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Analysis of Pedestrian Crash Characteristics and Contributing Causes in Central Florida

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ANALYSIS OF PEDSTRIAN CRASH CHARACTERISTICS AND CONTRIBUTING CAUSES IN CENTRAL FLORIDA

by

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ABSTRACT

This research investigates the main reasons leading the State of Florida to be ranked among the worst states in terms of pedestrian safety with four metro areas considered the most dangerous for pedestrians among all the United States as reported in the Dangerous by Design report. The study analyzes the characteristics and contributing causes of pedestrian crashes that occurred in Central Florida over a 5 year-period (2011-2015) at intersections and along roadway segments at mid-block locations using the data obtained from the Signal 4 Analytics database. All pedestrian related crashes were compiled and all the 6,789 crash reports were studied thoroughly. Intersection and roadway pedestrian related crashes were identified along with all the parameters and conditions related to the high crash risk of pedestrians. However, due to inconsistencies in the police report inputs such as miscoding and misinterpretation, a screening criteria was developed to exclude or disqualify crashes that do not meet the research requirements.

Preliminary descriptive statistics revealed the most common types of crashes at each location. For intersection-related crashes, it was found that left turn, right turn and through moving vehicles struck crossing pedestrians. At midblock locations, major crash types were through moving vehicles hitting pedestrians crossing and walking along the roadway.

The evaluated factors affecting pedestrian crashes were classified into four main categories; location characteristics (e.g. intersection, midblock, type of control, presence of crosswalk, presence of sidewalk), pedestrian factors (e.g. pedestrian under influence, failure to yield to the right of way), driver/vehicle characteristics (e.g. driving under influence, failed to yield

to traffic control device, aggressive driving), and environmental-related factors (e.g. weather conditions, road surface conditions and time of day) were among the factors studied.

Three different models were utilized in the analysis using the SPSS statistical software package. A multinomial logit model was developed to predict the likelihood that a pedestrian will be involved into one of the common crash types. A binary regression model was developed to understand the significant factors contributing to the main causes at each intersection type whether at signalized or un-signalized intersections. Lastly, an ordinal regression model was developed to identify the significant factors affecting the level of injury severity sustained by pedestrians.

The results of the multinomial logit model for intersection crashes revealed a high probability of right turn crashes associated with drivers at fault with no aggressive driving related crashes compared to left turn crashes. The results also showed that the probability of through moving vehicle crashes with no traffic control device was 2.437 times higher than left turn crashes. These results confirmed the results of the binary model that a lower likelihood of left or right turn crashes was associated with un-signalized intersections when compared to through crashes. Lastly, a greater probability of through crashes was associated with running the red light when compared to left turn crashes.

The results of the binary model revealed that the majority of the un-signalized intersection crashes were attributed to drivers at fault. Among other contributing factors was crossing at un-signalized intersections not equipped with the crosswalks. The chance of crashes at unsignalized intersections is 15.657 times higher in the absence of crosswalks compared to unsignalized intersections in which crosswalks are present. Conversely, signalized intersections related crashes were attributed to running the red light and pedestrians failing to obey traffic control devices.

For the ordinal models for crashes at either intersections or mid-block locations , the results revealed that a reduction in the likelihood of severe injuries was associated with drivers being at fault, daytime, no aggressive driving related crashes and sober pedestrians . However, red light running related to intersection crashes, as well as pedestrians failing to yield to the right of way, and drivers under influence related to midblock crashes were associated with high injury severity and an increase in the likelihood of severe injuries.

The findings of this research and examination of the factors affecting pedestrians’ crash likelihood and injury severity can lead to better crash mitigation strategies, countermeasures and policies that would alleviate this growing problem in Central Florida.

ACKNOWLEDGMENT

To my parents

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CHAPTER ONE: INTRODUCTION

1.1 Background

In 2011, Florida was ranked as the most dangerous state in the United States for pedestrians according to a study done by Transportation for America (T4A). Per the National Highway Traffic Safety Administration (NHTSA,2011), Florida had the highest pedestrian fatality rate among all states with 2.60 pedestrian fatalities per 100,000 persons. Moreover, in 2013, one in every five traffic-related fatalities was a pedestrian. Due to these alarming facts, pedestrian safety has become one of the most serious concerns in Florida.

There have been many pedestrian safety studies carried out in order to identify the common factors influencing the crash occurrence and level of injury the pedestrian sustained from a crash. Different factors were examined, such as vehicle speed, motorized vehicles size, and environmental , pedestrian and driver characteristics. The goal of these studies was to help engineers and planners to implement the proper countermeasures to mitigate the occurrence of those crashes and decrease their severity.

This research is a contribution to these efforts. The main objective of this research is to investigate why Florida is ranked No. 1 in the nation in terms of pedestrian crashes, injuries and fatalities. This study analyzes pedestrian crashes that have occurred in Central Florida over a 5 year-period (2011-2015) at intersections and along roadway segments at mid-block locations.

1.2 Research Approaches

Initially, a literature review of relevant studies was conducted, including research related to pedestrian crash frequency and pedestrian crash severity risk factors. It also includes some statewide studies, pedestrian safety indices, and pedestrian crossing guidelines.

Second data was collected from the crash reports available in the Signal 4 Analytics database of all the pedestrian crashes that occurred in Central Florida between 2011 and 2015. Preliminary descriptive statistics was prepared to reveal the most common types of crashes at intersection and mid-block location. Finally, several software packages including Microsoft Excel and SPSS were used to analyze the most common types of crashes at each location and build statistical models.

