PREDICTIVE AND EXPLANATORY ASSESSMENTS OF TRAFFIC-RELATED PEDESTRIAN INJURIES

by

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ABSTRACT

Pedestrians are an integral part of the modern transportation system but are often considered as the most vulnerable to severe traffic-related injury when compared to other road users. Between 1975 and 2009, annual pedestrian fatality counts in the United States have been decreasing steadily. However, after 2009, these counts have been increasing. Given that both the national demographic profile of the United States population and the physical makeup of transportation infrastructure show signs of aging, it is essential to understand how these affect pedestrian safety moving forward into future decades. This two-part thesis examines pedestrian safety trends from both of these perspectives. In the first part of this thesis, pedestrian fatality trends between 1975-2015, stratified by pedestrian age and sex, were analyzed and forecasted to the year 2035. Pedestrian fatality and exposure data were extracted from the NHTSA FARS and NHTS databases, respectively. Results showed that exposure-adjusted pedestrian fatality trends were consistently higher than observed pedestrian fatality counts across all ages and sexes, suggesting that interventions to reduce pedestrian fatalities have had a positive effect. Our fatality projection models indicated that traffic-related pedestrian deaths among children may continue to decrease, while pedestrian fatalities among adults aged 55 and older may increase significantly, which suggests that this cohort is at elevated risk. The second part of this thesis aimed at identifying factors that are significant in severe pedestrian injuries. Pedestrian injury data from the NHTSA GES database between 2011-2015 were examined. Odds ratios (ORs) of factors at the pedestrian, driver, crash, vehicle, environment and roadway levels were calculated. Results indicate that crashes at midblock had lower odds of fatal or serious pedestrian injury (OR = 0.79, 95% CI = 0.74 – 0.84) when compared to crashes at intersections with three or four approaches. Undivided roads (OR = 0.25, 95% CI = 0.23 – 0.27) and roads with painted medians

(OR = 0.37, 95% CI = 0.35 – 0.40) had protective effects against severe pedestrian injuries compared to roads with physical medians. Compared with locations with signalization, unsignalized locations with signage (OR = 1.57, 95% CI = 1.44 – 1.71) or without signage (OR = 1.36, 95% CI = 1.27 – 1.45) were associated with higher odds of severe pedestrian injuries. Other factors such as light conditions and road surface conditions were also found to be significant in affecting the odds of a severe pedestrian injury. The findings presented in the two parts of this thesis provide further insight into the relationship between traffic-related pedestrian injury, human factors and the built environment. Further quantitative research is recommended to expand our understanding of pedestrian injury causality.

AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revision, as accepted by my examiners. I understand that my thesis may be made electronically available to the public.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

List of Abbreviations

AADT	Annual Average Daily Traffic
AASHTO	American Association of State Highway and Transportation Officials
ANOVA	Analysis of Variance
ARIMA	Autoregressive Moving Average
ATS	American Travel Survey
CGEL	a model family consisting of the compound, growth, exponential and logistic models.
CRSS	Crash Report Sampling System
DOT	Department of Transportation
EMS	Emergency Medical Services
FARS	Fatality Analysis Reporting System
FHWA	Federal Highway Administration
GHSA	Governors Highway Safety Association
HAWK	High-Intensity Activated Crosswalk
KABCO	an injury classification scale consisting of five levels: K (fatal injury), A (incapacitating injury), B (non-incapacitating injury), C (possible injury) and O (no injury – property damage only).
LRT	Likelihood Ratio Test
MLE	Maximum Likelihood Estimation
MMUCC	Model Minimum Uniform Crash Criteria
MNL	Multinomial Logit (also referred to as Multinomial Logistic)

NASS GES	National Automotive Sampling System General Estimates System
NCSA	National Center for Statistics and Analysis
NHTS	National Household Travel Survey
NHTSA	National Highway Traffic Safety Administration
NPTS	Nationwide Personal Transportation Survey
PCO	Passenger Car Occupant
RIF	Roadway Infrastructural Factors
RRFB	Rectangular Rapid Flashing Beacon
SUV	Sports Utility Vehicle
TWLTL	Two-Way Left-Turn Lane
WHO	World Health Organization
UPA	Unsafe Pedestrian Action

List of Symbols

Trends & Forecasting Analyses

t	year index
t^*	travel survey year index
k	data year index
k^*	travel survey data year index
i	pedestrian sex index
j	pedestrian age group index
φ	pedestrian trip record index
ψ_φ	recorded distance (in miles) for trip φ
ω_φ	recorded duration (in minutes) for trip φ
τ	record weight
Φ	weighted pedestrian trip record
Ψ_φ	weighted distance walked for trip φ
Ω_φ	weighted duration walked for trip φ
$E_{\Phi/\Psi/\Omega}$	travel-based exposure estimate
P	census population estimate
Y	fatality trend/forecast count
f_t	travel-based exposure adjustment factor
f_p	population adjustment factor
r^2	coefficient of determination
AIC	Akaike Information Criterion
s	number of model parameters
LL	log-likelihood

Injury Severity Analysis

t'	year index
k'	data year index
i	pedestrian injury record index
j	pedestrian injury severity index
j^*	reference injury severity
π_{ij}	probability of record i having severity j
O_{ij}	odds of record i having injury severity j
l	predictor variable index
m	predictor variable attribute index
m^*	referent variable attribute
R_m^2	multiple correlation coefficient
α	intercept term in MNL model
β	estimated parameter in MNL model
$\mathcal{L}$	log-likelihood function
VIF	Variance Inflation Factor
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
LL_0	log-likelihood of null model
s_0	number of paramaters in null model
LL_a	log-likelihood of alternative model
s_a	number of parameters in alt. model
df_{χ^2}	degrees of freedom in LRT

CHAPTER 1: INTRODUCTION

This chapter contains the introduction of this two-part thesis. Background information on historical safety trends of passenger car occupants and pedestrians within the United States is described. This is followed by a description of the objectives and layout of this thesis.

1.1: Background

Of all modern modes of transportation, walking is the oldest and simplest. Generally speaking, all trips begin and end with walking, whether from a household, parking lot, transit stop, or otherwise. The well-known health benefits of walking are often complemented by other substantial advantages such as the reduction of air and noise pollution, mitigating traffic congestion, promoting social interaction, and the lack of an apparent monetary cost (Litman, 2010; R. Retting, 2016; Soni & Soni, 2016).

However, pedestrians are often considered vulnerable road users because they lack physical protection to sustain large magnitudes of kinetic energy, such as a collision with a motor vehicle (Constant & Lagarde, 2010; Vanlaar et al., 2016). According to the World Health Organization (WHO) in 2010, approximately 22% of all traffic-related fatalities were of pedestrians (WHO, 2013).

Moreover, traffic fatality trends from the United States (depicted in **Figure 1.1**) indicate that road traffic deaths have generally declined over the past 40 years. However, initiatives to improve road safety conditions within the United States have been primarily focused on motorists due to their ubiquity and potential for lethality. Traditionally, pedestrians have not received the same level of attention regarding safety improvements as motorists (Malek et al., 1990). In this sense, proponents of active transportation development argue that the safety needs of pedestrians have been neglected in the planning and design of the built environment (WHO, 2013).

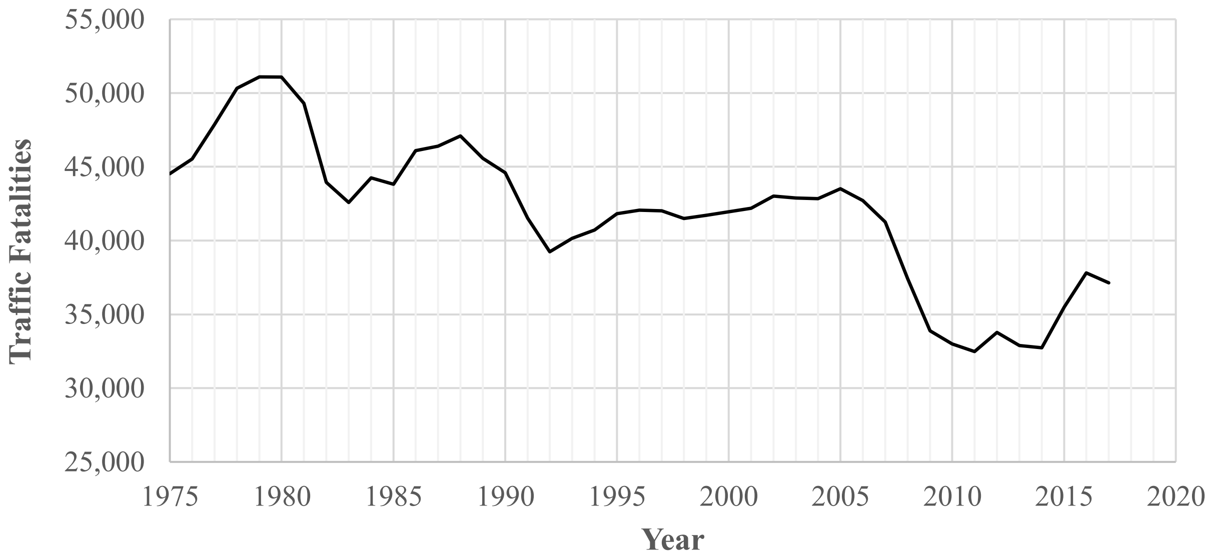

Figure 1.1: Annual traffic fatalities in the United States, 1975-2017 (NHTSA, 2018a).

1.2: Problem Statement

Figure 1.2 illustrates passenger car occupant (PCO) and pedestrian fatality trends within the United States from 1975 to 2017. Reductions in pedestrian fatalities are observed from 1995 to 2009. After 2009 however, pedestrian deaths have been rising. In 2011, approximately 4,100 pedestrians were fatally injured within the United States; this figure rose to nearly 6,000 fatalities in 2016. In a recent report from the Governors Highway Safety Association (GHSA), it was projected that 6,227 pedestrians were fatally injured within the United States in 2018, signifying a four percent increase from 2017 and the highest pedestrian death count since 1990 (R. Retting, 2019). Furthermore, the proportion of pedestrian fatalities relative to all motor vehicle crash deaths has increased from 11% in 2006 to 16% in 2017, which represents the highest proportion this metric has been within the past 30 years (Hu & Cicchino, 2018). Some researchers have suggested that this increase in the proportion of pedestrian fatalities is attributable to a decreasing trend of PCO deaths (Chong et al., 2018; R. Retting, 2018).

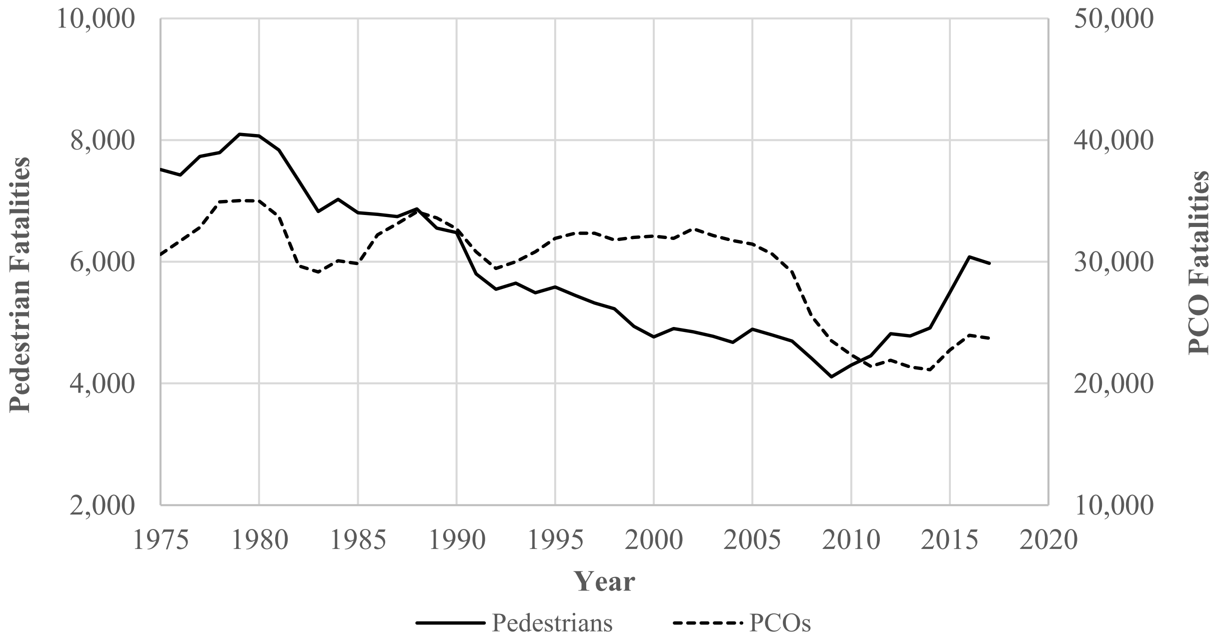

Figure 1.2: Annual pedestrian and passenger car occupant (PCO) fatality trends within the United States, 1975-2017 (NHTSA, 2018a).

1.3: Motivation for Thesis Research

Traffic-related pedestrian injuries incur various socioeconomic consequences such as increased medical costs, reduced productivity at work and home, and lost quality of life. In 2010, crashes involving pedestrians accounted for 13% of all road fatalities in the United States and led to $65 billion in societal impacts (Blincoe et al., 2015).

A report from the United States Federal Highway Administration (FHWA) indicates that the estimated economic and societal costs of a pedestrian crash at an intersection are $72,800 and $158,900, respectively. Moreover, the estimated economic and societal costs of a similar crash at a non-intersection (i.e., at midblock) are $107,800 and $287,900, respectively (Harmon et al., 2018).

As a result, this relatively recent rise in pedestrian injury has prompted road safety professionals and policymakers to undertake improvements in pedestrian safety. In 2016, the FHWA published its *Strategic Agenda for Pedestrian and Bicycle Transportation*. The agenda was intended to guide road safety professionals with improving pedestrian and bicyclist activity and safety for future years and consists of two national goals for active transportation modes. First, an 80 percent reduction in pedestrian and bicyclist severe and fatal injuries shall be attained within 15 years, along with zero pedestrian and bicyclist fatal and severe injuries within the next 20 to 30 years. Second, an increase in the proportion of short trips represented by walking and bicycling from an estimated 20 percent in 2009 to 30 percent by 2025. A short trip, as defined in the FHWA's Strategic Agenda, is a trip less than or equal to five miles in distance for bicyclists and one mile or less for pedestrians (Twaddell et al., 2016).

For pedestrians, the degree of vulnerability is primarily dependent on numerous factors such as pedestrian demographics and the roadway environment. As both the demographic profile of the United States population and the conditions of transportation infrastructure experience significant changes, opportunities to implement safety improvements for pedestrians are becoming increasingly apparent. Exploring past trends of pedestrian safety and making possible inferences into future years in conjunction with contributing factors that affect pedestrian crash severity may provide valuable insight to mitigate pedestrian traffic-related injuries.

In this sense, there has been significant research investigating past and future trends of road user mortality (Bédard et al., 2001; Farmer, 2017; Kopits & Cropper, 2005). However, due to limitations such as underreporting and the rare nature of pedestrian crashes, there are few identified time-series studies that are exclusive to pedestrian safety (Johnsson et al., 2018; Lavrenz et al., 2018).

Furthermore, while it has been suggested that traffic safety is dependant on numerous factors such as road user behaviour, demographics, land use characteristics and others (Lee & Abdel-Aty, 2005; Sze & Wong, 2007), some researchers have argued that roadway infrastructural factors (RIFs) are among the most critical in traffic safety (Papadimitriou et al., 2019). In this sense, there has been limited research studying the independent contribution of road infrastructure on the severity of pedestrian injuries (Gitelman et al., 2012; Hanson et al., 2013; Penmetsa & Pulugurtha, 2018).

As a result, this thesis aims to address these concerns by analyzing i) long-term pedestrian fatality trends to produce fatality forecasts, and ii) the independent contributions of roadway infrastructure on pedestrian injury severity. Moreover, research on pedestrian safety from these two perspectives is crucial for developing an understanding of the relationships between road users and the built environment, mainly when the characteristics of population and infrastructure show signs of aging. This study attempts to segregate some of these factors and to determine their potential impacts to pedestrian safety, which could lead to innovative countermeasures intended to mitigate or prevent fatal or incapacitating pedestrian collisions.

1.4: Research Objectives

This thesis consists of two parts. The first part is a fatality forecasting study whereby road user fatalities were disaggregated by demographics and forecasted to a future year. The first part is also referred to as the 'demographics analysis.' Previous studies (Bédard et al., 2001; Mullen et al., 2013) had focused on motor vehicle occupant fatalities within the United States and projected these deaths to 2015 and 2025, respectively. The current demographics analysis was intended to supplement these previous findings by examining past and future trends of pedestrian fatalities. Specifically, the aim is to address the following research questions:

1. How have pedestrian safety trends changed over the last 40 years?
2. Given the dynamic demographic profile of the United States population, who will be at higher risk of a traffic-related fatality as a pedestrian in coming decades?

As such, the objectives of the first part of this thesis were to:

1. Analyze pedestrian fatality trends by age and sex from 1975 through 2015.
2. Provide quantitative forecasts of pedestrian fatalities according to age and sex characteristics.

In the second half of this thesis, a regression analysis was undertaken to identify RIFs affecting pedestrian injury severity. Accordingly, this part is also referred to as the 'injury severity analysis.' Unlike the demographics analysis which exclusively examines pedestrian fatalities, the injury severity analysis included multiple severity levels ranging from no apparent injury to fatality. The research questions considered within the injury severity analysis were:

1. What are the most influential risk factors that contribute to pedestrian injuries?
2. How are different roadway infrastructure elements related to pedestrian injury severity?

Accordingly, the objectives of the second part of this thesis are to:

1. Develop a regression model to identify factors relating to the roadway environment that are influential in pedestrian injury severity.
2. Suggest infrastructure-specific countermeasures that may reduce the severity of pedestrian crashes.

1.5: Thesis Outline

This thesis is arranged into seven chapters and follows the format depicted in **Figure 1.3**. Following this introductory chapter, Chapter 2 contains a review of literature focusing on pedestrian safety, specifically on three topics: time series modelling and forecasting, injury severity modelling, and pedestrian injury risk factors. Chapter 3 describes the methodology used in the demographics analysis. In particular, the sources of pedestrian fatality and exposure data, and procedures to generate pedestrian fatality trends and fatality projections are presented. Chapter 4 presents the pedestrian fatality trends and forecasts by demographic cohorts. Inferences from the fatality forecasting analysis are presented here. Chapter 5 discusses the methodology for the pedestrian injury severity analysis. Details regarding model specifications and the variables considered are presented. Chapter 6 presents the modelling results of the injury severity analysis. Insights for potential engineering countermeasures and other improvements based on the results of this study are given. Chapter 7 summarizes the findings from this thesis. The key findings from the demographics and injury severity analyses are reported here. Limitations of the two analyses and recommendations for future research are also provided in this chapter.

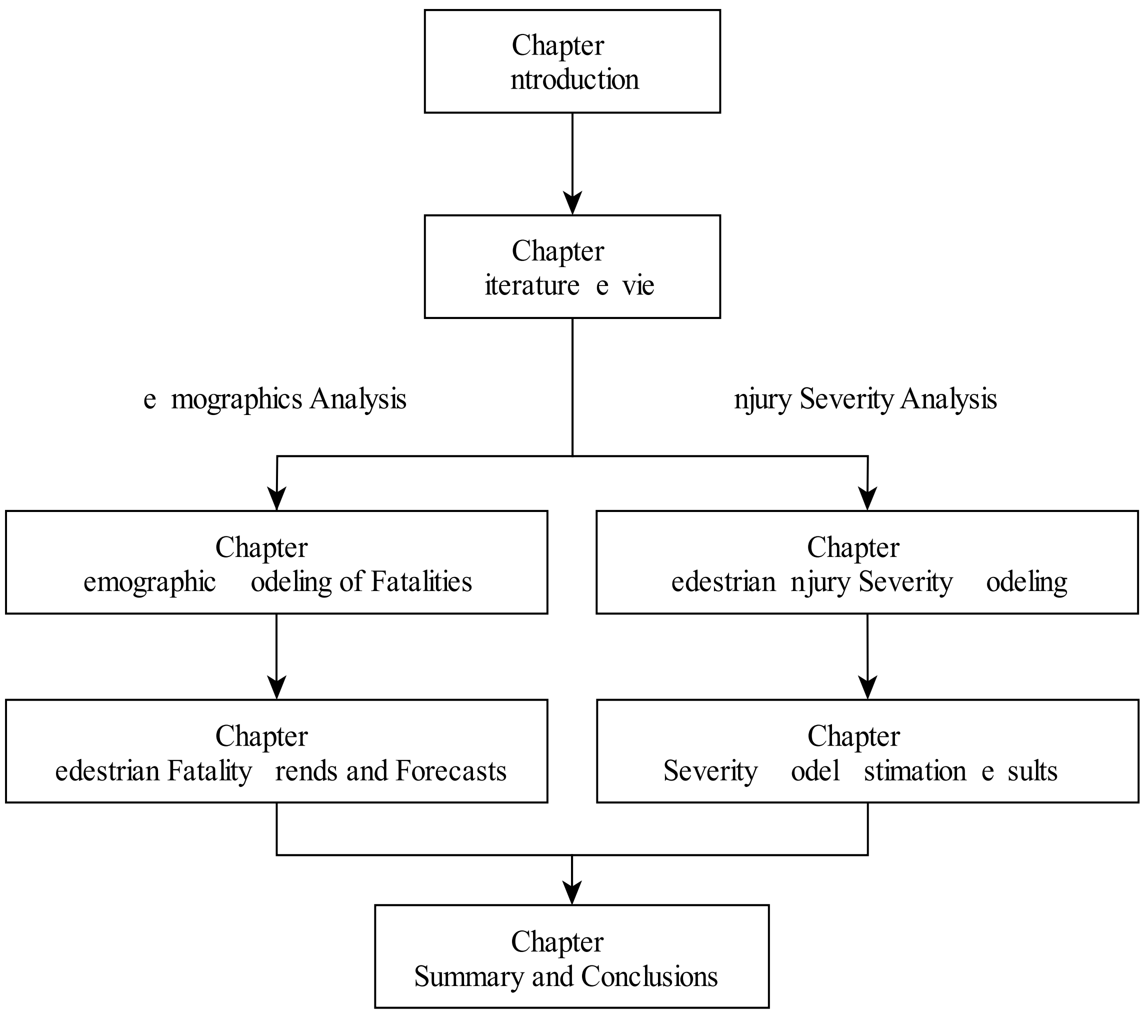

Figure 1.3: Flow chart of thesis organization.

CHAPTER 2: LITERATURE REVIEW

This chapter provides a review of literature regarding injury forecasting and injury severity modelling in the context of traffic safety. A review of road safety forecasting research and quantitative road safety targets is presented first. Second, various risk factors regarding pedestrian safety are discussed. Lastly, several statistical techniques for modelling crash injury severity are highlighted.

2.1: Road Safety Forecasting

Hauer (2010) describes two modeling approaches to predict road safety; the first approach involves extrapolating historical data to produce forecasts, while the second approach attempts to define causality through significant factors that affect road safety trends. In this sense, the t o mode ling approaches may be referred to as 'predictive' and 'explanatory' modeling, respectively (Shmueli, 2010). This section provides a discussion regarding several aspects of predictive modeling in road safety research. The sections succeeding this one describe explanatory modeling in more detail.

The application of using historical road safety data to produce predictions on future road safety has been used in the past for a variety of purposes, such as (Hauer, 2010; Mitchell & Allsop, 2014):

- identifying different sub-populations (e.g., by road user type or demographics) that are at heightened risk of traffic-related injury,
- establishing road safety targets and monitoring programs to evaluate the state of road safety over time,
- assessing historical road safety trends to evaluate the feasibility of meeting already-established road safety targets, or

- incentivizing transportation agencies and policymakers for the development of road safety improvements.

2.1.1: Subpopulations

Because crashes are considered random and rare events (AASHTO, 2010), road safety data are often aggregated into a single source. While it is possible to characterize overall safety trends for some geographical unit (e.g., a country) using aggregated data, doing so does not consider specific subpopulations that may have different safety trends (Karlis & Hermans, 2012). Analyzing safety characteristics by different subpopulations allows for the development of targeted measures to address specific safety concerns.

Disaggregating safety data based on one or more criteria (e.g., travel mode, age, location) allows for a more detailed examination of trends, as well as the flexibility to consider specific explanatory factors for specific sub-populations (Stipdonk et al., 2010). While multiple stratifications may provide useful results, in theory, an excessive amount of disaggregation is likely to result in insufficiently low sample sizes of data, thus leading to higher standard errors and ultimately producing unreliable predictions.

Subpopulations such as older road users have been considered to have increased risks of high-severity traffic-related injury involvement. Bédard et al. (2001) hypothesized that older motor vehicle occupants (i.e., those aged 65 and older) would represent an increasing proportion of traffic-related fatalities as a result of their increasing proportion within the population. Using United States traffic fatality data from 1975 through 1998, the researchers generated time-series forecasts to the year 2015 for three different age groups (younger than 30, 30 through 64, and 65 and older). They concluded that the fatality trends among middle-aged and older occupant cohorts were increasing, with the older cohort exhibiting a higher rate of increase. However, these forecasts were not adjusted for any travel or population-based exposure.

Mullen et al. (2013) used fatality data from 1975 through 2015 to update the earlier study by Bédard et al. Several changes within this study were noted such as the fatality projections created used 2025 as their target to extend previous work. Also, fatality data from 1975 were used as the baseline and adjusted for annual exposure. Furthermore, vehicle occupant age was subdivided into five groups as opposed to the three used in Bédard et al.; this allowed for a finer discussion of other age groups such as young and middle-aged drivers and passengers. Contrary to the findings from Bédard et al., results from this study indicated that between 1998 and 2008, fatality counts among older vehicle occupants had declined, suggesting that efforts to improve motor vehicle occupant safety had been effective.

Another subpopulation cited in the literature as having higher risk of traffic-related injury is child pedestrians. Roberts and Crombie (1995) analyzed the relationship between child pedestrian fatality rates (ages 9 and younger) and vehicular traffic exposure within the United States using data from 1970 to 1988. Even though traffic volume grew from 1.78 trillion vehicle-kilometres travelled in 1970 to approximately 3.24 trillion in 1988, there were declines in fatality rates among children. Children aged 0-4 showed the most considerable percentage reduction in fatality rates at 54%, whereas fatality rates from those aged 5-9 had the highest absolute reduction at 3.1 deaths per 100,000 population. The researchers suggested that mobility among children is primarily controlled by parents, which directly affects their risk of being involved in a traffic-related injury.

Similarly, Nakahara et al. (2016) examined child pedestrian injury rates (per population) in Japan from 1975 to 2013. Five three-year age groups from 0 to 15 were established to account for the dynamic lifestyles associated with childhood (e.g., attending different levels of school, varying degrees of autonomy, et cetera). Joinpoint regression was performed to fit log-linear models to the injury data. The analysis showed that fatality rates for pre-school aged children (children aged 0-6) exhibited consistent declining trends from 1975 to 2013. Furthermore, fatality rates of children aged 7 through 12 were relatively constant from 1975 to approximately 2000, after which point a significant decline was observed. The authors suggested that declines in child pedestrian exposure and vehicular volumes during the early to mid-2000s contributed to the decrease in child pedestrian fatality rates, as substantiated by the results of a Japanese travel survey. However, definitive causes for the differences in fatality trends between pre-school and school-aged children were not investigated.

More recently, Bandi et al. (2015) analyzed motorist fatality rates, stratified by age group (<1 – 14 years, 15 – 24 years, 25 – ye ars, ≥ years) and sex, within the United States from 1968 to 2010 using joinpoint regression. Per-capita fatality rates were adjusted for vehicular exposure (i.e., vehicle miles travelled). The authors reported significant declines in motor vehicle occupant fatalities from 1968 through 2010. However, traffic-related deaths among young and middle-aged adult males (ages 25 – 64 years) showed stabilizing trends, suggesting that this sub-population may have unique behavioural characteristics not observed with other cohorts. Moreover, the authors also indicated that fatality rates among males declined more sharply than for females in all age groups except ≥ ye ars.

2.1.2: Road Safety Targets

There is also a growing body of research examining road safety forecasts in conjunction with road safety targets. Marsden and Bonsall (2006) defined three approaches to establishing targets. First, the aspirational approach is based on an idealistic goal and does not consider data-driven evidence on the defined safety outcome. An aspirational target is generally created as a preparatory step until a data-driven target can be devised. Second, the model-based approach involves statistical models that are fit to safety data with assumptions made for contributing factors. Targets made with this approach are subject to how limited the elected model can reflect historical trends. Lastly, the 'extrapolation and evidence-led judgement' approach requires sufficient years of time-series data, accounting for variations in data (e.g., interventions to policy or engineering characteristics). From these three approaches, the 'extrapolation and evidence-led' approach is the most popular among policymakers, as it provides a higher degree of reliability. Moreover, many transportation agencies are adopting this approach to develop road safety targets, as target establishment was found to be associated with improvements in road safety levels (Wong & Sze, 2010).

There have been several research endeavours assessing road safety data to guide the establishment of injury reduction targets, particularly from Europe. In several studies from Broughton, injury rates (per vehicle exposure) were projected in tandem with traffic forecasts to produce injury count estimates (J. Broughton, 1988, 1991; Jeremy Broughton & Knowles, 2010). Broughton's injury forecasting procedure is described belo (Jeremy Broughton & Knowles, 2010):

1. Unadjusted projections of traffic-related injury rates (per unit of travel-based exposure) and future travel trends (e.g., vehicle volume) are prepared. These projections assume that no safety interventions will be implemented.
2. A baseline injury count forecast is created by combining the injury rate and travel trend forecasts (given that injury counts are the product of rate and exposure).

3. Effects of any planned road safety policy improvements are estimated and applied to the baseline forecast to produce an adjusted model.

This procedure was applied to guide the establishment of injury reduction targets in the U.K. The proposed target for the year 2000 was to reduce the number of fatal and serious injuries in Great Britain by 33 percent of the average injury count between 1981 to 1985. This target was met in 1997, where it was cited that fatal and serious injury counts were reduced by more than 40 percent (J Broughton et al., 2000). During the late 1990s, work was undertaken to define the next U.K. road safety target for 2010. This target consists of the following (Jeremy Broughton & Knowles, 2010):

- a 40 percent reduction in the number of people killed or seriously injured in traffic crashes,
- a 50 percent reduction in the number of children killed or seriously injured in traffic crashes, and
- a 10 percent reduction in the slight injury rate, described as the number of people slightly injured per 100 million vehicle kilometres.

Furthermore, progress towards meeting the new targets would be monitored every three years in order to evaluate the assumptions made regarding the effects of policy improvements.

Raeside and White (2004) criticized the process of deriving two separate forecasts. These researchers noted that a distance-based metric as the rate denominator may be misleading as many crashes occur relatively close to the casualty's residence. Further, they raised concerns regarding the accuracy of vehicular exposure estimates. As such, the authors elected to develop projections based on casualty counts as opposed to casualty rates using autoregressive integrated moving average (ARIMA) models. Monthly injury data from 1991 to 2001 were used to develop forecast models for fatal, serious and slight injuries. Pedestrian-centred models (total pedestrians and child pedestrians) were constructed as well. From these models, the authors predicted a pedestrian injury count of 34,523 (95% CI = 21,706 – 47,399) in 2010, which was 25.8 percent lower than the government baseline estimate (defined as the average injury count from 1994 to 1998). Moreover, for child pedestrians, the models from Raeside and White forecasted an injury count of 16,886 (95% CI = 12,353 – 21,419), representing a 9.6 percent reduction from the government-defined baseline.

Additionally, there has been extensive research in meeting road safety targets under a set of hypothetical scenarios. Kweon (2010) developed several road safety forecasts. The main objectives of this study were to evaluate the likelihoods of meeting existing and proposed road safety targets, while also assessing various engineering and legislative interventions. Such interventions include signal timing plan adjustments to promote pedestrian safety, centreline rumble strip installation of rural two-lane roadways and adjustments to seat belt law enforcement. Several engineering implementation level scenarios were defined: 90%, 50%, 30% and 20%. The percentage value corresponds to the level in which engineering treatments are implemented. For instance, a 50 percent implementation level for signal timing plan adjustments implies that 50 percent of all traffic signals in Virginia are subject to signal timing changes. Furthermore, legislative interventions were set up in two scenarios: optimistic (13 percent reduction in fatalities) and practical (8 percent reduction in fatalities). Kweon suggested a 10 percent fatality reduction target with a 5 percent non-fatal injury reduction target as being the most realistic goal for Virginia. This goal was based on a 20-30% engineering intervention scenario, along with the enactment and enforcement of a primary seat belt law.

Other studies, however, have modelled time-series road safety data to assess the feasibility of achieving an established road safety target such as the research by Wesemann et al. (2010) which considered several economic scenarios including factors like employment rates and gross domestic product to forecast and evaluate Dutch road safety trends in 2020. Other large-scale policy-based measures such as improvements in the driver licensing system and monetary investments to road infrastructure and enforcement were also considered into their forecasts. These researchers concluded that the fatality forecast under the scenario with the highest mobility growth would likely not meet fatality target values. Moreover, it was estimated that the implementation of the aforementioned policy-based measures would likely result in meeting the road safety targets. Sensibly, the study from Wesemann et al. made exclusive use of macro-level data as the road safety targets were defined for all of the Netherlands. Similarly, Commandeur et al. (2017) estimated the number of traffic-related fatalities in Cambodia based on motor vehicle ownership. In this sense, three levels of vehicle ownership growth were defined: low, medium, and high growth. In a similar approach to Broughton (1988), the researchers used latent risk time series models to forecast fatality rates per 1,000 motor vehicles and the annual number of motor vehicles to the year 2020. Significant quantitative differences in traffic fatalities among the various vehicle ownership growth scenarios were found in the forecast year of 2020, with the highest fatality projection corresponding to the highest level of vehicle growth. From their results, the results associated with the middle growth scenario were carried forward into defining fatality targets for 2020. This was done to support the development and implementation of road safety interventions.

In Australia, Gargett et al. (2011) examined the efficacy of a 2010 road safety target by analyzing fatality rates (per population) between 1971 to 2009. Data were also disaggregated by the state/territory-level to examine the progress of various jurisdictions. Fatality rates were forecasted using time-series models to the year 2020. The models were terminated if the 2010 target was met, or the year surpassed 2020. The focus was to assess at what point in the future would the 2010 target would be met. In lieu of the explanatory data needed to incorporate future potential changes in national road safety, the analysis assumed that contemporary trends in fatalities would continue with little to no considerable variation and did not include potential changes in future crash rates. In this sense, linear, logarithmic and quadratic models were rejected and instead, power law and exponential time-series models were chosen. It may be argued that adopting such an assumption is unrealistically optimistic. Results from the study from Gargett et al. indicated that the 2010 national road safety target may not be achieved until 2016. Moreover, their study demonstrated the need to produce road safety forecasts at smaller geographic scales (states/territories) to identify those areas that warrant additional resources.

More recently, Chang (2014) developed fatality rate projections using experience curve models to the target years of 2020 and 2030 for each state in the United States. From the fifty states, fatality rate forecasts from ten states (i.e., AL, IN, KS, LA, MD, MA, NH, NM, PA and VA) were created. These ten states were chosen given that long-term (i.e., within a 20-year horizon) fatality reduction targets were defined as per each respective state's Strategic High a y Safety Plan. In particular, the targets were to reduce existing traffic-related fatality rates by 50 percent. n regard to Chang's modeling approach, both a constant and a variable rate of change were considered for the experience curve methodology. The fatality rate projections incorporated vehicular exposure, but variations across transportation modes (i.e., walking, bicycling, et cetera) were not considered. Thus, it could not be ascertained if the degree of pedestrian or bicyclist fatalities was to change. Notwithstanding this limitation, the forecast model results for each state were compared to their respective fatality rate target, using the year 2030 as a reference. Results indicate that target values are significantly smaller than as calculated from the models, suggesting that additional interventions (engineering or legislative) may be warranted. Furthermore, Chang concluded that fatality rate reduction of at least 50 percent may not be achieved until after the year 2030, regardless of efforts to limit future growth of vehicular exposure.

2.1.3: Forecasting Methodologies

Traditionally, road safety forecasting was undertaken with deterministic models such as linear (Wittenberg et al., 2013), piece-wise linear (Kopits & Cropper, 2005; Yannis et al., 2011), log-linear (Jeremy Broughton & Knowles, 2010), exponential (Gargett et al., 2011), logistic (Bédard et al., 2001; Oppe, 1989), or polynomial (Mullen et al., 2013). In such cases, the safety forecast is dictated by initial conditions and the generated parameters, with no consideration for potential randomness.

However, as real-world phenomena (such as traffic crashes) are often subject to complexity and uncertainty, stochastic/probabilistic models such as ARIMA models (Mohammed A. Quddus, 2008; Rohayu et al., 2012), DRAG models (Gaudry & Lassarre, 2000), or state-space models (Antoniou & Yannis, 2013; Dupont et al., 2014) have been favoured. Reviews from Karlis and Hermans (2012), Commandeur et al. (2013), and Bergel-Hayat and Zukowska (2015) suggest that stochastic models are gaining popularity due to their ability to incorporate explanatory and intervention factors (Chang, 2014).

While it appears intuitive that adding such factors may result in more reliable forecasts, Elvik (2010) argued that models derived from a multivariate explanatory approach (i.e., including contributing factors) are not advantageous when compared to relatively simple deterministic models from extrapolated data. Furthermore, Elvik argued that historical data do not provide sufficient reliability future trends.

2.2: Risk Factors of Pedestrian Injury Severity

Traffic crashes are complex events that are associated with numerous contributing factors. Identifying and quantifying these factors are often considered a difficult and inaccurate and challenging process. Notwithstanding these difficulties, studying potential crash causality is an essential step in developing and implementing safety countermeasures to mitigate traffic-related injuries.

Many researchers have organized contributing factors into various categories such as pedestrian-related, driver-related, vehicle-related, environment-related, roadway-related, time-related, and other groups (Eluru et al., 2008; Islam & Jones, 2014; C. V. Zegeer & Bushell, 2012). A review of contributing factors across these categories is given in the following subsections.

2.2.1: Pedestrian Factors

From the various pedestrian-related variables seen in pedestrian safety literature, pedestrian age has been one of the most notable. In the event of a crash, older pedestrians (i.e., those aged 65 or older) are often cited to be at high risk for fatal or severe injuries due to increased fragility and the higher potential for health decline (Aziz et al., 2013; Z. Chen & Fan, 2019; Chong et al., 2018; Eluru et al., 2008; Jang et al., 2013; Lee & Abdel-Aty, 2005; Moudon et al., 2011; Pour-Rouholamin & Zhou, 2016; Tay et al., 2011; Uddin & Ahmed, 2018). Conversely, Jang et al. (2013) found that younger pedestrians (i.e., 15 years old or younger) were also at elevated risk of severe injury. However, other studies such as Sze & Wong (2007), Tay et al. (2011), and Islam & Jones (2014) have suggested that this cohort is less likely to be fatally or severely injured. A possible reason may include the low probabilities of children being struck along roads with higher speeds.

In reference to pedestrian sex, some studies show male pedestrians as being at higher risk of traffic injury (Chong et al., 2018; Clifton et al., 2009), and several others suggest that the likelihood of a severe or fatal injury is higher for females due to their lower tolerance to the kinetic energy of a collision (Islam & Jones, 2014; Lee & Abdel-Aty, 2005; Obeng & Rokonuzzaman, 2013; and Tay et al., 2011).

The association between alcohol (and/or drug) consumption and physical impairments (e.g., delayed reaction time, loss in concentration, inhibited motion tracking and blurred vision) means that pedestrians with such impairments may have higher risk of severe injuries in traffic crashes (Bradbury, 1991; Chong et al., 2018; Jang et al., 2013; Lee & Abdel-Aty, 2005; Shah et al., 2015; and Zajac & Ivan, 2003). Moreover, studies have demonstrated that young adult males (e.g., males under age 30) are more likely to be involved in severe injuries while under the influence of alcohol (Bradbury, 1991; Chong et al., 2018; Öström & Eriksson, 2001).

Lastly, several pedestrian actions/behaviours such as crossing against traffic signals (Clifton et al., 2009), dart-outs (Islam & Jones, 2014), inattentiveness (Jang et al., 2013) and being inconspicuous (Pour-Rouholamin & Zhou, 2016) were found to increase the probability of severe injuries.

2.2.2: Driver Factors

Severe studies have demonstrated that younger drivers (i.e., younger than 24) are associated with higher probabilities of being involved in a crash resulting in a severe pedestrian injury (Kim et al., 2008; Pour-Rouholamin & Zhou, 2016; Uddin & Ahmed, 2018). According to the study by Pour-Rouholamin & Zhou (2016), drivers aged over 65 were 13 percent more likely and 15 percent less likely to be involved in crashes resulting in no/possible pedestrian injury and severe pedestrian injury, respectively. Similarly, Uddin and Ahmed (2018) found that drivers aged over 65 were approximately 42 percent more likely to be associated with crashes leading to no/possible pedestrian injury. Using a multinomial logit modeling approach, Tay et al. (2011) also concluded that older drivers (aged over 65) were less likely to be involved in crashes with severe pedestrian injuries when compared to middle-aged drivers (aged between 26 and 65) (OR = 0.575, 95% CIs not available). A common reason for this relationship between driver age and injury risk is due to the low-risk driving behaviour associated with older drivers.

Furthermore, drivers that were male and/or impaired have been found to be associated with increased likelihoods of higher severity injuries to pedestrians, presumably due to males' tendencies of engaging in risky behaviour whilst operating a motor vehicle (Eluru et al., 2008; Kim et al., 2008; Mohamed et al., 2013; Moudon et al., 2011; Pour-Rouholamin & Zhou, 2016; Tay et al., 2011; Zajac & Ivan, 2003).

2.2.3: Vehicle Factors

A common vehicle-related factor considered is the type of vehicle involved in a pedestrian crash. Relative to passenger cars, larger vehicles such as buses, trucks, sport utility vehicles (SUVs), and vans are associated with increased likelihoods of severe and fatal pedestrian injuries due to higher amounts of kinetic energy transferred in the event of a crash (Aziz et al., 2013; Ballesteros et al., 2004; Z. Chen & Fan, 2019; Chong et al., 2018; Eluru et al., 2008; Jang et al., 2013; Kim et al., 2008; Lee & Abdel-Aty, 2005; Mohamed et al., 2013; Obeng & Rokonuzzaman, 2013; Pour-Rouholamin & Zhou, 2016; B. S. Roudsari et al., 2004; Tulu et al., 2017).

2.2.4: Environmental Factors

Common factors relating to the environment include weather and light conditions. Several studies have concluded that while pedestrian injury frequencies were higher during clear weather conditions, the likelihood of a severe injury was higher during inclement weather such as rain or snow events (Amoh-Gyimah et al., 2017; Islam & Jones, 2014; Lee & Abdel-Aty, 2005; Pei & Fu, 2014; Tay et al., 2011). However, other studies have suggested that inclement weather conditions lowered the likelihood of severe and fatal pedestrian injuries, attributable to heightened awareness among motorists (Kim et al., 2008; Mohamed et al., 2013; Pei & Fu, 2014). Moreover, other studies have examined roadway surface conditions as opposed to weather conditions. For instance, studies from Chen and Fan (2019) and Aziz et al. (2013) concluded that wet road surfaces had protective effects against fatal pedestrian crashes. Other studies have jointly assessed both weather and road surface conditions, but have generally conferred that adverse weather and road surface conditions decreased the probability of severe and fatal pedestrian injuries (Haleem et al., 2015; Pour-Rouholamin & Zhou, 2016; Zajac & Ivan, 2003).

Furthermore, some studies have indicated that crashes during daylight or under artificially lit conditions present were associated with lower severity injuries. Expectedly, dark and unlit conditions led to higher probabilities of fatal and incapacitating injuries (Amoh-Gyimah et al., 2017; Aziz et al., 2013; Z. Chen & Fan, 2019; Haleem et al., 2015; Islam & Jones, 2014; Kim et al., 2008; Lee & Abdel-Aty, 2005; D. Li et al., 2017; Mohamed et al., 2013; Pour-Rouholamin & Zhou, 2016; Siddiqui et al., 2006; Sullivan & Flannagan, 2011; Uddin & Ahmed, 2018; Zahabi et al., 2011).

2.2.5: Roadway Factors

Multiple studies have demonstrated that traffic signal implementation was associated with lower risks of fatal and severe pedestrian injuries when compared to locations with stop control or no traffic control (Aziz et al., 2013; Moudon et al., 2011; Sarkar et al., 2011; Wang et al., 2017). Also, Sze and Wong (2007) indicated that unsignalized intersections with some form of traffic control (such as signs) led to lower likelihoods of fatal and severe pedestrian injuries. Moreover, Islam & Jones (2014) suggested that drivers were more likely to be more cautious when entering intersections with no apparent traffic control, thus reducing the likelihood of high severity injuries.

Furthermore, Pour-Rouholamin & Zhou (2016) associated roadways with medians as having lower risks of severe pedestrian injury when compared to undivided roads. In particular, they found that raised medians led to higher probabilities of severe injuries than painted medians. However, the researchers suggested that the presence of medians was indicative of roads with higher posted speed limits, thus increasing the potential severity of pedestrian crashes. Nevertheless, contradictory results from Amoh-Gyimah et al. (2017) indicated that roads with medians were associated with lower likelihoods of major injuries, as medians provide refuge for pedestrians wishing to cross. However, no differentiation was made between physical and painted medians. As such, it could not be ascertained which type of median could provide more safety benefits for pedestrians.

Another factor such as the number of lanes of a roadway has been found to be significant in crashes in a few studies, such as in Aziz et al. (2013), Pour-Rouholamin & Zhou (2016), and Islam & Jones (2014). In particular, the results from these studies showed that crashes along two-lane roads (i.e., one lane in each direction) had lower likelihoods of resulting in fatal pedestrian injuries. Intuitively, multi-lane roads were found to have higher probabilities of pedestrian injuries with higher severities. These findings are appropriate given that multi-lane roads are primarily suited for providing mobility amongst motorists and are typically associated with high speeds and large volumes of vehicular traffic. Pedestrian movements may also be higher at these locations but are largely dependent on the degree of pedestrian accessibility and surrounding land use. To this extent, multi-lane freeways and expressways are used primarily for vehicle mobility purposes, whereas arterial roads with high capacities that provide a combination of mobility and access may be used by pedestrians, particularly when access to public transit service is present.

A prominent factor in the severity of pedestrian crashes is the speed at which a pedestrian is struck. In this sense, numerous studies have investigated the relationship between impact speed and the severe pedestrian injury risk (G. Davis, 2001; Gårder, 2004; Oh et al., 2005; B. S. Roudsari et al., 2004; Tefft, 2013). These studies indicated that the relationship between the likelihood of severe (fatal or incapacitating) injuries and impact speed is largely dependent on pedestrian age. In general, vehicle impact speed is positively associated with fatality risk (Rosén et al., 2011). In this sense, the higher relative frailty of older adults means that the minimum impact speed to cause a severe pedestrian injury is lower than that of younger cohorts (G. Davis, 2001; Hauer, 1988; Tefft, 2013).

Further, some studies have considered posted speed limits as a proxy for travel speeds because of challenges in acquiring accurate actual impact speeds. Results of many of these studies show a positive correlation between injury severity and posted speed limits (Jang et al., 2013; D. Li et al., 2017; Obeng & Rokonuzzaman, 2013; Tulu et al., 2017). Specifically, the likelihood of high severity injuries was found to increase on roads with posted speed limits between 25 and 50 mph (Eluru et al., 2008; Uddin & Ahmed, 2018) or higher than 50 km/h (Sze & Wong, 2007; Wang et al., 2017).

Other factors such as considered roadway curvature or inclination have been considered in few studies. Kim et al. (2008) concluded that straight roads with either a positive or negative grade were associated with higher risks of fatal pedestrian injuries. However, the contributions of uphill and downhill road segments could not be differentiated. Moreover, Amoh-Gyimah et al. (2017) and Chen and Fan (2019) found that straight and level roadways had lower probabilities of fatal and serious pedestrian injuries when compared to roads with either horizontal or vertical curvature. In this respect, roads with lateral curvature or non-zero gradients may have implications on vehicle speeds and pedestrian visibility (Z. Chen & Fan, 2019). Moreover, the angle and location of human impact in a pedestrian crash may change according to the roadway alignment configuration, thus affecting the severity of an injury (Kim et al., 2008).

2.2.6: Temporal Factors

The relationships between pedestrian injury severity and several crash temporal factors have been investigated by several researchers. Uddin and Ahmed (2018) suggested that crashes during daytime off-peak hours (i.e., between 10:00 a.m. and 3:59 p.m.) were less likely to result in pedestrian fatalities or serious injuries. This reduction in injury risk was likely attributed to low pedestrian exposure during such off-peak times. Moreover, Kim et al. (2008) found a similar finding using p.m. peak hours (i.e., between 3:00 p.m. and 5:59 p.m.). In this sense, peak hours are typically associated with evening rush hours and traffic congestion, which are indicative of significantly lower speeds than other times during the day. Conversely, crashes during night hours were found to increase the risk of severe pedestrian injury (Jang et al., 2013; Mohamed et al., 2013; Pour-Rouholamin & Zhou, 2016).

Regarding days of the week, crashes during weekends were more likely to result in severe pedestrian injuries (Z. Chen & Fan, 2019; Jang et al., 2013), while Uddin and Ahmed (2018) determined that weekdays were associated with lower probabilities of severe pedestrian injuries. Pedestrian exposure is generally higher during weekends, thus supporting this finding.

Some studies have considered the season of a crash (Islam & Jones, 2014; Mohamed et al., 2013; Pour-Rouholamin & Zhou, 2016). Mohamed et al. (2013) argued that the autumn and winter months were correlated with increased severe pedestrian injury risk. On the other hand, Islam and Jones (2014) suggested otherwise, as winter months were associated with lower pedestrian exposure and heightened driver caution in poor road conditions.

It should be noted, however, that many of these variables mentioned above interact with some roadway or environmental factors. For instance, in the previous discussion regarding crash seasons, the weather conditions are an apparent contributor to the surface conditions of the road. Similarly, the presence of artificial light is largely dependent on the time of the day. Lastly, the speeds of vehicles may vary depending on the traffic conditions of a roadway, which in turn have a relationship with the time of day (i.e., commuters during rush hour). Careful investigations of these potential interactions should be undertaken in order to obtain adequate model outputs.

2.2.7: Land Use Factors

Factors relating to land use characteristics have also been studied in the past. Ukkusuri et al. (2011) found that crashes (regardless of severity) were more likely to occur in industrial, commercial and open areas. Moreover, the likelihood of fatal or serious pedestrian injuries is higher in areas where pedestrian movement is most prevalent, such as commercial or mixed-use areas (Aziz et al., 2013; Mohamed et al., 2013; Zahabi et al., 2011). Such a relationship is expected, as interactions between pedestrians and motor vehicles are more frequent in such environments. Additionally, indicators of built-up areas with higher population and amenity densities such as transit routes, metered parking, and bike lanes were found to have a negative association with pedestrian injury severity (Clifton et al., 2009; Islam & Jones, 2014; Mohamed et al., 2013; Zahabi et al., 2011). These findings are intuitive, as these factors are characteristic of locations with lower vehicular speeds and improved pedestrian walkability.

2.3: Injury Severity Modeling

Traffic safety research may also pertain to crash/injury frequencies or severities. In crash frequency analyses, the number of crashes or injuries is estimated based on contributing factors within a defined geographical area (e.g., intersection, census tract, city) over a defined time period (e.g., months or years). Characteristics of crash frequency analysis include the use of non-negative integer crash count data and appropriate regression models such as the Poisson or Negative Binomial models (Lord & Mannering, 2010). In crash severity analyses, the emphasis is shifted from the number of expected crashes to the degree of severity of the potential injuries involved in traffic collision aftermath. An overview of crash severity analyses is provided in the following subsections.

2.3.1: Ordered Response Models

One distinction within injury severity modelling is how the various levels of severity are defined and organized. Given the natural order of injury severity, a common approach to injury severity modeling is to use an ordered response model, such as the ordered probit and logit models. The fundamental concept behind ordered response modeling is to determine a latent variable through user-defined predictor variables and a generalized linear model. Predictor variable coefficients and latent variable threshold parameters are then estimated to allow the prediction of the outcome variable. In this sense, a threshold represents a single injury severity level. Depending on the combination of predictor variable data of a pedestrian injury, the resultant latent variable is entered into a threshold, and the corresponding modelled injury severity can be estimated. Given *j* injury severity levels, a total of *j*-1 threshold parameters are to be estimated.

This approach has been used previously for analyzing injury severity among various subpopulations including older vehicle occupants (Austin & Faigin, 2003; Khattak et al., 2002), younger drivers (Gray et al., 2008), and motorcyclists (Eustace et al., 2011; M. A. Quddus et al., 2002; Srinivasan, 2002). In addition, some studies have used ordered probit models to study risk factors influencing motorist injury severity specifically at intersections (Abdel-Aty & Keller, 2005; Haleem & Abdel-Aty, 2010; Tay & Rifaat, 2007). Previous pedestrian safety studies from Zajac & Ivan (2003) and Lee & Abdel-Aty (2005) made use of ordered probit models to examine injury severities among pedestrians.

One noteworthy limitation regarding ordered response modeling is the assumption of proportional odds. In ordered response modeling, the effects of predictor variables are assumed to be approximately constant across the various thresholds. In other words, the predictor variable is assumed to have a similar effect on the predicted odds regardless of the threshold (Washington et al., 2011). This condition may not always be met, as there may be instances where at least one predictor variable's coefficient may differ significantly across thresholds (Mergia et al., 2013). Violation of the proportional odds assumptions may cause inaccuracies within the model and could lead to biased results.

2.3.2: Binary Logistic Models

The second perspective to injury severity modelling is to use an unordered response model, whereby the ordinality of severity is not considered. For cases such as these, logistic regression is adopted. There are two variants regarding logistic regression, where the first is when only two severity categories are defined (i.e., severity is a dichotomous outcome variable). The second variant involves the considerations of more than two severity categories (i.e., severity is a polytomous outcome variable). The second variant of logistic regression may also be thought of as a generalization of the first. This subsection examines research regarding the first variant. Common applications include examining fatal versus non-fatal injuries, or severe versus slight injuries. A discussion of the second variant is provided in the next subsection.

Oh et al. (2005) developed a binary logistic model to evaluate the effects of crash impact speed, pedestrian age, and vehicle type in fatal and non-fatal pedestrian crashes. However, the number of variables considered, and the sample sizes were insufficient to produce meaningful results. Sze and Wong (2007) used a logistic regression model to evaluate pedestrian injuries and various contributing factors. Severity was classified into two groups: fatal and serious injury and slight injury. The results from their model indicate that the risk of a fatal or serious injury was increased for crashes that are either near crosswalks, on roads with posted speed limits higher than 50 km/h, or at signalized intersections. Conversely, crashes occurring during daytime hours, or along road segments with high or average traffic congestion were found to decrease the odds of a severe pedestrian injury.

Furthermore, Sarkar et al. (2011) also used a binary logistic model to assess fatal and non-fatal pedestrian injuries. Several variables categories were considered such as pedestrian demographics, environmental characteristics, vehicle type, roadway attributes, and others. They found that collisions during rainy seasons were associated with increased risk of a fatal injury. Additionally, crashes at locations with either no traffic control devices, stop control, or dedicated pedestrian crossings had increased odds of resulting in a pedestrian fatality. While pedestrian age was considered, the referent age range was 15-55, which is considered to be relatively large and does not provide detail regarding intermediate ages within this range. In this regard, the differences between ages 15, 35 and 55 were not considered. Such information is useful, given that pedestrian behaviours among these ages are significantly different from one another (Holland & Hill, 2007; Oxley et al., 1997).

2.3.3: Multinomial Logit Regression

In this subsection, the second variant of unordered response modeling (i.e., injury severity is a polytomous outcome variable) is examined. The second variant of unordered response modeling is often referred to as multinomial logit (MNL) regression. MNL models have been used for analyzing injury risk factors for various road user types such as motorists (Bédard et al., 2002; Neyens & Boyle, 2007; P. Savolainen & Mannering, 2007; Shankar & Mannering, 1996; Ulfarsson & Mannering, 2004), and bicyclists (Kim et al., 2007).

Regarding pedestrians, Tay et al. (2011) and Amoh-Gyimah et al. (2017) developed MNL models to analyze pedestrian injury severity using South Korean and Ghanaian safety data, respectively. In both studies, the severity categories defined were fatal, severe, and minor. Several contributing risk factor categories from these studies include variables from the pedestrian, driver, roadway, vehicle and environment levels.

One advantage of the MNL approach is that it is able to provide more flexibility in parameter estimates for intermediate categories (e.g., minor, non-incapacitating injury severity levels) when compared to conventional ordered response models (Mohamed et al., 2013; P. T. Savolainen et al., 2011; Washington et al., 2011). In other words, the multinomial logit model allows for the determination of the significance of each contributing factor by severity category. For example, a given attribute may decrease the probability of no injury and increase the likelihood of a minor injury occurring, but the same may not necessarily be true for severe injuries.

2.3.4: Unobserved Heterogeneity

An assumption that is often violated with the traditional MNL model is that the parameter estimates obtained are assumed to apply for all observations (i.e., all pedestrian records) without considering any unobserved influences. To this extent, the MNL model is sometimes referred to as a fixed-effects MNL model. For example, a parameter estimate for pedestrian age may indicate that the risk of a minor injury increases with age. However, the actual risk may depend on other factors such as personal health, cognitive ability, physical characteristics, *et cetera*. These influences are referred to as unobserved heterogeneity and may result in unreliable estimates of coefficients. Researchers have addressed unobserved heterogeneity by allowing parameter estimates to randomly vary across pedestrian cases. The variation is dependent on a user-defined distribution, and the corresponding model is commonly referred to as a random-effects MNL model or a mixed logit model (Aziz et al., 2013; Haleem et al., 2015; Kim et al., 2010).

Several recent studies have used mixed logit models to evaluate pedestrian injury severities. Islam and Jones (2014) developed two mixed logit models to identify factors influencing pedestrian injury severities within urban and rural locations in Alabama. Several variable categories considered included land use, weather, intersection control, pedestrian behaviour, and others. The analysis indicated that certain variables were significant in one model, but not the other, suggesting that customized countermeasures based on the physical environment are recommended. Haleem et al. (2015) also used the mixed logit model approach to investigate contributing factors affecting pedestrian injury severity at signalized and unsignalized intersections in Florida. The researchers had available an extensive dataset that included variables such as traffic and roadway geometric properties, road user characteristics, and others. In this study, certain variables were found to be influential in increasing severe injury risk for a given type of intersection, but not the other. One criticism of the mixed logit model that the researchers noted was the necessary step of determining which parameters are to be designed as random or fixed. The process of designating variables as randomly-distributed becomes more complex as the number of considered variable attributes increases. Another study by Aziz et al. (2013) used a random-parameter multinomial logit model to study pedestrian crash severities within New York City. One model was created using aggregated data across the city's five boroughs. Variables relating to roadways, traffic, land use, and demographics were considered for the final model. The researchers indicated that the results from the final model do not necessarily reflect the conditions present from the individual boroughs and that separate models should be constructed per area in order to capture any characteristics unique to each borough.

While the review of the literature was limited to the most common methods of injury severity analyses, various methodologies to study crash injury severities have been adopted over the past several decades. Garrido et al. (2014) suggested that the outputs from ordered and unordered response models approximate each other relatively well. Comprehensive overviews of these statistical techniques are provided in Washington et al. (2011) and Savolainen et al. (2011).

CHAPTER 3: DEMOGRAPHIC MODELING OF FATALITIES

In this chapter, the methodology used in formulating fatality trends and fatality projections is described. First, the sources of pedestrian fatality and exposure data are described. Second, the various criteria used in selecting appropriate pedestrian records are discussed. Lastly, the processes by which the fatality trends and projections are modelled are explained.

3.1: Pedestrian Fatality Data

3.1.1: FARS

FARS is a census of all motor vehicle-related fatalities within the United States. This includes all 50 states, the District of Columbia (DC), and Puerto Rico. Collisions that have occurred within other United States territories such as American Samoa, Guam, or the U.S. Virgin Islands are not included. The system was first established in 1975 by the National Highway Traffic Safety Administration (NHTSA) and is updated annually. Between 1975 and some time during the 1990s, FARS was known as the *Fatal Accident Reporting System*. However, FARS was renamed to the *Fatality Analysis Reporting System* in response to the discouragement of the use of the term 'accident' during the mid-1990s (Anikeeff, 1997).

For a crash record to be included within FARS, the event must have involved a motor vehicle travelling along a roadway that is typically considered to be public. The event must have also resulted in at least one traffic-related fatality within 30 days of the crash. Fatal crash information is initially captured through local-level documentation, such as emergency medical service (EMS) reports, police accident reports (PARs), coroner/medical examiner reports or death certificates. The local data are then aggregated and subsequently translated onto standardized NHTSA forms by FARS analysts.[1] The flow of crash information is illustrated in **Figure 3.1**. Personal information such as names, addresses, or social security numbers is not recorded within the system. FARS analysts from the NH S A’s National Center for Statistics and Analysis (NCSA) are responsible for entering relevant crash data into a local-level computer. Daily updates are sent from these computers to an online, publicly-available database. The data go through various consistency and range checks, such that the analysts can make corrections as needed. The fatality data are organized by individual year from 1975 through 2017.[2] FARS data are publicly available through an NHTSA file transfer protocol (FTP) website (ftp://ftp.nhtsa.dot.gov/FARS).

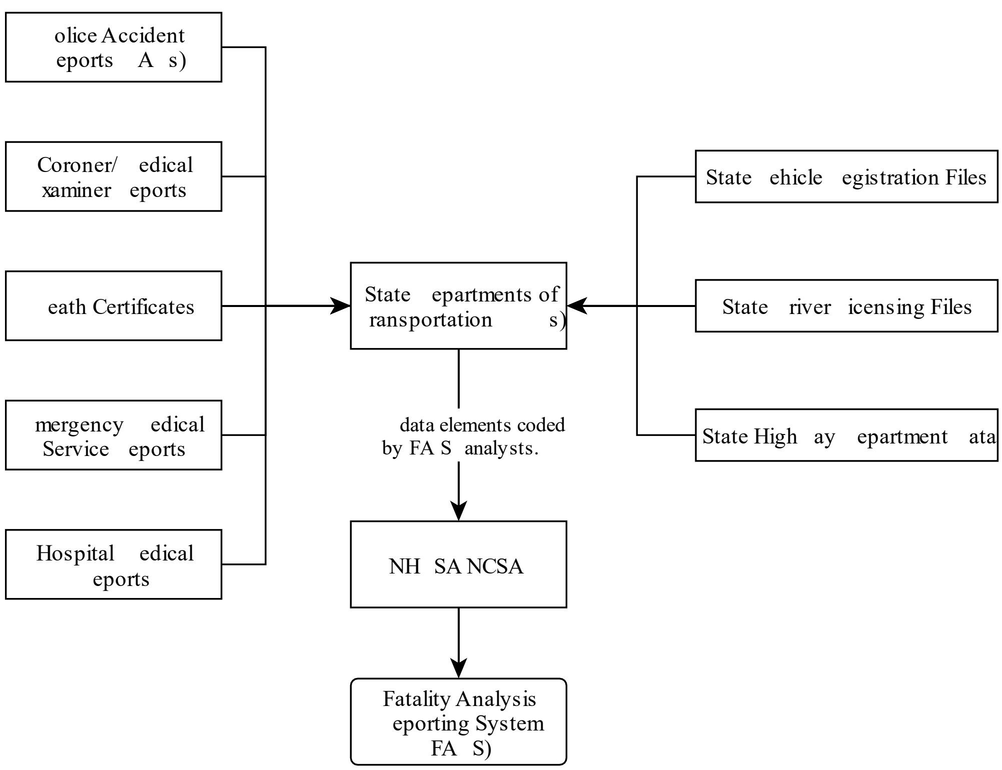

Figure 3.1: Flow chart illustrating the flow of crash information to FARS.

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[1] A FARS analyst is a state-level employee that gathers, translates, and transmits FARS data to the NHTSA. The number of FARS analysts per state varies on the magnitude of fatal crashes within the respective state. FARS analysts are trained by NHTSA staff in handling fatal crash data.
[2] As of January 2019, the most recent year of FARS data available was 2017.

FARS data files are made available to the public in several file types such as Statistical Analysis System (SAS), DataBase Files (DBF), or Comma Separated Values (CSV). Since the establishment of FARS in 1975, three data files have been designated to form the core of the database: the *crash* file, the *vehicle* file, and the *person* file. The crash level data file contains information regarding crash and environmental characteristics such as crash time and location or conditions of light and atmosphere. At the person level, data regarding the people involved in the crash are listed (e.g., age, sex, the involvement of alcohol, crash location), and the vehicle-level data include the type of vehicle involved, the most harmful event and other vehicle-specific information. These files are referred to in the remainder of this thesis as the core datasets.

In addition to the core datasets, several other datasets are available. To date, there are an additional 17 data files that complement the three core datasets. An overview of the 17 additional files is provided in **Table 3.1**. For the pedestrian demographics analysis, only variables from the three core datasets are used.

Table 3.1: Summary of non-core FARS data files.

Data File Name	Type of information found	Years of Availability
Parkwork	parked and working vehicles	2010 – current
Pbtype	crashes involving pedestrian, bicyclists or people on person conveyances	2014 – current
Cevent	sequence of crash events	2010 – current
Vevent	the sequence of crash events for each in-transport motor vehicle	2010 – current
Vsoe	the sequence of crash events for each in-transport motor vehicle (a subset of *Vevent* variables)	2010 – current
Damage	damaged areas of vehicles involved in crashes	2012 – current
Distract	driver distractions	2010 – current
Drimpair	physical impairments of motor vehicle operators	2010 – current
Factor	vehicle circumstances that are suspected of having contributed to a crash	2010 – current

Table 3.1: Summary of non-core FARS data files (continued).

Maneuver	actions performed by motorists to avoid crashes	2010 – current
Violatn	violations charged to motorists	2010 – current
Vision	motorist sight obstructions	2010 – current
Nmcrash	factors/actions contributing to a non-motorist crash	2010 – current
Nmimpair	physical impairments of non-motorists	2010 – current
Nmprior	prior contributory actions of non-motorists leading up to crash occurrences	2010 – current
Safetyeq	safety equipment of non-motorists	2010 – current
Vindecode	descriptive codes for vehicles	2013 – current

3.1.2: Selection of Study Period

The first half of this thesis examines past and future pedestrian fatality trends by age and sex. The current demographics study complements earlier works from Bédard et al. (2001) and Mullen et al. (2013) by providing a contrast between pedestrian and motor vehicle occupant mortality trends. In Bédard et al., FARS data from 1975 to 1998 were analyzed. The study from Mullen et al. served as an update by considering an additional ten years of data (i.e., 1975-2008).

The current demographics analysis makes use of FARS data from 1975 to 2015. A notable feature of the data used in this study that is not found in Bédard et al. or Mullen et al. is the consideration of socio-economic impacts on motorist and pedestrian exposure induced by the recession of the late 2000s-early 2010s.

3.1.3: Parameterizing Fatality Data

Let *t* represent the subject year. Since FARS data collection began in 1975, the possible values of *t* begin from this year:

$$t \in \mathbb{Z}: t \in [1975, T] \tag{3.1}$$

where,

T = the final year of forecasting (i.e., the target year), set as 2035 for this study.

As 41 years of FARS data were available, a second data year index, k, is defined to differentiate the various years of fatality data, with K representing the final year of available data:

$$k \in \mathbb{Z}: k \in [0, K] \tag{3.2}$$

To this extent, $k = 0$ and $K = 40$ represent the bounds for years in which fatality data are available. The following provision is defined to relate the year index t and the data year index k:

$$k = t - 1975 \tag{3.3}$$

The process of compiling annual FARS datasets into a single source began with the 1975 core datasets (i.e., the reference datasets) and adding core files from subsequent years to them. Core datasets for subsequent years were first examined for any discrepancies in variable definitions. Variable inconsistencies across time were addressed accordingly through manual coding. The resulting dataset would be added to the reference in a process referred to as stacking. The stacking procedure was repeated sequentially for subsequent years until the last year of available data was added. The stacks for the three core data files, which contain the 41 years of data, were merged into a single master FARS dataset. The stacking process is illustrated in **Figure 3.2** and was finalized prior to the production of this thesis by the Lakehead University Centre for Research on Safe Driving (CRSD).

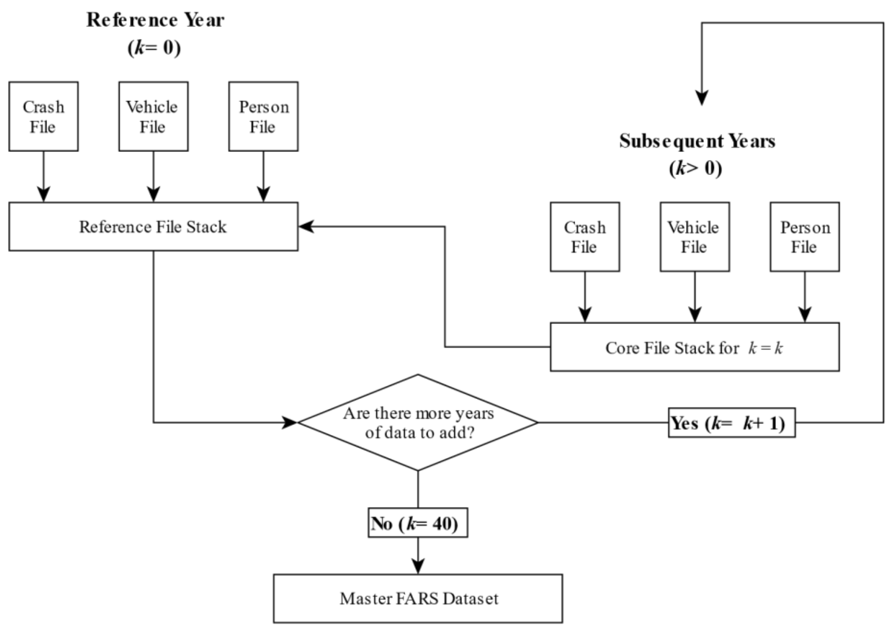

Figure 3.2: Overview of FARS dataset development process through stacking.

