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Pedestrian Safety Analysis through Effective Exposure Measures and Examination of Injury Severity

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PEDESTRIAN SAFETY ANALYSIS THROUGH EFFECTIVE EXPOSURE MEASURES AND EXAMINATION OF INJURY SEVERITY

by

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ABSTRACT

Pedestrians are considered the most vulnerable road users who are directly exposed to traffic crashes. In 2014, there were 4,884 pedestrians killed and 65,000 injured in the United States. Pedestrian safety is a growing concern in the development of sustainable transportation system. But often it is found that safety analysis suffers from lack of accurate pedestrian trip information. In such cases, determining effective exposure measures is the most appropriate safety analysis approach. Also it is very important to clearly understand the relationship between pedestrian injury severity and the factors contributing to higher injury severity. Accurate safety analysis can play a vital role in the development of appropriate safety countermeasures and policies for pedestrians.

Since pedestrian volume data is the most important information in safety analysis but rarely available, the first part of the study aims at identifying surrogate measures for pedestrian exposure at intersections. A two-step process is implemented: the first step is the development of Tobit and Generalized Linear Models for predicting pedestrian trips (i.e., exposure models). In the second step, Negative Binomial and Zero Inflated Negative Binomial crash models were developed using the predicted pedestrian trips. The results indicate that among various exposure models the Tobit model performs the best in describing pedestrian exposure. The identified exposure relevant factors are the presence of schools, car-ownership, pavement condition, sidewalk width, bus ridership, intersection control type and presence of sidewalk barrier. The t-test and Wilcoxon signed-rank test results show that there is no significant difference between the observed and the predicted pedestrian trips. The process implemented can help in estimating reliable safety performance functions even when pedestrian trip data is unavailable.

The second part of the study focuses on analyzing pedestrian injury severity for the nine counties in Central Florida. The study region covers the Orlando area which has the second-worst pedestrian death rate in the country. Since the dependent variable 'Injury' is ordinal, an 'Ordered Logit' model was developed to identify the factors of pedestrian injury severity. The explanatory variables can be classified as pedestrian/driver characteristics (e.g., age, gender, etc.), roadway traffic and geometric conditions (e.g.: shoulder presence, roadway speed etc.) and crash environment (e.g., light, road surface, work zone, etc.) characteristics. The results show that drug/alcohol involvement, pedestrians in a hurry, roadway speed limit 40 mph or more, dark condition (lighted and unlighted) and presence of elder pedestrians are the primary contributing factors of severe pedestrian crashes in Central Florida. Crashes within the presence of intersections and local roads result in lower injury severity. The area under the ROC (Receiver Operating Characteristic) curve has a value of 0.75 that indicates the model performs reasonably well. Finally the study validated the model using k-fold cross validation method. The results could be useful for transportation officials for further pedestrian safety analysis and taking the appropriate safety interventions.

Walking is cost-effective, environmentally friendly and possesses significant health benefits. In order to get these benefits from walking, the most important task is to ensure safer roads for pedestrians.

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Thank you
Md Imran Shah

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LIST OF ABBREVIATIONS

AIC	Akaike Information Criterion
AUC	Area Under Curve
BIC	Bayesian Information Criterion
CARS	Crash Analysis Reporting System
DHSMV	Department of Highway Safety & Motor Vehicle
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
FT	Feet
GLM	Generalized Linear Modeling
IIHS	Insurance Institute for Highway Safety
ITS	Intelligent Transportation System
MAD	Mean Absolute Deviation
MLE	Maximum Likelihood Estimation
MPH	Mile Per Hour
MSE	Mean Square Error
NB	Negative Binomial

NHTSA	National Highway Traffic Safety Administration
NZTA	New Zealand Transport Agency
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
RMSE	Root Mean Square Error
ROC	Receiver Operating Characteristics
T4A	Transportation for America
TRB	Transportation Research Board
UCF	University of Central Florida
US	United States
WHO	World Health Organization
ZINB	Zero Inflated Negative Binomial

CHAPTER 1. INTRODUCTION

1.1 Overview

Being classified as vulnerable road users, pedestrians are recognized as the worst victims of traffic crashes. In 2014, there were 4,884 pedestrians killed and 65,000 injured on roads that indicate on average, a pedestrian was killed every 2 hours and injured every 8 minutes (NHTSA, 2014). The proportion of pedestrian fatalities has steadily increased from 11% to 14% over the past decade. The number describes the importance of addressing the safety of pedestrians and raising awareness among the people about safe walking. Walking is one of the basic activities in human daily life that can contribute important health and economic benefits. According to the New Zealand Transport Agency the total health benefit of walking was estimated to be $2.6 per each kilometer walked (NZTA, 2010; Rahul and Verma, 2013). Walking is cost-effective and environmentally friendly that can reduce rates of chronic disease and ameliorate rising health care costs (Lee and Buchner, 2008). The extensive research in the sustainable transportation systems improvement increased the significance of pedestrian safety and sustainable pedestrian facilities. Several studies have shown pedestrian volume to be a significant measure for pedestrian exposure estimation (Raford and Ragland, 2005; Tobey et al., 1983). But in many studies pedestrian exposure has been observed as a measurement issue in the development of pedestrian safety models. So it has been a challenge for the researchers to carry out proper safety analysis due to the unavailability or inaccurate pedestrian volume data. Again the injury severity levels of pedestrians are relatively high compared to those in motor vehicle crashes. The reason behind this is unlike the passengers or drivers in motor vehicle crashes, pedestrians are directly exposed to the impact of traffic crashes. Therefore, the significance of understanding relationship between pedestrian injury severity level and the factors must be addressed by the traffic

engineers, planners and decision makers in order develop proper safety countermeasures as well as education and enforcement interventions. Individual region based safety analysis approach along with statewide policy analysis can help improve the safety of pedestrians.

1.2 Pedestrian Exposure Measurement

It has been a common practice in exposure science and environmental epidemiology to collect detailed and precise micro-environment data in which an individual stays or moves (Lassarre et al., 2007). Scientific crash risk analysis incorporates individual's activity-travel pattern as an exposure measurement. The underlying theory is that crash data as points-in-networks along with disaggregate exposure data can identify hazardous crash locations where road safety improvements can be made.

Figure 1. Exposed Pedestrian (source: Joe Raedle / Getty Images)

The first part of the study aims at identifying the exposure factors to pedestrian crashes at intersections. Intersections are among the significant pedestrian crash occurring locations. In 2014 there were 923 (18.9%) pedestrian fatalities occurred at or near intersections in the US. It is

obvious that the number of people walking on the road (i.e., pedestrian trips) is one of the best measures of exposure for pedestrians (Davis and Braaksma, 1988; Qin and Ivan, 2001; Lam et al., 2014). However, it is difficult to continuously measure the pedestrian trips at all locations as it involves using significant amount of resources. This study aims at addressing the situation when it is difficult to collect pedestrian trip data. The objective of this study is to analyze surrogate measures for pedestrian exposure to traffic crashes at intersections including the use of socio-demographic, land-use and geometric characteristics of the surrounding environment. The two-step process implemented in the study involves developing the exposure models first and then the crash models.

Figure 2. Pedestrian Crossing Intersection (source: Chris Urso/Tribune)

The exposure models were developed using Tobit and Generalized Linear Modeling (GLM) methods that predict the pedestrian trips. After identifying the best exposure model, Negative Binomial (NB) and Zero Inflated Negative Binomial (ZINB) crash models were developed using the predicted pedestrian trips as an exposure variable. The method can be described as an integrated pedestrian safety analysis around intersections (micro-level) with

macro-level data from census block groups. The study contributes to the research area of pedestrian safety through identifying the best exposure for pedestrian crashes at intersections and developing a process of safety analysis for locations where pedestrian data is not available. Proper knowledge of exposure factors can help transportation officials to develop safer roads for pedestrians through implementing the right safety interventions.

1.3 Pedestrian Injury Severity Analysis

The second part of the study focuses on analyzing pedestrian injury severity for the nine counties in Central Florida. The nine counties are Marion, Sumter, Lake, Seminole, Orange, Osceola, Polk, Hardee and Highlands. Central Florida has been known as a high risk zone for the people walking on roads. Every year more than 1100 Central Floridians are struck by cars and at least 900 suffer what police call 'incapacitating' injuries. The number of fatality ranges from 80 to 100 each year (FL-DHSMV, 2011-2015). It must be mentioned that the transportation system in Central Florida is mostly auto oriented. Public transportation system is also not much popular in this region. Very few people are seen walking on the road for purely commuting purpose.

Figure 3. Pedestrian Struck by Car (source: KMGH / The Denver Channel)

Despite these facts the death rate of pedestrian seems to be rising each year. The study region covers the Orlando area which has the second worst pedestrian death rate in the country. In this study an 'Ordered Logit' model was developed to identify the pedestrian injury severity factors since the dependent variable 'Injury' is ordinal in nature. The explanatory variables can be classified as pedestrian/driver characteristics (e.g., age, gender, etc.), roadway traffic and geometric conditions (e.g.: shoulder presence, roadway speed etc.) and crash environment (e.g., light, road surface, work zone, etc.) characteristics. The results show that drug/alcohol involvement, pedestrians in a hurry, roadway speed limit more than 40 mph, dark condition (lighted and unlighted) and presence of elder pedestrians are the primary contributing factors of severe pedestrian crashes in Central Florida. On the other hand crashes occuring within the presence of intersections and local roads are associated with lower injury severity. The area under the ROC (Receiver Operating Characteristic) curve has a value of 0.75 that indicates the model performs reasonably well. Finally the study validated the model using k-fold cross validation method. The outcome of the validation shows that the validation dataset has a ROC value of 0.72 (close to original c value) that indicates the model is good enough in describing the relationship between injury severity and the factors contributing to it. The results could be useful for transportation officials for further pedestrian safety analysis and taking the appropriate safety interventions for the pedestrian crashes in Central Florida. The study also recommends some safety countermeasures that can be adopted to make the traffic system in Central Florida more pedestrian friendly.

1.4 Research Objectives & Tasks Performed

Based on the understanding of the pedestrian safety problem the main objectives of the study can be listed as follows:

- Identification of pedestrian exposure factors at intersection using surrogate safety analysis.
- Developing pedestrian safety analysis process where pedestrian volume data is not available.
- Modeling pedestrian crash risk at intersection including socio-demographic, land use pattern and geometric characteristics of the surrounding environment.
- Application of Zero Inflated Negative Binomial model in census block group level (MICROSCOPIC) pedestrian safety analysis.
- Identification of significant factors contributing to severe pedestrian injuries in the Central Florida region.
- Application of 'Ordered Logit' model in injury severity analysis in the Central Florida using the FDOT crash database.
- Identification of appropriate pedestrian safety improvement countermeasures based on the analysis results.

In order to achieve these objectives the following tasks were performed:

- Collection of socio-demographic, geometric and land use data of the area under analysis. The crash data were obtained from FDOT crash database.
- Development of statistical models such as Tobit or Generalized Linear model for exposure, Negative Binomial or Zero Inflated Negative Binomial for crash models, Ordered Logit for injury severity.
- Application of statistical tests to determine whether the performances of the developed models are good enough to reach a conclusion.

- Recommendation of appropriate safety countermeasures that can be adopted to improve the safety of people walking on roads.