1.3 Project Goal and Objectives:

The goal of this research is to perform a comprehensive study to identify pedestrian crash characteristics and causes at both intersections and midblock locations in Central Florida for the period of 2011 to 2015.

Police reports of all the crashes that occurred in Central Florida between 2011 and 2015 were reviewed. Several steps were followed. First, all pedestrian related crashes were identified. Since the focus of this research was on pedestrian crashes that occurred at both intersections and midblock locations. The following most common crash types were identified to be analyzed.

1. Crashes that involved crossing pedestrians and right-turning vehicles at intersection.
2. Crashes that involved crossing pedestrians and left-turning vehicles at intersection.
3. Crashes that involved crossing pedestrians and through traffic at intersection.
4. Crashes that involved through moving vehicles struck pedestrians who were crossing at midblock locations.
5. Crashes that involved through moving vehicles that struck pedestrians who were walking along the roadway along the roadway segment.

Secondly, the causes and contributing parameters from the crash reports were determined. The factors affecting pedestrian crashes were classified into four main categories; location characteristics (e.g. intersection, midblock, type of control, presence of crosswalk, presence of sidewalk), pedestrian factors (e.g. pedestrian under influence, failed to yield to the right of way), driver/vehicle characteristics (e.g. driving under influence, failed to yield to traffic control device, aggressive driving), and environmental-related factors (e.g. weather conditions, road surface conditions and time of day).

Finally, models including the contributing factors were developed to identify the significant factors affecting the crashes whether at signalized or unsignalized intersections, crash types, and injury severity.

1.4 Report Organization:

The report is organized as follows:

Chapter 2 provides a review of existing literature on pedestrian safety, including risk factors influencing the pedestrian crashes' frequency and severity. Chapter 3 explains the data collection process and illustrates some preliminary descriptive statistics for the characteristics of the pedestrian crashes at both intersection and midblock locations. Chapter 4 discusses the modeling approach and the models developed for the analysis. Chapter 5 illustrates the analysis procedure and the results obtained from the developed models, and Chapter 6 discusses the conclusions and suggests some countermeasures based on the obtained results.

CHAPTER TWO: LITERATURE REVIEW

A significant increase in the safety research is corresponding to the growing concern of pedestrian safety. A great number of studies has been conducted to identify risk factors affecting pedestrian crashes including significant factors affecting frequency and severity of pedestrian crashes. This chapter highlights some related studies on this field.

2.1 Risk Factors Affecting Pedestrian Crashes

2.1.1 Pedestrian Crash Frequency Risk Factors

2.1.1.1Walking direction

Lauma and Peltona (2013) examined whether walking facing traffic improves pedestrian safety or not compared to walking with traffic direction in Finland. They observed that the number of accidents that involved pedestrians walking against traffic is less compared to the number of accident involved pedestrians walking with traffic. Also, the number of pedestrian crashes that occurred on secondary roads while none of the involved accidents' participants is intoxicated was found to be higher compared to the main roads. This was attributed to the fact that main roads are wider than the secondary ones, and when pedestrians facing traffic senses a risk coming from an approaching vehicle, he or she can take an evading action. It was also noticed that the percentage of pedestrians walking against the traffic increased when pedestrian was intoxicated. Moreover, the results showed a significant reduction in both fatal and injury pedestrian crashes (about 77%) when pedestrians were facing traffic compared to pedestrian walking with traffic.

2.1.1.2 Pedestrian and road characteristics, land-use, light and weather conditions, crash location, and speed

Ukkusuri et al (2012) used a 5-years pedestrian crash data from New York City to identify the significant socio-demographic and environmental characteristics affecting pedestrian crash frequency at different census tracts. Land-use, demographics, transit supply, road network and travel characteristics were the observed variables affecting the crash frequency.

The findings showed a positive correlation between the proportion of teenager population and the likelihood of crash risk while a negative correlation with the greater fraction of 65 years and over population. However, both populations (under 17 and 65 and over) were more vulnerable to fatal collisions. The results also indicated an increase of the likelihood of total and fatal crashes as result of the increase of the transit ridership and subway stations. The intersections with four and five approaches have a greater likelihood of total crashes compared to all-way-stop and T- intersections. Moreover, they observed that the greater the number of primary road without access restrictions the greater the probability of crash risk. Increasing the road width and the number of lanes increase the risk of crashes.

Finally, the findings showed an increasing likelihood of pedestrian crashes associated with the increase of the fraction of industrial and commercial land use compared to residential land use. Also, the increase of the number of schools increases the chance of crashes. These findings were consistent to those from Aty et al (2007). They examined the pedestrian and bicyclist crashes involving school-aged children at Orange County, Florida. They found that major number of those crashes occurred at locations near schools. An increasing number of lanes and posted speed was associated with greater number of crashes. The results indicated a high involvement of middle-aged, alcohol-impaired, male drivers in those crashes.

Another study done by Mohamed et al (2012) to analyze the pedestrian-vehicle crashes in New York, US and Montreal,Canada. They used a five-year crash data to identify contributing factors of pedestrian crashes. The authors found a negative correlation between the fraction of residential land and the likelihood of pedestrian crashes. In other words, the greater the fraction of residential land, the lower the crash frequency. They also found that denser and more urbanized areas were assosiated with lower crash frequncy.

The authors determined variables as heavy vehicle, dark lighting conditions, and mixed land as contributing factors that increase the fatal crashes risk . In addition, crossing without signal or crosswalk increased the likelihood of death. Therefore, crossing at intersections reduces the crash severity.In addition, the age of pedestrian was another contributing factor played a role to determine the injury severity.the findings showed that pedestrians aged 5 year or less and 65 year and more were more prone to fatal injuries when involved in crash.

