics, road design and situational characteristics, and vehicle characteristics. The table also illustrates the functional classification of each variable with their potential (expressed as percentages) to cause fatal injuries to pedestrians. For instance, the presence of alcohol and drugs under the pedestrian characteristics shows that 22 percent of the pedestrian fatality were intoxicated. In comparison, intoxicated pedestrians only constituted about 6 percent of total pedestrians involved in the crashes. It suggests that alcohol and drug are critical variables that require further analysis. Likewise, pedestrians above the age of 51, male pedestrians, the position of pedestrians during the crash (including pedestrians attempting to cross in places without marked crosswalks), and so on are some variables that might be driving the increase.

Table 1 also gives an overview of the unknown and missing values in the TITAN database. Other notable variables with disproportionate weights among fatal and total pedestrian crashes are driver's gender, driver's driving under the influence (DUI), crashes happening in non-intersection locations, high speed and multiple lane roads, land use, dark lighted and unlighted conditions, straight (midblock) maneuver, heavy vehicles, and front-end collisions.

Table 1 Frequency Table Illustrating Variables in Pedestrian Crashes for Non-Interstate Urban Tennessee (2009 – 2019)

Variables	Fatal	(%)	Crash	(%)
Pedestrian Characteristics				
Age				
15 years and below	38	4.7	2849	15.2
16 - 35	180	22.2	6582	35.1
36 - 50	197	24.3	3891	20.7
51 - 65	278	34.3	3749	20.0
66 years and above	118	14.5	1695	9.0
Sex				
Female	228	28.1	7822	41.7
Male	583	71.9	10944	58.3
Race				
Black	244	30.1	5691	30.3
White	449	55.4	8646	46.1
Other	26	3.2	377	2.0
Unknown	92	11.3	4052	21.6
Alcohol/ Drug				
Not Present	632	77.9	17670	94.2
Present	179	22.1	1096	5.8
Distance from Home				
Less than 2 mi	352	45.2	7957	43.6
2 mi or more	332	42.6	7836	43.0
Unknown	95	12.2	2443	13.4
Location[a]				
Road - Not in crosswalk	324	41.6	3929	21.5
Road – Crosswalk not available	162	20.8	1850	10.1
In the crosswalk	29	3.7	1472	8.1
Not in roadway	86	11	4631	25.4
Unknown	178	22.8	6354	34.8
Driver Characteristics				
Age				
14 - 25	145	17.9	3081	16.4
26 - 55	399	49.2	7351	39.2
56 years and above	157	19.4	3748	20
Others/unknown	110	13.6	4586	24.4
Sex				
Female	201	24.8	6511	34.7
Male	505	62.3	8581	45.7
Unknown	105	12.9	3674	19.6
Race				
Black	260	32.1	5063	27
White	432	53.3	9205	49.1
Other	13	1.6	481	2.6
Unknown	106	13.1	4017	21.4
Alcohol/ Drug				
Not Present/ Unknown	726	89.5	18266	97.3
Present	85	10.5	500	2.7
Driving License				
Valid	515	63.5	10032	53.5
Invalid/ Not licensed	162	20	3324	17.7
Unknown	134	16.5	5410	28.8
Built Environment and Situational Factors				
Posted Speed Limit				
15 mph or less	56	6.9	5772	30.8
16 - 34 mph	128	15.8	5262	28.0
35 mph and more	266	32.8	7732	10.5

[a] Partial Data - Data not available after September 2019

Variables	Fatal	(%)	Crash	(%)
Built Environment and Situational Factors contd.				
Intersection				
No	650	80.1	13807	73.6
Yes	161	19.9	4959	26.4
Number of lanes				
Three or less	449	55.4	11259	60
Four or more	325	40.1	3919	20.9
Unknown	37	4.6	3588	19.1
Weekdays/ Weekends				
Weekdays	574	70.8	14236	75.9
Weekend	237	29.2	4530	24.1
Time of Day				
Midnight - 6 am	133	16.4	1825	9.7
6 am - noon	100	12.3	3710	19.8
Noon - 6 pm	133	16.4	7143	38.1
6 pm - midnight	445	54.9	6088	32.4
Lighting				
Daylight	173	21.3	10753	57.3
Dark - lighted	460	56.7	5490	29.3
Dark - unlighted	144	17.8	1576	8.4
Others	34	4.2	947	5
Parking lot or private property				
Neither	764	94.2	13805	73.6
Parking lot	30	3.7	3615	19.3
Private property	17	2.1	1346	7.2
Land Use				
Residential	190	23.4	5190	27.7
Non-Residential	621	76.6	13576	72.3
Vehicle Characteristics				
Maneuver				
Straight (Intersection)	123	15.2	1966	10.5
Straight (Mid-block)	512	63.1	6962	37.1
Backing and parking	30	3.7	2848	15.2
Turning	35	4.3	2996	16
Other/unknown	111	13.7	3994	21.3
Vehicle Type				
Cars	336	41.4	9202	49
SUVs	156	19.2	3356	17.9
Pickups and Minivans	189	23.3	3580	19.1
Heavy Vehicle	66	8.1	792	4.2
Others/Unknown	64	7.9	1836	9.8
Model Year				
1999 and older	157	19.4	3199	17
2000 - 2009	389	48	7976	42.5
2010 - 2019	164	20.2	3714	19.8
Unknown	101	12.5	3877	20.7
Hit-and-run				
Yes	187	23.1	4405	23.5
No	624	76.9	14361	76.5
First Impact				
Front End	513	63.3	7732	41.2
Rear End	23	2.8	2048	10.9
Right Side	93	11.5	3400	18.1
Left Side	73	9	2350	12.5
Other	109	13.4	3236	17.24

4.2 Pedestrian Injury Trend Analysis

The TITAN database provided us with the injury profile of all reported pedestrian crashes that happened in the state of Tennessee (notwithstanding reporting errors). Using that information, we can demonstrate that most of the rise in pedestrian deaths in Tennessee is not due to the increase in the number of pedestrians exposed to the traffic but due to the increase in severity of the pedestrian crashes. We narrowed the scope of our analysis to the urban pedestrian crashes to look at the different variables, which can be broadly classified into pedestrians, drivers, road design and situational, and vehicle characteristics, investigate further and identify the significantly increasing trends of pedestrian fatality rate (PFR).

Again, utilizing the TITAN data with injury profiles, we calculated PFR by dividing the total fatalities by the total number of involved pedestrians for each variable's given functional classification (sub-feature). We calculated average PFR, percent change in PFR, and estimated a PFR change using the trend lines equation from 2009 to 2019. We also performed one-way ANOVA tests for the PFR values to ascertain that PFRs are statistically different for each functional classification of any variable. It is also common among studies to only look at fatal crashes and their trends. Emulating such studies, we also performed ANOVA to see if there is any significant statistical difference between pedestrian fatalities. Trend lines are regression lines fitted for each feature with years as the independent variable and PFR for that feature as the dependent variable. **Table 2** reports the PFRs for pedestrian, driver, road environment, vehicle characteristics, average rates, percentage changes, and the significance of trend lines.

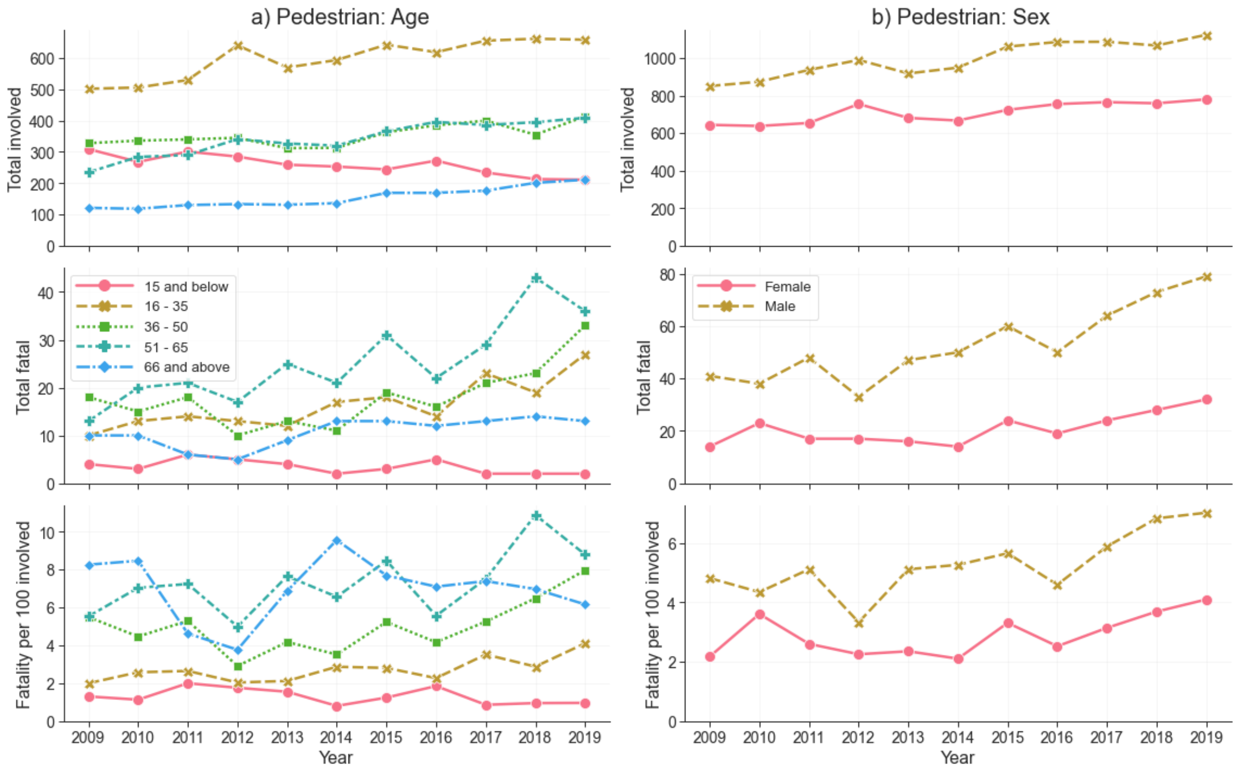


Figure 4.4 Pedestrian Crash Trends: a) Age and b) Gender of Pedestrians from 2009 – 2019

4.2.1 Pedestrian Characteristics

TITAN records critical pedestrian characteristics such as age, sex, race, and presence of alcohol/drugs, but does not capture other variables, such as income and education levels, that might influence pedestrian crash severity. Due to the missing information from October 2019 for distance from home and pedestrian's position during the crash, we could not carry the ANOVA tests out for fatal crashes for those variables. In the case of PFRs, except for pedestrians' distance from home, we found all variables varying significantly within themselves with a 0.05 significance level. Fatality and PFR have considerably high average values, compared to the others, for the age group 51 – 65 years. Age groups 16-35 and 51 – 65 show a statistically significant increasing PFR trends, and although the overall increase in PFR was higher for the age group 16 – 35 (coef. = 0.141; p-value = 0.012), compared to 59.1 for 51 – 65, the trend is strong for the latter (coef. 0.314; p-value = 0.045). It was interesting to see the decreasing PFR for children and elderly groups of pedestrians, despite being cited as the most vulnerable pedestrians in the literature, albeit the trends being not statistically significant (**Table 2** and Figure 4.4).

Figure 4.5 Pedestrian Crash Trends: a) Race and b) Position of the pedestrian during the crash

With the average PFR double that of females, male pedestrians are affected more by the increase in pedestrian fatality with twice the PFR slope of 0.240 (p-value = 0.008) compared to the female PFR of 0.12. Despite showing higher figures for the overall increase for both PFR and fatal crashes, female pedestrians, do not have a statistically significant coefficient for the increase (**Table 2** and Figure 4.4).

Potentially missing entries for races during 2009 – 2013 are potentially responsible for the large increase of 2000 percent and 500 percent for the Black and White pedestrians' deaths from 2009 to 2019. Only relying on the fatal entries for trend analyses would unfortunately give significant steep slopes of 10 (p-value = 0.000) and 9.6 (p-value = 0.000). We avoided the misrepresentation of data by employing the PFRs. The PFR side of **Table 2** illustrates that race does not have a significant role in the pedestrian severity increase, except for Others, which is only 3 percent of crashes (refer to **Table 2**). It is similar to the case of the pedestrian's position, which also has a large portion of missing data spanning 2009 – 2013. However, we still calculated PFR for these situations and curb the effect of unknown entries to some extent. While all entries were insignificant, pedestrian crashes were significantly increasing in severity in the places where no crosswalk was available (coef. = 0.024). Moreover, the largest growth since about 2012 in total fatal crashes has been in "not in crosswalk" locations, accounting for the bulk of the increased number of and rate of fatality growth. Figure 4.5 illustrates the effect of non-crosswalk fatality risk and the effect of poor crash coding, particularly for non-fatal cases.

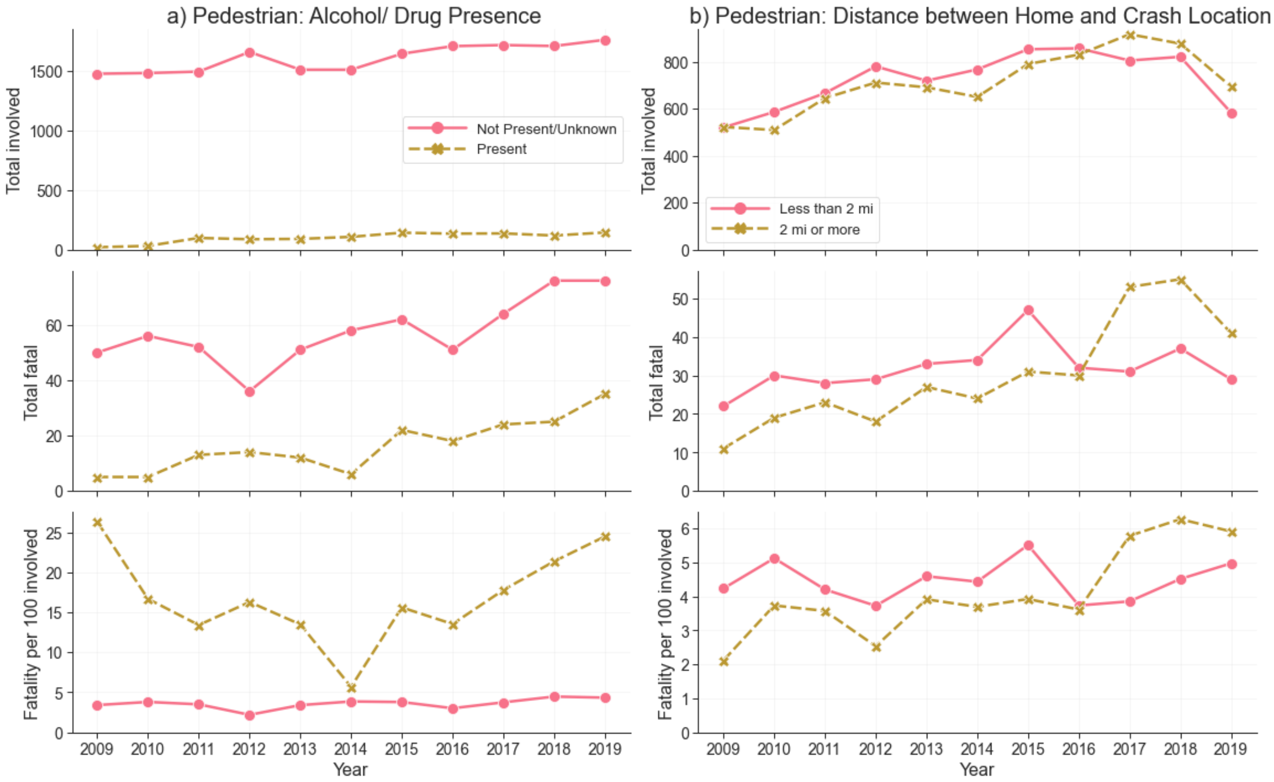


Figure 4.6 Pedestrian Crash Trends: a) alcohol or drug presence and b) distance from home of the pedestrians

Similar is the case of walking under the influence of alcohol or drugs. By only noticing the initial and final pedestrian fatality values of 5 and 35, we could see a large increase of 600 percent in fatal crashes for intoxicated pedestrians. However, the regression trends show otherwise, with non-significant increases (**Table 2**). One of the variables we extracted using the "home-based approach" analysis was Distance From Home. ANOVA results show that there is not enough variation between the variables "less than 2 miles" and "2 miles or more." However, the regression trend for crashes at 2 miles or more from the pedestrian's homes in **Table 2** shows a significant and large increase in PFR (coef. = 0.345 and p-value = 0.001). Figure 4.6 illustrates the trends related to intoxication and distance from home that has not shown strong differences over time.

4.2.2 Driver Characteristics

With the sheer number of details recorded by the TITAN about the driver, we were able to utilize driver demographic details and explore if drivers are associated with the pedestrian safety crisis in the state. While all variables significantly varied for fatal pedestrian frequency, two out of five did not pass the ANOVA test for the variation of PFR within the variables: driver's age and driving license status.

Regarding the driver's age, on average, thirteen pedestrians died in the 14-25 age group as drivers, while the average was 36 and 14 for the 26-55 and 56 and above age groups, respectively. Unsurprisingly, the PFR trend associated with the driver's age group of 26-55 is significant (coef. = 0.254, p-value = 0.031), with an almost 50 percent overall increase from 2009 to 2019 (**Table 2**). Although fatality linked with drivers under the influence of alcohol or drugs is 10 percent of the total fatality (see **Table 1**), **Table 2** shows that PFR associated with them has increased by 258 percent from 13 deaths per 100 involved to 47 deaths during 2009 – 2019. Figure 4.7 illustrates the pedestrian fatality trends for driver's age and their impairment status from alcohol or drugs.