3.2: Pedestrian Exposure Data

Three measures of pedestrian exposure were considered for the pedestrian fatality trend analysis: number of walk trips (trip-based), number of pedestrian miles walked (distance-based) and number of pedestrian minutes walked (time-based). Accordingly, there is one pedestrian fatality trend estimate per demographic cohort and exposure measure. In addition, population adjustments are also applied to the unadjusted fatality analysis.

3.2.1: Travel Based Exposure

The United States Department of Transportation (U.S. DOT) began to collect nation-wide travel data using the Nationwide Personal Transportation Survey (NPTS) in 1969. The purpose of data collection was to assist transportation planners and policymakers with quantifying travel behaviour and viewing relationships between the traveller, their demographics, and time (Research Triangle Institute, 1997). The first survey was conducted in 1969, and subsequent editions were intermittently administered every five to seven years after that. Surveys contain questions regarding household members, day trips, income, and other relevant travel information. Early versions of the NPTS were administered through personal visits by interviewers to sampled households. Typically, survey respondents had to recall day trip information from memory; however, in later editions of the NPTS, travel diaries were distributed with the surveys to assist with trip recollection and data entry. Household members aged 14 and older were interviewed for all trips. Trips taken by household members aged 5 to 13 were reported by a knowledgeable adult household member (aged 14 or older).

During the late 1990s, the Bureau of Transportation Statistics (BTS), FHWA and the NHTSA sponsored the development of a new travel survey – one that would integrate both the NPTS and the American Travel Survey (ATS)[3] existent at the time. This new survey was referred to as the National Household Travel Survey (NHTS), and the first one of its kind was implemented in 2001 (Center for Transportation Analysis, 2004).

An evolutionary summary of travel surveys is shown in **Table 3.2**. A detailed version of this evolution along with additional NPTS/NHTS information within Table 3-1 of the 2017 NHTS Data User Guide (FHWA, 2018).

Table 3.2: Evolutionary summary of the National Household Travel Survey (Adapted from Center for Transportation Analysis, 2004).

Travel Survey	Trip Data Recall Method	Walk Trip Data Included
NPTS 1969	Memory	No
NPTS[4] 1977	Memory	Limited
NPTS 1983	Memory	Limited
NPTS 1990	Memory	Limited
NPTS 1995	Travel Diary	Limited
NHTS 2001	Travel Diary	Yes
NHTS 2009	Travel Diary	Yes
NHTS 2017	Travel Diary	Yes

[3] The ATS was administered in 1977, and later once more in 1995.
[4] According to the User's Guide for N S 9 , N S meant *Nationwide Personal Transportation Study*.

The data contained within these files form the basis of pedestrian exposure. Transportation professionals, medical researchers, safety specialists, and social service agencies make extensive use of the travel data provided by these surveys (Clifton et al., 2016; Yu & Lin, 2016). NPTS/NHTS data from all surveys except NPTS 1969 and NPTS 1977 were acquired from the National Household Travel Survey website (https://nhts.ornl.gov/). Due to technological limitations of the latter half of the 20th century, travel survey data were kept on magnetic tape drives for NPTS 1969, NPTS 1977, NPTS 1983, and NPTS 1990. Electronic file storage began with NPTS 1995. Data from NPTS 1969 were not considered as it fell outside of the study period. NPTS 1977 data were converted from data tapes to electronic format and underwent several methodological changes in the process, including the adoption of NPTS 1995 methodology (variable names, weighting methods, record arrangement). The FHWA has chosen to not make NPTS 1977 publicly available as a precaution for the adjustments made to the dataset. Notwithstanding, this dataset was acquired upon request to the FHWA. The data from NPTS 1983 and NPTS 1990 were publicly available on the NHTS website.

3.2.2: Population-Based Exposure

As part of the pedestrian fatality trend analysis relative to 1975, a population-based exposure measure was incorporated into the pedestrian fatality trend estimation process. Intercensal population estimates by age and sex were extracted from the United States Census Bureau (http://www.census.gov/) for the calculation of the pedestrian fatality trend estimates.

3.2.3: Parameterizing Exposure Data

To differentiate the years in which a travel survey was administered from the normal timeline, the symbol t^* is used; the corresponding data year index is k^*. For example, the first data year in which a travel survey was undertaken ($k^* = 1$) is $t = 1977$ ($k = 2$).

Given that not all travel survey datasets originated electronically, a dataset partition is made for validation purposes; the partitions are listed in **Table 3.3**. The first partition is composed of travel survey datasets established before 1995, and the second partition is comprised of datasets from 1995 or later. Information regarding the partitioning of travel survey datasets is provided in Appendix A. Details on the validation processes for each partition can be found in Appendix B.

Table 3.3: Partitions and indices of NPTS/NHTS datasets for validation and categorization purposes.

Partition	Travel Survey	Survey Year Index, k^*	Actual Year Index, k	Actual Survey Year, t^*
Partition 1	NPTS 1977	1	2	1977
	NPTS 1983	2	8	1983
	NPTS 1990	3	15	1990
Partition 2	NPTS 1995	4	20	1995
	NHTS 2001	5	26	2001
	NHTS 2009	6	34	2009
	NHTS 2017	7	N/A	2017

Let φ_{ij} represent a record involving a walk trip undertaken by an individual belonging to demographic category *ij*. The index *i* represents the sex of the individual (male or female), while the index *j* represents the age group in which the individual belongs to. Since the raw travel survey data are not nationally representative, weights are applied to produce national-level estimates. These weights may be thought of as scaling factors to bring values up to population estimates. The symbol Φ_{ij} represents a weighted walk trip record. Travel survey weighting methodology consists of various weight types, each producing different population-level estimates. For the demographics analysis, three weights are employed:

- household weights (denoted as τ_{hh}),
- person weights (denoted as τ_{per}), and
- trip weights (denoted as τ_{trp}).

The choice of weight will depend on the type of information that is warranted. A record ith a pe rson eight value of $\tau_{per,\phi} = 500$) means that this individual represents themselves and 499 others with similar demographic characteristics within the United States. For partition 1 datasets, individual weights belong to a single corresponding file (household weights are provided in the household files, travel day trip weights are from travel day files, et cetera.). The following notation is used to represent weighted estimates:

$$\Phi_{hh,\varphi,ij} = \varphi_{ij} \times \tau_{hh,\varphi} \tag{3.4}$$

$$\Phi_{per,\varphi,ij} = \varphi_{ij} \times \tau_{per,\varphi} \tag{3.5}$$

$$\Phi_{trp,\varphi,ij} = \varphi_{ij} \times \tau_{trp,\varphi} \tag{3.6}$$

where,

Φ_{ij} = weighted population-level estimate of record φ_{ij}, and

φ_{ij} = an individual walk trip done by a person from sex-age category group *ij*.

Because the primary objective of extracting travel survey data is to derive pedestrian travel exposure, the trip weights were primarily used. Household and person weights were also used, but to a lesser extent for validation purposes.

Each record has variables that provide trip distance and trip duration estimates specific to the record; these two variables form the basis of the *pedestrian miles walked* and *pedestrian minutes walked* exposure measures. Let ψ_φ and ω_φ represent the distance and time travelled in trip φ, respectively. Then, their corresponding population-level estimates when weighted are:

$$\Psi_{\varphi,ij} = \left(\varphi_{ij} * \psi_\varphi\right) \tau_{trp,\varphi} \tag{3.7}$$

$$\Omega_{\varphi,ij} = \left(\varphi_{ij} * \omega_\varphi\right) \tau_{trp,\varphi} \tag{3.8}$$

where,

ψ_φ = the recorded distance travelled during trip ϕ (in miles),

Ψ_{φ} = the weighted population-level distance estimate of trip ϕ_{ij} (in miles),

$\Omega_{\varphi,ij}$ = the recorded time travelled during trip ϕ_{ij} (in minutes), and

Ω_{φ} = the weighted population-level time estimate of trip ϕ_{ij} (in minutes).

For example, if individual A undertakes a walk trip that is 0.5 miles long, lasts for 10 minutes, and has a trip weight of 500, then the weighted trip-based, distance-based, and duration-based national estimates are 500 trips, 250 miles walked, and 5,000 minutes walked, accordingly.

3.3: Data Processing

3.3.1: Record Selection Criteria

Injury Severity

Records were first filtered by injury severity for fatal and non-fatal records. The FARS variable attribute indicating fatal injury severity is `INJ_SEV` = 4. In the event of a vehicle-pedestrian crash, the record is likely to indicate the pedestrian as the fatally injured party. As such, it is reasonable to expect that most pedestrian records within FARS have a recorded injury severity of fatal. Note that it is possible to have a non-fatal injury severity recorded for a pedestrian, provided that the same crash record had at least one other fatality associated with it.

Transportation Mode

The FARS variable attribute specifying walking as the primary mode of transportation (i.e., pedestrians) between 1975 and 1981 is `PER_TYP` = 3. From 1982 to 2015, this attribute was changed to `PER_TYP` = 5. FARS records not meeting these criteria were dismissed from the analysis.

Regarding exposure data, the variable capturing the mode of transportation used for trips is TRPTRANS[5], with varying attribute values over time. The numbers of total and pedestrian records by travel survey are shown in **Table 3.4**.

Table 3.4: Summary of total and pedestrian records by travel survey.

Travel Survey	Total Records	Pedestrian Records	Proportion of Pedestrian to Total Records
NPTS 1977	136,136	12,227	8.98%
NPTS 1983	45,155	3,767	8.34%
NPTS 1990	149,546	10,062	6.73%
NPTS 1995	409,025	21,113	5.16%
NHTS 2001	642,292	51,526	8.02%
NHTS 2009	1,167,321	100,405	8.60%
NHTS 2017	923,572	81,288	8.80%

Pedestrian Age and Sex

Several of the travel surveys used have recorded ages ranging from 5 and older. However, NPTS 1977 and NHTS 2001 began recording individual age at age zero.[6] This was done to capture the travel behaviour of young cohorts.[7] In addition, some travel surveys provided the option to keep age undisclosed. To maintain consistency throughout all survey years, only records with a recorded age of at least 5 were included in the analysis.

Travel surveys such as NPTS 1990, NHTS 2001 and NHTS 2017 include multiple options for reported sex (SEX), such as '*male,*' '*female,*' '*refused/prefer not to answer,*' '*don't know,*' or '*unknown/other*'. For the demographics analyses, only records with a defined sex

[5] For NPTS 1983, TRPTRANS was replaced by the variable MEANS. There are no notable differences in the attributes between the two variants.
[6] A recorded age of 0 implies that the individual is less than one year old.
[7] Typical trips of young cohorts (ages 0 to 4) include trips with daycare providers, preschool activities, *et cetera* (FHWA, 2004).

(male or female) were included. **Table 3.5** and **Table 3.6** show the distributions of pedestrian fatality and trip records by age and sex, respectively.

Table 3.5: Distribution of pedestrian fatality records by age and sex.

Pedestrian Age & Sex		**FARS, 1975 – 2015 (*n*, %)**
Ages 0-4 (excluded from analysis)	Male	5807 (2.42%)
	Female	3477 (1.45%)
	Other	1 (0.00%)
Ages 5+ (valid)	Male	158800 (66.10%)
	Female	68968 (28.71%)
	Other	58 (0.02%)
Age Unknown/Missing (excluded from analysis)	Male	2304 (0.96%)
	Female	696 (0.29%)
	Other	120 (0.05%)
Total		240231

Table 3.6: Distribution of travel survey pedestrian records by age and sex.

Pedestrian Age & Sex			**NPTS 1977**	**NPTS 1983**	**NPTS 1990**	**NPTS 1995**	**NHTS 2001**	**NHTS 2009**	**NHTS 2017**
Ages 0-4 (excluded from analysis)		*n*	379	0	0	0	2684	0	0
		%	3.10	0.00	0.00	0.00	5.21	0.00	0.00
Ages 5+ (valid)	Male	*n*	5930	1728	4736	9787	21848	46241	37665
		%	50.05	45.87	47.47	46.36	45.51	46.05	46.41
	Female	*n*	5918	2039	5240	11326	26154	54164	43451
		%	49.95	54.13	52.53	53.64	54.49	53.95	53.54
Age Unknown/Missing (excluded from analysis)		*n*	0	0	86	0	840	0	134
		%	0.00	0.00	0.85	0.00	1.63	0.00	0.16
Total		*n*	12227	3767	10062	21113	51526	100405	81288

Trip Metrics

The derivation of distance and duration exposure measures used in the adjusted fatality analysis required that pedestrian trip distance or duration are known. An additional filter was applied to travel data to identify records with known pedestrian trip distance or duration. Records with missing data were disregarded from the analysis.

3.3.2: Record Classification

Records that meet the selection criteria described above were assigned a sex-age cohort index. The 12 demographic cohorts are tabulated in **Table 3.7**, where *i* and *j* represent the sex and age categories, respectively. Note that according to multiple dictionaries, a teenager is often referred to as any young person between the ages of 13 and 19 "teenager," n.d.-a; "teenager," n.d.-b; "teens," n.d.). However, for this thesis, teenagers are defined as those aged between 16 and 19. For discussion purposes, the six age groups were collectively divided into three broader age categories: young pedestrians (5-15 years, 16-19 years), adult pedestrians (20-34 years, 35-54 years), and senior pedestrians (55-64 years, 65+ years).

Table 3.7: Demographic cohort indices used in the demographics analysis.

Age Category Index, *j*	Age Ranges	Broad Age Category Description	Age Category Description	Demographic Cohort Indices (*i*, *j*)	
				Males (*i* = 1)	**Females (*i* = 2)**
0	5-15	Young	Children	Males, 5-15 (1 0)	Females, 5-15 (2 0)
1	16-19		Teenagers	Males, 16-19 (1 1)	Females, 16-19 (2 1)
2	20-34	Adult	Young Adults	Males, 20-34 (1 2)	Females, 20-34 (2 2)
3	35-54		Middle-Aged Adults	Males, 35-54 (1 3)	Females, 35-54 (2 3)
4	55-64	Senior	Mature Adults	Males, 55-64 (1 4)	Females, 55-64 (2 4)
5	65+		Elderly	Males, 65+ (1 5)	Females, 65+ (2 5)

3.3.3: Exposure Formulation

The demographics analysis makes use of three exposure measures: number of walk trips, number of miles walked, and number of minutes walked. Each exposure metric is disaggregated by the 12 demographic cohorts defined previously. For a given travel survey year (k*), an estimated number of total walk trips by demographic cohort, $E_{\Phi,ijk*}$, is obtainable by summing up the weighted walk trips:

$$E_{\Phi,ijk^*} = \sum_{\Phi_{ijk^*}} \left(\Phi_{trp,\varphi,ijk^*}\right) \tag{3.9}$$

where,

Φ_{trp,φ,ijk^*} = total weighted number of walk trips done by individuals of demographic cohort ij in survey year k^*.

Insertion of (3.6) into (3.10) yields:

$$E_{\Phi,ijk^*} = \sum_{\varphi_{ijk^*}} \left(\varphi_{ijk^*} * \tau_{trp,\varphi}\right) \tag{3.10}$$

The total number of pedestrian miles walked by demographic cohort and travel survey year, $E_{\Psi,ijk*}$, is obtained in a similar manner by summing up the weighted distances walked:

$$E_{\Psi,ijk^*} = \sum \left(\Psi_{\varphi,ijk^*}\right) \tag{3.11}$$

where,

$\Psi_{\phi_{ijk^*}}$ = total weighted number of person miles walked done by individuals of sex-age category ij in survey year k^*.

Supplanting (3.7) into (3.11) provides:

$$E_{\Psi,ijk^*} = \sum_{\varphi_{ijk^*}} \left(\left(\varphi_{ijk^*} * \psi_{\varphi}\right) \tau_{trp,\varphi}\right) \tag{3.12}$$

Lastly, the total number of pedestrian minutes walked by demographic cohort and travel survey year, E_{Ω,ijk^*}, is obtained by summing up the weighted durations walked:

$$E_{\Omega,ijk^*} = \sum(\Omega_{\varphi,ijk^*}) \tag{3.13}$$

where,

Ω_{φ,ijk^*} = total weighted number of person minutes walked done by individuals of sex-age category ij in survey year k^*.

Substitution of (3.8) into (3.13) gives:

$$E_{\Omega,ijk^*} = \sum_{\varphi_{ijk^*}} \left((\varphi_{ijk^*} * \omega_\varphi)\, \tau_{trp,\varphi}\right) \tag{3.14}$$

Seven estimates of pedestrian exposure per exposure measure and demographic cohort were derived, given there are seven travel survey years ($K^* = 7$). Pedestrian exposure estimates by exposure measure, demographic cohort, and travel survey year are listed in Appendix C.

To obtain exposure estimates for non-survey years (i.e., E_{Φ,ijk^*}, E_{Ψ,ijk^*}, and E_{Ω,ijk^*}), linear interpolation is used between the next lowest and next highest travel survey year. Using the walk trips exposure measure as an example, this process is illustrated in **Figure 3.3**.

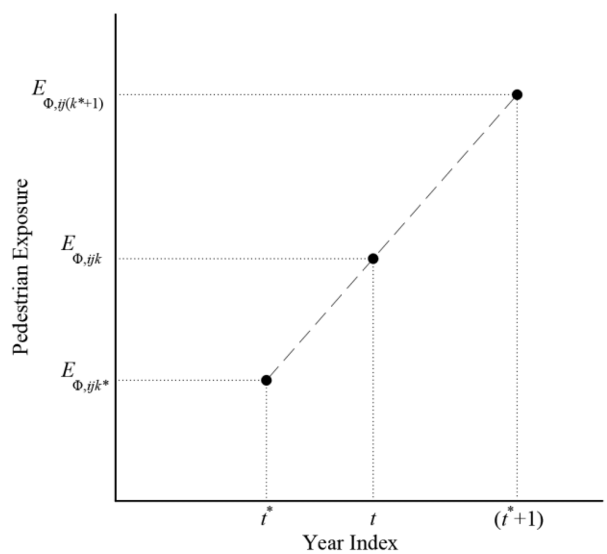

Figure 3.3: Graphical representation of linear interpolation of pedestrian exposure.

Interpolated pedestrian exposure estimates are computed using the following equations:

$$E_{\Phi,ijk} = \left[\frac{\left(E_{\Phi,ij(k^*+1)}\right)-\left(E_{\Phi,ijk^*}\right)}{(t^*+1)-(t^*)} \times (t-t^*)\right] + E_{\Phi,ijk^*}, \;\; t^* < t < (t^*+1), \tag{3.15}$$

$$E_{\Psi,ijk} = \left[\frac{\left(E_{\Psi,ij(k^*+1)}\right)-\left(E_{\Psi,ijk^*}\right)}{(t^*+1)-(t^*)} \times (t-t^*)\right] + E_{\Psi,ijk^*}, \;\; t^* < t < (t^*+1), \text{ and} \tag{3.16}$$

$$E_{\Omega,ijk} = \left[\frac{\left(E_{\Omega,ij(k^*+1)}\right)-\left(E_{\Omega,ijk^*}\right)}{(t^*+1)-(t^*)} \times (t-t^*)\right] + E_{\Omega,ijk^*}, \;\; t^* < t < (t^*+1). \tag{3.17}$$

For example, to obtain a pedestrian walk trip estimate for the year 1998 (1998 falls in between the survey years of NPTS 1995 and NHTS 2001), the following parameters are used: t^* = 1995, k^* = 4, (t^*+1) = 2001, (k^*+1) = 5 and t = 1998. As a result, Equation (3.15) becomes:

$$E_{\phi,ij,1998} = \left[\frac{\left(E_{\Phi,ij(5)}\right)-\left(E_{\Phi,ij(4)}\right)}{(2001)-(1995)} \times (1998-1995)\right] + E_{\Phi,ij,(4)}$$

Seven estimates of pedestrian exposure per exposure measure and demographic cohort were derived, given there are seven travel survey years (K^* = 7). Pedestrian exposure estimates by age and sex across all survey years are illustrated in **Figure 3.4**, **Figure 3.5**, and **Figure 3.6** for walk trips, miles walked, and minutes walked, respectively. Examination of these three figures shows that the pedestrians from the age groups 20-34 (young adults) and 35-54 (middle-aged adults) consistently had the highest estimates of the three exposure measures. Pedestrian exposure estimates by exposure measure, demographic cohort, and travel survey year are numerically provided in Appendix C.

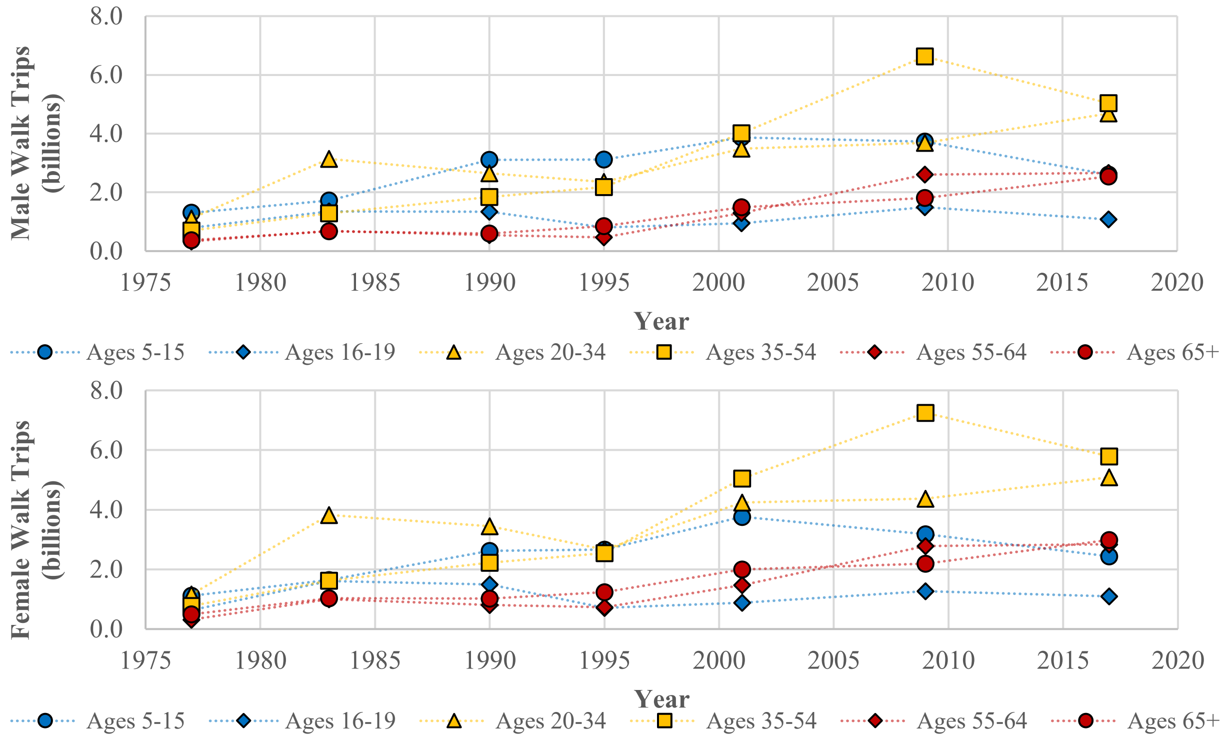

Figure 3.4: Trip-based pedestrian exposure estimates by survey year, age group and sex (top graph for males, bottom graph for females).

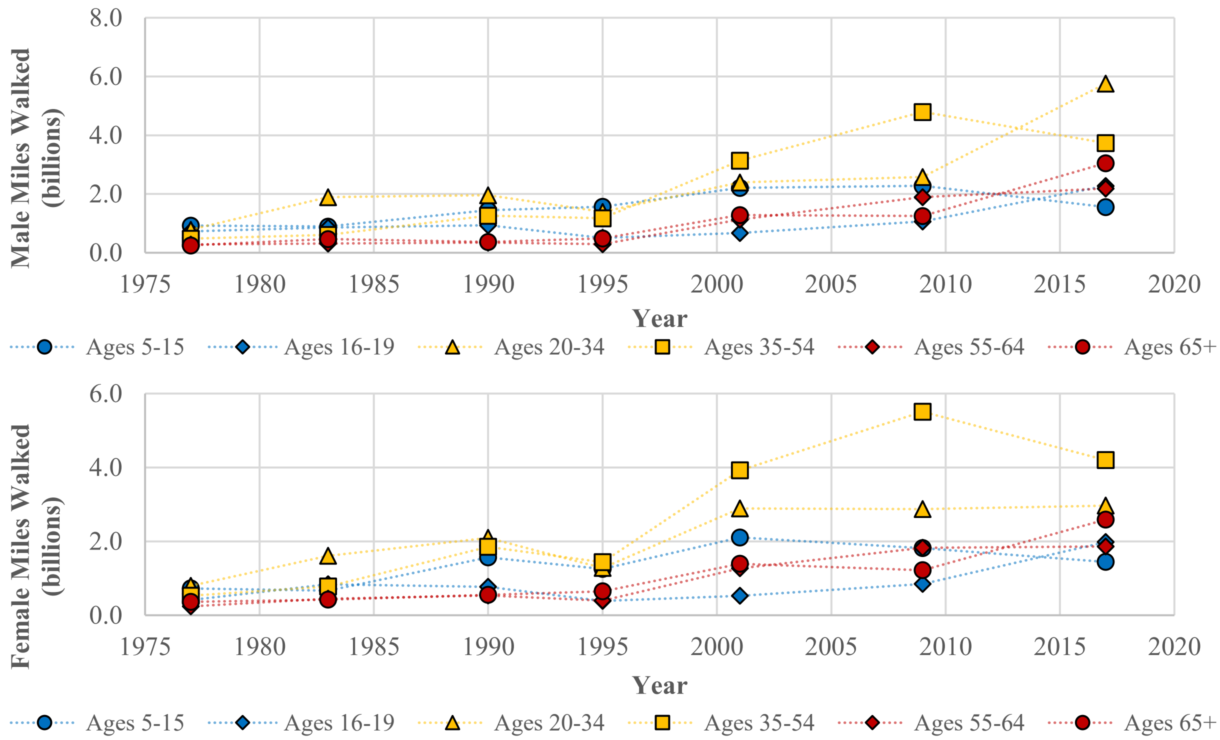

Figure 3.5: Distance-based pedestrian exposure estimates by survey year, age group and sex (top graph for males, bottom graph for females).

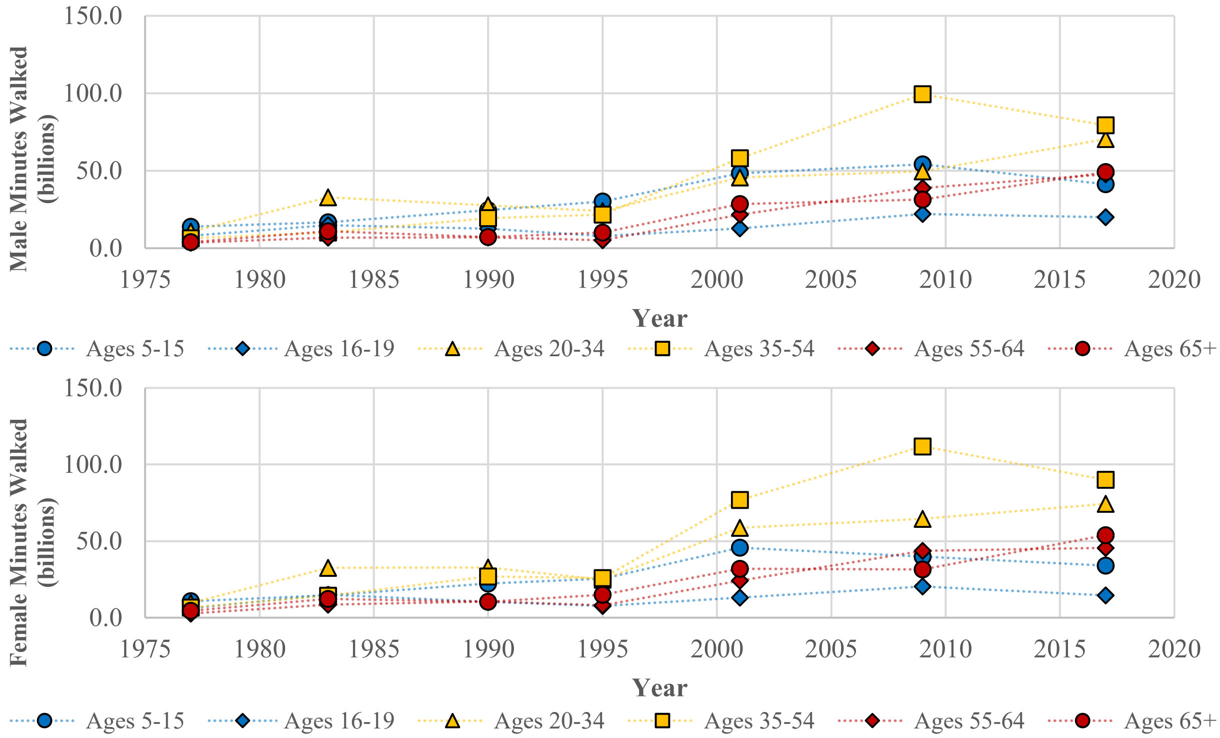

Figure 3.6: Time-based pedestrian exposure estimates by survey year, age groups and sex (top graph for males, bottom graph for females).

3.4: Pedestrian Fatality Forecasting

3.4.1: Selection of Forecast Timeline

There are several reasons why a forecast timeline ending in 2035 was chosen. Firstly, given the primary motivation of this study is to extend the works of Bédard et al. (2001) and Mullen et al. (2013) (with forecast termination years of 2015 and 2025, respectively), it was believed that a target year of 2035 was befitting. Secondly, having the forecast terminate too far into the future may result in a loss of forecast reliability. Conversely, choosing a target year that is not far enough into the future may prove impractical. When analyzing annual time-series data such as fatalities for long-term trends, an appropriate number of observations should be available to produce meaningful and reliable results. Elvik (2005) recommends having at least 10 years worth of road safety data to address issues from stagnating trends, regression to the mean, and other statistical limitations. It is believed that the 41 years of FARS data is adequate to enough to draw inferences of future pedestrian safety. Lastly, the target year of 2035 for fatality forecasting is congruent with the several objectives listed ithin the FHWA's Strategic Agenda for Pedestrian and Bicycle Transportation; one of which is to achieve an 80 percent national reduction in severe pedestrian and bicyclist injuries by (Twaddell et al., 2016).

3.4.2: Pedestrian Fatality Trends

In a similar manner to Mullen et al. (2013) with motor vehicle occupants, pedestrian fatality trends relative to 1975 were produced. The purpose was to estimate the magnitude of fatalities under a hypothetical situation whereby no safety interventions were implemented in the years following 1975. This was done to quantitatively assess efforts to reduce pedestrian fatalities. Travel-based and population-based pedestrian exposure metrics are incorporated into the computation as multiplicative factors, as represented below:

$$Y_{(\Phi,\Psi,\Omega),ijk} = Y_{ij(1975)} \times f_{t,(\Phi,\Psi,\Omega),ijk} \times f_{p,ijk} \tag{3.18}$$

where,

$Y_{\Phi,\Psi,\Omega),ijk}$: pedestrian fatality count for demographic group *ij* for year *k* based on exposure measure Φ, Ψ or Ω,

$Y_{ij(1975)}$: fatalities for demographic cohort *ij* for the reference year (1975),

$f_{t,\ \Phi,\Psi,\Omega),ijk}$: travel-based exposure adjustment factor for demographic group *ij* and year *k* based on exposure measure Φ, Ψ, or Ω, and

$f_{p,ijk}$: population-based exposure adjustment factor for demographic group *ij* and year *k*.

The travel-based exposure adjustment factor (f_t) is defined as the ratio between the travel-based exposure of year *k* and that of the reference year:

$$f_{t,(\Phi,\Psi,\Omega),ijk} = \frac{E_{(\Phi,\Psi,\Omega),ijk}}{E_{(\Phi,\Psi,\Omega),ij(1975)}} \tag{3.19}$$

where,

$E_{\Phi,\Psi,\Omega),ijk}$: exposure for demographic cohort *ij* for year *k*.

The population-based exposure adjustment factor (f_p) is determined using a similar approach. The variable P_{ijk} is defined to represent the population of individuals belonging to demographic cohort *ij* in year *k*. The population-based exposure adjustment factor is then calculated as:

$$f_{p,ijk} = \frac{P_{ijk}}{P_{ij(1975)}} \tag{3.20}$$

where,

P_{ijk}: census population estimate of persons in demographic group *ij* for year *k*.

If a travel-based exposure adjustment factor for year *k* is larger than one, it signifies that the amount of travel-based exposure (walk trips, miles walked, or minutes walked) is larger than that of 1975. Similarly, a population-based exposure factor greater than one implies that the population has grown relative to 1975. The only considerations affecting pedestrian fatality trends are population and travel; they do not account for potential changes to fatality trends induced by safety interventions. As such, the pedestrian fatality trends are also referred to as the 'no-intervention' fatality trends.

3.4.3: Forecast Model Fitting

To generate fatality forecasts to the target year of 2035, univariate models were fitted to the demographically disaggregated fatality data using the SPSS CURVEFIT procedure, as per Mullen et al. (2013). CURVEFIT allows for model fitting of relationships between one or more independent variables and a single dependent variable. The procedure is also suited to produce forecasts with time-series data. CURVEFIT contains 11 regression models that are available for the fitting procedure. The models are listed in **Table 3.8**, where $\boldsymbol{b_0}$ is an intercept term and $\boldsymbol{b_i}$ are estimable coefficients, respectively.

Table 3.8: SPSS CURVEFIT regression models.

Model Name	**Model Structure (*Y*)**
LINEAR	$Y = b_0 + (b_1\, k)$
LOGARITHMIC	$Y = b_0 + (b_1 * \ln(k))$
INVERSE	$Y = b_0 + (b_1 / k)$
QUADRATIC	$Y = b_0 + (b_1\, k) + (b_2\, k^2)$
CUBIC	$Y = b_0 + (b_1\, k) + (b_2\, k^2) + (b_3\, k^3)$
COMPOUND[8]	$Y = b_0 * (b_1{}^{k})$ **or** $\ln(Y) = \ln\,(b_0) + (\ln(b_1) * k)$
POWER[8]	$Y = b_0 * (k^{b1})$ **or** $\ln(Y) = \ln\,(b_0) + (b_1 * \ln(k))$
S[8]	$Y = \exp\,(b_0 + (b_1 / k)$ **or** $\ln(Y) = b_0 + (b_1 / k)$
GROWTH[8]	$Y = \exp\,(b_0 + (b_1\, k))$ **or** $\ln(Y) = b_0 + (b_1\, k)$
EXPONENTIAL[8]	$Y = b_0 * \exp\,(b_1\, k)$ **or** $\ln(Y) = \ln\,(b_0) + (b_1\, k)$
LOGISTIC[8,9]	$Y = 1/\,(1/u + (b_0 * (b_1{}^{k})))$ **or** $\ln\,(1/Y\text{-}1/u) = \ln\,(b_0) + (\ln(b_1) * k)$

It should be noted that the log-transformed variants of the COMPOUND, GROWTH, EXPONENTIAL and LOGISTIC models are identical graphically, due to their linear structure (i.e., a linear term plus a constant value). The regression coefficients will vary between these four models, but the model graph will have the same shape. For discussion, these four statistical models were grouped together into what is referred to as the CGEL model family (named after the first letters of the four models included). The CURVEFIT function was incorporated into a script that automated the regression operation.

[8] CURVEFIT provides log-transformed model forms as default. The dependent variable of the regression models indicated will include a natural logarithm term as a result.
[9] For the logistic model, the parameter $\boldsymbol{u}$ is the upper bound for logistic regression. The default value for $\boldsymbol{u}$ is ∞ (i.e., no upper limit), which results in the parameter $1/\boldsymbol{u}$ approximating zero and subsequently being disregarded in the regression process.

3.4.4: Forecast Model Selection

From the 11 models generated by CURVEFIT, three per demographic cohort were chosen based on two criteria. The first criterion is a visual inspection of the model shape to assess whether they fit observed pedestrian fatality data. Models showing an acceptable visual fit were carried forward, whereas models with acute rates of change or with poor visual fits were disregarded. While it is assumed that transportation and public health agencies would implement intensive corrective actions in cases of excessive rates of fatalities, it is possible for fatalities to increase or decrease over time mildly or moderately.

The second criterion involves the determination of the models' respective Akaike Information Criterion (AIC) values. The AIC value is a relative quality measure of model fit indicating the magnitude of information lost from the regression process. A lower AIC value represents less information lost, thus translating to a better fit. AIC values are calculated using the following equation:

$$\mathrm{AIC} = 2s + (-2\mathrm{LL}) \tag{3.21}$$

where,

s = the number of model parameters (i.e., the number of variables in each model plus the intercept term), and

-2LL = the model deviance[10] at maximum likelihood, typically obtained through a statistical output.

Based on equation (3.21), as the number of parameters in a model increases, the AIC will increase. The computation of AIC values was undertaken as part of the CURVEFIT procedure.

[10] Deviance is also referred to as '-2 * log-likelihood' (Field, 2013).

CHAPTER 4: TRENDS AND PROJECTIONS OF PEDESTRIAN FATALITIES

In this chapter, the results from the demographic analysis are presented. Descriptive statistics are shown first, followed by the fatality trends and projections. Results from the fatality trends and projections analyses by age group are presented last.

4.1: Descriptive Statistics

Descriptive statistics of annual pedestrian fatalities throughout the 41 years of FARS data are shown in **Table 4.1** and **Table 4.2** for males and females, respectively. The numbers in parentheses are the years in which the counts were observed. The descriptive statistics from these two tables indicate that male pedestrians experience higher numbers of annual deaths when compared to females, regardless of age. Annual pedestrian fatality counts from 1975 through 2015 by demographic cohort are provided in Appendix D.

Table 4.1: Descriptive statistics for male pedestrian fatalities, 1975-2015 by age group.

	Age Groups						
	5-15	**16-19**	**20-34**	**35-54**	**55-64**	**65+**	**All Ages**
Minimum	96 (2014)	119 (2015)	628 (2009)	954 (1983)	308 (1994)	472 (2009)	2742 (2009)
Maximum	843 (1975)	482 (1979)	1572 (1981)	1280 (2005)	703 (2015)	1099 (1977)	5324 (1979)
Mean	368	224	989	1111	437	744	3873
Standard Deviation	221	110	291	89	93	185	755

Table 4.2: Descriptive statistics for female pedestrian fatalities, 1975-2015 by age group.

	Age Groups						
	5-15	**16-19**	**20-34**	**35-54**	**55-64**	**65+**	**All Ages**
Minimum	61 (2014)	54 (1996)	200 (2001)	306 (1984)	130 (2001)	303 (2009)	1235 (2009)
Maximum	521 (1975)	174 (1977)	468 (1982)	510 (2015)	257 (2014)	680 (1977)	2261 (1980)
Mean	216	92	305	392	178	499	1682
Standard Deviation	129	37	70	51	33	119	295

4.2: Pedestrian Fatality Trends

Observed fatality counts and the results from the fatality trend analyses are presented here. Equation (3.18) was employed thrice to derive the expected fatality trends from 1975 – 2015 by exposure measure. This section is organized into six subsections, each consisting of the exposure-adjusted pedestrian fatality trend estimates for each age-sex cohort.

4.2.1: Child Pedestrians

Observed fatality counts and fatality trends among child pedestrians are shown below in **Figure 4.1** and **Figure 4.2** for males and females, respectively. Observed fatality counts for child pedestrians (regardless of sex) exhibited a declining trend since 1975. However; the rate of decline appears to have been decreasing over time. Males experienced consistently higher death counts than their female counterparts prior to 2000, after which point the counts of male and female fatalities began to converge and stabilize.

In both figures, the divergence between observed and trend numbers of fatalities began in the early 1980s and has been relatively consistent through to 2015. The apparent differences between observed and trendline fatalities indicate that relative to 1975, increases in child population or child travel-based pedestrian exposure have occurred. Exposure adjustments based on time walked (i.e., pedestrian minutes walked) produced the largest trend estimates, with peaks of 3649 and 2286 pedestrian deaths in 2010 for males and females, respectively.

The increasing nature of the expected fatality trendlines suggests that while pedestrian exposure (travel-based, population-based, or both) has been increasing, child pedestrian deaths have not done the same, thus providing an indication that protective measures against child pedestrian fatalities have been effective.

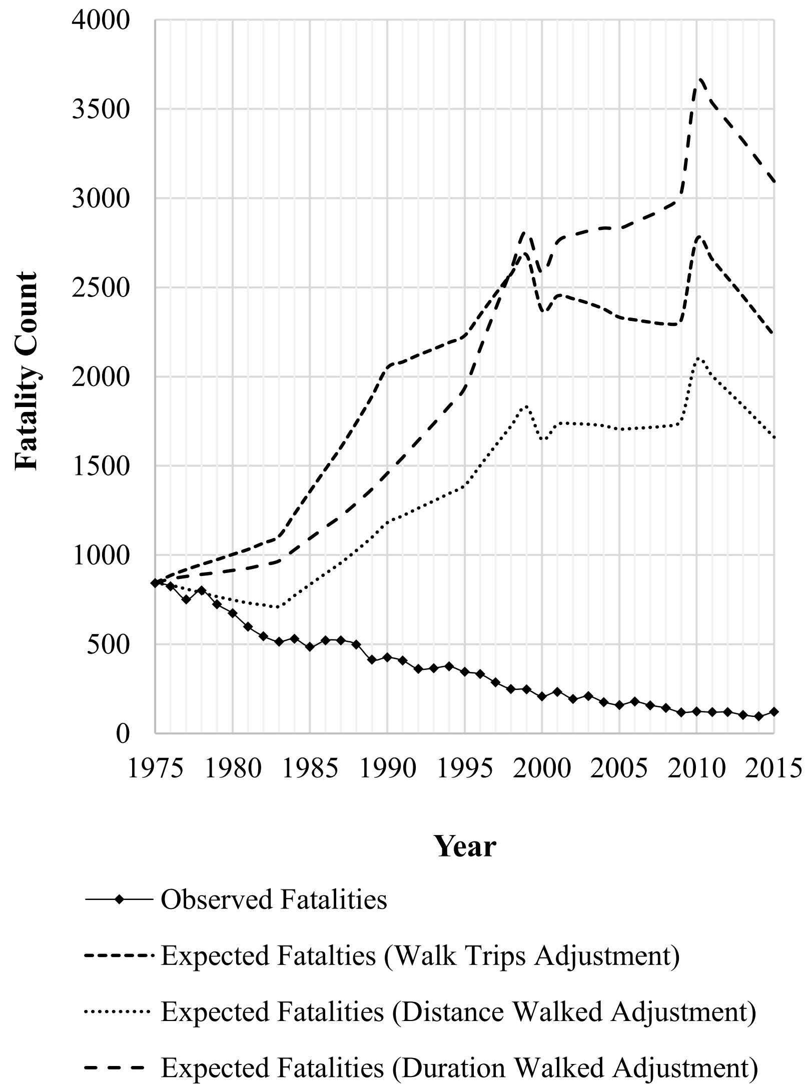

Figure 4.1: Observed and expected pedestrian fatality trends for males aged 5-15.

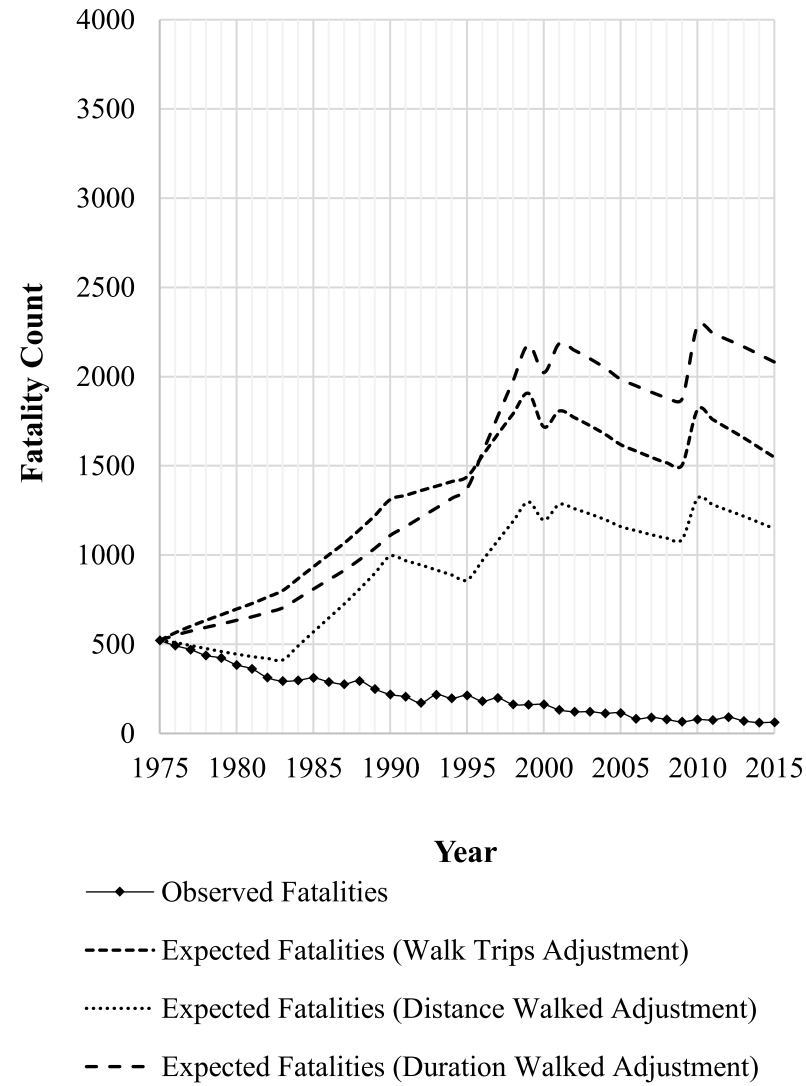

Figure 4.2: Observed and expected pedestrian fatality trends for females aged 5-15.

4.2.2: Teenage Pedestrians

For teenage pedestrian fatalities, observed fatalities and exposure-adjusted trends for males and females are depicted in **Figure 4.3** and **Figure 4.4**, respectively. This group has lower fatality counts relative to children, but observed fatality trends follow a similar decreasing pattern with a declining rate of reduction. It should be noted that this age group is the smallest of all those considered, as it only incorporates four discrete ages. The relatively small range of ages may be a source of bias when compared to other cohorts with larger age ranges. The differences between observed pedestrian fatalities and exposure-adjusted trends for teenagers are not as significant as compared to children, which may suggest that safety interventions targeting teenage pedestrians may not have been as effective as compared to younger children. The divergence between observed and expected fatalities began almost immediately in the mid-1970s and may be attributable to a transition among teenagers choosing private automobile trips over walking as a primary mode of transportation.

4.2.3: Young Adult Pedestrians

Observed fatalities and exposure-adjusted fatality trends for young adults are illustrated in **Figure 4.5** and **Figure 4.6**. Fatality trends among this cohort were higher than younger age groups; this is reflected in the upscaling of the vertical axes (from a maximum of 4,000 to 40,000). As with previous cohorts, fatality trends by all exposure measures are noticeably higher for males than for females. For males, observed fatalities have been lower than fatality trends by all exposure measures almost immediately after 1975. For females, however, the difference between observed fatalities and fatality trend counts based on miles walked is not as pronounced as the other two exposure measures. The relatively large divergence between observed and expected fatality counts suggests that pedestrian safety interventions have been effective.

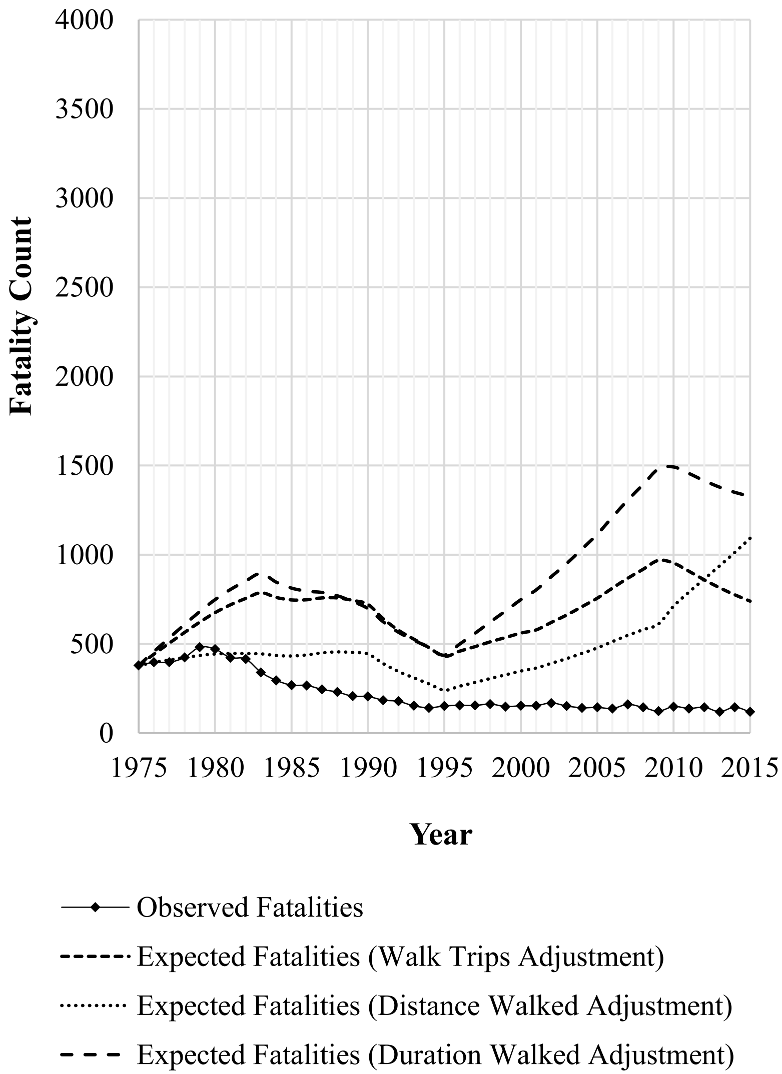

Figure 4.3: Observed and expected pedestrian fatality trends for males aged 16-19.

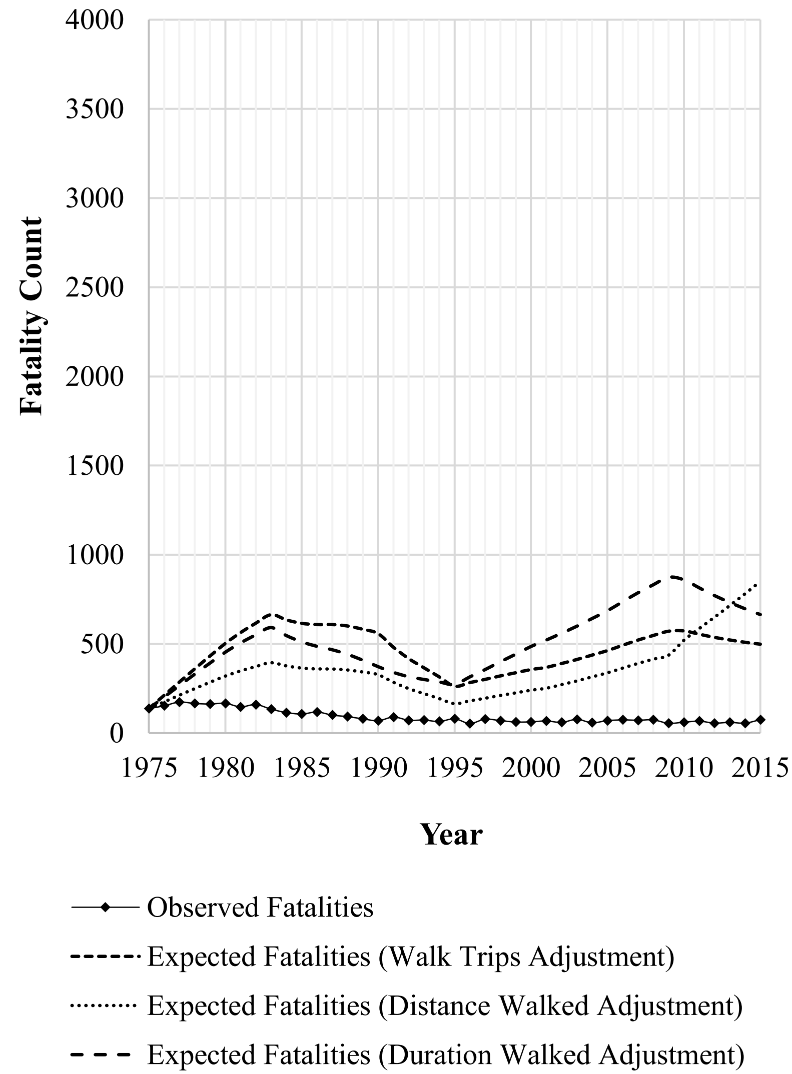

Figure 4.4: Observed and expected pedestrian fatality trends for females aged 16-19.

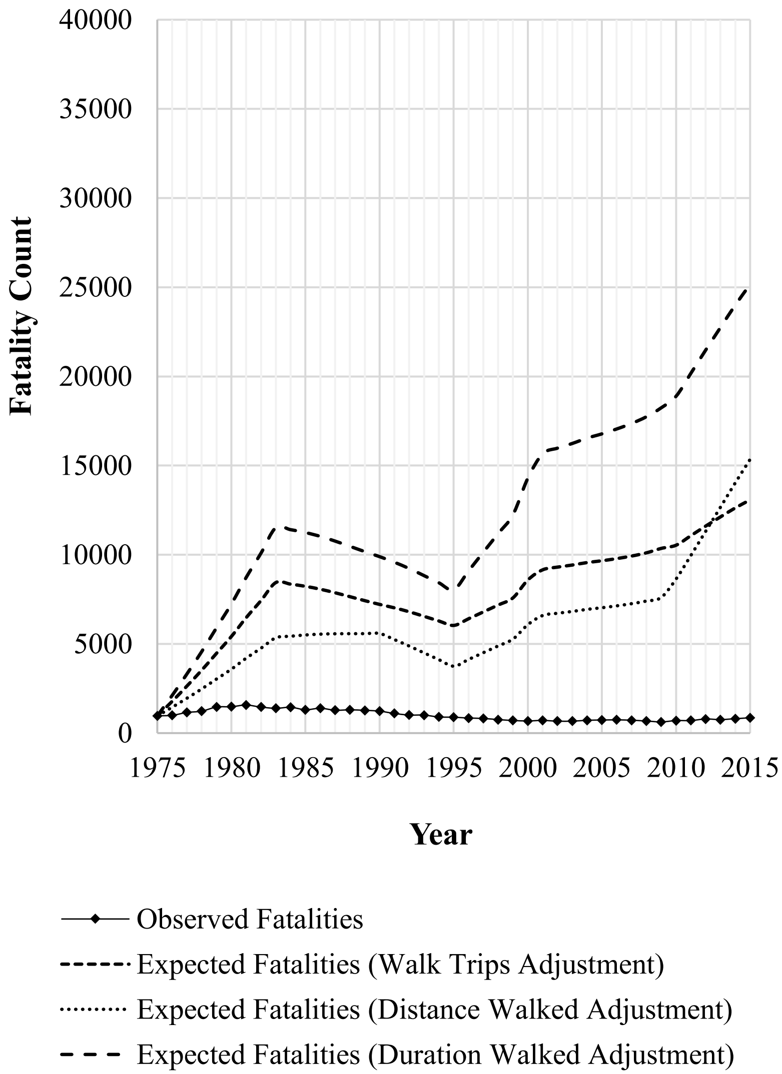

Figure 4.5: Observed and expected pedestrian fatality trends for males aged 20-34.

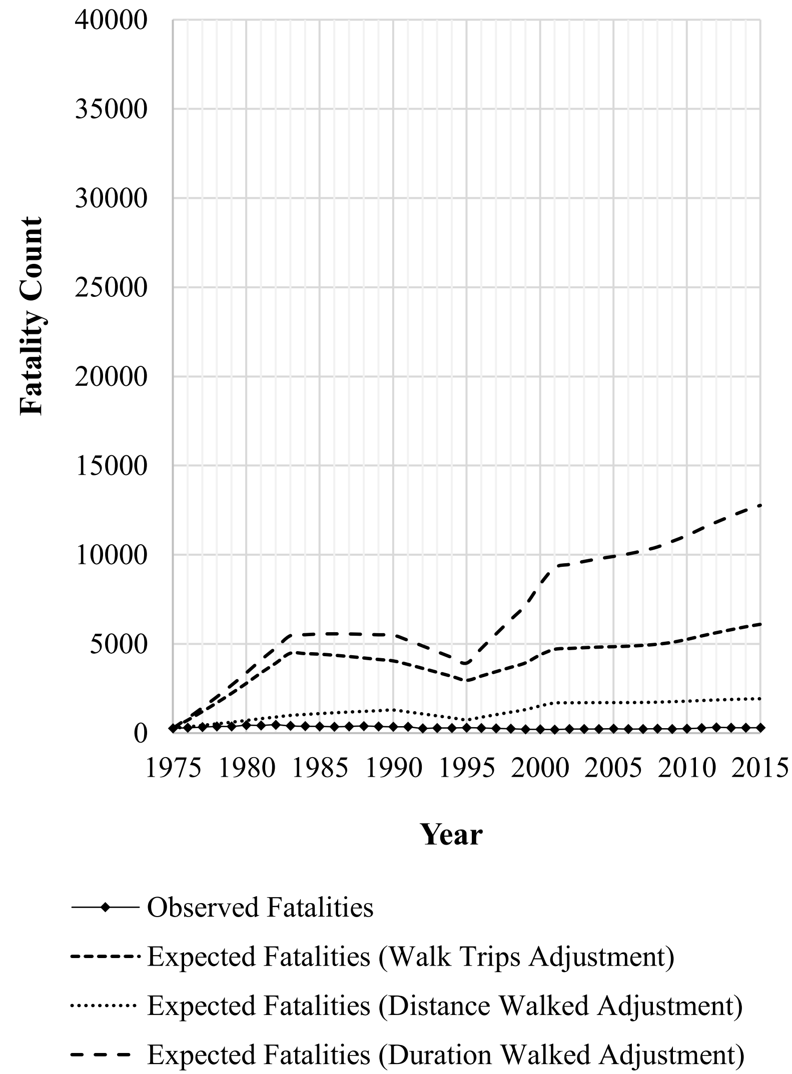

Figure 4.6: Observed and expected pedestrian fatality trends for females aged 20-34.

4.2.4: Middle Aged Adult Pedestrians

Figure 4.7 and **Figure 4.8** illustrate the observed fatalities and exposure-adjusted fatality trends for middle-aged adults for males and females, accordingly. The fatality trends based on walk trip durations show peaks in 2009 of 35,406 and 16,513 deaths for males and females, respectively. Significant divergence in exposure-adjusted fatality trends from observed fatalities is evident after 1995. The sharp increase is more apparent for males than for females. The differences between the observed and expected fatality trends indicate that fewer pedestrians were fatally injured than what was anticipated based on exposure, particularly post-1995 when the differences are significantly more evident. It is unlikely that the population adjustment factors had a significant effect on the visible escalation in fatality trends, given population trends typically do not show extreme changes over relatively short time periods. It is more likely, however, that the upsurge is due to a change in travel data collection methodologies during the shift from the NPTS to the NHTS in 2001.

4.2.5: Mature Adult Pedestrians

Exposure-adjusted pedestrian fatality trends and observed fatality counts for males and females aged 55-64 are presented in **Figure 4.9** and **Figure 4.10**, respectively. Trend counts began to diverge from observed fatality trends during the late-1970s with a significant escalation after 1995. While the proportion of mature adults has likely grown over time, this drastic upsurge is presumably due to changes in travel-based exposure data collection post-1995, similar to the fatality trends for middle-aged adults. Nevertheless, the large contrast between observed and expected fatalities among mature adult pedestrians serves as an indication that pedestrian safety has significantly improved than compared to what may have been expected based on historical exposure trends.

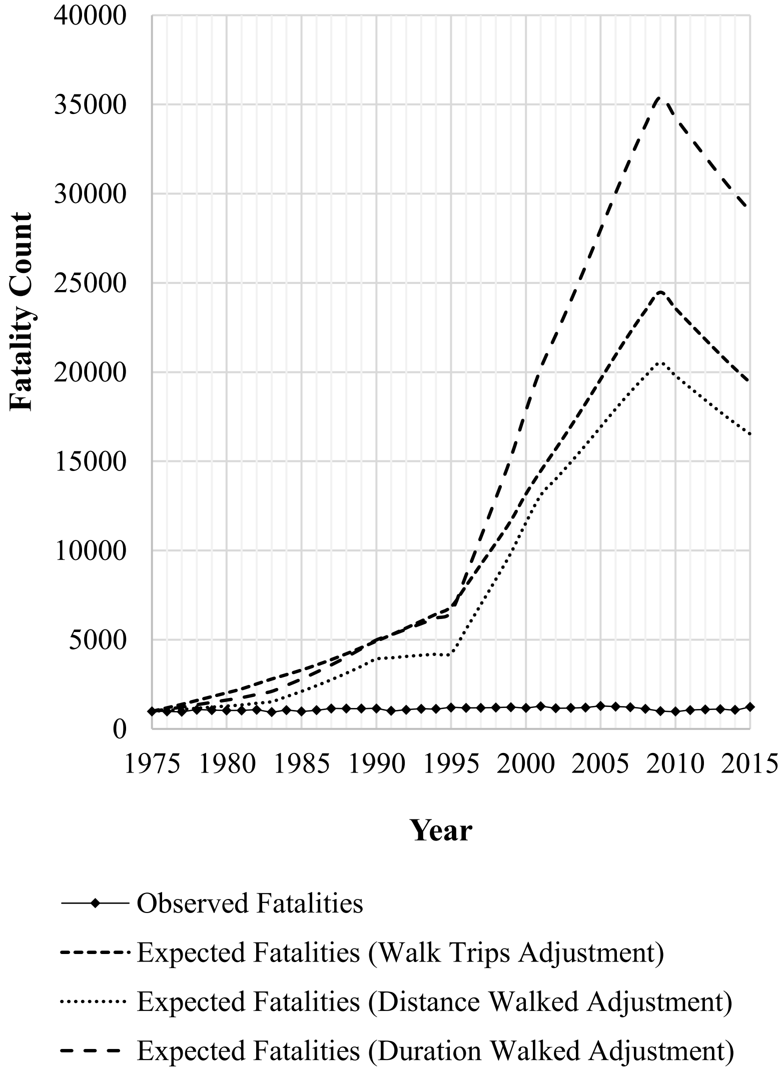

Figure 4.7: Observed and expected pedestrian fatality trends for males aged 35-54.

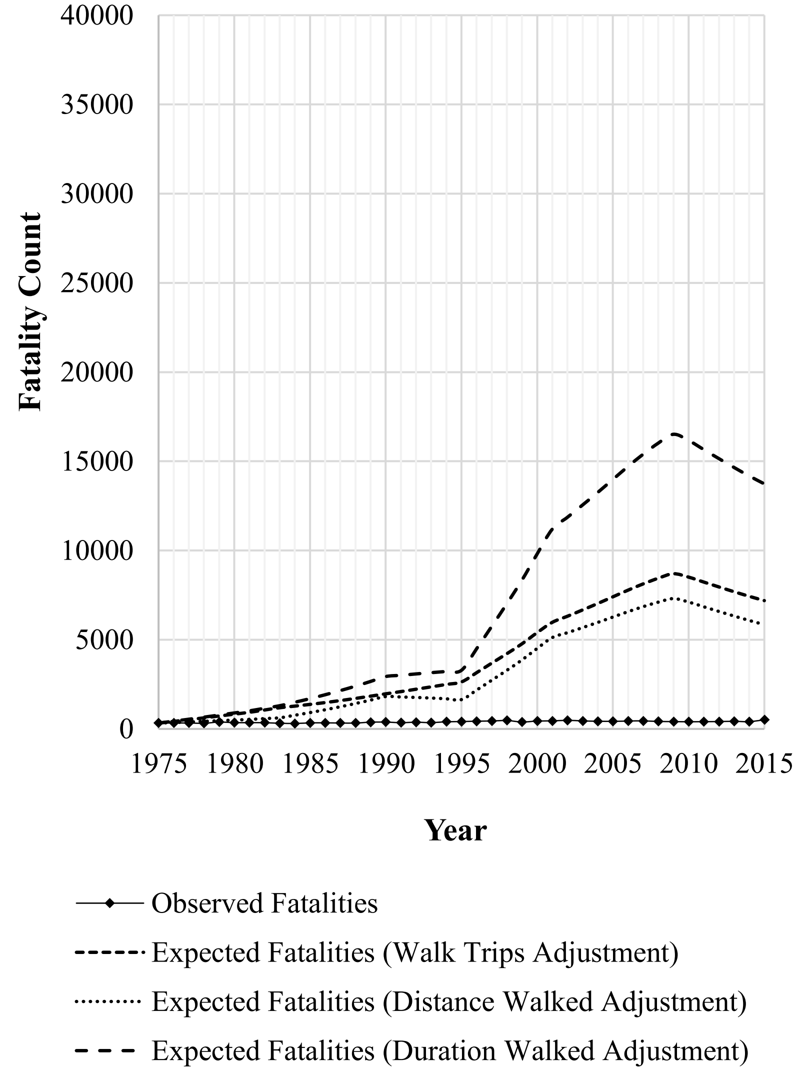

Figure 4.8: Observed and expected pedestrian fatality trends for females aged 35-54.

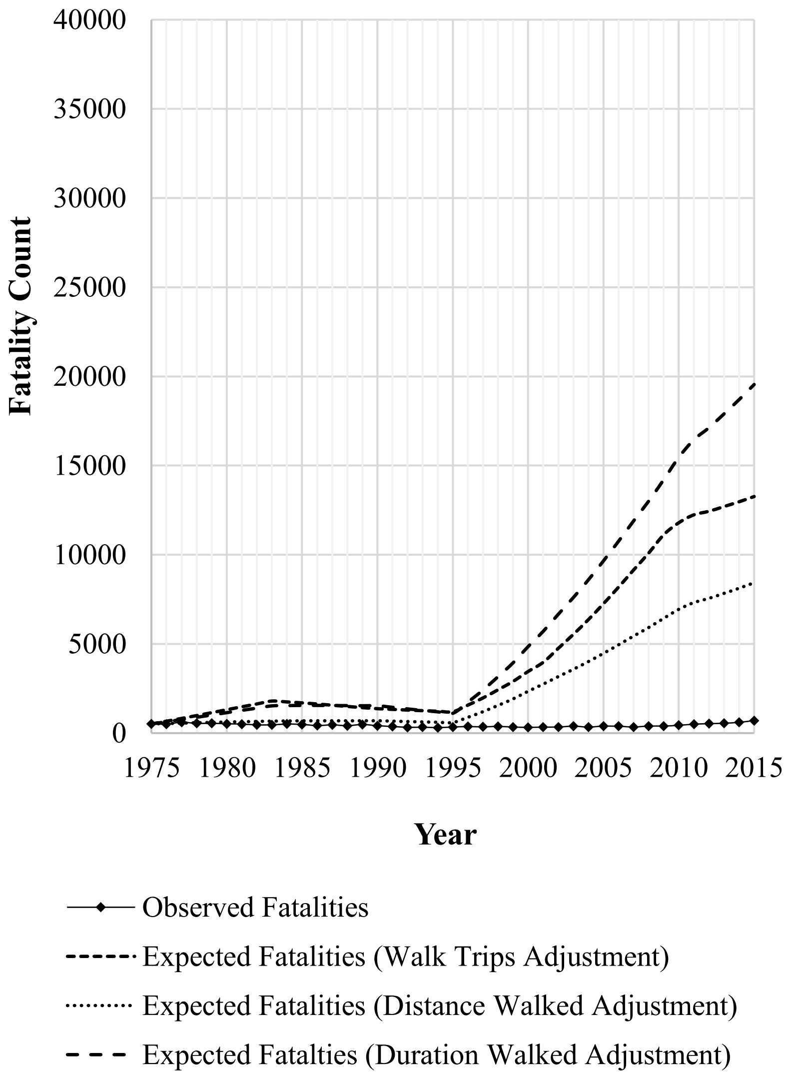

Figure 4.9: Observed and expected pedestrian fatalities for males aged 55-64.