1.5 Thesis Outline

The thesis has been organized according to the specific need. There are six chapters in the manuscript each of which is targeted for specific purpose. Chapter One contains general introduction of the thesis, the characteristic problem, objective, scope and all other introductory information. Chapter Two includes a brief literature review of the previous studies related to pedestrian exposure and injury severity. Critical review of the modeling techniques and the explanatory variables are also included in this chapter. Chapter Three describes the research methodologies followed in the thesis. It includes the concepts of all the statistical procedure adopted in this study. Chapter Four includes detail procedure of preparing the data for the model development. All the data preparation tools & techniques are presented in this section. Chapter Five shows the modeling results of the exposure study and the injury severity analysis. The explanations of the outcomes are presented in this section. Chapter Six provides the recommended safety countermeasures that can be adopted for the improvement of pedestrian safety based on the model results. Some possible future extensions of the current study are also included in this chapter.

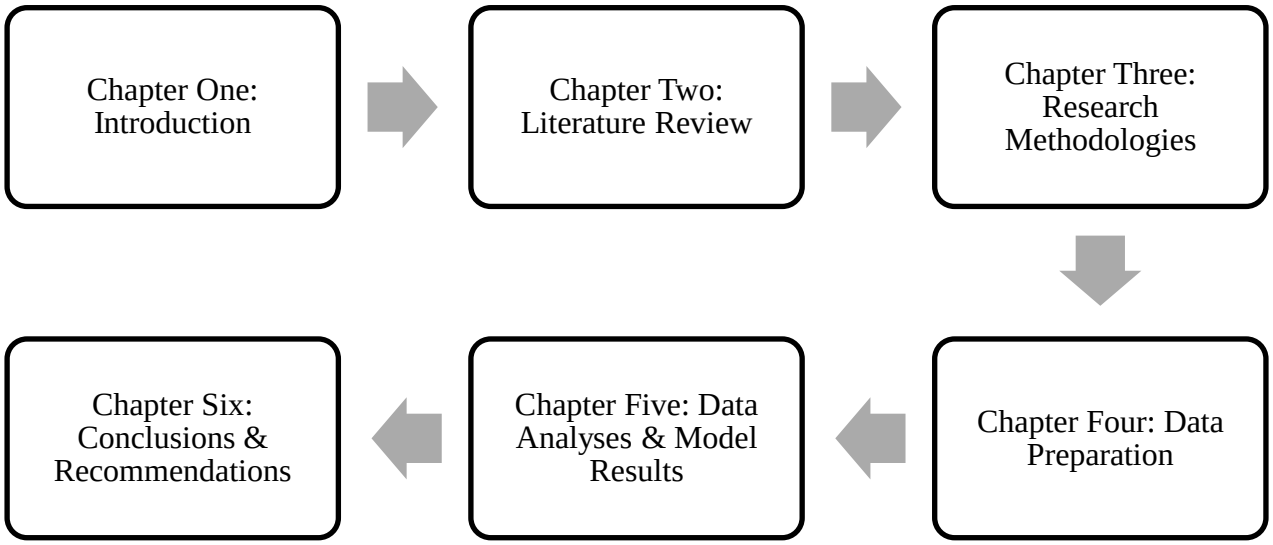


Figure 4. Thesis Organization Flow Chart

CHAPTER 2. LITERATURE REVIEW

The safety researchers are recently getting concerned about the traffic crashes involving pedestrians due to the increasing number of pedestrian injuries/fatalities in the past decade. Although many of the earlier research focused primarily on vehicle occupants but now a days non-motorist safety studies are drawing the attention of the transportation experts. Because of this there has been extensive research studies conducted to ensure the safe movement of pedestrians. Researchers are trying to figure out proper safety analysis process for pedestrian safety. Some of the major concerns are rare pedestrian crash events, difficulty in counting number of pedestrian trips, difficulty in understanding complex behavioral nature of pedestrians etc. Many previous studies have examined different risk factors associated with the walking related crash and injury severity to improve motorized vehicle and roadway design, enhance control strategies at conflict locations, design good pedestrian facilities, and formulate driver and pedestrian education programs. Before proceeding to the actual study a brief review of the previous studies has been carried out to better understand the underlying procedure of pedestrian safety analysis.

2.1 Brief Statistics of Pedestrian Crash Representing the Current Situation

A brief review of the recent pedestrian crash statistics in the United States shows that pedestrian safety should be prioritized on top of all other traffic safety issues. In 2015, 5,376 people were killed in pedestrian/motor vehicle crashes indicating nearly 15 people every day of the year (NHTSA 2015). This represents the highest number of pedestrians killed in one year since 1996. In spite of total traffic fatalities in the United States being reduced by nearly 18 percent from 2006 to 2015, pedestrian fatalities increased by 12 percent during the same ten year

period. There were an estimated 70,000 pedestrians injured in 2015, compared to 61,000 in 2006 indicating nearly 15 percent increase over ten years. These statistics are based on the reported crashes by the police officer. Analyzing hospital records of injury severity shows that only a fraction of pedestrian crashes causing injury are ever recorded by the police.

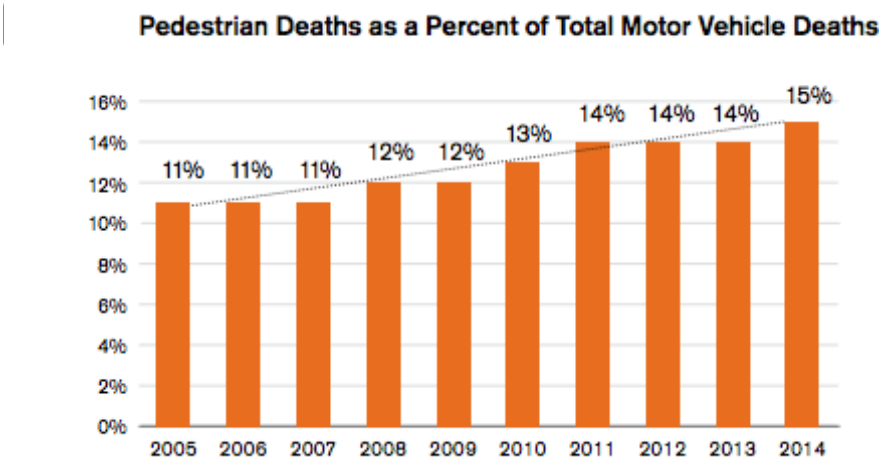


Figure 5. Pedestrian Death Rate over Last Decade (source: FARS)

The National Highway Traffic Safety Administration (NHTSA) and the Insurance Institute for Highway Safety (IIHS) fact sheets provide detailed information of the age, gender, location of pedestrian crash etc. Some of the more noteworthy trends or numbers are mentioned below:

- In 2014, 70 percent of pedestrian killed were males.
- The average age of pedestrian killed is 47 and the average age of those injured is 37.
- More than 26 percent pedestrian fatalities occurred between 6.00 p.m. and 8:59 p.m.
- Almost three out of every four pedestrian fatalities occur in urban areas.
- 34 percent of pedestrians killed had a blood alcohol concentration of 0.08 g/dL or higher.
- 14 percent of drivers in a pedestrian crash had a blood alcohol concentration of 0.08 g/dL or higher.

- California (697), Florida (588), and Texas (476) lead the nation in total pedestrian fatalities.

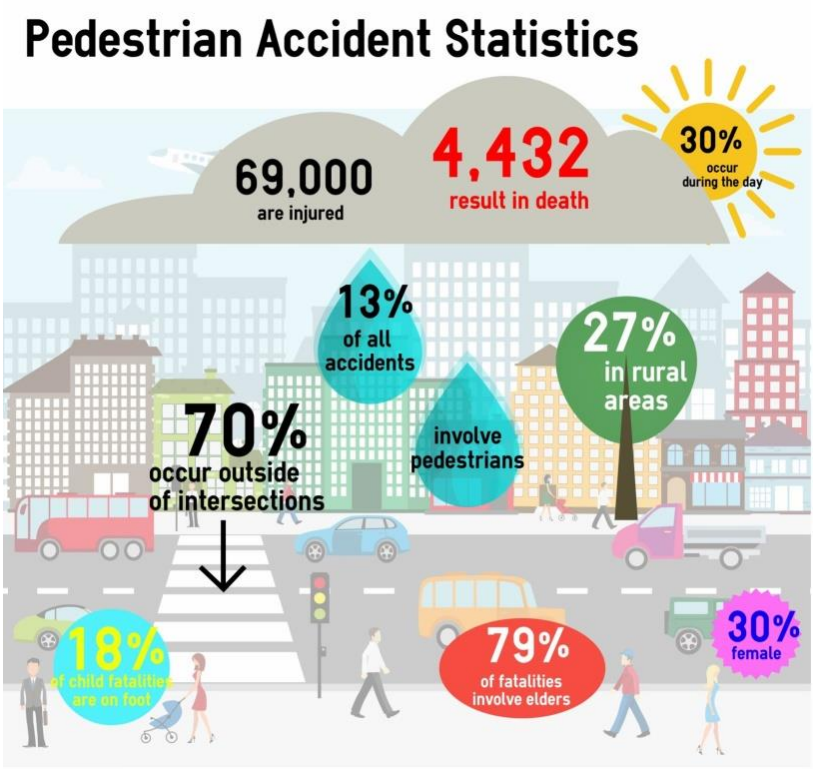


Figure 6. Pedestrian Crash Statistics (source: The Miley Legal Group/NHTSA)

Among the fifty states in the country, Florida has been ranked as the most dangerous state for pedestrians by Transportation for America (T4A, 2011). The top four locations of pedestrian crashes were identified as Orlando/Kissimmee, Tampa/St. Petersburg/Clearwater, Jacksonville, and Miami/Fort Lauderdale/Pompano. Based on the 2014 statistics the Pedestrian Fatalities per 100,000 Population is 2.96 in Florida where the nationwide average value is 1.53 (NHTSA, 2014). It is high time for the transportation officials in the state of Florida to take an in depth look at the safety of pedestrians.

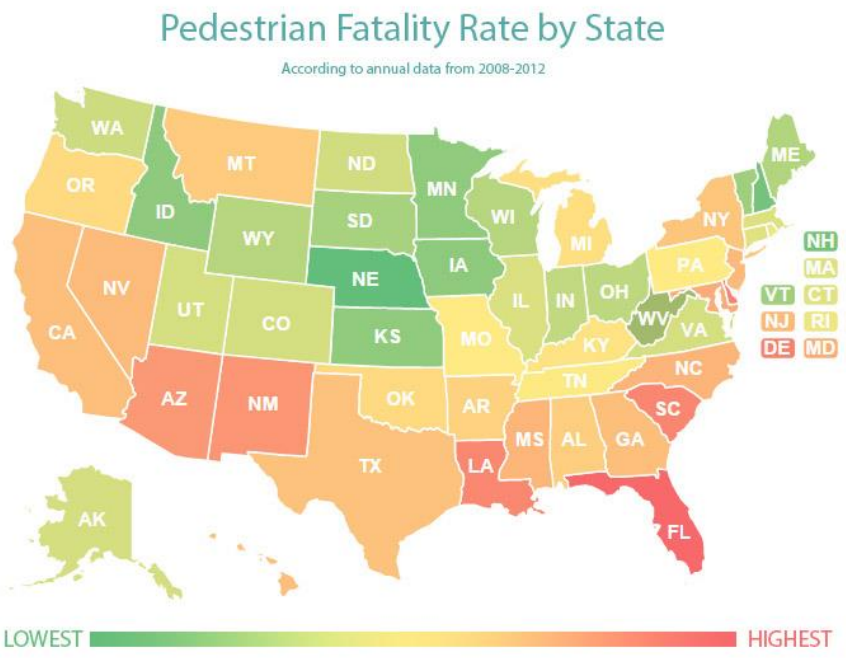


Figure 7. Florida is the most Dangerous State for Pedestrians (source: FARS/obrella.com)

Pedestrians account for 14 percent of all traffic fatalities but only 10.9 percent of trips which indicates pedestrians are over-represented in the crash data (FHWA, 2014). The reason behind this remains unclear since there is no reliable source of exposure data. Transportation professionals face difficulty in getting an accurate estimation of how many miles people walk each year or how many minutes/hours people spend walking/crossing the street (and thus how long they are exposed to motor vehicle traffic). It is difficult to evaluate if there is any safety improvement can be made without a better understanding of how many people are walking, where they are walking, and how far/often they are walking. A reduction in pedestrian crashes could be attributed to fewer people walking in general, or to improvements in facilities, law enforcement, education, and behavior.