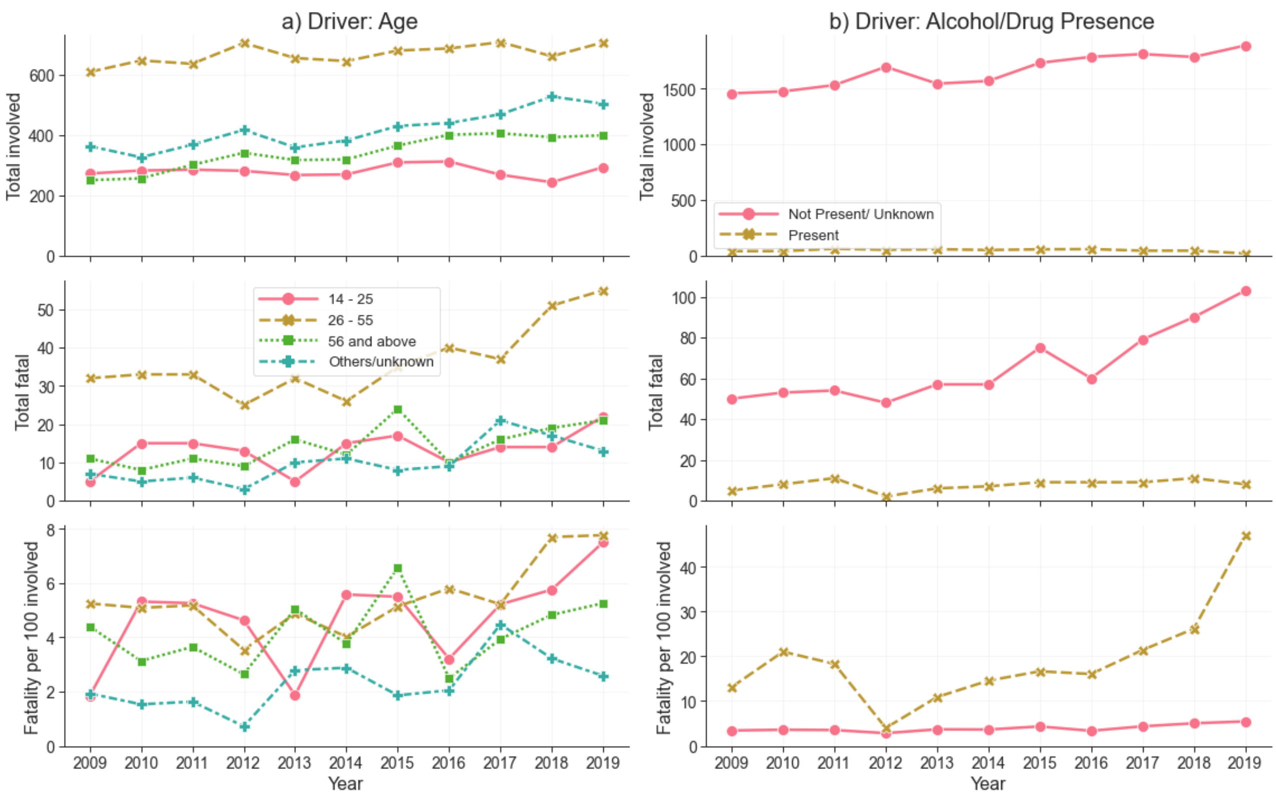


Figure 4.7 Pedestrian Crash Trends: a) Driver's Age and b) DUI status of the driver

Although PFR for the age group 14-25 has increased by more than 300 percent, it is not as substantial as others. Both percent increase in PFR and fatal crashes point to female drivers increasing the pedestrian fatality trend. Total pedestrians killed when struck by a vehicle driven by a female driver accounted for 21 percent in 2009 and increased to 38 percent in 2019. Even though male drivers were still associated with the majority of fatalities, female drivers contributed to more than three times more fatalities, from 11 pedestrian deaths to 38. Consequently, PFR associated with the female drivers is statistically significant, with a 215 percent overall increase (coef. = 0.278, p-value = 0.015) (refer to **Table 2**). During the same time, PFR associated with the male driver increased by 22.9 percent, which was not statistically significant. **Table 2** also depicts the annual mean pedestrian fatality associated with the Black drivers at 23.6 and White drivers at 39.3. However, both increased by 173.3 percent and 83.9 percent, respectively. PFR for Black driver doubled (coef. = 0.374, p-value = 0.002) and White drivers increase by 71 percent. We did not find that driving license status caused a significant rise in PFR. The most significant growth associated with the drivers' sex and race is illustrated in Figure 4.8.

Figure 4.8 Pedestrian Crash Trends: a) Sex and b) Race of the Drivers

4.2.3 Road Design and Situational Factors

All of the values of the variables of this group are sufficiently varied within themselves, as shown by the ANOVA results from **Table 2**, road design and situational factors section. We can see where the increase in fatality and PFR is taking place for the road design attributes. The variables that are linked to the positive growth of fatal pedestrian crashes and PFR are happening at non-intersection locations (coef. = 0.215, p-value = 0.005), with the high speed (speed limit equal to or more than 35 mph) roadways having four or more lanes (coef. = 0.486, p-value = 0.004). The roads with 35 mph or more speed limit have a regression line slope of 0.371 (0.01 significance). Figure 4.9 illustrates the nature of trends and how the PFR has increased for high-speed wide roads with multiple lanes and non-intersection locations.

Neither parking lots nor private property roads are causing the increase in fatalities. Although statistically insignificant, those variables have a negative slope causing a slight decrease. However, PFR in those locations that are not a parking lot or private property has increased by almost 60 percent (coef. = 0.242, p-value = 0.012) (see **Table 2**).

Table 2 shows that fatal crashes occurring in residential areas, as defined by the TITAN dataset, have barely increased from 17 in 2009 to 22 in 2019. Although it accounted for 23 percent of the overall fatal crashes, the proportion decreased from 31 percent to 20 percent in 11 years. On the other hand, fatal crashes happening in non-residential areas saw a 134 percent increase. The PFR trend for the latter is also statistically significant, with a 69 percent increase from 3.61 to 6.1 during the study period (coef. = 0.233, p-value = 0.010). Figure 4.9 (d) shows the respective PFR trends for pedestrian crashes happening in residential and non-residential areas.

Another set of variables under this category is the time of the day, lighting, and weekdays or weekends. 6 pm to midnight attribute of time of the day variable and dark attribute of lighting variable are almost relatable. Crashes happening from 6 pm to midnight have almost doubled, from 33 to 62, over the 11 years study period, with an annual average of 40.5 deaths.

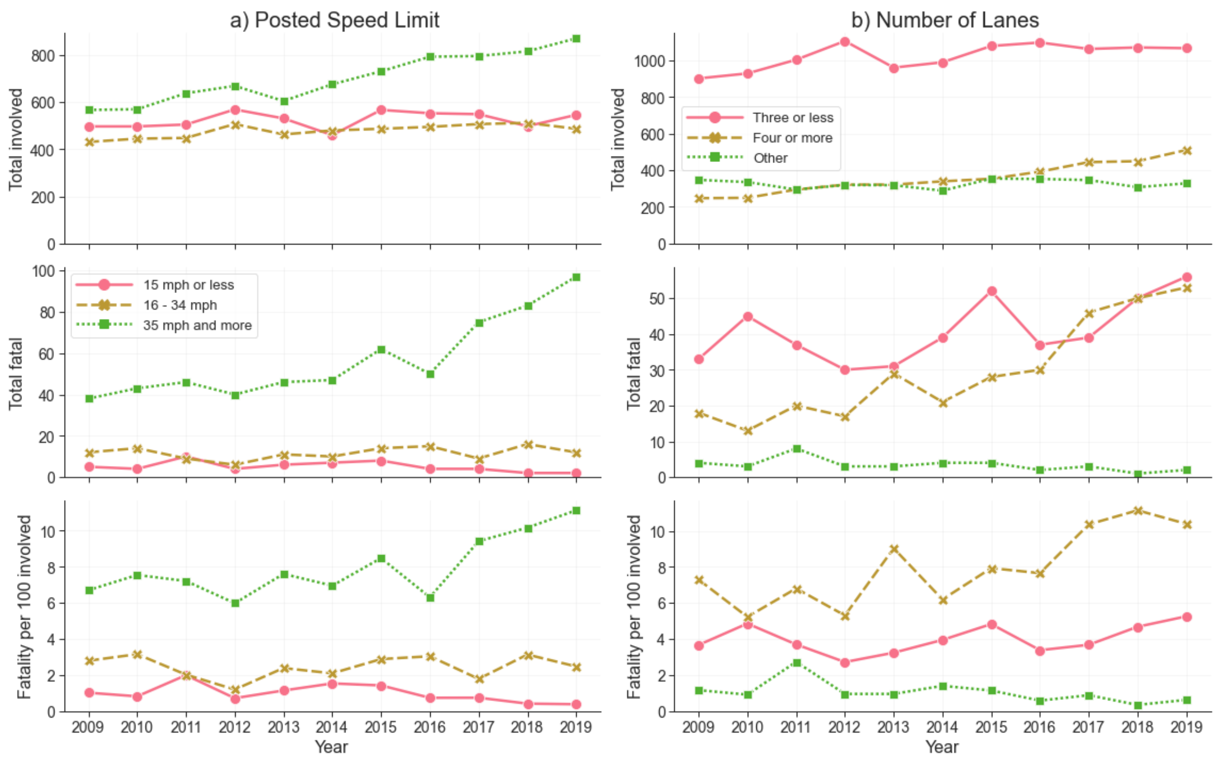


Figure 4.9 Pedestrian Crash Trends a) Posted Speed Limit, b) number of lanes, c) intersection and non-intersection locations d) Residential and non-residential land uses

Crashes in the dark–lighted and dark-unlighted conditions have also doubled from 33 to 65 and 11 to 24, respectively. However, only crashes happening from 6 pm to midnight and dark–lighted conditions are significant to PFR (p-value = 0.031 and 0.030), and both cause an overall increase of 39 percent. Daylight crashes are attributed to very few fatal crashes compared to nighttime ones. However, although not significant and very small, PFR for daylight crashes has doubled from 1.1 deaths per 100 pedestrians to 2.0 deaths in 11 years. Similarly, crashes happening from 6 am to noon (**Table 2**). Figure 4.10 shows the increasing trends for dark-lighted and unlighted conditions. Finally, weekend crashes are gradually associated with more severe injury outcomes in pedestrians. Crashes on the weekend saw a 57.5 percent increase in PFR from 4.78 in 2009 to 7.52 in 2019. The increase is statistically significant, with a regression coefficient of 0.387 and a p-value of 0.013. Weekday crashes are relatively less severe than weekend crashes and do not have a significant upward trend, as per the regression results (see **Table 2** and Figure 4.10).

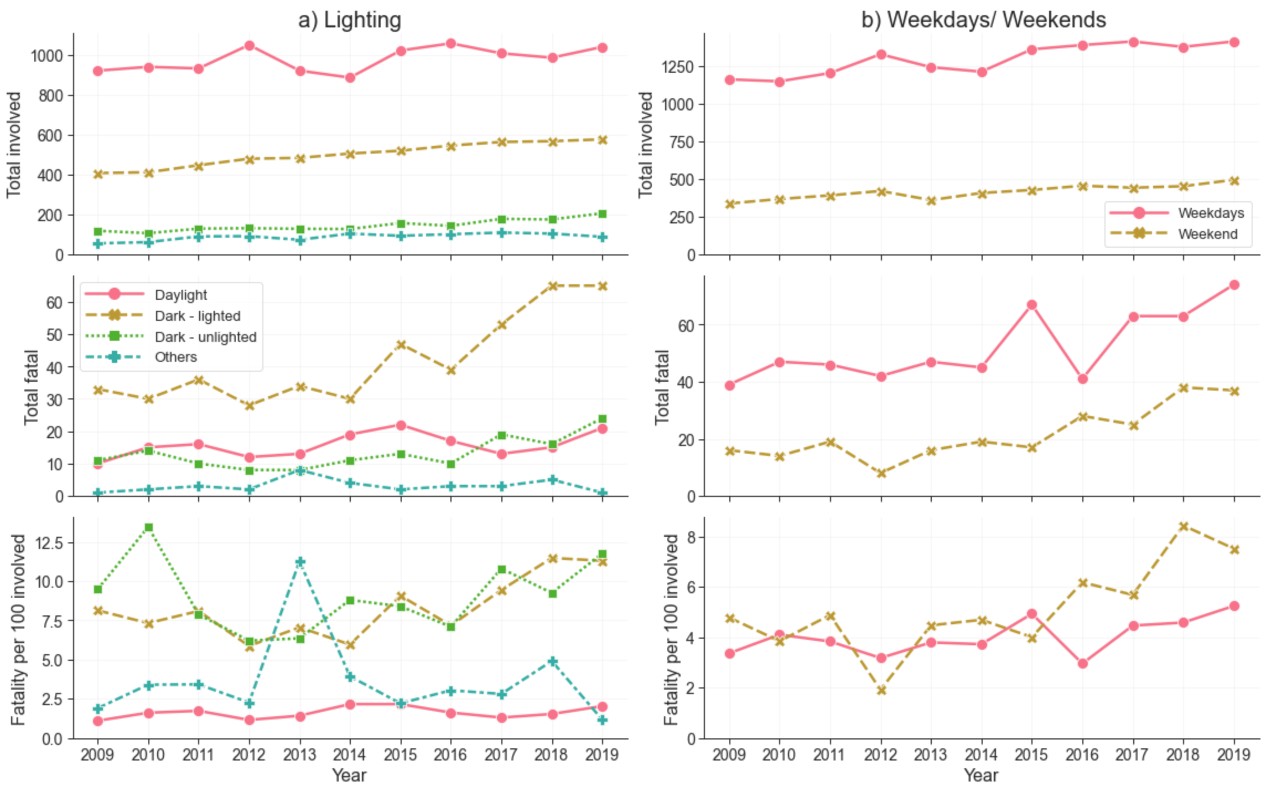


Figure 4.10 Pedestrian Crash Trends: a) lighting and b) weekends/ weekdays

4.2.4 Vehicle Characteristics

Vehicle characteristics are the final group of variables. Variables like vehicle type, hit and run, backing maneuver, and so on are often the most speculative variables in the media and literature, which we have classified under this category. Although all variables pass the ANOVA test for detecting variations relating to fatal crash frequencies, the ANOVA test for variation within the data finds that vehicle age classifications have no significant variation among themselves. Additionally, hit and run crashes do not distinguish themselves from non-hit-and-run crashes (see **Table 2**).

The straight maneuvers at intersection and midblock are the most common maneuver that causes fatal crashes. Other maneuvers include backing, parking, and turning; however, they constitute less than one in twenty total fatal crashes. The straight maneuver conforms with the overall increase in fatal pedestrian crashes, where the PFR caused by straight midblock maneuvers was 6.83 in 2009, and it became 10.36 in 2019, almost a 52 percent increase with significance (coef. = 0.327, p-value = 0.021). The straight maneuver at intersection is, however, not associated with a significant increase in PFR. Despite having a statistically significant downward slope, backing, parking, and turning maneuvers are responsible for only 6 percent of fatal crashes (refer **Table 2** and Figure 4.11, vehicle characteristics part).

Surprisingly, no vehicle type has shown a significant increase in the PFRs. We can observe higher chances of getting injured if struck by larger vehicles, but in terms of a trend, none of the regression lines are within the statistical significance threshold of 0.05. Heavy vehicles such as trucks, on average, killed six pedestrians yearly during the study period, and PFR associated with it is 8.36, the highest among the vehicle types. SUVs, too, on average, have higher chances of killing a pedestrian, with a PFR of 4.6, which is 26 percent higher than cars. Figure 4.11 will clarify the ambiguous trends associated with vehicle and pedestrian fatality. Vehicle age (model year minus crash year) and vintage (termed model year) in the **Table 2** do not have particularly strong differences over time. Neither the aging fleet nor advanced safety features, meant primarily to protect car occupants, have improved pedestrian severity over time. This is an area of future research since the rollout of new vehicles correlates perfectly with growth in severity of pedestrian crashes.

Despite the sizeable overall increase of over 800 percent (possibly due to the missing data) in fatality from 3 to 28 during the study period, hit and run pedestrian crashes had an overall decrease in PFR of 37.6 percent, accounting for 7.5 pedestrian deaths per 100 pedestrian crashes to 4.68 pedestrian deaths per 100 crashes. On the contrary, **Table 2** and Figure 4.12 shows that non-hit and run crashes have significantly contributed to the overall pedestrian fatality trend with a steady overall slope of 0.226 and within 0.05 significance level. Lastly, PFRs are associated significantly with left and right side collisions instead of front end collisions. Although PFR for the right side doubled (2.1 to 5.4) during the study period, fatal crashes due to collision on the left side of the vehicle were zero in 2009, increasing to 14 in 2019. Despite the significant increases in fatality associated with the right and left side collisions, front-end collision remains more than 100 percent more lethal. No rear-end crashes caused a fatality in 2019.