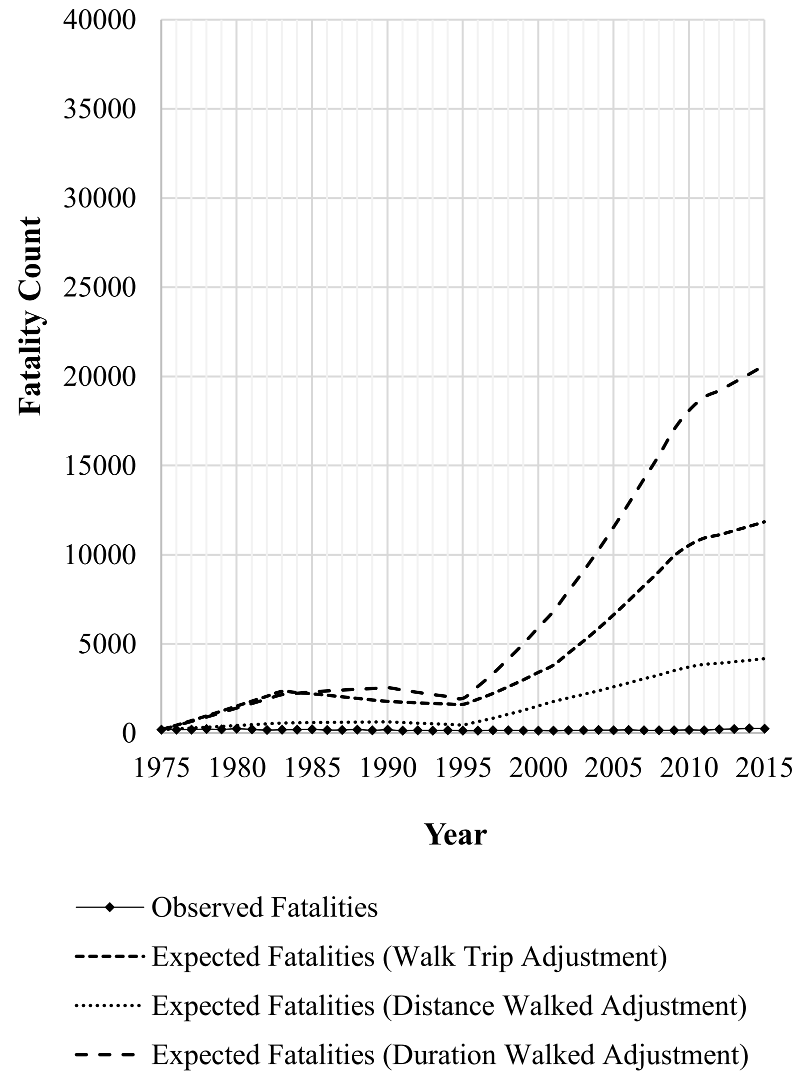

Figure 4.10: Observed and expected pedestrian fatalities for females aged 55-64.

4.2.6: Elderly Pedestrians

Adjusted fatality trends for elderly pedestrians are shown in **Figure 4.11** and **Figure 4.12** for males and females, respectively. Compared with other adult cohorts, the post-1995 rise in exposure-adjusted fatality trends is more pronounced; this is reflected through the upscaling of the vertical axis (from a maximum of 40000 to 80000). From the corresponding figures, peak expected fatality counts of approximately 68,264 and 33,114 were estimated for elderly males and females, respectively, based on equation (3.18).

Given the additional upscaling of the vertical axis, the divergence between observed and expected fatalities among elderly pedestrians is substantially higher than any of the preceding cohorts. The large differences in observed and expected fatalities may be attributable to a combination of increasing population numbers (i.e., higher population adjustment factors) and walk trips among the elderly. The differences may also be caused by improved data collection protocols (as argued previously for middle-aged and mature adults), resulting in more documented trips. Given that the elderly population is expected to increase in future decades, this divergence is expected to continue. Moreover, encouraging the elderly to reduce private automobile trips and instead, to choose walking as a primary mode of transportation will result in higher levels of travel-based pedestrian exposure.

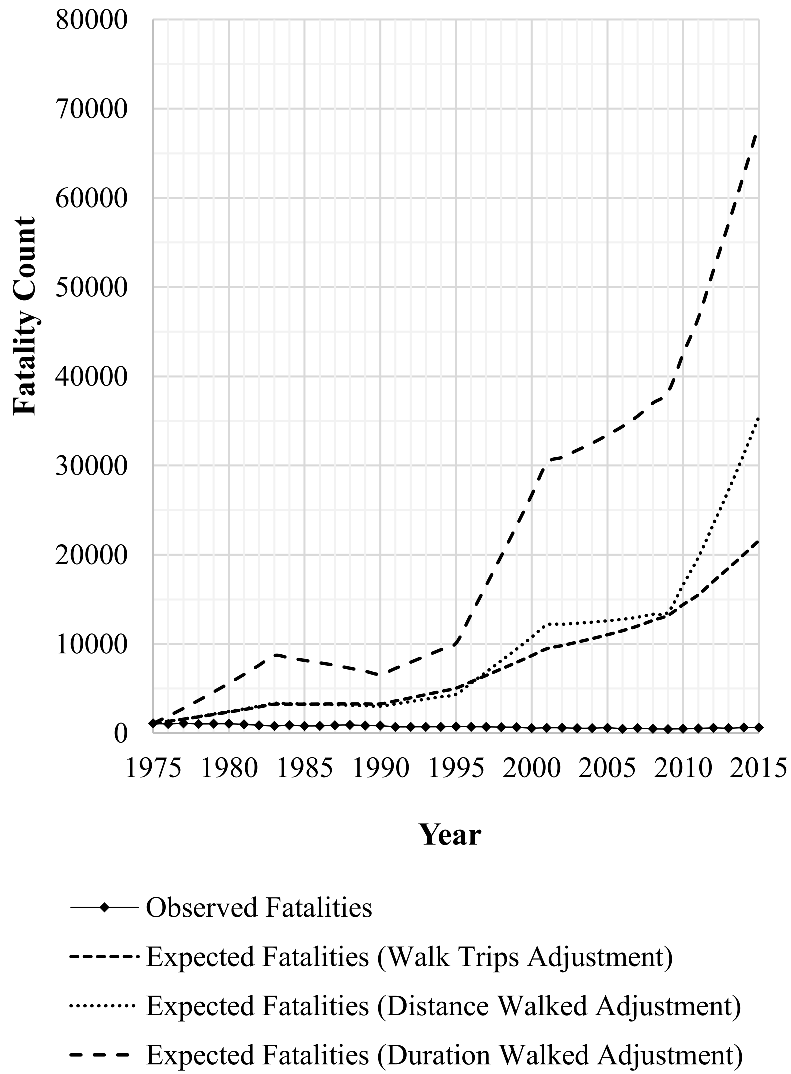

Figure 4.11: Observed and expected pedestrian fatalities for males aged 65+.

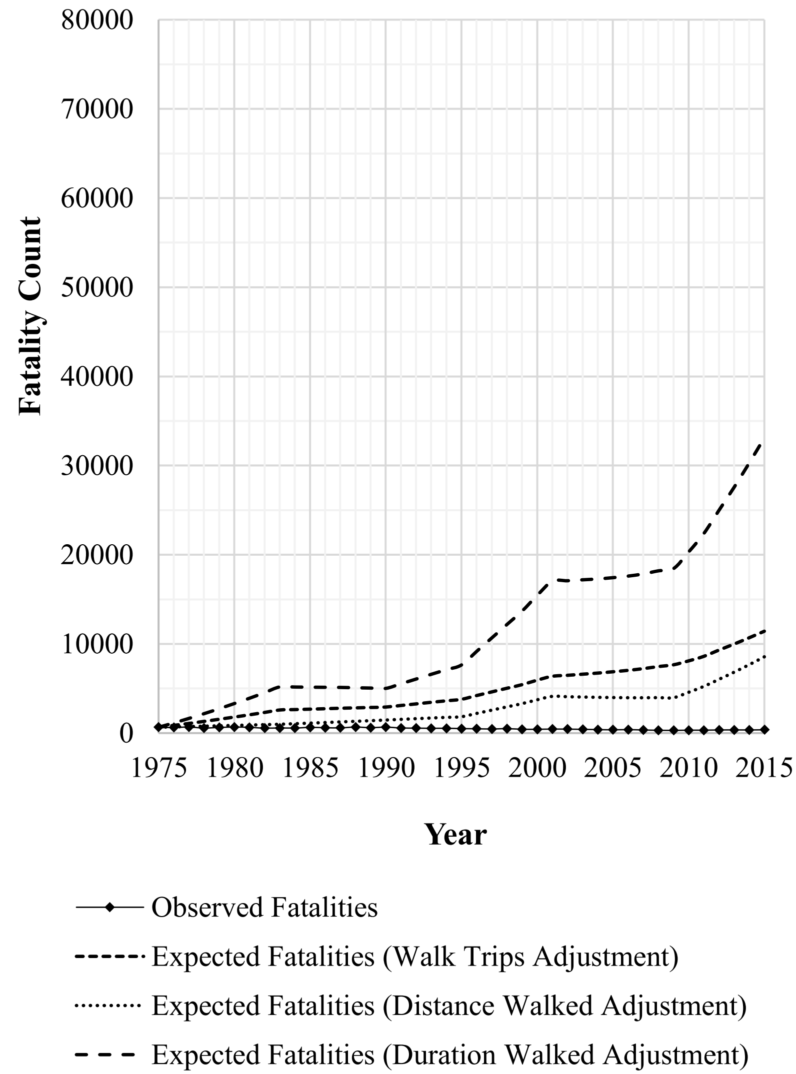

Figure 4.12: Observed and expected pedestrian fatalities for females aged 65+.

4.2.7: Pedestrian Fatality Trend Overview

Observed pedestrian fatalities were consistently lower than the exposure-adjusted fatality trends by significantly large margins. These differences were smallest for young pedestrians (children and teenagers aged 5-19), and largest for senior pedestrians (adults aged 55 or older). Furthermore, many of the exposure-adjusted fatality trends for adults and seniors showed high rates of increase after 1995. This finding was testamental to increasing levels of adult and senior pedestrian exposure (NHTS, 2019) as well as increasing elderly population (Mullen et al., 2013). However, given that both travel-based and population-based exposure adjustments were applied simultaneously within equation (3.18), it could not be ascertained whether the exposure-adjusted trends were more sensitive to changes in travel or changes in population (i.e., whether the travel-based exposure adjustment factor was significantly higher than the population adjustment factor, or vice-versa). Overall, however, these differences suggest that interventions to mitigate pedestrian fatalities have had a positive effect on road safety.

4.3: Pedestrian Fatality Projections

This section illustrates the various fatality forecast models fitted to observed data and is organized by demographic cohort. First, ANOVA test results for the three best-fitting models are presented, according to the model selection criteria. These results include *F*-scores, regression and residual degrees of freedom ($df_{regression}$ and df_{error}, respectively), *p*-values, adjusted R^2 values and AIC values. Next, univariate model coefficients are presented. Lastly, the three best-fitting forecast models are graphically illustrated. Magnified views of fatality trends post-2005 are also provided for enhanced visual clarity of recent changes in pedestrian fatalities. For the analysis, 95% confidence limits were computed. However, to minimized visual cluttering, these are not shown in this section. Readers interested in viewing the full range of regression models, as well as the 95% confidence limits are referred to Appendix E.

The cubic model was found to have the lowest AIC for most cohorts. However, the projections they illustrated were deemed unrealistic and were not carried forward. Even though the power and linear models showed some of the lowest AIC values in a few instances, in general, the analysis across all demographic cohorts showed that the quadratic, logarithmic, and CGEL models provided the best objective and visual fits to observed data. As a result, these three models were chosen throughout all 12 demographic cohorts for consistency. The following subsections present the results by cohort.

4.3.1: Child Pedestrians

In order of decreasing fit, **Table 4.3** contains the ANOVA test output and various model fit metrics for the three child pedestrian fatality forecast models by sex. The models are statistically significant at $p < 0.001$ and the adjusted r^2 values are high (i.e., adj. $r^2 > 0.9$). The corresponding model coefficients are tabulated in **Table 4.4**. The fatality forecasts for child pedestrians are shown in **Figure 4.13**. A magnified view of post-2005 trends is given in **Figure 4.14**. As described previously, fatality counts of child pedestrians have been consistently decreasing since 1975. For both sexes, the quadratic models project a slight upward trend towards 2035, whereas the remaining models illustrate near-constant rates of decline.

4.3.2: Teenage Pedestrians

Table 4.5 contains the ANOVA test output for the three best-fitting models for teenage male and female pedestrian fatalities. All forecast models are statistically significant at $p < 0.001$ with the quadratic forecasts having the lowest AIC values. Adjusted r^2 values range from 0.736 to 0.883, which are lower than those for child pedestrians. Forecast model coefficients are shown in **Table 4.6**. **Figure 4.15** contains the fatality forecasts for teenage pedestrians by sex. **Figure 4.16** provides additional visibility of post-2005 trends. The general tendencies of teenage pedestrian mortality mirror those of child pedestrians; the fatality counts are consistently higher for males than for females, the projection shows a decreasing trend and the rate of decrease is gradually declining. For males and females, the quadratic models forecast upward trends during the early- to mid-2020s while the remaining projections are sloped downward.

Table 4.3: ANOVA test results for child pedestrians.

Cohort	**Model**	F ($df_{regression}$, df_{error})	p	**Adjusted** r^2	**AIC**
Males 5-15	Quadratic	1142.236 (2,38)	< .001	0.983	154.0396
ij = (10)	CGEL	2161.275 (1,39)	< .001	0.982	157.2104
	Logarithmic	542.875 (1,39)	< .001	0.931	180.2418
Females 5-15	CGEL	1403.754 (1,39)	< .001	0.972	133.9277
ij = (20)	Quadratic	758.732 (2,38)	< .001	0.974	140.4170
	Logarithmic	794.965 (1,39)	< .001	0.952	151.4033

Table 4.4: Forecast model coefficients for child pedestrians.

Cohort	**Model**	b_0	b_1	b_2
Males 5-15	Quadratic	861.735	-33.910	0.376
	CGEL – Compound	951.490	0.947	
	CGEL – Growth	6.858	-0.055	
	CGEL – Exponential	951.490	-0.055	
	CGEL – Logistic	0.001	1.056	
	Logarithmic	1055.365	-247.004	
Females 5-15	CGEL – Compound	540.985	0.949	
	CGEL – Growth	6.293	-0.053	
	CGEL – Exponential	540.985	-0.053	
	CGEL – Logistic	0.002	1.054	
	Quadratic	509.110	-20.798	0.247
	Logarithmic	620.171	-145.351	

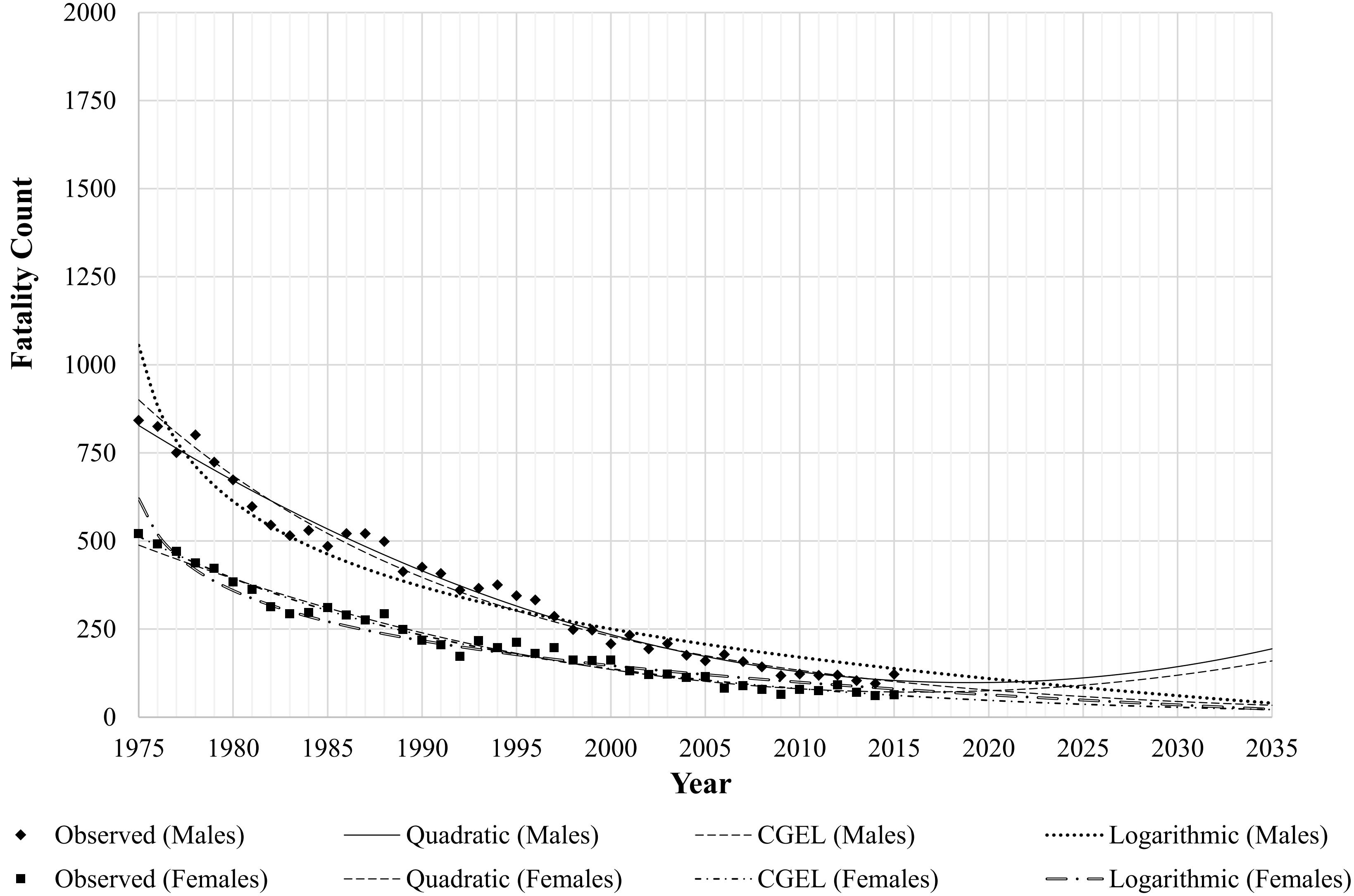

Figure 4.13: Observed and forecasted child pedestrian fatalities (ages 5-15) by sex.

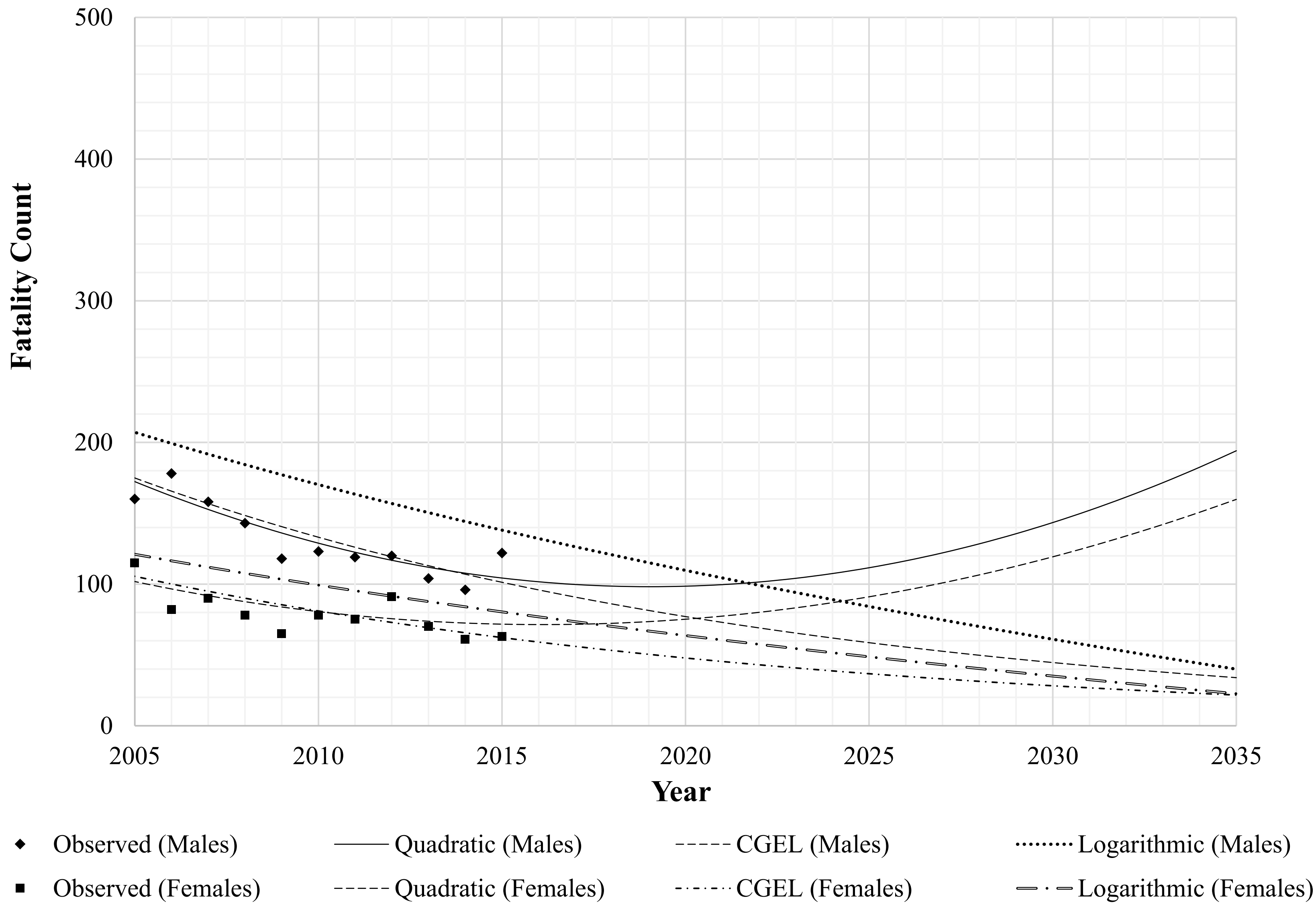

Figure 4.14: Magnified trends of child pedestrian fatalities post-2005.

Table 4.5: ANOVA test results for teenage pedestrians.

Cohort	**Model**	F ($df_{regression}$, df_{error})	p	**Adjusted** r^2	**AIC**
Males 16-19	Quadratic	151.618 (2,38)	< .001	0.883	164.5404
ij = (11)	CGEL	175.699 (1,39)	< .001	0.814	176.4668
	Logarithmic	139.530 (1,39)	< .001	0.776	176.0163
Females 16-19	Quadratic	135.853 (2,38)	< .001	0.871	123.1705
ij = (21)	CGEL	112.502 (1,39)	< .001	0.736	133.4637
	Logarithmic	127.676 (1,39)	< .001	0.760	134.0815

Table 4.6: Forecast model coefficients for teenage pedestrians.

Cohort	**Model**	b_0	b_1	b_2
Males 16-19	Quadratic	494.252345	-22.268012	0.339
	CGEL – Compound	404.973	0.967	
	CGEL – Growth	6.004	-0.033	
	CGEL – Exponential	404.973	-0.033	
	CGEL – Logistic	0.002	1.034	
	Logarithmic	537.228	-112.671	
Females 16-19	Quadratic	184.373	-7.748	0.121
	CGEL – Compound	149.950	0.974	
	CGEL – Growth	5.010	-0.027	
	CGEL – Exponential	149.950	-0.027	
	CGEL – Logistic	0.007	1.027	
	Logarithmic	197.09513	-37.777262	

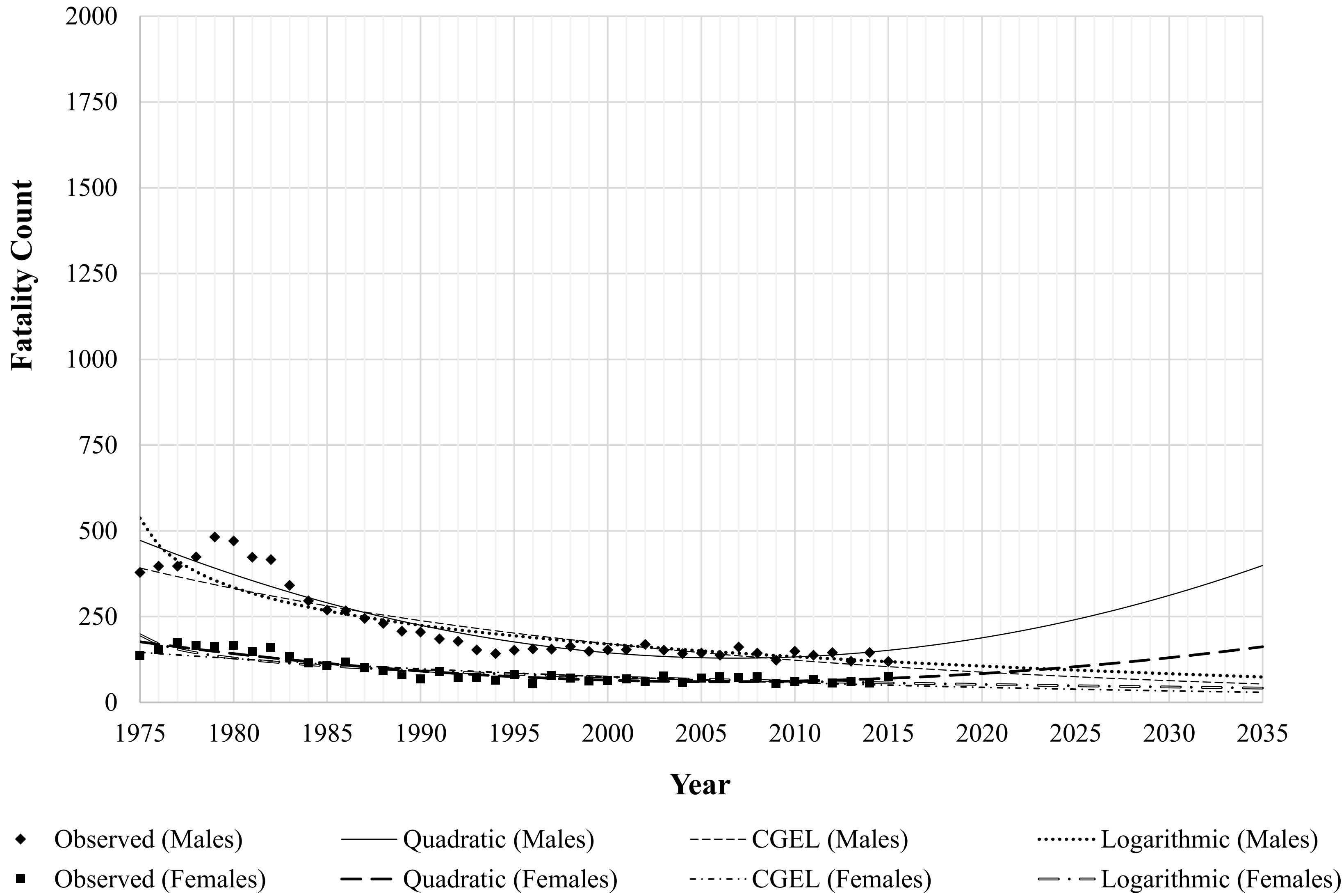

Figure 4.15: Observed and forecasted teenage pedestrian fatalities (ages 16-19) by sex.

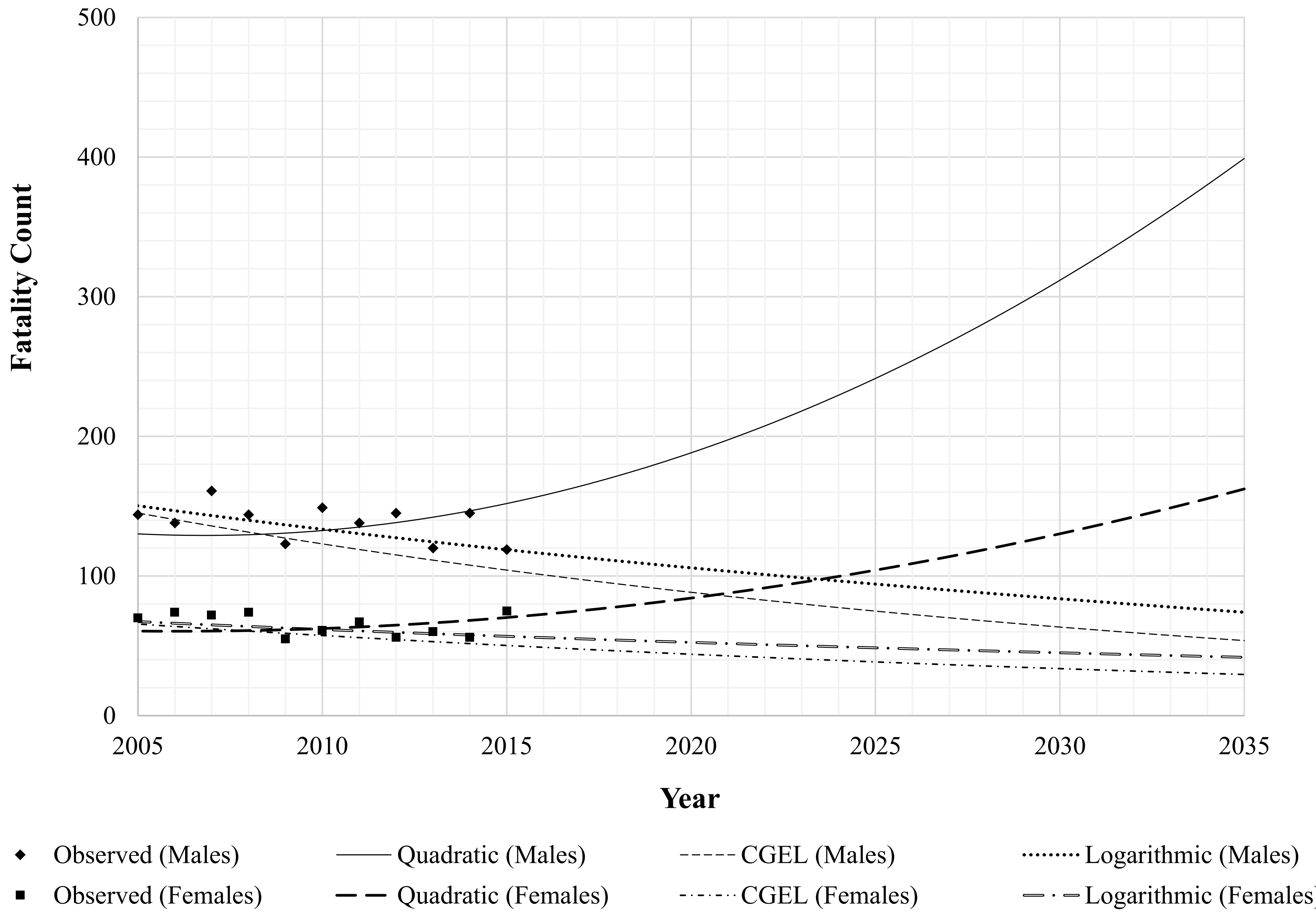

Figure 4.16: Magnified trends of teenage pedestrian fatalities post-2005.

4.3.3: Young Adult Pedestrians

Table 4.7 contains the ANOVA results for the fitted models for young adult pedestrians. The corresponding coefficients are shown in **Table 4.8**. The three best-fitting models are statistically significant at $p < 0.001$; however, average adjusted r^2 values were lower relative to younger cohorts, ranging from 0.395 to 0.661 for males and 0.239 to 0.410 for females. The loss in fitting properties may be a result of the evident fluctuations in fatalities over the past 41 years.

Figure 4.17 contains the forecast models for young adults. A magnified view of post-2005 trends is shown in **Figure 4.18**. Recent trends (i.e., post-2010) for young male adults show an increase in pedestrian deaths. However, the effect of the fatality reductions during the 1980s and 1990s appears to significantly influence this recent increase and cause the male fatality projections to slope downward. The female fatality forecasts show relatively constant projections, suggesting that young female adults are not at elevated risk of pedestrian fatality.

4.3.4: Middle Aged Adult Pedestrians

ANOVA test results for the fitted models for middle-aged adult pedestrians are given in **Table 4.9**. The three models chosen are statistically significant at $p < 0.001$. Compared to young adult pedestrians, adjusted r^2 values were lower for males but higher for females. The forecast model coefficients are provided in **Table 4.10**.

Fatality forecasts are shown in **Figure 4.19**. Post-2005 trends are shown in **Figure 4.20**. Overall, the observed fatality trends for males were consistently increasing since 1975; however, a noticeable decrease between 2005 and 2010 was observed, which likely caused the quadratic model to project downwards. The CGEL and logarithmic models show slight positive slopes. Females also exhibited a consistent increase over time since 1975, but the variability was lower than for males.

Table 4.7: ANOVA test results for young adult pedestrians.

Cohort	Model	F ($df_{regression}$, df_{error})	p	Adjusted r^2	AIC
Males 20-34	CGEL	78.892 (1,39)	< .001	0.661	224.8258
ij = (12)	Quadratic	35.266 (2,38)	< .001	0.631	226.2828
	Logarithmic	27.079 (1,39)	< .001	0.395	234.7262
Females 20-34	CGEL	25.149 (1,39)	< .001	0.376	177.5530
ij = (22)	Quadratic	14.922 (2,38)	< .001	0.410	178.5560
	Logarithmic	13.537 (1,39)	< .001	0.239	182.1894

Table 4.8: Young adult forecast model coefficients.

Cohort	Model	b_0	b_1	b_2
Males 20-34	CGEL – Compound	1438.500	0.980	
	CGEL – Growth	7.271	-0.020	
	CGEL – Exponential	1438.500	-0.020	
	CGEL – Logistic	0.001	1.020	
	Quadratic	1443.253	-25.157	0.128
	Logarithmic	1588.535	-215.391	
Females 20-34	CGEL – Compound	382.006	0.988	
	CGEL – Growth	5.945	-0.012	
	CGEL – Exponential	382.006	-0.012	
	CGEL – Logistic	0.003	1.012	
	Quadratic	414.419	-8.054	0.102
	Logarithmic	418.629	-40.951	

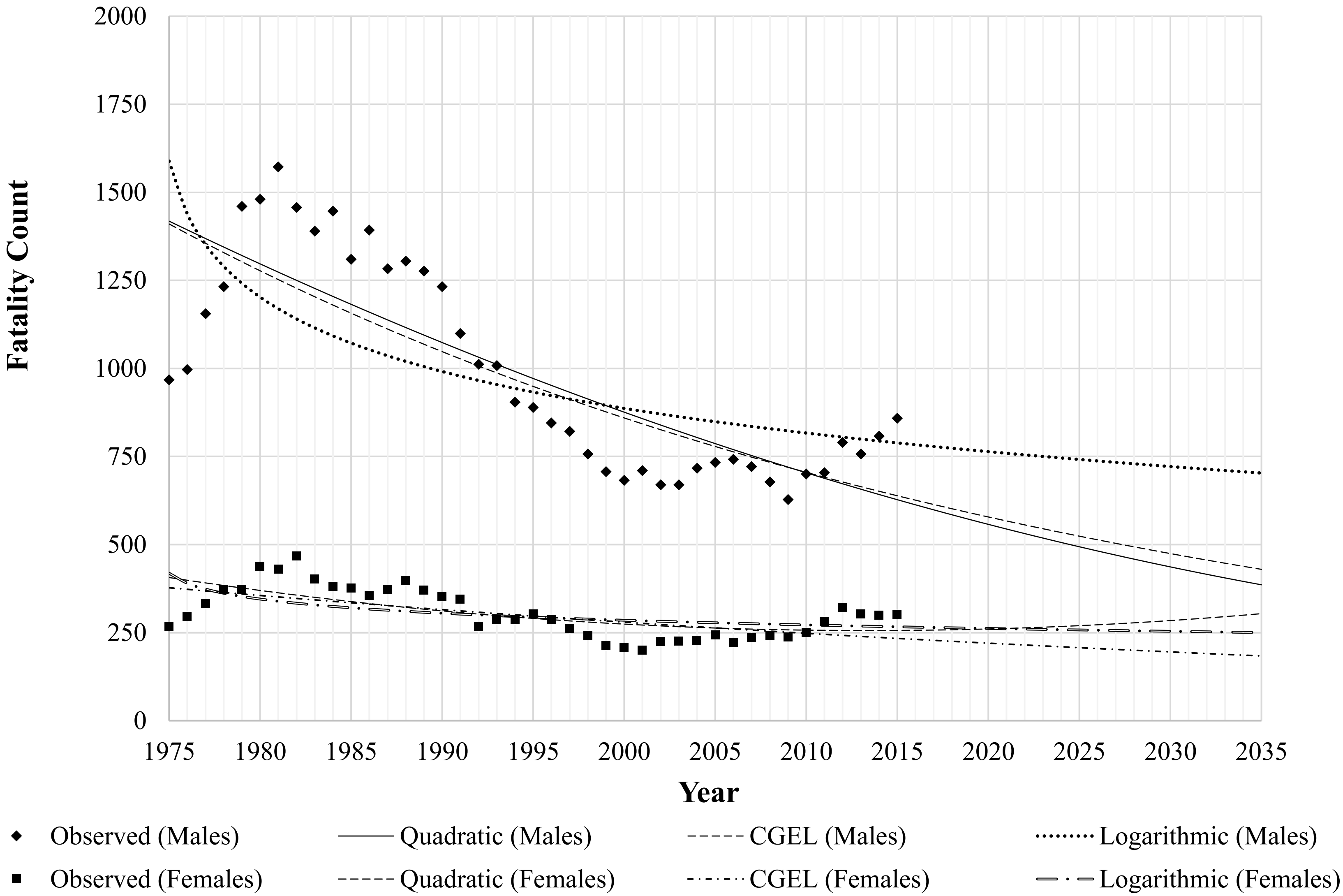

Figure 4.17: Observed and forecasted young adult pedestrian fatalities (ages 20-34) by sex.

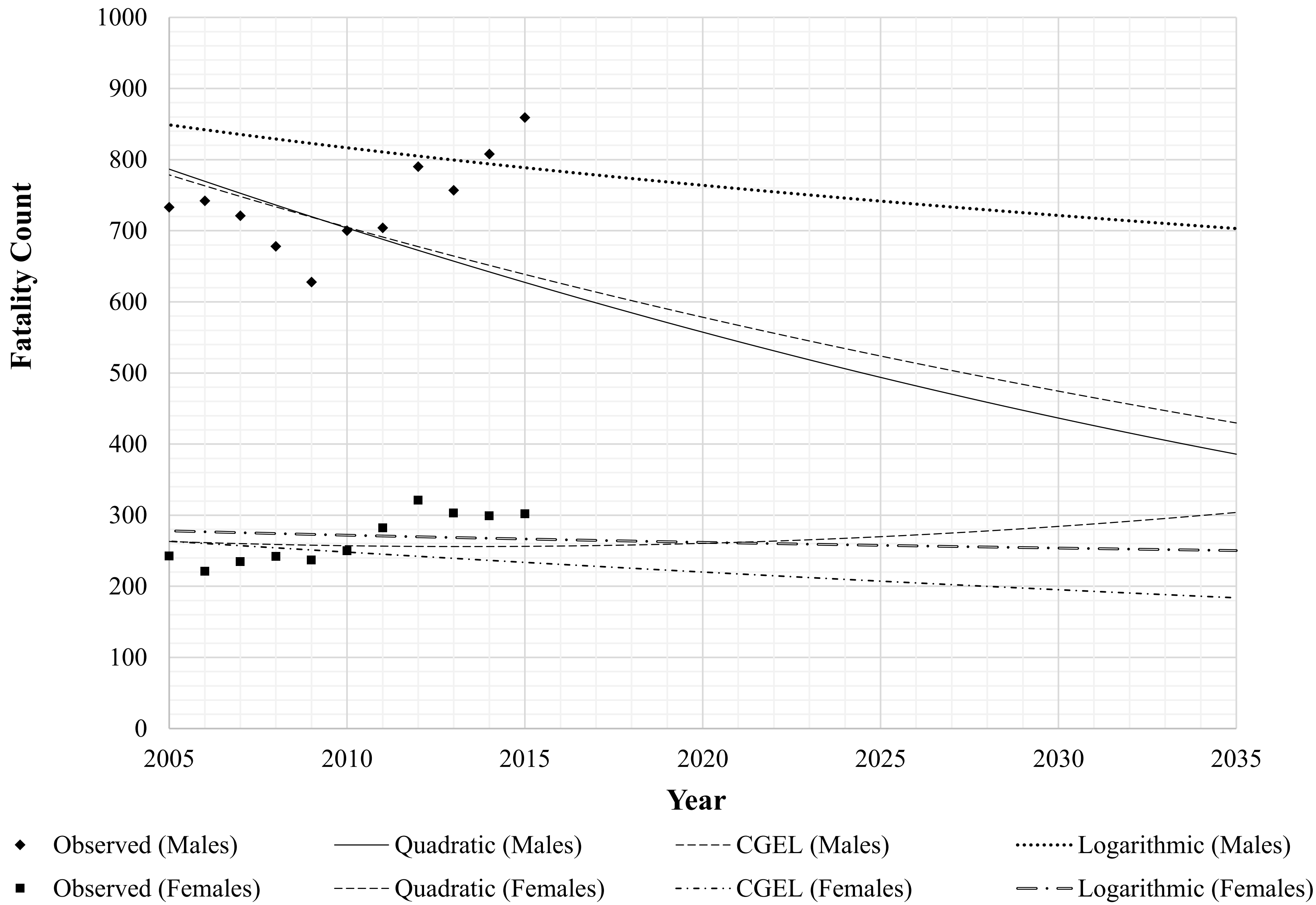

Figure 4.18: Magnified trends of young adult pedestrian fatalities post-2005.

Table 4.9: ANOVA test results for middle-aged adult pedestrians.

Cohort	Model	F ($df_{regression}$, df_{error})	p	Adjusted r^2	AIC
Males 35-54	Quadratic	15.670 (2,38)	< .001	0.423	187.7074
ij = (13)	Logarithmic	19.104 (1,39)	< .001	0.312	189.7628
	CGEL	12.429 (1,39)	< .001	0.222	192.4294
Females 35-54	CGEL	68.024 (1,39)	< .001	0.626	156.8257
ij = (23)	Quadratic	33.651 (2,38)	< .001	0.620	157.1657
	Logarithmic	43.812 (1,39)	< .001	0.517	160.4905

Table 4.10: Middle-aged adult forecast model coefficients.

Cohort	Model	b_0	b_1	b_2
Males 35-54	Quadratic	935.440	17.319	-0.325
	Logarithmic	947.026	58.789	
	CGEL – Compound	1032.234	1.003	
	CGEL – Growth	6.939	0.003	
	CGEL – Exponential	1032.234	0.003	
	CGEL – Logistic	0.001	0.997	
Females 35-54	CGEL – Compound	323.438	1.009	
	CGEL – Growth	5.779	0.009	
	CGEL – Exponential	323.438	0.009	
	CGEL – Logistic	0.003	0.991	
	Quadratic	304.305	5.723	-0.056
	Logarithmic	273.083	42.826	

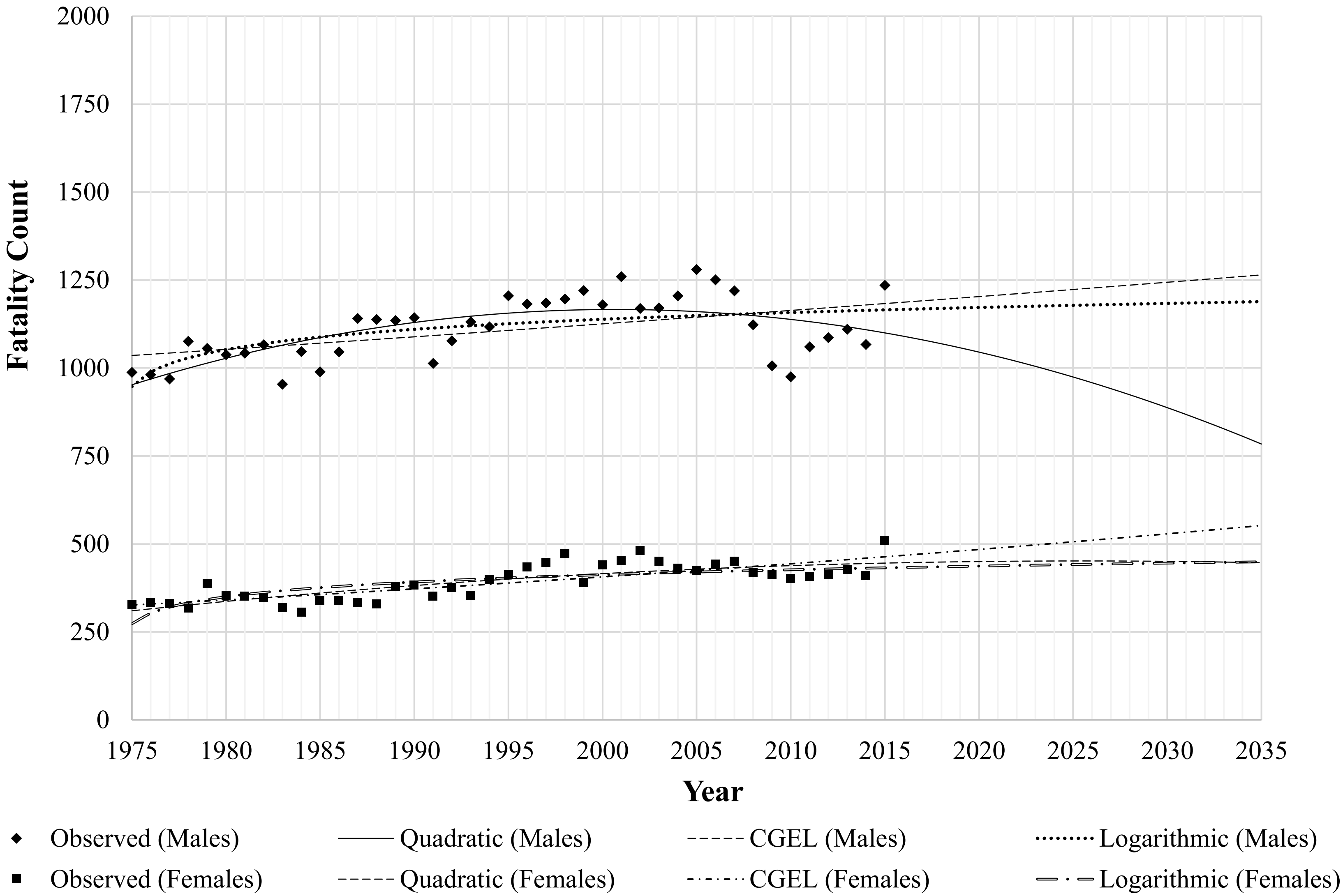

Figure 4.19: Observed and forecasted middle-aged adult pedestrian fatalities (Ages 35-54) by sex.

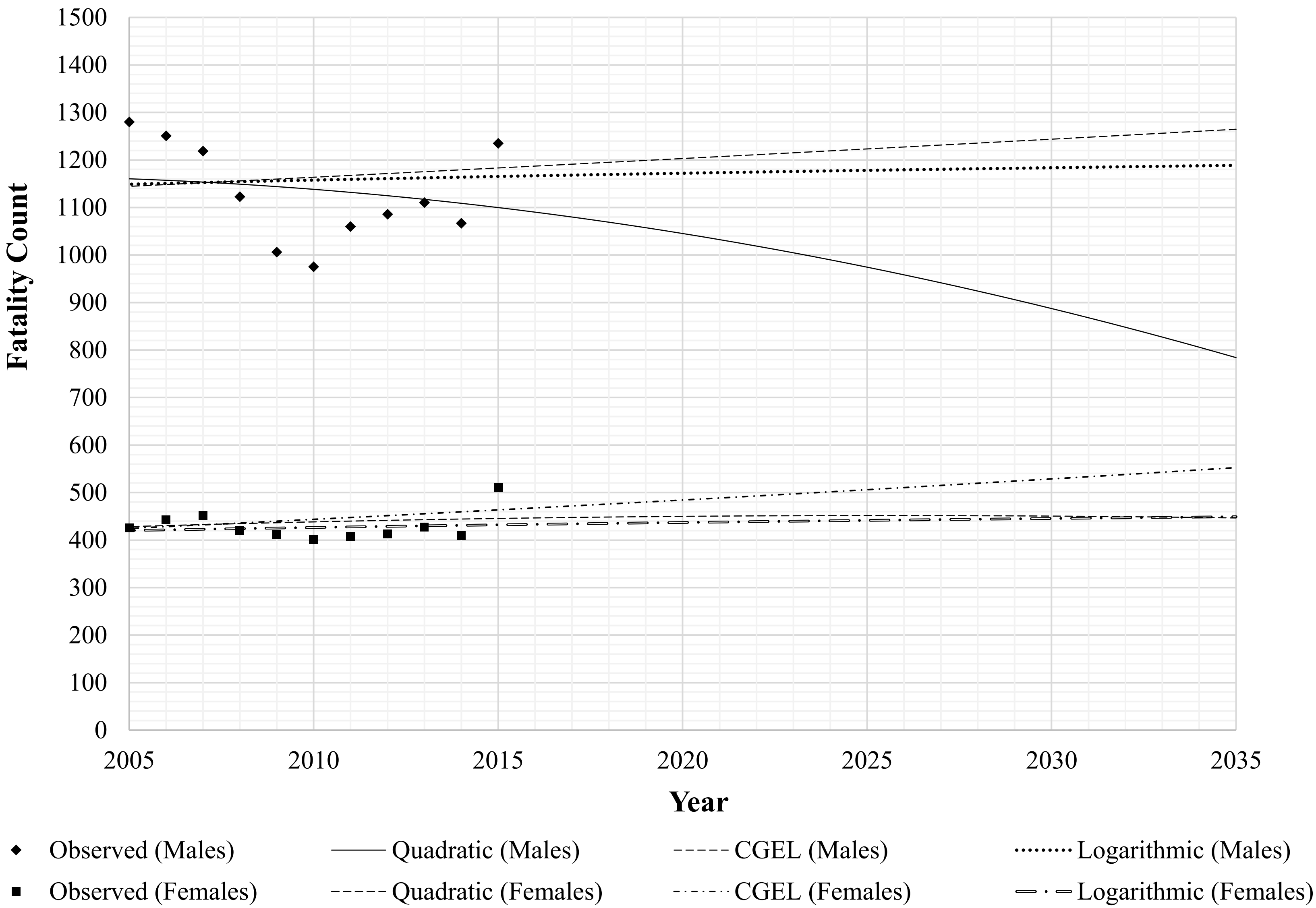

Figure 4.20: Magnified trends of middle-aged adult pedestrian fatalities post-2005.

4.3.5: Mature Adult Pedestrians

Table 4.11 contains the ANOVA test results for models considering mature adult pedestrian fatalities. All of the models except the quadratic models for both sexes, as well as the female logarithmic model, are not statistically significant at $p < 0.05$. The model coefficients are given in **Table 4.12**.

The forecasts for male pedestrian fatalities are shown in **Figure 4.21**. **Figure 4.22** shows a magnified view of the projections post-2005. Despite the logarithmic and CGEL projection models not being statistically significant, they show near-constant trends for both males and females towards 2035. Moreover, the quadratic models forecast increasing trends in the future (approximately post-2000 and post-2010 for males and females, respectively). The rate of increase for the quadratic models is steepest among males. Fatality trends for females were more stable than for males.

4.3.6: Elderly Pedestrians

The ANOVA test results the forecast models and their coefficients are listed in **Table 4.13** and **Table 4.14**, respectively. The models for elderly pedestrians are all statistically significant at $p < 0.001$, and the adjusted r^2 values are generally higher than for other adult cohorts. Pedestrian fatality projections for the elderly are shown in **Figure 4.23**. A zoomed-in view of post-2005 trends is provided in **Figure 4.24**. Steadily declining trends in observed fatalities among elderly male and female pedestrians are visible from 1975 to the late 2000s, then a brief period of increasing fatality counts after 2009 can be seen. The CGEL and logarithmic models illustrate downward projections for both sexes, while the directions of the quadratic model forecasts differ with sex.

Table 4.11: ANOVA test results for mature adult pedestrians.

Cohort	Model	F ($df_{regression}$, df_{error})	p	Adjusted r^2	AIC
Males 55-64	Quadratic	53.107 (2,38)	< .001	0.723	175.0718
ij = (14)	Logarithmic	5.717 (1,39)	0.022	0.105	197.0102
	CGEL	1.469 (1,39)	0.233	0.012	199.3566
Females 55-64	Quadratic	29.330 (2,38)	< .001	0.586	141.2483
ij = (24)	Logarithmic	3.305 (1,39)	0.089	0.048	156.4219
	CGEL	0.655 (1,39)	0.423	-0.009	157.8617

Table 4.12: Forecast model coefficients for mature adult pedestrians.

Cohort	Model	b_0	b_1	b_2
Males 55-64	Quadratic	651.886	-27.631	0.629
	Logarithmic	544.167	-38.548	
	CGEL – Compound	458.514	0.997	
	CGEL – Growth	6.128	-0.003	
	CGEL – Exponential	458.514	-0.003	
	CGEL – Logistic	0.002	1.003	
Females 55-64	Quadratic	244.286	-8.766	0.202
	Logarithmic	206.145	-10.181	
	CGEL – Compound	182.215	0.998	
	CGEL – Growth	5.205	-0.002	
	CGEL – Exponential	182.215	-0.002	
	CGEL – Logistic	0.005	1.002	

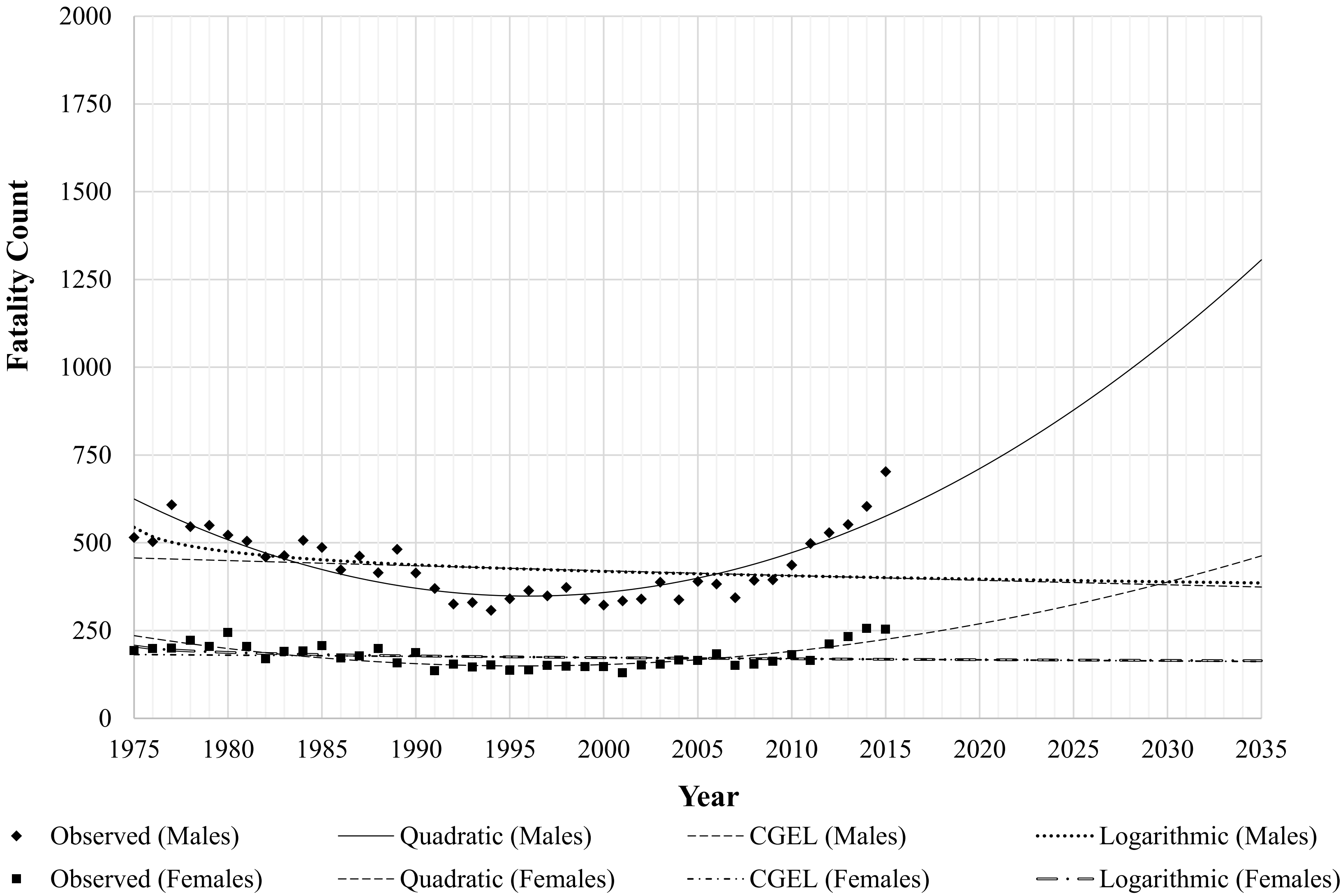

Figure 4.21: Observed and forecasted mature adult pedestrian fatalities (ages 55-64) by sex.

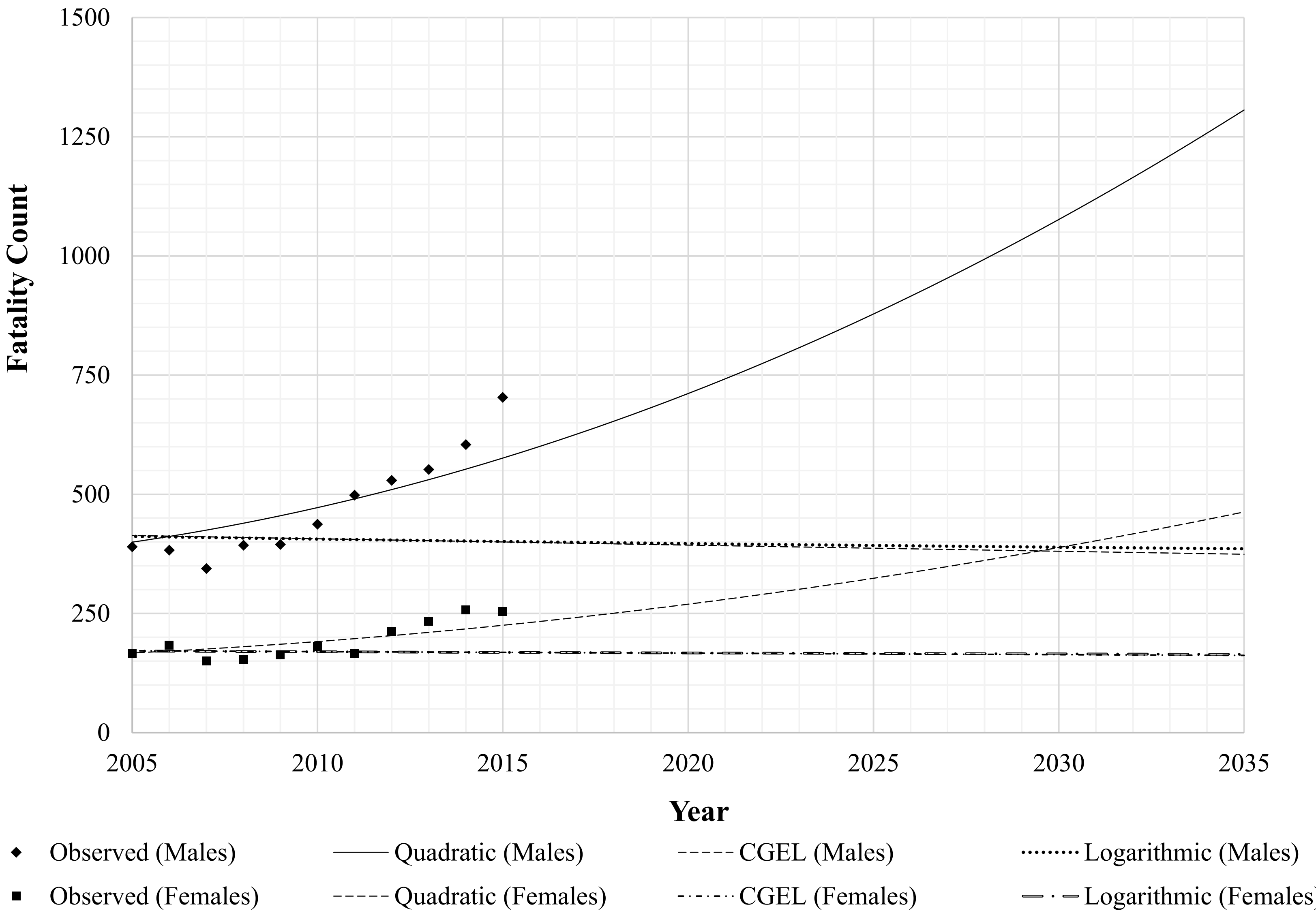

Figure 4.22: Magnified trends of mature adult pedestrian fatalities post-2005.

Table 4.13: ANOVA test results for elderly pedestrians.

Cohort	Model	F ($df_{regression}$, df_{error})	p	Adjusted r^2	AIC
Males 65+	Quadratic	221.691 (2,38)	< .001	0.917	178.3576
ij = (15)	CGEL	251.675 (1,39)	< .001	0.862	181.2169
	Logarithmic	205.348 (1,39)	< .001	0.836	190.4384
Females 65+	Quadratic	129.346 (2,38)	< .001	0.865	170.4009
ij = (25)	CGEL	242.623 (1,39)	< .001	0.858	173.8228
	Logarithmic	67.808 (1,39)	< .001	0.625	189.3537

Table 4.14: Forecast model coefficients for elderly pedestrians.

Cohort	Model	b_0	b_1	b_2
Males 65+	Quadratic	1152.974	-28.989	0.344
	CGEL – Compound	1084.142	0.981	
	CGEL – Growth	6.989	-0.019	
	CGEL – Exponential	1084.142	-0.019	
	CGEL – Logistic	0.001	1.020	
	Logarithmic	1289.206	-196.024	
Females 65+	Quadratic	669.447	-5.687	-0.087
	CGEL – Compound	730.956	0.981	
	CGEL – Growth	6.594	-0.020	
	CGEL – Exponential	730.956	-0.020	
	CGEL – Logistic	0.001	1.020	
	Logarithmic	804.378	-109.629	

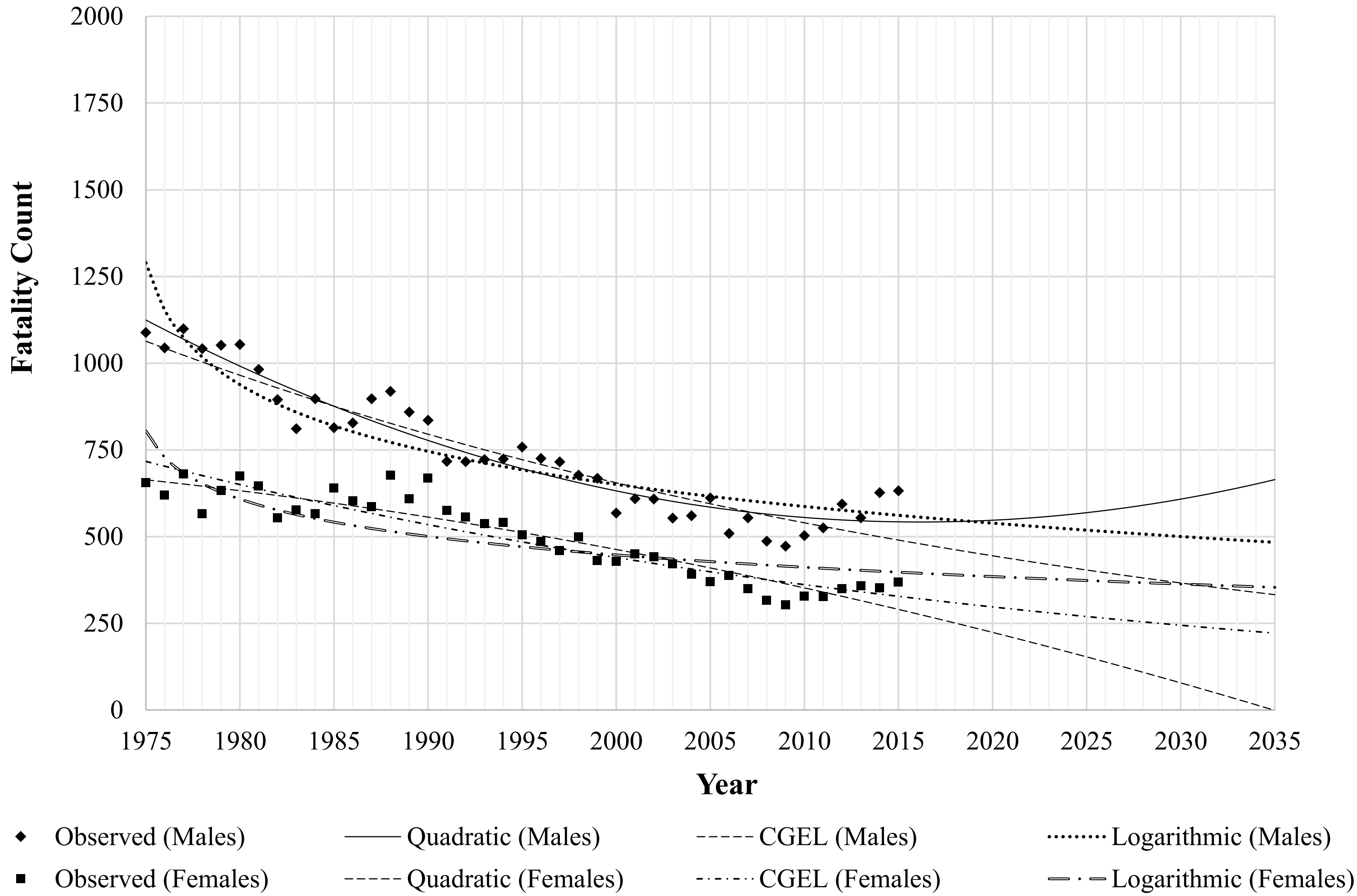

Figure 4.23: Observed and forecasted elderly pedestrian fatalities (ages 65+) by sex.

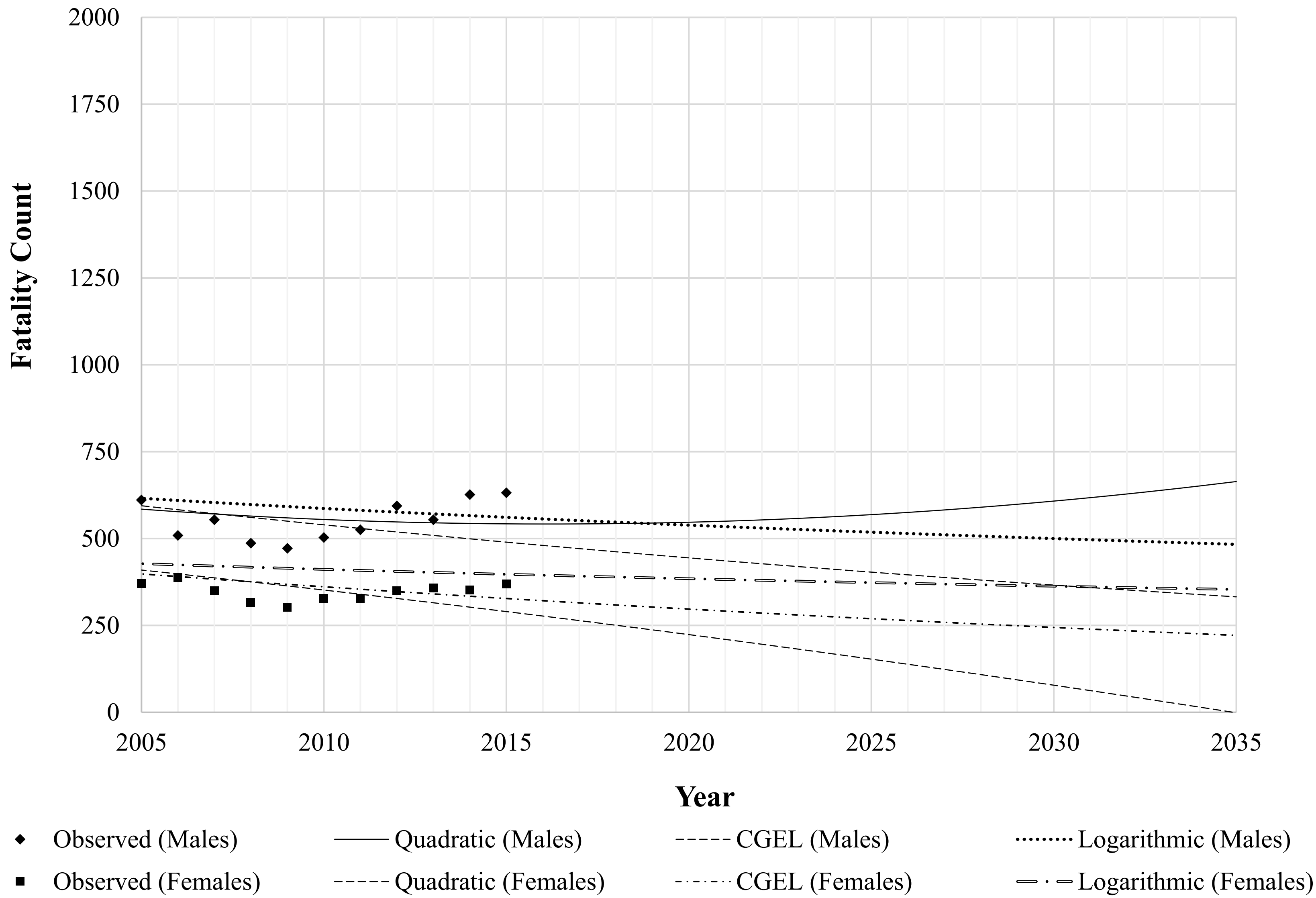

Figure 4.24: Magnified trends of elderly pedestrian fatalities post-2005.

4.4: Pedestrian Fatality Outlook

4.4.1: Implications for Children

Overall, the number of annual pedestrian fatalities over the past 40 years have been decreasing for children. Pedestrian fatalities for children were forecasted to continue decreasing towards 2035. Factors such as improved roadway infrastructure and pedestrian crash avoidance technologies may be attributable to this long-term decrease; however; it is more likely that depreciating levels of child pedestrian exposure to motor vehicles are ultimately responsible (Mickalide et al., 2012).

Several studies have demonstrated that perceived traffic-related danger consistently ranks second in the most common barriers to children walking to school, behind the walking distance to/from home (Martin & Carlson, 2005; Omura et al., 2019). Consequently, parents may choose to drive their children to their destinations, which forms a positive feedback loop for perceived pedestrian safety. This was reflected in a report from the National Center for Safe Routes to School, where it was reported that the proportion of children aged between 5 and 14 that walk to school has dropped from 48% in 1969 to 13% in 2009. Furthermore, the percentage of children within the same age range and over the same 40-year period who commuted to school via private vehicle had risen from 12% to 44% over the same 40-year period (Pedroso, 2017).