Increasing in road width was assosiated with increase of likelihood of pedestrian crashes which agrees with the findings of Garder (2004). The purpose of the study was to examine the influence of speed and other variables on the crash frequency. For that purpose, 70 crosswalks at intersections and 52 midblock locations were observed. The author concluded that locations with high speed , wide roads were associated with high crash frequency. Also, marked crosswalks were much safer than unmarked ones at non-signalized locations.

Patro et al. (2012) used a data of pedestrian fatal crashes that occurred between 2003-2006 in Isreal to construct design crash preventative measures using neural networks approach.

Five patterns of pedestrian accidents were observed: (i) elderly pedestrians crossing on crosswalks in metropolitan areas mostly far away from intrsections; (ii) pedestrians crossing suddenly or from hidden places and colliding with two-wheel vehicles in urban areas; (iii) male pedestrians crossing at night and struck by four-wheel vehicles in rural areas; (iv) young male pedestrians crossing at night in both urban and rural areas; and (v) children and teenagers pedestrians crossing in small rural communities. The results were similar to general findings represented in previous studies with respect to charesteristics of pedestrians accidents. Among accident charecteristics , relevant factors are (i) accident locations, (ii) accident cause, and (iii) demographic characteristics. For accident locations , the urban areas were found to be the prevalent crash locations (Beck et al.,2007 and Harruff et al.,1998), For accident cause, it was observed that drivers and pedestrians were equally responsible for the crashes causations .Preusser et al. (2002)

Finally, for demographic characteristics, the results emphasized on the high involvements of children and elderly in the pedestrian crashes (e.g. harruff et al., 1998; Preeusser et al.,2002; Eluru et al .,2008; and Kim et al.,2008b). Moreover, the findings of Patro et al. (2012) stressed on the larger involvements of male pedestrians (Harruff et al., 1998; Beck et al.' 2007; Kim et al., 2008a , and Al-madani and Al-Janahi,2006).The authors suggested countermeasures based on accident patterns and pointed to the importance of designing information campaigns in order to educate road users.

Harruff et al. (1998) analyzed pedestrian traffic fatalities in Seattle, Washington. They used 217 traffic fatalities occurred between 1990 and 1995. They found that the young children pedestrians were the most risky group in pedestrian crashes, however; elderly pedestrian were more likely to sustain fatal injuries. The results showed that low income groups were more susceptible to injuries. Consistent with other studies, male pedestrian fatalities outnumbered female pedestrian fatalities(Kong et al., 19961; Lee and Abdel-Aty,2005; Al-shammari et al.,2009, and Zhou et al.,2013).

Unlike other studies showing the fatal pedestrian crashes were more frequent during the weekend (Kong et al., 1996; National Highway Traffic Safety Administration, 1992), Harruff et al. observed that fatal crashes were most common during midweek, in the early evening,and during winter months. They also noticed most of the crashes occurred while pedestrians were crossing.Furthermore, in accordence to previous studies such as (Holubowycz, 1995; Jehle and Cottington, 1988; Lane et al., 1994), they noticed a contribution of pedestrian alcohol intoxication to pedestrian crashes. Moreover, the authors indicated that factors ,such as the absence of pedsterian safe crosswalks, sidewalks, and alcohol intoxication were contributing factors to fatal injuries in thoroughfare.

Abdel-Aty and Lee (2005) utilized crash data from 1999 to 2002 to analyze frequency and severity of pedestrian crashes at intersections in Florida.Compared to other age and gender groups, the analysis showed that middle -age male pedestrians and drivers were more involved in pedestrian crashes. Similar to the finding of Harruff et al. (1998), passenger car was found to be more involved in pedestrian crashes than other types of vehicles. In addition, increasing the number of lanes at undivided intersections leaded to an increase of crash frequency. Moreover,They observed higher numbers of crashes occurred when driver were intoxicated than when they were sober in dark lighting. The same was observed for pedestrians; however, the number of crashes involved intoxicated pedestrians was higher than the number of crashes involved intoxicated drivers at nighttime. The study identifies some factors affecting the injury severity of pedestrian when involved in crash.

The result showed that elderly pedestrian were more vulnerable compared to other age groups. Also, results indicated that female pedesrians were more likely to sustain severe injury than male pedestrians. Furthermore, the authors noticed that Alcoho/drug use by pedestrians, dark lighting, and adverse weather were correlated to severe injuries sustained by pedestrians, consistent to the finding of Garder (2004), as the speed of collision between the vehicle and the pedestrian increases, the injury severity is likely to be higher.Even though the number of crashes occurred at rural areas was less than the ones occurred at urban areas, the pedesrians sustained more severe injuries. In addition, the results showed higher injuries sustained at the intersections without traffic controls compared to other types of intrsections.

Finally, vehicle size showed a positive correlation to the injury severity,i.e., the larger the vehicle, the more severe was the injury. In addition, the findings showed that as the average volume increases the chance of conflicts between vehicles and pedestrians increases as well.

Jang et al. (2013) is another example of research conducted to analyze both frequency and injury severity of pedstrian crashes at the city of San fransisco, California. The researchers used data of pedestrian crashes from 2002 to 2007. The authors indicated that central business district was associated with high frequency of pedestrian crashes.In consistece with findings of Lee and Aty(2005), they concluded their study with the idenfication of alcohol consumption, nighttime, rainy weather, and larger vehicles as risk factors that increase the risk of severe injuries. Furthermore, they indicated that weekends , cell phone use, and vehicles proceeding straight and striking a pedestrian were other risk factors influencing the pedestrian injury severity.