2.2 Importance of Safe Walking

The statistics of pedestrian crash and injury severity presents a wide range of questions: Is walking more risky than other travel modes? Is walking safe? Who are getting killed in pedestrian crashes, where, when, and why? Walking is a common and basic mode of transport in all societies around the world. It can be virtually said that every trip begins and ends with walking. Walking comprises the sole mode of transport on some trips, whether a long trip or a short stroll to a shop. There are many well established health and environmental benefits of walking such as increasing physical activity can lead to reduced cardiovascular and obesity-related diseases.

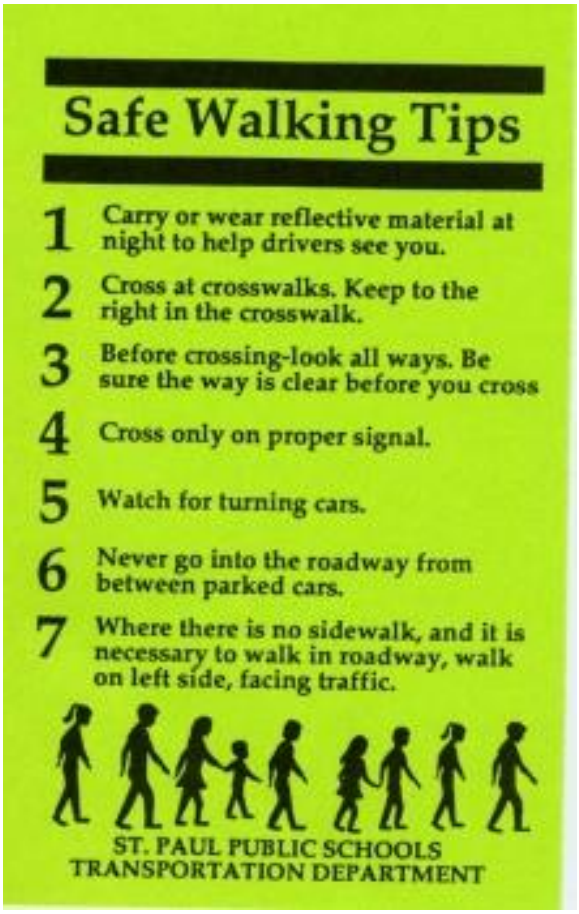


Figure 8. Safe Walking Tips (source: St. Paul Public Schools Transportation Department)

Walking is considered a healthy and inherently safe activity for tens of millions of people every year. Reduction in physical activity is a major contributor to the hundreds of thousands of deaths caused by heart attacks and strokes. In the year 2000 the number of deaths caused by poor diet and physical inactivity increased by approximately 66,000 which accounts for about 15.2 percent of the total number of deaths (Jacobs et al., 2004). Many countries have started implementing policies to promote walking as an important mode of transport. Unfortunately, in some conditions increasing walking activities can lead to higher risk of road traffic crashes and injury. Pedestrians are increasingly susceptible to road traffic injury because of the dramatic growth in the number of motor vehicles and the frequency of their use around the world. Also there is a general negligence of pedestrian needs in roadway design and land-use planning that increase the pedestrian vulnerability. Reduction or elimination of the risks faced by pedestrians is an important and achievable policy goal. It is unlikely to accept pedestrian collisions as inevitable since they are both predictable and preventable with appropriate safety countermeasures.

2.3 Studies Related to Pedestrian Exposure

Lee et al. (2015) applied different exposure variables for pedestrians and found that the product of 'Log of population' and 'Log of Vehicle-Miles-Traveled (VMT)' is the best exposure for 'Pedestrian crashes per crash location ZIP code area', whereas 'Log of population' is the best exposure variable for 'Crash-involved pedestrians per residence ZIP'. The authors combined hot zones from where vulnerable pedestrians originated with hot zones where many pedestrian crashes occur. It was expected that the proposed screening method would be helpful for the practitioners to suggest appropriate safety treatments for pedestrian crashes.

Ukkusuri et al. (2011) developed a random-parameter negative binomial model of pedestrian crash frequencies for New York City at the census tract level. The model found that the proportion of uneducated population, Black or Hispanic neighborhood areas, commercial areas, school areas, intersection operation characteristics, type of access control in the roads and number of lanes have positive impacts on pedestrian crashes. Based on the results the authors emphasized the focus on improved policy framework to improve pedestrian safety.

Lee and Abdel-Aty (2005) made a comprehensive study on vehicle-pedestrian crashes at intersections in Florida. The study followed Keall's method (1995) to develop a logical expression of pedestrian exposure to crash risk using the individual walking trip data collected from the household travel survey. The proposed exposure reflected different walking patterns by different age groups of pedestrians. In spite of applying certain assumptions and adjustments it was quite hard for the authors to identify pedestrian exposure.

Miranda-Moreno et al. (2011) analyzed two important relationships between land development and pedestrian which are: (a) between the land-use and pedestrian activities, and (b) between the risk exposure (pedestrian and vehicle activities) and the pedestrian crash frequency. The authors concluded that the land-use pattern affects the pedestrian activity level with limited direct effect on pedestrian safety. Land-use affects the pedestrian volume, which is an important component of exposure to risk. The authors also found a non-linear relationship between the exposure and the crash count. These outcomes and the difficulty in identifying the pedestrian exposure data mentioned by Lee and Abdel-Aty (2005) helped in justifying models that include exposure related variables.

Abdel-Aty et al. (2007) analyzed the safety of students around schools and found that middle and high school children are involved in crashes more frequently than younger children. It confirmed that school-aged children are exposed to high crash risk near schools. The authors figured out that driver's age, gender, alcohol use, pedestrian's/bicyclist's age, number of lanes, median type, speed limits, and speed ratio are correlated with the frequency of crashes. These pedestrians and bicyclists' demographic factors and geometric characteristics of the roads adjacent to schools are expected to be considered in determining safety interventions of school districts. The study presented an example of combining two approaches to safety improvement including identification of locations with pedestrian safety problems and evaluating specific safety interventions.

2.4 Review of Modeling Techniques & Variables for the Exposure Study

It has been observed in recent studies that the application of zero-inflated model in traffic safety analysis is questionable to many researchers (Kweon, 2011; Lord et al., 2005; Lord et al., 2007). The basic dual-state assumption for crash occurrence has been criticized specifically for micro-level analysis. Although the criticism may be acknowledged for micro-level analysis of vehicle crash count, it may not be applicable for the cases of pedestrian crashes. Since there may be cases where no pedestrian activity is observed due to the absence of walking infrastructure and for the same reason expected number of zero pedestrian crash is possible. In such circumstances the dual state representation can describe the excess zero cases in terms of exogenous variables. Hence, the present study considers the application of both single-state (negative binomial) and dual-state model (zero inflated negative binomial) for analyzing pedestrian crashes at the micro-level. It is obvious that developing negative binomial models without considering the excess zeroes may result in biased estimates.

In order to select the variables to be used in the suggested exposure model several previous studies have been analyzed. Previous researchers have shown that the volume of pedestrians is a significant exposure measure that has a positive impact on the occurrence of vehicle-pedestrian collisions (Davis and Braaksma, 1988; Qin and Ivan, 2001; Lam et al., 2014; Ukkusuri et al., 2011; Lee and Abdel-Aty, 2005). Another significant exposure measure is vehicular traffic that has significant impact on vehicle-pedestrian collisions (Lee and Abdel-Aty, 2005; Van den Bossche et al., 2005; Wier et al., 2009). The effects of land-use pattern have long been examined by researchers as well (Wier et al., 2009; Cervero, 1996; Graham and Stephens, 2008). It was found by Wier et al. (Wier et al., 2009) that the frequency of pedestrian crashes is relatively larger in commercial and residential areas. Lam et al. (2014) found that public transport facilities are significant in pedestrian collisions because of the fact that pedestrians are most often in a hurry to board buses or cross roads immediately after getting off. There exist quite a lot of studies that describe the impact of demographic and socio-economic characteristics on pedestrian safety (Graham and Stephens, 2008; Loo and Yao, 2010). Most of the studies found that pedestrian safety is a greater concern in socially deprived areas.

Although previous researchers put their effort to explain pedestrian exposure to risk, there are very few studies that identified the exact pedestrian exposure factors specifically at intersections. Another issue is the reliability of pedestrian volume data. There are many cases where pedestrian volume data is not available or accurate enough to do a safety analysis. A reliable process of identifying surrogate measures for pedestrian exposure needs to be established in such cases. Apart from these issues, the application of Zero Inflated Negative Binomial model at micro-level safety analysis has been questionable to many authors (Kweon, 2011; Lord et al., 2005; Lord et al., 2007) although some authors adopted it in macro-level analysis (Cai et al.,

2016). The current study is inspired by these aforementioned research questions. It investigates them with respect to socio-demographic, land-use and geometric characteristics of the ambient environment. The study included similar variables that have been used in previous studies, and also new variables have been included that could possibly affect pedestrian safety analysis.

2.5 Studies on Pedestrian Injury Severity

Eluru et al. (2008) applied the mixed generalized ordered response model for examining pedestrian and bicyclist injury severity level in traffic crashes in the USA using the 2004 General Estimates System (GES) database. The author classified the factors responsible to injury severity into following six categories: (1) characteristics of the pedestrians such as gender, age, alcohol-drug involvement (2) driver characteristics such as age, alcohol involvement (3) characteristics of the vehicle such as vehicle type, speed (4) roadway characteristics such as road classification, speed limit (5) environmental factors such as crash time, weather conditions, and (6) crash characteristics such as vehicle motion prior to accident. It was found that the general pattern and the relative magnitude of elasticity effects of injury severity determinants are similar for pedestrians and bicyclists. The study also identified several factors involved in non-motorist injury severity including individual age (elder people injury severity is high), roadway speed limit (higher roadway speed leads to higher injury levels), crash locations (signalized intersections are less injury prone relative to other locations), and time-of-day (the dark period of day leads to higher injury severity). The authors expected the results obtained can be useful for training & education, traffic regulation and control, and planning of pedestrian/bicycle facilities.

Saunier et al. (2013) showed that crash data segmentation into homogenous subset helps better understand the sophisticated relationship between the injury severity and the contributing

factors related to the demographics, built environment, geometric design and driver, pedestrian & vehicle characteristics. The author found that alcohol involvement, pedestrian age, driver lighting conditions, location type, driver age, vehicle type, and several built environment characteristics influence the likelihood of fatal crashes. Based on the identified risk factors the research provides recommendations for traffic engineers, policy makers, and law enforcement in order to reduce the severity of pedestrian–vehicle collisions.

Kim et al. (2010) applied a mixed logit model to evaluate the effect of several potential risk factors on the injury severity of pedestrians while considering for possible unobserved heterogeneity specifically unobserved pedestrian-related factors (e.g., physical health, strength, behavior). The authors used pedestrian crashes from 1997 to 2000 in North Carolina and their findings unveiled several significant factors affecting the likelihood of fatal injuries for pedestrians. For instance, darkness without streetlights, trucks, freeways, and speeding were found to increase the probability of fatalities by 400%, 370%, 330%, and 360%, respectively.