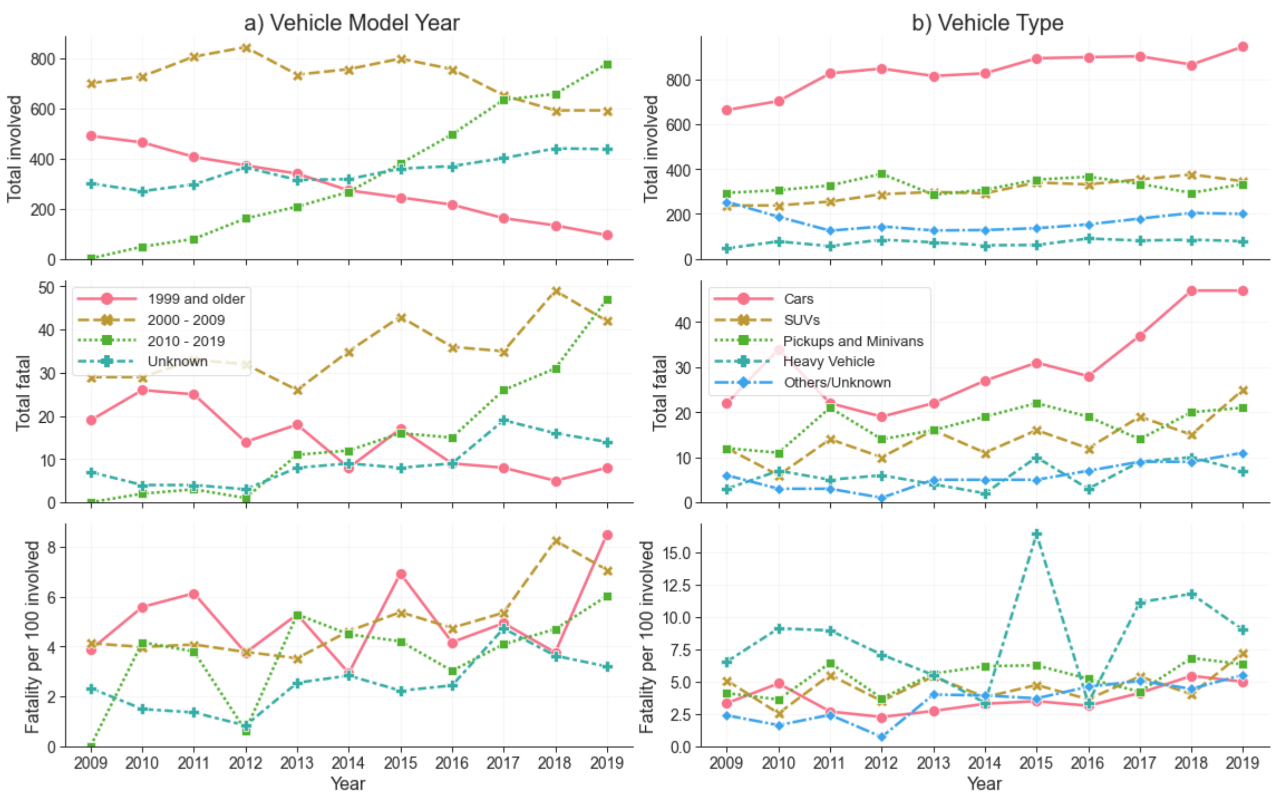


Figure 4.11 Pedestrian Crash Trends: a) Vehicle model year, b) Vehicle Type (Size)

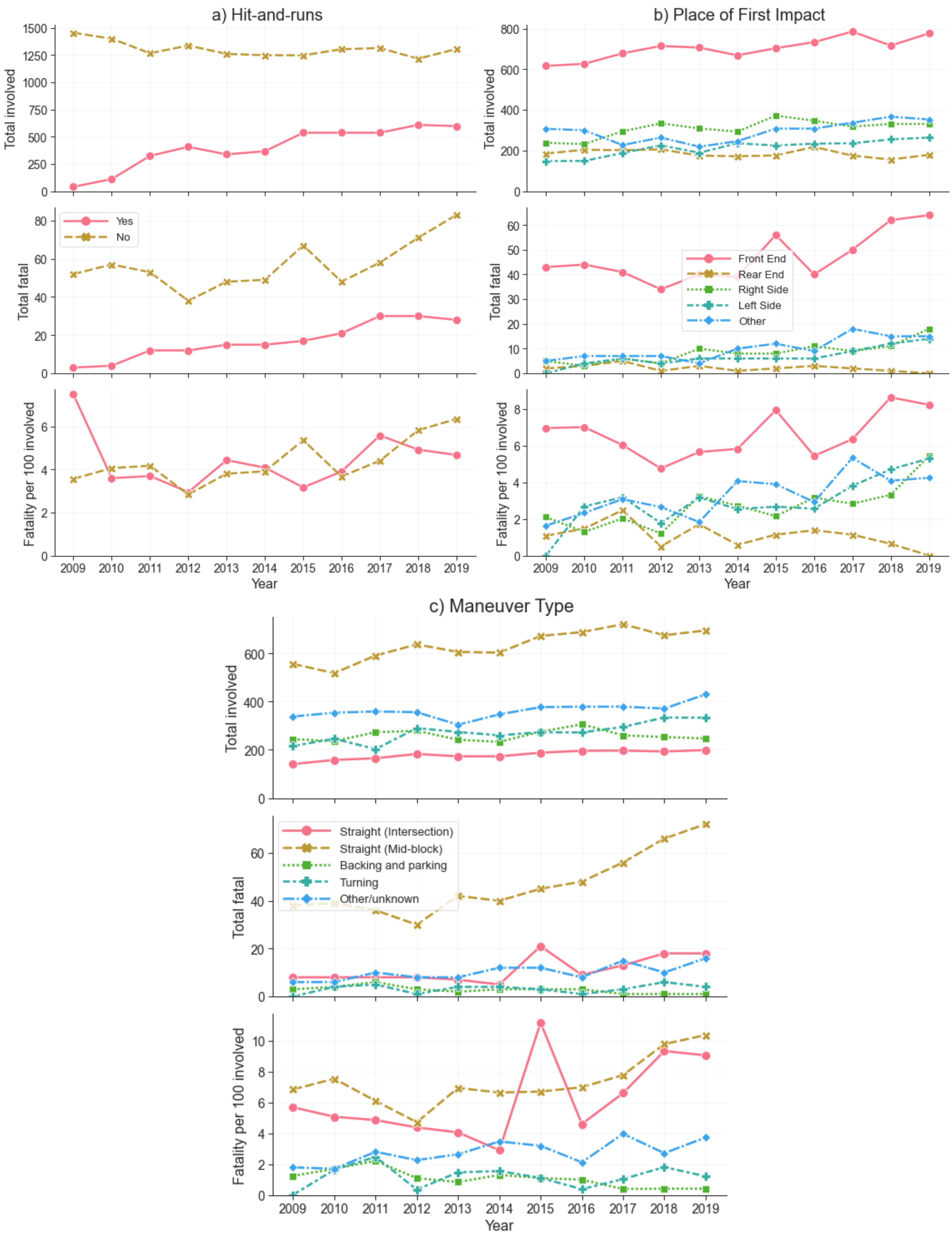


Figure 4.12 Pedestrian Crash Trends: a) Hit-and-runs and b) Place of first impact c) Type of maneuver

Table 2: One-way ANOVA tests (Pedestrian Fatality and PFR) and Linear Regression Results (PFR)

Variables		Fatal Crashes						Pedestrian Fatality Rate (PFR)								
		Fatal		Mean		ANOVA		PFR		Mean		ANOVA		Linear Regression		
		2009	2019	2009 - 2019	% increase	F	p	2009	2019	2009 - 2019	% increase	F	p	slope	t-Statistic	p
Pedestrian Characteristics																
Age	15 and below	4	2	3.5	-50.0	23.62	**0.000**	1.29	0.95	1.301	-26.8	46.02	**0.000**	-0.055	-1.43	0.188
	16 - 35	10	27	16.4	170.0			1.99	4.10	2.703	105.7			0.141	3.13	**0.012**
	36 - 50	18	33	17.9	83.3			5.49	7.97	4.992	45.2			0.217	1.79	0.107
	51 - 65	13	36	25.3	176.9			5.53	8.80	7.294	59.1			0.314	2.33	**0.045**
	66 and above	10	13	10.7	30.0			8.26	6.16	6.986	-25.5			-0.007	-0.04	0.969
Sex	Female	14	32	20.7	128.6	46.87	**0.000**	2.17	4.10	2.894	88.7	38.23	**0.000**	0.119	2.04	0.072
	Male	41	79	53.0	92.7			4.82	7.03	5.275	45.9			0.240	3.36	**0.008**
Race	Black	2	42	22.2	2000.0	26.10	**0.000**	7.14	5.71	4.527	-20.1	10.95	**0.000**	-0.010	-0.07	0.942
	White	11	68	40.8	518.2			4.87	6.76	5.131	38.9			0.122	1.80	0.105
	Other	1	1	2.4	0.0			14.29	2.63	7.875	-81.6			-1.118	-2.96	**0.016**
Alcohol/ Drug	Not Present	50	76	57.5	52.0	81.15	**0.000**	3.39	4.32	3.571	27.4	57.42	**0.000**	0.092	1.68	0.128
	Present	5	35	16.3	600.0			26.32	24.48	16.779	-7.0			0.176	0.31	0.766
Distance from Home[a]	Less than 2 mi	22	29	32.0	-			4.23	4.97	4.443	17.6	0.62	0.440	0.011	0.18	0.861
	2 mi or more	11	41	30.2	-	-	-	2.11	5.91	4.094	180.4			0.345	4.85	**0.001**
Position[a]	Not in crosswalk	9	35	29.5	-			14.06	9.64	8.745	-31.4	54.41	**0.000**	-0.088	-0.36	0.728
	Crosswalk not available	4	23	14.7	-	-	-	8.51	14.29	8.811	67.9			0.463	2.70	**0.024**
	In the crosswalk	0	4	2.6	-			0.00	2.63	1.804	-			0.126	1.26	0.240
	Not in roadway	1	7	7.8	-			0.77	1.77	1.818	129.8			-0.017	-0.22	0.831

Variables		Fatal Crashes						Pedestrian Fatality Rate (PFR)								
		Fatal		Mean		ANOVA		PFR		Mean		ANOVA		Linear Regression		
		2009	2019	2009 - 2019	% increase	F	p	2009	2019	2009 - 2019	% increase	F	p	slope	t-Statistic	p
Driver Characteristics																
Age	14 - 25	5	22	13.2	340.0	39.95	**0.000**	1.84	7.51	4.700	308.5	2.14	0.136	0.280	1.91	0.088
	26 - 55	32	55	36.3	71.9			5.25	7.77	5.419	48.1			0.254	2.55	**0.031**
	56 and above	11	21	14.3	90.9			4.40	5.26	4.158	19.6			0.120	1.04	0.327
Sex	Female	11	38	18.3	245.5	50.82	**0.000**	2.00	6.31	3.087	215.0	29.78	**0.000**	0.278	2.99	**0.015**
	Male	37	61	45.9	64.9			5.69	7.00	5.866	22.9			0.162	1.74	0.115
Race	Black	15	41	23.6	173.3	74.57	**0.000**	3.96	7.96	5.095	101.2	10.56	**0.000**	0.374	4.18	**0.002**
	White	31	57	39.3	83.9			4.04	6.90	4.699	71.0			0.211	2.32	**0.046**
	Other	2	0	1.2	-100.0			3.13	0.00	2.402	-100.0			-0.322	-2.37	**0.042**
Alcohol/ Drug	Not Present/ Unknown	50	103	66.0	106.0	113.3	**0.000**	3.43	5.46	3.934	59.1	20.68	**0.000**	0.183	3.69	**0.005**
	Present	5	8	7.7	60.0			13.16	47.06	19.041	257.6			2.084	2.43	**0.038**
Driving License	Valid	12	77	46.8	541.7	23.78	**0.000**	6.15	6.38	5.182	3.8	1.26	0.274	0.028	0.38	0.710
	Invalid/ Not licensed	0	30	14.7	-			0.00	6.30	4.421	-			0.354	2.00	0.077
Road Design and Situational Factors																
Intersection	No	46	89	59.10	93.47	77.78	**0.000**	4.05	6.44	4.678	59.01	9.81	**0.003**	0.215	3.64	**0.005**
	Yes	9	22	14.63	144.44			2.51	4.21	3.194	67.7			0.149	1.49	0.171
Number of Lanes	Three or less	33	56	40.8	69.7	5.10	**0.000**	3.66	5.25	3.989	43.4	74.59	**0.000**	0.092	1.24	0.247
	Four or more	18	53	29.5	194.4			7.29	10.39	7.937	42.6			0.486	3.76	**0.004**
Posted Speed Limit	15 mph or less	5	2	5.1	-60.0	65.71	**0.000**	1.01	0.37	0.980	-63.6	131.6	**0.000**	-0.075	-1.74	0.115
	16 mph - 34 mph	12	12	11.6	0.0			2.78	2.46	2.441	-11.5			0.016	0.26	0.800
	35 mph and above	38	97	57.0	155.3			6.70	11.13	7.96	66.1			0.371	3.33	**0.009**
Days	Weekdays	39	74	52.2	89.7	43.48	**0.000**	3.36	5.24	4.011	55.9	3.65	**0.000**	0.127	2.12	0.063

	Variables	Fatal Crashes						Pedestrian Fatality Rate (PFR)								
		Fatal		Mean		ANOVA		PFR		Mean		ANOVA		Linear Regression		
		2009	2019	2009 - 2019	% increase	F	p	2009	2019	2009 - 2019	% increase	F	p	slope	t-Statistic	p
	Weekend	16	37	21.5	131.3			4.78	7.52	5.127	57.5			0.387	3.08	**0.013**
Time of Day	Midnight - 6 am	7	22	12.1	214.3	50.29	**0.000**	6.31	10.28	7.251	63.0	29.88	**0.000**	0.227	0.78	0.457
	6 am - noon	7	16	9.1	128.6			2.35	4.27	2.664	81.6			0.102	1.13	0.286
	Noon - 6 pm	8	11	12.1	37.5			1.29	1.60	1.878	24.5			0.072	0.82	0.431
	6 pm - midnight	33	62	40.5	87.9			7.11	9.87	7.246	38.8			0.242	2.55	**0.031**
Lighting	Daylight	10	21	15.7	110.0	52.09	**0.000**	1.09	2.02	1.610	85.9	34.69	**0.000**	0.043	1.24	0.245
	Dark - lighted	33	65	41.8	97.0			8.13	11.30	8.260	39.1			0.375	2.58	**0.030**
	Dark - unlighted	11	24	13.1	118.2			9.48	11.76	9.042	24.1			0.065	0.29	0.781
	Others	1	1	3.1	0.0			1.89	1.16	3.656	-38.4			-0.063	-0.23	0.824
Parking lot or private property	Neither	51	109	69.5	113.7	117.0	**0.000**	4.73	7.52	5.466	58.9	95.01	**0.000**	0.242	3.15	**0.012**
	Parking lot	4	2	2.7	-50.0			1.35	0.57	0.838	-57.6			-0.082	-1.35	0.211
	Private property	0	0	1.5	-			0.00	0.00	1.208	-			-0.010	-0.13	0.901
Land use	Residential	17	22	17.2	29.4	50.19	**0.000**	3.84	4.95	3.67	28.9	5.37	**0.031**	0.076	1.43	0.186
	Non-residential	38	89	56.5	134.2			3.61	6.10	4.51	69.0			0.233	3.25	**0.010**
Vehicle Characteristics																
Maneuver	Straight(Intersection)	8	18	11.1	125.0	84.22	**0.000**	5.67	9.05	6.14	59.6	42.71	**0.000**	0.424	1.93	0.085
	Straight (Mid-block)	38	72	46.5	89.5			6.83	10.36	7.30	51.6			0.327	2.80	**0.021**
	Backing and parking	3	1	2.7	-66.7			1.23	0.40	1.052	-67.1			-0.134	-3.83	**0.004**
	Turning	0	4	3.2	-			0.00	1.20	1.174	-			0.018	0.26	0.804
Vehicle Type	Cars	22	47	30.5	113.6	31.52	**0.000**	3.31	4.96	3.641	49.8	9.60	**0.000**	0.159	1.75	0.115
	SUVs	12	25	14.2	108.3			5.06	7.23	4.599	42.7			0.145	1.20	0.261
	Pickups/Minivans	12	21	17.2	75.0			4.08	6.31	5.298	54.5			0.190	1.85	0.098

	Variables	Fatal Crashes						Pedestrian Fatality Rate (PFR)								
		Fatal		Mean		ANOVA		PFR		Mean		ANOVA		Linear Regression		
		2009	**2019**	**2009 - 2019**	**% increase**	**F**	**p**	**2009**	**2019**	**2009 - 2019**	**% increase**	**F**	**p**	**slope**	**t-Statistic**	**p**
	Heavy Vehicle	3	7	6.0	133.3			6.52	8.97	8.363	37.6			0.300	0.80	0.444
Model Year	1999 and older	19	8	14.3	-57.9	15.01	**0.000**	3.87	8.51	5.081	119.9	2.48	0.101	0.134	0.84	0.422
	2000 - 2009	29	42	35.4	44.8			4.13	7.08	4.996	71.4			0.359	4.11	**0.003**
	2010 – 2019[b]	0	47	14.9	-			4.17	6.03	3.675	44.6			0.336	2.28	**0.049**
Hit-and-run	Yes	3	28	17.0	833.3	69.49	**0.000**	7.50	4.68	4.414	-37.6	0.01	0.928	-0.023	-0.18	0.864
	No	52	83	56.7	59.6			3.57	6.36	4.368	77.8			0.226	3.03	**0.014**
First impact	Front End	43	64	46.6	48.8	116.3	**0.000**	6.97	8.24	6.629	18.2	33.67	**0.000**	0.159	1.40	0.195
	Rear End	2	0	2.1	-100.0			1.08	0.00	1.100	-100.0			-0.105	-1.80	0.105
	Right Side	5	18	8.5	260.0			2.10	5.44	2.682	158.9			0.273	3.65	**0.005**
	Left Side	0	14	6.6	-			0.00	5.30	2.947	-			0.341	4.00	**0.003**
	Other/Unknown	5	15	9.9	200.0			1.63	4.25	3.28	160.9			0.268	3.69	**0.005**

[a] Calculations skipped for missing values
[b] 2010 data used for calculation for the cars with make year 2010-2019

4.2.5 Residential and non-residential crashes

Crashes in commercial areas follow linear patterns along arterial corridors. These corridors, as we have shown above, are most dangerous. On the contrary, distributed residential crashes tend to be seemingly random but also tend to be less severe. By partitioning crashes by commercial and residential zones, analysts can highlight high injury networks and corridors to focus on safety interventions.