Charness et al.(2009) conducted a study to assess the sensitivity of both younger and older drivers to a pedestrian encroaching on an intersection in daylight. To assess the driver's sensitivity, velocity profiles from radar gun data was used.Drivers of all ages showed some sensitivity to the approaching pedestrian; however, in the presence of pedestrian, older driver drove more slowly on the track than did the younger drivers. Also, older drivers showed a greater sensitivity to whether the turn they were to make was a right or left turn. They drove more slowly for right turns. The authors indicated that most pedestrian crashes occur at night, which agrees with finding of (Langham and Moberly, 2003). They recommended further studies to examine the sensitivity of drivers at night in the presence of pedestrians varying in conspicuity since older drivers have much poorer night vision than the younger ones.

2.1.1.3 Alcohol

Doan,1996 examined the influence of alcohol consumption by pedestrians on the likelihood of dying. In consistence with several studies, the results showed that intoxicated pedestrians were more involved in pedestrian crashes. In addition, the author found that the odds of dying or sustaing severe injury relative to survival were greater in pedestrian under influence than sober pedestrians.The results also indicated the odds of dying increased when pedestians hit by straight ahead vehicles compared to other vehicles maneuvers. Moreover, the odds of dying of pedstrians involved in nighttime crashes were higher than pedestrian hit in daylight or dusk.

2.1.1.4 Built environment

Meranda-Moreno et al. (2011) have studied the influence of built environment on pedestrian activity and pedestrian- vehicle collission occurrence at signalized intersections at Montereal, Canada. The authors developed pedestrian activity and collision frequency models to jointly analyze data of 519 signalized intersections located in the central neighbourhoods. Population density, commercial land use, number of jobs, number of schools, presence of metro stations, number of bus stops, and average of street lengh are some built environment characteristics that have a strong positive relationship with pedestrian activity. However, percentage of major arterials has a powerful negtive assosiation with pedestrian activity.

The results showed indirect relation between built environment and pedestrian-vehicle collission at intersections, i.e., the built environment influences the pedestrian- vehicle collission through its effect on pedestrian activity and traffic volume. This study confirmed what indicated in previous literature that more pedestrian activity and traffic volume generate more crashes with the emphasise on the traffic volume being the primary cause of collision frequency at intersections.

The relationship of potential risk factors with the occurrence of pedestrian crashes at midblock crossings was evaluated by Diogenes and Lindau using the crash data of nine years (1998-2006) in the city of Porto Alegre, Brazil. The study included twenty-one midblock crosswalks. The result showed a positive correlation between pedestrian crash rates at midblock crossings and the presece of busway transit system or bus stops and in two-way roads. However, a negative correlation was observed between pedestrian crash rates and the sidewalk widths or the number of crossing stages. The crash rates was more sensitive to increasing the number of crossing stages on two-way roads than one-way roads. Thus, implemintation of refuge island on two-way road is more effective than on one-way road.In the existence of marked crosswalk with traffic signal, the crash rates decreased. It was also found that as the percentage of public transportation increased, the pedestrian crash rates significantly decreased.

2.1.1.5 Pedestrian volumes and traffic volumes

Many previous studies indicated that pedestrian volumes and traffic volumes are the main influencing factors on pedestrian crashes frequency. Elvik (2009) determined a positive relationship between the number of motor vehicles and crash frequency, i.e.,as the traffic volume increases the collision frequency increases. The same positive relationship between pedestrian volume and crash frequency at different type of intersections was found by Harwood et al.,2008. Lyon and Persaud (2003), and Leden (2002). However, Many previous studies ,such as Leden,2002; Jacobsen, 2003 identified the effect of " Safety in numbers", in which the risk faced by each pedestrian decreases as the number of pedestrian increases.

Historical crash data analysis is not the only approach to observe pedestrian-vehicle conflicts. There are alternatives ,such as pedestrian-vehicular conflict analysis, which was found to be an effective approach for safety analysis. There have been studies that applied the pedestrian-vehicular conflict analysis, such as Qi and Yuan (2012) and Pratt et al. (2013)

Qi and Yuan (2012) examined the impacts of intersections with permissive left-turn signal control on pedestrian safety. The authors conducted traffic engineers' survey, field traffic-conflict analysis, and historical crash data analysis. The studies were performed on eight intersections in Texas. The analysis's results showed that pedestrian volume, opposing through-vehicle volume, left-turn vehicle volume, and intersection width in the opposing direction were risky factors that influencing the safety of pedestrians negatively.In addition, under the operation of a permissive left-turn signal ,four-legged intersections were found to be much safer than T- intersections . Similarly, Pratt et al. (2013) conducted a study on 20 intersections in Taxes to invistigate the conflicts between pedestrians and left-turning vehicles. They observed a positive correlation between conflict frequeny and both pedestrian volume and left-turning vehicles volume.However, conflict frequency was observed to be lower with the provision of a protected left-turn phase.

Schneider et al.(2013) analyzed crash risk on the boundary of the University of California Berkeley campus. The study covered 22 intersections during typical spring and fall semester weekdays. They found that the crash risk increased as the pedestrian volume decreased. In addition, they noticed that pedstrian crash risk in the evening (6.00 p.m. to midnight) was estimated to be three times greater than in the daytime (10:00 a.**m**. to 4:00 p.**m**.).