Zhou et al. (2016) compared three proposed ordered-response models and showed that the partial proportional odds (PPO) model outperforms the conventional ordered (proportional odds—PO) model and generalized ordered logit model (GOLM). The author recognized many variables associated with severe injuries such as older pedestrians (more than 65 years old), pedestrians not wearing contrasting clothing, adult drivers (16–24), drunk drivers, time of day (20:00 to 05:00), divided highways, multilane highways, darkness, and heavy vehicles.

2.6 Appropriate Modeling Technique for Injury Severity

It can be said from the data structure point of view that injury severity levels are inherently ordered. The adjacent ordered outcomes are expected to share some common trend

depending on their proximity to each other. The closer they are the larger trend they share (Train, 2009). It potentially indicates that adjacent response alternatives could also share some unobservable effects. With respect to this fact, some of the standard unordered response models could provide inconsistent estimates when applied to ordered response outcomes since they are built on the assumption that unobserved effects are independent across alternatives. It suggests that it is a critical step to select the modeling framework that accounts for the ordinal nature of response outcomes of the injury severity. There has been extensive use of the ordered modeling framework to analyze the injury severity of traffic crashes. (Quddus et al., 2009; Abdel-Aty, 2003; Eluru and Bhat, 2007; Wang and Abdel-Aty, 2008; Zhu and Srinivasan, 2011).

CHAPTER 3. RESEARCH METHODOLOGIES

The study followed several statistical procedures to identify the pedestrian exposure and analyzed the crash frequency based on different model building techniques. The reason behind this is to identify the most appropriate modeling technique that works best with pedestrian exposure determination. Based on the data structure appropriate statistical modeling technique has been adopted for the injury severity analysis. Validation of the injury severity model has been performed using a data mining technique. Below are brief descriptions of the statistical techniques that are adopted in this study:

3.1 Methods Used for Exposure Models

3.1.1 Generalized Linear Model (GLM):

Generalized Linear Models (GLM) is a general class of statistical models that includes many commonly used models as special cases. The equation of GLM is given by:

$$Y = \sum_{i=1}^{m} \beta_i x_i + \varepsilon_i \quad (1)$$

Where $\sum_{i=1}^{m} \beta_i x_i = \eta\ (say)$ is the linear predictor and ε_i is the error term. There are three components to any GLM.

Random Component: It represents the probability distribution of the response variable (Y). In the generalized linear model, the assumptions of independent and normal distribution of the components of Y are relaxed. It allows the distribution to be any distribution that belongs to the exponential family of distributions. This includes distributions such as Normal, Poisson, Gamma and Binomial distributions.

Systematic Component: It refers to the explanatory variables (X_1, X_2, ... X_k) in the model. The linear combinations of the explanatory variables are called linear predictor in a linear regression or in a logistic regression.

Link Function, η or g(μ): Link function explains the link between random and systematic components. It indicates how the expected value of the response relates to the linear predictor of explanatory variables. Instead of modeling the mean, μ = E (y) directly as a function of the linear predictor η, some function g(μ) of μ is modeled. Thus, the model becomes g (μ) = η = $\sum_{i=1}^{m} \beta_i x_i + \varepsilon_i$. Where, the function g (·) is called a link function (Glosup, 2005).

There are some assumptions adopted in the generalized linear model

- The response cases (i.e. Y_1, Y_2, ..., Y_n) are independently distributed.
- It is not necessary that the dependent variable Y_i be normally distributed, but typically it assumes a distribution from an exponential family (e.g. binomial, poisson, multinomial, normal etc.)
- Instead of assuming a linear relationship between the dependent variable and the independent variables, Generalized Linear Model assumes linear relationship between the transformed response in terms of the link function and the explanatory variables; e.g., for binary logistic regression logit(π) = $\beta_0 + \beta_X$.
- The explanatory (independent) variables can have power terms or some other nonlinear transformations of the original explanatory variables.
- Generalized Linear Model does not require to satisfy the homogeneity of variance since it is not even possible in many cases given the model structure, and over-dispersion (when the observed variance is larger than what the model assumes) maybe present.

- The error structure is not necessarily to be independent or normally distributed.
- The technique relies on large-sample approximations since it uses maximum likelihood estimation (MLE) rather than ordinary least squares (OLS) to estimate the parameters.
- Sufficiently large sample ensures Goodness-of-fit of the model. A heuristic rule is that not more than 20% of the expected cells counts are less than 5.

The current study followed linear regression of generalized linear model to identify the exposure factors which models how mean expected value of a continuous response variable depends on a set of explanatory variables (McCullagh, 1984).

3.1.2 Tobit Model

Occasionally, dependent variables are encountered that are censored in. Their measurements are clustered at a lower threshold (left censored), an upper threshold (right censored), or both. Note that censored data are the result of observations beyond the censor limit being recorded at the limit whereas truncated data are the result of data beyond the truncation limit being discarded. When encountering censored or truncated data, there are at least three reasons for not simply conducting an analysis on all nonzero observations:

(1) It is apparent that by focusing solely on the non-zero observations some potentially useful information is ignored; (2) ignoring some sample elements would affect the degrees of freedom and the t- and F-statistics; and (3) a simple procedure for obtaining efficient and/or asymptotically consistent estimators by confining the analysis to the positive subsample is lacking (Washington et al., 2010).

In order to handle any negative prediction of pedestrian trips, the Tobit model was used to identify the exposure. The Tobit model is a statistical model used to describe the relationship

between a non-negative dependent variable (censored dependent variables) y_i and an independent variable (or vector) x_i. The Tobit model which is introduced by James Tobin (1958) takes the form:

$$y_i^* = \beta x_i + \varepsilon_i, \; i = 1, 2, \ldots, N \tag{2}$$

$$\text{and, } y_i = \begin{cases} y_i^* \; if \; y_i^* \geq 0 \\ 0 \; if \; y_i^* < 0 \end{cases} \tag{3}$$

where y_i^* is a latent variable that is observed only when positive, N is the number of observations, y_i is the dependent variable, x_i is a vector of explanatory variables, β is a vector of estimable parameters and ε_i is a normally and independently distributed error term with zero mean and constant variance σ^2 (Washington et al., 2010).

3.1.3 Variable importance for exposure model using Random Forest

The important explanatory variables in the exposure model were determined using Random Forest procedure. The first step of this process is to fit a random forest to the data. During the fitting process the out-of-bag error (a method of measuring the prediction error of random forests) for each data point is recorded and averaged over the forest. In order to measure the importance of the j-th feature after training, the values of the j-th feature are permuted among the training data and the out-of-bag error is again estimated on this perturbed data set. The difference in out-of-bag error before and after the permutation is averaged over all trees to determine the importance score for the j-th feature. Finally, the score is normalized by the standard deviation of these differences. Features with higher score values are ranked as more important than the others (Breiman, 2001).

3.1.4 Variable importance for exposure model using Principal Component Analysis (PCA)

Principal Component Analysis (PCA) aims at compressing the size of the data set by extracting the most important information from the data table. It analyzes the structure of the observations and the variables, and then computes new variables called principal components which are obtained as linear combinations of the original variables (Washington et al., 2010). The first principal component is required to have the largest possible variance. The second component that is uncorrelated with the first component captures most information not captured by the first component. PCA maximizes the variance of the elements of z=xu, such that uu'=1 where $z=[z_1,z_2,\ldots..z_n]$, $x=[x_1,x_2,\ldots.x_n]$ and $u=[u_1,u_2,\ldots.u_n]'$. The solution is obtained by solving the equation $(R-\lambda I)\ u=0$, where R is the sample correlation matrix of the original variables x, λ is the eigen-value and u is the eigen-vector.

3.2 Statistical Test to Compare Observed and Predicted Pedestrian Trips

3.2.1 Paired sample t-test:

Paired sample t-test is a statistical technique that is used to compare two population means in the case of two samples that are correlated. It is a parametric test procedure that assumes the population to be normally distributed. Paired sample t-test is used in 'before-after' studies, or when the samples are the matched pairs, or when it is a case-control study. The null hypothesis states that the mean of two paired samples are equal. The following formula is used to calculate the statistics of the test:

$$t = \frac{\bar{d}}{\sqrt{s^2/n}} \qquad (4)$$

Where d bar is the mean difference between two samples, s^2 is the sample variance, n is the sample size and t is the test statistics with n-1 degrees of freedom.

3.2.2 Wilcoxon Signed-Rank Test:

The study compared the observed and predicted pedestrian trips using the Wilcoxon Signed-Rank test. It is a non-parametric test procedure that can analyze matched-pair data based on differences to assess whether their populations mean ranks differ. The method does not require assuming the population to be normally distributed. The null hypothesis is that the difference between the pairs follows a symmetric distribution around zero. The absolute values are ranked and the test statistic is calculated by adding the ranks for either the positive or the negative values (Woolson, 2008).

3.3 Methods Used to Develop Crash Models

3.3.1 Negative Binomial (NB) Model:

Since the beginning of crash frequency analysis the Poisson model has been the most accepted by the researchers (Lord and Mannering, 2010). The basic assumption of Poisson model is equal mean and variance of the distribution. However, crash data are often over-dispersed. Because the Poisson model is not capable of dealing with the over-dispersed crash data, the Poisson models are not popularly used in traffic safety field nowadays. The NB model relaxes the equal mean variance assumption of the Poisson model. The NB model can generally account over-dispersion resulting from unobserved heterogeneity and temporal dependency, but may be improper for accounting for the over-dispersion caused by excess zero counts (Rose et al., 2006). The negative binomial distribution has an extra parameter ε_i than the Poisson regression

that adjusts the variance independently from the mean. The error term ε_i that considers over-dispersion parameter to the mean of the Poisson model according to the following equation:

$$\lambda_i = \exp(\beta x_i) \exp(\varepsilon_i) \quad (5)$$

Where λ_i is the expected number of Poisson distribution for entity i, x_i is a set of explanatory variables, and β_i is the corresponding parameter. Here the distribution of the error term $\exp(\varepsilon_i)$ is normally assumed to be gamma-distributed with mean 1 and variance α. It makes the variance of the crash frequency distribution $\lambda_i (1 + \alpha\lambda_i)$ which is not equal to the mean λ_i. The NB model for the crash count y_i of entity is given by:

$$P(y_i) = \frac{\Gamma\left(y_i+\frac{1}{a}\right)}{\Gamma(y_i+1)\,\Gamma\left(\frac{1}{a}\right)} \left(\frac{\alpha\lambda_i}{1+\alpha\lambda_i}\right)^{y_i} \left(\frac{1}{1+\alpha\lambda_i}\right)^{\frac{1}{\alpha}} \quad (6)$$

where y_i is the number of crashes y_i of entity i and $\Gamma(\bullet)$ refers to the gamma function.

3.3.2 Zero-Inflated Negative Binomial (ZINB) model:

The zero-inflated models assume that the data have a mixture with a degenerate distribution whose mass is concentrated at zero (Lambert, 1992). The first part of the mixture is the extra zero counts and the second part is for the usual single state model conditional on the excess zeros (Cai et al., 2016). The zero-inflated NB model can be regarded as an extension of the traditional NB specification as:

$$y_i \sim \begin{cases} 0, when\ probability\ p_i \\ NB, when\ probability\ 1 - p_i \end{cases} \quad (7)$$

The logistic regression model is employed to estimate p_i,

$$p_i = \frac{\exp(\beta_i' x_i)}{1+\exp(\beta_i' x_i)} \quad (8)$$

where β_i is the corresponding parameter. Substituting Eq. (7) into Eq. (8) we can define ZINB model for crash counts y_i of entity i as:

$$P(y_i) = \begin{cases} p_i + (1-p_i)\left(\frac{1}{1+\alpha\lambda_i}\right)^{\frac{1}{\alpha}}, & y_i = 0 \\ (1-p_i)\frac{\Gamma\left(y_i+\frac{1}{a}\right)}{\Gamma(y_i+1)\,\Gamma\left(\frac{1}{a}\right)}\left(\frac{\alpha\lambda_i}{1+\alpha\lambda_i}\right)^{y_i}\left(\frac{1}{1+\alpha\lambda_i}\right)^{\frac{1}{\alpha}}, & y_i > 0 \end{cases} \quad (9)$$

Initially, all the explanatory variables were used directly to predict the pedestrian trips GLM and Tobit models. Next the Random Forests process has been applied before running the GLM and Tobit models to identify the important variables in the dataset that should be given priority. Finally, Principal Component Analysis has been applied before running the GLM and Tobit models to the explanatory variables to find out the components that are related to specific group of variables. After the exposure model has been identified the corresponding predicted pedestrian trips were calculated. Finally using the predicted pedestrian trips, crash models were developed following the negative binomial and zero-inflated negative binomial modeling techniques.