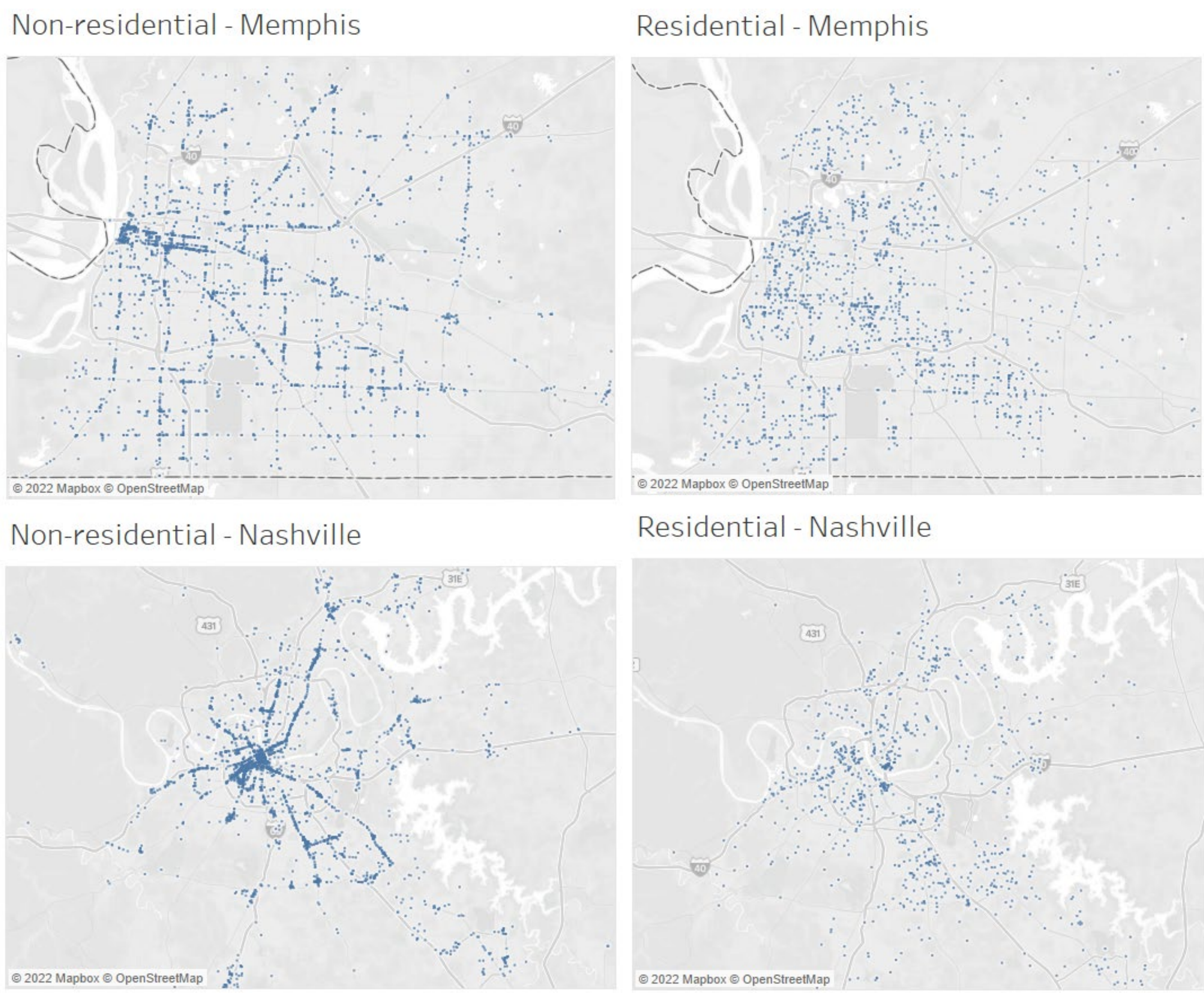


Figure 4.13. Crashes associated with non-residential (commercial/business) land uses and residential areas in Memphis and Nashville

4.2.6 Commercial vehicle crashes/ Freight vehicles

Freight-related crashes involving larger freight vehicles are more likely to cause severe injuries. On average, 30 percent of crashes involving single-unit trucks with three or more axles or tractors with trailers caused fatal or severe injuries.

Injury outcomes of freight-related crashes differ regarding pedestrian characteristics, driver characteristics, temporal and weather factors, and the crash environment. Specifically, freight-related crashes involving males, pedestrians over 40, White, and with alcohol or drug presence are more likely to have a higher probability of severe or fatal crashes. Similarly, freight vehicle drivers who are males, White, aged over 55 years, and have alcohol or drug presence are more likely to be involved in severe crashes. Crash severity is also greater if the freight vehicles are going straight. Crash severity is also positively associated with the time of day and weather. Crashes occurring during early morning and late night and inclement weather conditions, such as cloudy, rain, or snow, have a higher probability of severe injury outcomes. The environmental factors of crashes are also correlated with injury outcomes. Severe crashes are more likely to occur in dark conditions without lighting, and half of the crashes occurring in those conditions cause severe injuries. Crash severity is also greater if these crashes occur on the US- and state- routes, roads with a higher speed limit, and roads with more lanes. The road surface condition, including wet, snowy, and icy, is associated with crash severity.

Compared to nonfreight-related crashes, freight-related crashes are more likely to occur when freight drivers are backing the vehicle or maneuvering the vehicle for parking-related activities on private property or parking areas. If urban freight deliveries are completed with smaller vehicles, as some recent studies have suggested is likely, we might see fewer severe crash outcomes. As freight patterns change and delivery vehicles move increasingly to more urban and residential areas, there will be more opportunities for conflicts between commercial vehicles and pedestrians. However, if carriers continue using smaller vehicles for the last mile delivery, there is evidence to suggest that crashes between vulnerable road users and this type of delivery vehicle are less likely to be severe or fatal.

4.3 Multivariate modeling approach

It is informative to describe crash severity in a multivariate modeling approach to control for confounding variables and multiple correlations. As described in Chapter 3, we estimated a Binomial Logistic regression model to assess the factors contributing to the probability of a crash being fatal (i.e., the probability of death, given that a pedestrian was involved in a crash). This approach allowed us to understand the variables that significantly contribute to the increase in the severity of crashes, which is the main driving force behind the increase in overall pedestrian fatalities in Tennessee. Table 3 presents the results of the crash severity models. The table presents two models: 2013-2015 (the period of slow fatality growth) and 2016-2019 (the period of rapid fatality growth) with Average Discrete Change (ADC) for each period and the difference between the ADCs to determine if the ADCs are significantly different between the two periods. Both models are significant and have relatively high predictive values with relatively high pseudo-R^2 values. The results are discussed in the following pages. In all cases, the odds ratios reflect the relative change in odds compared to the base variable. An odds ratio of less than 1.0 reflects lower odds, and more than 1.0 reflects higher odds relative to the base variable. For example, young children (age <16 years) have lower odds (0.56) of fatal injury than 16-35-year-olds for the 2013-2015 model. The ADC differences were not within the acceptable significance level, suggesting the absence of severity disparity for the two periods. It could be due to an arbitrary disaggregation of a relatively continuous time variable or that the small increases across ADC differences (i.e., positive ADC differences) increased severity on many variables. Increases in severity span most variables.

4.3.1 Demographics

As we observed with the trendlines, age is a significant predictor of severity. In almost all cases, compared to the base age group (16-35), the odds of a fatal injury increase. The ADC values are significant among themselves with a small increase in the recent years (with insignificant differences) suggesting that these variables probably do not substantially drive the increase in fatality over time, although the difference is positive. Children had shifting odds ratios and ADC (negative to positive) between the two time periods, but those variables are insignificant in both models, meaning that the odds of death are practically the same as the 16-35 age group, given a crash. The pedestrian's race is significant and positive; White pedestrians were much more likely to experience a fatality in a crash. That value did not change between periods. Pedestrian gender was not significant in the model and was therefore excluded. Pedestrian intoxication was flagged as a contributor to increased severity as its ADC also doubled over time, although the difference in ADCs is not significant.

Including data from the census block group of pedestrians, pedestrians who live in affluent neighborhoods involved in crashes have a substantially lower chance of death, but the ADC has increased with the difference in ADCs being weakly significant (0.1 significance). As the proportion of residents in a neighborhood walking to the destination increases, the chance of fatal injury also decreases substantially. These two factors may relate to access to better walking infrastructure in affluent, walkable neighborhoods. Last, pedestrians who live in neighborhoods with a high proportion of Black residents (controlling for pedestrian's race) have a higher chance of fatal injury (statistically insignificant). The census-level variables could reflect various unobserved infrastructure and socio-economic variables that could contribute to diminished safety. For driver demographics, the model results show that men have a higher contribution to severe pedestrian crashes, though in recent years, female contribution is not statistically significant.

4.3.2 Impairment

Driver impairment (alcohol or drugs) had one of the most substantial effects in the model, and that effect has increased since 2016, based on the ADC values (albeit statistically insignificant). The average marginal effect or ADC was 4.3 percent for the period 2013-2015, which increase to 6.5 percent in 2016 - 2019. The odds of an impaired driver killing a pedestrian (given a crash) was 3.08 between 2013-2015, and 4.65 from 2016-2019. The chances of an impaired driver crashing are also likely higher. Moreover, we do not know the impairment status of the ~20 percent of drivers who fled the crash scene. We find that hit-and-run collisions have greater odds of fatal injury and have increased in the most recent time period, with ADC increased from 1.9 percent to 4.1 percent, with a weakly significant difference in ADCs.

4.3.3 Road and Situational conditions

Intersections have a lower relative risk (given a crash) than midblock locations, likely because of reduced speeds, driver awareness, and traffic control devices. The improvement of the most recent performance of intersections (relative to midblock conditions) is explained by the observation that midblock crossings have become more dangerous and have contributed more significantly to fatal crashes in recent years (see **Table 3**, difference in ADC is not significant). A related variable, the driver continuing straight (i.e., not turning) and striking a pedestrian crossing midblock, has one of the most substantial chances of increasing severity. Being hit mid-block increases odds of death by a factor of three but hasn't changed substantially between periods with almost similar ADCs. The two most remarkable roadway/situational variables are known pedestrian risk factors. First is the speed of the roadway. Compared to typical urban street speeds advocated by safety advocates (16-34 mph), faster roads double or quadruple injury risk. The most common speeds on urban arterials range from 35-40 mph, with double-fatal injury risk compared to slower streets. Urban arterials (often state highways in urban areas) with speed limits of 35 mph or above increase fatal injury risk by a factor of three. This type of street has become more dangerous – the ADC increased from 3.3 percent to 4.7 percent, highly significant among themselves but with statistically insignificant difference.

Another significant risk factor is lighting. Nighttime fatality risk increases substantially compared to daylight and has become riskier recently. For the earlier time period, ADC for lighted dark conditions was 3.9 percent and unlighted dark conditions was 3.8 percent. For the recent time periods, ADC increased by 1.6 percent and 1.9 percent for lighted and unlighted dark conditions, respectively. Taken together, high-speed arterials, at midblock locations, in dark conditions are among the most influential factors contributing to the increase in fatalities in the built environment. These also tend to be multilane roadways responsible for a large proportion of Tennessee's fatalities growth (Figure 4.9).

4.3.4 Vehicle characteristics

Finally, the oft-cited reason for increasing fatalities is related to vehicle type. First, we look at vehicle age at the time of the crash, precisely the difference between the model year and the crash year. We found that age did not influence the severity of the crash. Being struck by a newer vehicle was equally severe than an older vehicle. This indicates that vehicle safety interventions have not affected improving pedestrian safety in the event of a collision. This also means that vehicles have not become systematically more dangerous over time. It could be that attributes of vehicle safety have cancelled each other out, e.g., infotainment system distraction cancelling the benefits of antilock brakes.

When looking at specific body types, we found that larger and heavier vehicles contribute to increased fatality rates, which has been well described in the literature. Pickup trucks were significantly causing more harm in 2013 – 2015 with ADC value of 2.8 percent. In the recent years, pickups were no more significantly causing pedestrian deaths compared to the base (cars). ADC associated with SUVs decreased by 0.5 percent from 2 percent, with a statistically insignificant difference. Surprisingly, the ADC have decreased in recent years for trucks, from 6.1 to 5 percent. The explosion in urban truck use still results in slightly higher injury severity than cars but has perhaps resulted in lower injury severity than in earlier years. The overall crash trends imply that trucks (or SUVs) are not driving the surge in pedestrian fatalities in urban areas in Tennessee. Of note, we interacted vehicle age with trucks and found no significant change. Based on our limited data, newer pickup trucks do not result in a higher chance of severe injury than older pickup trucks. An overwhelming majority of pedestrian deaths are still a result of a collision with a car. Heavy vehicles (e.g., freight vehicles) have a very high odds (4.93 during the earlier years and 3.31 during the recent years) of fatality than a car, but their overall crash numbers are low.

Table 3: Binomial Logistic Regression Model Estimations for Pedestrian Crashes in Tennessee (2013 – 2019)

Dependent Variable: Fatal injury given that a Pedestrian is involved in a crash	2013 – 2015 (i)				2016 – 2019 (ii)				ADC (ii – i)	
	Odds Ratio	Std. Err.	ADC	Std. Err.	Odds Ratio	Std. Err.	ADC	Std. Err.	Difference	Std. Err.
Pedestrian Age (Base: 16 - 35 years)										
15 and younger	0.56	0.23	-0.022	0.015	1.03	0.34	0.001	0.014	0.023	0.021
36 - 50 years	1.23	0.30	0.008	0.009	1.76**	0.34	0.024**	0.008	0.016	0.012
51 to 65 years	2.86***	0.61	0.040***	0.008	3.51***	0.64	0.052***	0.008	0.012	0.011
66 years and above	5.36***	1.48	0.064***	0.011	5.47***	1.25	0.071***	0.010	0.006	0.014
White Pedestrian (Base: Otherwise)	1.79**	0.37	0.022**	0.008	1.74**	0.30	0.023**	0.007	0.001	0.011
Alcohol or Drug Presence in Pedestrian (base: not present)	1.52•	0.34	0.016•	0.009	2.17***	0.37	0.032***	0.007	0.016	0.011
Driver Gender (Base: Male)										
Female	0.65*	0.12	-0.016*	0.007	0.78	0.12	-0.010	0.006	0.006	0.010
Unknown	1.26	0.66	0.009	0.020	0.37•	0.21	-0.041•	0.023	-0.050	0.031
Driver Alcohol or Drug Presence (Base: not present)	3.06***	0.86	0.043***	0.011	4.72***	1.12	0.065***	0.010	0.022	0.015
Lighting (Base: Daylight)										
Dark - Lighted	2.77***	0.55	0.039***	0.008	3.78***	0.67	0.056***	0.007	0.016	0.011
Dark - not lighted	2.68***	0.73	0.038***	0.011	3.94***	0.84	0.057***	0.009	0.019	0.014
Dawn or Dusk	2.18•	0.92	0.030•	0.016	1.66	0.72	0.021	0.018	-0.009	0.024
Intersection (Base: otherwise)	0.77	0.15	-0.010	0.008	0.66*	0.11	-0.017*	0.007	-0.008	0.010
Posted Speed Limit (Base: 16 - 34 MPH)										
15 MPH and lower	0.55•	0.17	-0.023•	0.012	0.30**	0.11	-0.050**	0.015	-0.027	0.019
35 MPH and higher	2.38***	0.51	0.033***	0.008	3.07***	0.58	0.047***	0.008	0.014	0.011
Vehicle age (at the time of impact)	0.99	0.01	0.000	0.000	0.99	0.01	0.000	0.000	0.000	0.001
Vehicle Type (Base: Cars)										
Pickup	2.08**	0.45	0.028**	0.008	1.34	0.26	0.012	0.008	-0.016	0.012
SUVs	1.69*	0.37	0.020*	0.008	1.44*	0.25	0.015*	0.007	-0.005	0.011
Heavy Vehicle	4.93***	1.64	0.061***	0.013	3.31***	0.86	0.050***	0.011	-0.011	0.017
Minivan	1.40	0.57	0.013	0.016	1.26	0.44	0.010	0.014	-0.003	0.021
Other/ Unknown vehicle	0.70	0.74	-0.014	0.041	0.37	0.28	-0.042	0.032	-0.028	0.052
Hit-and-run Vehicle (base: otherwise)	1.64•	0.44	0.019•	0.010	2.68***	0.55	0.041***	0.008	0.022•	0.013
Straight Midblock Maneuver (base: otherwise)	3.16***	0.65	0.044***	0.008	2.82***	0.51	0.043***	0.008	-0.001	0.011
Pedestrian home census block with "p" proportion of people earning >$100K	0.07**	0.06	-0.100**	0.034	0.57	0.32	-0.024	0.023	0.077•	0.041
Pedestrian home census block with "p" proportion of people walking to work	0.02*	0.04	-0.146*	0.065	0.05*	0.06	-0.126*	0.054	0.020	0.085
Pedestrian home census block with "p" proportion of Black population	1.76•	0.53	0.022•	0.012	1.44	0.37	0.015	0.011	-0.006	0.016
Constant	0.00***	0.00	-	-	0.00***	0.00	-	-	-	-
Number of observations = 9,399	3,976		-		5,423		-		-	

Dependent Variable: Fatal injury given that a Pedestrian is involved in a crash	2013 – 2015 (i)				2016 – 2019 (ii)				ADC (ii – i)	
	Odds Ratio	**Std. Err.**	**ADC**	**Std. Err.**	**Odds Ratio**	**Std. Err.**	**ADC**	**Std. Err.**	**Difference**	**Std. Err.**
LR chi2(27)	336.51		-		663.84		-		-	
Prob > chi2	0.000		-		0.000		-		-	
Pseudo R2	0.2249		-		0.2869		-		-	
Log likelihood = -1405.063	-579.891		-		-825.172		-		-	

· p-value < 0.1, * p-value < 0.05, ** p-value<0.01, *** p -value < 0.001

4.4 Home-Based Approach

With the pedestrian home coordinates, we uncovered and explored patterns of pedestrian crashes from a different perspective – distance. Since we knew the crash and home-based coordinates, we calculated the distance between those locations. One thing to note about the distance analyses is outliers. Pedestrian Home to Crash Distance (PHCD) for out-of-state and out-of-country visitors and tourists is exceptionally high and possibly distorts the trends and findings. As such, we capped the distance to home at 50 miles for our home-based analyses, which also helped filter out travelers in an urban area.