It should be noted that typical walking distances to schools have changed over previous decades. During the 1960s, schools were primarily located within the centre of communities, which promoted walking among children. However, starting in the 1970s, the development of new schools mainly took place at the edges of communities where land was more available and the costs of land were generally lower. Furthermore, schools were generally built larger in size beginning in this time period to increase student catchment areas. As a result, school placements have become more spatially dispersed, thus encouraging the use of private-automobile trips and decreasing walkability (McDonald, 2010).

This rationalization of parents regarding unsafe road conditions for child pedestrians appears justified as there are several factors supporting the elevated risk among children. First, the under-developed cognitive and perceptual skills associated with children have implications on motor vehicle detection. A child's field of vision is one-third narro e r than an adult's, hich directly affects vehicle detection and gap acceptance (Jacobsen et al., 2000; Meir et al., 2015). Secondly, due to the smaller physical profile of children, they are less conspicuous to motorists than an older pedestrian, thus reducing sight distances. Thirdly, children not educated in road safety have a poor understanding of safe crossing behaviour, which may lead to increased carelessness, impulsivity, and a false over-reliance on motorist behaviour and traffic control devices (Pande et al., 2015).

Furthermore, fatalities may increase in the future if efforts to promote independent walking are implemented without adequate considerations for safety. Research into countermeasure development has been increasingly prevalent within recent decades. Given that opinions regarding targeted educational countermeasures appear ambivalent (Percer, 2009; Schieber & Vegega, 2002), physical road improvements through traffic engineering have been otherwise proven to improve child pedestrian safety more effectively that educational interventions (Jones et al., 2005; R. A. Retting et al., 2003). Therefore, future efforts to improve child pedestrian safety should be focused on changes to the built environment. Examples of such improvements include speed limit reductions and providing adequate visibility where children walk. These improvements are discussed in greater detail as part of the injury severity analysis (section 6.4:).

4.4.2: Implications for Adults

The fatality trends of several cohorts showed multiple fluctuations in annual fatality counts of varying magnitudes. The magnitude of these fluctuations was greatest for young adults (ages 20-34) and decreased with age. Moreover, the fluctuations in fatalities appear to coincide with major economic crises (e.g., the 1973 oil embargo and the financial crises of the late-2000s). For young adults, pedestrian fatality counts for males have generally decreased between the late 1970s and the late 2000s. During the late 2000s, fatality counts underwent a significant increase. However, the fatality projections showed forecasted declining trends towards 2035. It is likely that the relatively long history of decreasing fatalities had a stronger influence on the projection model than the relatively short time period of increasing fatality counts that followed.

The trendlines of observed fatalities presented in this study appear to emulate those from Mullen et al. (2013) with passenger car occupants for the age groups of 20-34, 35-54, and 55-64. Furthermore, these researchers suggested that the risk of traffic-related fatality among young adult occupants is more sensitive to significant economic changes. The results presented here are in agreeance with those from Mullen et al., but should be supported with further research.

Overall, our projections show slight increasing trends in fatalities among adults aged 35-54 in the coming decades. As such, safety interventions to manage the number of annual fatalities for this cohort should be implemented.

4.4.3: Implications for Older Adults

Annual pedestrian fatality counts for older adults (ages 65 and older) have steadily declined between 1975 and the late 2000s. However, a slightly increasing trend was observed from 2009 to 2015. The fatality projections presented for this cohort were inconsistent and did not illustrate definitive forecasts. Therefore, more insight may be acquired if the underlying characteristics of travel among older adults are examined.

The number of older adults in the United States has been forecasted to increase significantly by 2050 (Ortman et al., 2014; Su & Bell, 2009). Additionally, the proportion of trips by seniors undertaken by walking has increased, from an estimated 9% in 2009 to 10% in 2017 (NHTS, 2019). These indications suggest that population-based and travel-based pedestrian exposure among older adults in the United States may increase in the coming decades. As a result, it may be expected that older adults may transition from driving to relying on other modes of transportation (i.e., driving cessation).

However, the opposite appears to be the case. Older drivers are choosing to keep their licenses for longer (Insurance Information Institute, 2018) The same NHTS report listed previously also indicated that the proportion of seniors that self-reported driving for at least one trip increased from 80% in 2009 to 82% in 2017 (NHTS, 2019). **Figure 4.25** illustrates the change in the proportions of licensed older drivers (those aged 65 and older) to all licensed drivers from 1999 to 2017. The figure clearly shows that this proportion has been increasing over time.

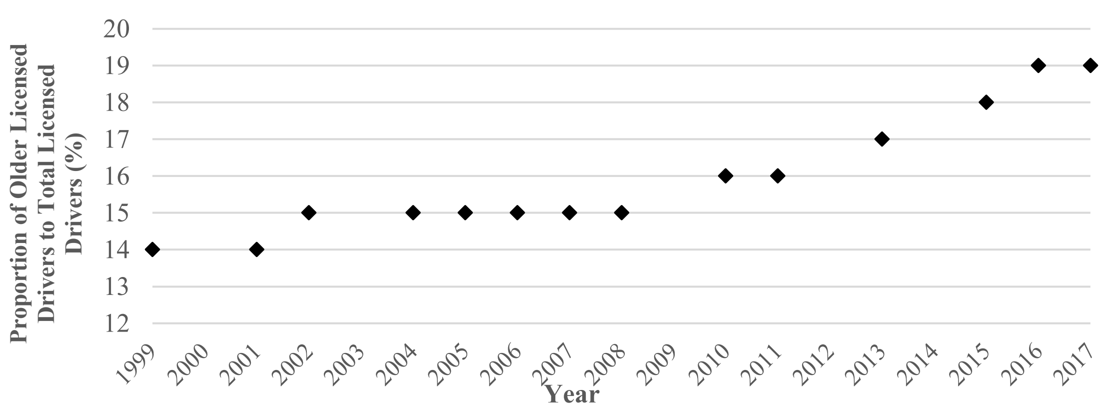

Figure 4.25: Proportions of older licensed drivers to total licensed drivers in the United States, 1999 to 2017 (NHTSA, 2011b, 2012, 2014, 2015, 2016b, 2017b, 2018b, 2019)

Given that older adults are associated with age-related impairments that inhibit their abilities of safely operating motor vehicles (such as declining eyesight and slower reaction times) (Dickerson et al., 2007; G. Li et al., 2017), they are often cited as posing as increased risks to other road users (Braver & Trempel, 2004; Dulisse, 1997). The relationship between driver age and pedestrian injury risk is examined in more detail in the injury severity analysis (section 6.3.2:).

Therefore, to control the risks posed by older drivers without sacrificing their freedom of mobility, interventions to ensure that older adults are physically capable of driving safely should be implemented. hese interventions may include imposing specific restrictions to drivers' licenses among older adults, such as driving only in daylight hours, distance restrictions from home, or speed limitations (Joyce et al., 2018). Moreover, roadway improvements that are more forgiving to older driver error and vehicle crash avoidance technologies may also be applied (NHTSA, 2013). These efforts aim to control the risk of traffic-related injury that older drivers pose and may reduce pedestrian fatalities in the future.

CHAPTER 5: PEDESTRIAN INJURY SEVERITY METHODOLOGY

In this chapter, the methodology used in analyzing pedestrian injury severities is described. The chapter begins with background information on the source of injury severity data. Next, the steps used to operationalize these data are discussed. Lastly, variable and model specifications are presented.

5.1: Pedestrian Injury Data

5.1.1: NASS-GES

The National Automotive Sampling System General Estimates System (NASS GES, hereinafter referred to as ‘G S ’) a s established in 988 a nd is structured around a nationally-representative sample of police-reported motor vehicle crashes within the United States. Unlike FARS, GES contains information on crashes of various severity levels. A record is considered valid for GES if the following criteria are met:

1. the subject crash involved at least one motor vehicle travelling along a public roadway,
2. the subject crash resulted in either property damage, personal injury, or death, and
3. a PAR was completed for the subject crash.

Given that the NASS GES is derived from a probability sample of PARs, national-level estimates are obtainable through nationally-representative weights. While this study will make extensive usage of these national-level estimates, the derivation of these weights is not discussed here; readers interested in the derivation of the national weights are advised to refer to the *GES Analytical User’s Manual* (NHTSA, 2016a). Relevant crash data are continuously monitored and checked for consistency. Personal data such as names, addresses, medical information, or vehicle registrations are not coded within GES.

Similar to FARS, GES uses crash, vehicle, and person files to form core datasets. These core datasets are used for the infrastructural analysis. However, the injury severity analysis made use of the *Drimpair*, *Nmimpair*, and *Nmcrash* non-core data files (as described previously in Table 3.1), as they contain several variables regarding road user (pedestrian and driver) impairment and pedestrian-related actions.

GES datasets are publicly available through an NHTSA file transfer protocol (FTP) website (ftp://ftp.nhtsa.dot.gov/GES). The datasets are available in several formats, including SAS and DBF. Unlike the demographics analysis and FARS, where the master dataset was pre-built, construction of the master GES dataset was undertaken concurrently with the time of the injury severity analysis.

5.1.2: Selection of Study Period

The injury severity analysis considers all severity levels listed in the KABCO injury severity scale. The timeframe of the injury severity analysis was restricted to the years 2011 through 2015 (i.e., five years of estimated injury data).

There are several reasons why this timeframe was chosen. Firstly, standardization of data elements between FARS and GES was undertaken in 2006 and was operational by 2010 (NHTSA, 2011a). During this standardization, definitions and attributes of FARS and GES variables were modified to those from the Model Minimum Uniform Crash Criteria (MMUCC) to simplify the coding process while minimizing costs and errors. Having a similar data structure between the two crash data systems improves the comparability of the two halves of this thesis. Secondly, GES was discontinued in 2016 and was replaced by the Crash Report Sampling System (CRSS). Fundamental differences between the two systems involve the methodology used for crash sampling. During the time of producing this thesis, it was determined that the

CRSS is not backward-compatible with GES data, meaning that there were no methods of comparing GES and CRSS data. By defining the study years from 2011 to 2015, the last five years of available GES data were utilized without needing to address any issues regarding data standardization.

5.1.3: Parameterizing Injury Data

For parameterizing GES data, the reference year was set at 2015, with the stacking process done in reverse-chronological order (2014 was added first, followed by 2013 and so on). A modified year index, *t*' is defined to differentiate bet e en the FA S and G S timelines

$$t' \in \mathbb{Z}: t' \in [2011,2015] \tag{5.1}$$

The corresponding GES data year index is *k*', and is mapped to *t*' by

$$k' = 2015 - t' \tag{5.2}$$

The compiling process began with assembling a data file stack for the reference year (i.e., 2015). File stacking was done similarly to FARS with the demographics analysis, where datasets from non-reference years were compared against the one from 2015 to examine the structure of variables. The stacking process for the GES dataset is illustrated in **Figure 5.1**.

5.2: Data Processing

5.2.1: Record Selection Criteria

To simplify the analysis only crashes with a single motor vehicle and a single pedestrian were examined. Crash events with multiple vehicles or pedestrians were not considered due to the associated challenges in file stacking. From the five years of data (2011 to 2015), a total of 10481[11] records meeting this criterion were identified. Each record represents a single crash event that contains information on the roadway, vehicle, driver, and pedestrian involved.

[11] When weighted, the total number of records equalled 331,996.

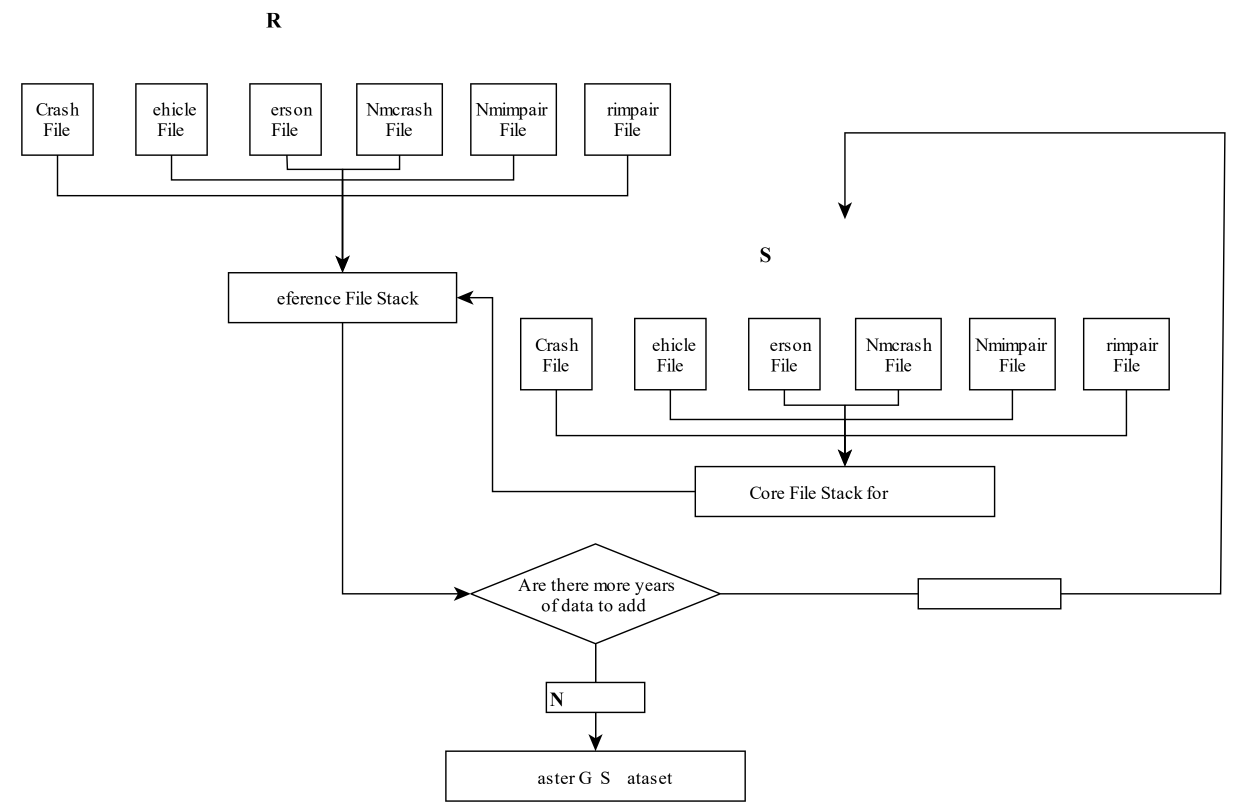

Figure 5.1: Overview of GES dataset development process through stacking.

5.2.2: Injury Severities

Injury severities within the master GES dataset were inputted according to the KABCO injury severity scale. To address issues from records with unknown injury severities, imputed severities were used for the analysis. **Table 5.1** contains the distribution of pedestrian injury records by injury severity defined using the KABC sc ale). his t able sho s that c ounts of ‘no apparent injury’ and ‘possible injury’ are relatively lo . As suc h, these t o categories e re combined to form the ‘no/possible injury’ category representing . pe rcent of valid pedestrian injury records. Furthermore, counts of ‘fatal injury’ ere also relatively lo a nd e re aggregated together ith the ‘incapacitating/serious injury’ records to create the ‘severe injury’ category consisting of 32.9 percent of valid records. Non-incapacitating/minor injuries composed 60.0

percent of data, while 0.7 percent of records had missing injury severity data. **Table 5.2** shows pedestrian injury counts by the aggregated severity groups used in the current analysis. In the current analysis, pedestrian injury severity is indexed by the symbol *j*.

Table 5.1: KABCO-based distribution of pedestrian injury severities from 2011-2015.

Pedestrian Injury Severity	**KABCO Code**	**Recorded**		**Imputed**	
		n	%	*n*	%
No Apparent Injury	**(O)**	37	0.4	51	0.5
Possible Injury	**(C)**	615	5.9	618	5.9
Non-Incapacitating/Minor Injury	**(B)**	6285	60.0	6286	60.0
Incapacitating/Serious Injury	**(A)**	2910	27.8	2912	27.8
Fatal Injury	**(K)**	537	5.1	537	5.1
Injured, Severity Unknown	**(U)**	75	0.7	77	0.7
Unknown		22	0.2	N/A	N/A
Total		10481	100.0	10481	100.0

Table 5.2: Distribution of pedestrian injury severities in injury severity analysis.

Pedestrian Injury Severity	*j*	*n*	%
No/Possible Injury	1	669	6.4
Non-Incapacitating/Minor Injury	2	6286	60.4
Severe Injury	3	3449	33.2
Total		10404	100.0

5.2.3: Variable Derivation

he G S Analytical User’s anua l and Coding & a lidation a nual e re referenced to compile a tentative list of data elements to consider. Based on existing literature, six explanatory variable categories were defined: pedestrian, driver, crash, environment, vehicle, and roadway infrastructure. Land use variables were not available within GES.

A syntax script was written to derive 21 variables for the current analysis. All but four of the factors were coded as categorical. Age (pedestrian and driver) and speed (travel speed and posted speed limit) variables were coded as continuous data. **Table 5.3** and **Table 5.4** contain descriptive statistics for the continuous variables and the categorical variables by injury severity, respectively. The percentages listed to the right of each count by injury severity are relative of the total number of records for that variable.

Table 5.3: Descriptive statistics for continuous variables.

Predictor Variable	Valid *n*	Missing	Mean	S.D.	Minimum	Maximum
Pedestrian Age (years)	10075 (96.13)	406 (3.87%)	36.97	21.07	0	96
Driver Age (years)	8333 (79.51%)	2148 (20.49%)	43.06	17.37	12	100
Travel Speed (mph)	2776 (26.49%)	7705 (73.51%)	22.02	14.63	0	99
Posted Speed Limit (mph)	7680 (73.3%)	2801 (22.70%)	32.92	9.27	5	75

Figure 5.2 and **Figure 5.3** illustrate the frequency distributions of pedestrian and driver age by injury severity, respectively. Moreover, **Figure 5.4** and **Figure 5.5** show the frequency distributions for recorded travel speeds and posted speed limits, accordingly. Note that for Figures 5.2 through 5.5, the scales of the vertical axes on the no/possible injury record graphs are smaller (by a factor of one-third) than for non-severe and severe injuries. This was done to provide enhanced visual clarity of the distribution of GES records by speed.

Table 5.4: Pedestrian injury counts and percentage distributions by categorical predictor variable and injury severity category.

Predictor Variable	No/Possible Injury		Non-Severe Injury		Severe Injury		Total	
Pedestrian Sex	664	6.40%	6266	60.42%	3440	33.17%	10370	
Male	361	3.48%	3531	34.05%	2177	20.99%	6069	58.52%
Female	303	2.92%	2735	26.37%	1263	12.18%	4301	41.48%
Pedestrian Impairment	537	6.99%	4820	62.71%	2329	30.30%	7686	
Impaired	16	0.21%	317	4.12%	324	4.22%	657	8.55%
No apparent impairment	521	6.78%	4503	58.59%	2005	26.09%	7029	91.45%
Pedestrian Action	585	6.24%	5720	60.97%	3076	32.79%	9381	
Unsafe pedestrian action reported	188	2.00%	2547	27.15%	1852	19.74%	4587	48.90%
No improper action noted	397	4.23%	3173	33.82%	1224	13.05%	4794	51.10%
Driver Sex	582	6.52%	5362	60.10%	2978	33.38%	8922	
Male	392	4.39%	3220	36.09%	1941	21.76%	5553	62.24%
Female	190	2.13%	2142	24.01%	1037	11.62%	3369	37.76%
Driver Impairment	520	6.46%	4765	59.21%	2763	34.33%	8048	
Impaired[2]	12	0.15%	92	1.14%	125	1.55%	229	2.85%
No apparent impairment	508	6.31%	4673	58.06%	2638	32.78%	7819	97.15%
Driver Movement	549	6.02%	5487	60.19%	3080	33.79%	9116	
Turning Left	188	2.06%	1488	16.32%	494	5.42%	2170	23.80%
Turning Right	82	0.90%	700	7.68%	200	2.19%	982	10.77%
Through / Straight	279	3.06%	3299	36.19%	2386	26.17%	5964	65.42%

Table 5.4: Pedestrian injury counts and percentage distributions by categorical predictor variable and injury severity category (continued).

Crash Hour	662	6.42%	6224	60.33%	3430	33.25%	10316	
Afternoon	269	2.61%	2376	23.03%	964	9.34%	3609	34.98%
Evening	191	1.85%	2011	19.49%	1385	13.43%	3587	34.77%
Morning	163	1.58%	1431	13.87%	667	6.47%	2261	21.92%
Overnight	39	0.38%	406	3.94%	414	4.01%	859	8.33%
Crash Day*	668	6.45%	6253	60.33%	3443	33.22%	10364	
Weekend[3]	122	1.18%	1554	14.99%	1011	9.75%	2687	25.93%
Weekday	546	5.27%	4699	45.34%	2432	23.47%	7677	74.07%
Crash Season	669	6.43%	6286	60.42%	3449	33.15%	10404	
Winter	187	1.80%	1607	15.45%	945	9.08%	2739	26.33%
Fall	215	2.07%	1754	16.86%	994	9.55%	2963	28.48%
Spring	136	1.31%	1548	14.88%	806	7.75%	2490	23.93%
Summer	131	1.26%	1377	13.24%	704	6.77%	2212	21.26%
Crash Location	551	5.95%	5553	59.98%	3154	34.07%	9258	
Midblock Location	262	2.83%	2782	30.05%	1941	20.97%	4985	53.85%
3-/4- leg intersection	289	3.12%	2771	29.93%	1213	13.10%	4273	46.15%
Light Condition	666	6.48%	6219	60.48%	3398	33.04%	10283	
Dark, unlit	33	0.32%	458	4.45%	470	4.57%	961	9.35%
Dark, artificially lit	176	1.71%	1683	16.37%	1279	12.44%	3138	30.52%
Daylight	457	4.44%	4078	39.66%	1649	16.04%	6184	60.14%

Table 5.4: Pedestrian injury counts and percentage distributions by categorical predictor variable and injury severity category (continued).

Surface Condition	632	6.36%	5965	59.99%	3346	33.65%	9943	
Adverse	135	1.36%	985	9.91%	529	5.32%	1649	16.58%
Dry	497	5.00%	4980	50.09%	2817	28.33%	8294	83.42%
Traffic Control Device	627	6.36%	5957	60.40%	3279	33.25%	9863	
No traffic control device	321	3.25%	3384	34.31%	2277	23.09%	5982	60.65%
Regulatory sign	51	0.52%	515	5.22%	206	2.09%	772	7.83%
Traffic signal	255	2.59%	2058	20.87%	796	8.07%	3109	31.52%
Vehicle Type	614	6.45%	5744	60.36%	3159	33.19%	9517	
Trucks	182	1.91%	1268	13.32%	833	8.75%	2283	23.99%
Utility Vehicles	94	0.99%	1052	11.05%	550	5.78%	1696	17.82%
Automobiles	338	3.55%	3424	35.98%	1776	18.66%	5538	58.19%
Roadway Alignment	596	6.37%	5537	59.22%	3217	34.41%	9350	
Horizontal Curvature	8	0.09%	133	1.42%	102	1.09%	243	2.60%
Straight Roadway	588	6.29%	5404	57.80%	3115	33.32%	9107	97.40%
Roadway Profile	523	6.53%	4725	58.98%	2763	34.49%	8011	
Vertical Curvature	35	0.44%	465	5.80%	344	4.29%	844	10.54%
Level Roadway	488	6.09%	4260	53.18%	2419	30.20%	7167	89.46%
Median Type	321	4.39%	4307	58.94%	2680	36.67%	7308	
No median/undivided	248	3.39%	2975	40.71%	1605	21.96%	4828	66.06%
Painted median	44	0.60%	914	12.51%	690	9.44%	1648	22.55%
Raised/physical median	29	0.40%	418	5.72%	385	5.27%	832	11.38%

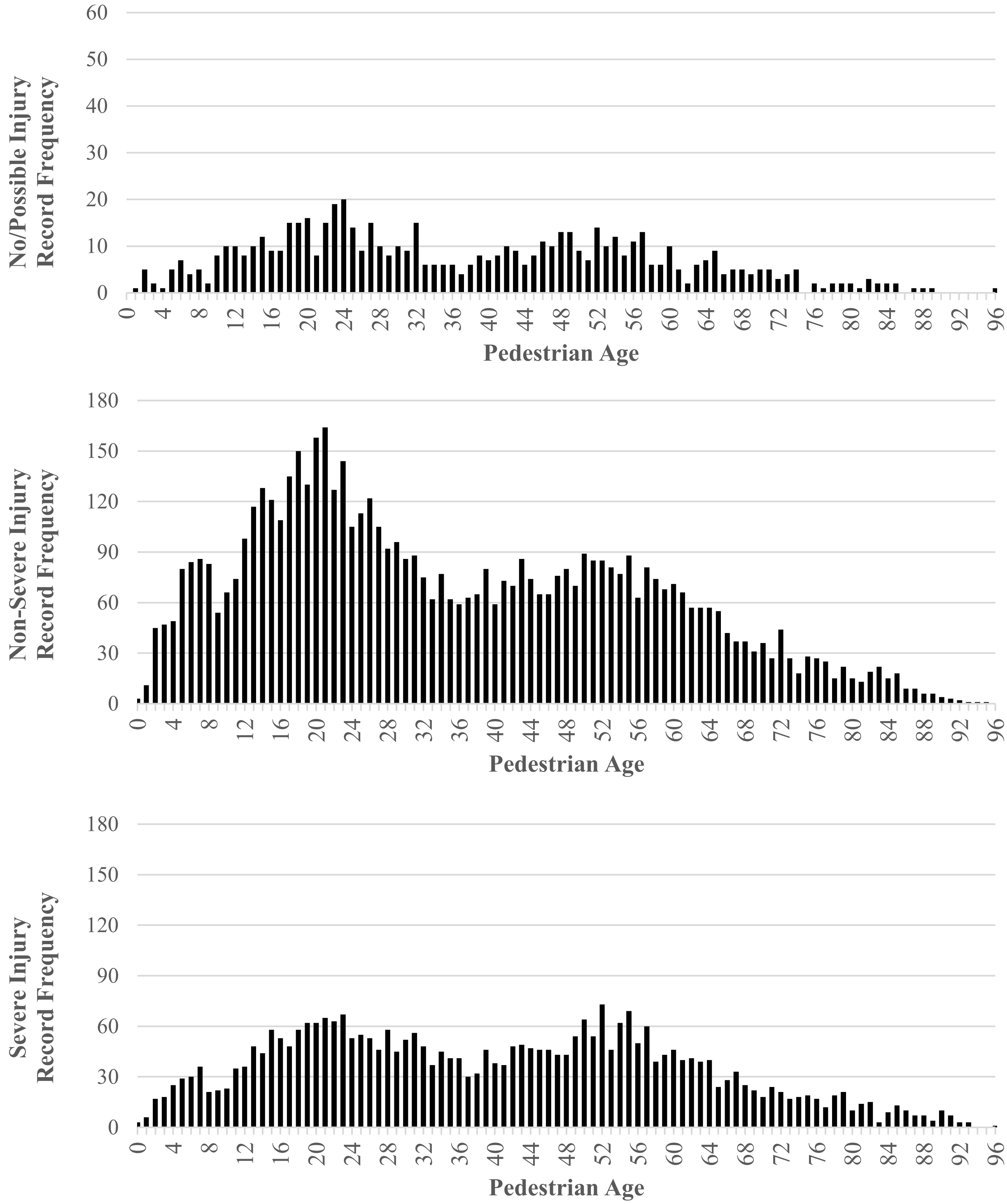

Figure 5.2: Pedestrian injury frequency distributions by pedestrian age for no/possible injuries (top graph), non-severe injuries (middle graph) and severe injuries (bottom graph).

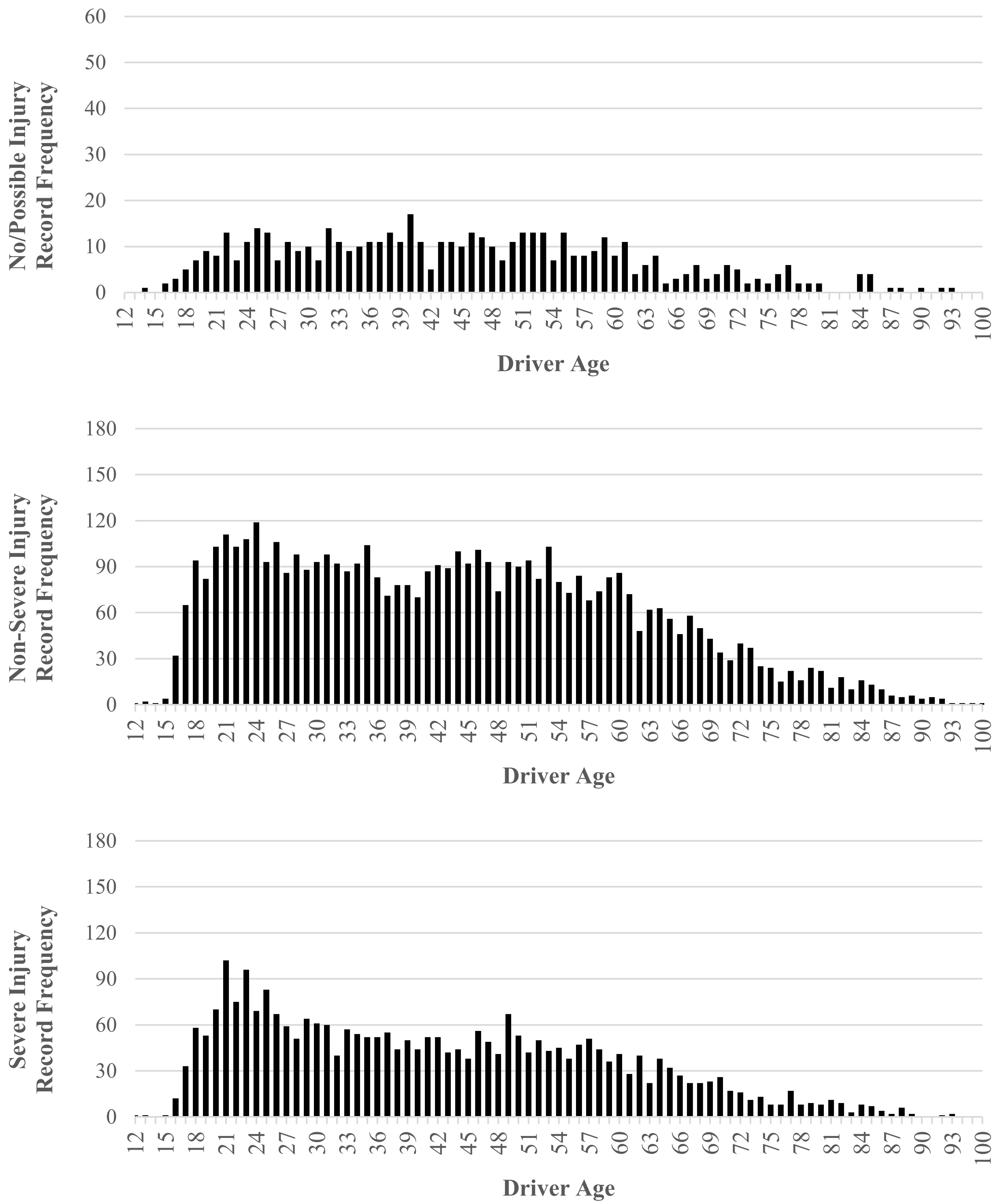

Figure 5.3: Pedestrian injury frequency distributions by driver age for no/possible injuries (top graph), non-severe injuries (middle graph) and severe injuries (bottom graph).

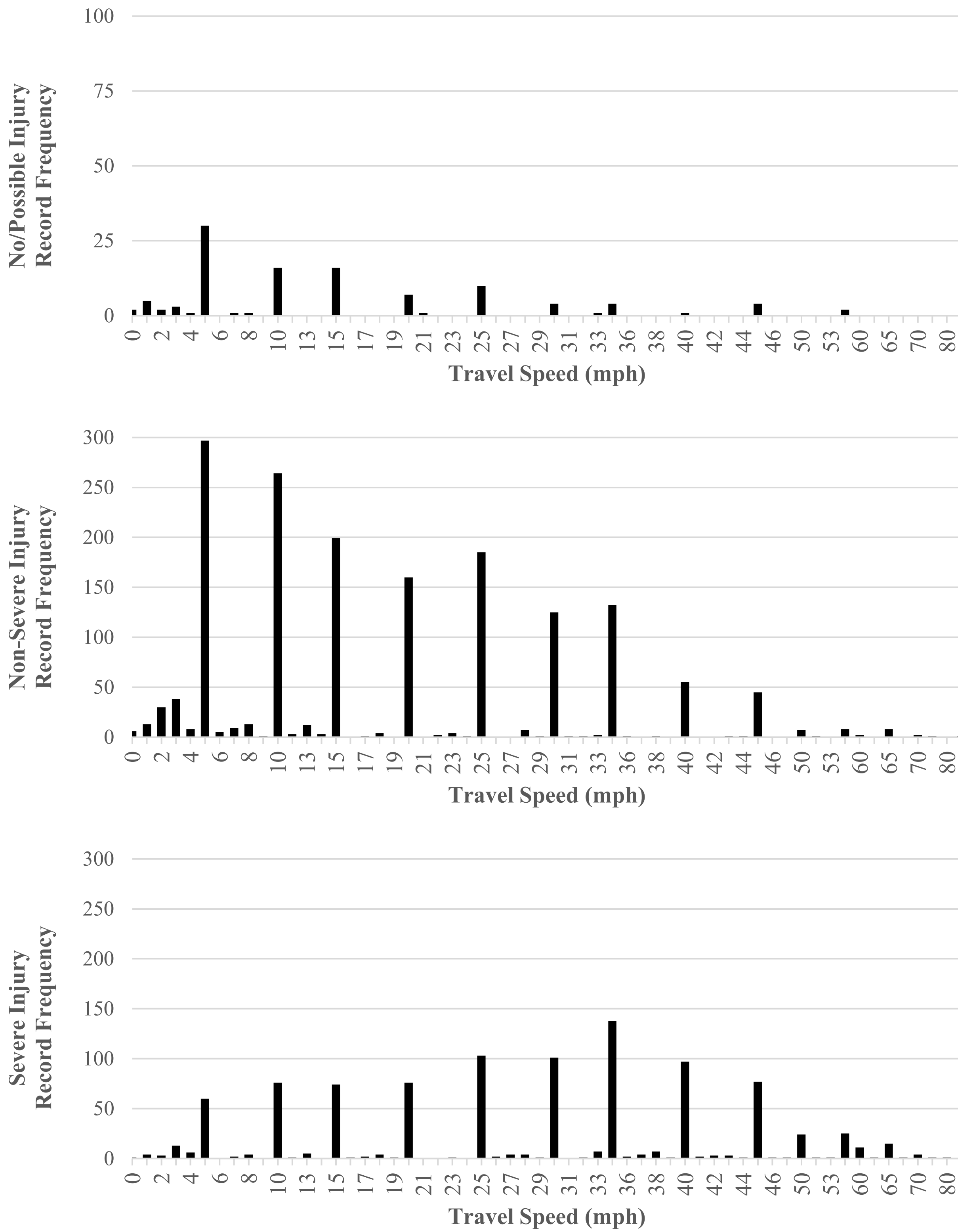

Figure 5.4: Pedestrian injury frequency distributions by recorded travel speed for no/possible injuries (top graph), non-severe injuries (middle graph) and severe injuries (bottom graph).

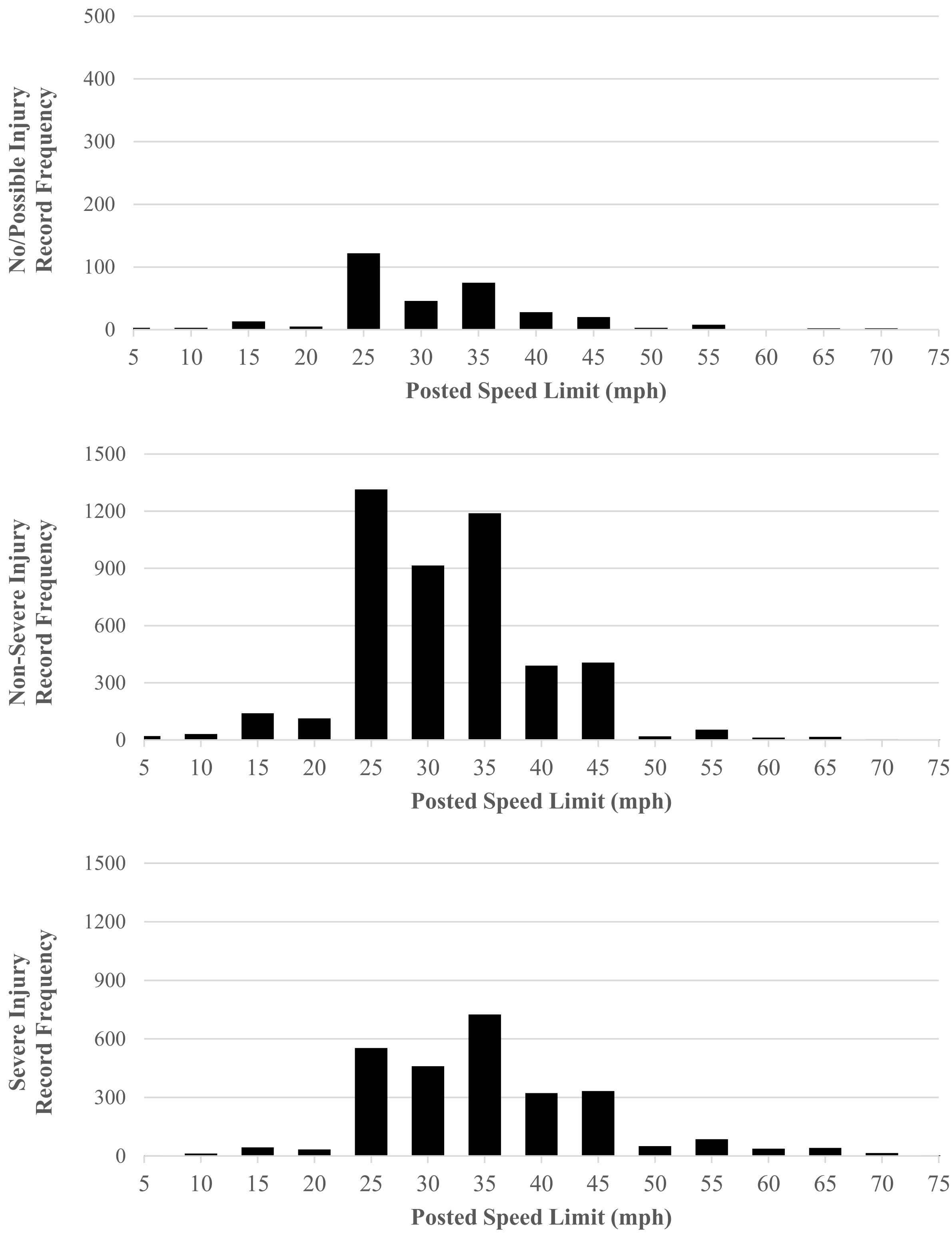

Figure 5.5: Pedestrian injury frequency distribution by recorded posted speed limit for no/possible injuries (top graph), non-severe injuries (middle graph), and severe injuries (bottom graph).

5.3: Multinomial Logistic Regression

5.3.1: Model Specification

The process of MNL regression requires that at least three discrete categories are defined for the dependent/outcome variable (i.e., pedestrian injury severity). Let π_{ij} represent the probability that pedestrian record *i* has a recorded injury severity *j*:

$$\pi_{ij} \equiv \mathrm{P}(j = j), j = 1, 2, 3 \tag{5.3}$$

A fundamental rule of the outcome probabilities is that for each pedestrian injury record, the probabilities must sum to one:

$$\sum_{j=1}^{3} \pi_{ij} = \pi_{i1} + \pi_{i2} + \pi_{i3} = 1 \tag{5.4}$$

To address redundancy associated with MNL regression, one outcome category must be designated as a reference. For the current analysis, the first category (no/possible injury) was defined as the reference category (denoted as j^*). All other severity levels were compared to ‘no/possible injury.’ he selection of the reference category ill not affect the overall fit of the MNL model (Amoh-Gyimah et al., 2017), but the interpretation of results are subject to change. Comparisons were made through odds, which were defined as the ratio of the probability of a record having a given non-reference injury severity to the probability of the same record not having the referent injury severity:

$$O_{ij} = \frac{\pi_{ij}}{1 - \pi_{ij}} \tag{5.5}$$

where,

O_{ij} = the odds of pedestrian record *i* having an injury of severity *j*.

A general logit function, which represents the log-odds of a pedestrian injury record having a specified injury severity, is defined next:

$$\text{logit}(\pi_{ij}) = \ln(O_{ij}) = \ln\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) \tag{5.6}$$

In a MNL model, the logit is assumed to be equated to a linear function which contains L regressors:

$$\text{logit}(\pi_{ij}) = \alpha_j + \beta_{j1}x_{i1} + \beta_{j2}x_{i2} + \cdots + \beta_{jL}x_{iL} = \alpha_j + \boldsymbol{\beta}_{jl}\mathbf{X}_{il}^{\mathrm{T}} \tag{5.7}$$

where,

α_j = an intercept term,

l = the regressor index,

$\boldsymbol{\beta}$ = a set of estimable parameters associated with regressor l, and

$\mathbf{X}^{\mathrm{T}}$ = a set of observed predictor variables to be used in regression.

The set of estimated parameters, $\boldsymbol{\beta}$, takes the form of a l x 1 matrix. To allow for matrix multiplication, the l x 1 vector of predictor variables, $\mathbf{X}$, must be transposed (hence the superscript T). Solving Equation (5.7) for π_{ij} provides the basis for the multinomial logistic distribution:

$$\begin{aligned} P(j = j|\mathbf{X}) &= \frac{\exp(\alpha_j + \boldsymbol{\beta}_{jl}\mathbf{X}_{il}^{\mathrm{T}})}{1 + \sum_j \exp(\alpha_j + \boldsymbol{\beta}_{jl}\mathbf{X}_{il}^{\mathrm{T}})}, j \neq j^* \\ P(j = j^*|\mathbf{X}) &= \frac{1}{1 + \sum_j \exp(\alpha_j + \boldsymbol{\beta}_{jl}\mathbf{X}_{il}^{\mathrm{T}})} \end{aligned} \tag{5.8}$$

Additional algebraic manipulation and contextualization to Equation (5.8) gives the following:

$$\begin{aligned} \ln\left(\frac{\pi_{i3}}{\pi_{i1}}\right) &= \alpha_3 + \boldsymbol{\beta}_{3k}\mathbf{X}_{il}^{\mathrm{T}} \\ \ln\left(\frac{\pi_{i2}}{\pi_{i1}}\right) &= \alpha_2 + \boldsymbol{\beta}_{2k}\mathbf{X}_{il}^{\mathrm{T}} \end{aligned} \tag{5.9}$$

where $\left(\frac{\pi_{i3}}{\pi_{i1}}\right)$ and $\left(\frac{\pi_{i2}}{\pi_{i1}}\right)$ represent the relative risk ratios between severe or non-severe injuries and no/possible injuries, respectively.

Equation (5.9) shows that the regression parameters, $\boldsymbol{\beta}$, represent the effect on the log-odds of association in injury severity category j and the reference group. Therefore, the objective of multinomial logistic regression is to determine values for the regression coefficient vector $\boldsymbol{\beta}$ for all parameters. If J represents the total number of severity categories defined, a total of $((J-1)(l+1))$ parameters are to be estimated. To obtain parameter estimates, maximum likelihood estimation (MLE) is used. This process determines the coefficients that maximize the likelihood of the recorded injury severity occurring. The log likelihood function to be maximized is (Czepiel, 2002):

$$\mathcal{L}(\boldsymbol{\beta}) = \sum_{i=1}^{N} \sum_{j \neq j^*} \left(y_{ij} * \boldsymbol{\beta}_{jk} \mathbf{X}_{il}\right) - n_i log\left(1 + \sum_{j \neq j^*} e^{\boldsymbol{\beta}_{jl} \mathbf{X}_{il}}\right) \tag{5.10}$$

The MLE method is not described in detail here as the process is relatively complex and typically warrants the use of a numerical method, such as the Newton-Raphson method. MNL model parameters were estimated via MLE using a syntax script utilizing the NOMREG procedure in SPSS V25.

5.3.2: Interpretation

Let m represent the index for predictor variable l's possible attributes. For each categorical predictor variable, one attribute is designated as the referent (denoted as m^*). Referents were hypothesized to be the attributes which represent the safest conditions for pedestrians (e.g., not impaired, presence of traffic signal, dry road surface conditions). In this sense, all other attributes are treated as 'changes' to the referent.

he influence of a variable attribute's effect on injury severity hen compared to the referent) is reflected by an odds ratio[12], which represents the change in odds after the predictor variable is incremented by one:

$$\mathrm{OR}_{jm} = \frac{O_{ijlm}}{O_{ijlm^*}}, m \neq m^* \tag{5.11}$$

where,

m^* = the referent attribute for predictor variable k, and

OR_{jm}= an indicator of the change in odds for an injury severity j induced by a change in the predictor variable l.

As a predictor variable l is changed, the respective odds for injury severity j are magnified by a factor of $e^{\beta_{jl}}$. Given that the definitions of the regression coefficients and odds ratios both describe the change in log-odds after a unit change of a predictor variable, they can be equated:

$$\mathrm{OR}_{jlm} = \exp\left(\beta_{jlm}\right) \tag{5.12}$$

Odds ratios larger than one imply that the subject attribute contributes to higher odds of an injury of severity j when compared to the referent attribute. Conversely, odds ratios less than one indicate that the subject attribute is associated with decreased odds (i.e., a protective effect) of an injury with severity j.

For continuous variables, several modifications have been made to improve the interpretability of odds ratios, since there is no apparent referent attribute. Based from past literature (Kröyer, 2015; Regev et al., 2018), the age-related variables considered in the current study (i.e., pedestrian age and driver age) were presumed to have a curvilinear relationship with

[12] A formal definition for odds ratio is "a measure of association bet e en an exposure and an outcome." (Szumilas, 2010). n this sense, 'an exposure' is any non-referent condition that is presumed to be attributable to higher pedestrian injury severities.

pedestrian injury. Therefore, curvature is allowed by implementing a second-order polynomial interaction term for each continuous predictor variable. However, doing so induces collinearity within the model, which will likely produce misleading results. To address this issue of collinearity, the continuous variables are centred on relevant values before computing their squared variants (Tabachnick & Fidell, 2013). Variable centring is considered helpful in cases where continuous variables do not have a meaningful value of zero, such as age or speed. Further, given that odds ratios describe the change in odds caused by a unit increase of the predictor, scale adjustments specific to each continuous variable were applied. **Table 5.5** summarizes the adjustments made to continuous variables.

Table 5.5: Summary of modifications to continuous variables.

Variable	Modified Variable	Rationale
Pedestrian Age (PED_AGE)	$\text{PED\_AGE\_MOD} = \frac{(\text{PED\_AGE} - 10)}{5}$	Previous research has suggested that children around the age of 10 have sufficient physical and cognitive abilities for unsupervised walking (National Center for Safe Routes to School, 2008). Therefore, pedestrian age is centred on age 10, with a scale adjustment represent 5-year unit increases.
Driver Age (DRV_AGE)	$\text{DRV\_AGE\_MOD} = \frac{(\text{DRV\_AGE} - 16)}{5}$	Graduated driver licensing information from the IIHS[13] indicates that on average, the minimum age for unsupervised driving is 16 in the United States (Witmer, 2019). As such, driver age is centred around 16 years of age with a scale adjustment to represent 5-year unit increases.
Travel Speed (SPEED)	$\text{SPEED\_MOD} = \frac{(\text{SPEED} - 30)}{5}$	Multiple studies have demonstrated that pedestrian fatality risk begins to significantly increase at impact speeds of approximately 30 mph (G. Davis, 2001; B. S. Roudsari et al., 2004; Tefft, 2013). Moreover, the choice to define unit increments of 5 mph is justified as posted speed limits follow a similar structure.
Posted Speed Limit (SPDLIM)	$\text{SPDLIM\_MOD} = \frac{(\text{SPDLIM} - 30)}{5}$	

[13] IIHS: Insurance Institute for Highway Safety

To evaluate the relationship between roadway infrastructure and pedestrian injury severity, a sequential block-wise regression entry method of predictor variables was adopted. In this method, the arrangement of predictors and order of entry into the model is user-specified. Regressor variables known to be influential (based on literature) are entered first, followed by additional variables to be investigated. For the injury severity analysis, two blocks of variables were defined. The first block consisted of non-roadway-related variables based on previous studies. The second block was composed of various roadway infrastructural factors (RIFs). Variables were excluded from block-wise entry if previous research suggested little to no relationship with pedestrian injury severity, or the data from the master GES dataset did not support the consideration of the subject variable (i.e., sample sizes were sufficiently small).

Two models were fitted using MNL regression. The first model, referred to as the baseline model, contains the explanatory variables from block 1. The second model, referred to as the full model, contains the variables from the baseline model, as well as the RIFs. The organization of variable blocks and models is illustrated in **Figure 5.6**.

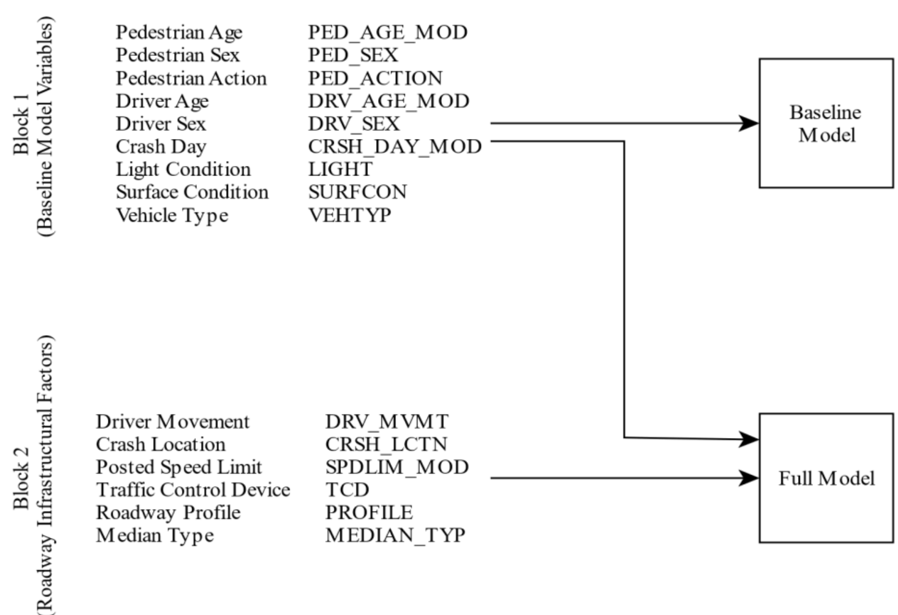

Figure 5.6: Organizational layout of variable blocks and MNL models.

Collinearity was first assessed by examining correlation coefficients (R) from a bivariate correlation matrix. However, this method only considers two variables at a time and does not consider correlations of higher complexity, such as between three or more variables (Akinwande et al., 2015). This is referred to as multicollinearity. Potential issues of multicollinearity were detected by computing variance inflation factors (VIFs) for each predictor variable. A VIF is a metric indicating how much the estimated regression coefficient has inflated by collinearities from the other predictor variables. VIFs are calculated using the following equation:

$$\mathrm{VIF}_k = \frac{1}{1 - R_m^2} \tag{5.13}$$

where,

R_m^2 = the multiple correlation coefficient between predictor variable *m* and all other predictor variables.

As correlations between predictor variables decrease (i.e., R_m^2 approaches zero), the denominator of Equation (5.13) (and subsequently, the VIF) approaches one. A general rule of thumb regarding VIFs is that values larger than 10.0 are indicative of multicollinearity (Akinwande et al., 2015; Mansfield & Helms, 1982; Miles & Shevlin, 2001). Additionally, Bo e rman & ’ Connell (1994) suggested that the output of a regression analysis may be deemed unreliable if the average VIF is substantially larger than 1.00. VIFs for the regressors are tabulated in **Table 5.6**. The results shown in the aforementioned table indicate that model multicollinearity is not problematic.

Table 5.6: Variance inflation factors for the predictor variables considered in regression.

Predictor Variable	VIF	
	Baseline Model	Full Model
Pedestrian Age	1.080	1.148
Pedestrian Sex	1.036	1.059
Pedestrian Action	1.114	1.477
Driver Age	1.023	1.037
Driver Sex	1.050	1.061
Crash Day	1.025	1.039
Light Conditions	1.081	1.193
Surface Conditions	1.029	1.031
Vehicle Type	1.045	1.059
Driver Movement	N/A	1.944
Crash Location	N/A	2.174
Posted Speed Limit	N/A	1.360
Traffic Control Device	N/A	2.117
Roadway Profile	N/A	1.010
Median Type	N/A	1.234
Average	1.054	1.330

5.4: Model Evaluation

This section describes the various metrics considered when evaluating the baseline and full models. Two model evaluation procedures were adopted: a likelihood-ratio hypothesis test and the determination of Akaike information criterion (AIC) and Bayesian information criterion (BIC) values. The following subsections describe each of these in greater detail.

5.4.1: Likelihood-Ratio Tests

As a first step, the goodness-of-fit for the baseline and full models was evaluated using likelihood-ratio statistic tests (LRTs). An LRT involves the determination of the difference between two deviance values corresponding to two different models. The null hypothesis of an LRT is that a null/reduced model provides a better fit for the given data when compared to a larger, alternative model. The test statistic, χ^2, is chi-square distributed with degrees of freedom, df_{χ^2}, equal to the difference in degrees of freedom of the two models being compared. The LRT statistic and the required degrees of freedom are, therefore, calculated as:

$$\chi^2 = (-2\mathrm{LL}_0) - (-2\mathrm{LL}_a) \tag{5.14}$$

$$df_{\chi^2} = s_a - s_0 \tag{5.15}$$

where,

LL_0 = the log-likelihood of a null model,

s_0 = the number of parameters within the null model,

LL_a = the log-likelihood of an alternative model, and

s_a = the number of parameters within the alternative model.

To bring LRTs into context, the test can be undertaken in two ways. First, the baseline or full models can be inspected individually. In this sense, the null model corresponds to a situation in which the only parameter to be estimated is the intercept term (α). Conversely, the alternative model contains all relevant variables for the respective model. As a result, the degrees of freedom from using this perspective is equal to the number of parameters in the alternative model minus one, since the null model only has a single degree of freedom (i.e., the intercept term). The second perspective is to compare the baseline and full models simultaneously by considering the baseline model as the null and the full model as the alternative. Both of these perspectives have been considered, and the results of such are shown in the next chapter.

5.4.2: Akaike and Bayesian Information Criteria

To supplement the results of the LRTs, AIC and BIC values were also calculated to quantitatively assess the fit of the baseline and full multinomial logit models. AIC values were computed using Equation (3.21) for null and alternative models, considering the two perspectives discussed previously. A description of AIC can be found in section 3.4.4. BIC, also known as Sch a rz's Bayesian criterion (Schwarz, 1978), was calculated in a similar manner to AIC:

$$BIC = (-2\text{LL}) + s * ln(n) \tag{5.16}$$

where,

LL = the log-likelihood of the subject model at maximum likelihood,

s = the number of parameters within the subject model, and

n = the sample size (i.e., the number of observations) utilized to develop the subject model.

It can be seen that BIC has a positive relationship with the number of parameters in the subject model as well as the number of observations used in the model.

CHAPTER 6: SEVERITY MODEL ESTIMATION RESULTS

This chapter presents the results of the injury severity analysis. In the first section, results from the univariable analyses are presented. The following two sections contain the results from the baseline and full multivariable multinomial logit models. The last section in this chapter summarizes the findings from the injury severity analysis regarding RIFs. The last section also discusses potential engineering countermeasures for pedestrian injuries.

6.1: Univariable Model Estimation Results

Table 6.1 contains the results from the univariable MNL regression models, which include values for parameter estimates, unadjusted odds ratios, and 95% confidence intervals. Only minor inferences are made, given the univariable results do not consider the effects of other factors. For RIFs, univariable analysis results are provided in section 6.4:

6.1.1: Pedestrian Factors in Univariable Analysis

Pedestrian age was statistically significant for both non-severe and severe injuries at $p < 0.001$. For non-severe injuries, the odds ratio for pedestrian age was 0.86. This essentially represents a protective effect for a 5-year age increase from age 10 to age 15. However, this protective effect was removed when the squared variant of pedestrian age was considered, as the corresponding odds ratio was 1.01. Regarding severe injuries, the unadjusted odds ratios for pedestrian age and pedestrian age-squared were relatively close to one (0.96 and 1.00, respectively), suggesting that pedestrian age alone did not have a discernible effect on the odds of a severe pedestrian injury.

Table 6.1: Univariable logistic model estimation results.

Predictor Variable	Non-Severe Injury					Severe Injury				
	β	S.E.	p	Unadjusted OR	95% CI	β	S.E.	p	Unadjusted OR	95% CI
Pedestrian Age										
Modified	-0.147	0.003	< 0.001	0.86	(0.86 - 0.87)	-0.045	0.004	< 0.001	0.96	(0.95 - 0.96)
Modified-Squared	0.009	0.000	< 0.001	1.01	(1.01 - 1.01)	0.005	0.000	< 0.001	1.00	(1.00 - 1.01)
Pedestrian Sex										
Male	0.201	0.008	< 0.001	1.22	(1.20 - 1.24)	0.479	0.010	< 0.001	1.61	(1.58 - 1.64)
Female*	0			1.00		0			1.00	
Pedestrian Impairment										
Impaired	1.053	0.023	< 0.001	2.87	(2.74 - 3.00)	1.794	0.023	< 0.001	6.02	(5.75 - 6.29)
No apparent impairment*	0			1.00		0			1.00	
Pedestrian Action										
UPA reported	0.569	0.009	< 0.001	1.77	(1.74 - 1.80)	1.208	0.010	< 0.001	3.35	(3.28 - 3.41)
No UPAs reported*	0			1.00		0			1.00	
Driver Age										
Modified	-0.165	0.004	< 0.001	0.85	(0.84 - 0.86)	-0.221	0.005	< 0.001	0.80	(0.79 - 0.81)
Modified & Squared	0.010	0.000	< 0.001	1.01	(1.01 - 1.01)	0.013	0.000	< 0.001	1.01	(1.01 - 1.01)
Driver Sex										
Male	-0.272	0.009	< 0.001	0.76	(0.75 - 0.78)	-0.093	0.010	< 0.001	0.91	(0.89 - 0.93)
Female*	0			1.00		0			1.00	

Table 6.1: Univariable logistic model estimation results (continued).

Predictor Variable	β	S.E.	p	Unadjusted OR	95% CI	β	S.E.	p	Unadjusted OR	95% CI
Driver Impairment										
Impaired	0.073	0.031	0.020†	1.08	(1.01 - 1.14)	1.010	0.028	< 0.001	2.74	(2.60 - 2.90)
No apparent impairment*	0			1.00		0			1.00	
Driver Movement										
Turning left	-0.559	0.010	< 0.001	0.57	(0.56 - 0.58)	-1.387	0.013	< 0.001	0.25	(0.24 - 0.26)
Turning right	-0.424	0.013	< 0.001	0.65	(0.64 - 0.67)	-1.305	0.018	< 0.001	0.27	(0.26 - 0.28)
Through / Straight*	0			1.00		0			1.00	
Crash Hour										
Afternoon	-0.139	0.018	< 0.001	0.87	(0.84 - 0.90)	-1.034	0.018	< 0.001	0.36	(0.34 - 0.37)
Evening	0.087	0.018	< 0.001	1.09	(1.05 - 1.13)	-0.339	0.017	< 0.001	0.71	(0.69 - 0.74)
Morning	-0.116	0.018	< 0.001	0.89	(0.86 - 0.92)	-0.915	0.019	< 0.001	0.40	(0.39 - 0.42)
Overnight*	0			1.00		0			1.00	
Crash Day[14]										
Weekend	0.434	0.010	< 0.001	1.54	(1.51 - 1.57)	0.551	0.011	< 0.001	1.73	(1.70 - 1.77)
Weekday*	0			1.00		0			1.00	
Crash Season										
Winter	-0.349	0.012	< 0.001	0.71	(0.69 - 0.72)	-0.185	0.013	< 0.001	0.83	(0.81 - 0.85)
Fall	-0.296	0.012	< 0.001	0.74	(0.73 - 0.76)	-0.314	0.013	< 0.001	0.73	(0.71 - 0.75)
Spring	-0.098	0.012	< 0.001	0.91	(0.88 - 0.93)	-0.167	0.014	< 0.001	0.85	(0.82 - 0.87)
Summer*	0			1.00		0			1.00	

[14] Weekends were modified to include the hours of 8:00 p.m. Friday – 8 p.m. Sunday, to reflect " e ekend leisure/nightline alk ing."

Table 6.1: Univariable logistic model estimation results (continued).

Predictor Variable (k)	β	S.E.	p	Unadjusted OR	95% CI	β	S.E.	p	Unadjusted OR	95% CI
Crash Location										
Midblock	0.270	0.009	< 0.001	1.31	(1.29 - 1.33)	0.705	0.010	< 0.001	2.02	(1.99 - 2.07)
3-/4- leg Intersection*	0			1.00		0			1.00	
Travel Speed										
Modified	0.080	0.004	< 0.001	1.08	(1.08 - 1.09)	0.321	0.004	< 0.001	1.38	(1.37 - 1.39)
Modified & Squared	-0.017	0.001	< 0.001	0.98	(0.98 - 0.98)	-0.024	0.001	< 0.001	0.98	(0.97 - 0.98)
Posted Speed Limit										
Modified	0.047	0.003	< 0.001	1.05	(1.05 - 1.06)	0.231	0.004	0.000	1.26	(1.22 - 1.23)
Modified & Squared	-0.003	0.001	< 0.001	1.00	(0.99 - 1.00)	-0.001	0.001	0.275‡	0.99	(1.00 - 1.01)
Light Condition										
Dark, Unlit	0.469	0.016	< 0.001	1.60	(1.55 - 1.65)	1.451	0.016	< 0.001	4.27	(4.13 - 4.40)
Dark, Artificially Lit	0.055	0.009	< 0.001	1.06	(1.04 - 1.08)	0.646	0.010	< 0.001	1.91	(1.87 - 1.95)
Daylight*	0			1.00		0			1.00	
Surface Condition										
Adverse	-0.333	0.011	< 0.001	0.72	(0.70 - 0.73)	-0.401	0.012	< 0.001	0.67	(0.65 - 0.69)
Dry*	0			1.00		0			1.00	
Traffic Control Device										
No traffic control device	0.453	0.009	< 0.001	1.57	(1.55 - 1.60)	0.935	0.011	< 0.001	2.55	(2.49 - 2.60)
Regulatory sign	0.357	0.016	< 0.001	1.43	(1.38 - 1.47)	0.378	0.020	< 0.001	1.46	(1.40 - 1.52)
Traffic signal*	0			1.00		0			1.00	

Table 6.1: Univariable logistic model estimation results (continued).

Predictor Variable (*k*)	*β*	S.E.	*p*	Unadjusted OR	95% CI	*β*	S.E.	*p*	Unadjusted OR	95% CI
Vehicle Type										
Trucks	-0.262	0.010	< 0.001	0.77	(0.75 - 0.78)	-0.078	0.011	< 0.001	0.93	(0.91 - 0.95)
Utility Vehicles	0.054	0.012	< 0.001	1.06	(1.03 - 1.08)	0.076	0.013	< 0.001	1.08	(1.05 - 1.11)
Automobiles*	0			1.00		0			1.00	
Roadway Alignment										
Horizontal Curvature	0.997	0.033	< 0.001	2.71	(2.54 - 2.89)	1.287	0.034	< 0.001	3.62	(3.39 - 3.87)
Straight Roadway*	0			1.00		0			1.00	
Roadway Profile										
Vertical Curvature	0.462	0.017	< 0.001	1.59	(1.54 - 1.64)	0.863	0.017	< 0.001	2.37	(2.29- 2.45)
Level Roadway*	0			1.00		0			1.00	
Median Type										
No median/undivided	-0.173	0.020	< 0.001	0.84	(0.81 - 0.87)	-0.795	0.020	< 0.001	0.45	(0.43- 0.47)
Painted median	0.269	0.023	< 0.001	1.31	(1.25 - 1.37)	0.033	0.023	0.151‡	1.03	(0.99- 1.08)
Raised/physical median*	0			1.00		0			1.00	

S.E. is standard error. OR is odds ratio. CI is confidence interval.
* This attribute is the referent. † his attribute a s not statistically significant at α . . ‡ h is attribute a s not statistically significant at α . .

Pedestrian sex and impairment were found to be statistically significant at $p < 0.001$. Male pedestrians had higher odds than their female counterparts for non-severe and severe injuries, with odds ratios of 1.22 and 1.61, respectively. The odds of a non-severe injury were increased by 2.87 times in events where the subject pedestrian is under some form of impairment. For severe injuries, the odds were increased further at 6.02 times. Regarding pedestrian action, the odds of non-severe and severe pedestrian injuries were found to increase by factors of 1.77 and 3.35, respectively, if an UPA was reported. Unsafe actions or behaviours included dart-/dash-outs, failing to yield right-of-way, having insufficient visibility to motorists, improper crossings of roadways or intersections (i.e., jaywalking), and others.

6.1.2: Driver Characteristics in Univariable Analysis

For non-severe injuries, the odds ratio for driver age was 0.85. This value was representative of a minor protective effect as driver age increases. However, when the squared variant of driver age was considered, the odds ratio increased to 1.01. This value is relatively close to one and implies that driver age did not have a substantial effect on non-severe pedestrian injuries. These findings were nearly identical for severe injuries, with odds ratios of 0.80 and 1.01 for driver age and driver age-squared, respectively.

Male drivers, when compared to their female counterparts, were found to have lower odds of non-severe and severe injuries, as indicated by the odds ratios being lower than one (0.76 and 0.91 for non-severe and severe injuries, respectively). In the event of a pedestrian traffic collision, the odds of a severe injury were 2.74 times higher when the involved driver was impaired. Driver impairment may include being ill, fatigued, emotional or under the influence of alcohol, drugs, or medication.

The turning movements of drivers were found to have lower odds of non-severe and severe injuries. For left-turns, the odds of a non-severe injury were 0.57 times that of a motorist travelling straight. The odds are reduced further when considering severe injuries, at 0.25 times (i.e., drivers travelling straight have four times the odds of a fatal or incapacitating injury than when performing a left turn). Crashing involving right-turns had similar results, with the odds of non-severe and severe injuries 0.65 and 0.27 times that of a motorist travelling in a through movement. This reduction in odds of injuries for turning movements was plausible since motorists will typically reduce their speeds prior to performing a turning movement, thus significantly reducing the likelihood of a major injury in the event of a collision. **Figure 6.1** shows a vehicle performing a right turn movement.

Figure 6.1: Motorist performing a right turning maneuver (Lim, 2018).

Driver age, sex, impairment, and turning movement were found to be statistically significant at $p < 0.001$ for severe injuries. However, only driver age, sex, and turning movement were found to be statistically significant for non-severe injuries. Driver impairment was determined to be not statistically significant at $p < 0.05$.

6.1.3: Crash Characteristics in Univariable Analysis

All crash/temporal variables analyzed in univariable analysis were statistically significant at $p < 0.001$. Defining overnight hours as the reference attribute, crashes occurring in morning (06:00 – 11:59) or afternoon (12:00 – 17:59) hours were found to have lower odds of non-severe injuries, with odds ratios of 0.87 and 0.89, respectively. Conversely, crashes during evening hours (18:00 – 23:59) had a slightly higher odds of non-incapacitating injuries (OR = 1.09). For fatal and incapacitating injuries, crashes in overnight hours had higher odds than any other time during the day, given that the odds ratios of morning, afternoon, and evening hours were less than one.

For crash days, weekends were associated with higher odds of non-severe and severe pedestrian injuries (non-severe injury OR = 1.54, severe injury OR = 1.73). It should be reiterated that weekend hours were modified to include the hours of 20:00 Fridays to 20:00 Sundays to capture any pedestrian activity during Friday nightlife hours, as illustrated in **Figure 6.2**.

Figure 6.2: Increased pedestrian activity near night clubs during weekend hours (Mearns, 2018).

It was initially hypothesized that summer would represent the safest season for pedestrians, given the tendencies of optimal surface and atmospheric conditions. However, the univariable model results for crash season indicated that summer is associated with the highest odds of non-severe and severe pedestrian injuries, as demonstrated by the odds ratios of all other crash seasons being less than one. One explanation for this is that pedestrians may feel more comfortable in walking during summer months, thus increasing pedestrian travel-based exposure. Another cause may be that drivers also feel more comfortable travelling at higher speeds in conditions representative of summer months.

6.1.4: Vehicular Characteristics in Univariable Analysis

For vehicle type, automobiles were defined as the referent attribute on the basis that a pedestrian struck by a larger vehicle, such as a truck or utility vehicle, would prove more harmful. Trucks were found to be associated with lower odds of non-severe injuries when compared to automobiles (OR = 0.77). For severe injuries, trucks had 0.93 times the odds than automobiles. Further, utility vehicles, such as the one shown in **Figure 6.3**, were associated with higher odds of non-severe (OR = 1.06) and severe (OR = 1.08) injuries.