3.4 Methodologies Used in Injury Severity Analysis

This study adopted prominent approach of discrete choice models for the pedestrian injury severity analysis. The injury severity levels in CARS database have been combined into a three point scale from the lowest to the highest level (1 = possible injury, 2 = injury, 3 = fatal injury). An ordered-response model appears to be the most appropriate approach. The ordered logit model is based on the cumulative probabilities of the response variable. It is assumed that

the logit of each cumulative probability is a linear function of the explanatory variables with the regression coefficients being constant across outcome categories.

Let Y_i be an ordinal response variable with M categories for the i-th subject, alongside with a vector of covariates $\mathbf{x_i}$. A regression model establishes a relationship between the covariates and the set of probabilities of the categories $p_{mi}=Pr(Y_i = y_m \mid x_i)$, m=1,…,M. It is a common practice that regression models for ordinal responses refer to the convenient one-to one transformations such as the cumulative probabilities $g_{mi}=Pr(Yi \leq y_m \mid x_i)$, m=1,…,M instead of being expressed in terms of probabilities of the categories. The model specifies only M-1 cumulative probabilities since the final cumulative probability is necessarily equal to 1 (Williams, 2006). An ordered logit model for an ordinal response Yi with M categories is defined by a set of M-1 equations where the cumulative probabilities $g_{mi}=Pr(Y_i \leq y_m \mid x_i)$ are related to a linear predictor $\boldsymbol{\beta}'\mathbf{x_i} = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots$ through the logit function:

$$\text{logit}(g_{mi}) = \log(g_{mi}/(1- g_{mi})) = \alpha_m - \boldsymbol{\beta}'\mathbf{x_i}, \; m = 1,2,\ldots,M\text{-}1 \qquad (10)$$

The parameters α_m, called thresholds or cut points, are in increasing order ($\alpha_1 < \alpha_2 < \ldots < \alpha_{c-1}$). It is not possible to simultaneously estimate the overall intercept β_0 and all the M-1 thresholds: in fact, adding an arbitrary constant to the overall intercept β_0 can be counteracted by adding the same constant to each threshold α_m. This identification problem is usually solved by either omitting the overall constant from the linear predictor (i.e. $\beta_0 = 0$) or fixing the first threshold to zero (i.e. $\alpha_1 = 0$). The vector of the slopes $\boldsymbol{\beta}$ is not indexed by the category index m, thus the effects of the covariates are constant across response categories. This feature is called the parallel regression assumption: indeed, plotting $\text{logit}(g_{mi})$ against a covariate yields M-1 parallel lines (or parallel curves in case of a non-linear specification, e.g. polynomial regression).

In model (1) the minus before β implies that increasing a covariate with a positive slope is associated with a shift towards the right-end of the response scale, namely a rise of the probabilities of the higher categories. Some authors write the model with a plus before β, in that case the interpretation of the effects of the covariates is reversed.

From equation (1), the cumulative probability for category c is

$$g_{mi} = \exp(\alpha_m - \boldsymbol{\beta}'\mathbf{x_i})/(1+ \exp(\alpha_m - \boldsymbol{\beta}'\mathbf{x_i}))=1/(1+ \exp(-\alpha_m + \boldsymbol{\beta}'\mathbf{x_i})) \quad (11)$$

3.5 k-fold Cross Validation

The purpose of cross-validation is to determine how well a given statistical learning procedure can be expected to perform on independent data; in this case, the actual estimate of the test MSE is of interest. This approach involves randomly dividing the set of observations into k groups, or folds, of approximately equal size. The first fold is treated as a validation set, and the method is fit on the remaining k − 1 folds. The mean squared error, MSE1, is then computed on the observations in the held-out fold. This procedure is repeated k times; each time, a different group of observations is treated as a validation set. This process results in k estimates of the test error, MSE1,MSE2, . . . ,MSEk. The k-fold CV estimate is computed by averaging these values,

$$CV_{(k)} = \frac{1}{k}\sum_{i=1}^{k} MSE_i \quad (12)$$

It must be mentioned that there is a bias-variance trade-off associated with the choice of k in k-fold cross-validation. Typically, given these considerations, one performs k-fold cross-validation using k = 5 or k = 10, as these values have been shown empirically to yield test error rate estimates that suffer neither from excessively high bias nor from very high variance (James et al., 2013). An AUC score is calculated for each runs, and then calculate average AUC.

CHAPTER 4. DATA PREPARATION

4.1 Data Collection Source for the Exposure Analysis

The explanatory variables were classified into three categories namely 'Demographic and Socioeconomic', 'Land-use', and 'Traffic and Geometric'. There were in total of 134 intersections in Orange and Seminole Counties of Central Florida that were used for the analysis. The data were collected for each intersection from various data sources. Geographic Information Systems (GIS) and SAS software were used to extract and process the data. In order to extract the data, a circular area (referred as "buffer" in this paper) with the intersection as center was defined to extract the data for each specific variable category.

4.1.1 U.S. Census Bureau

American Community Survey data that is a 5 year estimates was used in this study. A buffer size of 0.25-mile radius was defined to extract the census data from the American Fact Finder database. The buffer size was chosen with 0.25 miles radius since over the past 2 decades, 0.25 miles (400 m or a 5-minute walk) has been assumed to be the distance that "the average American will walk rather than drive"(Boer et al., 2007; Yang and Diez-Roux, 2012).

4.1.2 Florida Department of Revenue Property Tax Oversight Program

The database provides land-use pattern of District 5, Florida from which the land-use of the study area was extracted from the department of revenue land-use code. Similar to the census variables a buffer size of 0.25-mile radius was used for extracting the data.

4.1.3 LYNX

In order to find the bus ridership and number of bus stops around intersections the LYNX GIS database was used. LYNX is the official company that operates the public transport system in the study area. The buffer size is same as FDOT GIS data.

Table 1. List of Variables and Data Sources

Category	Variable Name	Data Source
Demographic & Socioeconomic	Population	U.S. Census Bureau
	Age: Below 15 years	
	Age: 15 to 30 years	
	Age: 31 to 45 years	
	Age: 46 to 60 years	
	Age: 61 to 75 years	
	Age: Above 75 years	
	Education: Less than or equal to high school	
	Education: Greater than high school	
	Household size: Less than or equal to 4 persons	
	Household size: Greater than 4 persons	
	Commuters: Walking	
	Commuters: Public transit	
	Household car ownership: Less than two vehicles	
	Household car ownership: Greater than or equal to two	
	Household below poverty line	
	Proportion of unemployed people	
Land-use Pattern	Residential Area	Florida Department of Revenue
	Commercial Area	
	Industrial Area	
	Agricultural Area	
	School Area	

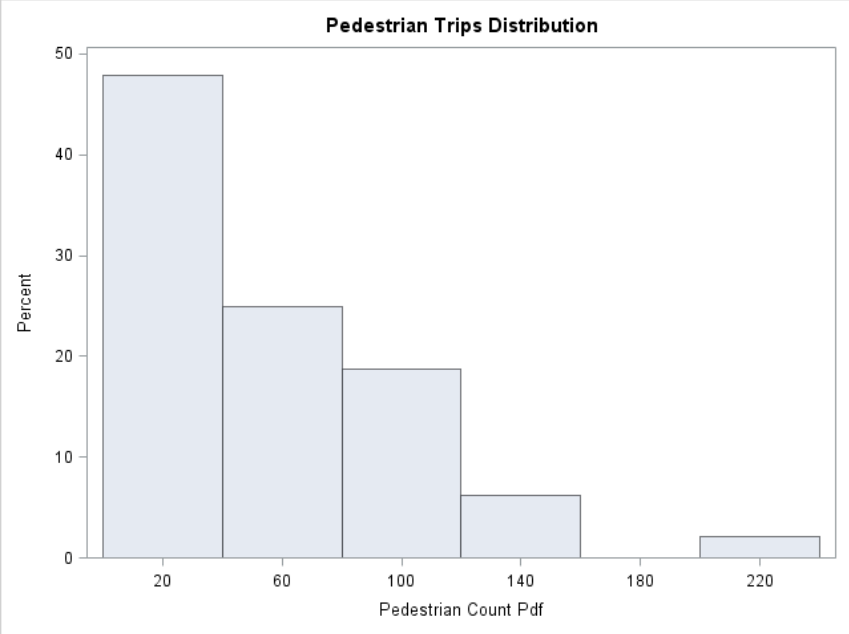
Category	Variable Name	Data Source
	Bar Area	Property Tax Oversight
	Hotel Area	
Geometric & Traffic	Number of Intersection legs	Florida Department of Transportation (FDOT) Roadway Characteristics Inventory
	Intersection control type	
	No of lanes on the major road	
	No of lanes on the minor road	
	AADT	
	Maximum speed limit around intersection	
	Average median width	
	Average pavement condition	
	Average sidewalk width	
	Presence of sidewalk barrier	
	Pedestrian crash counts (2013-2015)	
	Number of bus riders	Lynx GIS Data
	Number of bus stops around intersection	

4.1.4 FDOT Roadway Characteristics Inventory (RCI) Data

FDOT Roadway Characteristics Inventory is a useful data source of traffic crashes, road infrastructure and traffic characteristics. The crash data was extracted from the 2013-2015 crash database produced by the Florida Department of Transportation (FDOT) Safety Office. Since crashes are not reported exactly at the intersection a circular buffer size of 50 ft. radius from the stop bar (the pavement marking line behind which vehicles stop at intersections) of the intersection is defined to extract the number of crashes. The traffic and geometric characteristics data were extracted from the FDOT RCI (Roadway Characteristics Inventory). In order to extract traffic and geometric data a buffer size of 100 ft. radius was defined.

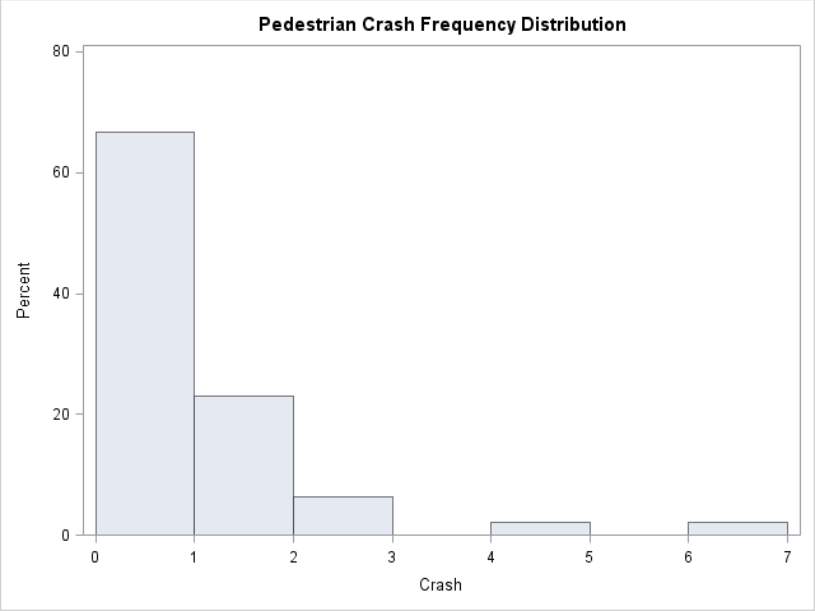
4.2 Data Processing for the Exposure Analysis

Figure 9 shows the pedestrian trips distribution of the 134 intersections in the dataset. It can be seen from the distribution that most of the intersections have a volume ranging 20-60 trips (more than 50%). The average number of pedestrian trips of an intersection is around 56 trips. The distribution is positively skewed with the peak towards the right. The pedestrian volume count was taken from eight-hour turning movement of a typical weekday. The hours of pedestrian counting operations are 7 A.M - 9 A.M, 11 A.M - 1 P.M and 4 P.M-8 P.M.