2.1.2 Pedestrian Crash Severity Risk Factors

2.1.2.1 Pedestrian, road, and vehicle characteristics, crash location, weather and light condition, intoxication, and speed

Pedestrian crash severity risk Factors is another focus area in the field of pedestrian safety. Many studies have been conducted to determine those factors.Tarko and Azam (2011) used linked police-hospital data in order to investigate pedestrian injury severity factors. They used bi-variate probit model for the analysis. Pedestrian, road, and vehicle characteristics were identified as severity factors.

The results showed that male and older pedestrians were more susceptible to severe injuries, which was consistent with numerous results found in the published work (for example, Lee and Abdel-Aty, 2005; Kim et al., 2008; Eluru et al., 2008). Pedestrians involved in rural roads and high-speed urban roads were found to be more susceptible to sustain more severe injuries, particularly when crossing such roads. The danger of sustain more severe injuries was found to be higher when crossing between intersections (e.g. midblock locations). The size and the weight of the vehicle involved in the crash were also found to have a positive correlation with the injury severity level, i.e., the larger the vehicle was, the more severe the injury was.

Sarkar et al. (2011) used crash data from 1998 to 2006 to identify factors associated with pedestrian fatality risk along Bangladesh's roadway. The analysts delevoped binary logistic regression models. The result showed that the probability of fatality increased among elderly pedestrians (individuals older than 55 years of age) and young pedestrians (individuals younger than 15 years of age. The risk of fatality was higher for pedestrians who crossed the road than for those who walked along the edges of the road.

Collision between pedestrian and cars had a lower risk of fatality than collisions with trucks, buses, baby taxis or tempos , and tractors. Also, a higher risk of fatality was observed in the rainy season compared to other seasons. Furthermore, risk of fatal injuries was observed to be greater for pedestrian crashes occurring at location without traffic control or stop control than those occurring at locations with traffic signals.

Mohamed et al. (2013) applied the ordered probit and multinomial logit models to identify factors influencing injury severity level of pedestrian. The analysts used two pedestrian injury severity datasets from New York City (2002-2006) and Montreal, Canada (2003-2006). It was found that many variables, including presence of heavy vehicles, dark lighting, crosssing from locations other than intersections, and prevalence of mixed land use increased the probability of injury severity in both cities.In the analysis of the NYC dataset, the risk of fatal injury was found to be the highest among the elderly and young pedestrians (indivisuals under 5 years old). The likelihood of fatal crash was found to be higher in the absence of signal or crosswalk at the intersections. However, the risk of fatal crashes was found to be lower in the presence of bus rout and on-street bike lane at signalized intersections, and metered parking.

Khattak and Tung (2015) employed an ordered probit model to identify factors influencing pedestrians injury severity sustained in crashes occurred at highway-rail grade crossings using crash data from 2007 to 2010. The model showed that females, higher train speed, and commercial land use were found to be associated with higher likelihood of fatality; however, less severe injuries were observed during clear weather.In addition, highway-rail crossings with greater number of crossing highway lanes and equipped with flashing light signal were assoisiated with less severe injuries.

2.1.2.2 Mobile phone use

Nasar and Troyer (2013) conducted a study on pedstrian injuries caused due to the use of mobile phone in public places. For that purpose, they used data from the US Consumer Product Safety Commission on injuries in hospital emergency rooms from 2004 through 2010. Relative to total pedestrian injuries, they observed an increase of mobile-phone related injuries. The results showed that males and pedestrians under 31 had higher pedestrians injuries related to mobile- phone use.However, it was found that women had higher driving injuries related to mobile -phone use than men , which was consistent with the findings that women use mobile devices more than men while driving (Glassbrennen and Ye, 2007).

Similatr to the previous study, Byington and Schwebel (2013) conducted a study to examine the effect of mobile phone use on college-age pedestrian safety. They hypothesized that pedestrians' behavior was generally riskier when simultaneously using mobile internet and crossing the street than when crossing with no distraction. The focus of study was only on mid-block pedestrian crossing. The findings of this study and other previous studies, such as (Hatfield and Murphy,2007; Neider et al.,2010; Stavrinos et al.,2009,2011) confirmed that pedestrian safety decreased when using mobile phone.

2.2 Statewide studies

Haleem et al.(2013) conducted a comperhensive study on pedestian crashes that occurred on state roads of Florida. They suggested potential countermeasures to mitigate crash occurrence and enhance pedestrian safety. Their study included identifying statewide pedestrian crash patterns and causes, identifying factors contributing to pedestrian injury severity, and identifying and analyzing pedestrian high crash locations at both signalized and nonsignalized locations for crash causes and potential countermeasures. They used 6,434 pedestrian crashes that occurred on state roads during 2008-2010.

The authors concluded that the highest number of pedestrian crashes per million population and also the highest pedestrian crash rate per million walk trips per year were associated with young pedestrian groups (16-25 years); however, a slightly higher number of fatal crashes per million walk trips per year were associated with elderly pedestrians at both signalized and non signalized locations. In addition, rainy weather , higher speed limit ,the night and dawn off-peak periods, and increasing the AADT and the percentage of trucks were found to be positively correlated with the injury severity level. Crashes involving crossing pedestrians were found to be more severe than crashes involving pedestrians walking along roadway at non signalized locations. Overall, it was noticed that crashes in which pedestrian was at fault were much more than crashes in which driver was at fault. Also, they were more severe at both signalized and non-signalized locations. Injuries associted with crashes involving at fault pedestrian were found to be more severe at non signalized locations compared to signalized ones.