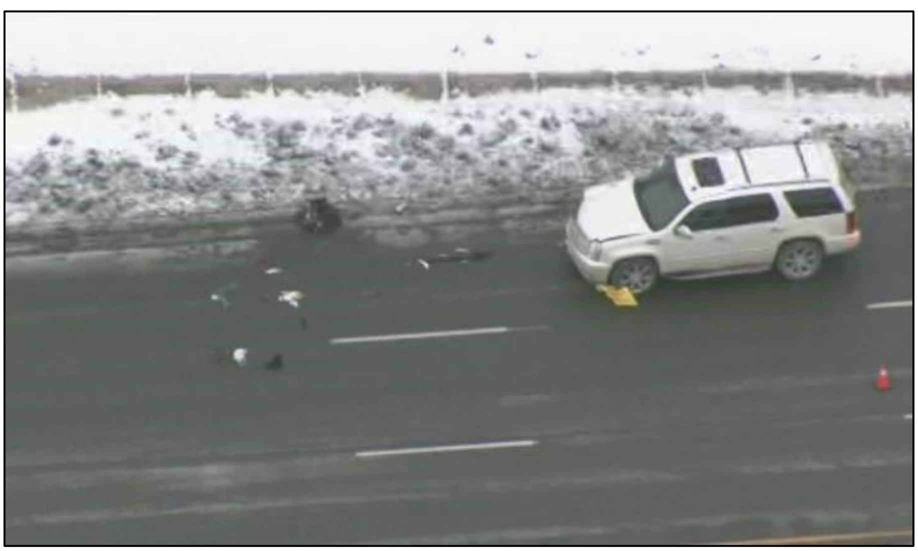

Figure 6.3: View of a pedestrian crash scene involving a sports utility vehicle (Shum, 2017).

Increasing travel speeds were associated with higher odds of non-severe and severe injuries (unadjusted ORs = 1.08 and 1.38, respectively). However, when the squared terms were considered instead, the odds ratios decreased to 0.98. Both vehicle type and travel speed were statistically significant at $p < 0.001$.

6.1.5: Environmental Characteristics in Univariable Analysis

The surface conditions during the time of a crash may be directly related to the crash season. The adverse surface conditions considered (icy, slippery, wet, slush, et cetera) were characteristic of winter or spring months, despite being dependent on geography (southern states may not receive any precipitation below the freezing point). Regardless, adverse surface conditions were found to be associated with lower odds of non-severe and severe injuries (odds ratios of 0.72 and 0.67, respectively). It is likely that in cases of unfavourable road surface conditions (such as those shown below in **Figure 6.4**), motorists may exert more caution by heightening awareness and reducing operating speeds, thus substantially reducing the probability of a pedestrian sustaining an injury in the event of a collision.

Figure 6.4: Adverse road conditions may encourage motorists to drive more cautiously (Laird, 2018).

As the degree of surrounding light decreases, the odds of non-severe and severe injuries were found to increase. For dark conditions with artificial light present, the odds for non-severe and severe injuries were by 1.06 and 1.91 times, respectively. Correspondingly, when there is an insufficient level of light (i.e., unlit condition), the respective odds increased further to 1.60 and 4.27, correspondingly. These results are intuitive, as a low level of light severely inhibits visibility for both the subject pedestrian and motorist (as illustrated in **Figure 6.5**). As a result, corrective actions by either road user may not be applied quickly enough. Surface and light conditions were statistically significant at $p < 0.001$.

Figure 6.5: Image of pedestrians walking in poorly lit conditions (Trendell-Jensen, 2012).

6.2: Baseline Multivariable Logit Model Estimation Results

Table 6.2 contains the results of the baseline multivariate multinomial logit models for non-severe and severe pedestrian injuries. It is worth mentioning that the results contained in this section are of a model that simultaneously considers all other variables within the model. The relatively large chi-square statistic and the low *p*-value are indicative of a good statistical fit for the baseline model.

Table 6.2: Baseline multivariable logistic model estimation results.

	Non-Severe Injury (j = 2)					Severe Injury (j = 3)				
	β	S.E.	p	Adjusted OR	95% CI	β	S.E.	p	Adjusted OR	95% CI
ntercept α)	0.355	0.020	< 0.001			-1.076	0.023	< 0.001		
Pedestrian Age										
Modified	-0.095	0.004	< 0.001	0.91	(0.90 - 0.92)	-0.006	0.004	0.205‡	0.99	(0.99 - 1.00)
Modified & Squared	0.007	0.000	< 0.001	1.01	(1.01 - 1.01)	0.005	0.000	< 0.001	1.01	(1.00 - 1.01)
Pedestrian Sex										
Male	0.166	0.010	< 0.001	1.18	(1.16 - 1.21)	0.349	0.012	< 0.001	1.42	(1.38 - 1.45)
Female†	0			1.00		0			1.00	
Pedestrian Action										
UPA reported	0.603	0.011	< 0.001	1.83	(1.79 - 1.87)	1.161	0.013	< 0.001	3.19	(3.12 - 3.27)
No UPAs reported†	0			1.00		0			1.00	
Driver Age										
Modified	-0.172	0.005	< 0.001	0.84	(0.83 - 0.85)	-0.239	0.006	< 0.001	0.79	(0.78 - 0.80)
Modified & Squared	0.012	0.000	< 0.001	1.01	(1.01 - 1.01)	0.015	0.000	< 0.001	1.02	(1.01 - 1.02)
Driver Sex										
Male	-0.258	0.011	< 0.001	0.77	(0.76 - 0.79)	-0.103	0.013	< 0.001	0.90	(0.88 - 0.93)
Female†	0			1.00		0			1.00	
Crash Day										
Weekend	0.333	0.013	< 0.001	1.40	(1.36 - 1.43)	0.293	0.014	< 0.001	1.34	(1.30 - 1.38)
Weekday†	0			1.00		0			1.00	

Table 6.2: Baseline multivariable logistic model estimation results (continued).

Light Condition										
Dark, Unlit	0.399	0.023	< 0.001	1.49	(1.42 - 1.56)	1.406	0.022	< 0.001	4.08	(3.91 - 4.27)
Dark, Artificially Lit	-0.028	0.013	0.025†	0.97	(0.95 - 1.00)	0.527	0.014	< 0.001	1.69	(1.65 - 1.74)
Daylight†	0			1.00		0			1.00	
Surface Condition										
Adverse	-0.317	0.014	< 0.001	0.73	(0.71 - 0.75)	-0.558	0.016	< 0.001	0.57	(0.55 - 0.59)
Dry†	0			1.00		0			1.00	
Vehicle Type										
Trucks	-0.156	0.013	< 0.001	0.86	(0.83 - 0.88)	0.108	0.014	< 0.001	1.11	(1.08 - 1.15)
Utility Vehicles	0.125	0.014	< 0.001	1.13	(1.10 - 1.16)	0.252	0.016	< 0.001	1.29	(1.25 - 1.33)
Automobiles†	0			1.00		0			1.00	

Number of Observations (*n*)	211399.566
Log-Likelihood at Intercept	-226495.014
Log-Likelihood at Convergence	-212519.855
χ	27963.530
df	26
p-value	< 0.001
AIC at Intercept	452994.028
BIC at Intercept	453014.551
AIC at Convergence	425095.710
BIC at Convergence	425383.033

S.E. is standard error. OR is odds ratio. CI is confidence interval.
* This attribute is the referent. † his attribute a s not statistically significant at α . . ‡ h is attribute a s not statistically significant at α . .

6.2.1: Pedestrian Characteristics in the Baseline MNL Model

In the baseline model, only age, sex, and action were considered as the pedestrian-related variables. Pedestrian impairment was disregarded due to the relatively high skew towards pedestrians with no recorded impairment (8.55% of records contained pedestrian impairment information).

The odds ratios for pedestrian age within the baseline multivariable model were 0.91 and 0.99 for non-severe and severe injuries, respectively. When considering pedestrian age as a squared term, the odds ratios for non-severe and severe injuries were 1.01 which indicates that the effects of accounting for curvilinearity are not as strong. These odds ratios did not differ significantly than those from the univariable analyses as they were only representative of a comparison between pedestrians aged 10 and 15 (i.e., a single 5-year increase).

Regarding pedestrian sex, the odds ratios for non-severe and severe injuries (using females as the referent) from the baseline multivariable model were 1.18 and 1.42, respectively. These new odds ratios indicate that male pedestrians are more associated with non-severe injuries, and even more so with injuries of higher severities, after controlling for non-roadway factors.

The odds ratios for pedestrian actions were relatively similar to the results from the univariable analyses, at 1.83 and 3.20 for non-severe and severe injuries (as compared to 1.77 and 3.35 from the univariable analysis results), respectively.

Nevertheless, unsafe pedestrian actions remain associated with higher odds of pedestrian injury, even after controlling for other variables.

6.2.2: Driver Characteristics in the Baseline MNL Model

Driver-related variables in the baseline model included driver age and sex. Driver impairment, while considered influential in pedestrian injury severity on a theoretical basis, was not included in the baseline model on account of an extremely low sample size of impaired driver records (2.85%). Both driver age and sex were statistically significant at $p < 0.001$.

The baseline multivariable model odds ratios for driver age regarding non-severe and severe injuries were 0.84 and 0.79, respectively. These values were less than one, which was indicative of a protective effect. However, as these odds ratios only consider the change in driver age from 16 to 21, they do not explain the possible change in odds among older drivers. Analysis of the driver age squared term showed odds ratios of 1.01 and 1.02 for non-severe injuries and severe injuries, respectively. Similarly to the pedestrian age squared variable, the small differences between these odds ratios and 1.00 mean that the effects of introducing curvature for driver age are not as strong.

The odds ratios for driver sex underwent a slight increase when the effects of other variables were considered. For non-severe injuries, the odds of a male driver being involved was 0.77 times higher than female drivers. When compared to the unadjusted odds ratio of 0.76 found from the univariable analysis, this result is suggestive that driver sex does not influence pedestrian injury severity even after controlling for additional non-roadway variables. Despite the minor increase in odds, the ratio remained less than one, suggesting that males were less associated with non-severe pedestrian injuries after controlling for non-roadway infrastructure factors. A similar finding was found for severe injuries, where the odds ratio for male drivers in the baseline model was 0.90 (which does not differ significantly than the unadjusted odds ratio of 0.91).

6.2.3: Crash Characteristics in the Baseline MNL Model

From the various crash temporal variables considered, the only factor included in the baseline model was crash day. Crash hour and crash season were rejected, as it was believed that light and surface conditions served as better indicators of the crash information required. The crash day variable was statistically significant in the baseline model at $p < 0.001$.

After adjusting for other non-roadway factors, the odds ratios for non-severe and severe pedestrian injuries decreased slightly. However, crashes occurring on weekends were still associated with higher odds of non-severe pedestrian injuries (adjusted OR = 1.40) and severe (adjusted OR = 1.34) when compared to crashes during weekdays. This contrast in odds between weekends and weekdays may be attributable to higher pedestrian activity during Fridays through Sundays, as eluded to in the univariable analysis section.

6.2.4: Vehicular Characteristics in the Baseline MNL Model

Regarding vehicle-related variables, the only variable included in the baseline model was vehicle type. Travel speed was disregarded due to large amounts of missing data (73.51% of travel speed data were unusable). Vehicle type was statistically significant in the baseline model at $p < 0.001$. After controlling for additional variables, the odds ratios for trucks increased from 0.77 to 0.85 for non-severe injuries, and 0.93 to 1.11 for severe injuries. For utility vehicles, the respective odds ratios also increased from 1.06 and 1.08 to 1.13 and 1.28. Overall, larger vehicles such as trucks and utility vehicles consistently have higher odds than automobiles of being involved in severe pedestrian injuries.

6.2.5: Environmental Characteristics in the Baseline MNL Model

Light and surface conditions were the primary environment-related variables included in the baseline model. Light condition was statistically significant at $p < 0.05$ (non-severe injuries in dark and artificially lit conditions were significant at $p = 0.024$). For dark and artificially lit conditions, the odds ratios for non-severe and severe injuries fell from 1.06 and 1.91 to 0.97 and 1.69, respectively, after controlling for non-roadway factors. Similarly, when the light conditions are sufficiently absent (i.e., an unlit condition), the odds ratios for non-severe and severe injuries decreased 1.60 and 4.27 to 1.49 and 4.08, respectively. Notwithstanding, even after the consideration of additional variables, dark conditions with either artificial light or the absence of sufficient light were associated with higher odds of severe injuries.

The results regarding surface condition from the baseline multivariable model were very similar to those from the univariable analyses. Adverse surface conditions were associated with lower odds of non-severe and severe injuries (adjusted ORs of 0.73 and 0.57, respectively) since their odds ratios were less than one. Surface condition within the base multivariate model was statistically significant at $p < 0.001$.

6.3: Full Multivariable Logit Model Estimation Results

Table 6.3 contains the parameter estimates, adjusted odds ratios, and 95% confidence intervals from the full multivariable logit model. Whereas the baseline model did not incorporate any effects of roadway infrastructure, the full model now considers the six additional variables regarding roadway features and geometry. As expected, the addition of RIFs improve the explanatory power of the multinomial logit model. **Table 6.4** presents a comparative summary of model fitting information between the baseline and full multivariate models. Using the values of the deviances and degrees of freedom from the baseline and full MNL models, an LRT was undertaken to assess the goodness-of-fit of the full model. Equations (5.14) and (5.15) are applied to determine the required chi-square test statistic:

$$\chi^2 = (-2\mathrm{LL}_0) - (-2\mathrm{LL}_a) \tag{5.14}$$

$$\chi^2 = (425039.710) - (153242.849)$$

$$\chi^2 = 271796.862$$

$$df_{\chi^2} = k_a - k_0 \tag{5.15}$$

$$df_{\chi^2} = 44 - 26 = 18$$

With a chi-square score of approximately 271797 and 18 degrees of freedom, the resulting p-value is less than 0.001. As such, the results of the LRT indicate that the full MNL model provides a better statistical fit over the baseline model.

Table 6.3: Full multivariable logistic model estimation results.

	Non-Severe Injury					Severe Injury				
	β	S.E.	p	Adjusted OR	95% CI	β	S.E.	p	Adjusted OR	95% CI
ntercept α)	2.104	0.060	< 0.001			1.023	0.063	< 0.001		
Pedestrian Age										
Modified	-0.087	0.007	< 0.001	0.92	(0.90 - 0.93)	0.005	0.008	0.559‡	1.00	(0.99 - 1.02)
Modified & Squared	0.009	0.001	< 0.001	1.01	(1.01 - 1.01)	0.007	0.001	< 0.001	1.01	(1.01 - 1.01)
Pedestrian Sex										
Male	-0.370	0.020	< 0.001	0.69	(0.66 - 0.72)	-0.256	0.022	< 0.001	0.77	(0.74 - 0.81)
Female†	0			1.00		0			1.00	
Pedestrian Action										
UPA reported	0.540	0.024	< 0.001	1.72	(1.64 - 1.80)	0.782	0.026	< 0.001	2.19	(2.08 - 2.30)
No UPAs reported†	0			1.00		0			1.00	
Driver Age										
Modified	-0.157	0.009	< 0.001	0.85	(0.84 - 0.87)	-0.204	0.010	< 0.001	0.82	(0.80 - 0.83)
Modified & Squared	0.012	0.001	< 0.001	1.01	(1.01 - 1.01)	0.012	0.001	< 0.001	1.01	(1.01 - 1.01)
Driver Sex										
Male	-0.257	0.020	< 0.001	0.77	(0.74 - 0.80)	0.078	0.022	< 0.001	1.08	(1.03 - 1.13)
Female†	0			1.00		0			1.00	
Crash Day										
Weekend	0.326	0.024	< 0.001	1.39	(1.32 - 1.45)	0.334	0.025	< 0.001	1.40	(1.33 - 1.47)
Weekday†	0			1.00		0			1.00	

Table 6.3: Full multivariable logistic model estimation results (continued).

Light Condition										
Dark, Unlit	-0.059	0.038	0.114‡	0.94	(0.88 - 1.01)	0.691	0.037	< 0.001	1.99	(1.86 - 2.14)
Dark, Artificially Lit	-0.256	0.023	< 0.001	0.77	(0.74 - 0.81)	0.390	0.024	< 0.001	1.48	(1.41 - 1.55)
Daylight†	0			1.00		0			1.00	
Surface Condition										
Adverse	-0.345	0.026	< 0.001	0.71	(0.67 - 0.75)	-0.635	0.030	< 0.001	0.53	(0.50 - 0.56)
Dry†	0			1.00		0			1.00	
Vehicle Type										
Trucks	-0.020	0.023	0.365‡	0.98	(0.94 - 1.02)	0.291	0.024	< 0.001	1.34	(1.28 - 1.40)
Utility Vehicles	1.069	0.032	< 0.001	2.91	(2.73 - 3.10)	1.219	0.034	< 0.001	3.38	(3.16 - 3.62)
Automobiles†	0			1.00		0			1.00	
Driver Movement										
Turning Left	-0.044	0.033	0.181‡	0.96	(0.90 - 1.02)	-0.797	0.037	< 0.001	0.45	(0.42 - 0.48)
Turning Right	-0.308	0.037	< 0.001	0.73	(0.68 - 0.79)	-1.008	0.045	< 0.001	0.37	(0.33 - 0.40)
Through / Straight†	0			1.00		0			1.00	
Crash Location										
Midblock	-0.018	0.031	0.562‡	0.98	(0.93 - 1.04)	-0.238	0.032	< 0.001	0.79	(0.74 - 0.84)
3-/4- leg intersection†	0			1.00		0			1.00	
Posted Speed Limit										
Modified	-0.056	0.005	< 0.001	0.95	(0.94 - 0.96)	-0.036	0.006	< 0.001	1.04	(1.02 - 1.05)
Traffic Control Device										
No traffic control	0.017	0.030	0.575‡	1.02	(0.96 - 1.08)	0.305	0.034	< 0.001	1.36	(1.27 - 1.45)
Regulatory Sign	0.050	0.038	0.191‡	1.05	(0.98 - 1.13)	0.451	0.045	< 0.001	1.57	(1.44 - 1.71)
Traffic Signal†	0			1.00		0			1.00	

Table 6.3: Full multivariable logistic model estimation results (continued).

Roadway Profile										
Vertical Alignment	0.352	0.037	< 0.001	1.42	(1.32 - 1.53)	0.934	0.038	< 0.001	2.55	(2.36 - 2.74)
Level Roadway†	0			1.00		0			1.00	
Median Type										
No median/undivided	-1.167	0.042	< 0.001	0.31	(0.29 - 0.34)	-1.401	0.043	< 0.001	0.25	(0.23 - 0.27)
Painted median/TWLTL	-0.807	0.044	< 0.001	0.45	(0.41 - 0.49)	-0.995	0.045	< 0.001	0.37	(0.35 - 0.40)
Raised/physical median†	0			1.00		0			1.00	
Number of observations (n)						79233.637				
Log-Likelihood at Intercept						-84940.554				
Log-Likelihood at Convergence						-76621.424				
χ						16638.259				
df						44				
p-value						< 0.001				
AIC at Intercept						169885.108				
BIC at Intercept						169903.669				
AIC at Convergence						153334.849				
BIC at Convergence						153761.736				

S.E. is standard error. OR is odds ratio. CI is confidence interval.
* This attribute is the referent. † his attribute a s not statistically significant at α . . ‡ h is attribute a s not statistically significant at α . .

Table 6.4: Model fitting information summary for baseline and full MNL models.

	Baseline MNL Model	Full MNL Model
-2 Log-Likelihood at Convergence	425039.710	153242.849
df	26	44
AIC	425095.710	153334.849
BIC	425383.033	153761.736

6.3.1: Pedestrian Characteristics in the Full MNL Model

After controlling for the effects of roadway infrastructure, the odds ratios regarding pedestrian age for non-severe and severe pedestrian injuries increased slightly from 0.91 and 0.99 (as indicated in the baseline model) to 0.92 and 1.01, respectively. It should be noted that these odds ratios represent the change in injury probabilities between pedestrian age 10 and 15 (i.e., a one-unit increase). A discussion regarding the comparison of varying pedestrian ages is provided in the next subsection.

The odds ratios for the pedestrian age squared terms, for both non-severe injuries and severe injuries were 1.01. As noted previously in the baseline model discussion, the small differences between these odds ratios and 1.00 mean that the effects of inducing curvilinearity in the relationship between pedestrian injury severity and pedestrian age are substantially negligible. Pedestrian age and its squared variant were statistically significant at $p < 0.001$, except for pedestrian age with severe injuries (this parameter estimate was not statistically significant at $p < 0.05$).

Furthermore, after controlling for roadway infrastructure, the non-severe and severe injury odds ratios for male pedestrians (as compared to females) decreased considerably, from 1.18 and 1.42 in the baseline model to 0.69 and 0.78, respectively. This is indicative that male pedestrians were less associated with non-severe and severe injuries when compared to females, which is in contrast to what was reported in both the univariable and baseline multivariable analyses. In reference to UPAs, the indication of any of them was related to higher odds of non-severe and severe injuries, even after controlling for roadway infrastructure features (full model adjusted ORs = 1.72 and 2.31, respectively), as expected. Pedestrian sex and action were statistically significant at $p < 0.001$.

6.3.2: Driver Characteristics in the Full MNL Model

The odds ratios for non-severe and severe pedestrian injuries regarding driver age did not change significantly after controlling for roadway factors. However, it should be reiterated that the values listed in

Table 6.3 are only representative of the 5-year increase of driver age from 16 to 21. Furthermore, these odds ratios are reflective of injuries to a pedestrian aged 10 years old.

To gain further insight on how pedestrian and driver age affects non-severe and severe pedestrian injuries, odds ratios (relative to 10-year-old pedestrians and 16-year-old drivers) were converted into predicted probabilities (using equations (5.5) and (5.11)) and plotted on surface graphs. **Figure 6.6** and **Figure 6.7** contain surface plots that depict predicted probabilities for non-severe and severe injuries by driver age, respectively. Even after controlling for roadway infrastructural factors, the curved relationship between driver age and pedestrian injury remains evident, particularly when the subject pedestrian is older (i.e., at least 65 years of age). The odds ratio profiles show that younger and older drivers are more associated with being involved in fatal or incapacitating pedestrian injuries. Also, the odds ratios for driver sex did not change significantly from those reported in the baseline model. However, after controlling for roadway factors, the odds ratio for severe injuries increased from 0.90 in the baseline model to 1.07 in the full model. This suggests that male drivers are associated with higher odds of severe pedestrian injuries.

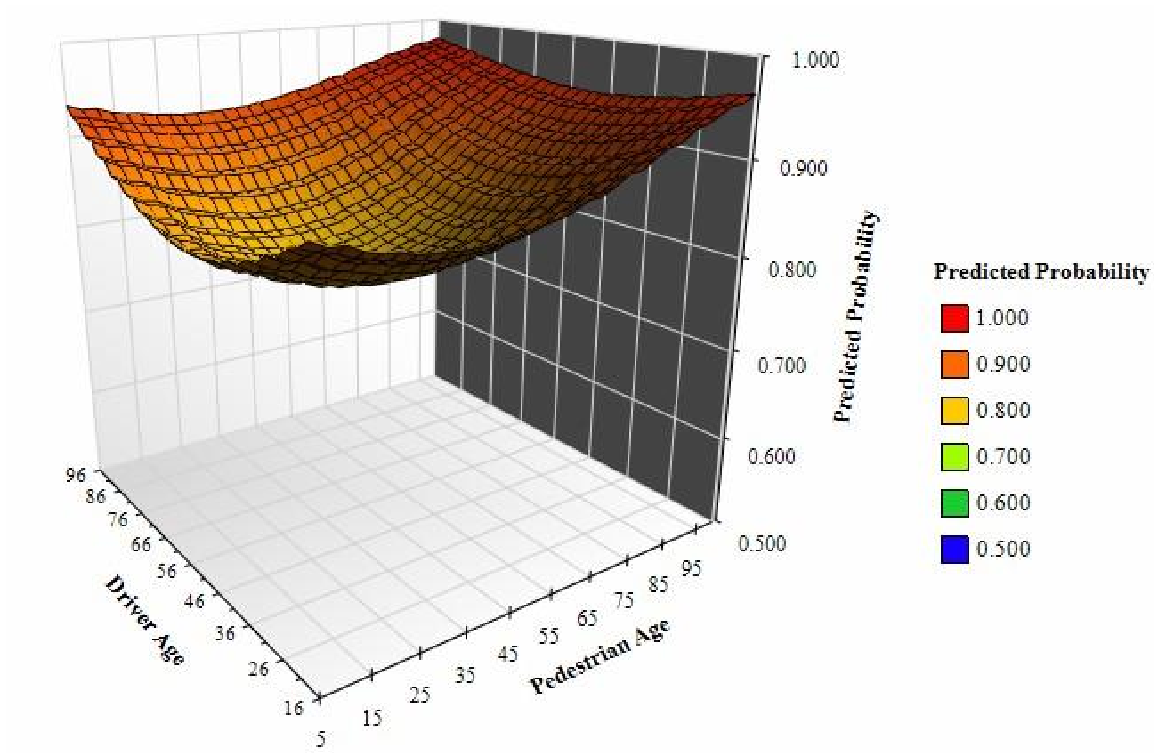

Figure 6.6: Predicted probability surface plot for non-severe pedestrian injuries by pedestrian and driver age.

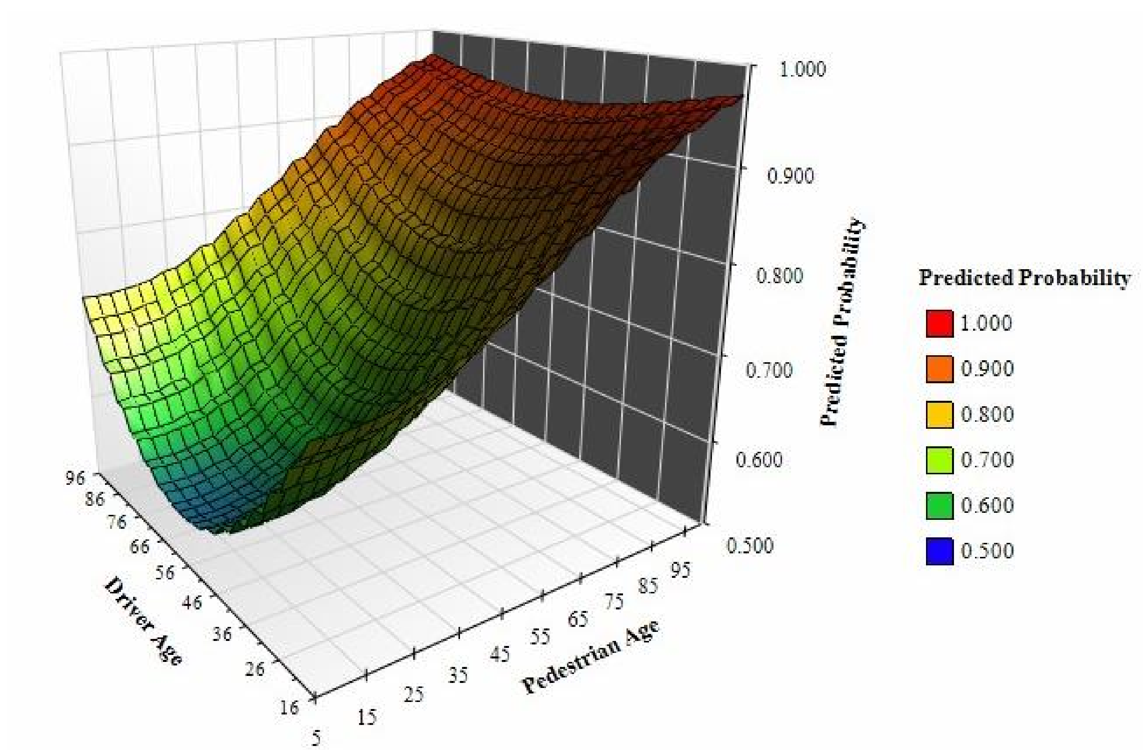

Figure 6.7: Predicted probability surface plot for severe pedestrian injuries by pedestrian and driver age.

6.3.3: Crash Characteristics in the Full MNL Model

The non-severe and severe injury odds ratios for crash day underwent a minor decrease when roadway factors were considered. After controlling for roadway infrastructure, weekends had 1.39 and 1.35 times the odds of non-severe and severe pedestrian injuries, respectively. Despite the small reduction in odds ratios, weekends remain more associated with pedestrian injuries, regardless of severity, when compared to weekdays.

6.3.4: Vehicular Characteristics in the Full MNL Model

The odds of trucks over automobiles being involved in a non-severe pedestrian injury increased from 0.85 in the baseline model to 0.98 when roadway factors were considered. Since this value is relatively close to one, this suggests that trucks and automobiles have roughly the same odds of causing a non-severe pedestrian injury. Additionally, for severe pedestrian injuries, the odds ratio also increased from 1.11 in the baseline model to 1.34, suggesting an even stronger association between trucks and fatal or incapacitating pedestrian injuries.

Utility vehicles were found to have approximately 2.94 times the odds than automobiles of being involved in non-severe pedestrian injuries. Furthermore, utility vehicles had 3.33 times the odds of involvement in severe pedestrian crashes than automobiles. While it may appear intuitive that trucks may have higher odds of more serious pedestrian injuries, the speed gains of larger trucks are largely dependent on surrounding traffic and terrain characteristics. Utility vehicles do not experience acceleration penalties in the same way as heavier vehicles, such as trucks.

6.3.5: Environmental Characteristics in the Full MNL Model

Regarding light condition, the odds ratios of non-severe and severe pedestrian injuries decreased relative to the baseline model. When controlling for RIFs, the non-severe odds ratios for dark & unlit and dark & artificially lit conditions decreased from 1.49 and 0.97 (as reported in the baseline model) to 0.94 and 0.77, respectively. As the odds ratios from the full model are less than one, this suggests that dark conditions (regardless of the presence of light) are not as associated with non-severe pedestrian injuries. However, when analyzing the odds of severe injuries, the odds ratios from the full multivariable model were 1.91 and 1.52 for dark and unlit, and dark and artificially lit conditions, respectively. Despite the minor reduction in odds ratios compared to the baseline model's, dark conditions remain associated ith pede strian injuries of higher severities.

With respect to the road surface condition, the odds ratios corresponding to adverse road conditions underwent a slight change after controlling for roadway factors, from 0.73 and 0.57 (as indicated in the baseline MNL model) to 0.71 and 0.53 for non-severe and severe pedestrian injuries, respectively. However, as these odds ratios remained lower than one, this means that crashes on adverse road conditions were associated with a lower odds of resulting in a non-severe or severe pedestrian injury, as compared to crashes under dry surface conditions. In other words, dry road surface conditions were found to have a higher odds of resulting in non-severe or severe pedestrian injury.

6.4: Effects of Roadway Infrastructure

In this section, the effects of the RIFs in the univariable analyses, as well as the full multivariable multinomial model are discussed and critiqued in greater detail. Additionally, several suggestions for engineering countermeasures per RIF are provided.

The first (and arguably the most critical) RIF discussed is posted speed limit, due to its influence on travel speed, which is directly related to pedestrian injury severity risk. Analysis results pertaining to crash location are also discussed. In this sense, comparisons in injury severity risk are made between crashes occurring at midblock and at intersections. Vehicle turning movements and traffic control are discussed next. These factors are primarily connected to intersections but may also apply to midblock locations as well. The last two RIFs discussed are roadway geometry and the presence of medians.

6.4.1: Vehicle Speeds

From the full MNL model, the odds ratios corresponding to posted speed limits for non-severe and severe pedestrian injuries were 0.95 and 1.04, respectively. These two values were statistically significant at $\alpha = 0.01$. Regarding non-severe injuries, the odds ratio was less than one which indicates that the odds of a non-severe pedestrian injury are lower when a 5-mph increase is applied to the posted speed limit. This is illustrated in the surface plot shown in **Figure 6.8**, which illustrates the relationship between pedestrian age, posted speed limit of the incident roadway, and the predicted probabilities of a non-severe pedestrian injury.

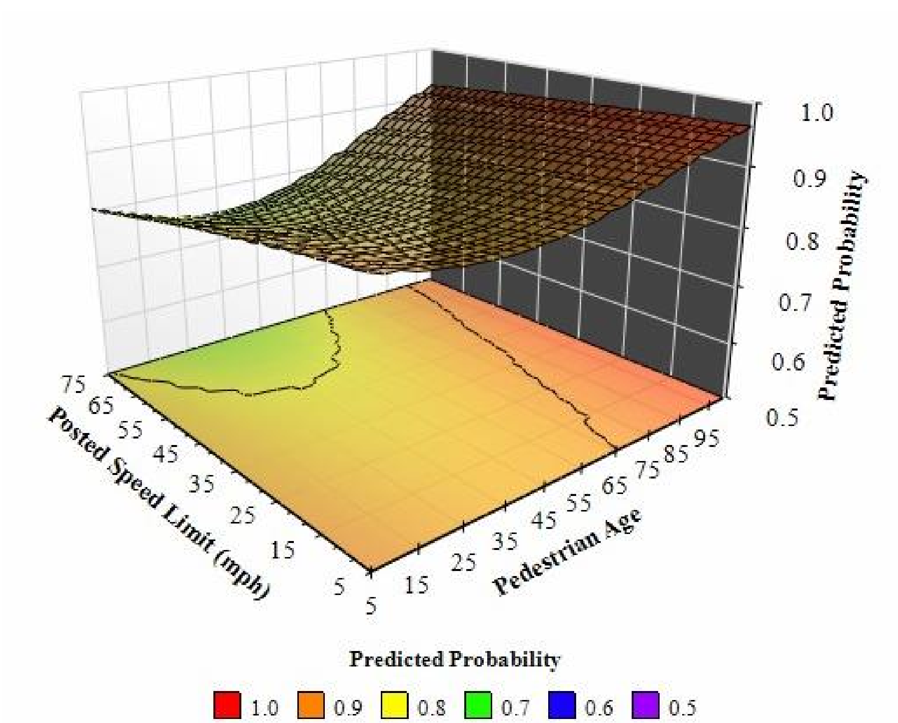

Figure 6.8: Predicted probability surface plot for non-severe pedestrian injuries by pedestrian age and posted speed limit.

The surface plot shows that as posted speed limit increased, the probability of a pedestrian sustaining a non-severe injury decreased. This trend was consistent across pedestrian age. Furthermore, a U-shaped relationship between pedestrian age and non-severe injury probability (regardless of posted speed limit) was observed.

Figure 6.9 shows the surface plot for predicted probabilities of a severe pedestrian injury by pedestrian age and posted speed limit. The surface plot illustrates that the probability of a severe pedestrian injury increases with pedestrian age or posted speed limit. The relationship between severe injury probability and posted speed limit is positive and linear. Additionally, the relationship between severe injury probability and pedestrian age was curvilinear, with the highest rates of increases in severe injury probability for pedestrians aged older than 25.

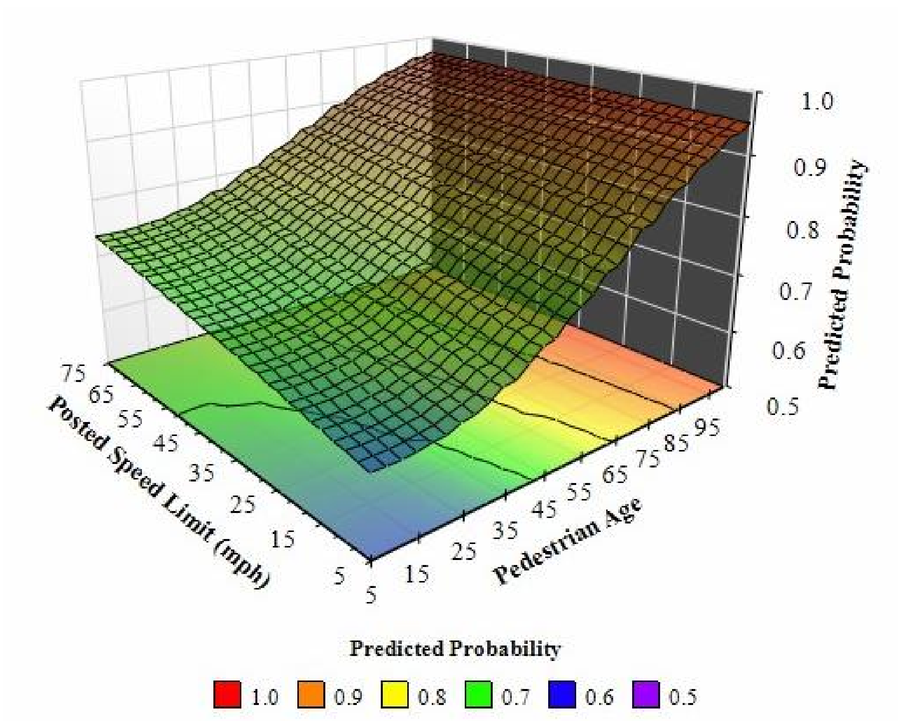

Figure 6.9: Predicted probability surface plot for severe pedestrian injuries by pedestrian age and posted speed limit.

It should be noted that posted speed limits do not accurately reflect the speed at which a vehicle strikes a pedestrian (i.e., impact speed). However, due to GES data limitations, impact speeds were not available for each pedestrian crash record, as the only two indicators of speed were travel speed and posted speed limit. From the two speed metrics listed, travel speeds provide the best estimates of the relationship between vehicle speed and pedestrian injury severity. Nevertheless, travel speed values were deemed unreliable due to a large proportion of missing data (approximately 73.5%). Additionally, closer inspection of the frequency distribution of travel speeds (**Figure 5.4**) shows a bias towards speeds in multiples of 5 mph. Regarding GES data, travel speeds are estimates of a vehicle's speed pre-crash and do not account for possible changes in speed from evasive maneuvers or braking (Leaf & Preusser, 1999). From these limitations, posted speed limits were favoured over travel speeds in terms of inclusion in the full MNL model. It should also be noted that posted speed limits do not act as direct indicators of a vehicle's speed. ot orists that are decelerating to provide right-of-way to another road user (e.g., approaching a STOP sign or a red light at a traffic signal) or to execute a turning maneuver are more likely to have their speeds controlled by the maneuver that they are performing rather than the speed limit in the area (Leaf & Preusser, 1999). Notwithstanding, the findings regarding posted speed limits were expected as the positive correlation between posted speed limit and pedestrian injury severity is well documented in the literature (Ballesteros et al., 2004; Jensen, 1999; Lefler & Gabler, 2004; Miles-Doan, 1996; Sze & Wong, 2007).

Moreover, Tefft (2013) investigated the relationship between impact speed and severe/fatal injury risk. **Figure 6.10** illustrates his findings. The curvilinear relationship between impact speed and injury risk found by Tefft was not reflected in **Figure 6.9** based on posted speed limits, thus reinforcing the point made earlier regarding the discrepancies between impact speeds and posted speed limits.

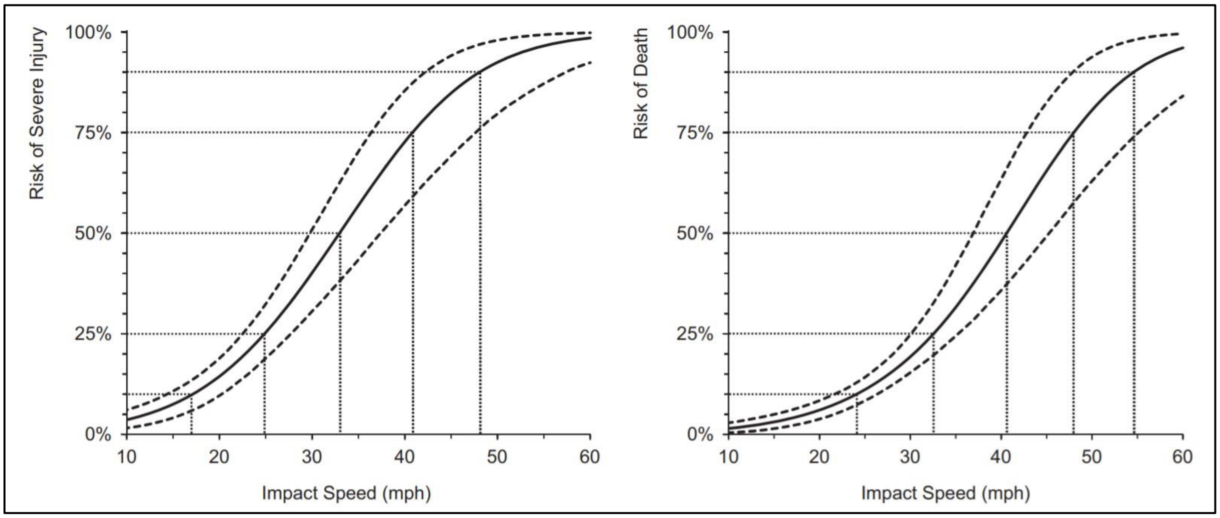

Figure 6.10: Severe injury (left graph) and fatality (right graph) risk curves for vehicle-pedestrian collisions by impact speed. Dotted lines represent the 95% confidence intervals (Tefft, 2013).

Further, Pitt et al. (1990) analyzed injury data of pedestrians younger than 20 years of age. Using multivariate regression, the researchers concluded that vehicle travel speeds higher than 30 mph were associated with higher injury severity levels. However, travel speed data were only available for approximately 45% of records. To supplement their findings, the researchers conducted a secondary multivariate analysis, using posted speed limits (which were available for approximately 99% of records) instead of travel speeds. They determined that the relationship between posted speed limits and injury severity was relatively weaker than that of travel speed. Furthermore, using the age range of 5-9 years of age as a reference, Pitt et al. found that pedestrians between 10 and 19 years of age were associated with lesser injury severities. The results presented from the full MNL model do not reflect the findings from Pitt et al., as the changes in probabilities of non-severe and severe injuries are relatively flat between ages 5 and 20. This discrepancy in results may be due to the limited age ranges used in the study by Pitt et al. It may also be possible that a cohort effect may be a contributing factor for child pedestrians, as the data used in their study was collected from 1977 through 1980.

Additionally, using FARS and GES data from 1994 to 1996, Leaf and Preusser (1999) found that less than 1% of fatal records were on roads with speed limits of less than or equal to 20 mph (≈ 32 km/h). The distribution of their records by injury severity is illustrated in **Figure 6.11**. From this depicted distribution, a positive correlation can be observed between increased posted speed limits and fatal and incapacitating pedestrian injuries. Moreover, a negative correlation between posted speed limits and the proportion of non-incapacitating and no/possible injuries is also apparent. Both of these relationships substantiate the findings presented in Figure 6.8 and Figure 6.9. Additionally, Leaf and Preusser also experienced a similar shortcoming regarding missing travel speed data. In their dataset, approximately 77% of values for travel speed were missing.

Furthermore, Tingvall and Haworth (1999) recommended speed limits of 30 km/h (≈ 18.6 mph) in areas where vehicle-pedestrian conflicts are observed. This value was derived on the basis that impact speeds higher than km/h il l exceed a human's tolerance for kinetic energy. In cases where speeds cannot be reduced feasibly, it was recommended that measures to separate pedestrians from motor vehicle traffic be put in place.

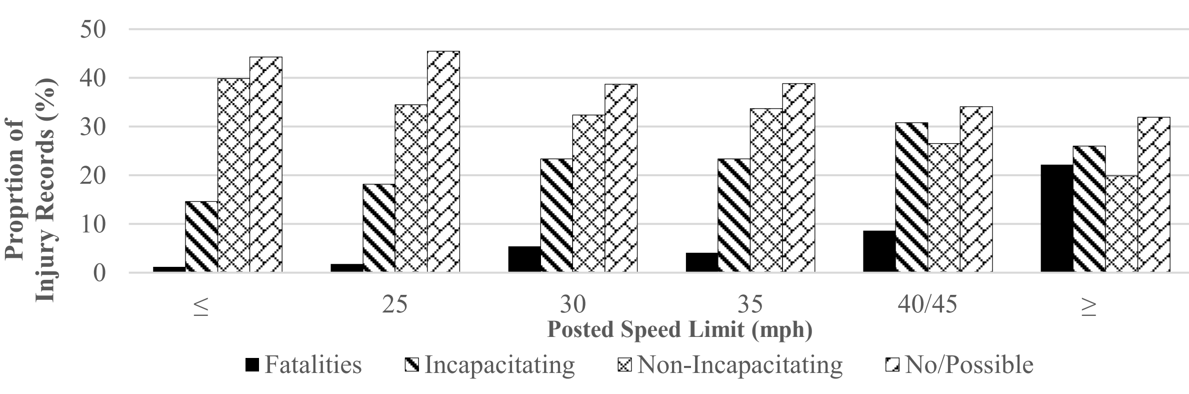

Figure 6.11: Proportions of GES-based pedestrian injuries by injury severity, 1994-1996 (Leaf & Preusser, 1999).

Using a quasi-experimental research design, Chen et al. (2013) assessed the effects on pedestrian safety caused by posted speed limit reduction, among other countermeasures. The researchers provided examples of the nature of the speed limit reductions (i.e., from 35 mph to 30 mph or from 30 mph to 25 mph), but exact specifications were not provided. While the difference in pedestrian crash counts was not determined for roadway segments, results indicate that intersections subjected to the speed limit reduction treatment experienced a 36% reduction in pedestrian crashes. However, this result was not found to be statistically significant at a 5% significance level.

Overall, the results of the analyses reviewed indicated that lower speed limits were associated with decreased probabilities of severe injuries but increases in the likelihoods of non-severe injuries. The lower vehicular speeds provide motorists with a larger window of time to perceive and react to pedestrians that may unexpectedly enter the path of vehicles. Moreover, pedestrian crashes in areas of reduced vehicle speeds are more likely to result in non-severe injuries rather than ones of higher severity. However, reductions in speed limits will likely cause the operational capacity of the subject roadway facility to decline. Therefore, vehicle speeds should be managed to provide an optimal level of safety for all road users while allowing sufficient capacity and minimizing delays (Forbes et al., 2012).

6.4.2: Crash Location

The distribution of non-severe injuries by crash location was an approximate 50/50 split in records between crashes at midblock locations (n = 2782) and intersections (n = 2771). For severe injuries, crashes at midblock made up 61.54% of fatal records (n = 1941) while the remaining 38.46% were records of fatalities at intersections. The results from the univariable model regarding crash location indicated that crashes at midblock locations were associated with higher odds of non-severe and severe pedestrian injuries (unadjusted ORs for non-severe and severe injuries of 1.31 and 2.02, respectively). From these findings, it appeared that crashes at midblock were associated with higher injury severities for pedestrians.

However, when the other control variables were considered, the odds ratios were reduced to 0.98 and 0.79, respectively. Moreover, the parameter estimate corresponding to non-severe injuries was found to be not statistically significant at a 95% confidence level. These results were indicative of a virtually small difference in odds between non-severe injuries at midblock locations and intersections with three or four legs. Regarding severe pedestrian injuries, the full model odds ratio of 0.79 suggests that crashes at midblock locations had lower odds of severe pedestrian injuries when compared to crashes at intersections with three or four legs.

These results regarding crash location obtained in this research were in general disagreement with previous studies, as midblock locations are typically associated with higher speeds (and subsequently, higher probabilities of severe pedestrian injuries). To investigate the relationship between speed and crash location further, average posted speed limits were computed for pedestrian crashes at midblock and intersection locations. Descriptive statistics show that on average, recorded posted speed limits for pedestrian injuries at midblock locations were higher than injuries at intersections. The difference in the average posted speed limits was assessed using a two-sample *t*-test (Sandt & Zegeer, 2006); the results of which are shown in **Table 6.5**. Test results show that regardless of the application of record weights, the difference in average posted speed limits between intersection and midblock crash locations was statistically significant at a 95% confidence level. Other studies have found that crashes at midblock locations were more likely to result in higher severity injuries (Koopmans et al., 2015; Siddiqui et al., 2006; Sze & Wong, 2007; Tarko & Azam, 2011).

Table 6.5: Two-sample *t*-test at a 95% confidence interval of posted speed limits by crash location.

	Crash Location	*n*	Average PSL (mph)	Standard Deviation (mph)	Standard Error Mean	*t*-statistic	df	*p*-value
Unweighted	Midblock	3817	33.9756	10.76898	0.17431	9.992	7048	< 0.001
	Intersection	3233	31.7383	7.37794	0.12976			
Weighted	Midblock	103816	34.1106	11.71090	0.03635	54.400	194594	< 0.001
	Intersection	90781	31.6056	7.95551	0.02640			

Siddiqui et al. (2006) demonstrated that regardless of light conditions, midblock crashes were associated with higher likelihoods of pedestrian fatalities. In particular, the researchers determined that, when compared to midblock locations, the odds of fatal injuries were 49%, 24%, and 5% lower at intersections with daylight, dark and artificially lit, and dark and unlit conditions, respectively. Moreover, Koopmans et al. (2015) concluded that midblock locations without any formal traffic control were more associated with severe injuries for children and adults, as opposed to intersections. However, the statistical analysis conducted by Koopmans et al. consisted of only a Cochran-Armitage test for trend and did not consider the fitting of any regression models to quantify the association between injury severity and crash location. Lastly, Rothman et al. (2012) quantitatively analyzed pedestrian injury severity by crossing locations. After controlling for the presence of traffic control, pedestrian age and road type, it was determined that crashes at midblock locations had consistently higher odds of injuries of all severities when compared to intersections. Specifically, Rothman et al. concluded that the odds of a major or fatal injury were 1.75, 2.55 and 1.68 times higher at uncontrolled midblock locations than signalized intersections for children (ages less than 18), adults (ages between 18 and 64) and older adults (ages 65 and up), respectively.

In contrast, Bagloee and Asadi (2016) modelled the relationship between pedestrian injury severity and the distances from incident crash locations to the nearest intersection, to discern differences between intersection and non-intersection (i.e., midblock) crashes. Injury severity was found to be not statistically significant in their model. The researchers suggested that the severity of injuries does not differ substantially between midblock and intersection locations. However, the scope of the Bagloee and Asadi study was confined to crashes in a central business district (CBD), where vehicle speeds were likely to be lower and less varied due to higher densities of intersections. Pedestrian exposure may also have been a contributing factor and could provide further insight into a potential discrepancy between injury severities at midblock locations and intersections.

Results of the full multinomial model indicated that crashes at intersections had relatively the same odds of non-severe pedestrian injuries as crashes at midblock. However, this finding was not statistically significant at a 95% confidence level. As such, it cannot be ascertained if crashes at midblock have similar likelihoods of non-severe pedestrian injuries as crashes at intersections. Furthermore, higher odds of severe pedestrian injuries were found for crashes at intersections with three or four approaches over midblock crashes. Therefore, it is recommended that engineering interventions be implemented at intersections to separate pedestrians from motor vehicles by either space or time.

One possible intervention to improve separation between pedestrian flows from vehicle traffic is to convert traditional signalized or STOP-controlled intersections with known pedestrian conflicts into roundabouts (as shown in **Figure 6.12**).

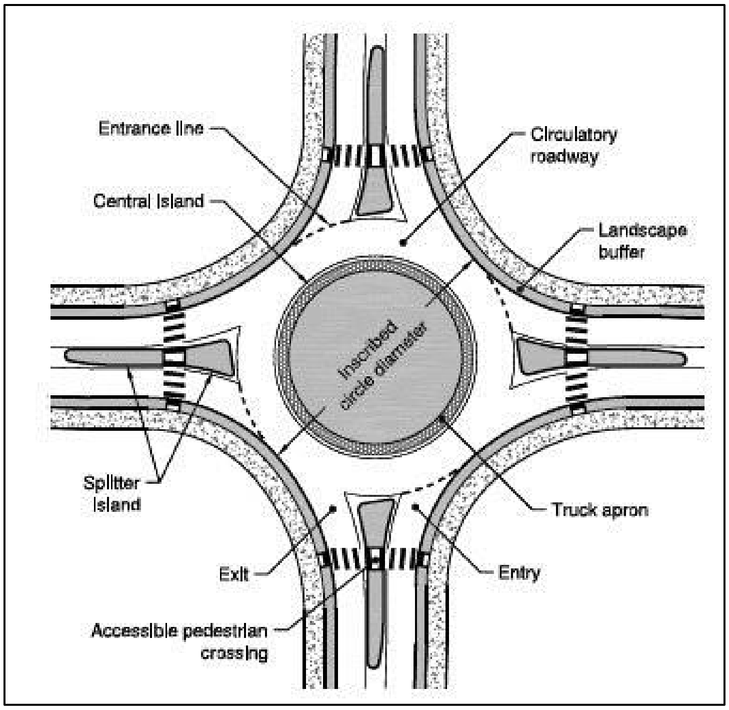

Figure 6.12: Design elements of a typical roundabout (FHWA, 2010).

Given the growing popularity of intersection conversion projects within North America in recent years, there have been several studies that assessed the potential pedestrian safety benefits of roundabout implementation (Persaud et al., 2001). For instance, Stone, Chae & Pillalamarri (2002) performed various analyses (i.e., a before-and-after analysis, a statistical regression model examining various street and intersection characteristics and a simulation analysis) to assess the safety advantages of converting a conventional signalized intersection to a modern roundabout. In particular, the site considered for intersection conversion had the fourth-highest counts of pedestrian crashes in North Carolina. Findings from the regression model, which consisted of variables such as pedestrian and conflicting vehicle traffic flows and crossing distances, indicated that a 7 percent reduction in pedestrian crashes (from 1.28 crashes per year to 1.37 post-implementation). However, the model constructed had a relatively low correlation coefficient of approximately 0.50, meaning that approximately half of the crashes were explained by the variables considered. Furthermore, results from a Swedish study indicated that roundabouts are relatively safer than conventional YIELD-controlled, two-way STOP-controlled or signalized intersections. This study also noted that two-lane roundabouts, on average, have higher pedestrian crashes counts than ones with a single-lane configuration (Brüde & Larsson, 1999).

The splitter islands along each approach to a roundabout provide refuge to pedestrians and allow them to cross conflicting traffic in two stages (i.e., once for each direction of traffic). Additionally, pedestrian conflicts involving left-turning vehicles are removed entirely, as vehicles must turn right to enter or exit the roundabout. Moreover, the speed reductions associated with traffic flows within roundabouts mean that any pedestrian crashes experienced are likely to be of lower severity (FHWA, 2010). However, practitioners should be mindful of higher pedestrian volumes, due to the limited space of splitter islands. If such pedestrian flows are met, the use of signals and crosswalk widening should be considered (C. V. Zegeer et al., 2013).

Another possible intervention to improve pedestrian safety at intersections is the implementation of pedestrian overpasses/underpasses (as shown in **Figure 6.13**). Such structures are intended to separate pedestrians from vehicular traffic by space.

Figure 6.13: A pedestrian overpass treatment at a signalized intersection (Rodegerdts et al., 2004).

In this sense, a Japanese before-and-after study investigated the safety benefits of constructing pedestrian overpasses at 31 locations in Tokyo (Campbell et al., 2004). As part of the study, pedestrian crashes within 200-metre and 100-metre sections on either side of each study site were documented. Results from the study indicated that on average, pedestrian crash frequencies within 200 metres and 100 metres of the sites decreased by 85 and 91 percent after overpass implementation, respectively. However, it could not be determined whether the reduction was solely attributable to the pedestrian overpasses or if other factors independent of the overpasses (e.g., changes in pedestrian exposure) may have had an effect. Additionally, it should be noted that the relationship between pedestrian overpasses/underpasses and injury trends has not been extensively researched in recent years. This may be attributable to the relatively high cost of building such structures. As such, several researchers have noted that grade separation as a pedestrian safety intervention should be considered as a last resort when compared to other potential treatments (Campbell et al., 2004; Mead et al., 2013).

6.4.3: Turning Movements

In terms of driver/vehicle movement, through movements (i.e., vehicles travelling straight) were hypothesized to represent the safest conditions on the basis that the mental workload for drivers is relatively higher when they want to perform a turning movement (Hancock et al., 1990; Harms, 1991; Lord et al., 1998). However, approximately two-thirds of cases (65%) within the master GES dataset had recorded pre-crash vehicle movements as straight. Just under one-quarter of records involved left-turning vehicles, while the remainder (approximately 10%) involved right-turning vehicles. Regarding injury severity, about 24% of cases involved a turning movement and had non-severe pedestrian injuries as the recorded severity level. Moreover, under 8% of cases involved a turning vehicle and led to a severe pedestrian injury.

When defining through/straight vehicle movements as the referent attribute, the odds ratios of a non-severe pedestrian injury when a driver was performing a turning movement were 0.96 for left turns and 0.73 for right turns. However, the odds ratio for left-turning vehicles (i.e., 0.96) was not statistically significant at a confidence level of 0.95. Notwithstanding, these findings are similar to the results from previous studies where pedestrians were found to have a higher risk of crash involvement when a vehicle turned left as opposed to right (Habib, 1980; Lord et al., 1998).

Moreover, the injury involvement rates of pedestrians are said to be higher at intersections (signalized or otherwise) rather than midblock locations, due to the prevalence of turning movements in such areas (Schneider et al., 2010). **Figure 6.14** shows the pedestrian conflict zones at intersections for turning vehicles. **Table 6.6** shows the distribution of injury records by vehicle movement, injury severity and crash location. The crosstabulation shows that the majority of injuries (non-severe or severe) caused by left-turning or right-turning vehicles were at intersections rather than midblock.

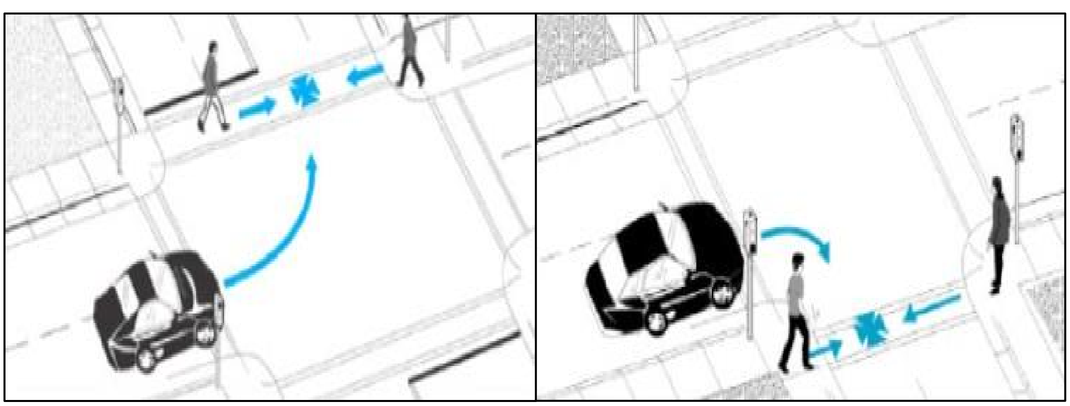

Figure 6.14: Pedestrian conflict areas for turning vehicles at intersections (C. V. Zegeer et al., 2013).

Table 6.6: Crosstabulation of injury records by crash location, turning movement and injury severity.

Crash Location	Turning Movement	None/Possible Injury	Non-Severe Injury	Severe Injury	Total
Midblock	Left	12 (0.15%)	144 (1.78%)	51 (0.63%)	207 (2.56%)
	Right	7 (0.09%)	69 (0.85%)	19 (0.24%)	95 (1.18%)
	Straight	171 (2.12%)	2046 (25.33%)	1591 (19.70%)	3808 (47.14%)
	Subtotal	190 (2.35%)	2259 (27.96%)	1661 (20.56%)	4110 (50.88%)
Intersection	Left	123 (1.52%)	1114 (13.79%)	367 (4.54%)	1604 (19.86%)
	Right	57 (0.71%)	480 (5.94%)	143 (1.77%)	680 (8.42%)
	Straight	79 (0.98%)	968 (11.98%)	637 (7.89%)	1684 (20.85%)
	Subtotal	259 (3.21%)	2562 (31.72%)	1147 (14.20%)	3968 (49.12%)
Total		449 (5.56%)	4821 (59.68%)	2808 (34.76%)	8078(100.00%)

Several possible factors explaining the differences in non-severe injury probability by turning movement include possible obstructions to driver visibility (as illustrated in **Figure 6.15**), initial vehicle speed prior to the beginning of the turning movement and tendencies for drivers to scan for opposing through-vehicle traffic rather than conflicting crossing pedestrians (Hurwitz & Monsere, 2013; Knodler & Noyce, 2005; B. Roudsari et al., 2006; Snyder, 2013; Yoshitake & Shino, 2018).

Figure 6.15: Examples of obstructed left-side driver visibility (Insight Legal, 2017; NYCDOT, 2016).

For severe injuries, the corresponding odds for left and right turning movements were 0.45 and 0.37 times that of a motorist travelling straight. These values are statistically significant at a significance level of $\alpha = 0.001$ and imply that motorists travelling straight are more likely to be involved in a fatal or incapacitating pedestrian injury than a driver performing a turning movement.

There have been several studies that have also reported that turning movements are associated with a lower odds of severe injuries, as compared to vehicles travelling straight (Abay, 2013; B. Roudsari et al., 2006; Salon & McIntyre, 2018; Zahabi et al., 2011). These results were expected, given that drivers must typically reduce their speeds prior to performing a turning movement, thus reducing the likelihood of a severe pedestrian injury. In particular, Roudsari et al. (2006) demonstrated that on average, pedestrian impact speeds were substantially higher for vehicles travelling straight. On the other hand, results from Mohamed et al. (2013) indicate that pedestrian crashes involving left-turning vehicles were associated with higher likelihoods of severe injuries. These authors argue that motorists wishing to turn left must do so in a relatively rushed manner, in order to avoid potential collisions with opposing through-moving traffic.

The results presented in this subsection establish that pedestrian crashes involving vehicles travelling straight have higher odds of resulting in a severe injury to the pedestrian rather than if the vehicle was turning. Therefore, it is recommended that the visibility of pedestrians be improved at locations such that the sight distances for motorists sufficiently exceeds minimum standards. One such way to improve visibility is by providing adequate lighting at locations where it is deficient. While the provision of lighting may be expensive due to the relatively high infrastructure and maintenance costs, modern technologies such as networked LED systems and smart lighting are gaining popularity in multiple cities across the United States due to their improved efficiency and ability to collect traffic data (Scott, 2016). In this sense, research by Nambisan et al. (2009) examined the safety effects of implementing a smart lighting system that automatically detects pedestrians wishing to cross. In lieu of pedestrian crash data, measures of evaluation included motorist compliance rates (with respect to yielding right-of-way), the yielding distance of motorists from the subject crosswalk, delays, and others. The researchers reported several improvements in road user behaviour (reduced jaywalking, increased percentages of pedestrians scanning left and right prior to crossing, higher motorist compliance rates). As expected, motorist delays increased slightly due to the relatively higher compliance rates, but pedestrians delays were found to lower correspondingly.

Further improvements to visibility may be achieved by ensuring that obstructions blocking sightlines between the pedestrian and the motorist are kept at a minimum. Implementing treatments to provide clear sightlines is also known as daylighting. One such way to ‘daylight’ a pedestrian crossing is to impose parking restrictions ithi n the vicinity of the crossing, as illustrated in **Figure 6.16**. A case study from Hoboken, New Jersey examined the safety benefits of intersection daylighting through the installation of vertical delineators (shown in **Figure 6.17**) (Sacs, 2009). Results from the case study indicated that daylighting was a cost-effective way to improve visibility, while also contributing to a 30% reduction in pedestrian injuries post-implementation.

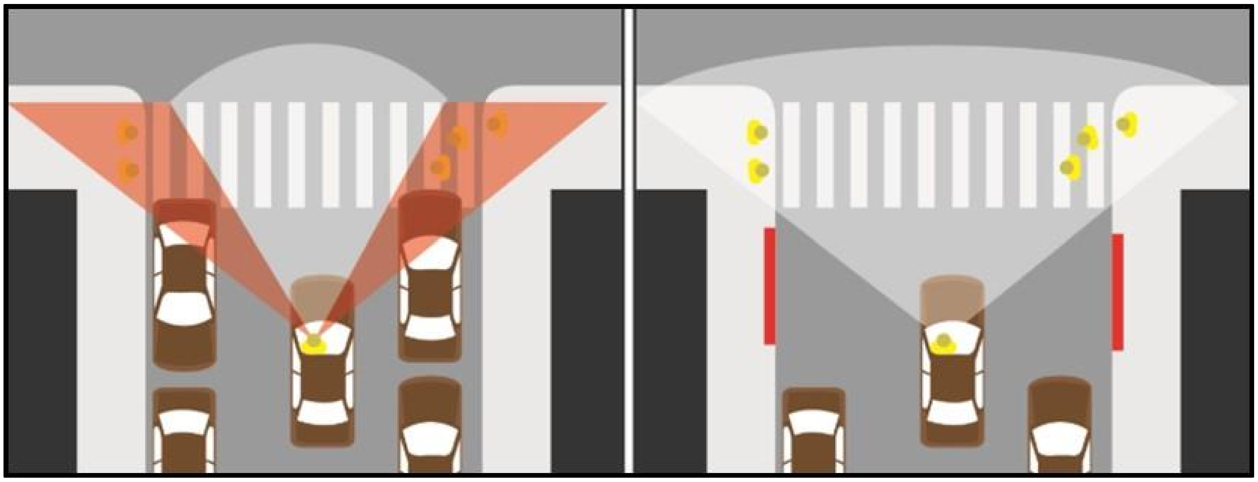

Figure 6.16: Daylighting aims to provide clear sightlines between motorists and pedestrians (Jose, 2015).

Figure 6.17: Daylit intersection through the use of vertical delineators (Sacs, 2009).

Lastly, curb radii reductions have been proven to improve pedestrian visibility (C. V. Zegeer & Bushell, 2012). **Figure 6.18** shows a series of intersection diagrams with different curb radii. Large curb radii are associated with higher speeds during right-turning movements, hence increasing the likelihood of a severe pedestrian injury in the event of a crash. By reducing curb radii, average speed reductions of right-turning vehicles may be expected. However, since vehicles must significantly reduce their speeds prior to turning, rear-end conflicts between vehicles may increase. To alleviate this drawback, dedicated right-turn lanes should be provided to separate vehicles of differing movements (Rodegerdts et al., 2004).

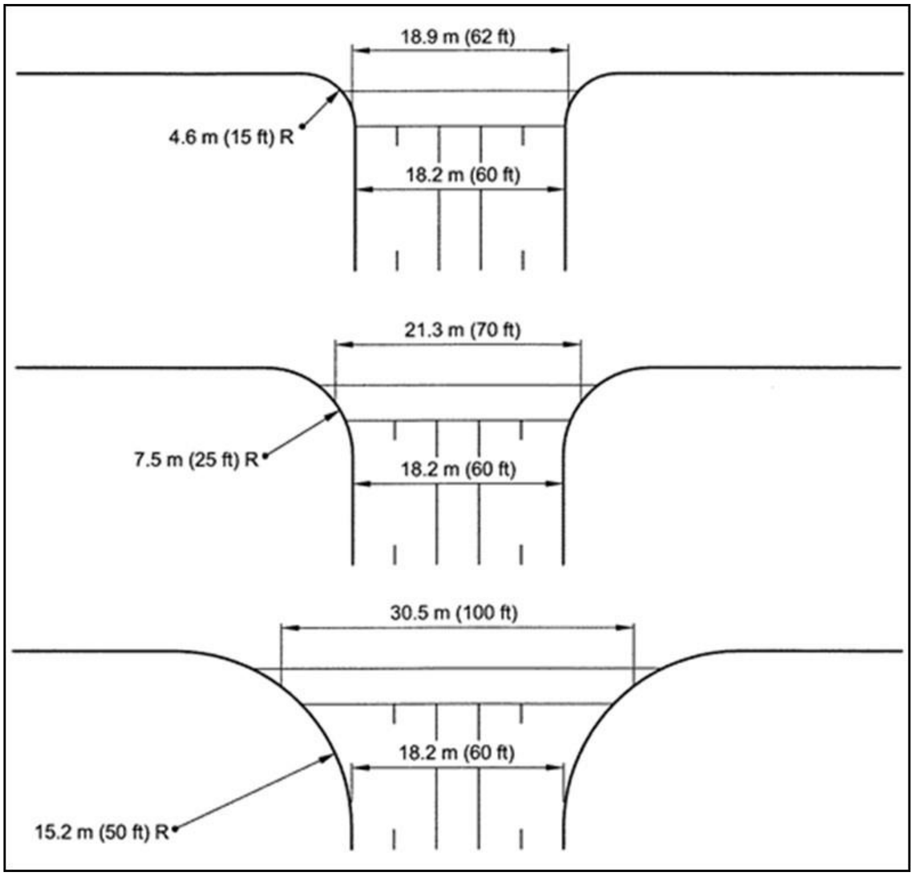

Figure 6.18: Reductions of intersection curb radii (bottom to top diagram) promote speed reductions of right-turning vehicles with the advantages of reducing crossing distance and improving visibility (Rodegerdts et al., 2004).

6.4.4: Traffic Control

Approximately 32% of records listed a traffic signal was the primary means of traffic control at the incident location (*n* = 3109), while 60% of records indicated locations without any traffic control devices (*n* = 5982). An example of an uncontrolled intersection is shown in **Figure 6.19**. The remaining 8% (*n* = 772) featured regulatory signs, such as STOP or YIELD signs, as the primary traffic control device. In terms of severity, the highest proportion of records (34%) were associated with non-severe injuries at locations with no traffic control. The next highest proportion (23%) were severe injuries at uncontrolled locations. Together, over half of injury records (57%) took place at uncontrolled locations, suggesting that pedestrians are at higher risk of injury in environments without traffic control.

Figure 6.19: An uncontrolled four-leg intersection within a residential area (Koeske, 2016).

The univariable results regarding traffic control devices showed that locations with no traffic control had 1.57 and 2.55 times the odds of non-severe and severe injuries when compared to locations with some form of signalization, respectively. Furthermore, locations with regulatory signs as the primary traffic control also had higher odds of non-severe and severe injuries, with odds ratios of 1.43 and 1.46, respectively.

Regarding non-severe pedestrian injuries in the full MNL model, the presence of a regulatory sign as the primary means of traffic control, as well as the absence of any traffic control device had odds ratios of 1.02 and 1.05, respectively. From these findings, crash locations with regulatory signs or no traffic control were associated with a slightly higher odds of non-severe injuries when compared to locations with signalization. However, these two attributes were not statistically significant at $\alpha = 0.05$. For severe injuries, the corresponding odds ratios were 1.57 (regulatory signs) and 1.36 (no traffic control). These values were statistically significant at $\alpha = 0.001$ and were indicative of higher odds of severe injuries than signalized locations.