Mean:	55.833
Std Deviation:	44.786
Skewness:	1.443
Kurtosis:	3.193

Figure 9. Histogram of Pedestrian Trips Distribution



Mean:	0.563
Std Deviation:	1.128
Skewness:	3.178
Kurtosis:	12.17

Figure 10. Histogram of Pedestrian Trips Distribution

These counts were prepared for Florida Department of Transportation District 5 that also includes traffic volume along with pedestrian trips. It was considered that if a pedestrian crossed any of the one legs of the intersection in any direction that will be taken as one pedestrian count. The total number of pedestrian over the eight hours was taken as the dependent variable of the exposure model.

Figure 10 shows the pedestrian crash frequency distribution of the intersections selected for the analysis. It can be seen that most of the intersections have zero pedestrian crashes (around 66%) which shows pedestrian crashes are rare events. The average number of crashes of an intersection is 0.563. Again the distribution is positively skewed with the peak towards right. The crashes within the 50 ft distance of the intersection are considered as the crash frequency of that particular intersection since the crash may not exactly be reported at the intersection.

The correlation between the dependent variable and explanatory variables used in the Tobit model were cheked before the modeling process. It was found that the explanatory variables are not much correlated with each other.

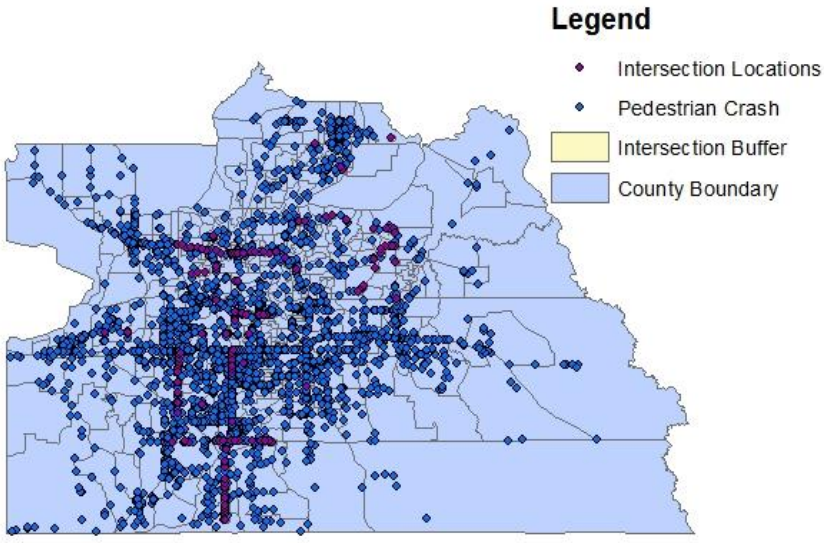


Figure 11. Crash mapping using GIS

A threshold value of 0.4 was considered while selecting the explanatory variables. The variables having correlation value above the threshold were not included in the model. In the modelling process the explanatory variable with the smallest correlation value was included first in the model and the variables with relatively smaller correlation values were given preference in the model. Table 2 shows the correlation values of some selected explanatory variables.

Table 2. Pearson correlations coefficient of some selected explanatory variables

	Trips	Crash	TEV	Walk	Pub	Pop	Emp	Res	Com	No
Trips	1.00	0.23	0.22	0.01	0.14	0.38	0.34	-0.11	0.28	0.39
Crash	0.23	1.00	-0.01	0.20	-0.01	0.39	0.37	-0.12	0.43	0.20

TEV= Total Entering Vehicle at the Intersection, Walk= Number of Commuter by Walking, Pub Trn = Number of Commuter by Public Transit, Emp Den = Employment Density, Res Area= Residential Area around Interction, Com Area= Commertial Area around Interction, No Vehicle= Number of Household with No Vehicle.

4.3 Data Processing for Injury Severity Analysis

The datasets developed for injury severity analysis were obtained from Florida Department of Transportation (FDOT). The crash information is collected by the FDOT Safety Office or the Crash Analysis Reporting System (CARS) for the purpose of identifying, evaluating, or planning safety enhancements on Florida's roadways and to develop highway safety improvement projects. The data source includes three types of files named 'Crash System Information', 'Occupancy Information' and 'Vehicle Information' for crashes occurring on 'State Highway System'. The same files are available for crashes not occurring on 'State Highway System'. The crash records for the 9 counties in Central Florida were collected and processed for the model development. The final dataset contains 1105 observations and 35 variables. The following steps were followed to develop the final model data.

- The crash records involving 'Single Vehicle', 'Pedestrian' and those which occurred within the 9 counties in Central Florida were sorted from the 'Crash System Information' file.
- The 'Crash System Information', 'Occupancy Information' and 'Vehicle Information' files include a common identifier variable named 'CRASHNUM'.
- The crash records form first step were matched from the other two files 'Occupancy Information' and 'Vehicle Information' using the 'CRASHNUM'

variable in order to extract the information of vehicle and person in the crash. The extracted information was merged with the original crash information for 'State Highway System' crashes.

- The previous three steps were repeated for crashes not occurring on 'State Highway System' and the two files obtained were combined to get the pedestrian crashes occurred in Central Florida.
- The same procedure was followed for the 2014 crash information. The combined data of 2013 and 2014 crash records make the final dataset for the model.
- The model dataset includes 'Un-coded' or 'Unknown' values for many variables which were removed before proceeding to the model development.
- The dependent variable 'INJURY' was divided into three categories named as 'Minor Injury', 'Major Injury' and 'Fatal'. The dependent variable has inherent ordinal nature.

Table 3. Variables Available for Injury Severity Analysis

Variable	Description
FL_WRNGWAY	=1, if the crash involves wrong way driving. =0, otherwise.
FL_SPEEDNG	=1, if the crash involves over speeding. =0, otherwise.
FL_CMV	=1, if the crash involves commercial vehicle (CMV)=0, otherwise
FL_LANEDEP	=1, if the crash involves lane departure event. =0, otherwise.
FL_AGGRSV	=1, if the crash involves aggressive driving. =0, otherwise.
Alc_drg	=1, if the crash involves aggressive driving. =0, otherwise.
FLAG_DIST	=1, if the crash involves driver distraction. =0, otherwise.
Weekend	=1, if the crash occurred during weekends. =0, otherwise.
Local_Rd	=1, if the crash occurred in local road. =0, otherwise.
Unpaved_Shldr	=1, if the road with unpaved shoulder. =0, otherwise.

Variable	Description
Curb_Shldr	=1, if the road with curb shoulder. =0, otherwise.
Dusk_Dawn	=1, if the crash occurred during dusk or dawn. =0, otherwise.
Lighted_Dark	=1, if the crash occurred in street lighted dark condition. =0, otherwise.
UnLighted_Dark	=1, if the crash under dark condition without light. =0, otherwise.
Road_Wet	=1, if the road surface condition is wet. =0, otherwise
TwoWay_ntdiv	=1, if the roadway is two way not divided. =0, otherwise
DrAct_frow	=1, if the driver failed to give right of way to pedestrian. =0, otherwise
workzone_true	=1, if the crash occurred within work zone. =0, otherwise
Ped_CrossRd	=1, if the pedestrian was crossing road during crash. =0, otherwise
Ped_dash	=1, if the pedestrian involved in crash was in a hurry. =0, otherwise
Ped_fos	=1, if the pedestrian involved in crash failed to obey sign. =0, otherwise
vbody_car	=1, if the vehicle involved in crash is passenger car. =0, otherwise
vbody_vanpick	=1, if the vehicle involved in crash is van or pickup. =0, otherwise
vbody_utility	=1, if the vehicle involved in crash is utility type. =0, otherwise
vmov_tright	=1, if the vehicle was turning right during crash. =0, otherwise
drivage_16_20	=1, if the driver involved in crash aged 16 to 20. =0, otherwise
drivage_21_25	=1, if the driver involved in crash aged 21 to 25. =0, otherwise
drivage_26_35	=1, if the driver involved in crash aged 26 to 35. =0, otherwise
drivage_36_50	=1, if the driver involved in crash aged 36 to 50. =0, otherwise
drivage_51_65	=1, if the driver involved in crash aged 51 to 65. =0, otherwise
drivage_66_plus	=1, if the driver involved in crash aged more than 66. =0, otherwise
hitrun_yes	=1, if the driver hit & run during crash. =0, otherwise
rdspeed_40Plus	=1, if the roadway speed limit is above 40. =0, otherwise
Ped_elder	=1, if the crash involved elder pedestrian (age above 65). =0, otherwise

Before developing the actual model the correlations among the explanatory variables were tested. It was observed that the correlation among the explanatory variables were not significant.

CHAPTER 5. DATA ANALYSES AND MODEL RESULTS

5.1 Exposure Analysis Results

There were six exposure models in total developed in this study. Since the modeling technique is different (GLM vs Tobit) it is unsuitable to compare the Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) to find the best model. In order to compare the models, the Mean Absolute Deviation (MAD) and Root Mean Square Error (RMSE) were calculated for each model using the following formulas:

$$MAD = \frac{\sum_{i=1}^{n} |y_{pred} - y_{obs}|}{n} \quad (12)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_{pred} - y_{obs})^2}{n}} \quad (13)$$

MAD and RMSE can measure the differences between values predicted by a model and the values actually observed. The model with lower MAD and RMSE value is considered to be relatively accurate than the other models. It was found that the models developed by using significant variables from the random forests process and principal component analysis did not perform well. It was also found that compared to GLM, Tobit models performed better in every case. Table 3 below provides list of all the models developed and compared in terms of MAD and RMSE.

Table 4 shows that the Tobit model using all variables performs best with the lowest MAD and RMSE values. The Tobit model also handles any negative predicted pedestrian trips with the value zero since the lower bound is set at 0. In this study the significance level of identifying exposure is relaxed to 10% since the exposure factor identification is the primary objective rather than the value of the parameters.

Table 4. Comparison of the exposure models developed

Model Type (Exposure)	MAD	RMSE
Exposure Model (GLM) Using All Variables	28.91	42.12
Exposure Model (GLM) Using PCA Variables	34.21	46.26
Exposure Model (GLM) Using Random Forests Variables	32.06	45.40
Exposure Model (Tobit) Using All Variables	**27.69**	**41.99**
Exposure Model (Tobit) Using RF Variables	30.76	45.43
Exposure Model (Tobit) Using PCA Variables	32.61	46.24

Table 5 presents the significant factors obtained from the best Tobit model to predict the pedestrian trips.