Chu (2006) analyzed Florida crash data of 17 years (1986-2003) using the ordered probit model to identify the significant contributing factors impacting pedestrian Injury Severity. The study determined the impact speed, impact configuration, and pedestrian attributes as the direct determinants of the pedestrian injury severity. For the purpose of the study, the focus was on the role of light condition and crossing location as indirect determinants. The study findings determined the largest risk factors for fatal injuries facing pedestrian when involving in vehicle crash. The largest risk factors in decreasing order were found to be: being over than 64 years old, being struck by impaired driver, walking in foggy weather, walking while intoxicated, being hit by driver with physical disability, and being hit by a large vehicle. 65 years old pedestrians were found to be more vulnerable to fatal injury than pedestrian aged between 25-64 years old.

The chance of fatality risk for pedestrians struck by intoxicated driver was higher than being under influence by pedestrians themselves. Also, the fatality risk increased when the pedestrian involved in the crash was under influence compared to a sober pedestrian. The results showed that the probability of fatality risk at midblock locations was observed to be higher than at intersection for any light conditions. Additionally, the results showed that the effect of daylight in reducing the fatality risk was greater than the effect of street lighting for both intersection and midblock locations, however, the effect of the daylight was noticed to be greater at intersections than at midblock locations.

2.3 Pedestrian safety indices

Safety and secure measures were the most important evaluation measures to evaluate the safety of pedestrian crossings. Zeeger et al.2006 conducted a study to develop intersection safety indices ISI model to evaluate intersections crosswalks with respect to pedestrian safety. The study included 68 intersection crosswalks from cities of Philadelphia,Pa; San Jose,CA; and Miami-Dade County,FL. Crashes, behavioral measures (consist of conflicts and avoidance maneuvers), and intersection expert safety ratings were the four safety measures included in the ISI. However, the crashes indicator was excluded due the fact that motor vehicle crashes are so sparse which make it difficult to base the identification of intersection safety problems solely on pedestrian crashes.

Ratings model and behavioral model were developed . Both models were incorporated to the final Ped ISI model and all significant variables in both models were included into the final ISI model.Intersection control type (sign or signal), number of through lanes, 85^{th} percentile vehicle speed, main street traffic volume, and area type were the indicative variables of pedestrian safety indices model ISI.

Through a user-friendly guide, the safety indices can be used by practitioners to determine which crosswalks have the highest priority for in-depth pedestrian safety evaluation, subsequently; they can identify the potential safety problems by using other tools and determine available countermeasures through the guidelines.

2.4 Pedestrian Crossing Guidelines

Crossing a roadway exposes pedestrians to danger. For that reason, statewide guidelines have been created to address pedestrian safety problems associated with roadway crossings. Those guidelines recommend guidance to safe and convienient pedestrians crossings. Although the guidelines should be used by engineers and planners who are responsible for planning, designing, operating , and maintaining pedestrian facilities, engineering judgement should be used in applying these guidelines.

There are primary design references, such as TxDOT Highway Design Division's Operations and Procedures Manual, 1994, Manual on Uniform Traffic Control Devices (MUTCD), 2000 , and Americans with Disabilities Act Accessibility Guidelines (ADAAG) . However, the guidelines are aggregated of best practices from pedestrian guidebooks and design manuals to supplement the traffic engineering references .Several states have their traffic manuals.

Guidelines provide the creteria to address the problem of pedestrian safety.Also, various treatments and alternatives are recommended in the pedestrian crossing guidelines. The guidelines determine the nessesary treatment warrant and its feature according to the roadway situation. The basic pedestrian crossing consists of crosswalk markings and pedestrian warning signs . To improve the visibility of the crosswalk or warn motorists that pedestrians are present, pedestrians crosswalk can be enhanced by in-roadway flashing lights, Supplemental Pedestrian Crossing Channelizing Devices (SPCCD), "YIELD HERE" signs, YIELD lines, an advanced warning marking for speed humps, and devices to increase awareness of pedestrians, such as animated eyes display and text pavement markings in crosswalks.

To reduce vehicle speeds in the vicinity of pedestrian crossings, traffic calming measures, such as curb extensions , center island narrowing and median refuge islands, roadway narrowing, raised crosswalks and intersections, traffic circles, and speed humps can be applied.

The high number of pedestrian–motor vehicle conflicts associated with other specific conditions,which are determined in the guidelines, warrant grade-separated pedestrian crossings. pedestrian overpass/bridge, skywalk/skyway pedestrian tunnel/underpass, and underground pedestrian network are types of grade-seperated pedestrian crossings. There should be a balance between the engineering treatment and the cost when choosing the effective treatment for the problem of pedestrian safety. School crossings and special events are also addressed in specific guidelines and separate chapter in several states' traffic manuals.

2.5 Research overview and goal

The research goal is to understand the main contributing factors for pedestrians' crashes in Central Florida. Like previous studies, it considered conditions that are most involved in pedestrian crashes as causes, e.g. factors such as presence of crosswalk, presence of sidewalk, type of control, causes associated with driver fault (driving under influence DUI, careless driving, failure to yield right of way…. etc.), and causes associated with pedestrian fault (e.g. failure to yield right of way, walking under influence PUI), time of the day, weather and road surface conditions prevailing at the crash time.

In addition, the study will consider the effect of the involvement of handicapped pedestrian on the crash occurrences, location, and the level of severity that pedestrian sustained from the collision with the motor vehicle.

Currently, Signal 4 Analytics database includes only different crash types identified for vehicle crashes, such as run-off-road, rear-end, head-on, etc. Therefore, another objective is to develop different pedestrian crash types based on the main contributing causes same as for vehicular crash types.