These findings were expected, and are in general agreement with previous studies (Eluru et al., 2008; Kim et al., 2008; Lee & Abdel-Aty, 2005; Moudon et al., 2011; Pour-Rouholamin & Zhou, 2016). Specifically, Kim et al. (2008) found that signalized locations corresponded to an approximate 35% reduction in the probability of pedestrian fatality, whereas locations with traffic signs as the primary traffic control devices were associated with a 7% increase in fatal injury likelihood. These researchers also remarked that pedestrian right-of-way may not be upheld at locations with traffic signs as the primary method of traffic control. Moreover, results from Pour-Rouholamin & Zhou (2016) indicate that traffic signals or signs were associated with reductions in injury probabilities. In particular, traffic signals corresponded to probability reductions in minor and severe injuries of -1.1% and -7.3%, respectively. Similarly, traffic signs were associated with 3.2% and 20.6% probability reductions for minor and severe injuries, respectively. Furthermore, Lee & Abdel-Aty (2005) suggested that vehicle speeds were higher at areas with no traffic control, thus increasing the likelihood of a severe pedestrian injury in the event of a collision. Moudon et al. (2011) concluded that pedestrians crossing at intersections without signalization were associated with four times the likelihood of succumbing to a severe injury. However, their conclusion was restricted to state routes, which were characterized by having significant pedestrian flows and relatively higher vehicle speeds. In other words, locations with ambiguous right-of-way guidelines (i.e., uncontrolled locations) that are used by multiple types of road users are problematic for those most vulnerable to traffic-related injury. Additionally, Zajac and Ivan (2003) indicated that the implementation of a traffic control (either by signal or sign) reduces average travel speeds, since motorists may be required to stop and provide right-of-way, thus reducing conflicts between vehicles and pedestrians.

In contrast, some studies have found that crashes at signalized intersections are more likely to result in severe injuries. A New York City-based study from Aziz et al. (2013) found that uncontrolled locations had lower likelihoods of pedestrian fatalities, particularly in the boroughs of Brooklyn, Manhattan and Queens. The authors argued that motorists tended to exert more caution upon approaching an intersection without apparent traffic control. It should be noted that their analysis did not consider non-severe injuries; thus no inferences regarding non-incapacitating injuries could be made. Sze and Wong (2007) arrived at a similar finding, whereby they found that pedestrian injuries at signalized intersections had 1.09 times the odds of being severe when compared with intersections with signs as the primary traffic control method.

While the findings regarding non-severe injuries from the full MNL model were not statistically significant, the model demonstrated that pedestrian crashes at either uncontrolled or unsignalized locations have higher likelihoods of resulting in severe injuries. As such, results indicate that signs alone do not provide sufficient safety benefit to pedestrians. It is, therefore, recommended that signs be complemented with devices such as high-intensity activated crosswalk beacons (HAWK beacons) or rectangular rapid flashing beacons (RRFBs) to attract the attention of motorists and encourage them to yield the right-of-way to pedestrians.

HAWK beacons (shown in **Figure 6.20**) are associated with substantial reductions in pedestrian crashes. In particular, Fitzpatrick and Park (2010) reported a 69% reduction in pedestrian crashes resulting from the installation of HAWK beacons at several treatment sites. This finding was statistically significant at a 95% confidence level. Moreover, Zegeer et al. (2017) indicated a 54.7% pedestrian crash reduction that was attributable to the installation of

HAWK beacons. Furthermore, the combination of HAWK beacons with advanced STOP or YIELD markings and signs led to an improve reduction in pedestrian crashes of 56.8%. Among the various treatments considered in their study, Zegeer et al. commented that HAWK beacon implementation corresponded to the largest safety benefits for pedestrians. Also, past research has indicated that the installation of HAWK beacons led to higher compliance rates among motorists, and were found to be more cost-effective when compared to traditional traffic signal installation projects (C. V. Zegeer et al., 2013).

Figure 6.20: Example of a HAWK beacon in conjunction with a pedestrian crossing warning sign (Fitzpatrick et al., 2016).

Other devices that could also be considered include RRFBs (shown in **Figure 6.21**), which are designed to supplement pedestrian crossing warning signs by emitting lights that flash at a strobe-like rate to attract the attention of motorists. These lights are pedestrian-actuated via push buttons and are typically linked wirelessly through radio frequency transmitters and receivers (Shurbutt & Van Houten, 2010). From the same report from Zegeer et al. listed above, it was found that RRFB installations were associated with a 47.4% reduction in pedestrian crashes. However, due to a limited sample size, this result was not statistically significant at a

95% confidence level. On the other hand, a before-and-after study by Monsere et al. (2018) concluded that RRFBs reduced vehicle/pedestrian crashes by 36%. While this result was statistically significant at a 5% significance level, the relatively large standard errors and the lack of pedestrian exposure considerations mean that such an analysis should be repeated in the future when more data becomes available.

Figure 6.21: Example of a RRFB being activated by a pedestrian (FHWA, 2017b).

In summary, research results for the installations of HAWK beacons and RRFBs have shown positive safety benefits for pedestrians by commanding right-of-way more effectively than traffic signs alone. These signal systems should be installed at crossing locations with known pedestrian conflicts, provided that the relevant vehicle speed, crossing length and road user volume warrants are met.

Signal timing plans at signalized intersections may also be augmented to minimize conflicts between pedestrians and motorists. One such adjustment is a leading pedestrian interval (LPI). In a LPI, pedestrian walk signals are shown 3 to 7 seconds prior to the motorist green signals. By doing so, turning motorists have improved visibility of crossing pedestrians, and the likelihood of yielding the right-of-way is increased (C. V. Zegeer et al., 2013). Fayish and Gross (2010) performed a before-after with comparison group study to assess the benefits of LPI implementation at signalized intersections. Crash and exposure data for 10 signalized intersections and 14 STOP-controlled intersections within the municipality of State College, Pennsylvania were used. It was reported with a 95% confidence that LPI treatments led to a 58.7% reduction of pedestrian crashes. Recently, a similar study evaluated the pedestrian safety effects of LPIs (Goughnour et al., 2018). 10 years of crash data from several North American cities including Charlotte, Chicago and New York City were analyzed. It was found for Chicago and New York City that LPI implementation reduced pedestrian crashes by 19% and 9%, respectively. However, only the results from Chicago were statistically significant at a 95% confidence level. Moreover, a reliable crash reduction estimate for Charlotte data could not be ascertained due to a large standard error.

In addition to supplementing traffic signs with signal systems, providing advance warning to motorists at locations where pedestrians tend to cross through the use of signage and pavement markings may likely prove beneficial to pedestrians. In particular, such interventions should be placed where pedestrian desire lines are apparent. Placement of STOP or YIELD pavement markings in advance of pedestrian crosswalks enhance pedestrian visibility, thus reducing the likelihood of a pedestrian crash. Previous research studies (Samuel et al., 2013; Van Houten et al., 2001; C. Zegeer et al., 2017) have demonstrated that advance STOP/YIELD signs and pavement markings can reduce vehicle-pedestrian conflicts and improve motorist yielding compliance rates. Furthermore, Samuel et al. (2013) recommended that the improvements in pedestrian safety induced by placing STOP/YIELD signs and markings in advance can be further enhanced by ‘daylighting’ the crossing, as discussed previously.

6.4.5: Roadway Geometry

Roadway geometric characteristics include factors such as horizontal alignment, vertical profile and roadway cross-sectional properties. **Figure 6.22** illustrates how a three-dimensional rendering of a roadway can be broken down into its horizontal alignment and vertical profile components.

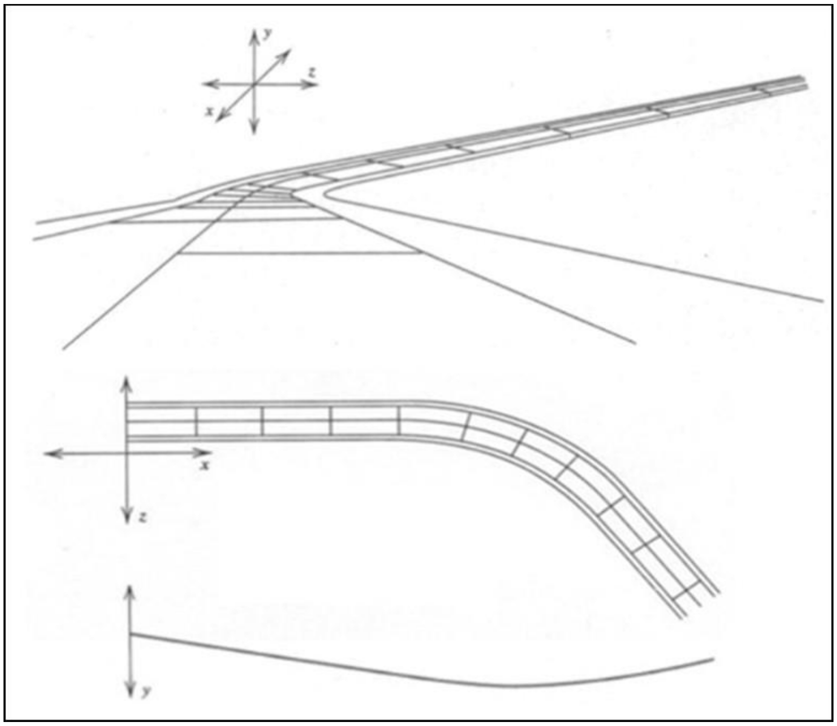

Figure 6.22: Deconstruction of a three-dimensional roadway image (top diagram) into its horizontal alignment (middle diagram) and vertical profile (bottom diagram) components (AASHTO, 2004).

When roadway alignment was examined through univariable analysis, the resulting odds ratios for non-severe and severe injuries were 2.71 and 3.62, respectively. These values imply that crashes on roads with some degree of horizontal curvature (either to the left or right) have higher odds of resulting in pedestrian injuries as opposed to straight roads. While these univariable estimates were statistically significant at a confidence level of 99.9%, there were a few caveats. The first and most obvious implication was that these estimates were not controlled for other variables (such as posted speed limit, pedestrian age, et cetera). Second, roadway alignment data were significantly skewed towards straight roads (97.4% of records involved straight roads, whereas the remaining 2.6% of records featured roads with horizontal curvature). Due to the significant skew in roadway alignment data, this variable was not included in the full MNL model.

Regarding roadway profile, approximately 89% of records involved level roadways (11% featured some form of vertical curvature). Although there was an apparent skew in roadway profile data, the skew was not as egregious as the roadway alignment variable, and therefore, was considered for the full MNL model. Designating level roadways as the referent attribute, univariable analysis results indicated that pedestrian crashes on roads with some form of vertical curvature had 1.59 times the odds of resulting in a non-severe injury and 2.37 times the odds of severe injuries. These estimates were statistically significant at a significance level of $\alpha = 0.05$. When roadway profile was controlled for other variables in the full MNL model, the corresponding odds ratio regarding non-severe pedestrian injuries decreased from 1.59 to 1.42. Conversely, for severe pedestrian injuries, the corresponding odds ratio increased slightly from 2.37 (univariable model result) to 2.55. The roadway profile variable remained statistically significant at a 95 percent confidence. Given that the odds ratios remain above one after controlling for other variables, the results mean that crashes along roads with vertical curvature are associated with a higher odds of resulting in a non-severe or severe pedestrian injury.

In this sense, results from a study by Kim et al. (2008) were similar in part. These researchers found that crashes on straight roads with a non-zero grade (i.e., uphill or downhill) were associated with higher probabilities of pedestrian fatalities (+40% probability) and decreased probabilities of lower severity injuries (-3.8% probability for incapacitating, non-incapacitating and no/possible injuries, respectively). Kim et al. attributed their findings through possible changes in driving behaviour or impact angle (which affects the point of impact on the human body) along downgrade road segments. Furthermore, research by Amoh-Gyimah et al. (2017) examined relationships between built environment characteristics and pedestrian injury severity. They indicated that compared to straight and level roads, roads with curves or non-zero gradients had 1.92 and 1.33 times the odds of fatal and serious pedestrian injuries, respectively.

Recently, Ma et al. (2018) analyzed intersection-related pedestrian injury severities by age. They determined that for middle-aged drivers (ages 25 through 64), the presence of horizontal and vertical curvature at an intersection decreased the probabilities of non-incapacitating, incapacitating, and fatal pedestrian injuries by 15.3, 11.7 and 0.6 percent, respectively. Their results were statistically significant with a 90 percent confidence. However, the individual contributions of horizontal and vertical road curvature could not be ascertained since the roadway geometry indicator variable used by Ma et al. was conditional on both road alignment and profile.

Further, curved road ay geometry may have implications on motorists' visibility, hich of itself, has direct effects on the ability of motorists to execute maneuvers to avoid colliding with pedestrians. However, based on the existing literature, few studies were identified that examined roadway geometric characteristics and their relationship with pedestrian injury severity in elaborate detail. In particular, a study by Kim et al. (2008) sought to identify a correlation between curved roads and pedestrian crash severity levels. They found that crashes on curved roads were 25 percent more likely to result in an incapacitating pedestrian injury. This result was statistically significant at a 95 percent confidence. However, their results regarding fatal pedestrian injuries were not found to be statistically significant. This may be attributable to a significant skewing of crash data, given that approximately 6 percent of records indicated curved roads (i.e., approximately 93 percent of data indicated straight roadways). Moreover, a recent study by Chen and Fan (2019) also examined roadway curvature in relation to pedestrian injury severity. Results from their study indicate that the probability of a fatal or serious pedestrian injury is increased by 0.03 and 0.055 when curved roads are compared to straight roads. However, similar to the previously-discussed study from Kim et al., road curvature data were significantly skewed towards straight roads; approximately 93 percent of data indicated straight road alignment (approximately 6 percent of data were classified as curved road).

The results from the full MNL model indicate that pedestrian crashes along roads with non-zero gradients have higher odds of resulting in non-severe and severe injuries to the pedestrian. Road alignment data were not included in the full MNL model, given that approximately 97 percent of data corresponded with crashes along straight roads. Furthermore, detailed lane configuration information, such as intersection skew angles and lane/shoulder widths, were not available as part of GES. As a result, additional research into the relationship between roadway geometric characteristics and pedestrian injury severity is recommended.

Regarding potential interventions, adjustments to roadway geometry through speed control traffic calming measures have been proven to reduce motor vehicle speeds, thus significantly reducing the probability for a severe injury in the event of a pedestrian crash (Leaf & Preusser, 1999). Such speed control treatments may be categorized into one of two groups: vertical and horizontal. Vertical speed control measures typically consist of a localized change in roadway elevation to induce discomfort for drivers travelling at higher speeds, thus encouraging motorists to traverse over the vertical deflection slowly. Examples of vertical speed control measures include raised crosswalks, speed tables and speed humps (such as the one shown in **Figure 6.23**). Multiple studies have reported reductions in non-severe and severe pedestrian injuries post-installation of speed humps, particularly along local residential roads where children may be most exposed to traffic-related injury (Rothman et al., 2015; Tester et al., 2004).

Figure 6.23: A speed hump placed along a local residential road (NACTO, 2013).

On the other hand, horizontal speed-control measures generally include roadway features that force motorists to reduce speeds or to maneuver around physical obstructions (Pande et al., 2015). Examples of such interventions include road narrowing, lane elimination (i.e., road diets) and curb extensions. Many aspects associated with road diets are known to have safety benefits for pedestrians. These include (FHWA, 2017a; Hu & Cicchino, 2018; Mead et al., 2013; C. V. Zegeer et al., 2002):

- reducing the number of lanes that a pedestrian has to cross (thus, reducing exposure to vehicles),
- encouraging compliance with posted speed limits and
- providing opportunities to create refuge spaces such as bike lanes or parking spaces.

Further, curb extensions also reduce the distances that pedestrian are required to cross while also enhancing pedestrian visibility, as illustrated in **Figure 6.24**.

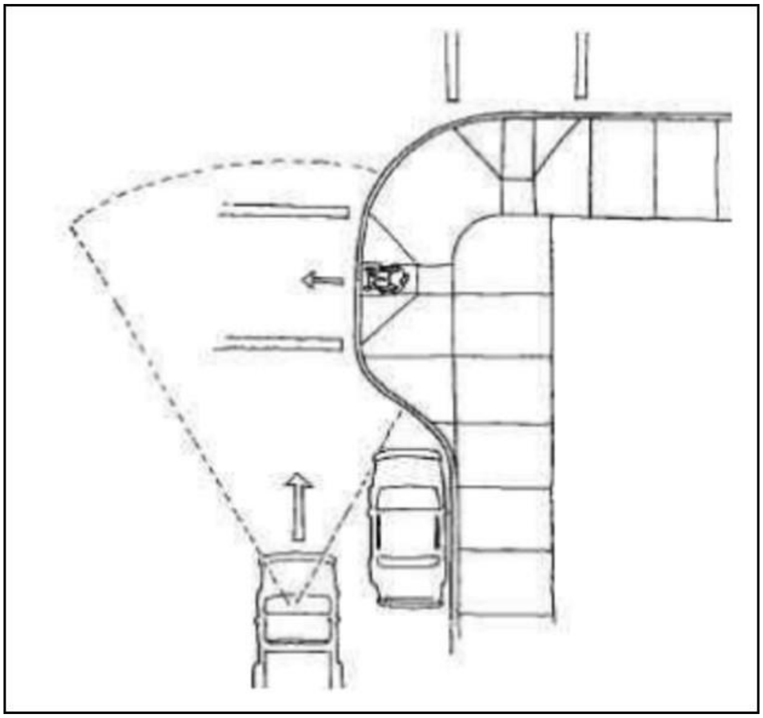

Figure 6.24: Curb extensions shorten crossing distances for pedestrians while also improving visibility for motorists (Mead et al., 2013).

However, past research appears to indicate conflicting results regarding the effects on pedestrian safety. An analysis of curb extensions by King (2000) concluded that from the six sites subjected to curb extension treatments, two showed reductions in overall pedestrian crash severity. The remaining sites examined were associated with increases in pedestrian crash severity or could not have conclusions drawn due to limited sample sizes of crashes. In addition, a study by Huang and Cynecki (2000) could not report any statistically significant findings regarding motorist yielding after curb extensions were installed. Small sample sizes were also noted for the Huang and Cynecki study. As such, additional research into the safety benefits of curb extensions should be conducted.

6.4.6: Presence of Medians

The majority of crash records (66%) from the master GES dataset were along undivided roads (i.e., roads without a median). Approximately 22% were along roads with a painted median, which may include two-way left-turn lanes (TWLTL) such as the one shown in **Figure 6.25**. Lastly, crashes on roads with a physical median (depicted in **Figure 6.26**) made up approximately 11% of records within the master dataset.

Figure 6.25: Pedestrians crossing a road with a painted two-way left-turn lane median (S. L. Davis, 2014).

Figure 6.26: Roadway with a physical median (FHWA, 2016).

Results from the univariable analysis for median type indicated that roads without medians (i.e., undivided roads) had a protective effect against non-severe and severe injuries, with odds ratios of 0.84 and 0.45, respectively. Conversely, roads with painted medians or TWLTL were associated with higher odds of non-severe injuries relative to roads with a physical median (unadjusted OR = 1.31). For severe injuries along roads with painted medians, the odds ratios were 0.45 and 1.03 for non-severe and severe pedestrian injuries, respectively. However, the odds ratio corresponding to severe pedestrian injuries at roads with painted medians was found to not be statistically significant at a 95 percent confidence level. This conclusion may be attributable to a relatively low proportion of corresponding observations (approximately 9 percent of records corresponded to severe pedestrian injuries at roads with painted medians).

It was initially presumed that raised/physical medians would provide the safest condition for pedestrians since they act as refuge areas for pedestrians wishing to cross. As such, raised/physical medians were chosen to be the referent attribute for the median type variable.

However, after controlling for other variables in the full MNL model, the odds ratios corresponding to non-severe pedestrian injuries on undivided roads and roads with a painted median were 0.31 and 0.45, respectively. Moreover, the odds ratios for severe pedestrian injuries along roads with no median or a painted median were 0.25 and 0.37, respectively. Interestingly, as these odds ratios were significantly less than one, the results obtained suggest that crashes along roads with raised medians have increased odds of resulting in a non-severe or severe injury (i.e., a harmful effect among raised medians was determined). Despite physical medians providing refuge for pedestrians crossing the road, these are characteristic of roadways with higher speeds or volumes, which, as discussed in previous subsections, are associated with higher odds of severe pedestrian injuries.

Similar results were obtained by Al-Ghamdi (2002), Kim et al. (2010), and Pour-Rouholamin and Zhou (2016). These researchers reported that the presence of a median (painted or physical) increased the probabilities of fatal pedestrian injuries. Regarding the relationship between median implementation and posted speed limits, Hanson et al. (2013) noted the following:

- Medians on roads with higher speed limits (i.e., 50-65 mph) are meant to discourage pedestrians from crossing the road, thus limiting their exposure to the risk of injury.
- The purpose of medians on roads with posted speed limits between 30 and 45 mph is primarily to provide safe refuge outside of the flow of vehicular traffic.
- For roads with posted speed limits less than or equal to 25 mph, medians are typically not installed.

Similar comments were noted by Chen et al. (2012), where these researchers provided a comparable description of divided roads with posted speed limits of 70 and 80 km/h (approximately 43 to 50 mph). In a New Jersey-based before-and-after study, King et al. (2003) reported reductions in vehicle speeds (average and 85th percentile) of between 2 and 3 mph after the installation of a raised median, suggesting that pedestrian safety had been improved in the subject area.

Furthermore, multiple studies have reported that raised medians were associated with lower pedestrian crash frequencies (Bowman & Vecellio, 1994; Schneider et al., 2010; C. V. Zegeer et al., 2002). Bowman and Vecellio (1994) found that arterial roads with physical medians were associated with relatively lower pedestrian crash rates when compared to roads with undivided arterial roads. However, the researchers also determined that there was no significant difference in pedestrian crash rates between arterials with physical medians and arterials with TWLTLs. The findings from Bowman and Vecellio were substantiated by Zegeer et al. (2001), where these researchers found that raised medians along multilane roads were associated with lower pedestrian crash rates when compared to roads without raised medians. Furthermore, Schneider et al. (2010) reported that the presence of raised medians was associated with lower pedestrian crash counts at intersections.

Moreover, a recent study by Zhang et al. (2017) reported a 86% reduction in fatal pedestrian and bicyclist crashes after physical median treatments were applied at locations with high frequencies of pedestrian or bicyclist crashes. This result was statistically significant at a 99% confidence level. In terms of total pedestrian and bicyclist crashes, a 12% increase in crash counts was found but was not statistically significant. The authors commented that median treatments may not decrease crash frequency but may cause severe or fatal pedestrian crashes to be less likely to occur.

It has been suggested that raised medians provide a false sense of security for pedestrians, especially when there are several lanes of traffic that must be crossed (Marosi, 1999). To this extent, the presence of a raised median may entice pedestrians to jaywalk, particularly when one or more significant pedestrian trip generators, such as transit stops or commercial service amenities, are present. However, there have been no recent identified research efforts that support this perspective. Overall, previous research indicates that locations with raised medians are associated with lower crash rates for pedestrians. In this sense, given the occurrence of a pedestrian collision, crashes at locations with raised medians are more likely to result in a severe injury to the affected pedestrian. Therefore, interventions to reduce pedestrian injury severity should be focused at locations with raised medians.

One possible intervention that may prove useful in discouraging pedestrians crossings outside of crosswalks is the implementation of pedestrian fencing along a raised median. An example is provided in **Figure 6.27**. Installing fencing assists in channelizing pedestrians to controlled crossing points. Several studies have demonstrated that pedestrian channelization barriers and fences can reduce pedestrian crash rates, particularly at midblock locations (R. A. Retting et al., 2003). However, consideration should be given to the potential obstruction of sightlines among pedestrians and drivers that may result. Additionally, consideration should also be provided for the potential of increased walking distance that may arise.

Figure 6.27: Median fencing to channelize pedestrians into marked crosswalks (City of Tampa, 2017).

CHAPTER 7: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

This chapter provides brief summaries of the two analyses performed, the key findings of the two analyses, limitations of the demographics and injury severity analyses and recommendations for future research regarding pedestrian injury forecasting and pedestrian injury severity modelling.

7.1: Summary

Pedestrians are an integral part of the modern transportation system but are arguably the most vulnerable to severe injury in the event of a traffic crash. Between the mid-1970s and late 2000s, pedestrian fatality counts in the United States have been decreasing. However, since 2009, pedestrian fatalities have been increasing.

The main objectives of this two-part thesis were to investigate i) long-term trends of pedestrian fatalities stratified by pedestrian age and sex, and ii) the independent contributions of roadway infrastructure on pedestrian injury severity. The two parts of this thesis are summarized in the following subsections.

7.1.1: Demographics Analysis

This first part of the thesis explored pedestrian fatality counts stratified by age and sex from 1975 through 2015. This part was divided into two subparts: an investigation of pedestrian fatality trends, and an analysis of projected pedestrian fatalities. In both subparts, pedestrian fatality data for the 41-year timeframe were acquired from the NHTSA FARS database and were disaggregated according to six age groups (younger than 16, 16 to 19, 20 to 34, 35 to 54, 55 to 64, older than 64) and two sexes (male and female).

The first subpart involved the analysis of observed and exposure-adjusted fatality trends from 1975 through 2015. The exposure-adjusted trends were relative to 1975 and served as indicators of expected fatality counts under a scenario in which no safety interventions were applied. Three measures of travel-based pedestrian exposure (number of walk trips, person miles walked, person minutes walked) were derived using data from multiple instances of the NHTS. Survey years considered in this analysis include 1977, 1983, 1990, 1995, 2001 and 2009. Linear interpolation was employed to determine exposure for years in which a survey had not been conducted. Moreover, population-based exposure adjustments derived from the United States Census Bureau were applied to the fatality trends.

Results from the fatality trends analysis showed that observed pedestrian fatality counts were consistently lower than the exposure-adjusted fatality trends across all ages and sexes. The magnitude of these differences was smallest for children and teenagers (ages 5-19) and largest for seniors (ages 55 or older). There were no discernable differences in exposure-adjusted fatality trends between males and females. In general, the differences in observed and exposure-adjusted fatality counts suggest that interventions to reduce fatal pedestrian crashes have been effective. The large differences between observed and exposure-adjusted trends suggest that, despite increasing pedestrian exposure, efforts to mitigate pedestrian fatalities have been effective.

The second subpart of the demographics analysis comprised projecting annual pedestrian fatality counts to the year 2035. Pedestrian fatality projection models were fitted using the SPSS (V25) CURVEFIT procedure. Selected models were limited to the following: logarithmic, quadratic, compound, growth, exponential, logistic.

Results indicated that males had consistently higher counts of pedestrian fatalities than females across all age groups and years. Pedestrian fatalities for those aged 5 through 15 gradually declined between 1975 and 2015. It is likely that this long-term decrease in child pedestrian fatalities was attributable to lower child pedestrian exposure. Similar fatality trends were found for teenagers aged 16 through 19 but were lower in frequency. Moreover, fatalities for these two cohorts were projected to decrease further towards 2035, but at a slower rate than in previous years. Pedestrian fatalities for young male adults (ages 20 to 34) showed fluctuating trends from 1975 to 2015 and were projected to decline further towards 2035. For young female adults, observed fatality counts showed similar fluctuations, but were significantly less in frequency. Fatalities for this cohort were forecasted to remain relatively stable through to 2035. The time periods of the fluctuations corresponded to significant changes in the U.S. economy, suggesting that the relationship between pedestrian fatality risk and socioeconomics is more sensitive for younger adults. Observed counts of pedestrian fatalities for middle-aged adults (ages 35 to 54) showed steadily increasing trends with relatively minor fluctuations as of 1975 and were forecasted to continue increasing at a slight rate. For males aged 55-64, pedestrian fatality counts were relatively stable from 1975 to approximately 2008, after which point a significant increase was observed. A similar post-2008 increase was found for females of the same age group. Lastly, pedestrian fatalities among the elderly (ages 65 and older) had decreased steadily from 1975 to 2009 but reversed direction afterwards. Possible changes to older pedestrian exposure may be expected in the future.

In summary, this part of the research highlights specific pedestrian age-sex cohorts which are at higher count-based risk of traffic-related fatality. Furthermore, this study provides model-based forecasts for future counts of pedestrian fatalities. The forecasts may be used as tools by policymakers to guide the development of quantitative road safety targets exclusive to pedestrian fatalities.

7.1.2: Injury Severity Analysis

In the second part of this thesis, multinomial logit models were fitted to identify significant roadway infrastructural factors that may affect the severity of a pedestrian crash. Pedestrian injury severity was classified into three categories: no/possible injury, non-severe (non-incapacitating) injury, and severe (fatal or incapacitating) injury. Pedestrian injury data from the NHTSA GES database from 2011 to 2015 were obtained for this analysis. The multinomial logit models were developed using the SPSS NOMREG procedure. First, as a preliminary step, univariable models were fitted to each variable to examine associations with pedestrian injury severity. Next, a baseline multinomial logit model was developed using variables pertaining to pedestrians, drivers, vehicle types, the crash day, and the crash environment. Lastly, a full multinomial logit model was estimated by including the variables above and incorporating various roadway infrastructure and geometric features.

Results from the univariable, baseline and full multinomial models show that the odds of non-severe and severe pedestrian injuries changed after controlling for roadway-related variables. In this sense, the full multinomial model showed that the following factors at the pedestrian, driver, temporal, environmental and vehicle levels were significant in increasing the probability of a severe pedestrian injury: female pedestrians, unsafe pedestrian actions (e.g., darting/dashing out into traffic, jaywalking, failing to yield right-of-way), male drivers, weekends (Fridays 20:00 – Sundays 20:00), light conditions (unlit or artificially lit), dry road conditions and vehicle type (trucks or utility vehicles). In addition to the aforementioned factors, the following roadway infrastructural factors were also found to increase the probability of a severe pedestrian injury: increased posted speed limits, vehicles travelling straight, intersections with three or four legs, locations without signalization (uncontrolled or unsignalized), roads with vertical curvature (e.g., upgrade, downgrade, hillcrest) and physical/raised medians. Regarding posted speed limits, a negative linear relationship between posted speed limits and non-severe pedestrian injury probability was observed. On the other hand, a positive linear relationship was found between posted speed limit and severe injury probability.

Moreover, the results of the full multinomial model showed that the following factors were significant at increasing the probability of a non-severe injury: female pedestrians, unsafe pedestrian actions, female drivers, weekends, dry roadway conditions, roads with vertical curvature and physical/raised medians.

Several engineering countermeasures that may reduce the severity of pedestrian crashes based on the factors identified previously were suggested. Countermeasures were organized into six areas: vehicle speed management, pedestrian crash location, vehicle turning movements, method of traffic control, roadway geometric properties, and the influence of medians. Speed limit reductions and other traffic calming strategies may be implemented to encourage motorists to travel at lower speeds, while improved pedestrian-level lighting and crosswalk daylighting can improve visibility of pedestrians to motorists. Truck routes can be reviewed and changed such that trucks avoid operating in areas of known pedestrian activity.

In summary, this part of the research demonstrates significant associations between roadway features and pedestrian injury severity. The findings obtained in this study provide further insight into the nature of pedestrian injuries and may be used to guide the development of effective pedestrian injury countermeasures.

7.2: Limitations

A number of limitations for the pedestrian fatality forecasting and injury severity modelling analyses were noted. These are discussed in the following subsections.

7.2.1: Fatality Trends and Projections

The FARS database provides vast amounts of information regarding crashes within the United States. However, the information is limited to crashes on public roads in which at least one fatality was recorded within 30 days of the crash incident. This restriction of crash data carries several potential research limitations. First, fatal pedestrian crashes on private roads (such as access routes or private driveways) are not included as part of FARS, as they do not constitute as crashes on public roads according to the NHTSA. While it is unlikely that the speeds of vehicles travelling on private roads would be sufficiently high to pose any significant fatality risk, there may be a few cases failing to meet the criterion above. Second, only fatal pedestrian injuries were examined in this study. In this sense, trends and projections of non-fatal pedestrian injuries were not examined. Doing so may provide a comprehensive profile of pedestrian safety within the past 40 years. Lastly, fatal pedestrian crashes occurring outside of the 30-day threshold criterion were not included. Whereas injuries associated with pedestrian crashes tend to be more definitive when compared to those motor vehicle crashes, there may likely be additional fatalities that have occurred after the 30-day threshold which have not been included in FARS.

As part of the pedestrian fatality trends analysis, three travel-based exposure measures of pedestrian activity were considered (walk trips, miles walked, and minutes walked). Pedestrian exposure data were derived from multiple instances of the NHTS, which is administered intermittently (i.e., every 5 to 8 years). Data from the NHTS is extracted from self-reported trip information at the household and person levels, which may be subject to human error and self-report biases. Interventions to minimize human-based error in walk trip reporting have been implemented (such as administering travel diaries and travel logs to survey respondents), but it is highly likely that such application can eliminate this errors and biases. Furthermore, as the

NHTS is sample-based, the use of nationally representative weights may also be a source of error for pedestrian exposure estimates.

Exposure for years in which a survey had not been administered was estimated using linear interpolation between the preceding and upcoming survey year. However, assuming a linear relationship of pedestrian exposure between survey years ignores the possibility of significant intra-survey exposure fluctuations. A notable example includes the period between the administering of NHTS 2009 and NHTS 2017, where the effects of the recession during the late 2000s may have influenced rates of walking.

The fatality trends analysis also incorporated demographic-stratified population adjustments. However, the application of such an adjustment assumes that the entire sub-population walks and may not adequately represent individuals who live in remote areas where motor vehicle dependency is higher or are unable to walk due to health-related disabilities. In this sense, the population exposure adjustments may overestimate fatality trend estimates.

Regarding the fatality projections analysis, it was decided that the quadratic, logarithmic, and CGEL models would be represented in detail over the remaining projections models. These models were consistently among the best fitting subjectively (good visual fit) and objectively (low AIC). However, in many instances, the quadratic model showed inconsistent projections when compared to the CGEL and logarithmic models. This is mainly because higher-order polynomial-based models (e.g., quadratic, cubic) have a fixed number of turning points. Furthermore, in some instances (e.g., for mature adults), other models such as the linear, power, or cubic models showed better objective fits than the CGEL, logarithmic or quadratic models. In this sense, the range of models considered was limited to the 11 models included as part of the SPSS CURVEFIT procedure. The application of other statistical software packages, such as

Stata's curvefit procedure   hich includes   curve estimation regression models) may prove more useful in future studies.

The fatality projections illustrated in this thesis provide quantitative estimates of pedestrian fatalities for future years. However, such projections are representative of the United States as a whole and did not consider any elements of spatial distribution (states, cities, *et cetera*). Spatial disaggregation of data within FARS was possible, as FARS data include the latitude and longitude of crash locations. Using this geographical data, crashes may be mapped to locations using geofences around spatial units of interest. Doing so could uncover spatial patterns in pedestrian fatalities and stimulate the development of location-specific countermeasures. However, such an undertaking was beyond the scope of this thesis.

7.2.2: Injury Severity Modeling

Several data limitations pertaining to GES were present in the injury severity analysis. Given that GES data are derived from a nationally representative sample of police-reported crashes of varying severities, there may be errors between actual census-level statistics and GES records. In this sense, one common limitation with regards to analyzing injury severity is the underreporting of lower-severity injuries. Pedestrian crashes that result in little to no personal injury or property damage are often not reported to the police or medical services, and as a result, are not reflected in the relevant datasets.

The GES dataset used as part of the injury severity analysis comprised of crash data from 2011 to 2015. Prior to 2011, the GES database was subject to a large data standardization undertaking, which involves significant changes in variable and attribute definitions to match those used in FARS. The inclusion of years prior to 2011 to the master GES dataset used in this study required that the data go through a similar standardization process. This would have not been feasible given the thesis timeline. Furthermore, after 2015, GES was discontinued and was replaced by the CRSS in 2016. It was found that CRSS data are not comparable with GES data, thus limiting the study period to 2015.

The injury severity analysis was restricted to pedestrian crashes involving only one pedestrian and one vehicle per event. As such, no inferences could be made regarding crashes involving multiple vehicles or pedestrians. It may be possible that the factors investigated as part of the injury severity analysis may have different effects on multi-pedestrian or multi-vehicle crashes and could be explored further, provided that sufficient data on multi-vehicle or multi-pedestrian crashes exist.

Several variables considered in the injury severity analysis had counts which were skewed towards one attribute, such as horizontal roadway alignment or pedestrian impairment. This resulted in these variables being rejected from entry into the multivariable analysis. Moreover, many of the attributes among a variable either had to be collapsed into groups in order to provide sufficient sample sizes or disregarded from the analysis entirely. This resulted in a loss of detail that may have provided useful insight into the causes of severe pedestrian injuries. For instance, crashes involving buses or on roundabouts could not be considered given their small sample sizes in the GES dataset.

Given that a large proportion (approximately 73.5%) of pedestrian crash records within the GES dataset had missing travel speed data, posted speed limits were utilized as a proxy measure for impact speed. However, posted speed limits do not accurately reflect the speed at which a pedestrian may be struck.

In addition, other roadway factors such as crosswalk properties (type, condition, *et cetera*), roadway configuration (number of lanes, lane and shoulder widths, presence of sidewalk), intersection skew or presence of transit stops were also not included as part of GES. Such factors may provide insight into possible roadway improvements for pedestrians.

Finally, one of the most significant limitations in variables was the inability to incorporate data from the *Pbtype* data file into the master GES dataset. This data file contains details on crashes involving pedestrians, bicyclists or people on personal conveyances (e.g., segway-style devices, wheelchairs, handicapped scooters). The *Pbtype* data files from 2011 through 2013 were removed by the NHTSA due to major changes in pedestrian crash data collection. The NHTSA implemented new data collection methodology effective 2014 and included variables such as pedestrian position (in relation to the respective vehicle), pedestrian initial direction of travel, motorist direction, and intersection leg. This information would have likely provided additional information into pedestrian crash causality.

7.3: Future Research

This section describes several recommendations for future research regarding temporal and explanatory modelling of traffic-related pedestrian injuries.

7.3.1: Fatality Trends and Projections

Future research into pedestrian injury trends and projections should consider crashes of lower severities (such as incapacitating or non-incapacitating injuries), provided that a suitable dataset can be acquired. Doing so may provide additional comprehensibility of pedestrian safety and can assist with the planning of future developments.

Several improvements can be made to refine the injury forecasting framework presented here; it is worth performing a similar fatality projection analysis using a different methodology. Other deterministic methods (such as joinpoint or piece-wise linear regression) or stochastic approaches (such as ARIMA or structural time series models) could be applied; the results of which could be compared and used to validate the projections created as part of this study.

It may also be worth undertaking a similar forecasting analysis with data from smaller geographic units, such as separate states or cities. The resulting sets of forecasts could be compared with one another and assessed to determine which state or city warrants additional interventions. This approach potentially has improved cost-effectiveness over employing the national-level forecast methodology presented in this thesis.

Forecasting historical fatality trends is undoubtedly subject to uncertainty, given the relationships between transportation safety and other external factors such as technological change, improvements in healthcare, and potential socioeconomic change. Injury forecasts may be more reliable if they accounted for the factors above but doing so would unequivocally be a lengthy undertaking.

Lastly, the pedestrian injury exposure metrics considered as part of this thesis may not accurately represent the risk experienced by those who walk. For instance, a pedestrian trip may consist of portions he re the pedestrian must a lk on a vehicle’s travel ay i.e., a cross alk). In this sense, while the subject pedestrian is not fully immune to a risk of a traffic-related injury, the risk is much more apparent when the pedestrian is crossing the road via a crosswalk (i.e., the probability of a pedestrian and vehicle occupying the same space is a positive value). Therefore, the most practical exposure measure for pedestrian injury, in theory, is one that accounts for the potential of pedestrians and vehicles being in the same location at the same time. Examples of this include the number of pedestrians crossing at a crosswalk, the cumulative distance walked by pedestrians on crosswalks or the cumulative time spent by pedestrians on a crosswalk. However, it should be noted that this exposure metric is more suitable for microscopic analyses (e.g., at the intersection or midblock level), rather than those of a larger spatial scale (e.g., city-wide, state-wide, nation-wide). Future studies could consider deriving and implementing such exposure measures.

7.3.2: Injury Severity Modeling

Given that intersections and midblock crossing locations pose different types of risk for pedestrians, separate models could be developed to investigate how pedestrian injury risk changes among these two roadway environment types. Exposure-related variables, such as annual average daily traffic (AADT) and pedestrian volumes could also be included in future models. However, these data are difficult to acquire for a national-level model and are more suited for analyses at the state or city levels. Therefore, it may be worthwhile to model pedestrian injury severities at these smaller geographical units and assess the results contemporaneously. Doing so may reveal injury patterns otherwise not detected with a model based on national-level data.

Overall, the injury severity analysis aimed to identify roadway properties and features that are significant in increasing the likelihood of a severe pedestrian injury. The results obtained in the injury severity analysis are at best, approximate, given that GES is based on a nationally representative sample of police-reported crashes. Furthermore, other modelling approaches, such as ordered-response or random-parameter logit, could be used to validate the results obtained as part of this thesis.

Furthermore, a count-based injury severity analysis could be undertaken to complement the findings presented in this work. In this respect, such an analysis could identify significant factors that are characteristic of locations with high frequencies of fatal or serious pedestrian injuries; the results of which could be compared with the results presented in this research to further guide the development of targeted countermeasures.

Lastly, future work should include built environment and land use features, particularly ones that are generally considered major pedestrian trip generators. These may include commercial retail or service uses, schools or transit stations/stops. It should also be noted that certain pedestrian trip generators may not affect specific cohorts similarly. For example, child pedestrians are more likely to travel in the vicinity of schools, whereas younger and middle-aged adults are more likely to be located at places of employment, such as commercial or industrial areas.

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APPENDICES

APPENDIX A: EXPOSURE DATASET STACKING

This appendix contains flow charts that illustrate the process of building pedestrian exposure datasets as part of the pedestrian trends analysis. The flow charts are organized according to the partitions listed in **Table 3.3**. Details on the stages of validation are provided in Appendix B.

A.1: Partition 1 Travel Surveys

Partition 1 travel surveys include NPTS 1977, NPTS 1983 and NPTS 1990. **Figure A.1** contains the study flow diagram for partition 1 datasets. Sample sizes (*n*) by screening process and travel survey are listed in **Table A.1**.

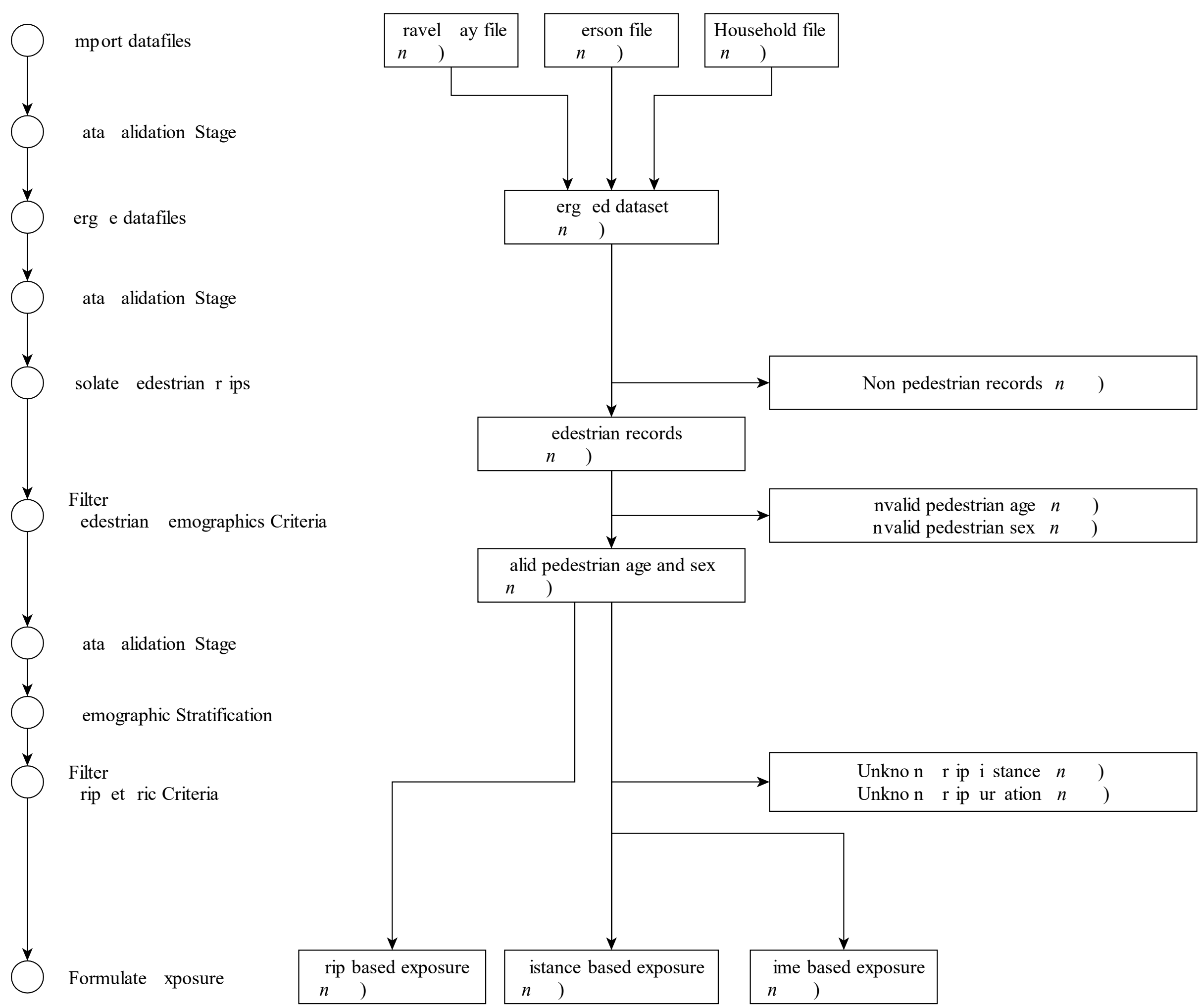

Figure A.1: Study flow diagram for partition 1 travel survey datasets.

Table A.1: Summary of sample size evolution for partition 1 travel survey datasets.

Number of Records (*n*)		**NPTS 1977**	**NPTS 1983**	**NPTS 1990**
Travel Day file	*a*	136136	45155	149546
Person file	*b*	51194	17382	48385
Household file	*c*	17948	6438	22317
Merged dataset	*d*	136136	45155	149546
Pedestrian records	*e*	12227	3767	10062
Non-pedestrian records	*f*	123909	41388	139484
Records with pedestrian age and sex	*g*	11848	3767	9976
Invalid pedestrian age	*h*	379	0	86
Invalid pedestrian sex	*i*	0	0	0
Invalid trip distance	*j*	72	87	104
Invalid trip duration	*k*	174	72	487
Valid trip distance	*l*	11776	3680	9872
Valid trip duration	*m*	11674	3695	9489

A.2: Partition 2 Travel Surveys

Partition 2 travel surveys include NPTS 1995, NHTS 2001, NHTS 2009 and NHTS 2017. **Figure A.2** contains the study flow diagram for partition 2 datasets. Sample sizes (*n*) by screening process and travel survey are listed in **Table A.2**.

The file merging process was not included as part of building partition 2 travel survey datasets. The travel day files of partition 2 datasets contained age and sex information, thus reducing the amount of data management required.

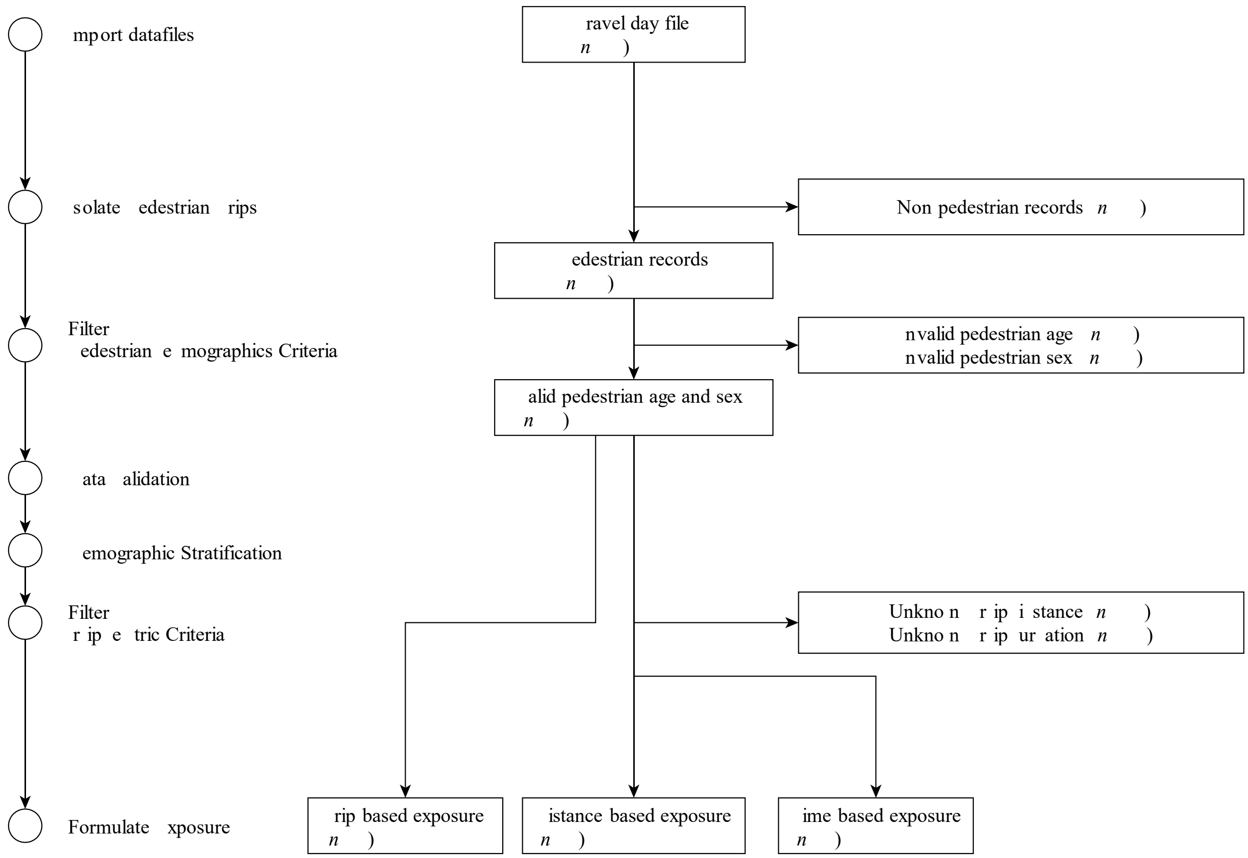

Figure A.2: Study flow diagram for partition 2 travel survey datasets.

Table A.2: Summary of sample size evolution for partition 2 travel survey datasets.

Number of Records (*n*)		**NPTS 1995**	**NHTS 2001**	**NHTS 2009**	**NHTS 2017**
Travel Day file	*a*	409025	642292	1167321	923572
Non-pedestrian records	*b*	387912	590766	1066916	842284
Pedestrian records	*c*	21113	51526	100405	81288
Invalid pedestrian age	*d*	0	3524	0	134
Invalid pedestrian sex	*e*	0	2	0	68
Valid pedestrian age and sex	*f*	21113	48002	100405	81116
Invalid trip distance	*g*	6	517	1859	297
Invalid trip duration	*h*	614	4688	424	128
Valid trip distance	*i*	21107	47485	98546	80819
Valid trip duration	*j*	20499	43314	99981	80988

APPENDIX B: DATA VALIDATION

This appendix describes the processes by which the injury and exposure data was validated. The appendix is organized by individual data source.

B.1: FARS Data

FARS data was validated using an online-based NHTSA FARS encyclopedia (https://www-fars.nhtsa.dot.gov/Main/index.aspx). Within the encyclopedia, users have the choice of examining pre-made summary data tables or creating custom year-specific queries with univariate reports (i.e., analysis of a single variable) or cross-tabulations (i.e., two variables are analyzed). The count data illustrated within these reports can be of the number of crashes, the number of persons involved, or the number of vehicles/drivers involved.

B.2: NPTS/NHTS Data

For partition 2, validation was done by comparing computed values to online sources. For N S 99 , NH S a nd NH S 9, the FH WA's NH S ata xtraction ool a s used (found on https://nhts.ornl.gov/det/default.aspx). Using the *Total Travel by Survey Year and Selection Trip Characteristics* option, online estimates of pedestrian trips and pedestrian miles walked were compared against computed values. One limitation of the Data Extraction Tool is that it does not provide estimates of pedestrian minutes walked. To our knowledge, there was no public documentation containing time-based pedestrian exposure. As a result, validation of pedestrian minutes walked was not possible.

The process of validating NHTS 2017 was slightly different, as the Data Extraction Tool does not display information from the 2017 travel survey. As an alternative, the NHTS website allows for users to examine NHTS 2017 data through a custom Table Designer (found on https://nhts.ornl.gov/). Specifically, cross-tabulations of pedestrian exposure (number of walk trips and number of pedestrian miles walked only, pedestrian minutes walked was not available) by age and sex were generated and compared to calculated values.

Given that the Data Extraction Tool only goes as far back as NPTS 1995, partition 1 datasets were validated using a multiple-stage process. The stages are described in the following subsections.

B.2.1: Stage 1 Validation

The first stage of validating partition 1 datasets involved calculating (1) the estimated total number of persons, (2) the estimated total number of person trips, and (3) the estimated total number of person miles of travel. These calculated values are based on all modes of transportation and not exclusive to just walk trips. We define ϕ' and Φ' as an unweighted and weighted case, respectively, where the superscript prime is used to represent trips of any transportation mode. The calculated values are compared to control values found within various sources.

Stratifications by age and sex were considered, depending on the availability of control values. Stage 1 control values and their respective sources for each of the partition 1 travel surveys are tabulated in **Table B.1**. The total number of persons was calculated as such:

$$\sum_{\phi'} \Phi'_{per,ij} = \sum_{\phi'} \left(\phi'_{ij} \times \tau_{per,\phi'}\right) \qquad \text{(B.1)}$$

where,

$\Phi'_{per,ij}$ = population-level estimate of the number of people belonging to sex-age category *ij* (all modes of transportation), with all other terms previously defined.

Similarly, the total number of person trips (regardless of transportation mode) was determined using the following:

$$\sum_{\phi'} \Phi'_{trp,ij} = \sum_{\phi'} \left(\phi'_{ij} \times \tau_{trp,\phi'}\right) \tag{B.2}$$

where,

Φ'_{trp} = population-level estimate of the number of person trips (all modes of transportation), with all other terms previously defined.

Lastly, the total number of person miles travelled (all modes of transportation) was found by:

$$\sum_{\phi'} \Psi'_{\phi'} = \sum_{\phi'} \left(\left(\phi'_{ij} \times \psi_{\phi'}\right) \times \tau_{trp,\phi'}\right) \tag{B.3}$$

where,

Ψ' = population-level estimate of the number of person miles travelled (all modes of transportation), with all other terms previously defined.

Table B.1: Stage 1 validation properties and control value sources.

Partition 1	**Control Value**	**Sex Category**	**Age Category**	**Sex-Age Category**	**Stage 1 Control Value Sources**
NPTS 1977	$\sum_{\phi'_i} \boldsymbol{\Phi'}_{\boldsymbol{per,i}}$	i = all	j = all	both sexes, all ages	• Table 3 & Table 4, Supplement to the User's Guide for the Public Use Data Files [Draft] (NPTS 1977, 2000) • 9 N S User's Guide for the Public Use Tapes (Asin, 1980)
	$\sum_{\phi'_i} \boldsymbol{\Phi'}_{\boldsymbol{trp,i}}$	i = all	j = all	both sexes, all ages	
	$\sum_{\phi'} \boldsymbol{\Psi'}_{\boldsymbol{\phi'}}$	i = all	j = all	both sexes, all ages	

Table B.1: continued.

NPTS 1983	$\sum_{\phi'_i} \boldsymbol{\Phi'}_{\boldsymbol{per,i}}$	i = all	j = all	both sexes, all ages	• N S 98 U ser's Guide for the Public Use Tapes, pg. 25 • Personal Travel in the United States 1983-1984, Volume I, Chapter 6, pg. 6-1 • Summary of Travel Trends: 1995 Nationwide Personal Transportation Survey, Table 1
		i = all	j = 0	both sexes, 5-15	
		i = all	j = 1	both sexes, 16-19	
		i = all	j = 2	both sexes, 20-34	
		i = all	j = 3	both sexes, 35-64	
		i = all	j = 4	both sexes, 65+	
		i = 1	j = all	males only, all ages	
		i = 2	j = all	females only, all ages	
	$\sum_{\phi'_i} \boldsymbol{\Phi'}_{\boldsymbol{trp,i}}$	i = all	j = all	both sexes, all ages	
	$\sum_{\phi'} \boldsymbol{\Psi'}_{\boldsymbol{\phi'}}$	i = all	j = all	both sexes, all ages	
NPTS 1990	$\sum_{\phi'_i} \boldsymbol{\Phi'}_{\boldsymbol{per,i}}$	i = all	j = all	both sexes, all ages	• 1990 Nationwide Personal Transportation Survey, User's Guide to the Public Use Tapes, pg. A-1 (Research Triangle Institute, 1991)
		i = all	j = 1	both sexes, 5-17	
		i = all	j = 2	both sexes, 18-34	
		i = all	j = 3	both sexes, 35-64	
		i = all	j = 4	both sexes, 65+	
		i = 1	j = all	males only, all ages	
		i = 2	j = all	females only, all ages	
	$\sum_{\phi'_i} \boldsymbol{\Phi'}_{\boldsymbol{trp,i}}$	i = all	j = all	both sexes, all ages	
	$\sum_{\phi'} \boldsymbol{\Psi'}_{\boldsymbol{\phi'}}$	i = 1	j = all	all ages, both sexes	

B.2.2: Stage 2 Validation

In stage 1, control values regarding all modes of transportation were used. In the second stage, only control values regarding walk trips were used. Again, demographics disaggregation was considered if appropriate sources were available. The control values and their respective sources for stage 2 validation are shown in **Table B.2**. For NPTS 1977, the control values took the form of percentages of male and female walk trips by age group relative to all walk trips. The symbol ρ is used to represent walk trip proportions. Calculated values were first computed using the following:

$$\rho_{males,j} = \left(\sum_{i=males} \sum_{j} \Phi_{trp,ij} \div \sum_{i=males} \sum_{j=all} \Phi_{trp,ij} \right) \times 100\% \qquad \text{(B.4)}$$

$$\rho_{females,j} = \left(\sum_{i=females} \sum_{j} \Phi_{trp,ij} \div \sum_{i=females} \sum_{j=all} \Phi_{trp,ij} \right) \times 100\% \qquad \text{(B.5)}$$

where,

$\rho_{male,j}$ = percentage of walk trips done by males of age group *j* (relative to all walk trips by males), and

$\rho_{female,j}$ = percentage of walk trips done by females of age group *j* (relative to all walk trips by females).

The control value tables for NPTS 1977 are shown below in **Figure B.1** and **Figure B.2** for males and females, respectively. Note that only the numbers in the *Walk* row are used as the control values. For NPTS 1983, control values percentages of walk trips by only age were computed using a generalized version of the previous equation:

$$\rho_{j} = \left(\sum_{i=all} \sum_{j} \Phi_{trp,ij} \div \sum_{i=all} \sum_{j=all} \Phi_{trp,ij} \right) \times 100\% \qquad \text{(B.6)}$$

where,

ρ_{j} = percentage of walk trips done by age group *j* (relative to all walk trips).

Lastly, for NPTS 1990, the only available control value for walk trips was the weighted number of walk trips. As such, the compared value was calculated using Equation (B.2.

MALES										
	Age of Tripmaker (Years)									
Means of Transportation	Under 5	5-15	16-19	20-29	30-39	40-49	50-59	60-64	65 & Over	All Males
Private Vehicles										
Auto, Vanbus, Minibus	5.5	12.0	9.3	22.6	16.4	12.5	11.3	4.1	6.3	100.0
Pickup	3.0	7.4	5.4	24.0	21.8	16.1	13.8	4.1	4.4	100.0
Other Private Vehicle	3.2	6.0	10.2	32.1	22.5	10.3	11.1	2.1	2.5	100.0
Subtotal-Private	5.1	11.2	8.7	23.0	17.3	13.0	11.7	4.1	5.9	100.0
Public Transportation										
Bus, Streetcar	1.7	25.6	15.8	19.3	10.7	7.5	9.0	2.8	7.6	100.0
Train	0.7	4.9	0.4	25.9	25.1	18.4	19.4	4.3	0.9	100.0
Subway, Elevated Rail	0.0	5.2	2.8	35.9	27.6	12.6	9.5	4.2	2.2	100.0
Subtotal-Public	1.4	20.2	12.1	22.5	14.8	9.5	10.3	3.2	6.0	100.0
Other Means										
Walk	2.6	27.9	17.2	18.3	9.2	7.0	6.8	2.9	8.1	100.0
Bike	1.4	49.3	19.9	17.8	5.7	1.3	1.8	0.8	2.0	100.0
School Bus	0.4	84.5	12.8	1.8	0.1	0.4	0.0	0.0	*	100.0
Airplane	2.0	2.1	0.0	26.6	19.4	17.1	18.4	8.7	5.7	100.0
Other	2.1	8.9	9.7	23.7	24.2	11.1	14.4	3.3	2.6	100.0
Subtotal-Other	2.0	39.0	15.9	15.4	8.4	5.7	5.7	2.2	5.7	100.0
Total	4.6	15.4	9.8	21.9	16.0	11.9	10.8	3.7	5.9	100.0 1/

1/ 107,594,800,000 trips
*Less than 0.1 percent.

Figure B.1: Proportions of male person trips by mode of transportation and age of individual (Asin, 1983).

FEMALES										
	Age of Tripmaker (Years)									
Means of Transportation	Under 5	5-15	16-19	20-29	30-39	40-49	50-59	60-64	65 & Over	All Females
Private Vehicles										
Auto, Vanbus, Minibus	5.1	11.9	8.9	22.3	18.0	13.0	11.0	3.6	6.2	100.0
Pickup	8.8	13.8	8.0	25.1	17.5	12.0	9.5	1.9	3.4	100.0
Other Private Vehicle	5.2	11.0	10.9	38.9	15.9	5.2	9.1	1.5	2.3	100.0
Subtotal-Private	5.2	11.9	8.9	22.6	18.1	12.9	10.9	3.5	6.0	100.0
Public Transportation										
Bus, Streetcar	2.0	22.7	11.5	18.2	11.3	7.2	10.6	5.0	11.5	100.0
Train	0.0	1.8	6.8	33.6	21.1	18.5	11.8	5.4	1.0	100.0
Subway, Elevated Rail	3.4	5.7	5.6	42.1	19.2	12.9	7.5	1.7	1.9	100.0
Subtotal-Public	2.0	19.2	10.5	22.2	12.9	8.7	10.3	4.6	9.6	100.0
Other Means										
Walk	2.9	24.4	13.9	19.0	10.3	7.7	7.6	3.5	10.7	100.0
Bike	2.1	34.6	29.0	15.3	11.8	4.0	1.0	1.5	0.7	100.0
School Bus	0.2	83.4	14.1	1.2	0.6	0.4	*	0.0	0.1	100.0
Airplane	3.1	6.1	0.0	37.5	21.3	3.9	15.5	2.6	10.0	100.0
Other	5.1	15.8	3.3	18.5	15.3	12.7	6.9	5.0	17.4	100.0
Subtotal-Other	2.4	37.3	13.9	15.1	8.4	6.2	5.7	2.7	8.3	100.0
Total	4.8	15.5	9.6	21.6	16.6	11.9	10.2	3.4	6.4	100.0 1/

1/ 104,174,100,000 trips
*Less than 0.1 percent.

Figure B.2: Proportions of female person trips by mode of transportation and age of individual (Asin, 1983).

Table B.2: Stage 2 validation properties and control value sources.

Partition 1	Control Value	Sex Category	Age Category	Sex-Age Category	Stage 2 Control Value Sources
NPTS 1977	$\rho_{males,j}$	i = males	$j = 1$	males only, 5-15	• Person Trip Characteristics: Report 11, 1977 NPTS – Table 5 and Table 6 (Asin, 1983)
			$j = 2$	males only, 16-19	
			$j = 3$	males only, 20-29	
			$j = 4$	males only, 30-39	
			$j = 5$	males only, 40-49	
			$j = 6$	males only, 50-59	
			$j = 7$	males only, 60-64	
			$j = 8$	males only, 65+	
	$\rho_{males,j}$	i = females	$j = 1$	females only, 5-15	
			$j = 2$	females only, 16-19	
			$j = 3$	females only, 20-29	
			$j = 4$	females only, 30-39	
			$j = 5$	females only, 40-49	
			$j = 6$	females only, 50-59	
			$j = 7$	females only, 60-64	
			$j = 8$	females only, 65+	
NPTS 1983	ρ_j	i = all	$j = 1$	both sexes, 5-15	• Personal Travel in the United States 1983-1984 Nationwide Personal Transportation Survey Vol. II Part 3, Table E-99 (Klinger & Kuzmyak, 1986)
			$j = 2$	both sexes, 16-19	
			$j = 3$	both sexes, 20-29	
			$j = 4$	both sexes, 30-39	
			$j = 5$	both sexes, 40-49	
			$j = 6$	both sexes, 50-59	
			$j = 7$	both sexes, 60-64	
			$j = 8$	both sexes, 65+	
NPTS 1990	$\sum_{\phi} \boldsymbol{\Phi}_{trp,i}$	i = all	j = all	both sexes, all ages	• 1990 Nationwide Personal Transportation Survey, User's Guide to the Public Use Tapes, pg. A-12 (Research Triangle Institute, 1991)
			$j = 1$	both sexes, 5-17	
			$j = 2$	both sexes, 18-34	
			$j = 3$	both sexes, 35-64	
			$j = 4$	both sexes, 65+	
		$i = 1$	j = all	males only, all ages	
		$i = 2$	j = all	females only, all ages	

B.2.3: Stage 3 Validation

In the third and last stage of validation, calculated values are compared to values reported by Santos et al. (2011). This stage involves the determination of an average number of annual walk trips per household, as indicated in the *Walk* sub-table from Table 7 in Santos et al.). To compute this metric, the household files of the travel surveys needed to be included. First, a calculation was done to obtain an annual walk trip count per household (symbolized by the letter ζ). This was done using the following:

$$\zeta = \sum_{\phi} \Phi_{trp} \div \sum_{\phi'} \Phi'_{hh} \tag{B.7}$$

where,

ζ = weighted average annual walk trips per household.

Also within the sub-table are ζ values by Metropolitan Statistical Areas[15], or MSAs. An MSA is a geographic area defined and used by federal-level statistics agencies. MSAs are typically made of one or more counties with at least one urbanized area of at least 50,000 population (U.S. Census Bureau, 2016). In Table 7 of Santos et al., MSAs are categorized into 6 groups based on size; these are tabulated below in **Table B.3**.

Table B.3: MSA size groups and codes.

MSA Size (pop.)	MSA Size Code, *m*
< 250,000	1
250,000 – 499,999	2
500,000 – 999,999	3
1,000,000 – 2,999,999	4
3,000,000+	5
Not in MSA	6

[15] In NPTS 1977 and NPTS 1983, MSAs were known as Standard Metropolitan Statistical Areas (SMSAs) (Santos et al., 2011).

If the index m is used to differentiate different MSA size groups, then the average annual number of walk trips per household by MSA size, ζ_m is calculated as such:

$$\zeta_m = \sum_{\phi} \sum_{m} \Phi_{trp,m} \div \sum_{\phi'} \sum_{m} \Phi'_{hh,m} \qquad \text{(B.8)}$$

where,

ζ_m = weighted average annual walk trips per household in MSA size group m,

$\Phi_{trp,m}$ = weighted annual number of walk trips from MSA size group m, and

$\Phi'_{hh,m}$ = weighted number of households belonging to MSA size group m.

B.3: GES Data

Since there were no known online resources for GES estimates, datasets were validated using annual editions of *Traffic Safety Facts* reports. These reports contain injury data of all severities by numerous explanatory variables. Tables within *Traffic Safety Facts* illustrate fatal crash data, non-fatal injury crash data, property-damage-only (PDO) crash data, and totals. Because all severity levels are examined, the tables listed within these reports draw data from both FARS and GES. An example of such a table is shown in **Figure B.3**. To validate GES data, only sub-tables with non-fatal injury crash data and PDO crash data were used. *Traffic Safety Facts* reports from 2011 through 2015 are identical in table organization, which simplified the validation process.

For validating the crash files, Table 26 (Number of Crashes by Weather Condition, Light Condition, and Crash Severity) was used. Similarly, Table 33 (Number of Vehicles Involved in Crashes by Posted Limit, Crash Type, and Crash Severity) was used to validate the vehicle files. Lastly, Table 70 (Vehicle Occupants Killed or Injured, by Age, Person Type, and Sex) was used for the person files. These reports are publicly available online through the NHTSA.

Weather Condition	Light Condition					Total
	Daylight	Dark, But Lighted	Dark	Dawn or Dusk	Other	
			Fatal Crashes			
Normal	13,804	5,275	7,970	1,269	6	**28,385**
Rain	1,016	521	819	100	3	**2,464**
Snow/Sleet	251	39	141	30	0	**465**
Other	136	68	242	46	2	**497**
Unknown	101	16	144	4	1	**355**
Total	**15,308**	**5,919**	**9,316**	**1,449**	**12**	***32,166**
			Injury Crashes			
Normal	1,086,000	232,000	132,000	51,000	**	**1,502,000**
Rain	95,000	39,000	23,000	8,000	**	**165,000**
Snow/Sleet	23,000	7,000	6,000	2,000	**	**38,000**
Other	4,000	2,000	3,000	1,000	**	**10,000**
Total	**1,208,000**	**280,000**	**164,000**	**62,000**	**	**1,715,000**
			Property-Damage-Only Crashes			
Normal	2,814,000	542,000	401,000	136,000	1,000	**3,894,000**
Rain	274,000	93,000	61,000	20,000	**	**447,000**
Snow/Sleet	102,000	37,000	27,000	8,000	**	**174,000**
Other	13,000	8,000	9,000	3,000	**	**33,000**
Total	**3,204,000**	**679,000**	**498,000**	**167,000**	**1,000**	**4,548,000**
			All Crashes			
Normal	3,915,000	779,000	541,000	189,000	1,000	**5,424,000**
Rain	370,000	132,000	85,000	28,000	**	**615,000**
Snow/Sleet	125,000	44,000	33,000	10,000	**	**213,000**
Other/Unknown	17,000	10,000	12,000	4,000	**	**43,000**
Total	**4,427,000**	**966,000**	**671,000**	**231,000**	**1,000**	**6,296,000**

*Includes 162 fatal crashes for which light conditions were unknown.
**Less than 500.