Table 5. Tobit model result (Best exposure model obtained)

Parameter	Estimate	Std Err	p-value
Intercept	-128.298	36.361	0.0004
Presence of school near intersection (1=yes, 0=no)	22.386	8.664	0.0098
Household car ownership (Number of households with less than two vehicles within buffer of 0.25 miles radius)	81.096	22.884	0.0004
Pavement condition (1= very poor, …, 5= very good)	11.165	6.697	0.0955
Sidewalk width (Average value of all legs)	7.355	1.989	0.0002
Bus ridership (Number of bus user within buffer of 0.25 miles radius)	0.183	0.068	0.0075
Intersection control type (1=signal, 0=stop)	39.428	11.467	0.0006
Presence of sidewalk barrier (1=yes, 0=no)	26.196	9.976	0.0086
σ (see Equation (4))	44.852	2.905	<.0001

The exposure factors obtained in the Tobit model are described in the following section:

Presence of school near intersection (1= yes, 0=no):

There are more pedestrian activity near schools due to parent's drop off and pick up, children walking along the route in groups, etc. Intersections near schools are expected to have higher pedestrian exposure especially at the start and ending times of schools. In this study the school is used as a dummy variable and the positive coefficient in the model demonstrates that the presence of schools around the intersection contributes to higher exposure of pedestrians at intersections.

Figure 12. Intersection near School with Crossing Guard (source: Dreams-time)

Household car ownership: (Number of households with less than two vehicles within the buffer of 0.25-mile radius):

Households with less than two vehicles (0 or 1 vehicle) are another significant source of pedestrian activities. Car ownership is directly related to household income level that reflects the socio-economic impact on pedestrian activity. It is obvious that household members with no vehicles satisfy their transportation needs by means of public transportation or walking. Also for households with only one vehicle it may not be possible to accommodate all the members with

one vehicle due to different travel schedules and trip purposes. The result shows that the more frequent the number of such households, more pedestrians exposed at the intersections.

Bus ridership (Number of bus users within the buffer of 0.25-mile radius):

Daily Bus users walk through the route and intersections reaching the bus stops. The distance between home and bus stops leads the bus riders walk the route and cross intersections.

Figure 13. Public Transit in Central Florida (source: LYNX)

Most of the bus stops are at a certain distance from the intersection (100-200 ft.) which may lead the pedestrian to be exposed at the intersections. It is likely to be true that these bus users are exposed to intersections two times a day during ride-on and ride-off.

Pavement condition (1= very poor, …, 5= very good):

Better pavement condition around the intersection provides more accessibility for pedestrian walking. The model in this study includes the variable in the scale of 1 to 5 where 1

indicates poor pavement and 5 indicates the best pavement. It has been found higher value of pavement condition yields more pedestrians.

Sidewalk width (Average value of all legs):

If the pedestrian activity is higher, it is expected to have wider sidewalks to be installed at the particular intersection. In other words, it can be said that if the sidewalk has larger width more pedestrians are walking around the intersection. The model showed that the large sidewalk width can be attributed to more pedestrian activity at the intersection.

Presence of sidewalk barrier (1=yes, 0=no):

The study incorporated the physical sidewalk barrier like guardrail, traffic barrier, etc. as a dummy variable. Sidewalk barriers are installed in places where more pedestrians are seen.

Figure 14. Pedestrian Sidewalk Barrier (source: goldengate.org)

In other words, more pedestrians are exposed when crossing even where sidewalk barriers are present. Pedestrians are completely separated from traffic that makes the walking safe. Intersections that have sidewalk barriers are more likely to have more pedestrians.

Intersection control type (1=signal, 0=stop):

Signalized intersection control type leads to increasing pedestrian activity since it is relatively safer than the other control types. The study included intersection control type as a dummy variable and the positive coefficient indicates that if the control type is signal it is more likely to have higher pedestrian exposure.

5.2 Statistical Test Results Comparing Observed & Predicted Pedestrian Trips

Most of the models identified almost similar significant exposure-related variables that have been described in the previous section. The predicted pedestrian trips were calculated using the best exposure model. In order to check the significance of the difference between observed pedestrian trips and predicted pedestrian trips, both t-test and Wilcoxon signed-rank test were performed. The results of the tests are shown in Table 6.

Table 6. Statistical test to compare observed and predicted pedestrian trips

Test	Statistic	p-Value
Student's (t)	-1.596	0.1173
Signed Rank (S)	-160	0.1013

The results of both tests yielded a p-value greater than 0.05, which indicates there is no significant difference between the mean of the observed pedestrian trips and the predicted pedestrian trips. It implies that the predicted pedestrian trips could be used in lieu of the actual pedestrian trips if there were no pedestrian counts available in the study area.

5.3 Results of the Crash Models Developed using Predicted Pedestrian Trips

Using the predicted pedestrian trips from the Tobit model, Negative Binomial and ZINB crash models were developed. In these models pedestrian trips have been used as exposure to predict the number of crash at a particular intersection. In order to evaluate how the predicted pedestrian trips perform relative to observed pedestrian trips, a similar type of crash model was developed using the original observed pedestrian trips as exposure. The Negative Binomial crash models are described in Table 7 and Table 8.

Table 7. NB crash model using predicted trips from exposure model

Parameter	Estimate	Standard	p-value
Intercept	-0.962	0.254	0.0002
Predicted Pedestrian Trips	0.0166	0.004	<.0001
Dispersion	0.851	0.276	.

Table 8. NB crash model using original pedestrian trips as exposure

Parameter	Estimate	Standard Error	p-value
Intercept	-0.667	0.179	0.0002
Original Pedestrian Trips	0.010	0.002	<.0001
Dispersion	0.728	0.259	.

All the developed models are summarized in Table 9 based on AIC and BIC values.

Table 9 shows that the crash models from observed and predicted pedestrian trips have almost the same AIC and BIC values for both modeling techniques. It indicates that the predicted pedestrian trips performed almost the same as the original pedestrian trips in the crash models. Thus the approach of surrogate measures for pedestrian exposure is justified here. It was also found that the NB crash model performed slightly better than the ZINB model in terms of AIC

and BIC values although the dataset contained almost 66% of intersections with no pedestrian crashes. In this two-step safety analysis not only the predicted crashes but also the predicted volume of pedestrian trips can be obtained.

Table 9. Comparison of developed crash models

Negative Binomial (NB) Crash Models	AIC	BIC
NB using predicted trips from pedestrian exposure model (Tobit model using all variables)	349.04	357.73
NB using observed pedestrian trips	351.25	359.99
Zero-Inflated Negative Binomial (ZINB) Crash Models	AIC	BIC
ZINB using predicted trips from pedestrian exposure model (Tobit model using all variables)	351.04	362.63
ZINB using observed pedestrian trips	352.79	367.28

5.4 Injury Severity Analysis Results

The response profile of the pedestrian injury severity is inherently ordered that lead to the application of 'Ordered Logit' model. The results of the 'Ordered Logit' model are summarized in Table 10, 11, 12. The log likelihood value of the model is 1303.51 which is the smallest possible value obtained after using different combinations of the explanatory variables. Also there is a reduction in the log likelihood value with the presence of covariates along with the intercept. In this analysis a significance level $\alpha = 0.05$ is taken to define the significant factors.

Table 10. Model Fit Statistics of 'Ordered Logit' Model

Criterion	Intercept Only	Intercept & Covariates
AIC	1526.606	1327.513
SC	1536.175	1384.926
-2 Log L	1522.606	1303.513

Table 11. Significant Explanatory Variables of Injury Severity Analysis

Parameter	Estimate	Standard	p-value
Intercept	-3.112	0.219	<.0001
Intercept	-1.081	0.186	<.0001
Intersection Presence (1=yes, 0=No)	-0.330	0.154	0.0317
Crash in Local Rd (1=yes, 0=No)	-0.895	0.182	<.0001
Alcohol/Drug Involve (1=yes, 0=No)	1.393	0.213	<.0001
Lighted Dark Condition (1=yes, 0=No)	0.515	0.194	0.0079
Unlighted Dark Condition (1=yes, 0=No)	1.026	0.192	<.0001
Pedestrian in a Hurry (1=yes, 0=No)	0.546	0.190	0.0041
Road Speed 40 mph or more (1=yes, 0=No)	0.612	0.171	0.0003
Elder Pedestrian Involve (1=yes, 0=No)	0.766	0.239	0.0013

Table 12. Association of Predicted Probabilities and Observed Response

Percent Concordant	73.8	Somers' D	0.499
Percent Discordant	23.9	Gamma	0.511
Percent Tied	2.3	Tau-a	0.259
Pairs	202531	c	0.750

Table 12 shows that 73.8 percentage of pairs where the observation with the desired outcome (event) has a higher predicted probability than the observation without the outcome (non-event). The model has a c-statistics (Area under ROC) curve value of 0.75 which indicates the model performs reasonably well in distinguishing fatal, severe injury and minor injury. The next section provides a brief explanation of the explanatory variables obtained in Table 11.

Intersection Presence (1=yes, 0=No):

It can be observed from the model that pedestrian injury severity levels tend to have lower order (possible or minor injury) if there is intersection involvement associated with the crash. In other words it can be said that the injury severity is higher if the crash location is other than intersection (midblock, driveway access etc.). The effect can be explained in the way that when any vehicle approaches the intersection, it usually gets slow down either to follow the signal/signs or to negotiate the turning movement. Besides the drivers are more careful to yield the pedestrians at the intersection (Zajac and Ivan, 2003). It results in the reduction of number of vehicle-pedestrian conflicts at the intersection. On the other hand, the impact of vehicle pedestrian collision is relatively higher due to high speed and continuous movement for the crash locations other than intersection. The resulting collision leads to higher injury for such locations.

Crash in Local Rd (1=yes, 0=No):

The functional classification of road system is defined as interstate, freeway, arterial, collector and local. It is obvious that the presence of pedestrian (so the pedestrian crash) is rare in interstate and freeway roads. The pedestrian injury severity for the crashes occurring in local road has lower order relative to other road system. Since the vehicle travelling speed in local roads is relatively low and the roads are narrow with relatively high volume of traffic, the crash

is relatively less severe. The driver pedestrian interaction in local roads is relatively safe than the other road system since drivers obviously expect the presence of pedestrian. The higher co-efficient value for the road system variable indicates that the injury is highly severe for the pedestrian crashes occurring other than local roads.

Alcohol/Drug Involve (1=yes, 0=No):

The model shows that alcohol drug has the highest co-efficient value in magnitude compared to other variables. It implies that Alcohol drug involvement in crashes is the most important factor responsible for higher injury severity of pedestrians. Pedestrians under the influence of drug or alcohol may accidently fall on the roadway from the sidewalk and stuck with the vehicle heavily since they have less control over their brain.

Figure 15. Alcohol leads to Fatality (source: Mother Jones / NHTSA)

They may be less careful while walking on the road and during night condition the situation get worsen. Even if the drivers are careful they can hardly do anything if a pedestrian under alcohol comes suddenly in front of the vehicle. The resulting injury severity is incapacitating or fatal.

Lighted Dark Condition (1=yes, 0=No):

Light condition plays a significant role in pedestrian crash severity. During the day it is easy to see the pedestrian walking or crossing on the road but it becomes hard for the drivers to screen the pedestrians during the night if they are not wearing any reflective clothes or shoes. Unless the drivers approach close to the pedestrian even with the presence of street light or other source of light, they couldn't realize if there is actually a pedestrian walking.

Unlighted Dark Condition (1=yes, 0=No):

The crashes are more severe if there is no source of light under dark condition. It must be mentioned that the impact of the unlighted dark condition on injury severity is higher than the impact of lighted dark condition. The higher value of the co-efficient for the unlighted dark variable confirms this in the model.