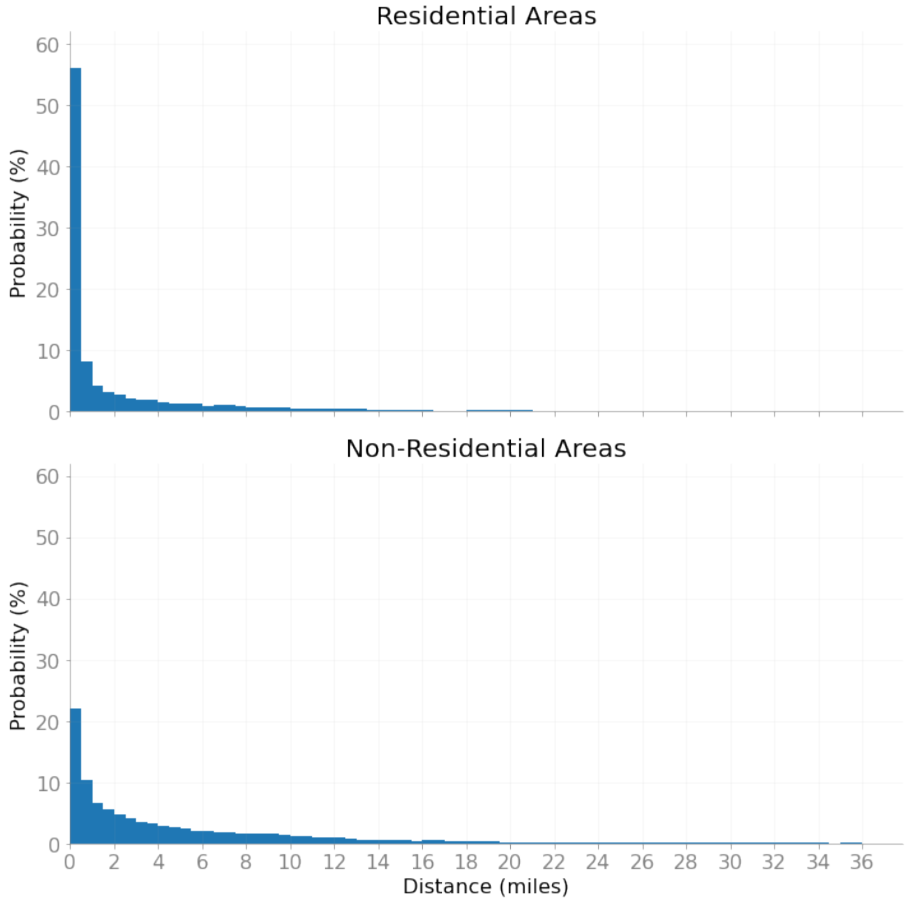


Figure 4.14: Histogram showing PHCD distribution for all pedestrians

We explore the PHCD distribution profile with the help of a distance histogram (see Figure 4.14). The histogram observes the distance profiles for non-residential and residential areas. These are all urban, non-interstate crashes that occur in the residential or non-residential areas. PHCD profiles for pedestrian crashes were different for residential and non-residential areas. Forty percent of pedestrians were struck by a vehicle within a mile of their home in non-residential areas with a wide distribution of PHCD. In contrast, 70 percent of pedestrians hit in residential areas were within one mile of their home.

We wanted to see if there were any notable differences in the PHCDs over the years. Upon only investigating the fatal pedestrian crashes in Tennessee, we find that median PHCD has increased by sixfold, from 0.47 miles in 2009 to 2.68 miles in 2019. This increase is also significant as determined by a regression trend line (coef. = 0.230, p-value = 0.003) (Figure 4.15). We use median values of PHCD for this analysis to avoid the outliers even if the data is capped at 50 miles because it is still substantial compared to the reported median distances. This finding suggests that pedestrians are involved in fatal crashes further from home and could potentially explain why the crashes are more severe in Tennessee.

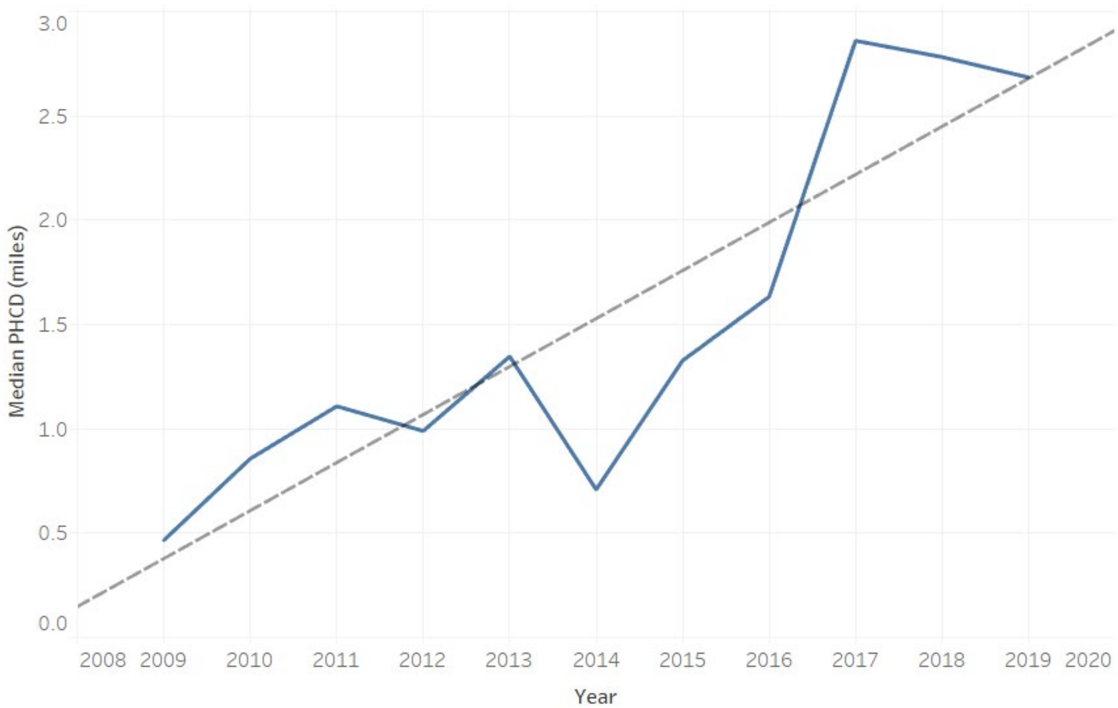


Figure 4.15 Trend illustrating the increase in median Pedestrian Home to Crash Distance (PHCD)

We can conclude that pedestrians are dying further from home on high-speed roads with a speed limit of 35 mph or higher. Those roads comprise around 80 percent of fatal crashes. This increase also links up with nighttime and non-residential or commercial area crashes, accounting for approximately 75 percent of the total fatal crashes. This novel finding might also be related to the suburbanization of poverty and gradual change in walking behavior in the urban areas of Tennessee, rendering the population to work at places further from their homes with increased exposure to a hostile pedestrian environment. More detailed work is needed to investigate the possibility of suburbanization aggravating the pedestrian injury severity.

Chapter 5 Risk Analysis and Decision Support Framework

5.1 Background

Popular quantitative prediction models for practitioners are developed in the Highway Safety Manual (HSM) (*74*). The HSM predicts the distribution of annual crashes using safety performance functions (SPFs) and Crash Modification Factors (CMFs). While these models can be used to identify hot spots for crashes, it can be difficult or impossible to model the impact of interventions not captured by current CMFs, such as building a new sidewalk, reducing speeds on a major roadway, or non-locational countermeasures (CMs) (i.e., improving vehicle standards). Quantitative risk measures have been developed to identify crash hot spots and fairly compare safety performance across locations and over time. Decision-makers seek to find CMs that produce the most significant reduction in risk to pedestrians for the least cost. Decision makers may also screen new projects for pedestrian risk before construction.

The need to transition to proactive, data-driven, and area-wide safety solutions has been highlighted in the Safe System approach proposed as a part of the US Department of Transportation's "Road to Zero" effort [68]. Decision-makers need tools to quantitatively characterize system risk in a region or location to understand the implications of their choices. Current decision frameworks sometimes qualitatively characterize risk [69]. Current quantitative metrics often focus on likelihood and consequence separately, failing to simultaneously address all three components of the risk triplet (scenario, likelihood, consequence) developed in (*75*).

This section expands on existing concepts of risk and decision frameworks using relatively simple but effective quantitative tools to allow for easy quantitative risk assessment. This expanded framework will leverage the HSM model to predict the number of crashes on a total roadway and illustrate the use of probabilistic validation metrics to assess the quality of these predictions. We will train a separate model to predict the outcome of each crash. A probabilistic, quantitative risk profile is developed using the predictions for the number of crashes and the outcome and used to select the optimal subset of CMs via a linear program. Additionally, if a decision maker wants to consider uncertainty, a dynamic programming approach is developed to select the optimal subset of CMs based on the possible risk reduction values distribution.

5.2 Methodology

5.2.1 The Decision Framework and Quantitative Risk

Leveraging existing consequences and likelihood, this section proposes an expanded quantitative risk measure as follows:

$$\begin{aligned} risk &= exposure \times \frac{likelihood\ of\ crash\ exposure}{exposure} \times consequence\ of\ crash \\ &= number\ of\ crashes\ \times consequence\ of\ crash \end{aligned}$$

… (eq. 1)

Consequently, an alternative formulation of risk (or total harm) is proposed (shown in … (eq. 1)) which collapses the scenario and likelihood terms into a single factor - the number of crashes.

Given that a crash has occurred, the consequence represents its severity. These three factors represent the “levers” by which decision makers can impact the risk via their decisions about the three E’s and the ordering of preference for intervention types (limit exposure > reduce likelihood given exposure > reduce consequences given crash).

Lastly, we must convert the number and outcomes of crashes to a risk profile. One way to accomplish this is to represent the risk as a unit less weighted sum of the crashes of each outcome type. In the TITAN database, crash outcomes are labeled as property damage only (PDO), possible injury (PI), non-incapacitating injury (NI), incapacitating injury (I), or fatal (K). The random forest classifier model developed in this article to predict class outcome struggled to distinguish PI from NI crashes. The weights given to each outcome type are dependent on the decision maker’s aversion to each type of outcome - with higher weights given to more severe outcomes. For example, crashes involving vulnerable populations - such as children, the elderly, and people with disabilities - can be weighted more severely. We can accomplish this by further predicting if a crash involves the population of interest (based on existing or projected trends) and weighing it accordingly. Such an approach can be valuable in ensuring equity in decisions about pedestrian systems. By setting weights to estimate the cost incurred by each crash outcome, this approach could also convert the risk to an expected dollar consequence of pedestrian crashes (*76*). However, we recommend caution when placing a dollar amount to prevent the loss of human life.

An advantage of this definition of risk is its scalability, that is, its ability to define risk over a city or region. To define risk over a region, one needs to add the risk in each road segment and intersection within that region. Using the above definition of risk is a straightforward summation but characterizing the risk on each roadway and intersection of a city/region may be too labor-intensive to be practical.

5.2.2 Predicting the Number of Crashes

We used the HSM model to predict the number of crashes at a location and discuss a method to validate the accuracy of these predictions. The HSM method is applicable to a roadway network, a facility, or an individual site (*74*). This method is applicable to rural two-lane, two-way roads, rural multi-lane highways, and urban and suburban arterials. This chapter focuses on pedestrian crashes, which primarily occur in urban regions on arterials, and proposes continuous rank probability score (CRPS), which is a probabilistic validation metric, to validate the model.

5.2.3 Predicting Crash Consequences

A prediction of the consequence of each crash is necessary to characterize the risk profile. From the TITAN dataset, crash outcomes are categorized as property damage only, possible injury, non-incapacitating injury, incapacitating injury, or fatal. From the TITAN database, the features found to be meaningful covariates are age of the pedestrian, posted speed limit, number of lanes, gender of the pedestrian, body type of the striking vehicle (truck or not truck), light conditions (daylight, dark - not lit, and dark - lit). Speed is a significant driver of the crash outcome. Ideally, crash speed or traffic conditions at the time of the crash would be used as a covariate. However, this isn’t easy to obtain. As a surrogate, an estimate of typical traffic conditions is obtained from an INRIX data set. This dataset is a collection of speed measurements made on significant roadways in Tennessee. We took these readings at 5-minute intervals and for multiple days across months and years. A speed snapshot is taken by finding the hour most similar (i.e., closet year, closest month, closest hour) to when the crash occurred. The maximum, minimum, and mean speeds within this hour provide a snapshot of similar traffic conditions.

As shown in Figure 5.1b, the TITAN data has significant class imbalance. To correct for this, the synthetic minority over-sampling (SMOTE) technique is used, using Python's built-in "SMOTE" package from the imbalanced-learn library, to synthetically generate samples from less frequently occurring classes [37]. SMOTE generates synthetic data from the underrepresented classes (see Ref. (*77*) for further details). The classes after performing SMOTE are shown in Figure 5.1a.

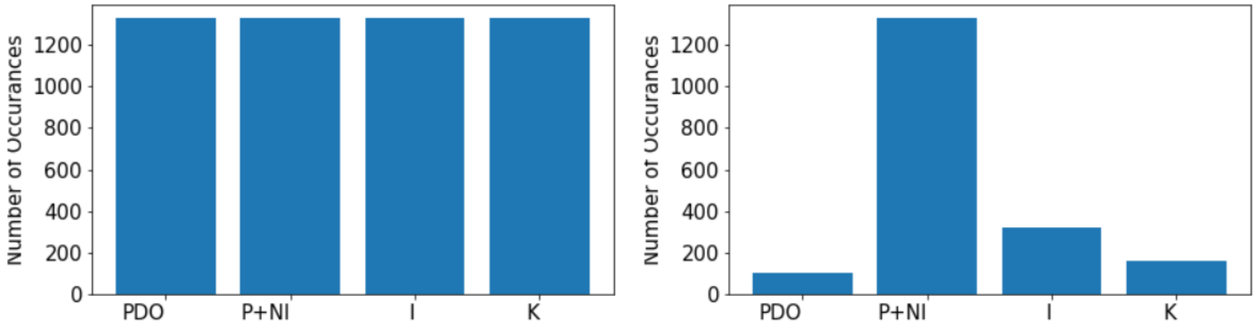


Figure 5.1 a) Crash outcomes after SMOTE, b) crash outcomes before SMOTE

Then, the data is split into training and validation sets, with 30 percent of the data held back for validation. We explored various model forms, including logistic regression, random forest (RF), decision tree, k-nearest neighbors (KNN), and support vector classification (SVC). Both KNN and RF the had similar accuracy results (85 percent on the test set) and misclassification errors (Mean Absolute Error of 0.2 on the test set). KNN had slightly better performance, but RF allows for the prediction of a class probability, not just a single class prediction. This is a useful property for risk assessment, given the inherent randomness of crash outcomes. Thus, the RF model is selected. The most critical covariates are shown in Figure 5.2. The essential features are age and speed, confirming results found elsewhere in the literature (*44; 78; 79*). Interestingly, we did not find vehicle body type and gender (of the pedestrian) significant predictors (*80*).

A confusion matrix representing model accuracy on the validation set is shown in Figure 5.3. The model performs very well in the most extreme classes: property damage only and fatal crashes. Most errors occur in the central, standard classes: potential injury + non-incapacitating injury and incapacitating injury. This could indicate that the extreme cases are easily differentiated from the rest of the crashes, while the significant crash types are similar, and their outcomes depend more on chance. This could also highlight the somewhat arbitrary nature of crash classification and errors in injury classification inherent in police crash data. For example, two similar crashes could be classified differently based on the preference of the responding officer, or a crash could be classified as NI, only to develop into a more severe injury later.