Figure B.3: Excerpt of Table 26 from Traffic Safety Facts 2015 (NHTSA, 2017a).

APPENDIX C: PEDESTRIAN EXPOSURE ESTIMATES

This appendix contains the estimated pedestrian exposure metrics. **Table C.1**, **Table C.2**, and **Table C.3** contain the pedestrian exposure estimates for walk trips, miles walked, and minutes walked, respectively. Details regarding the derivation of pedestrian exposure are provided in sections 3.2 and 3.3.

Table C.1: Trip-based pedestrian exposure estimates by pedestrian age, pedestrian sex, and survey year.

Pedestrian Exposure Measure (*E*)	**Pedestrian Sex Category, *i***	**Pedestrian Age Category, *j***	**Survey Year (k^*)**						
			1977	**1983**	**1990**	**1995**	**2001**	**2009**	**2017**
Walk Trips (**Φ**), in millions	1 (males)	0	1303.792	1723.137	3102.002	3120.652	3868.220	3724.236	2604.153
		1	790.958	1350.276	1344.785	800.540	952.595	1493.777	1080.423
		2	1112.638	3140.692	2648.050	2356.277	3488.315	3682.060	4684.483
		3	700.243	1284.164	1839.570	2184.219	4011.647	6622.182	5039.436
		4	331.095	680.549	539.902	468.107	1295.167	2600.407	2659.570
		5	372.493	680.105	599.714	844.465	1489.902	1805.262	2539.010
	2 (females)	0	1117.620	1644.960	2620.790	2659.310	3762.676	3180.414	2440.374
		1	633.152	1610.119	1491.744	706.088	880.390	1267.818	1097.032
		2	1162.850	3819.613	3451.549	2669.696	4237.820	4365.873	5086.628
		3	776.953	1624.302	2221.299	2543.636	5051.176	7250.707	5789.810
		4	318.727	1000.353	805.288	731.973	1473.653	2778.398	2841.117
		5	495.551	1028.815	1017.812	1240.193	1999.738	2190.683	2986.347

Table C.2: Distance-based pedestrian exposure estimates by pedestrian age, pedestrian sex, and survey year.

Pedestrian Exposure Measure (*E*)	**Pedestrian Sex Category, *i***	**Pedestrian Age Category, *j***	**Survey Year (k^*)**						
			1977	**1983**	**1990**	**1995**	**2001**	**2009**	**2017**
Miles Walked (**Ψ**), in millions	1 (males)	0	929.611	896.356	1445.108	1571.942	2207.798	2279.424	1555.442
		1	727.544	861.462	934.259	505.450	678.525	1065.258	2278.386
		2	786.283	1895.988	1954.999	1396.761	2395.278	2578.648	5759.111
		3	479.401	607.021	1264.949	1170.812	3138.772	4795.779	3733.574
		4	282.372	319.770	342.957	290.608	1127.039	1892.912	2187.858
		5	254.014	471.660	372.095	490.222	1282.241	1246.903	3052.929
	2 (females)	0	723.094	666.077	1565.803	1252.034	2105.261	1813.025	1440.470
		1	409.969	834.925	764.441	386.583	524.173	845.996	1979.324
		2	796.494	1606.206	2092.581	1280.012	2892.851	2870.815	2966.039
		3	529.142	774.112	1853.475	1437.408	3917.451	5509.752	4200.298
		4	240.104	449.358	530.316	392.185	1272.083	1822.319	1861.699
		5	362.591	423.950	549.108	647.048	1392.420	1222.410	2589.270

Table C.3: Time-based pedestrian exposure estimates by pedestrian age, pedestrian sex, and survey year.

Pedestrian Exposure Measure (E)	**Pedestrian Sex Category, i**	**Pedestrian Age Category, j**	**Survey Year (k^*)**						
			1977	**1983**	**1990**	**1995**	**2001**	**2009**	**2017**
inu tes Walked Ω), in millions	1 (males)	0	13906.140	16771.170	24550.915	30138.660	48358.008	54154.878	41349.561
		1	8092.982	14842.494	12571.743	7853.399	12776.326	22079.638	20013.237
		2	10705.378	32799.012	27781.469	24015.220	45645.528	49617.203	70495.780
		3	6436.701	10018.086	19327.001	21638.170	58126.900	99353.093	79244.985
		4	3565.914	6751.035	7063.488	5065.197	21729.750	38775.217	47710.044
		5	3947.104	10930.196	7241.607	10126.278	28539.642	31341.379	49125.328
	2 (females)	0	10721.879	14511.019	22283.871	25485.540	45689.426	39811.016	34011.103
		1	6185.301	15059.409	10454.863	7688.109	13079.980	20355.658	14478.232
		2	9607.272	32606.246	32782.087	24769.613	58596.363	64538.941	74345.604
		3	6625.342	14448.519	26925.607	25778.818	76916.373	111846.075	90051.831
		4	2746.491	8466.938	10576.407	8114.962	24216.640	43681.241	45603.226
		5	4499.093	12296.183	10441.169	14939.545	31959.937	31537.338	53904.206

APPENDIX D: PEDESTRIAN FATALITY DESCRIPTIVE STATISTICS

This appendix contains descriptive statistics of the 41 years of FARS data utilized as part of the demographics analysis. **Table D.1** and **Table D.2** show descriptive statistics for male and female pedestrian fatalities, respectively. Column and row percentages are also provided.

Table D.1: Frequency distribution of male pedestrian fatalities by year and age group.

Frequency Row Pct Col Pct	Age Group (Males)						Total
Year	**5-15**	**16-19**	**20-34**	**35-54**	**55-64**	**65+**	
1975	843 17.63 5.58	379 7.93 4.13	968 20.25 2.39	988 20.67 2.17	515 10.77 2.87	1088 22.76 3.57	4781 100.00 20.71
1976	825 17.38 5.46	397 8.36 4.33	997 21.00 2.46	981 20.67 2.15	503 10.60 2.81	1044 21.99 3.42	4747 100.00 20.63
1977	751 15.08 4.97	397 7.97 4.33	1155 23.20 2.85	969 19.46 2.13	608 12.21 3.39	1099 22.07 3.60	4979 100.00 21.27
1978	801 15.64 5.30	424 8.28 4.62	1232 24.06 3.04	1076 21.01 2.36	546 10.66 3.05	1042 20.35 3.42	5121 100.00 21.79
1979	724 13.60 4.79	482 9.05 5.25	1460 27.42 3.60	1056 19.83 2.32	550 10.33 3.07	1052 19.76 3.45	5324 100.00 22.48
1980	674 12.87 4.46	471 8.99 5.13	1480 28.25 3.65	1038 19.81 2.28	522 9.96 2.91	1054 20.12 3.46	5239 100.00 21.89
1981	598 11.68 3.96	423 8.26 4.61	1572 30.69 3.87	1042 20.34 2.29	505 9.86 2.82	982 19.17 3.22	5122 100.00 20.77
1982	545 11.26 3.61	416 8.60 4.53	1457 30.11 3.59	1066 22.03 2.34	460 9.51 2.57	895 18.50 2.93	4839 100.00 19.58
1983	515 11.51 3.41	341 7.62 3.72	1390 31.06 3.43	954 21.32 2.10	464 10.37 2.59	811 18.12 2.66	4475 100.00 17.90
1984	530 11.22 3.51	296 6.27 3.23	1447 30.63 3.57	1047 22.16 2.30	507 10.73 2.83	897 18.99 2.94	4724 100.00 18.37
1985	485 11.14 3.21	269 6.18 2.93	1310 30.09 3.23	989 22.71 2.17	487 11.19 2.72	814 18.70 2.67	4354 100.00 16.93
1986	521 11.63 3.45	267 5.96 2.91	1393 31.11 3.43	1046 23.36 2.30	423 9.45 2.36	828 18.49 2.71	4478 100.00 17.17

Frequency Row Pct Col Pct	**Age Group (Males)**						**Total**
Year	**5-15**	**16-19**	**20-34**	**35-54**	**55-64**	**65+**	
1987	521 11.45 3.45	245 5.39 2.67	1283 28.20 3.16	1141 25.08 2.51	462 10.16 2.58	897 19.72 2.94	4549 100.00 17.31
1988	499 11.07 3.30	230 5.10 2.51	1305 28.96 3.22	1138 25.26 2.50	415 9.21 2.32	919 20.40 3.01	4506 100.00 16.86
1989	413 9.45 2.73	207 4.73 2.26	1276 29.19 3.15	1135 25.96 2.49	482 11.02 2.69	859 19.65 2.82	4372 100.00 16.13
1990	426 10.01 2.82	205 4.82 2.23	1232 28.95 3.04	1143 26.86 2.51	414 9.73 2.31	835 19.62 2.74	4255 100.00 15.65
1991	408 10.76 2.70	185 4.88 2.02	1099 28.98 2.71	1013 26.71 2.22	370 9.76 2.07	717 18.91 2.35	3792 100.00 14.07
1992	361 9.84 2.39	178 4.85 1.94	1012 27.57 2.49	1077 29.35 2.37	326 8.88 1.82	716 19.51 2.35	3670 100.00 13.36
1993	366 9.87 2.42	153 4.12 1.67	1008 27.17 2.48	1131 30.49 2.48	330 8.89 1.84	722 19.46 2.37	3710 100.00 13.27
1994	376 10.53 2.49	142 3.98 1.55	904 25.32 2.23	1117 31.28 2.45	308 8.63 1.72	724 20.27 2.37	3571 100.00 12.81
1995	345 9.35 2.28	152 4.12 1.66	889 24.09 2.19	1205 32.66 2.65	341 9.24 1.90	758 20.54 2.48	3690 100.00 13.17
1996	333 9.24 2.20	156 4.33 1.70	845 23.44 2.08	1182 32.79 2.60	364 10.10 2.03	725 20.11 2.38	3605 100.00 12.99
1997	286 8.15 1.89	155 4.41 1.69	821 23.38 2.02	1185 33.75 2.60	349 9.94 1.95	715 20.36 2.34	3511 100.00 12.50
1998	249 7.29 1.65	163 4.77 1.78	757 22.17 1.87	1196 35.02 2.63	373 10.92 2.08	677 19.82 2.22	3415 100.00 12.22
1999	247 7.42 1.64	149 4.47 1.62	707 21.23 1.74	1220 36.64 2.68	339 10.18 1.89	668 20.06 2.19	3330 100.00 11.76
2000	208 6.68 1.38	153 4.91 1.67	682 21.90 1.68	1180 37.89 2.59	323 10.37 1.80	568 18.24 1.86	3114 100.00 10.98
2001	233 7.06 1.54	154 4.67 1.68	710 21.51 1.75	1260 38.17 2.77	335 10.15 1.87	609 18.45 2.00	3301 100.00 11.60

Frequency Row Pct Col Pct	Age Group (Males)						Total
Year	**5-15**	**16-19**	**20-34**	**35-54**	**55-64**	**65+**	
2002	194 6.16 1.28	169 5.37 1.84	670 21.27 1.65	1169 37.11 2.57	340 10.79 1.90	608 19.30 1.99	3150 100.00 11.24
2003	209 6.65 1.38	152 4.84 1.66	670 21.32 1.65	1171 37.26 2.57	388 12.34 2.17	553 17.59 1.81	3143 100.00 11.24
2004	176 5.61 1.17	142 4.53 1.55	717 22.85 1.77	1205 38.40 2.65	338 10.77 1.89	560 17.85 1.84	3138 100.00 10.85
2005	160 4.82 1.06	144 4.34 1.57	733 22.09 1.81	1280 38.58 2.81	390 11.75 2.18	611 18.41 2.00	3318 100.00 11.43
2006	178 5.56 1.18	138 4.31 1.50	742 23.18 1.83	1251 39.08 2.75	383 11.97 2.14	509 15.90 1.67	3201 100.00 11.07
2007	158 5.00 1.05	161 5.10 1.75	721 22.84 1.78	1219 38.61 2.68	344 10.90 1.92	554 17.55 1.82	3157 100.00 10.99
2008	143 4.82 0.95	144 4.85 1.57	678 22.84 1.67	1123 37.84 2.47	393 13.24 2.19	487 16.41 1.60	2968 100.00 10.44
2009	118 4.30 0.78	123 4.49 1.34	628 22.90 1.55	1006 36.69 2.21	395 14.41 2.20	472 17.21 1.55	2742 100.00 9.63
2010	123 4.26 0.81	149 5.16 1.62	700 24.25 1.73	975 33.77 2.14	437 15.14 2.44	503 17.42 1.65	2887 100.00 10.39
2011	119 3.91 0.79	138 4.53 1.50	704 23.13 1.74	1060 34.82 2.33	498 16.36 2.78	525 17.25 1.72	3044 100.00 10.86
2012	120 3.68 0.79	145 4.44 1.58	790 24.20 1.95	1086 33.27 2.39	529 16.21 2.95	594 18.20 1.95	3264 100.00 11.61
2013	104 3.25 0.69	120 3.75 1.31	757 23.68 1.87	1110 34.72 2.44	552 17.27 3.08	554 17.33 1.82	3197 100.00 11.20
2014	96 2.87 0.64	145 4.33 1.58	808 24.14 1.99	1067 31.88 2.34	604 18.05 3.37	627 18.73 2.06	3347 100.00 11.98
2015	122 3.32 0.81	119 3.24 1.30	859 23.41 2.12	1235 33.65 2.71	703 19.16 3.92	632 17.22 2.07	3670 100.00 12.93
Total	15103 9.51 100.00	9178 5.78 100.00	40568 25.55 100.00	45532 28.67 100.00	17915 11.28 100.00	30504 19.21 100.00	158800

Table D.2: Frequency distribution of female pedestrian fatalities by year and age.

Frequency Row Pct Col Pct	Age Group (Females)						Total
Year	5-15	16-19	20-34	35-54	55-64	65+	
1975	521 24.77 5.89	137 6.51 3.63	268 12.74 2.15	328 15.60 2.04	193 9.18 2.65	656 31.19 3.20	2103 100.00 19.55
1976	492 23.55 5.56	153 7.32 4.06	295 14.12 2.36	332 15.89 2.06	198 9.48 2.72	619 29.63 3.02	2089 100.00 19.78
1977	470 21.49 5.31	174 7.96 4.61	332 15.18 2.66	331 15.13 2.06	200 9.14 2.74	680 31.09 3.32	2187 100.00 20.70
1978	437 21.01 4.94	166 7.98 4.40	372 17.88 2.98	317 15.24 1.97	222 10.67 3.04	566 27.21 2.76	2080 100.00 20.09
1979	422 19.36 4.77	163 7.48 4.32	372 17.06 2.98	386 17.71 2.40	205 9.40 2.81	632 28.99 3.09	2180 100.00 20.36
1980	384 16.98 4.34	167 7.39 4.43	438 19.37 3.51	353 15.61 2.20	245 10.84 3.36	674 29.81 3.29	2261 100.00 21.12
1981	362 16.90 4.09	147 6.86 3.90	430 20.07 3.44	352 16.43 2.19	205 9.57 2.81	646 30.16 3.15	2142 100.00 19.58
1982	313 15.56 3.54	160 7.95 4.24	468 23.26 3.75	348 17.30 2.16	169 8.40 2.32	554 27.53 2.71	2012 100.00 18.71
1983	293 15.30 3.31	134 7.00 3.55	402 20.99 3.22	319 16.66 1.98	190 9.92 2.61	577 30.13 2.82	1915 100.00 17.49
1984	297 15.99 3.36	115 6.19 3.05	381 20.52 3.05	306 16.48 1.90	192 10.34 2.63	566 30.48 2.76	1857 100.00 16.75
1985	311 15.70 3.51	107 5.40 2.84	377 19.03 3.02	339 17.11 2.11	207 10.45 2.84	640 32.31 3.13	1981 100.00 17.44
1986	289 15.41 3.26	118 6.29 3.13	356 18.98 2.85	340 18.12 2.11	171 9.12 2.35	602 32.09 2.94	1876 100.00 16.64

Frequency Row Pct Col Pct	Age Group (Females)						Total
Year	**5-15**	**16-19**	**20-34**	**35-54**	**55-64**	**65+**	
1987	276 14.96 3.12	101 5.47 2.68	373 20.22 2.99	332 17.99 2.06	177 9.59 2.43	586 31.76 2.86	1845 100.00 16.13
1988	294 14.80 3.32	92 4.63 2.44	397 19.98 3.18	329 16.56 2.05	198 9.96 2.72	677 34.07 3.31	1987 100.00 17.00
1989	249 13.50 2.81	80 4.34 2.12	370 20.07 2.96	379 20.55 2.36	158 8.57 2.17	608 32.97 2.97	1844 100.00 15.39
1990	218 11.61 2.46	69 3.68 1.83	352 18.75 2.82	383 20.40 2.38	187 9.96 2.56	668 35.59 3.26	1877 100.00 15.32
1991	205 12.05 2.32	90 5.29 2.39	345 20.28 2.76	351 20.63 2.18	135 7.94 1.85	575 33.80 2.81	1701 100.00 14.30
1992	172 10.78 1.94	72 4.51 1.91	266 16.67 2.13	376 23.56 2.34	154 9.65 2.11	556 34.84 2.72	1596 100.00 13.15
1993	217 13.45 2.45	73 4.53 1.93	286 17.73 2.29	354 21.95 2.20	146 9.05 2.00	537 33.29 2.62	1613 100.00 13.50
1994	197 12.02 2.23	65 3.97 1.72	286 17.45 2.29	399 24.34 2.48	152 9.27 2.08	540 32.95 2.64	1639 100.00 13.44
1995	213 12.90 2.41	80 4.85 2.12	303 18.35 2.43	413 25.02 2.57	137 8.30 1.88	505 30.59 2.47	1651 100.00 13.87
1996	181 11.46 2.04	54 3.42 1.43	287 18.18 2.30	434 27.49 2.70	138 8.74 1.89	485 30.72 2.37	1579 100.00 12.73
1997	198 12.42 2.24	78 4.89 2.07	262 16.44 2.10	447 28.04 2.78	150 9.41 2.06	459 28.80 2.24	1594 100.00 13.48
1998	162 10.17 1.83	70 4.39 1.86	242 15.19 1.94	471 29.57 2.93	149 9.35 2.04	499 31.32 2.44	1593 100.00 13.03
1999	161 11.48 1.82	62 4.42 1.64	213 15.18 1.70	390 27.80 2.43	147 10.48 2.02	430 30.65 2.10	1403 100.00 11.71
2000	162 11.19 1.83	63 4.35 1.67	208 14.36 1.66	440 30.39 2.74	147 10.15 2.02	428 29.56 2.09	1448 100.00 12.01
2001	132 9.22 1.49	68 4.75 1.80	200 13.98 1.60	452 31.59 2.81	130 9.08 1.78	449 31.38 2.19	1431 100.00 11.68

Frequency Row Pct Col Pct	Age Group (Females)						Total
Year	**5-15**	**16-19**	**20-34**	**35-54**	**55-64**	**65+**	
2002	121 8.18 1.37	60 4.05 1.59	224 15.14 1.79	481 32.50 2.99	152 10.27 2.08	442 29.86 2.16	1480 100.00 11.98
2003	122 8.41 1.38	77 5.31 2.04	226 15.59 1.81	450 31.03 2.80	154 10.62 2.11	421 29.03 2.06	1450 100.00 12.19
2004	113 8.15 1.28	58 4.18 1.54	228 16.44 1.82	431 31.07 2.68	166 11.97 2.28	391 28.19 1.91	1387 100.00 11.51
2005	115 8.29 1.30	70 5.04 1.86	243 17.51 1.94	425 30.62 2.64	165 11.89 2.26	370 26.66 1.81	1388 100.00 11.81
2006	82 5.90 0.93	74 5.32 1.96	221 15.90 1.77	442 31.80 2.75	183 13.17 2.51	388 27.91 1.89	1390 100.00 11.81
2007	90 6.68 1.02	72 5.35 1.91	235 17.45 1.88	451 33.48 2.80	150 11.14 2.06	349 25.91 1.70	1347 100.00 11.37
2008	78 6.08 0.88	74 5.77 1.96	242 18.86 1.94	419 32.66 2.61	154 12.00 2.11	316 24.63 1.54	1283 100.00 11.04
2009	65 5.26 0.73	55 4.45 1.46	237 19.19 1.90	412 33.36 2.56	163 13.20 2.24	303 24.53 1.48	1235 100.00 10.37
2010	78 6.00 0.88	61 4.70 1.62	250 19.25 2.00	401 30.87 2.49	181 13.93 2.48	328 25.25 1.60	1299 100.00 11.08
2011	75 5.66 0.85	67 5.06 1.78	282 21.30 2.26	408 30.82 2.54	165 12.46 2.26	327 24.70 1.60	1324 100.00 11.28
2012	91 6.31 1.03	56 3.88 1.48	321 22.25 2.57	413 28.62 2.57	212 14.69 2.91	350 24.26 1.71	1443 100.00 12.27
2013	70 4.82 0.79	60 4.14 1.59	303 20.88 2.43	427 29.43 2.66	233 16.06 3.20	358 24.67 1.75	1451 100.00 12.41
2014	61 4.25 0.69	56 3.91 1.48	299 20.85 2.39	409 28.52 2.54	257 17.92 3.52	352 24.55 1.72	1434 100.00 12.35
2015	63 4.01 0.71	75 4.77 1.99	302 19.20 2.42	510 32.42 3.17	254 16.15 3.48	369 23.46 1.80	1573 100.00 13.57
Total	8852 12.83% 100.00%	3773 5.47% 100.00%	12494 18.12% 100.00%	16080 23.32% 100.00%	7291 10.57% 100.00%	20478 29.69% 100.00%	68968

APPENDIX E: FATALITY FORECAST MODELS

This appendix contains all the pedestrian fatality forecast models that were constructed as part of the CURVEFIT procedure as described in subsection 3.4.3. The models are shown in ascending order of age and beginning with males. 95% confidence limits are also shown as dashed lines. Several fatality projection models showed negative counts of fatalities but were not shown due to their impracticality.

E.1: Males, 5-15

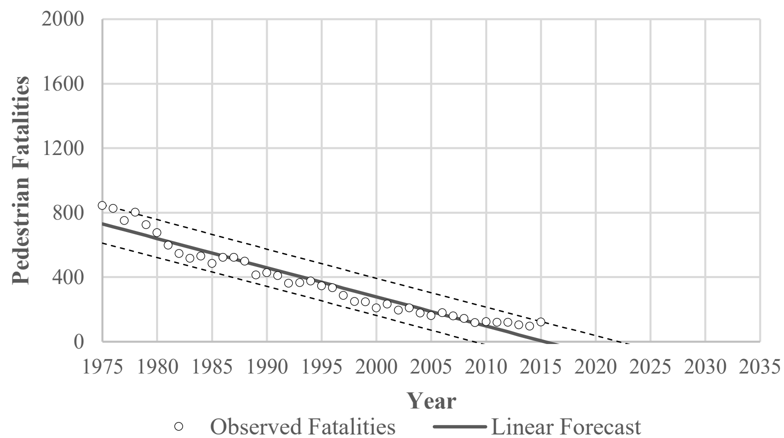

Figure E.1: Linear forecast model for males aged 5-15.

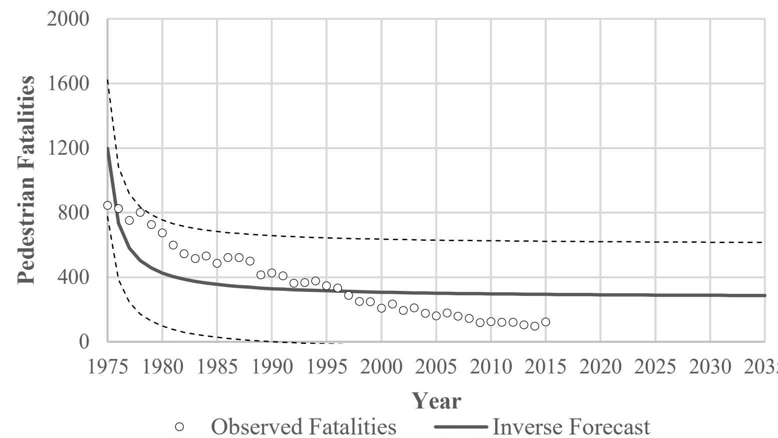

Figure E.3: Inverse forecast model for males aged 5-15.

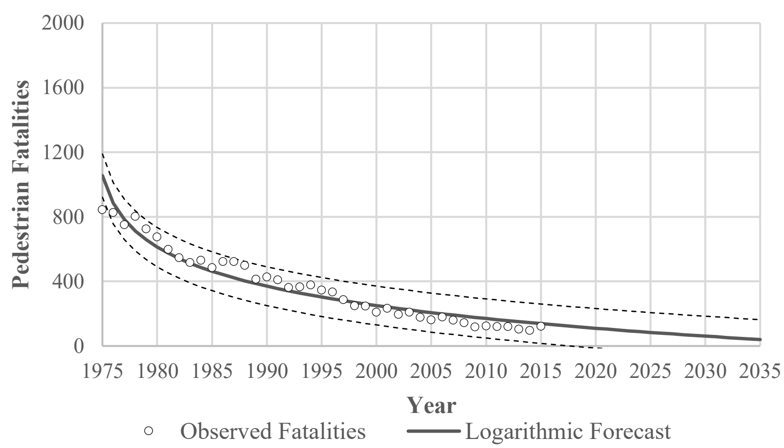

Figure E.2: Logarithmic forecast model for males aged 5-15.

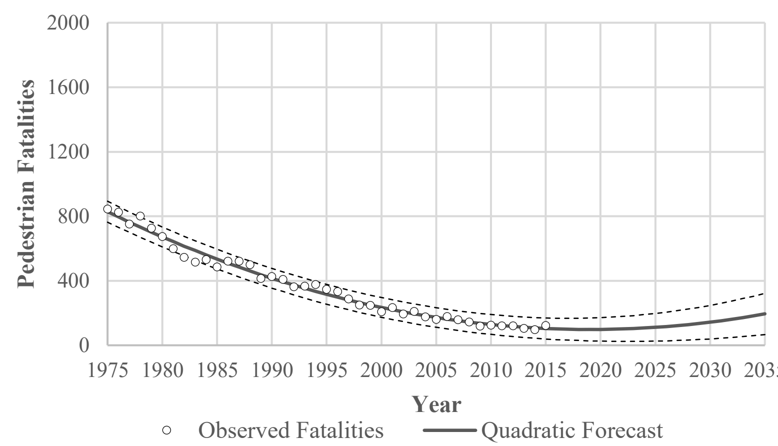

Figure E.4: Quadratic forecast model for males aged 5-15.

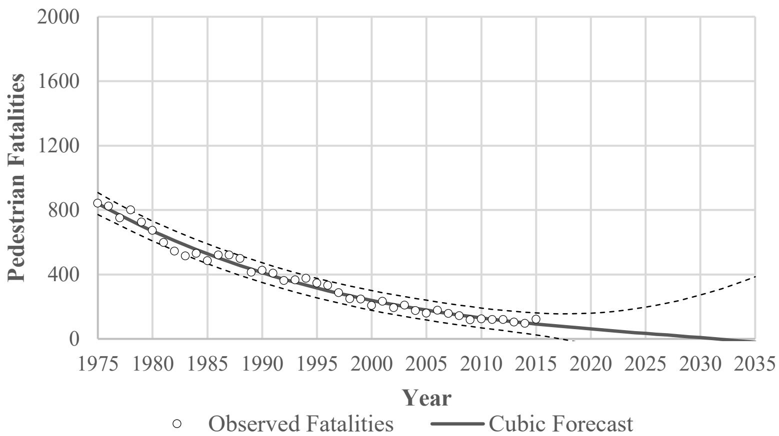

Figure E.5: Cubic forecast model for males aged 5-15.

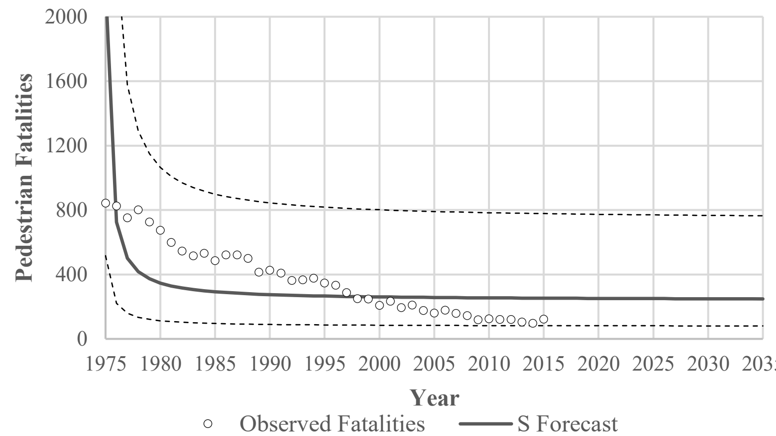

Figure E.7: S forecast model for males aged 5-15.

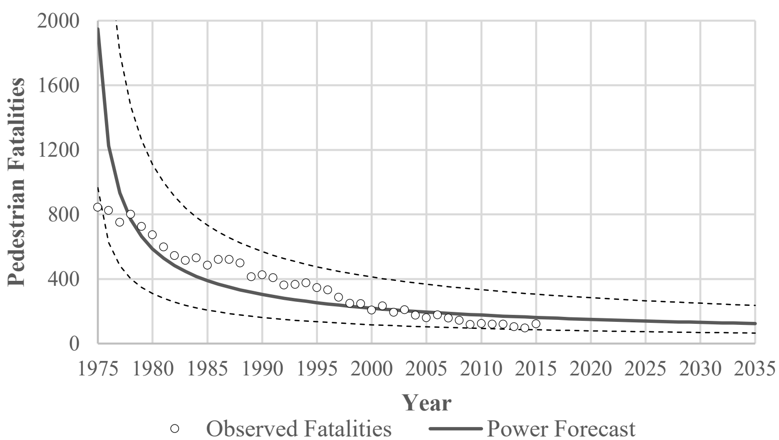

Figure E.6: Power forecast model for males aged 5-15.

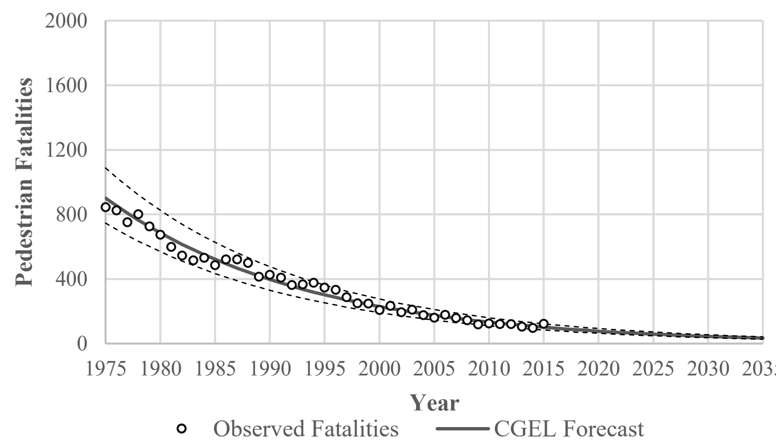

Figure E.8: CGEL forecast models for males aged 5-15.

E.2: Males, 16-19

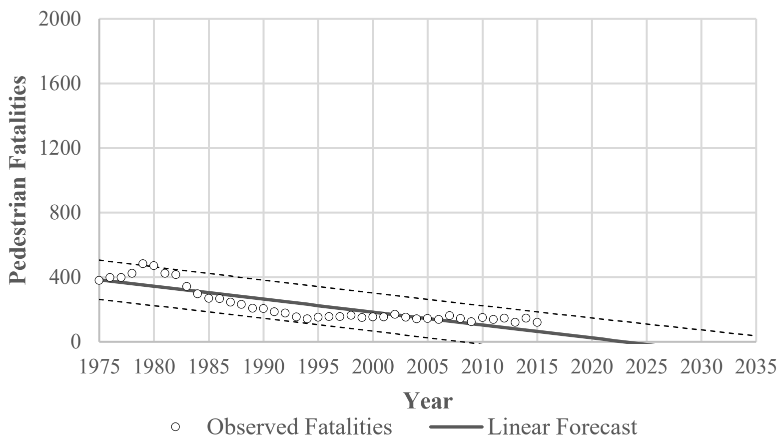

Figure E.9: Linear forecast model for males aged 16-19.

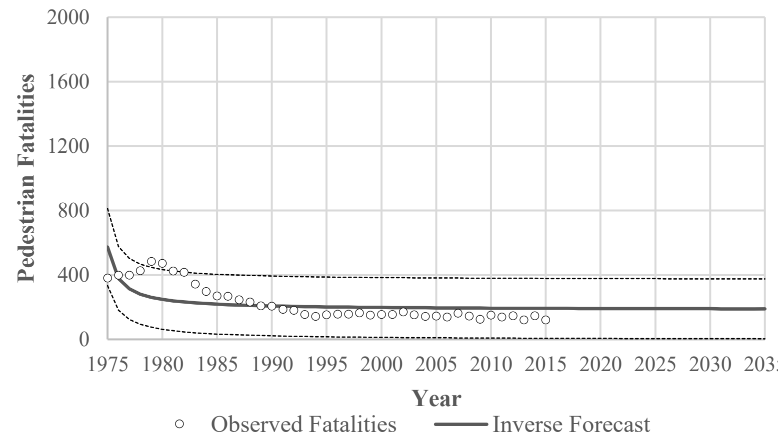

Figure E.11: Inverse forecast model for males aged 16-19.

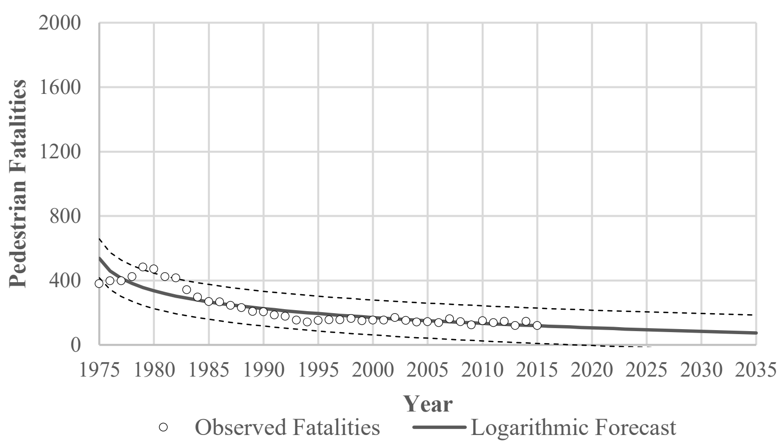

Figure E.10: Logarithmic forecast model for males aged 16-19.

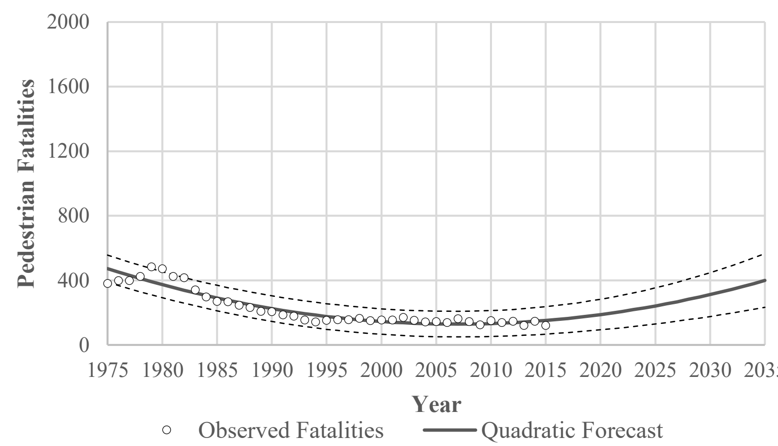

Figure E.12: Quadratic forecast model for males aged 16-19.

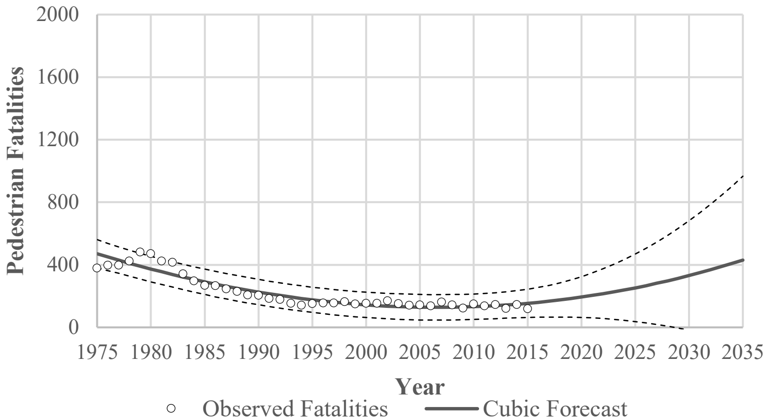

Figure E.13: Cubic forecast model for males aged 16-19.

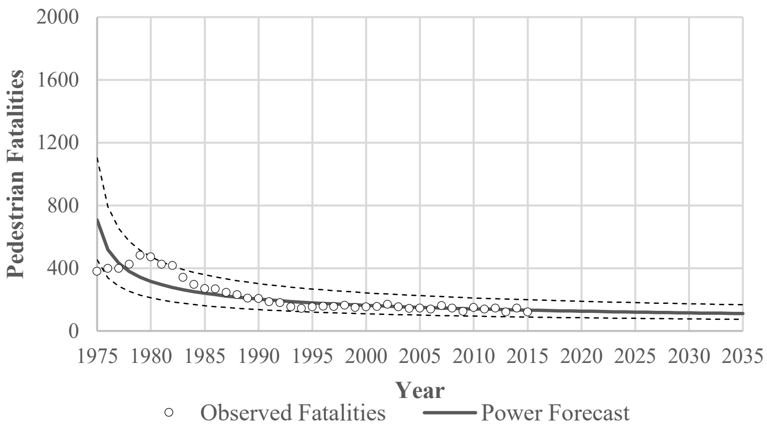

Figure E.14: Power forecast model for males aged 16-19.

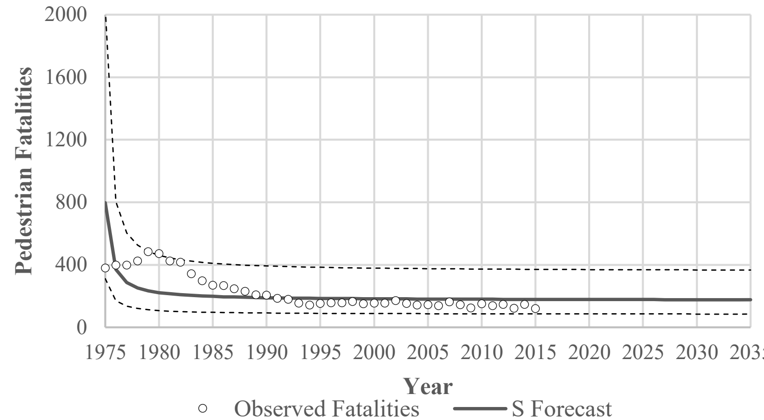

Figure E.15: S forecast model for males aged 16-19.

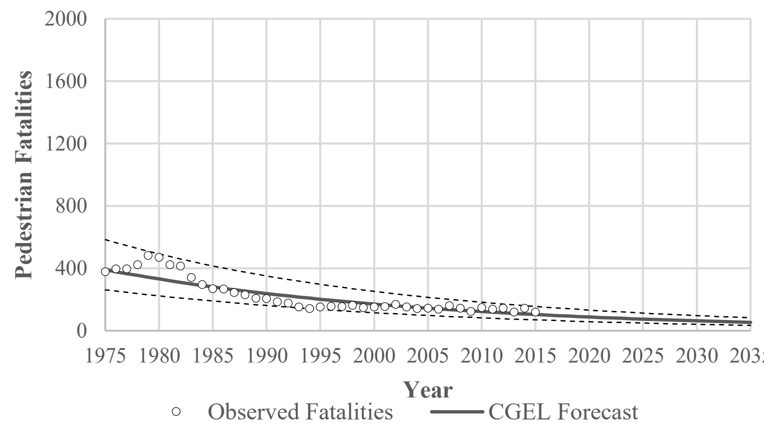

Figure E.16: CGEL forecast models for males aged 16-19.

E.3: Males, 20-34

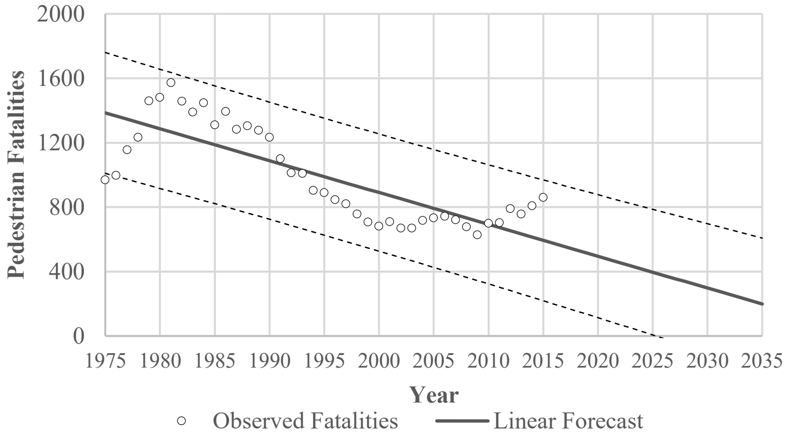

Figure E.17: Linear forecast model for males aged 20-34.

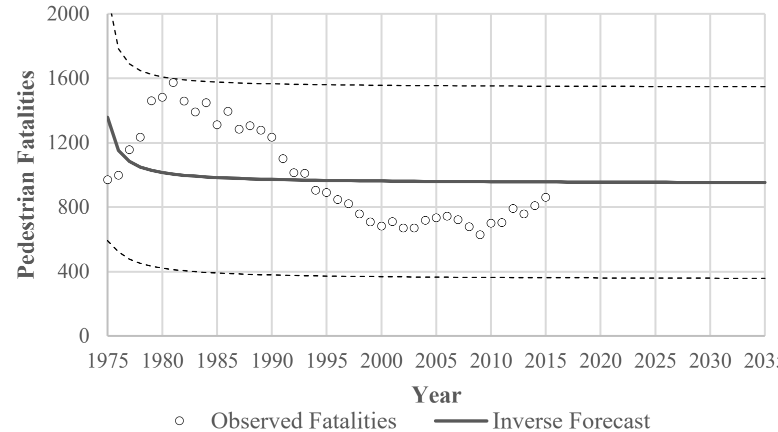

Figure E.19: Inverse forecast model for males aged 20-34.

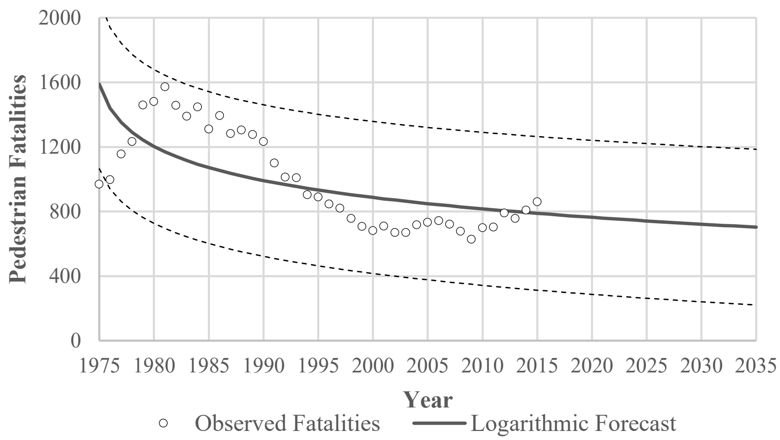

Figure E.18: Logarithmic forecast model for males aged 20-34.

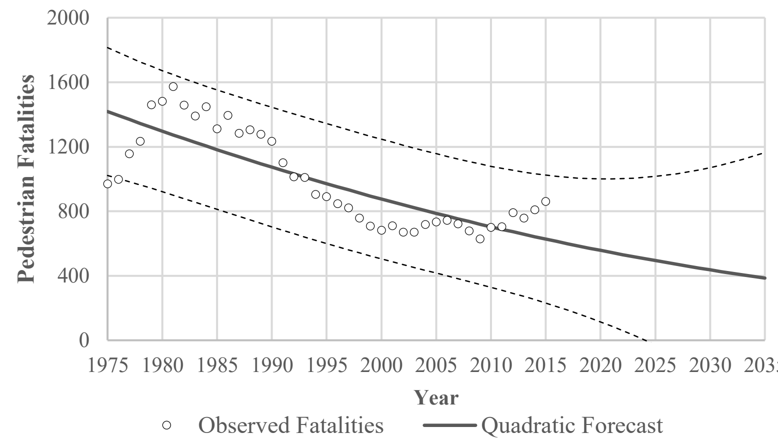

Figure E.20: Quadratic forecast model for males aged 20-34.

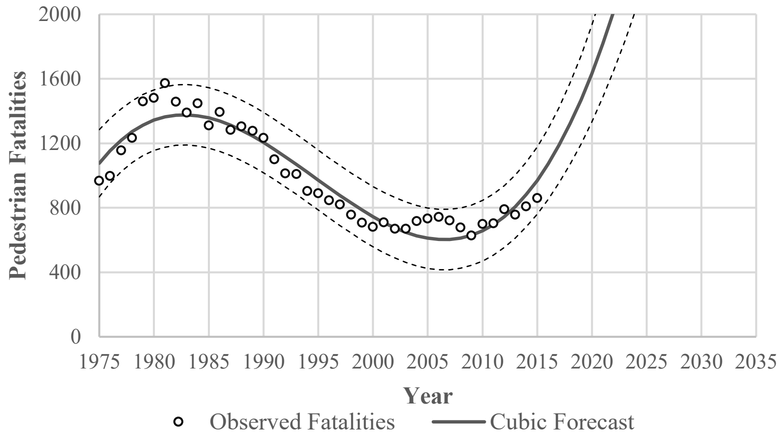

Figure E.21: Cubic forecast model for males aged 20-34.

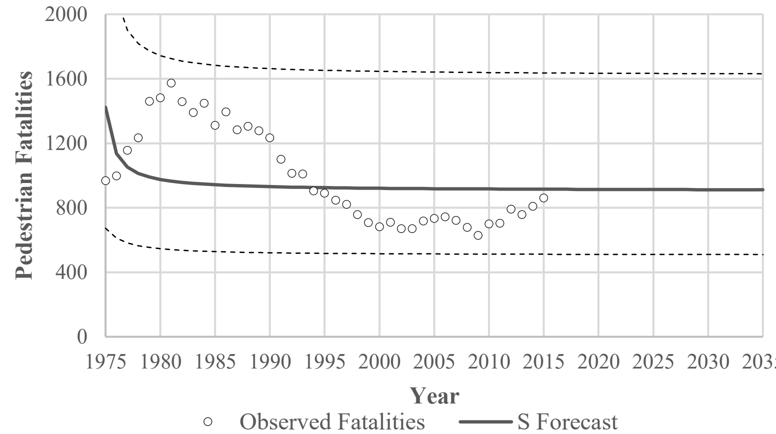

Figure E.23: S forecast model for males aged 20-34.

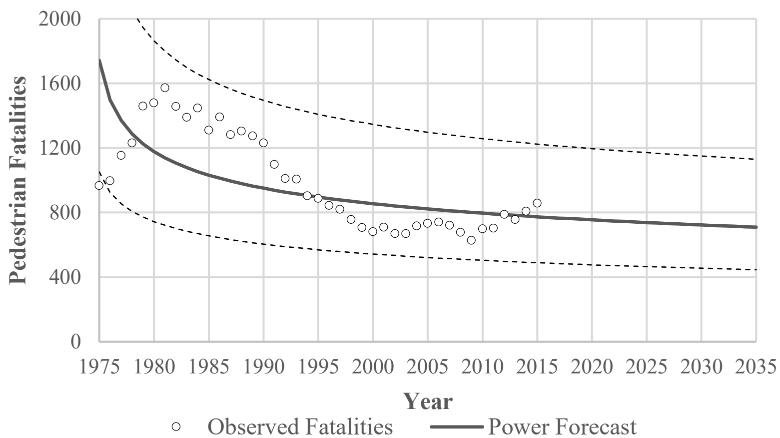

Figure E.22: Power forecast model for males aged 20-34.

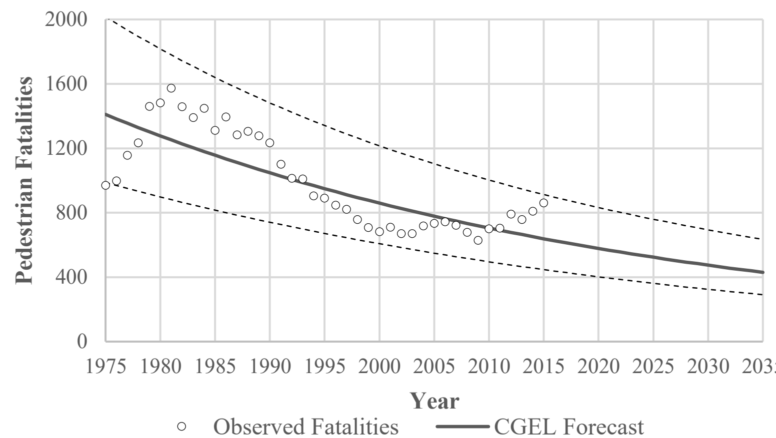

Figure E.24: CGEL forecast models for males aged 20-34.

E.4: Males. 35-54

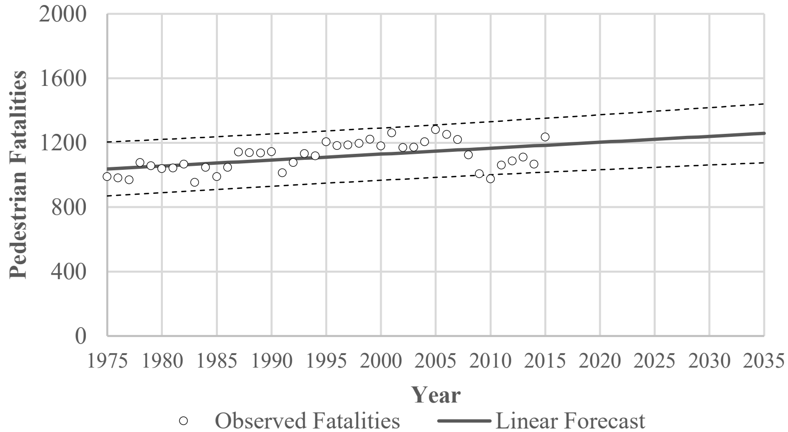

Figure E.25: Linear forecast model for males aged 35-54.

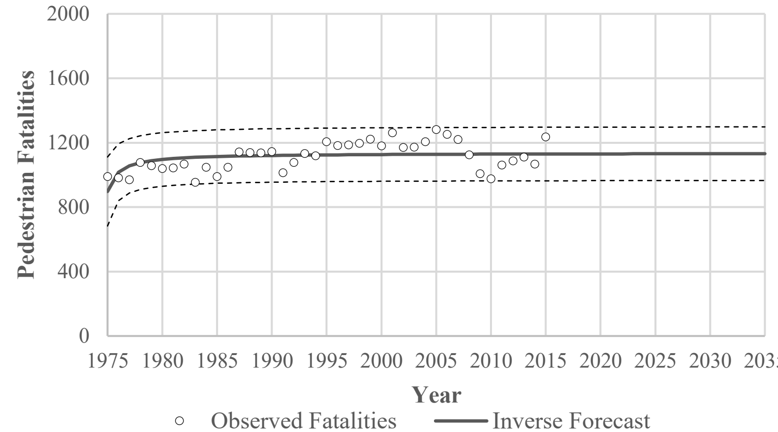

Figure E.27: Inverse forecast model for males aged 35-54.

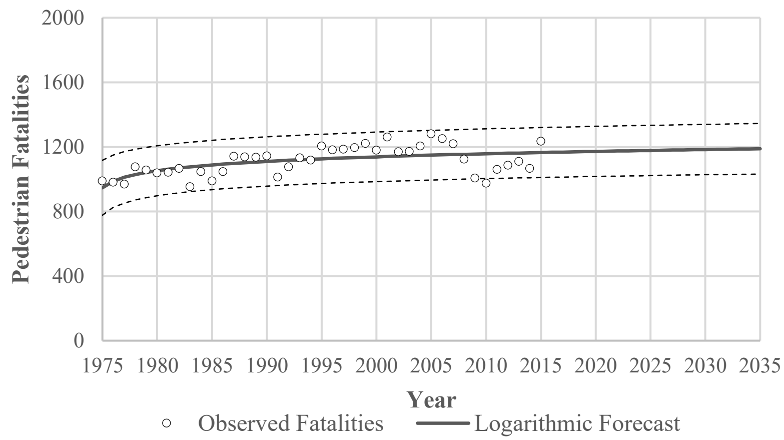

Figure E.26: Logarithmic forecast model for males aged 35-54.

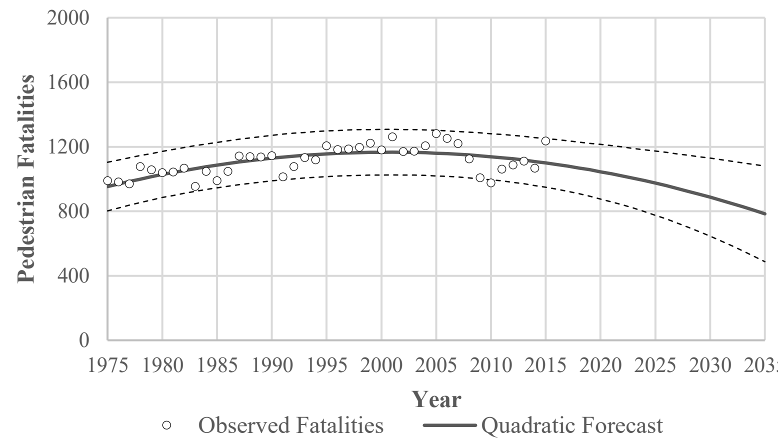

Figure E.28: Quadratic forecast model for males aged 35-54.

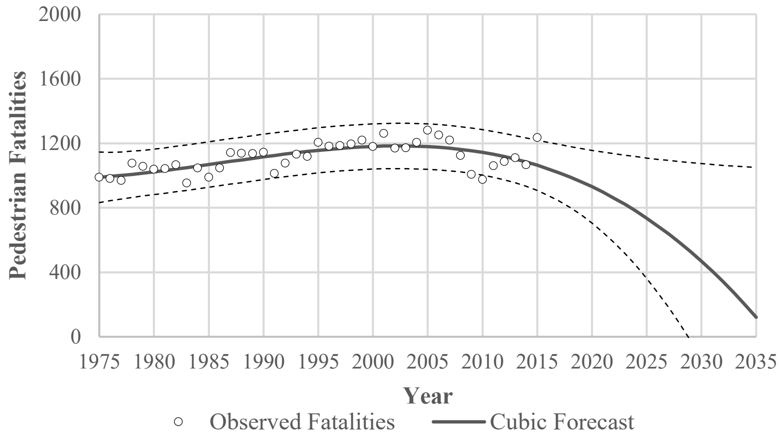

Figure E.29: Cubic forecast model for males aged 35-54.

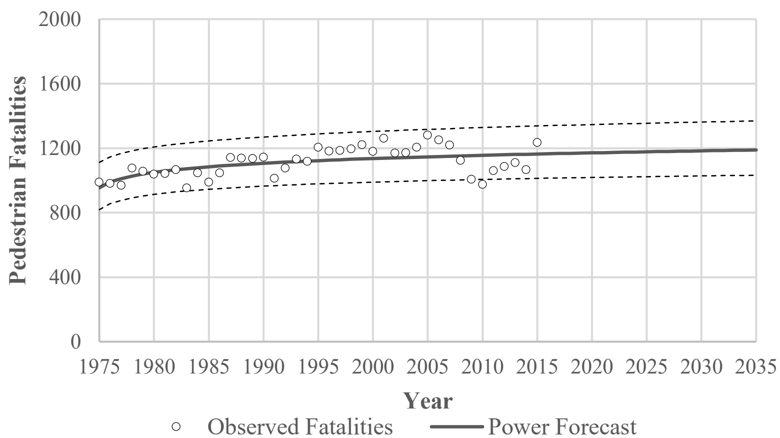

Figure E.30: Power forecast model for males aged 35-54.

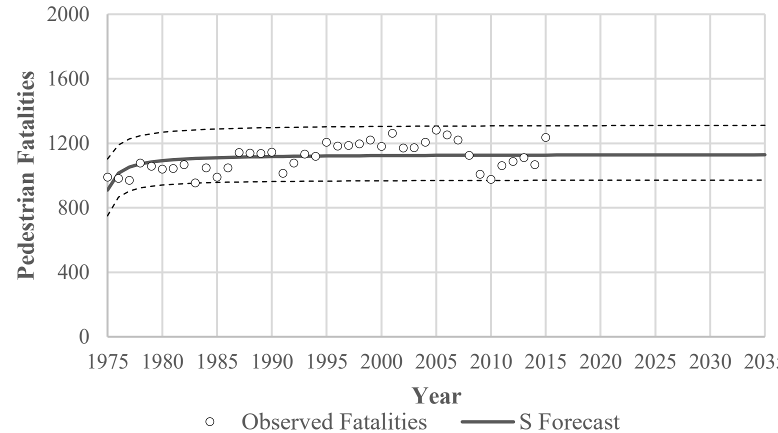

Figure E.31: S forecast model for males aged 35-54.

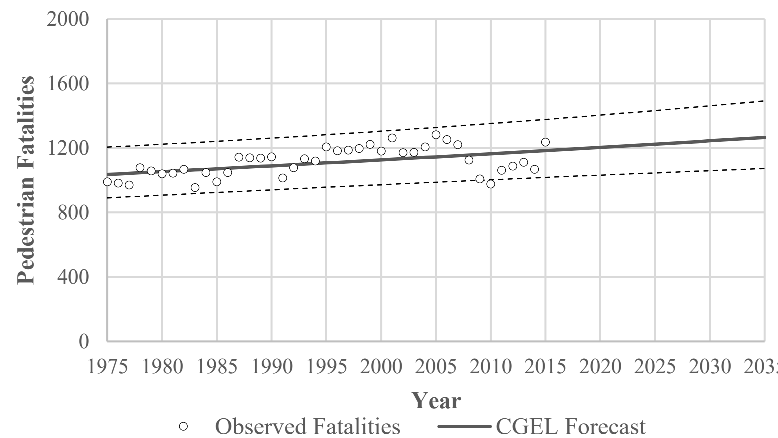

Figure E.32: CGEL forecast models for males aged 35-54.

E.5: Males, 55-64

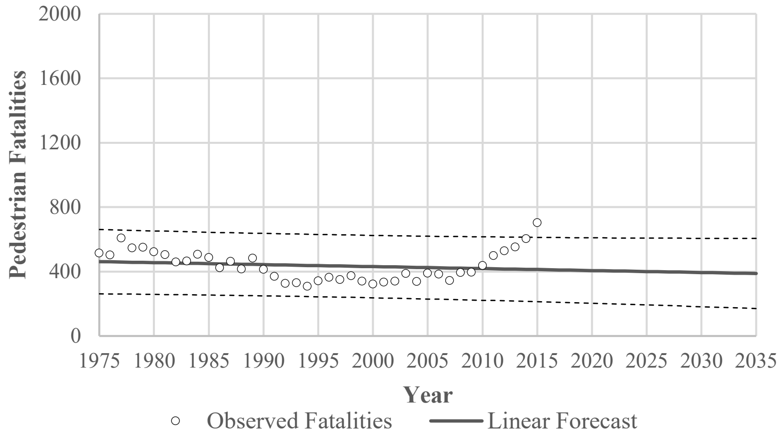

Figure E.33: Linear forecast model for males aged 55-64.

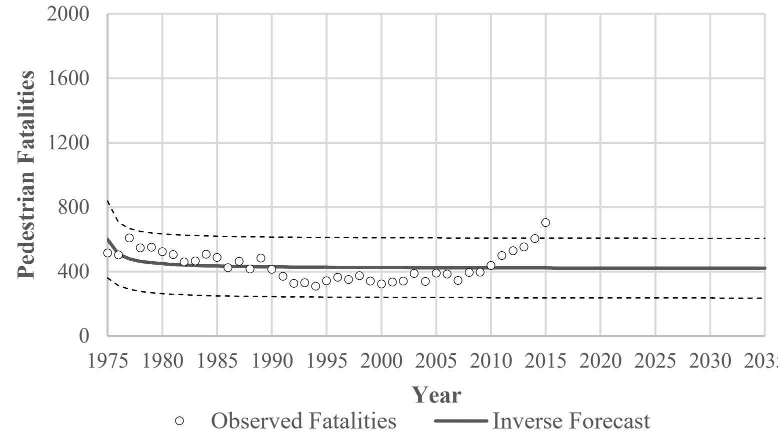

Figure E.35: Inverse forecast model for males aged 55-64.

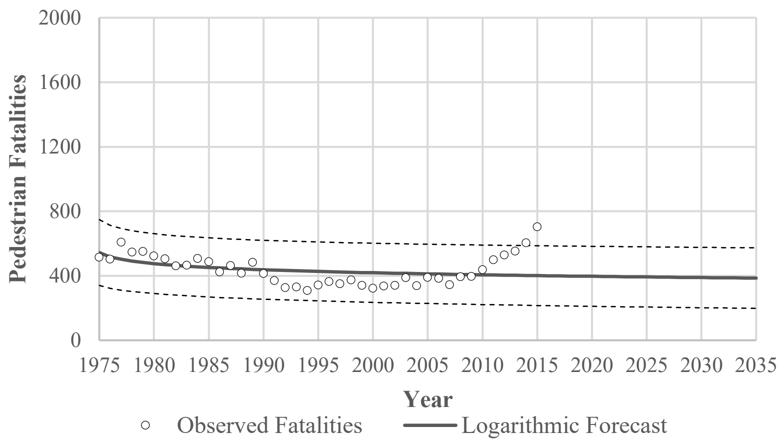

Figure E.34: Logarithmic forecast model for males aged 55-64.

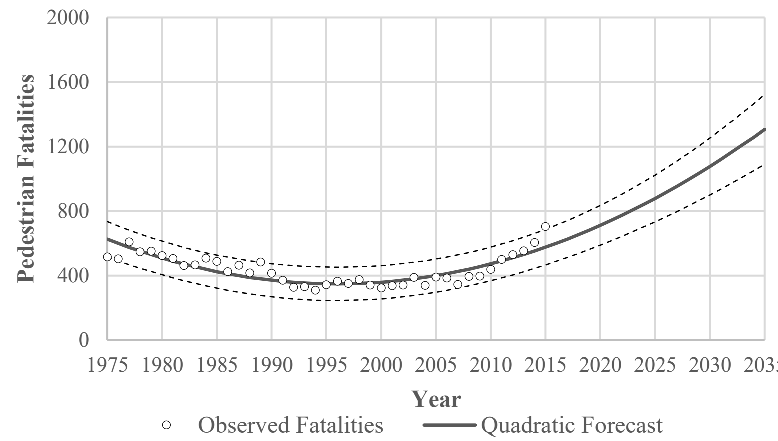

Figure E.36: Quadratic forecast model for males aged 55-64.

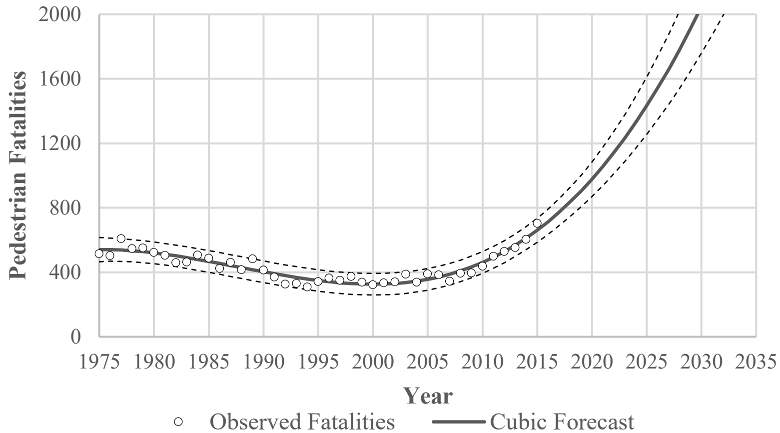

Figure E.37: Cubic forecast model for males aged 55-64.

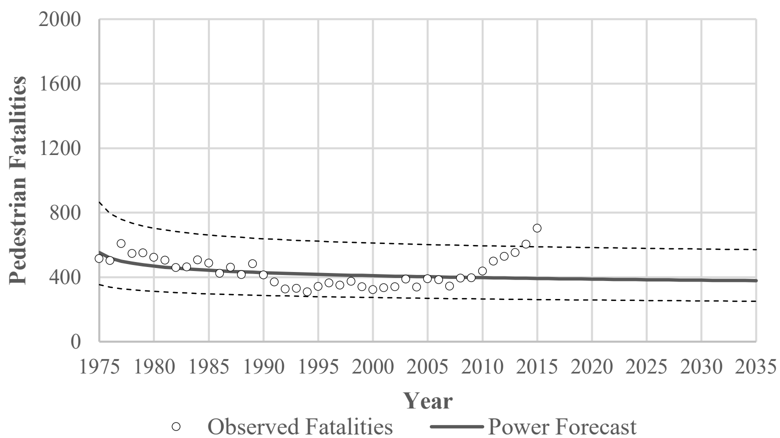

Figure E.38: Power forecast model for males aged 55-64.

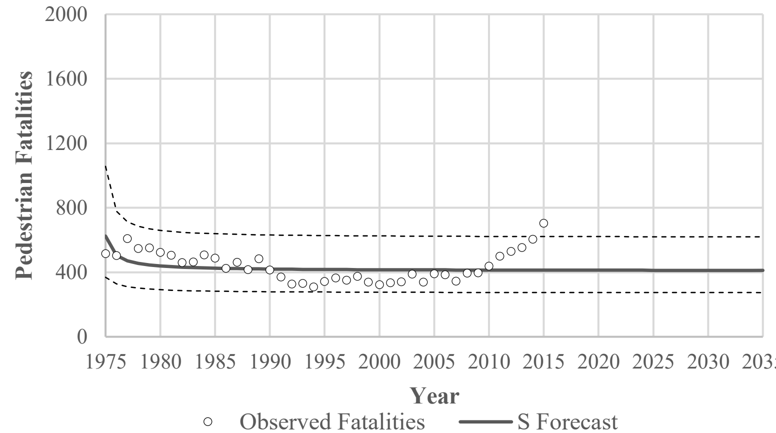

Figure E.39: S forecast model for males aged 55-64.

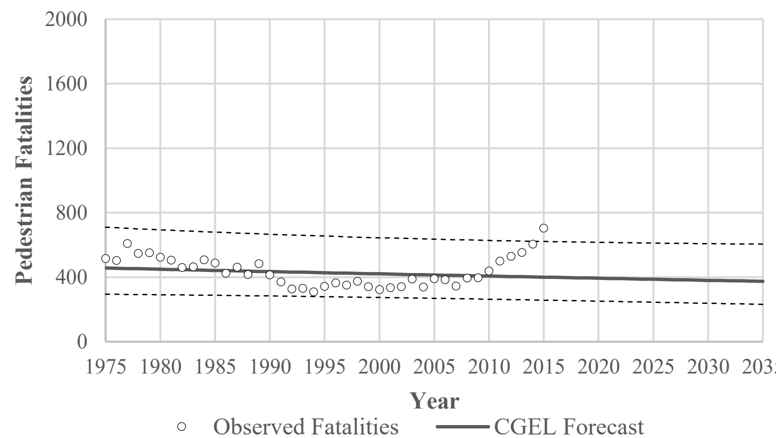

Figure E.40: CGEL forecast models for males aged 55-64.

E.6: Males, 65+

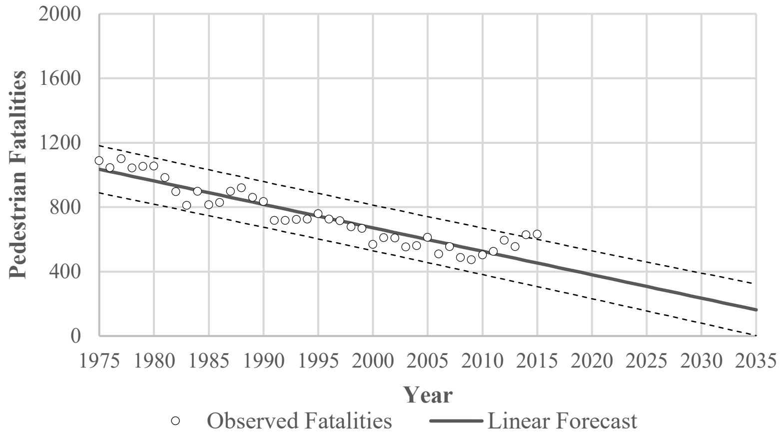

Figure E.41: Linear forecast model for males aged 65+.

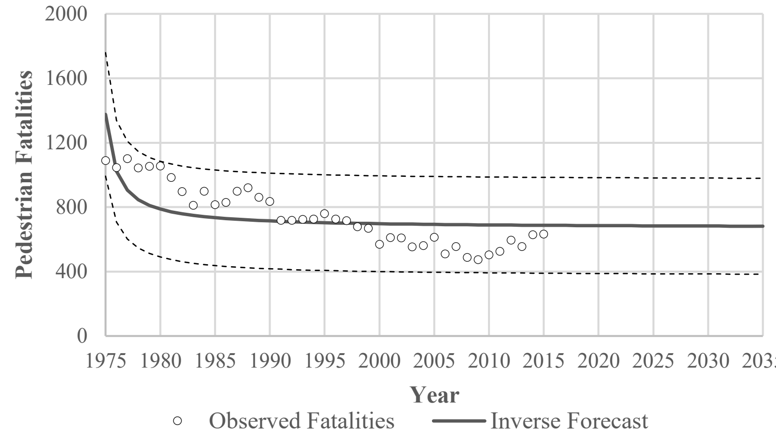

Figure E.43: Inverse forecast model for males aged 65+.