CHAPTER THREE: DATA PROFILE

3.1 Introduction

This chapter describes the data collection and preparation efforts to analyze pedestrian crashes. It also discusses the police reports' review process. Furthermore, it discusses the identification of the pedestrian crashes' characteristics, types, and causes.

This study analyzed pedestrian crashes that have occurred in Central Florida over a 5 year-period (2011-2015) at intersections and along roadway segments at mid-block locations. The data was obtained from the Signal 4 Analytics database.

Signal 4 Analytics is a statewide interactive, web-based geospatial crash analytical tool. This system is developed by the GeoPlan Center at the University of Florida, and funded by the state of Florida through the Traffic Records Coordinating Committee (TRCC). It was designed to support the crash mapping and analysis needs of law enforcement, traffic engineering, transportation planning agencies, and research institutions in the state of Florida to identify the critical safety areas on the roadway, so they can apply effective countermeasures to save lives on Florida's roadways. The data is up to date, and includes all short and long forms of the crash reports provided by the Florida Highway Patrol (FHP) to the Department of Highway Safety and Motor Vehicles (DHSMV).

The data sheet includes all the pedestrian crashes reported in Signal four analytics system during this period. Approximately 6,789 crashes were included in the database. A pedestrian was defined by the department of transportation (DOT) as any person on foot, walking, running, jogging, hiking, sitting, or lying down who is involved in a motor vehicle traffic crash on a public traffic way, such as a road or highway. Therefore, crashes that occurred on private property, including parking lots and driveways, were excluded from the analysis. Also, any person using a non- motorized device such as a bicyclist was not considered in this study.

Police reports of these 6,789 crashes were downloaded and reviewed in detail to collect information that is not typically available in the crash summary records. This information includes data related to the location of the crash, type of traffic control device, at fault party, presence of crosswalk, presence of side walk, the cause or causes of the crash, the action or the movement of the pedestrian at the time of the crash occurrence, weather condition, time of day, road surface condition, handicapped involvement, injury severity level, and the vehicle movement at the time of the crash.

All the details of the crashes were collected by reviewing descriptions and illustrative sketches in the police reports. Also, google maps were used to investigate whether crosswalks or sidewalks existed at the crash locations.

3.2 Crash Screening Criteria

As mentioned earlier, the main objective of this research is to investigate why Florida is ranked No. 1 in the nation in terms of pedestrian crashes, injuries & fatalities according to the "Dangerous by Design" report (ref). Several steps were essential. The first step was to identify all pedestrian related crashes, and the second was to determine the causes and significant parameters from the crash reports. However, due to inconsistencies in the police report inputs as well as miscoding, a screening criteria was developed to exclude or "disqualify" crashes that do meet the following requirements:

a- The crash occurred in a parking lot, driveway, driveway access, limited access roadway (e.g. interstate, turnpike), off roadway (e.g. beach, woods, work zones).

b- The crash does not involve pedestrian (vehicles only, or bicycle involved).

c-The crash was between pedestrian and non- motorized device (e.g. bicycle, scooter)

d- The crash was reported to the law enforcement after the time it occurred or after the parties involved left the scene with no witnesses, and/or conflicting statements.

e- There was more than one report for the same crash, however, one of them was disqualified.

f- The pedestrian injury severity was either none or unknown with insufficient information.

g- Crashes occurred under different circumstances were also excluded. For example, pedestrian was committing a suicide attempt, driver intentionally struck a pedestrian, pedestrian was riding on the hood of a vehicle and fell after it moved, driver was hit by the door or run over by the tire of his own vehicle because he got out of it and failed to put it on park, pedestrian's leg was run over during a parade, pedestrian hit a still vehicle.

About 48% of these crashes were excluded from this analysis based on the above-mentioned criteria. Of those excluded, 1,401occurred at parking lots, 262 driveway related crashes, 195 occurred at driveway/ building access, 18 reports of crashes were missing, 2 locations of crashes were unknown, 89 vehicular related crashes without pedestrian involvement, 607 cyclists related crashes, and 666 crashes were classified as others. The crashes classified as others were excluded for several reasons, including insufficient information in the police reports and/ or being reported a while after the crash occurrence, not serious crashes in which the pedestrian sustained no or possible injuries, along with other unclear reasons. Finally, a total of 3,549 pedestrian crashes were included in the analysis. Of these crashes, 1,583 occurred at intersections, and 1,966 occurred at roadway locations (between intersections).