Figure 16. Pedestrian under Dark Condition (Source: Getty Images)

Obviously the situation is worst for the unlighted dark condition to detect the pedestrians. In Central Florida the majority of the streets are unlighted and the vehicle light is the only source. But the vehicle light is more focused on directing the roadway direction rather than the

pedestrian detection. The resulting pedestrian vehicle collision causes injury severity of higher order (incapacitating, fatal).

Pedestrian in Hassle:

The injury severity of pedestrian depends a lot on the action of pedestrian during the crash. If the pedestrians are aware of the surrounding environment there is less chance of a crash. Even if the crash occurs there is more likely to happen minor injury. The variable pedestrian in hassle describes that if the pedestrians were in a hurry during the crash occurrence the resulting injury severity is of higher order. It also shows that the injury severity is higher for pedestrian in hassle relative to other improper action such as failure to yield right-of-way, failure to obey traffic signs, signals etc.

Figure 17. Pedestrians walking in a Hurry (source: Inhabitat)

It is obvious that the pedestrian in hassle is less attentive on walking which may cause improper road crossing, jump off the sidewalk, sudden fall on roadway etc. It indicates that pedestrian in a hurry may lead to many other action that may results in crash and higher injury severity.

Pedestrians are known as vulnerable road users which increase to a higher level of vulnerability when they rush on road.

Road Speed 40 mph or more (1=yes, 0=No):

Roadway speed limit is a relative measurement of vehicle traveling on road. More often it is seen that vehicles are travelling at a higher speed than the specified limit of the roadway section. The variable ‘rdspeed40plus’ shows that there is an increased probability of higher injury particularly incapacitating and fatal injuries. Waiz et al. (1983) reported that the reduction of the speed limit from 60 to 50 km/h in Zurich was accompanied by a reduction of 20% in pedestrian casualties and a 25% decrease in pedestrian fatalities.

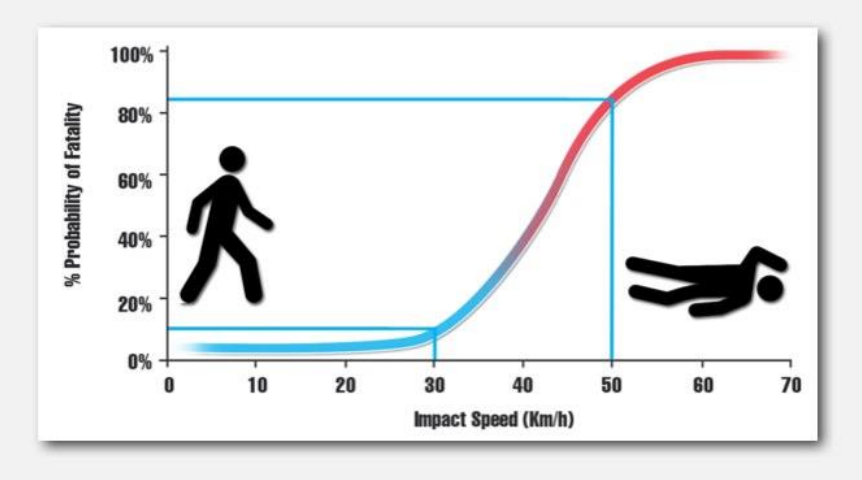


Figure 18. Impact of vehicle Speed on Pedestrian Fatality (Source: saferspeedarea.org.nz)

In Central Florida region vehicle with roadway speed limit more than 40 may cause a serious threat to the safety of people walking on the road.

Elder Pedestrian Involve (1=yes, 0=No):

Central Florida has a higher proportion of people aged more than 65. These people may be reluctant to drive or walk on the road for their commuting. The elder pedestrians exposed to high speed vehicle are more vulnerable to injury severity. It can be seen from the model that the crashes where elderly pedestrians are involved results in higher injury severity. The health condition of elder pedestrian is more vulnerable to higher injury. Moreover the elder pedestrians while walking on the road are less likely to pay attention of the surrounding environment.

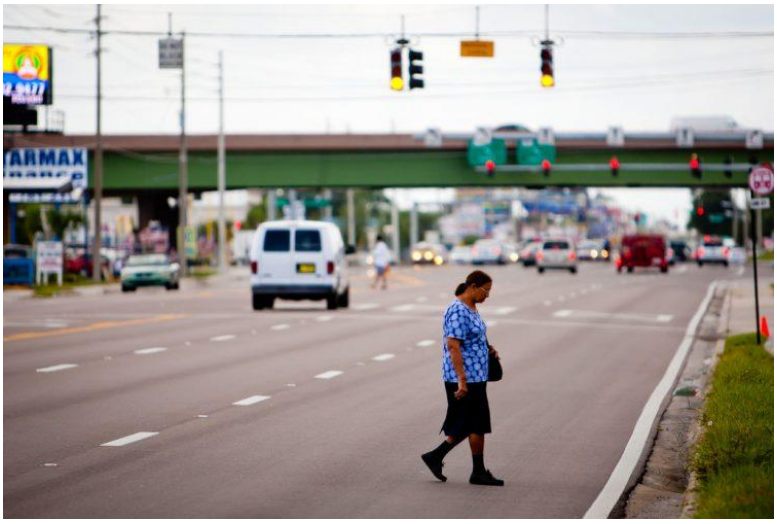


Figure 19. Elder Pedestrian Requires Special Assistant (source: Chip Latherland/NY Times)

5.5 k fold cross validation result

The primary purpose of the ordered logit model is to identify the contributing factors of higher pedestrian injury severity rather than predicting the injury. Although it is not essential to validate the model since the data used are the actual crash data but in order to evaluate modeling performance 10-fold cross validation method was adopted. The k-fold cross validation method

calculated the area under ROC curve (c value) for each of the 10 subsets and the average c value is obtained to see whether it significantly drops from the actual model c statistics that uses all the training data. The result obtained in the 10-fold cross validation is summarized in Table 13.

Table 13. c Statistics for 10 fold Cross Validation

Optimistic c	Optimism Correction	Corrected c
0.7517	0.0242	0.7275

The table shows that the average c value of the 10-subset of the original data is 0.72 where the original value of the c statistics is 0.75. The difference is much smaller indicating the model performed reasonably well in representing pedestrian injury severity.

Table 14. Lift Table Created for Injury Severity Profile

Injury Severity			
	No=0	Yes=1	Total
Minor Injury =1	125	575	700
Major Injury=2	97	197	294
Fatal=3	80	31	111
Total	302	803	1105

Table 14 shows the lift table for the injury severity profile. It can be seen from the table that the model can correctly classify 803 observations out of 1105 data sample which indicates the model performs moderately well in injury severity distinguishing.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

Over the past decades, practitioners have adopted various approaches to develop knowledge and guidelines for pedestrian safety. Recently, many researchers have focused on pedestrians' safety by identifying risk factors. However, depending only on crash counts without considering the underlying risk factors may provide limited and even biased information about where safety measures are needed and what measures would be the best to be used to improve pedestrian safety (Wang et al., 2016).

In the exposure estimation part of this study, a systemic approach has been developed that uses pedestrian surrogate measures in terms of exposure information. The two-steps procedure described in the study can be utilized in cases where it is difficult to collect the pedestrian volume data. The study recommends using the two-steps procedure as it provides important exposure information to better understand the pedestrian activity and crash frequency relation. The study applied negative binomial and zero-inflated negative binomial models in micro-level pedestrian safety analysis and found that the negative binomial model performed slightly better. Apart from these, the identification of the factors affecting pedestrian exposure such as the presence of school, car-ownership, pavement condition, sidewalk width, bus ridership, intersection control type, and presence of sidewalk barrier was another important contribution of the study to the pedestrian safety research approach. The study emphasizes focusing on these factors while determining the safety measures for pedestrians. For example, if there is a school near an intersection, strict enforcement of speeding and traffic calming is required, and also pedestrian education programs should be promoted for the school children (Abdel-Aty et al., 2007).

There are several possible extensions of this study that could be made in the future. The proposed two-steps procedure in this study involves two consecutive modeling processes. The first model estimates the number of pedestrians; and the second model estimates pedestrian crash counts using the predicted pedestrian counts from the first model. Nevertheless, the procedure has a limitation as the result can be biased due to the accumulated errors from the first step. It is possible that the issue can be overcome by adopting simultaneous modeling approach. The influential area around each intersection (buffer size) considered in the study for extracting socio-economic and land-use variables was determined based on the average walking distance (Boer et al., 2007; Yang and Diez-Roux, 2012). However, it is common to have a longer trip distance than the average walking distance. It may be possible that the variables found to be insignificant in the current study may become significant using other buffer sizes. The study can be done using different buffer sizes to identify other significant factors. In such case mixed models or random variables would be better approach for the analysis.

The injury severity analysis part of the study recognizes the responsible conditions or factors for severe pedestrian injury severity in Central Florida. Based on the identified contributing factors it would be helpful to select the appropriate countermeasures to alleviate pedestrian injury severity of this region. The results may also be useful in the region based pedestrian safety policy evaluation. However, the study can further be extended in several ways. More complex modeling techniques such as mixed ordered logit model or random effects model can be applied to see if the model results remain similar. It is obvious that many of the pedestrian crashes are not reported to the police. The results obtained in the safety studies are approximate since there could be more information that is lost due to this unwillingness of crash reporting. The injury severity study can be further extended including several crash databases specifically

combining the safety office crash data and hospital records. The explanatory variables used in the model can further be combined to identify any other significant factor that may cause severe pedestrian injury.

Based on the study it is recommended that proper safety measures be taken before the condition get worse. The following safety measures can be adopted depending on the cost and desired efficiency to improve pedestrian safety (Table 15).

Infrastructure Measures:

Table 15. Engineering/ITS Based Safety Countermeasures (FHWA, 2014).

Engineering/ITS based Countermeasures	Cost	Efficiency
Advanced Yield Markings for Motorists	Low	High
In-roadway Knockdown Signs	Low	
Pedestrian Countdown Signals with Animated Eyes	Medium	
Danish Offset	High	
Median Refuge	High	
Portable Speed Trailer	High	
Pedestrian Activated Flashing Yellow	High	
Pedestrian Call buttons that Confirm Call (Visible/Audible confirmation)	Low	Medium
Turning Vehicles Yield to Pedestrians	Low	
ITS No-Turn on Red Signs	Medium	
ITS Automatic Pedestrian Detection Devices	High	

Engineering/ITS based Countermeasures	Cost	Efficiency
Warning Signs for Motorists	Low	Low
High Visibility Crosswalk Treatment	Medium	
Pedestrian Channelization	High	
Smart Lighting	High	

Educational Measures:

- Intensifying road safety awareness and publicity campaign including pragmatic measures to improve and correct road user behaviors through public motivational programs.
- Education can help to bring about a climate of concern and develop sympathetic attitudes towards effective interventions.
- Road Safety Education for school children of various age groups.
- Enhancing programs of law enforcement with public information and education campaigns.

Enforcement Measures:

- Strong, but fair and targeted, enforcement is critical to the safe and efficient use of road system. Traffic law enforcement requires professional skills that are different from other types of police work.
- Effective enforcement of laws and sanctions against alcohol/drugs impaired drivers and to bring about changes in attitudes of drivers towards safe operations.

- Combined with enforcement, road safety publicity campaigns improve road user behavior and reduce road accident.
- An information briefing, educating police forces about the issue and importance of specific enforcement measures.
- Extensive public information and advertising.

It is expected that the study can be a good platform for further analysis of pedestrian safety not only at intersections but also on segments with surrounding environments. The injury severity analysis results and the methodologies implemented in the study including surrogate exposure variables can estimate reliable safety performance functions for pedestrian crashes even though pedestrian trip data is not available. With the reliable pedestrian safety performance functions, it would be possible to identify crash hotspots for pedestrians and provide appropriate countermeasures to prevent pedestrian crashes.

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