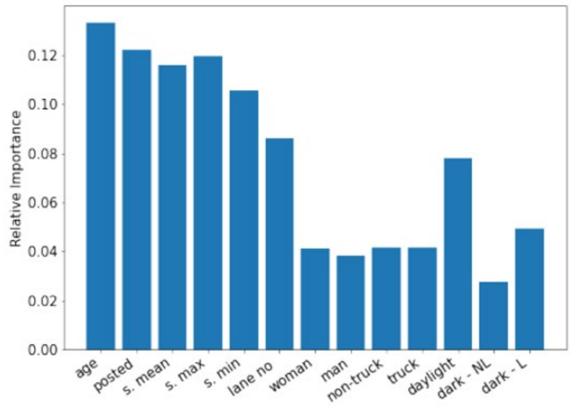


Figure 5.2 Relative Importance of covariates

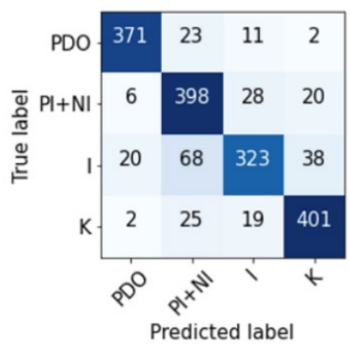


Figure 5.3 Confusion matrix: validation set accuracy

5.2.4 Evaluating and Selection Counter Measures

Choosing from competing proposed interventions can be difficult. Decision makers (DMs) often seek to minimize cost, minimize motor vehicle transit times, or remedy issues identified by public complaints. However, such heuristic decision rules have been shown to inadvertently favor wealthy, well-served communities and motor vehicle commuters (*81; 82*). A quantitative, risk-based decision framework can systematize the decision process - making it more transparent and robust against bias. Such quantitative approaches will favor projects with the largest reduction in risk for the least cost. They can also quantify the "do-nothing" risk, that is, the increase in risk if no action is taken to mitigate the impact of on-going societal changes like the aging population and increasing use of trucks and SUVs (*4*). Several risk-based decision frameworks have been developed to choose the CMs which will result in the largest reduction pedestrian risk - including the Systematic Safety Project Selection Tool (*76*) and linear programming based approaches (*83; 84*). However, these approaches use deterministic estimates of the number of crashes, with no considerations for the crash outcomes or uncertainty in the predictions or use qualitative risk assessments. this article expands on these approaches to use quantitative, probabilistic approaches and to include crash outcomes.

To model the risk reduction (or increase) of various CMs, one must predict the risk distribution in the current conditions (i.e., base case), predict the risk distribution following implementation of each proposed CM, and quantify the increase or reduction in risk. The shift between the predicted risk distribution in the base case and the risk distribution after the implementation of the CM represents the risk impact. This shift is itself a distribution of potential risk reduction (or increase) values. By convention, we define a positive value to indicate a reduction in risk and a negative value to indicate an increase in risk. Thus, the greater these values, the greater the risk impact of the CM. In order to account for the cost of a CM, these risk reduction values can be normalized (divided) by the cost of the CM. We refer to this as the distribution of cost-normalized risk (CNR) values. If the risk is expressed in a dollar cost amount, this CNR is equivalent to the benefit to cost ratio proposed elsewhere in the literature (*76*).

After quantifying the risk impact of proposed CMs, one can select from them in multiple ways. The simplest approach is to select the CM with the greatest expected CNR. We refer to this measure as the risk reduction metric (RRM), and it is given as:

$$RRM = \frac{E[R_{reduc}]}{C}$$

where $E[]$ is the expected value, R_{reduc} is risk impact of the CM, and C is the cost of the CM in dollars. The numerator of this equation is the expected change in risk. This is a measure of the expected total risk impact of the CM. As will be shown below, it may be used in select the optimal subset of CMs.

We quantified the risk impact of countermeasures and selected the optimal countermeasure with the following approaches.

1. Characterize the risk profile in the base case using N Monte Carlo (MC) samples.
    a. Determine the local conditions (AADT, geometry) and calibrate for local conditions. Determine the predicted distribution for the number of annual crashes for each road segment or intersection using the HSM approach. Validate the predictions using CRPS or an alternative probabilistic validation metric. Adjust the input assumptions and/or Empirical Bayes (EB) weights until the model prediction satisfies the desired level of accuracy.
    b. Determine the population distribution for speeds traveled on each road segment/intersection, population distribution for the age of pedestrians who are struck, portion of trucks involved in pedestrian crashes, and gender ratio of pedestrians involved in crashes.
    c. Generate *N* MC scenarios. For each *N* MC scenario, predict the number of crashes by drawing from the predicted distribution from part (a). For each crash, randomly draw the pedestrian's age, pedestrian gender, speed conditions, and motor vehicle body type. Predict the crash outcome based on the probability of each crash type predicted with the RF model. Optional step to sort crashes into crash typologies (i.e., crash while vehicle turning, crash while pedestrian crossing outside the crosswalk, etc.).
    d. Convert crash numbers and outcomes to risk via a weighted sum.
2. Model the impacts of proposed CMs (including population changes).
    a. If changes in AADT or road length, re-run the HSM prediction.

b. If the proposed CMs are designed to mitigate the number of crashes, determine which crash types are prevented by this intervention and the predicted level of efficacy. If the proposed CMs impact crash severity, one should update the population distributions for age, speed, gender, and striking vehicle body distributions. Repeat the MC scenarios. If a crash is a type that is mitigated by the proposed CM, randomly determine if that crash is prevented based on the predicted CM efficacy. If the crash is not mitigated, predict its outcome with the updated population distributions.
c. Convert crash numbers and outcomes to risk via a weighted sum.

3. Calculate the distribution of possible risk reduction values and the RRM of each proposed CMs.
4. If selecting one CM from a group, select the CM with the highest RRM or expected risk reduced (deterministic approach) or select the CM whose distribution of CNR (or risk reduction) values stochastically dominates the other CMs (stochastic approach).
5. If selecting a subset of CMs, use the *vanilla knapsack optimization* or *dynamic knapsack optimization.*

5.3 Numerical Illustrations

This section contains two numerical illustrations demonstrating how to use the concepts developed in this chapter. The first demonstrates how a DM could model the impact of a group of CMs and select one from them. The second demonstrates how a DM could select a subset of DMs that transit authorities have proposed across regions.

5.3.1 Numerical Illustration 1: Invest in pedestrian safety on Nolensville Pike or Hillsboro Pike?

This synthetic example evaluates whether Nashville city transit officials should install sidewalks, install new crossing facilities, or invest in strategies to limit super-speeding on Nolensville Pike - a major, high-speed arterial in south Nashville - or Hillsboro Pike - a major, high-speed arterial running through a higher-income area of Nashville. This synthetic example illustrates how these risk assessment and decision methods can prioritize CMs in high-risk areas (like Nolensville), even if they are more expensive than CMs in lower-risk areas (like Hillsboro). This example only examines crashes away from existing intersections and crossing facilities (as designated in the TITAN database). These are '5-T' type roads (two lanes in each direction with a turning lane) with no medians. For both roads, there is assumed to be on-street, parallel parking. For Nolensville Pike, each of these interventions is assumed to cost the same amount - nominally $1 million. The length of Nolensville is approximated as 9.3 miles using Google maps. Also, the number of driveways is estimated at ten major commercial driveways, 50 minor commercial driveways, 400 minor residential, and five other driveways.

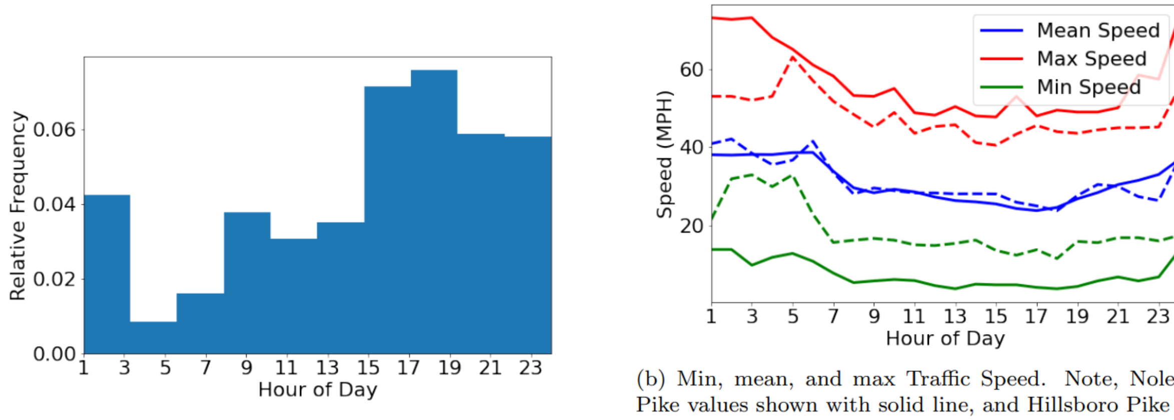
The annual average daily traffic (AADT) is taken from a TDOT database [47] and is shown in **Table 4**. An AADT value is provided for most years. Missing years are linearly interpolated. The local calibration factor is calculated as .0118, representing the expected ratio of pedestrian crashes to motor vehicle-only crashes. Using these factors, the distribution of the number of annual crashes is predicted using the HSM. The mean number of annual crashes is predicted to be 1.02. Each crash type is further sorted into two typologies: crashes that occur when a pedestrian is walking along the road shoulder or sidewalk (if one is installed) and crashes which occur when a pedestrian is trying to cross the street. This sorting follows current trends, with 43 percent of crashes crossing and all others walking-along crashes. Note, since this example explores non-intersection crashes (as designated by the location code in the TITAN database), these crossing crashes occur when a pedestrian is trying to cross outside designated crossing facilities. While this use may be contrary to designer intention, decision-makers must construct risk profiles in the as-used conditions, not as-intended conditions, especially given the lack of safe, convenient crossing facilities on major roadways like Nolensville Pike and the significant number of crossing crashes. These predictions are validated using CRPS, and the validation results are shown in **Table 4**. The average CRPS value is 0.75 crashes.

Table 4 HSM prediction model validation results

Year	Nolensville Pike			Hillsboro Pike		
	Crashes	AADT	CRPS	Crashes	AADT	CRPS
2011	0	22,239	0.39	0	30,577	0.13
2012	0	25,667	0.38	0	30,577	0.13
2013	0	23,916	0.38	0	30,350	0.18
2014	0	22,165	0.38	0	29,570	0.14
2015	0	22,590	0.37	0	30,197	0.13
2016	4	26,591	2.45	1	29,228	0.43
2017	3	28,297	1.53	1	28,321	0.43
2018	1	30,003	0.28	1	27,414	0.38
2019	1	27,132	0.28	1	24,535	0.44
2020	3	30,641	1.53	1	25,912	0.43
2021	1	30,461	0.28	0	25,912	0.15

Similarly, for Hillsboro Pike, each of these interventions is assumed to cost the same amount - nominally *$0*.8 million. The length of Hillsboro is approximated as 6.5 miles using Google maps. Also, the number of driveways is estimated at ten major commercial driveways, 50 minor commercial driveways, 400 minor residential, and five other driveways. The AADT is taken from a TDOT database (*8*). The local calibration factor is calculated as 0.0126. The mean number of annual crashes is predicted to be 0.52 crashes. These predictions are validated using CRPS, and the validation results are shown in **Table 4**. The average CRPS value is 0.27 crashes. Similarly, each crash type is further sorted into crashes that occur when a pedestrian is walking along the road shoulder or sidewalk and crashes which occur when a pedestrian is trying to cross the street.

For each crash, the crash outcome also needs to be predicted. To that end, distributions need to be assumed for the hour of the crash (used to find traffic speed conditions), age of pedestrian struck, gender ratio, and the portion of trucks in the vehicle fleet. The relative frequency of the hour when the crash occurs is assumed to follow current trends, and these trends are shown in Figure 5.4a. After the crash hour is selected, this is used to determine the typical traffic speed conditions (mean speed, max speed, and min speed). These values are taken from the INRIX database and are shown in Figure 5.4b. As shown in this Figure 5.4, Nolensville Pike has higher top speeds and lower minimum speeds, but they have similar mean speeds. The striking vehicles are assumed to be 45 percent trucks, and the pedestrians struck are assumed to be 31 percent women (following current trends).



(a) Hour of pedestrian crashes

(b) Min, mean, and max Traffic Speed. Note, Nolensville Pike values shown with solid line, and Hillsboro Pike values shown with dashed line.

Figure 5.4 Assumed Distributions of Crash Hour and Traffic Conditions

The distribution of the age of pedestrians struck is shown in Figure 5.5 (following current trends). After predicting the crash outcomes, the number of crashes of each type is converted to a unitless risk via weighted summation. These weights are taken as: 9.5 (PDO), 115 (NI/PI), 500(I), and 10500 (K). These weights are left to user preference. Next, the impact of the proposed interventions is modeled. The new sidewalk installations are only assumed to prevent walking along crashes, and the improved crossing facilities are assumed to prevent only crossing crashes. Each of these proposals is deemed 30 percent effective by a traffic safety professional, preventing 30 percent of crashes of the appropriate type. These interventions have no impact on the crash outcome (i.e., severity once a crash occurs). The last proposed countermeasure is assumed to only impact crash outcomes by reducing super-speeding. This CM assumes that the maximum hourly speed will be reduced by 10 percent. This is assumed to impact crash outcome only, though it may also impact the number of crashes.

The base case risk and the risk after implementing the CM are shown in Figure 5.6. The expected value of risk for the base case and after implementing each CM is shown in **Table 5**. Even though these roads have similar AADTs and mean travel speeds, they have very different risk profiles; Nolensville Pike has a much higher expected risk, indicating that it is significantly riskier to pedestrians. The expected risk reduction and the RRM for each CM are also shown in **Table 5**.

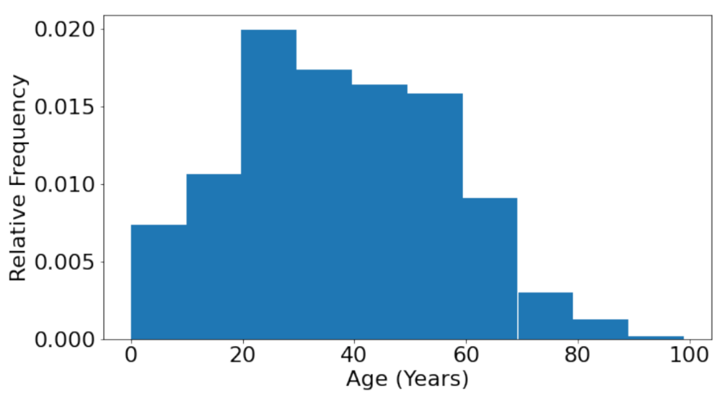
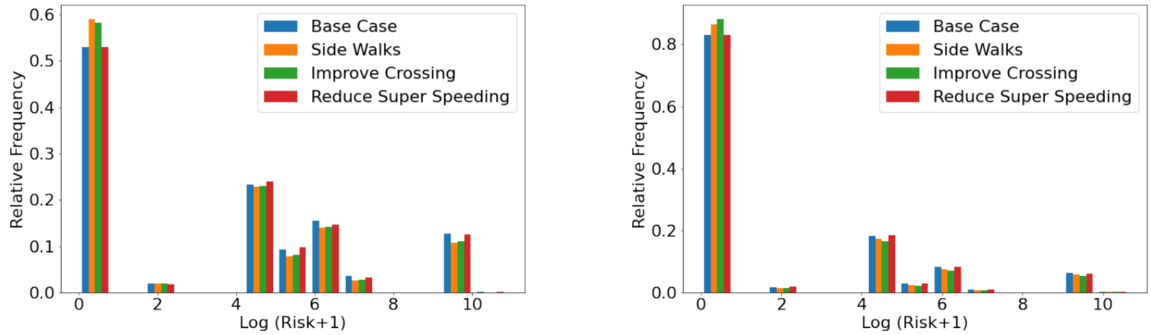


Figure 5.5 Predicted age of pedestrians struck



(a) Nolensville Pike (b) Hillsboro Pike

Figure 5.6 Predicted risk in base case and after interventions

Table 5 Risk reduction metrics of the proposed interventions

Case	Expected Risk (Mean)	E[Risk Reduced]	RRM
Base Case (Nolensville)	1422	NA	NA
Install Sidewalks (Nolensville)	1191	231	2.3×10^{-4}
Crossing Facilities (Nolensville)	1219	202	2.02×10^{-4}
Reduce super-speeding (Nolensville)	1409	13.4	1.34×10^{-4}
Base Case (Hillsboro)	679	NA	NA
Install Sidewalks (Hillsboro)	601	78	9.73×10^{-5}
Crossing Facilities (Hillsboro)	560	118	1.48×10^{-4}
Reduce super-speeding (Hillsboro)	652	27	3.32×10^{-5}

Even though each CM is more expensive to implement on Nolensville, a rational decision maker should still invest in this road due to the more significant risk reduction and greater risk per dollar spent (i.e., higher RRM values). The optimal CM is installing sidewalks on Nolensville since it has the highest RRM value. However, thus far, we have only considered the expected risk reduction, failing to consider the uncertainty in our prediction of risk reduction. To do so, we must consider the distribution of cost normalized risk reduction values for each CM using a stochastic dominance approach. To this end, the cumulative distribution functions (CDFs) of cost-normalized risk reduction values for each CM is computed; these are shown in Figure 5.7 (with Nolensville Pike CDFs shown with solid lines and Hillsboro Pike CDFs shown with dashed lines). We assume the DM is only interested in CNR values rather than the distribution of risk reduction values since they desire to spend their money as efficiently as possible. As shown in this Figure, installing sidewalks on Nolensville first-order stochastically dominates the other CMs since its CDF is less than or equal to all other CDF values (i.e., its CDF is to the right of the others) at all values. Thus, when considering uncertainty, installing sidewalks in Nolensville is the optimal CM.