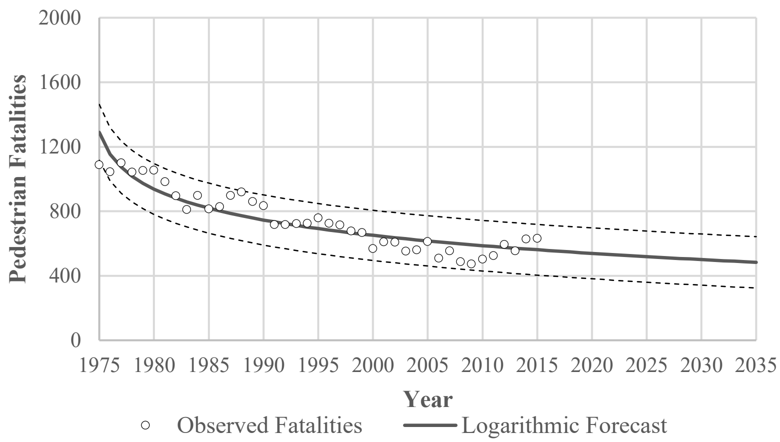

Figure E.42: Logarithmic forecast model for males aged 65+.

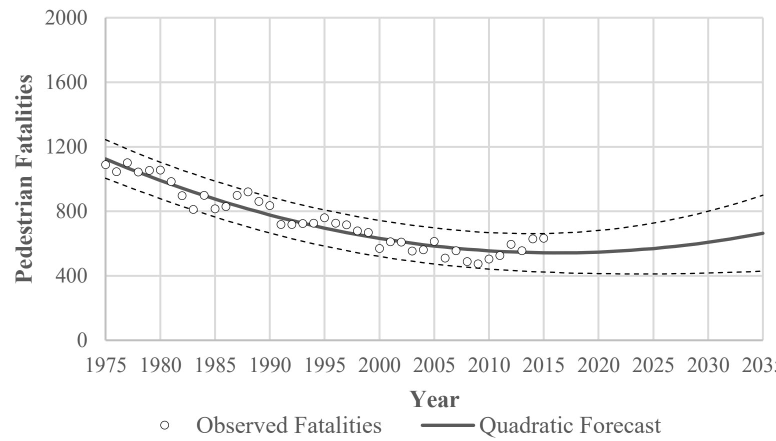

Figure E.44: Quadratic forecast model for males aged 65+.

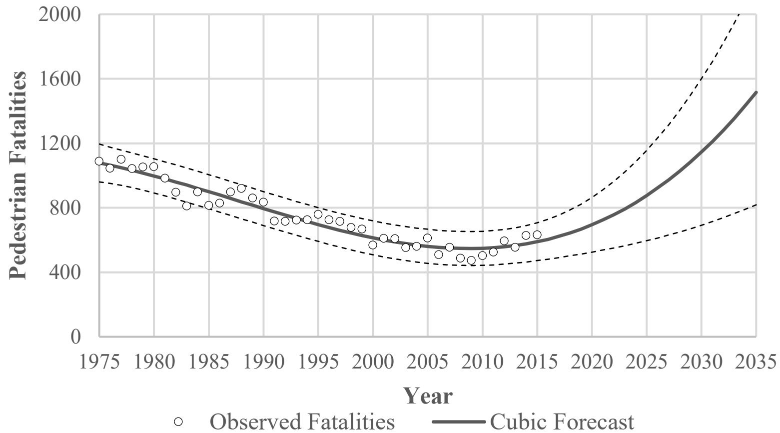

Figure E.45: Cubic forecast model for males aged 65+.

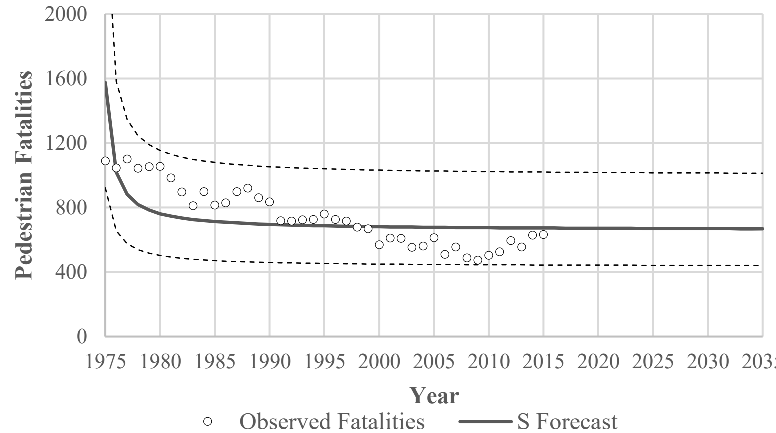

Figure E.47: S forecast model for males aged 65+.

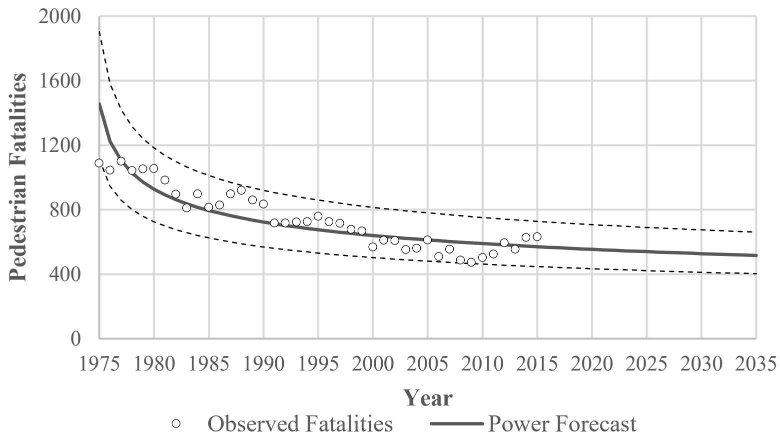

Figure E.46: Power forecast model for males aged 65+.

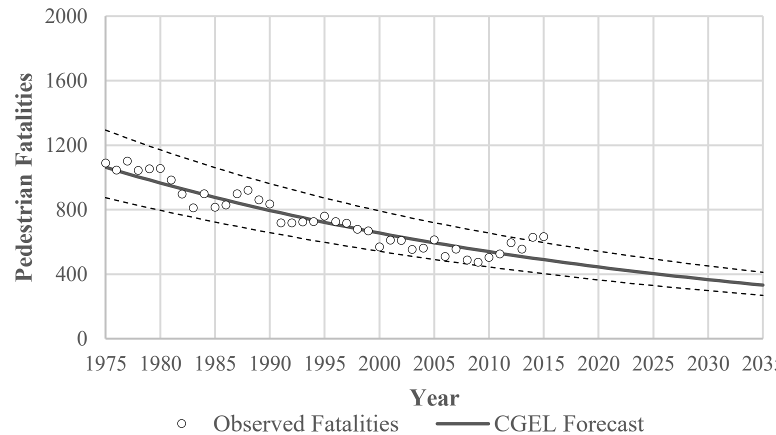

Figure E.48: CGEL forecast models for males aged 65+.

E.7: Females, 5-15

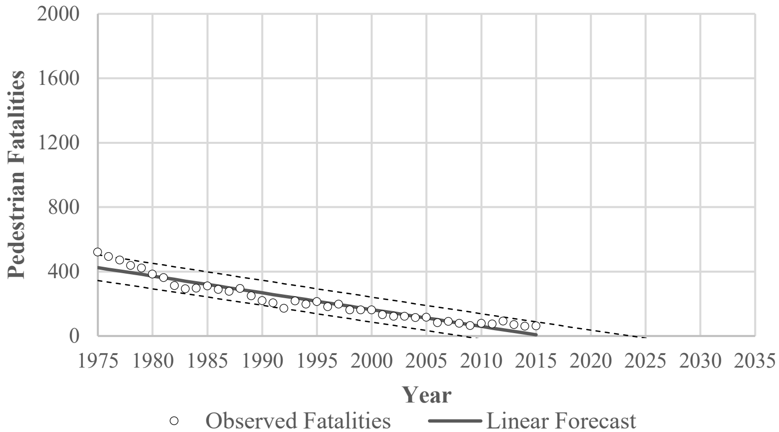

Figure E.49: Linear forecast model for females aged 5-15.

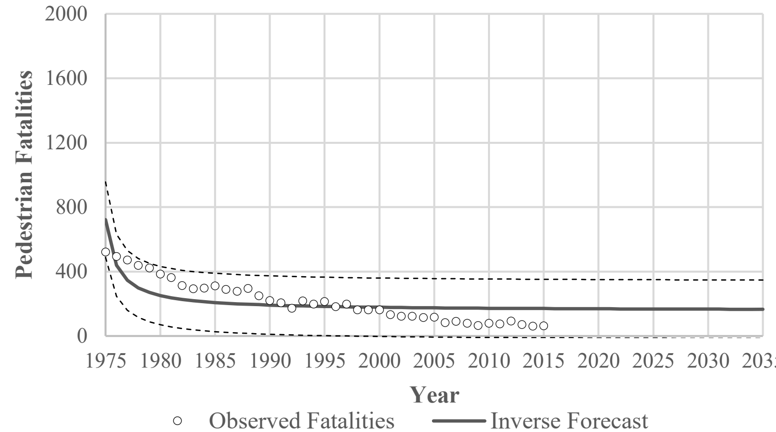

Figure E.51: Inverse forecast model for females aged 5-15.

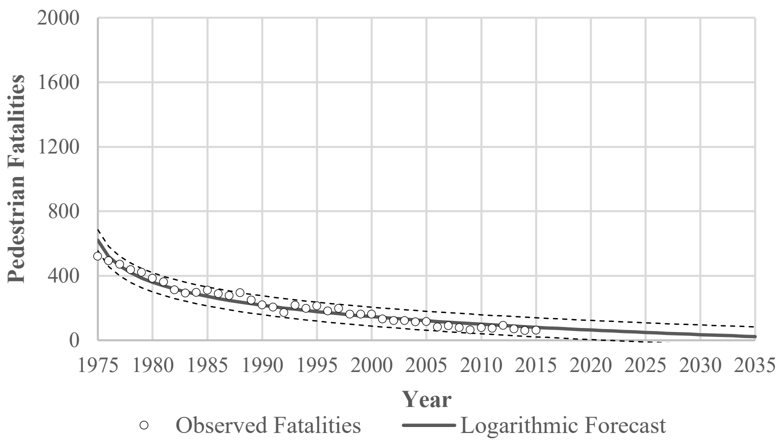

Figure E.50: Logarithmic forecast mode for females aged 5-15.

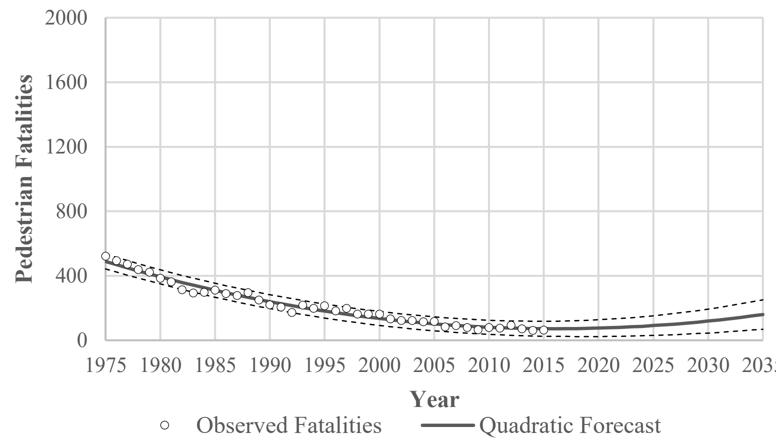

Figure E.52: Quadratic forecast model for females aged 5-15.

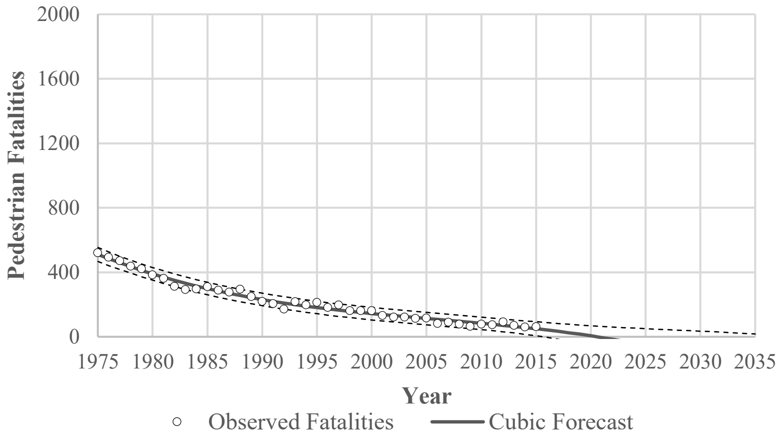

Figure E.53: Cubic forecast model for females aged 5-15.

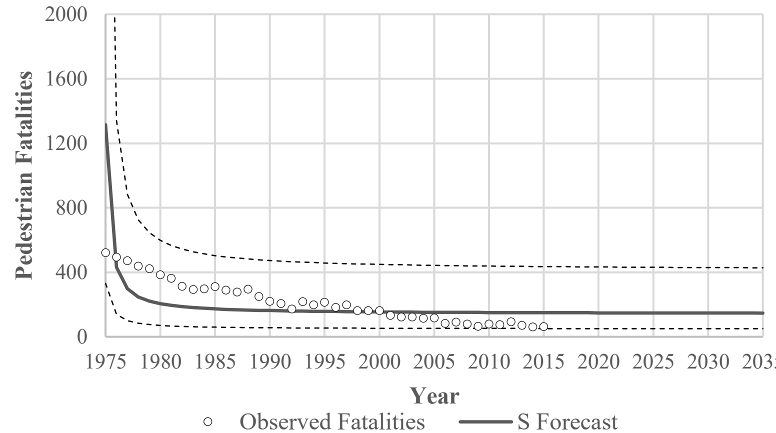

Figure E.55: S forecast model for females aged 5-15.

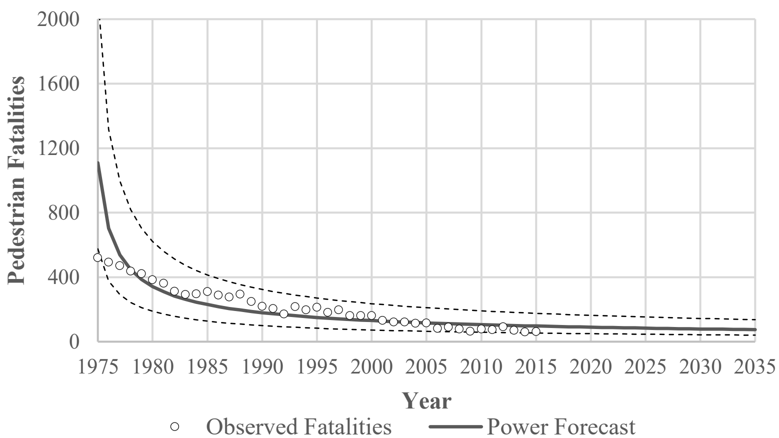

Figure E.54: Power forecast model for females aged 5-15.

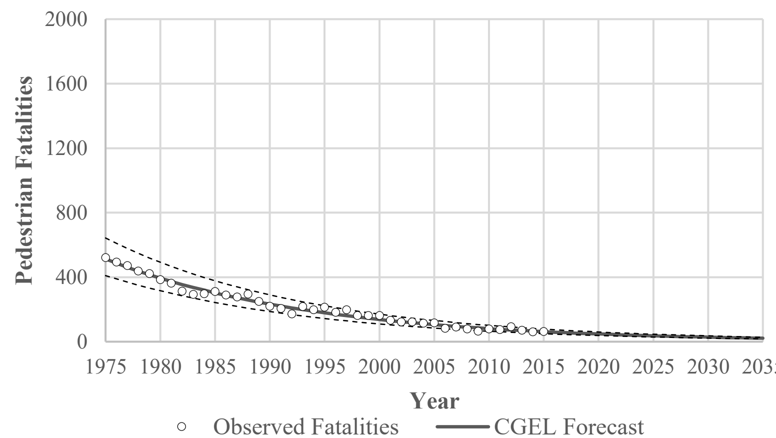

Figure E.56: CGEL forecast models for females aged 5-15.

E.8: Females, 16-19

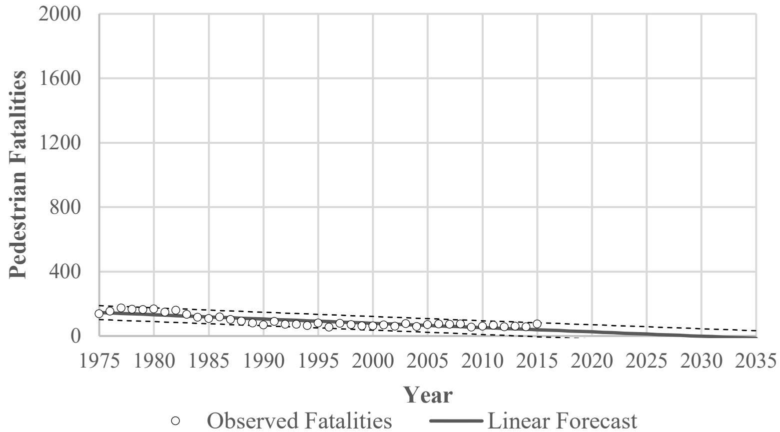

Figure E.57: Linear forecast model for females aged 16-19.

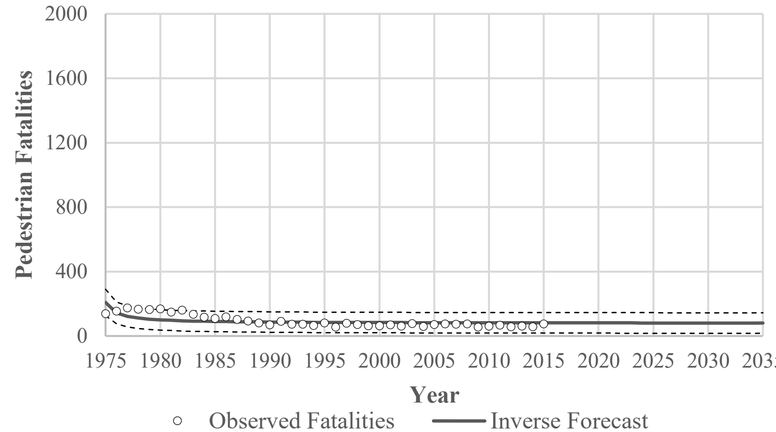

Figure E.59: Inverse forecast model for females aged 16-19.

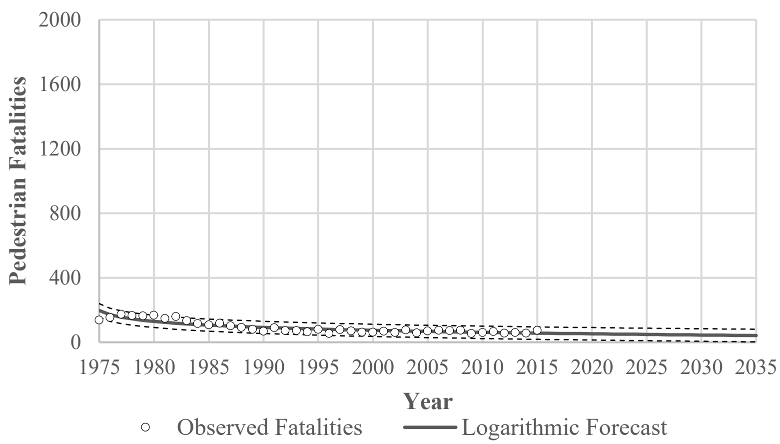

Figure E.58: Logarithmic forecast model for females aged 16-19.

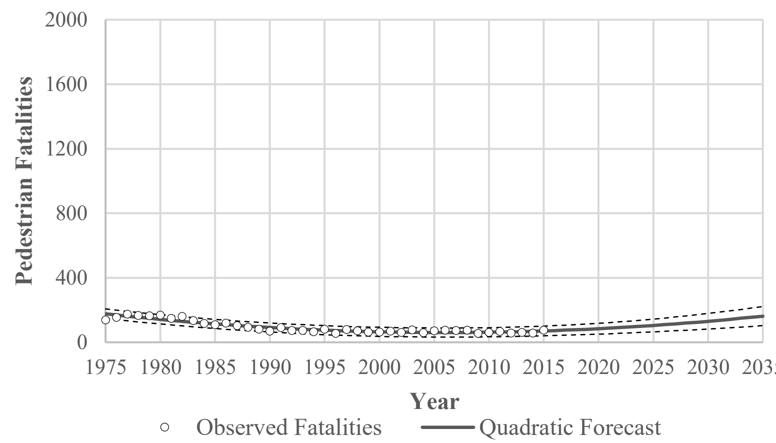

Figure E.60: Quadratic forecast model for females aged 16-19.

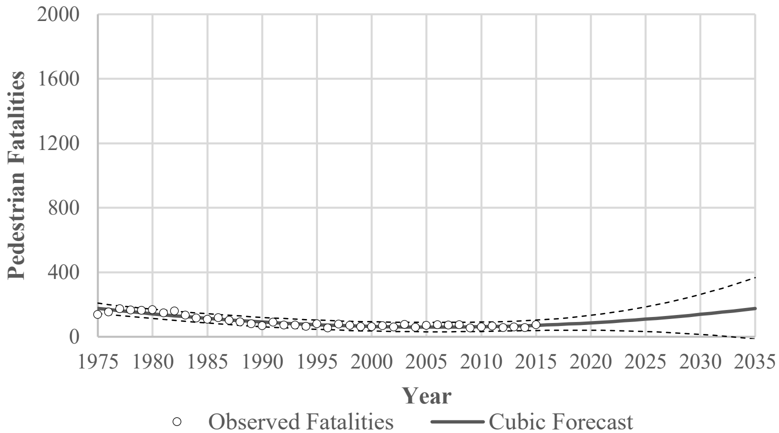

Figure E.61: Cubic forecast model for females aged 16-19.

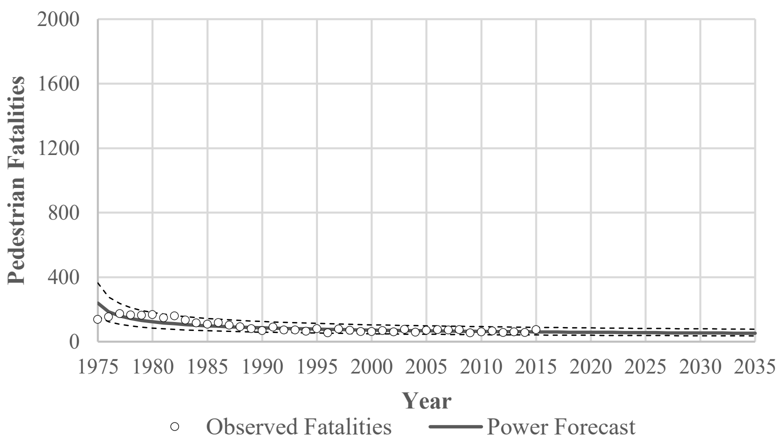

Figure E.62: Power forecast model for females aged 16-19.

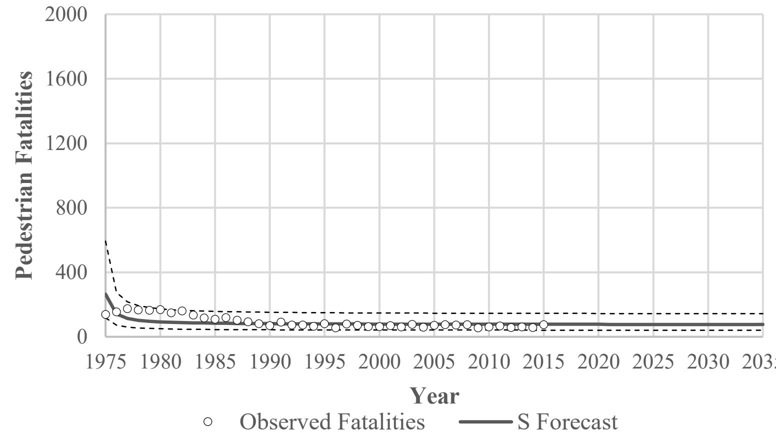

Figure E.63: S forecast model for females aged 16-19.

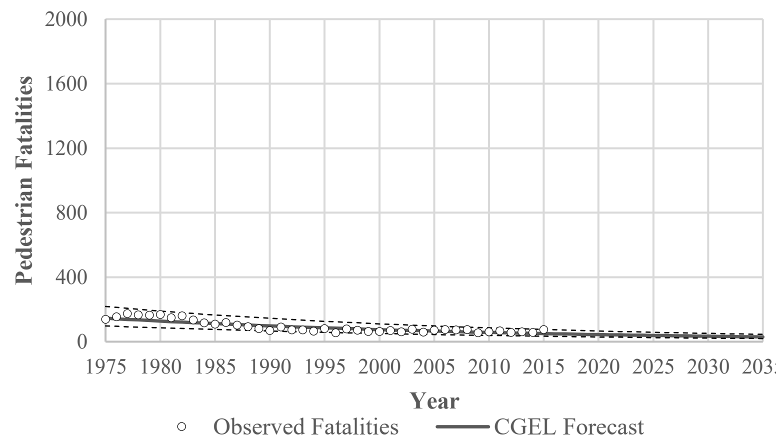

Figure E.64: CGEL forecast models for females aged 16-19.

E.9: Females, 20-34

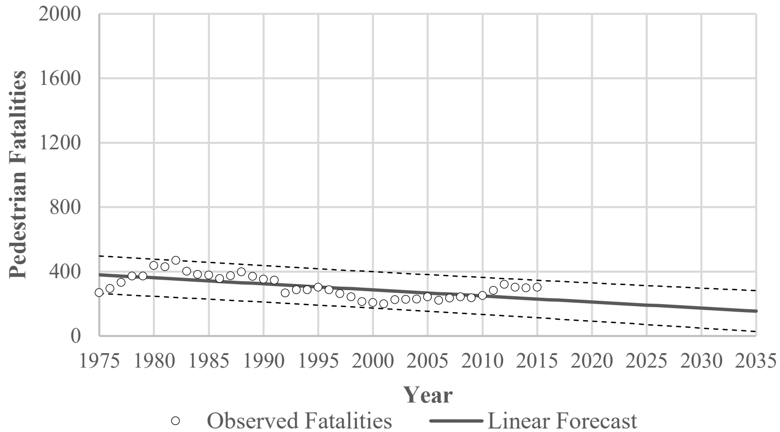

Figure E.65: Linear forecast model for females aged 20-34.

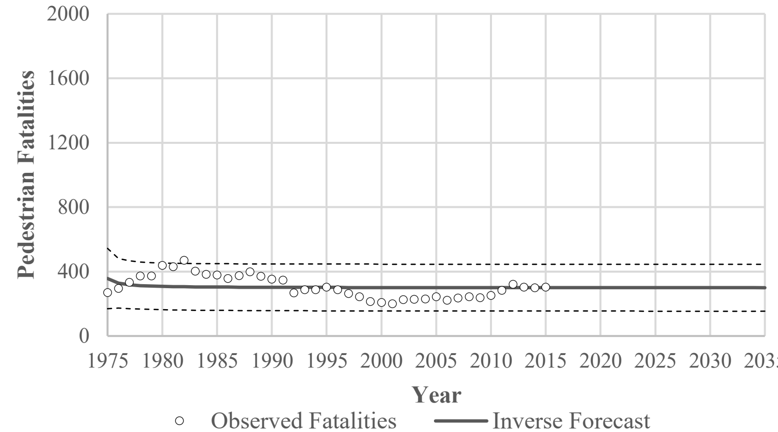

Figure E.67: Inverse forecast model for females aged 20-34.

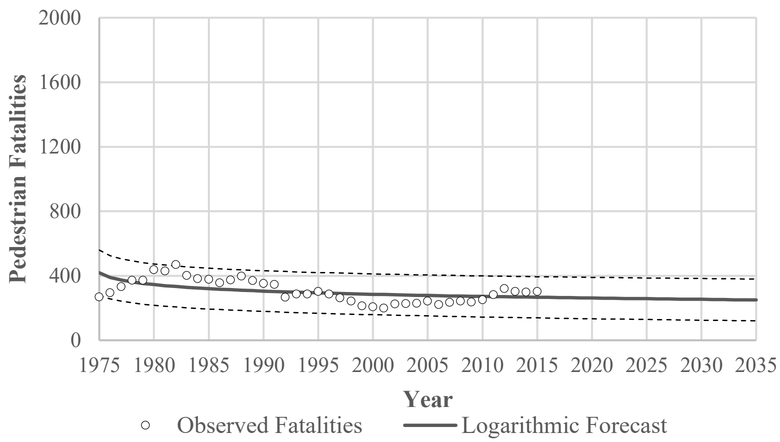

Figure E.66: Logarithmic forecast model for females aged 20-34.

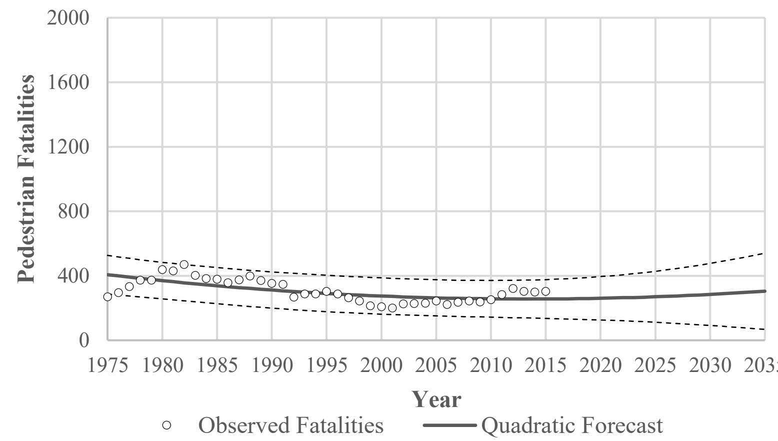

Figure E.68: Quadratic forecast model for females aged 20-34.

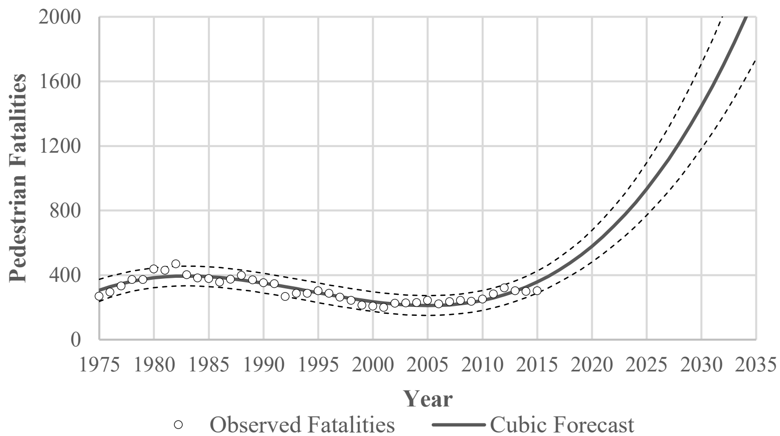

Figure E.69: Cubic forecast model for females aged 20-34.

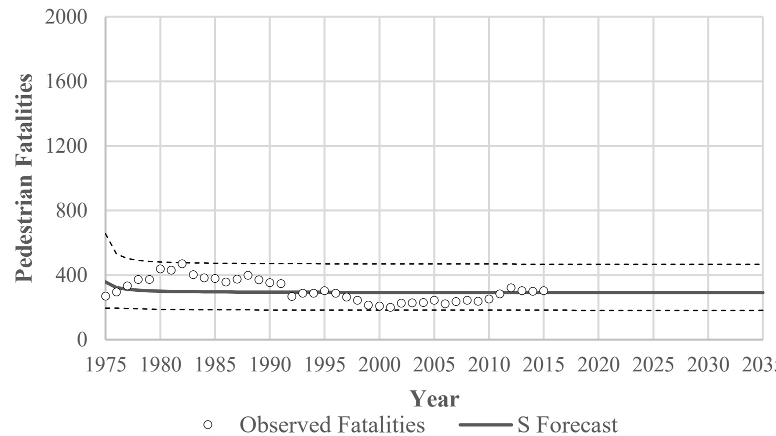

Figure E.71: S forecast model for females aged 20-34.

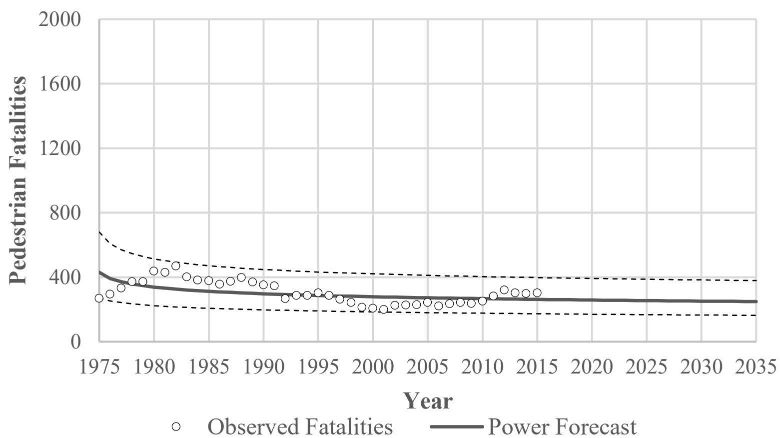

Figure E.70: Power forecast model for females aged 20-34.

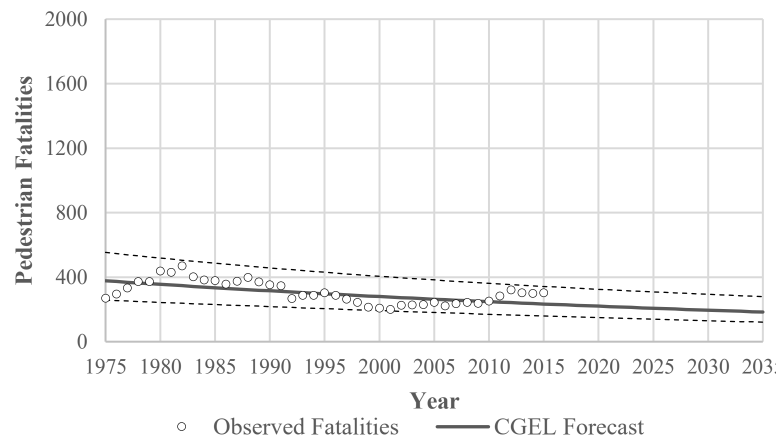

Figure E.72: CGEL forecast models for females aged 20-34.

E.10: Females, 35-54

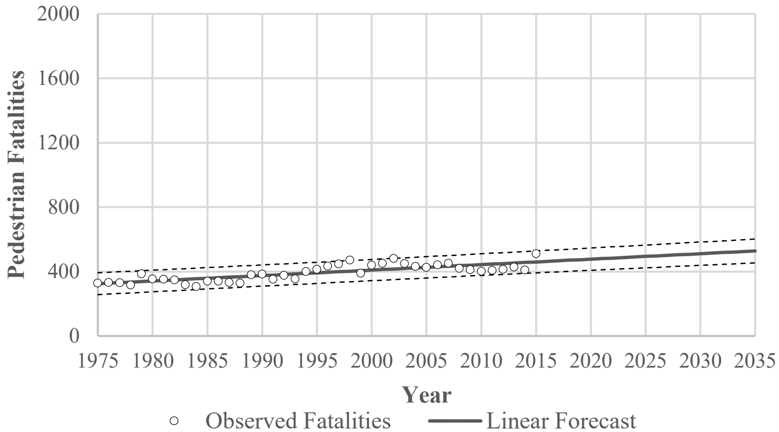

Figure E.73: Linear forecast model for females aged 35-54.

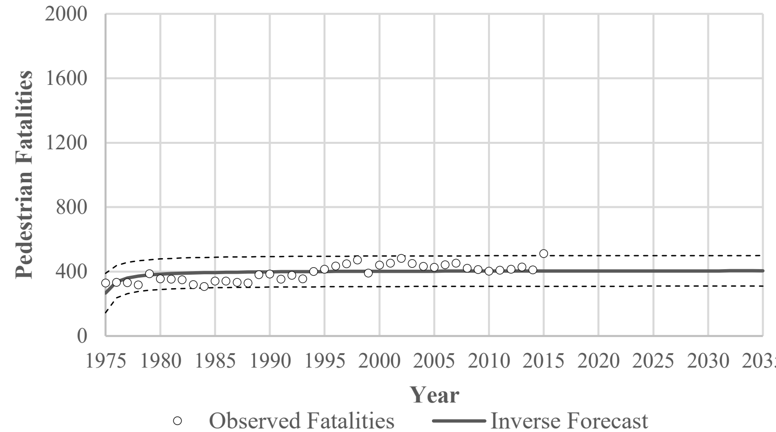

Figure E.75: Inverse forecast model for females aged 35-54.

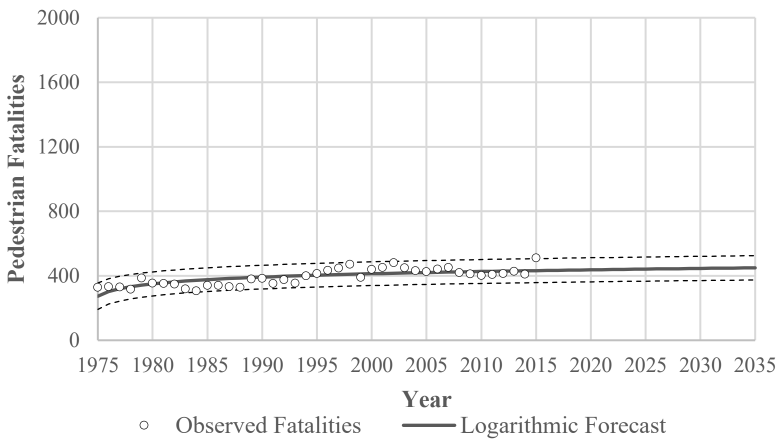

Figure E.74: Logarithmic forecast model for females aged 35-54.

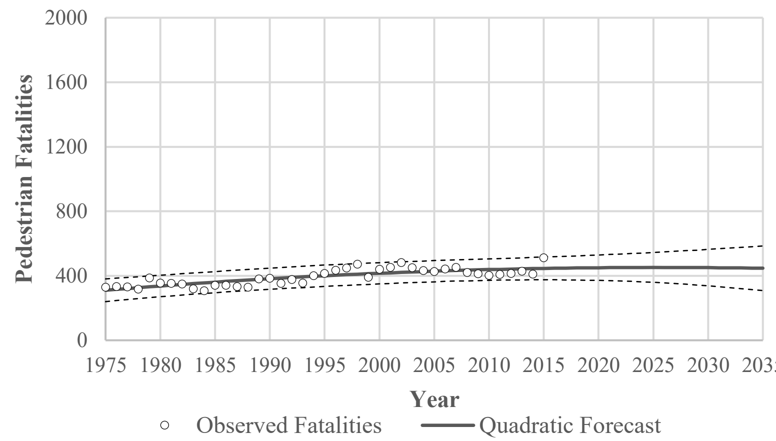

Figure E.76: Quadratic forecast model for females aged 35-54.

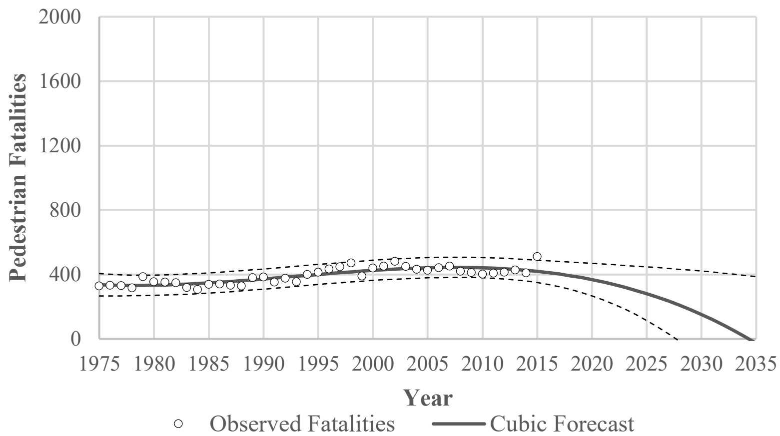

Figure E.77: Cubic forecast model for females aged 35-54.

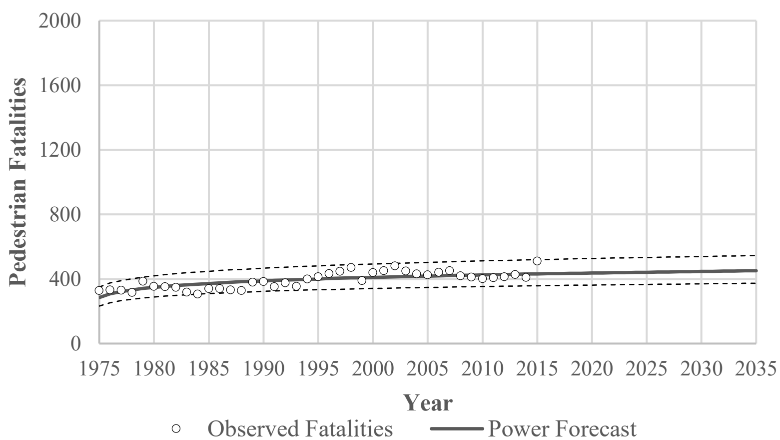

Figure E.78: Power forecast model for females aged 35-54.

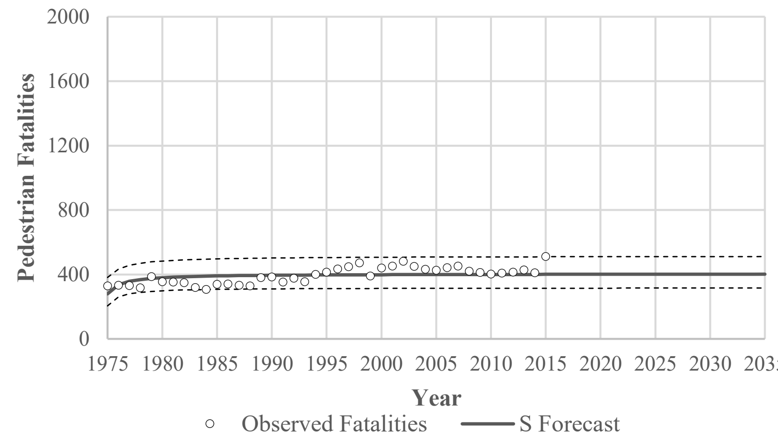

Figure E.79: S forecast model for females aged 35-54.

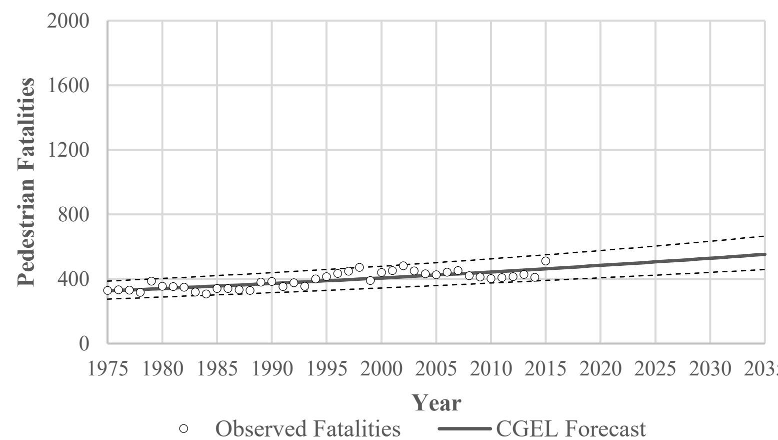

Figure E.80: CGEL forecast models for females aged 35-54.

E.11: Females, 55-64

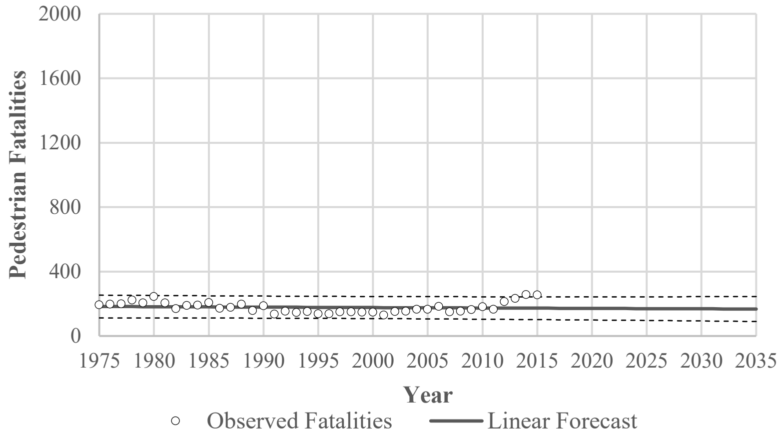

Figure E.81: Linear forecast model for females aged 55-64.

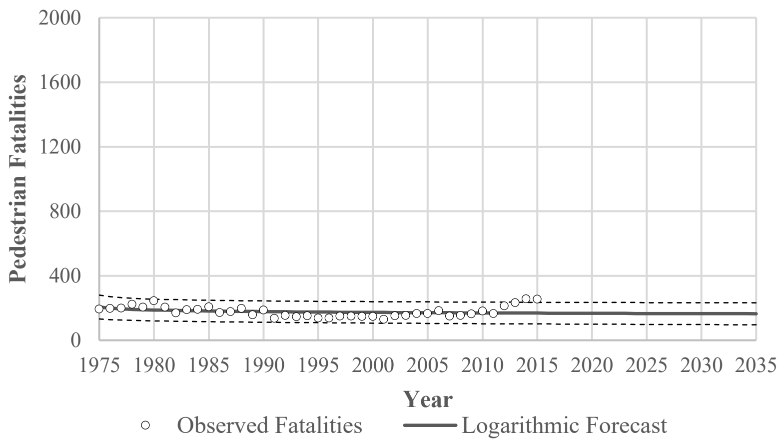

Figure E.82: Logarithmic forecast model for females aged 55-64.

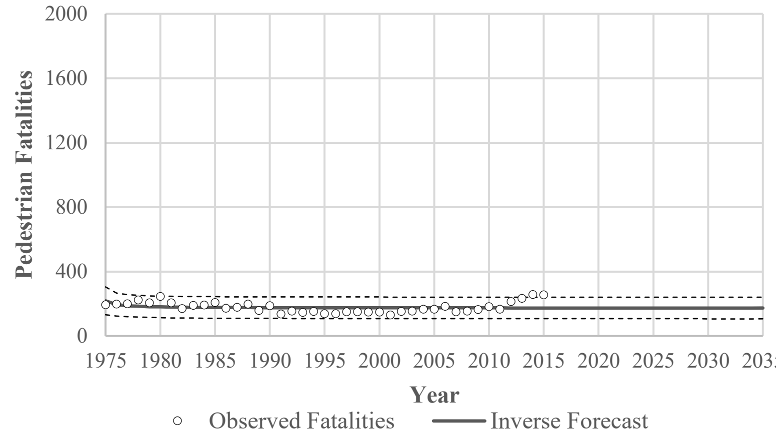

Figure E.83: Inverse forecast model for females aged 55-64.

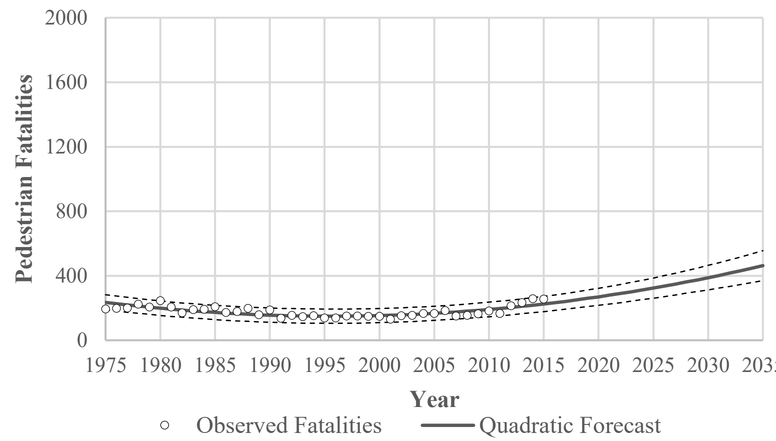

Figure E.84: Quadratic forecast model for females aged 55-64.

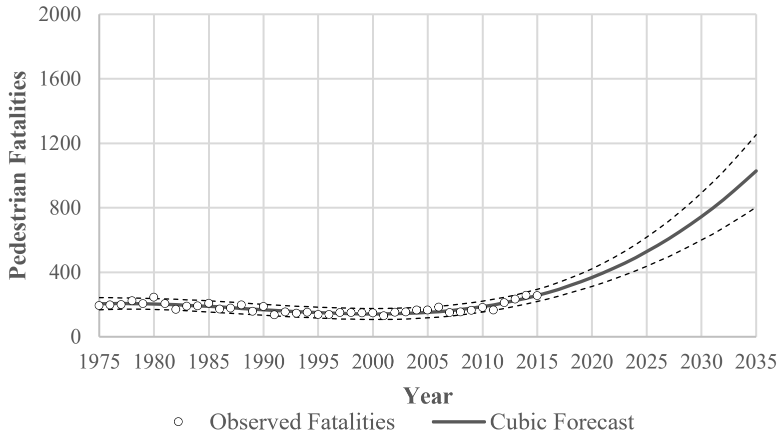

Figure E.85: Cubic forecast model for females aged 55-64.

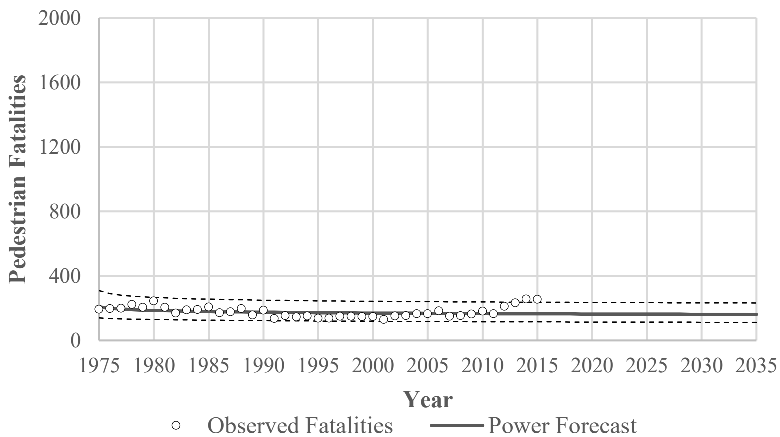

Figure E.86: Power forecast model for females aged 55-64.

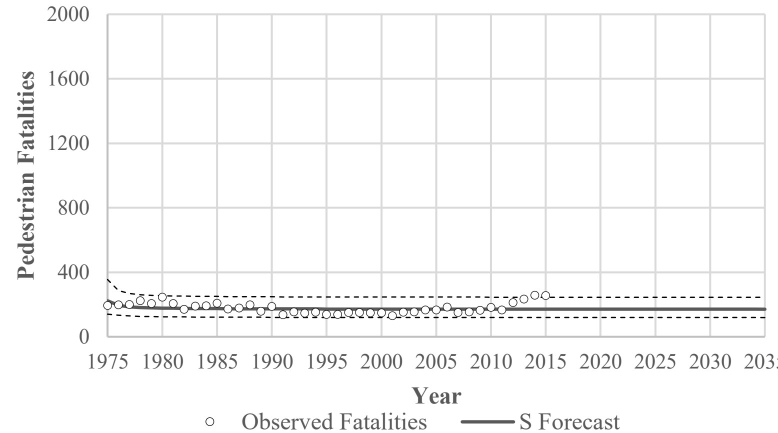

Figure E.87: S forecast model for females aged 55-64.

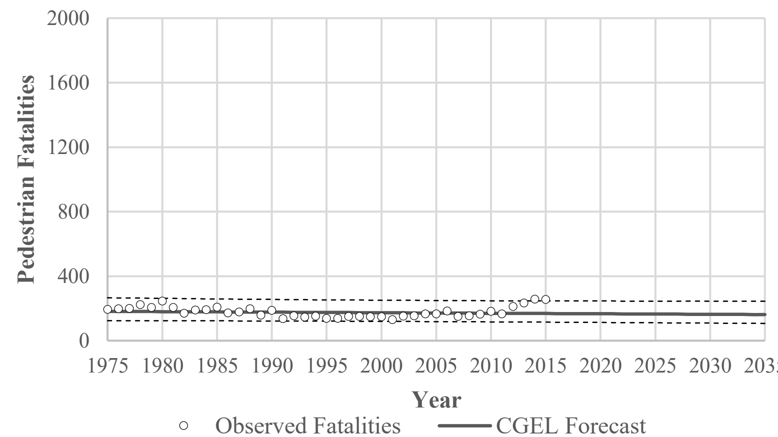

Figure E.88: CGEL forecast models for females aged 55-64.

E.12: Females, 65+

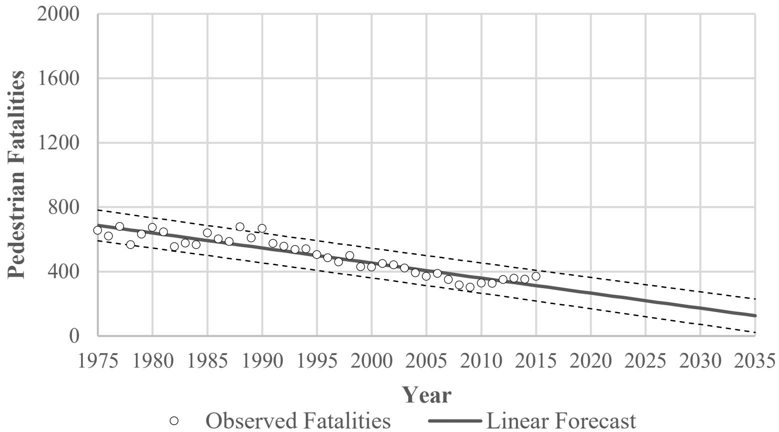

Figure E.89: Linear forecast model for females aged 65+.

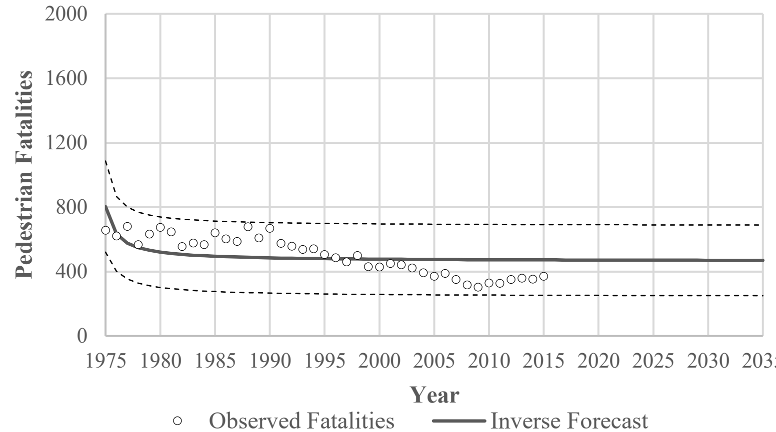

Figure E.91: Inverse forecast model for females aged 65+.

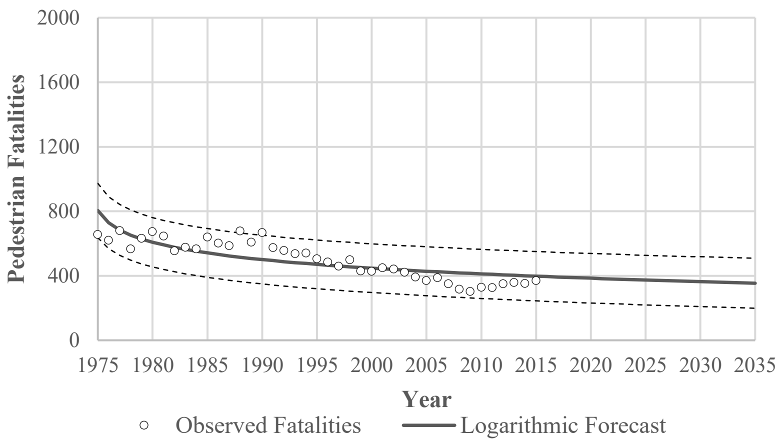

Figure E.90: Logarithmic forecast model for females aged 65+.

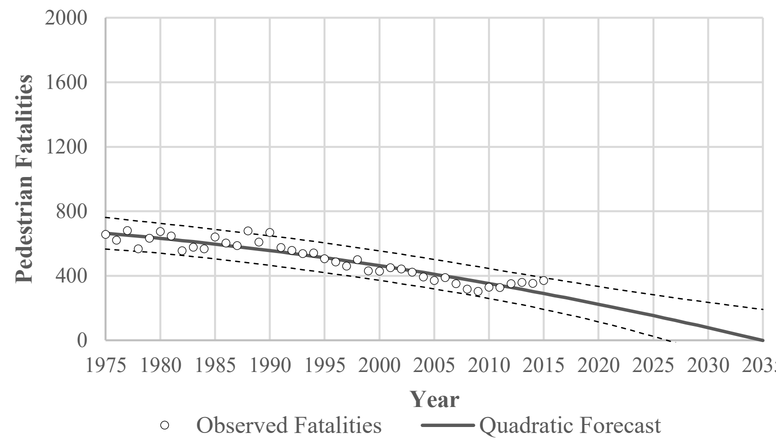

Figure E.92: Quadratic forecast model for females aged 65+.

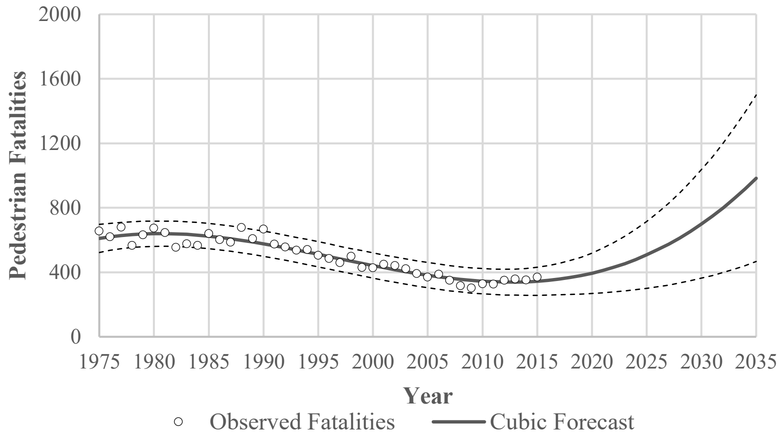

Figure E.93: Cubic forecast model for females aged 65+.

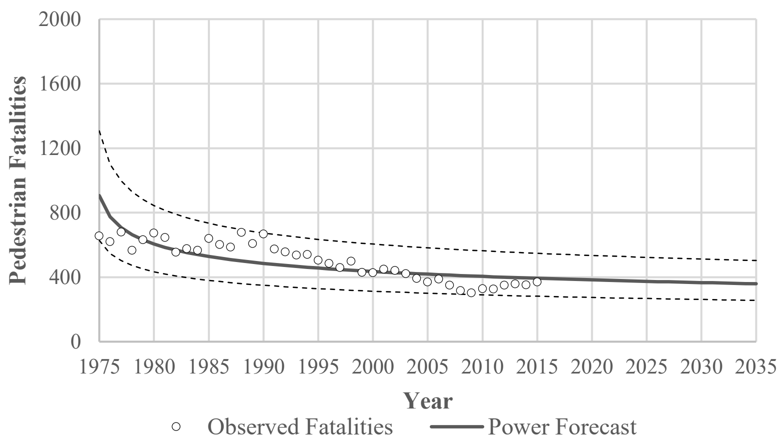

Figure E.94: Power forecast model for females aged 65+.

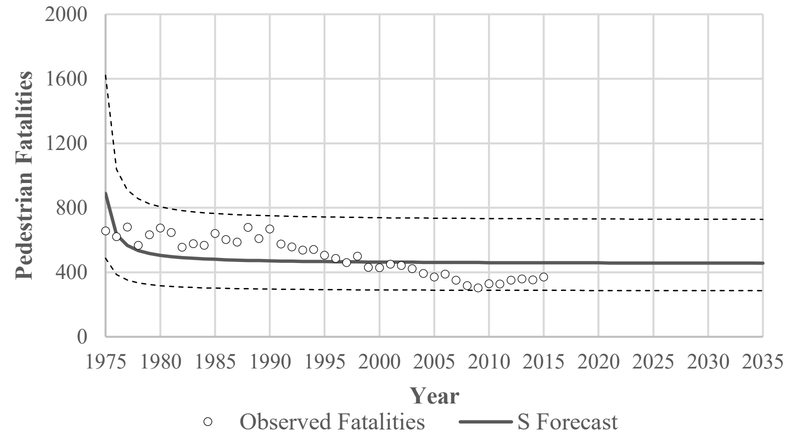

Figure E.95: S forecast model for females aged 65+.

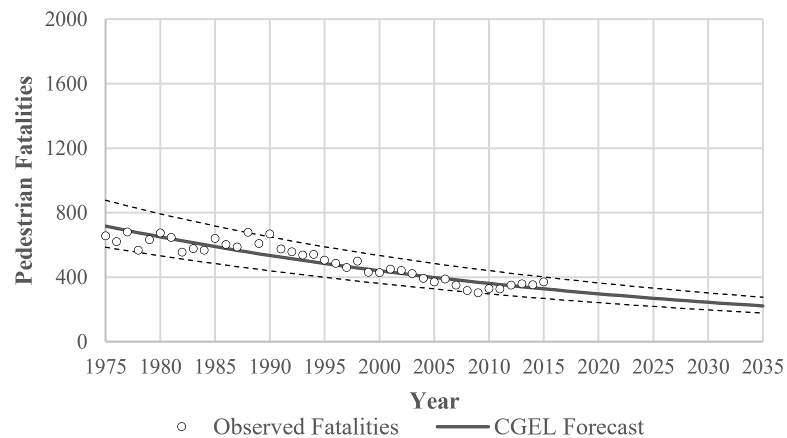

Figure E.96: CGEL forecast models for females aged 65+.

APPENDIX F: PEDESTRIAN INJURY SEVERITY ANALYSIS VARIABLE SUMMARY

This appendix contains details on how the variables used in the injury severity analysis were extracted from GES. **Table F.1** provides a summary of the variable attribute derivations. Note that variable attributes with the highest attribute values were defined as the referents.

Table F.1: Injury severity model variable summary.

ID	Predictor Variable	Variable Name	Attribute Code	Coding Interpretation	Description
1	*Pedestrian Age*	PED_AGE		P_AGE, MISSING VALUES (998,999)	Pedestrian age.
		PED_AGE_MOD		(PED_AGE - 10) / 5	Modified pedestrian age (centered on age 10, unit increase of 5 years).
		PED_AGE_MOD_SQ		PED_AGE_MOD * PED_AGE_MOD	Squared modified pedestrian age.
2	*Pedestrian Sex*	PED_SEX	0	P_SEX = 1	Pedestrian was male.
			1	P_SEX = 2	Pedestrian was female.
3	*Pedestrian Impairment*	PED_IMPAIR	0	NMIMPAIR = 9	Pedestrian was impaired by alcohol, drugs or medication.
			1	NMIMPAIR = 0	Pedestrian had no apparent impairment.
4	*Pedestrian Action*	PED_ACTION	0	MTM_CRSH = 1 OR 11 OR 12	Improper entrance onto roadway.
			1	MTM_CRSH = 4	Improper presence of roadway.
			2	MTM_CRSH = 3 OR 6	Pedestrian non-compliance with right-of-way.
			3	MTM_CRSH = 19	Visibility of pedestrian was poor.
			4	MTM_CRSH = 0	Pedestrian did not perform an improper action.

Table F.1: continued.

5	*Driver Age*	DRV_AGE		AGE, MISSING VALUES (998, 999)	Driver age.
		DRV_AGE_MOD		(DRV_AGE - 16) / 5	Modified driver age (centered on age 16, unit increase of 5 years).
		DRV_AGE_MOD_SQ		DRV_AGE_MOD * DRV_AGE_MOD	Squared modified driver age.
6	*Driver Sex*	DRV_SEX	0	SEX = 1	Driver was male.
			1	SEX = 2	Driver was female.
7	*Driver Impairment*	DRV_IMPAIR	0	DRIMPAIR = 1 OR 2 OR 8 OR 9 OR 10 OR 96	Driver was ill, blacked out, asleep/fatigued, emotional, under the influence, et cetera.
			1	DRIMPAIR = 0	Driver had no apparent impairment.
8	*Driver Movement*	DRV_MVMT	0	P_CRASH1 = 11	Vehicle was turning left.
			1	P_CRASH1 = 10	Vehicle was turning right.
			2	P_CRASH2 = 1 OR 2 OR 3	Vehicle was travelling straight.
9	*Crash Hour*	CRSH_HOUR	0	HOUR = 12 THRU 17	Crash occurred in 'afternoon'.
			1	HOUR = 18 THRU 23	Crash occurred in 'evening'.
			2	HOUR = 6 THRU 11	Crash occurred in 'morning'.
			3	HOUR = 0 THRU 5	Crash occurred in 'overnight'.

Table F.1: continued.

10	*Crash Da*	CRSH_DAY	0	DAY_WEEK = 2	Crash occurred on a Monday.
			1	DAY_WEEK = 3	Crash occurred on a Tuesday.
			2	DAY_WEEK = 4	Crash occurred on a Wednesday.
			3	DAY_WEEK = 5	Crash occurred on a Thursday.
			4	DAY_WEEK = 6	Crash occurred on a Friday.
			5	DAY_WEEK = 7	Crash occurred on a Saturday.
			6	DAY_WEEK = 1	Crash occurred on a Sunday.
		CRSH_DAY_MOD	0	DAY_WEEK = 6 AND HOUR = 20 OR 21 OR 22 OR 23	Crash occurred between Friday 20:00 and Sunday 20:00.
			0	DAY_WEEK = 7	Crash occurred between Friday 20:00 and Sunday 20:00.
			0	DAY_WEEK = 1 AND HOUR = 1 THRU 20	Crash occurred between Friday 20:00 and Sunday 20:00.
			1	CRSH_DAY_MOD ≠ 0	Crash did not occur between Friday 20:00 and Sunday 20:00.
11	*Crash Season*	CRSH_SEASON	0	MONTH = 12 THRU 2	Crash occurred in 'winter'.
			1	MONTH = 9 THRU 11	Crash occurred in 'fall'.
			2	MONTH = 3 THRU 5	Crash occurred in 'spring'.
			3	MONTH = 6 THRU 8	Crash occurred in 'summer'.
12	*Crash Location*	CRSH_LCTN	0	TYP_INT = 1 OR 10	Crash occurred at midblock location.
			1	TYP_INT = 2 OR 3 OR 4	Crash occurred at a three- or four-leg intersection.
13	*Travel Speed*	SPEED		TRAV_SP, MISSING VALUES (997, 998, 999)	Recorded travel speed.
		SPEED_MOD		(SPEED - 30) / 5	Modified recorded travel speed (centered on 30 mph, unit increase of 5 mph).
		SPEED_MOD_SQ		SPEED_MOD * SPEED_MOD	Squared modified recorded travel speed.

Table F.1: continued.

14	*Posted Speed Limit*	SPDLIM		VSPD_LIM, MISSING VALUES (0,98,99)	Posted speed limit.
		SPDLIM_MOD		(SPDLIM - 30) / 5	Modified posted speed limit (centered on 30 mph, unit increase of 5 mph).
		SPDLIM_MOD_SQ		SPDLIM_MOD * SPDLIM_MOD	Squared modified posted speed limit.
15	*Lighting Conditions*	LIGHT	0	LGT_COND = 2	Crash was in dark and unlit conditions.
			1	LGT_COND = 3	Crash was in dark but artificially lit conditions.
			2	LGT_COND = 1 OR 4 OR 5	Crash was within daylight conditions.
16	*Surface Conditions*	SURFCON	0	VSURCOND = 2 OR 3 OR 4 OR 6 OR 10	Surface conditions were adverse (icy, slippery, wet, et cetera).
			1	VSURCOND = 1	Surface conditions were dry.
17	*Traffic Control Device*	TCD	0	VTRAFCON = 0	No traffic control devices present.
			1	VTRAFCON = 20 OR 21 OR 28	Regulatory sign (STOP, YIELD, *et cetera*)
			2	VTRAFCON = 1 OR 2 OR 3	Traffic signal.
18	*Vehicle Type*	VEHTYP	0	BODY_TYP = 20-22, 28, 29, 30-33, 39-41, 45, 48, 49, 60-64, 66-68, 71, 72	Trucks
			1	BODY_TYP = 14-16, 19	Utility Vehicles (e.g., SUVs)
			2	BODY_TYP = 1-9, 10-13	Automobiles
19	*Horizontal Alignment*	ALIGNMENT	0	VALIGN = 2 OR 3	Horizontal curvature (e.g., to the left or right) was present.
			1	VALIGN = 1	Straight roadway alignment.
20	*Vertical Profile*	PROFILE	0	VPROFILE = 2 OR 3 OR 4 OR 5 OR 6	Vertical curvature (e.g., sag, hillcrest, upgrade, downgrade) was present.
			1	VPROFILE = 1	Level roadway.
21	*Median Type*	MEDIAN_TYP	0	VTRAFWAY = 1 OR 4	Crash location did not have a median (i.e., undivided road).
			1	VTRAFWAY = 2 OR 5	Crash location had a painted median.
			2	VTRAFWAY = 3	Crash location had a raised median.