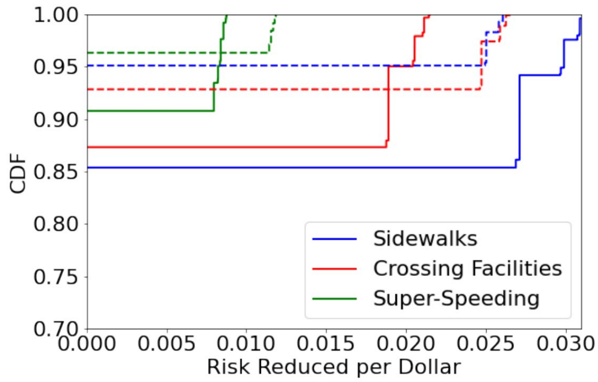


Figure 5.7 CDF of risk reduced per dollar (Nolensville - solid line, Hillsboro Pike - dashed lines)

5.3.2 Numerical Illustration 2: Optimizing CMs for an entire region

A decision-maker could also use these concepts when selecting which proposed countermeasures to implement for an entire region. This could optimize the expenditures at a city, state, or regional level. In this approach, a decision maker seeks to maximize the risk reduced while satisfying budget constraints. In this example, various synthetic CMs are proposed and scored for their potential risk reduction and cost. These values are shown in **Table 6**.

For each CM, the cost is assumed to be known, and the risk reduction is assumed to be an independent Gaussian distribution. This risk scoring can be done with sophisticated methods, like those proposed in this chapter, or with simple expert elicitation (i.e., expert prediction of several crashes prevented and prediction of change in outcomes). Using an arbitrary budget of $5 *million*, the optimal subset of CMs is chosen using a vanilla knapsack optimization. Alternatively, the budget could be varied at a different amount, and the amount of risk reduced by the optimal subset at each budget level computed. For budgets varying between 0 to *$5 million*, the amount of risk reduced by the optimal subset of CMs is shown in Figure 5.8.

Table 6 Numerical Example 2: Selecting optimal sub-set of CMs (Budget $5MM)

Option	E[Risk Reduced]	Std. Dev.	Cost (MM)	RRM × 10^7	Selected (Det.)	Selected (Stoch.)
1	200	20	$1	20	N	N
2	500	30	$2	25	N	N
3	50	10	$0.10	50	Y	N
4	1000	200	$4	25	Y*	Y
5	1000	50	$4	25	Y*	Y
6	100	50	$0.50	20	Y	Y
7	300	40	$3	10	N	N
8	900	20	$3.80	23.7	N	N
9	30	5	$0.20	15	N	N
10	200	30	$0.30	66.7	Y	Y
11	300	50	$1	30	N	N
12	50	7	$0.50	10	N	N
13	40	5	$2.20	1.8	N	N

Note: no preference between Y* options

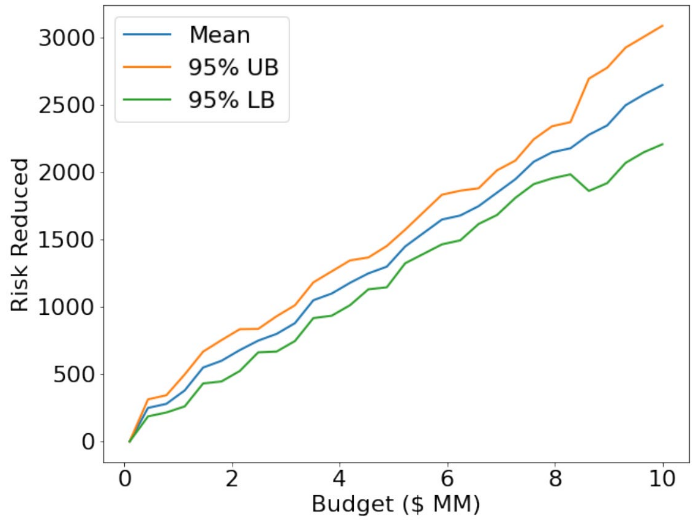


Figure 5.8 Alternative problem formulation: How much risk can be reduced with a budget of $X MM?

This approach can determine the required budget expenditure to achieve the desired level of risk reduction. However, by failing to consider uncertainty, a DM cannot differentiate between option 4 and option 5 since they have the same expected risk reduction and cost, but option 5 has significantly less uncertainty (variance). When using stochastic methods to select the optimal subset of CMs, a DM would choose option 5. A DM can place bounds on the expected risk reduction by considering uncertainty, as shown in Figure 5.8. In this manner, a DM can identify events that occur around a budget of $8 million, where the uncertainty increases sharply due to the addition of CM option 4, which has significant uncertainty in its outcome. A decision maker may not pursue this option due to its high uncertainty.

5.4 Proposed Actions

Existing approaches to pedestrian safety are often reactive and hyper-local - with conditions being improved at the location of a crash, while similar risky road conditions in nearby areas are ignored. Road safety audits and interventions are the main engineering tool used in this regard. This hyper-local approach fails to consider systemic changes (i.e., regulation to improve the safety of cars, aging populations, etc.). Existing decisions are sometimes made in an ad-hoc manner that implicitly favors privileged communities rather than a quantitative, risk-informed manner. This chapter adopts an existing data-driven method to predict the number of crashes in the roadway - the HSM method - and proposes using probabilistic validation metrics, such as CRPS, to validate these predictions before deploying them. A classification model using a random forest classifier is developed to predict the outcome of crashes. Using this prediction for crash number and crash outcome, a risk profile can be obtained via a weighted summation of crash count and outcome.

Then, this section develops an approach to predict the impact of proposed countermeasures (including population changes). A risk reduction metric and a stochastic dominance approach are proposed to select from a single potential countermeasure. Alternatively, linear programming approaches are developed to select the optimal subset from a group of proposed CMs. While the HSM approach and random forest model are the crash number and crash outcome models deployed here, this general approach and decision framework are agnostic to the exact model forms. Based on user preference, any model could be used, including sophisticated statistical or deep learning tools or simple approaches, like expert elicitation. Regardless of the model form, validation is recommended to ensure the selected model captures local conditions. Future research is needed to capture the local conditions further when predicting risk, such as the inclusion of local land use and local socio-economic factors to account for health disparities when predicting the crash outcome.

The current efforts to improve traffic pedestrian safety in the United States are not working. Nationally, pedestrian fatalities have increased by 51 percent from 2009 to 2019, despite decision makers' stated support for improving pedestrian safety (*85*), as well as advocacy groups and governments' efforts to reduce the number and consequence of crashes. Government officials have overemphasized the contribution of individual pedestrian and motor vehicle user behavior to the poor state of traffic safety in the US. Government officials have particularly emphasized the impact of pedestrian actions (*86*). Decision makers are caught in a "correlation equals causation" bias (*87*). Because certain pedestrian behaviors and characteristics - like risky midblock crossing or older pedestrians - are over-represented in the pedestrian fatality data, traffic decision-makers assume that they cause the rise in pedestrian fatalities. When examining the cause of an individual crash, this may be true. An older individual may die in a crash that a younger person could have survived, and reducing mid-block crossings in high traffic, often lower-income areas, will decrease the rate of crashes. However, decision-makers fail to recognize that these phenomena are further *symptoms* of the pedestrian traffic safety problem. Individuals, pedestrians, and bicyclists exhibit risky behavior because the current system is fundamentally not designed for them or easy to use.

Furthermore, if "non-normative" risky behaviors like mid-block crossing are so common as to have a significant impact on pedestrian safety, they are no longer non-normative; instead, they are a feature of how users are adopting to the system. In the case of the mid-block crossing issue, pedestrians are displaying this risky behavior because they have no safe or convenient location at which to cross, they do not know how to use existing facilities, or they do not know or appreciate the consequences (or enforcement implications) of mid-block crossing. Decision-makers must transition the way they think about non-expected behaviors. If pedestrians, bicyclists, and motor vehicles routinely use the system in a risky manner contrary to the designer's intentions, decision-makers must understand this is a symptom of poorly designed infrastructure and inadequate enforcement or education. Decision-makers should intervene to encourage less risky behavior, particularly by making the safer option the easiest option.

Decision makers are also caught in an anchoring bias (*87*). Existing and historical decisions or designs represent the starting point from which incremental adjustments to improve pedestrian safety are made. This is even the case with new construction projects, often built to replicate the existing, risky systems. Decision-makers are also struggling to balance the competing criteria by which decision alternatives are evaluated. America is a driving-heavy culture, and decision-makers often prioritize motor vehicle needs at the expense of pedestrian safety. While safety or the number of crashes eliminated is often an evaluation criterion, it is often just one criterion among many competing criteria, including traffic delays (*88*). Decision-makers should consider transitioning to a "safety as a value" approach (*89*). Rather than treating pedestrian and bicyclist risk as one of many competing priorities, decision-makers can treat safety as a core value that must be met in all projects. Decision-makers can set a maximum level of pedestrian risk and design all projects to satisfy this constraint or only consider projects that satisfy this constraint.

Quantitative risk and decision frameworks - such as the methods proposed in this section, can assist decision-makers in compensating for these biases. By predicting risk in the as-used (rather than as-intended) condition, decision-makers can better predict the risk experienced by pedestrians. Further, decision-makers can screen projects for risk before implementing them, potentially disrupting the anchoring trap since replications of current high-risk designs will be flagged before implementation. In addition to selecting from two competing interventions, this approach could be used to select from multiple proposed interventions on a larger scale. This could disrupt the cycle of under-investment in low-income, high-risk areas - since projects in these areas are more likely to have higher risk reduction and RRM values.

By developing a quantitative risk profile, rather than the qualitative profiles (i.e., number of risk factors) previously developed, risk assessment can be scaled to develop a risk profile of an entire city, region, or state. This regional risk profile can be obtained by simply summing the risk profiles of that region's roadways and intersections. Since this is computationally expensive, a reasonably good risk profile can be obtained by summing the *M* largest (or riskiest) roadways and *N* most prominent (or riskiest) intersection. In this manner, the risk-reduction impact of large-scale, non-location specific (i.e., improving vehicle standards, improving driver education, etc.) countermeasures can be compared to location-specific CMs.

Statewide agencies (specifically the Department of Transportation) have an incredible responsibility and opportunity to improve pedestrian safety statewide. Specifically, urban areas are where the bulk of overall crashes and severe and fatal injuries occur. Focusing specifically on severe crashes, roadways in TDOT jurisdiction are disproportionately responsible for a large amount of pedestrian injury and death. Some of the highest risk factors are related to the built environment. Traffic speed (and the number of lanes) is a core driver of pedestrian crashes.

TDOT cannot wait until technology solutions are developed to improve safety for pedestrians. Auto manufacturers are marketing *more* dangerous-to-pedestrian vehicles, and every indication points to a riskier fleet on the roadway – more large trucks and SUVs. Urban freight trends will continue to push larger vehicles into dense and mixed urban environments. Meanwhile, our population continues to age, and older pedestrians and drivers will continue to become more vulnerable. To counter this trend, TDOT should be more aggressive at building safe pedestrian infrastructure on its state highways (urban arterials).

This starts with the following core recommendations:

1) Adopt a Safe Systems Approach to safety, particularly pedestrian safety. This involves addressing many aspects of road safety across the network, in addition to targeting hyper local high-risk hotspots.
2) Reform standard designs and drawings that mandate pedestrian accommodation in urban areas. This includes high-quality pedestrian infrastructure, crossings, and signalization as a standard design. Never follow design standards to replicate current failing practices that routinely contribute to vulnerable road user deaths.
3) Reduce maximum design speeds to 35 mph on any urban arterial that will include pedestrian destinations. This includes any roadway that has commercial land uses adjacent or connects or bisects residential locations.
4) Work with local agencies to reduce existing speed limits on urban arterials and accompany those speed limit changes with quick-build traffic calming interventions to

reduce the severity of inevitable conflicts with pedestrians. These could include interim design solutions that reduce the crossing width.

5) Focus on midblock interventions to reduce speeds (and speeding) and increase pedestrian midblock crossing opportunities. Pedestrians have little tolerance for long detours, particularly when crossing at a signalized intersection is as perilous as a midblock crossing. Develop and widely deploy known midblock safety countermeasures like Rectangular Rapid Flashing Beacons with sufficient pedestrian islands and lighting.
6) Work with transit agencies to ensure that transit corridors (often along commercial arterials) include sufficient pedestrian crossing opportunities supporting transit. Every transit rider accessing a transit stop on an arterial must cross the arterial for the return trip. Injured and killed pedestrians, particularly from lower-income neighborhoods are often killed farther from home than walking distance.

In a Safe Systems approach, many other factors can improve pedestrian safety. Specifically enforcing speed limits and drunk or drugged driving will improve the safety of all road users, but particularly the most vulnerable of them, pedestrians. However, TDOT should work to ensure its designs, particularly its new designs, are self-enforcing so that overburdened law enforcement is not saddled with growing enforcement needs because road design encourages unsafe speed and vehicle operations.

Chapter 6 Conclusions

The objectives of this research are to look at the overall growth of pedestrian crashes in the last decade and determine the factors causing it, classify and investigate the trends from the perspective of diverse variables, and utilize home-based approaches to explain the causes of the rise further and implement a quantitative decision framework for selecting countermeasures. With the help of TITAN data, after determining the home coordinates of pedestrians and combining it with the census data, we were able to conduct pedestrian injury trend analysis in detail while verifying the significance with statistical tests such as one-way ANOVA, regression trend analysis, and multivariate severity modeling. We performed injury severity modeling and aptly compared two time periods using average discrete change (ADC) and utilized home-based approaches to perform distance analyses.

The substantial causes that lead to the current condition of pedestrian safety in the US mirror Tennessee. Pedestrian crashes are more severe in the urban areas of Tennessee, and the roadway design bears a large burden. We found that most fatal crashes happened on straight high-speed roads with speeds of more than 35 mph and multiple lanes (typically the characteristics of urban arterials in Tennessee) during the nighttime and significantly far from the residential areas (pedestrians' homes). Our findings conform with the most recent US pedestrian safety research, which associates the urban pedestrian safety crisis in the US with the functional classification of the roadways (*10; 64; 65; 67*). Other variables that also accounted for the disproportionate increase were the male pedestrians, middle-aged older adults (51 – 65), female drivers, DUIs, driving on the weekends, and being struck by newer vehicle models.

Many speculative claims regarding aggravating pedestrian safety do not hold for Tennessee. We discovered that increased pedestrian crash severity in Tennessee was not associated with the vehicle sizes, such as in the case of SUVs, pickups, or heavy trucks, although the US pedestrian fatality trend studies assert that larger vehicles, such as SUVs and pickups, are largely responsible for the increase in fatality (*10; 64; 65; 67*). The severity increase was also not associated with the alcohol or drug impairment of the pedestrians, as it only affected a small proportion of fatalities with weak significance. While we did see an overall increase in the total fatality from 2009 – 2019 concerning these variables, our trends do not suggest a significant change in severity over time. Although we see a significant increasing trend of pedestrian severity in the older adults (51 – 64) group, trends associated with elderly pedestrians are almost constant. Thus, the overall increase is also not associated with the aging population. That said, our injury severity models reveal the higher odds of being fatally injured while struck by larger vehicles if the pedestrian is impaired with alcohol or drugs or is elderly. Still, this finding should not be confused with Tennessee's longitudinal increase in severity.

Using the home-based approach, we explored the distance between the pedestrian crash locations and their respective homes. We discovered that those distances' median value consistently increased from 2009 – 2019, almost a sixfold increase from 0.5 miles to 3 miles. It suggested that people are getting hit further from their homes. Suppose we combine this finding with the defective road design narrative. In that case, we can picture a scenario where pedestrians are getting hit on the urban arterials far from their homes, shifting even further over the years. To that end, we can speculate a sprawled suburban scenario that fits this story, causing the increase in the severity of pedestrian crashes (*51*). Further investigation is necessary to explore the effect of suburbanization on pedestrian crashes.

One limitation of this study is the use of police-reported data. Although we have alleviated the risk of injuries being underreported by only looking at the fatal and total reports, police data still have other parts and potentially subjective reporting that is based on the police officer's discernment or as informed by the (surviving) witnesses. Variables such as the pedestrian's position during the crash, injury outcomes except for fatal injury, and residential and non-residential crashes suffer from this issue. The data also suffers from only containing those crashes that were reported. Unreported crashes and critical near misses, which would have resulted in injury, are not considered, underreporting the total exposure. This study attempts to understand the overall situation of pedestrian safety during the last decade in Tennessee. However, during the process, it reveals essential factors without diving deeper into any one of them. Future studies should dissect each factor and explore its effect on increasing the severity of pedestrian crashes. Likewise, this study focuses only on the urban areas of the cities of Tennessee. The results from this study can only be generalized in states with similar urban structures and socioeconomic conditions. Similar studies in multiple US cities are required to answer the pedestrian crisis in the US. Another limitation is that the study relies only on a decade of data for the trend analyses from 2009 to 2019. Sophisticated time-series models demand a large number of observations while also accounting for autocorrelation. Nonetheless, this report provides the clearest picture yet of Tennessee’s pedestrian injury and fatality crisis with some fundamental steps forward to improve safety.

References

1. Centers for Disease Control and Prevention. National Center for Injury Prevention and Control. Web-based Injury Statistics Query and Reporting System (WISQARS).In.
2. National Center for Statistics and Analysis. Pedestrians: 2019 data.In *Traffic Safety Facts. Report No. DOT HS 813 079*, 2021.
3. ---. Pedestrians: 2009 data.In *Traffic Safety Facts. Report No. DOT HS 811 394*, 2011.
4. Buehler, R., and J. Pucher. The growing gap in pedestrian and cyclist fatality rates between the United States and the United Kingdom, Germany, Denmark, and the Netherlands, 1990–2018. *Transport reviews,* Vol. 41, No. 1, 2021, pp. 48-72.
5. Australian Road Deaths Database. *Road deaths: Calender Year Australia 2020.* Department of Infrastructure, Transport, Regional Development and Communications, Australia.
6. UK Department for Transport. Reported road casualties in Great Britain: 2019 annual report.In, United Kingdom, 2020.
7. European Transport Safety Council. Urgent action needed to tackle deaths of pedestrians and cyclists.In, 2020.
8. Tennessee Highway Safety Office. Tennessee Integrated Traffic Analysis Network.In, 2021.
9. Schmitt, A. *Right of Way: Race, Class, and the Silent Epidemic of Pedestrian Deaths in America*. Island Press, 2020.
10. Tefft, B. C., L. S. Arnold, and W. J. Horrey. Examining the Increase in Pedestrian Fatalities in the United States, 2009-2018 (Research Brief).In, AAA Foundation for Traffic Safety, Washington, D.C., 2021.
11. Grembek, O. The relative vulnerability index: A framework for evaluating multimodal traffic safety. 2012.
12. Clifton, K. J., C. V. Burnier, and G. Akar. Severity of injury resulting from pedestrian–vehicle crashes: What can we learn from examining the built environment? *Transportation research part D: transport and environment,* Vol. 14, No. 6, 2009, pp. 425-436.
13. Keller, C. G., T. Dang, H. Fritz, A. Joos, C. Rabe, and D. M. Gavrila. Active pedestrian safety by automatic braking and evasive steering. *IEEE Transactions on Intelligent Transportation Systems,* Vol. 12, No. 4, 2011, pp. 1292-1304.
14. Aziz, H. A., S. V. Ukkusuri, and S. Hasan. Exploring the determinants of pedestrian–vehicle crash severity in New York City. *Accident Analysis & Prevention,* Vol. 50, 2013, pp. 1298-1309.
15. Davis, G. A. Relating severity of pedestrian injury to impact speed in vehicle-pedestrian crashes: Simple threshold model. *Transportation Research Record,* Vol. 1773, No. 1, 2001, pp. 108-113.
16. Gårder, P. E. The impact of speed and other variables on pedestrian safety in Maine. *Accident Analysis & Prevention,* Vol. 36, No. 4, 2004, pp. 533-542.
17. Niebuhr, T., M. Junge, and E. Rosen. Pedestrian injury risk and the effect of age. *Accident Analysis & Prevention,* Vol. 86, 2016, pp. 121-128.
18. Loo, B. P., and K. L. Tsui. Pedestrian injuries in an ageing society: insights from hospital trauma registry. *Journal of Trauma and Acute Care Surgery,* Vol. 66, No. 4, 2009, pp. 1196-1201.

19. Kim, J.-K., G. F. Ulfarsson, V. N. Shankar, and S. Kim. Age and pedestrian injury severity in motor-vehicle crashes: A heteroskedastic logit analysis. *Accident Analysis & Prevention,* Vol. 40, No. 5, 2008, pp. 1695-1702.
20. Kröyer, H. R. G. Is 30km/h a 'safe' speed? Injury severity of pedestrians struck by a vehicle and the relation to travel speed and age. *IATSS Research,* Vol. 39, No. 1, 2015, pp. 42-50.
21. Zajac, S. S., and J. N. Ivan. Factors influencing injury severity of motor vehicle–crossing pedestrian crashes in rural Connecticut. *Accident Analysis & Prevention,* Vol. 35, No. 3, 2003, pp. 369-379.
22. Dultz, L. A., and S. G. Frangos. The impact of alcohol in pedestrian trauma. *Trauma,* Vol. 15, No. 1, 2013, pp. 64-75.
23. Prijon, T., and B. Ermenc. Influence of alcohol intoxication of pedestrians on injuries in fatal road accidents. *Forensic Science International Supplement Series,* Vol. 1, No. 1, 2009, pp. 33-34.
24. Oxley, J., B. Fildes, E. Ihsen, J. Charlton, and R. Day. Differences in traffic judgements between young and old adult pedestrians. *Accident Analysis & Prevention,* Vol. 29, No. 6, 1997, pp. 839-847.
25. Schwebel, D. C., A. L. Davis, and E. E. O'Neal. Child pedestrian injury: A review of behavioral risks and preventive strategies. *American journal of lifestyle medicine,* Vol. 6, No. 4, 2012, pp. 292-302.
26. Pitcairn, T., and T. Edlmann. Individual differences in road crossing ability in young children and adults. *British Journal of Psychology,* Vol. 91, No. 3, 2000, pp. 391-410.
27. Oxley, J., M. Lenné, and B. Corben. The effect of alcohol impairment on road-crossing behaviour. *Transportation Research Part F: Traffic Psychology and Behaviour,* Vol. 9, No. 4, 2006, pp. 258-268.
28. Roll, J., and N. McNeil. Race and income disparities in pedestrian injuries: Factors influencing pedestrian safety inequity. *Transportation research part D: transport and environment,* Vol. 107, 2022, p. 103294.
29. Noland, R. B., N. J. Klein, and N. K. Tulach. Do lower income areas have more pedestrian casualties? *Accident Analysis & Prevention,* Vol. 59, 2013, pp. 337-345.
30. Sanders, R. L., and R. J. Schneider. An exploration of pedestrian fatalities by race in the United States. *Transportation research part D: transport and environment,* Vol. 107, 2022, p. 103298.
31. Goddard, T., K. B. Kahn, and A. Adkins. Racial bias in driver yielding behavior at crosswalks. *Transportation Research Part F: Traffic Psychology and Behaviour,* Vol. 33, 2015, pp. 1-6.
32. Coughenour, C., S. Clark, A. Singh, E. Claw, J. Abelar, and J. Huebner. Examining racial bias as a potential factor in pedestrian crashes. *Accident Analysis & Prevention,* Vol. 98, 2017, pp. 96-100.
33. Hickox, K. L., N. Williams, L. F. Beck, T. Coleman, J. Fudenberg, B. Robinson, and J. Middaugh. Pedestrian traffic deaths among residents, visitors, and homeless persons—Clark County, Nevada, 2008–2011. *MMWR. Morbidity and mortality weekly report,* Vol. 63, No. 28, 2014, p. 597.
34. Lee, J., M. Abdel-Aty, K. Choi, and H. Huang. Multi-level hot zone identification for pedestrian safety. *Accident Analysis & Prevention,* Vol. 76, 2015, pp. 64-73.

35. Chakravarthy, B., C. L. Anderson, J. Ludlow, S. Lotfipour, and F. E. Vaca. The relationship of pedestrian injuries to socioeconomic characteristics in a large Southern California County. *Traffic injury prevention,* Vol. 11, No. 5, 2010, pp. 508-513.
36. Haule, H. J., T. Sando, A. E. Kitali, and R. Richardson. Investigating proximity of crash locations to aging pedestrian residences. *Accident Analysis & Prevention,* Vol. 122, 2019, pp. 215-225.
37. Hezaveh, A. M., and C. R. Cherry. Walking under the influence of the alcohol: A case study of pedestrian crashes in Tennessee. *Accident Analysis & Prevention,* Vol. 121, 2018, pp. 64-70.
38. Ryb, G. E., P. C. Dischinger, J. A. Kufera, and C. A. Soderstrom. Social, behavioral and driving characteristics of injured pedestrians: a comparison with other unintentional trauma patients. *Accident Analysis & Prevention,* Vol. 39, No. 2, 2007, pp. 313-318.
39. Lee, C., and M. Abdel-Aty. Comprehensive analysis of vehicle–pedestrian crashes at intersections in Florida. *Accident Analysis & Prevention,* Vol. 37, No. 4, 2005, pp. 775-786.
40. Liu, J., A. Hainen, X. Li, Q. Nie, and S. Nambisan. Pedestrian injury severity in motor vehicle crashes: an integrated spatio-temporal modeling approach. *Accident Analysis & Prevention,* Vol. 132, 2019, p. 105272.
41. Tay, R., J. Choi, L. Kattan, and A. Khan. A multinomial logit model of pedestrian–vehicle crash severity. *International journal of sustainable transportation,* Vol. 5, No. 4, 2011, pp. 233-249.
42. Lym, Y., and Z. Chen. Influence of built environment on the severity of vehicle crashes caused by distracted driving: A multi-state comparison. *Accident Analysis & Prevention,* Vol. 150, 2021, p. 105920.
43. Rothman, L., A. W. Howard, A. Camden, and C. Macarthur. Pedestrian crossing location influences injury severity in urban areas. *Injury prevention,* Vol. 18, No. 6, 2012, pp. 365-370.
44. Jurewicz, C., A. Sobhani, J. Woolley, J. Dutschke, and B. Corben. Exploration of Vehicle Impact Speed – Injury Severity Relationships for Application in Safer Road Design. *Transportation Research Procedia,* Vol. 14, 2016, pp. 4247-4256.
45. Vision Zero SF. Vision Zero action strategy: Eliminating traffic deaths in San Francisco. *San Francisco, CA*, 2015.
46. MCRP, S. L., and L. Thomas. Speed, kinetic energy, and the safe systems approach to safer roadways. *Institute of Transportation Engineers. ITE Journal,* Vol. 89, No. 4, 2019, pp. 32-36.
47. Kröyer, H. R. G., T. Jonsson, and A. Várhelyi. Relative fatality risk curve to describe the effect of change in the impact speed on fatality risk of pedestrians struck by a motor vehicle. *Accident Analysis & Prevention,* Vol. 62, 2014, pp. 143-152.
48. Salon, D., and A. McIntyre. Determinants of pedestrian and bicyclist crash severity by party at fault in San Francisco, CA. *Accident Analysis & Prevention,* Vol. 110, 2018, pp. 149-160.
49. Strandroth, J., S. Sternlund, A. Lie, C. Tingvall, M. Rizzi, A. Kullgren, M. Ohlin, and R. Fredriksson. Correlation between Euro NCAP pedestrian test results and injury severity in injury crashes with pedestrians and bicyclists in Sweden. *Stapp car crash journal,* Vol. 58, 2014, p. 213.
50. Damsere-Derry, J., B. E. Ebel, C. N. Mock, F. Afukaar, P. Donkor, and T. O. Kalowole. Evaluation of the effectiveness of traffic calming measures on vehicle speeds and pedestrian injury severity in Ghana. *Traffic injury prevention,* Vol. 20, No. 3, 2019, pp. 336-342.

51. Ewing, R., R. A. Schieber, and C. V. Zegeer. Urban sprawl as a risk factor in motor vehicle occupant and pedestrian fatalities. *American journal of public health,* Vol. 93, No. 9, 2003, pp. 1541-1545.
52. Li, D., P. Ranjitkar, Y. Zhao, H. Yi, and S. Rashidi. Analyzing pedestrian crash injury severity under different weather conditions. *Traffic injury prevention,* Vol. 18, No. 4, 2017, pp. 427-430.
53. Rouse, J. B., and D. C. Schwebel. Supervision of young children in parking lots: Impact on child pedestrian safety. *Journal of safety research,* Vol. 70, 2019, pp. 201-206.
54. Kim, S., and G. F. Ulfarsson. Traffic safety in an aging society: analysis of older pedestrian crashes. *Journal of transportation safety & security,* Vol. 11, No. 3, 2019, pp. 323-332.
55. Stutts, J. C., W. W. Hunter, and W. E. Pein. Pedestrian crash types: 1990s update. *Transportation Research Record,* Vol. 1538, No. 1, 1996, pp. 68-74.
56. Preusser, D. F., J. K. Wells, A. F. Williams, and H. B. Weinstein. Pedestrian crashes in Washington, DC and Baltimore. *Accident Analysis & Prevention,* Vol. 34, No. 5, 2002, pp. 703-710.
57. Fontaine, H., and Y. Gourlet. Fatal pedestrian accidents in France: A typological analysis. *Accident Analysis & Prevention,* Vol. 29, No. 3, 1997, pp. 303-312.
58. Sasidharan, L., K.-F. Wu, and M. Menendez. Exploring the application of latent class cluster analysis for investigating pedestrian crash injury severities in Switzerland. *Accident Analysis & Prevention,* Vol. 85, 2015, pp. 219-228.
59. Agran, P. F., D. N. Castillo, and D. G. Winn. Limitations of data compiled from police reports on pediatric pedestrian and bicycle motor vehicle events. *Accident Analysis & Prevention,* Vol. 22, No. 4, 1990, pp. 361-370.
60. Janstrup, K. H., S. Kaplan, T. Hels, J. Lauritsen, and C. G. Prato. Understanding traffic crash under-reporting: linking police and medical records to individual and crash characteristics. *Traffic injury prevention,* Vol. 17, No. 6, 2016, pp. 580-584.
61. Harmon, K. J., K. Peticolas, E. M. Redding, A. Ising, and A. E. Waller. Examining the effect of pedestrian crashes on vulnerable populations in North Carolina. *North Carolina medical journal,* Vol. 82, No. 4, 2021, pp. 237-243.
62. Hezaveh, A. M., R. Arvin, and C. R. Cherry. A geographically weighted regression to estimate the comprehensive cost of traffic crashes at a zonal level. *Accident Analysis & Prevention,* Vol. 131, 2019, pp. 15-24.
63. Eluru, N., C. R. Bhat, and D. A. Hensher. A mixed generalized ordered response model for examining pedestrian and bicyclist injury severity level in traffic crashes. *Accident Analysis & Prevention,* Vol. 40, No. 3, 2008, pp. 1033-1054.
64. Schneider, R. J. United States pedestrian fatality trends, 1977 to 2016. *Transportation Research Record,* Vol. 2674, No. 9, 2020, pp. 1069-1083.
65. Hu, W., and J. B. Cicchino. An examination of the increases in pedestrian motor-vehicle crash fatalities during 2009–2016. *Journal of safety research,* Vol. 67, 2018, pp. 37-44.
66. Tyndall, J. Pedestrian deaths and large vehicles. *Economics of Transportation,* Vol. 26-27, 2021, p. 100219.

67. Ferenchak, N. N., and M. G. Abadi. Nighttime pedestrian fatalities: A comprehensive examination of infrastructure, user, vehicle, and situational factors. *Journal of safety research,* Vol. 79, 2021, pp. 14-25.
68. National Highway Traffic Safety Administration. *NASS General Estimates System*. https://www.nhtsa.gov/national-automotive-sampling-system/nass-general-estimates-system.
69. ---. MMUCC Guideline: Model Minimum Uniform Crash Criteria.In, National Highway Traffic Safety Administration (NHTSA), US Department of Transportation, 2017.
70. Federal Highway Administrations. KABCO Injury Classification Scale and Definitions.In.
71. Mood, C. Logistic regression: Why we cannot do what we think we can do, and what we can do about it. *European sociological review,* Vol. 26, No. 1, 2010, pp. 67-82.
72. Kuha, J., and C. Mills. On group comparisons with logistic regression models. *Sociological Methods & Research,* Vol. 49, No. 2, 2020, pp. 498-525.
73. Mize, T. D., L. Doan, and J. S. Long. A general framework for comparing predictions and marginal effects across models. *Sociological Methodology,* Vol. 49, No. 1, 2019, pp. 152-189.
74. Part, D. Highway safety manual. *American Association of State Highway and Transportation Officials: Washington, DC, USA,* Vol. 19192, 2010.
75. Kaplan, S., and B. J. Garrick. On the quantitative definition of risk. *Risk analysis,* Vol. 1, No. 1, 1981, pp. 11-27.
76. Preston, H., R. Storm, J. B. Dowds, B. Wemple, C. M. Hill, and C. Systematics. Systemic safety project selection tool.In, United States. Federal Highway Administration. Office of Safety, 2013.
77. Chawla, N. V., K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer. SMOTE: synthetic minority over-sampling technique. *Journal of artificial intelligence research,* Vol. 16, 2002, pp. 321-357.
78. Tefft, B. C. Impact speed and a pedestrian's risk of severe injury or death. *Accident Analysis & Prevention,* Vol. 50, 2013, pp. 871-878.
79. Alnawmasi, N., and F. Mannering. The impact of higher speed limits on the frequency and severity of freeway crashes: Accounting for temporal shifts and unobserved heterogeneity. *Analytic Methods in Accident Research,* Vol. 34, 2022, p. 100205.
80. Lefler, D. E., and H. C. Gabler. The fatality and injury risk of light truck impacts with pedestrians in the United States. *Accident Analysis & Prevention,* Vol. 36, No. 2, 2004, pp. 295-304.
81. Sandt, L., T. Combs, and J. Cohn. Pursuing equity in pedestrian and bicycle planning. 2016.
82. Berg, A., and G. L. Newmark. Incorporating equity into pedestrian master plans. *Transportation Research Record,* Vol. 2674, No. 10, 2020, pp. 764-780.
83. Pechac, P., M. Saga, A. Guran, and L. Radziszewski. Implementation of memetic algorithms into structural optimization. *Communications-Scientific letters of the University of Zilina,* Vol. 18, No. 1A, 2016, pp. 64-69.
84. Mishra, S., M. M. Golias, S. Sharma, and S. D. Boyles. Optimal funding allocation strategies for safety improvements on urban intersections. *Transportation research part A: policy and practice,* Vol. 75, 2015, pp. 113-133.
85. Nhtsa and fhwa celebrate national pedestrian safety month.In, Washington, DC, Oct 2021.

86. NHTSA. Pedestrian Safety Month Playbook.In, 2020.
87. Kahneman, D. *Thinking, fast and slow*. Macmillan, 2011.
88. Turner, S., I. N. Sener, M. E. Martin, S. Das, R. C. Hampshire, K. Fitzpatrick, L. J. Molnar, M. Colety, S. Robinson, and E. Shipp. Synthesis of methods for estimating pedestrian and bicyclist exposure to risk at areawide levels and on specific transportation facilities.In, United States. Federal Highway Administration. Office of Safety, 2017.
89. *Safety as a value, not a priority*.