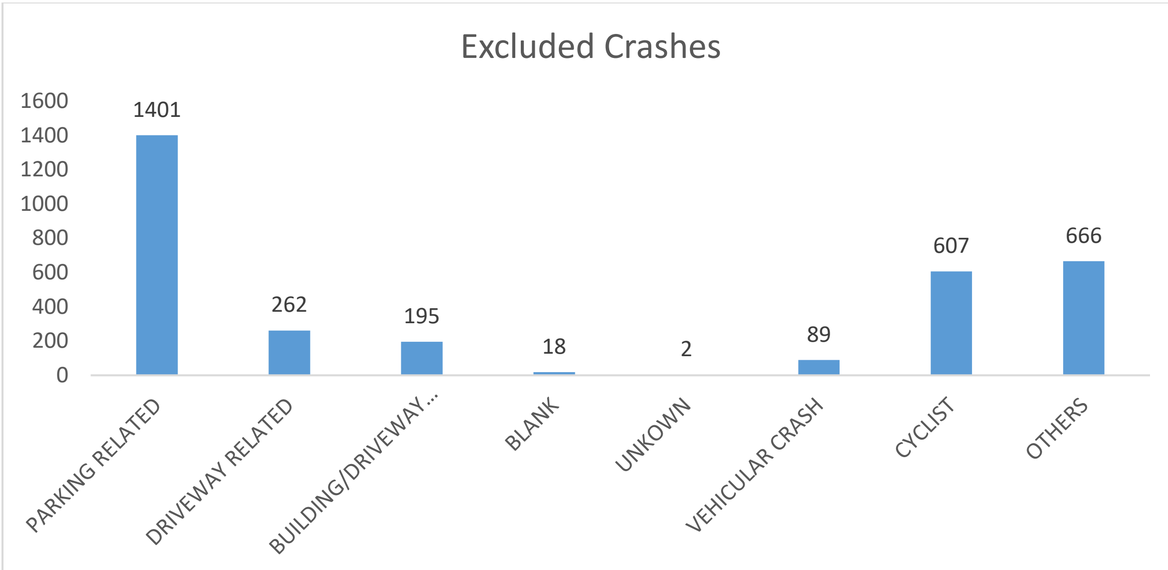

Figure 1: Criteria of crashes' Exclusion

3.3 Characteristics of Pedestrian–Motor Vehicle Crashes

The following section provides a descriptive statisitcs summary for the qualified 3,549 pedestrian crashes in central Florida for the five year period (2011-2015). Crashes were classified based on several factors including location, severity, time of day, traffic control devices among other factors as follows.

3.3.1 Crash location

The analysis showed that more than 55% of the pedestrian crashes occured along roadway segments.

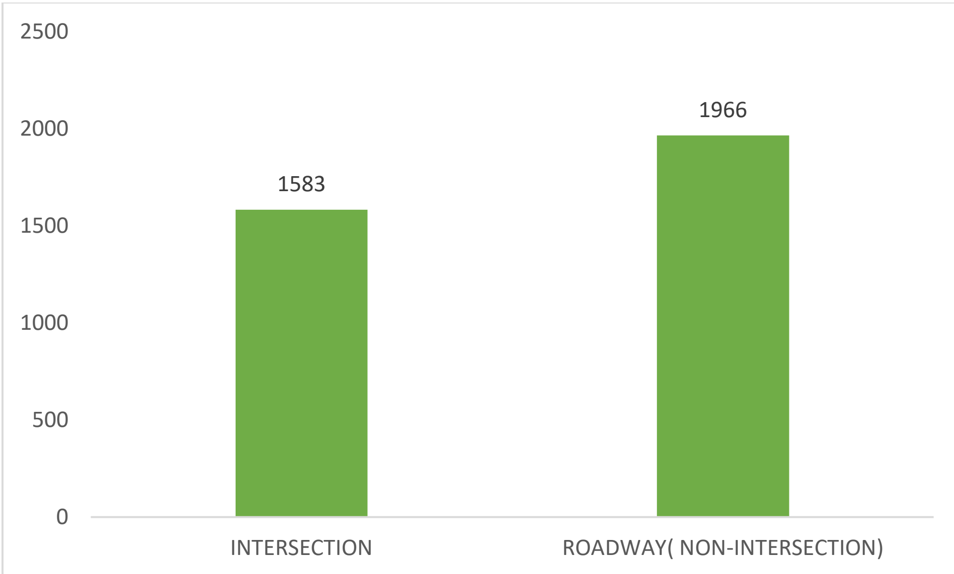

Figure 2: Locations of crashes

3.3.2 Injury Severity by Year and Location

As it is illustrated in Figures (3,4), the analysis shows that the number of fatalities is constant over the 5-year period at intersections However, a higher number of fatal crashes occurred at midblock locations (16.5)% compared to (7%)at intersections..

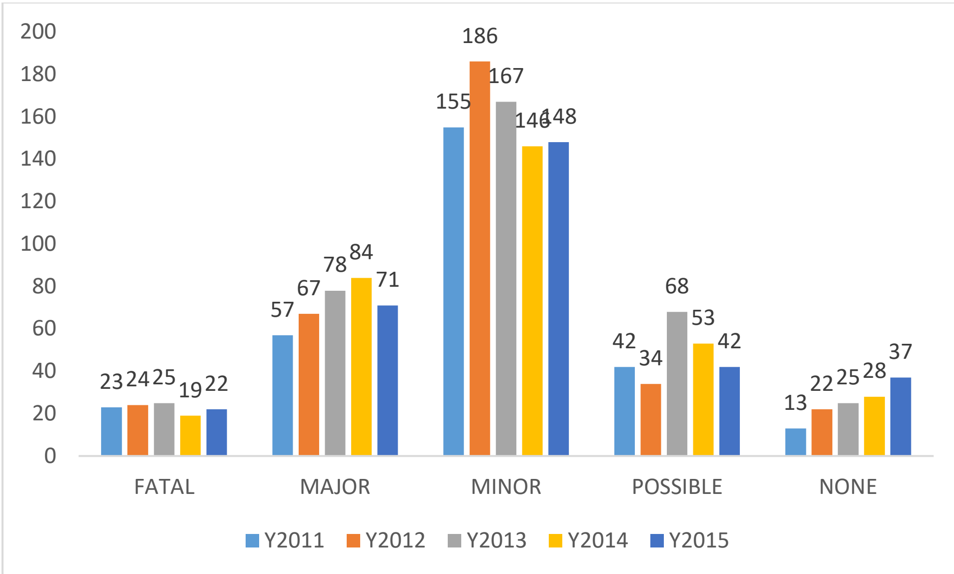

Figure 3: Total pedestrian crashes at intersection for five years (2011-2015)

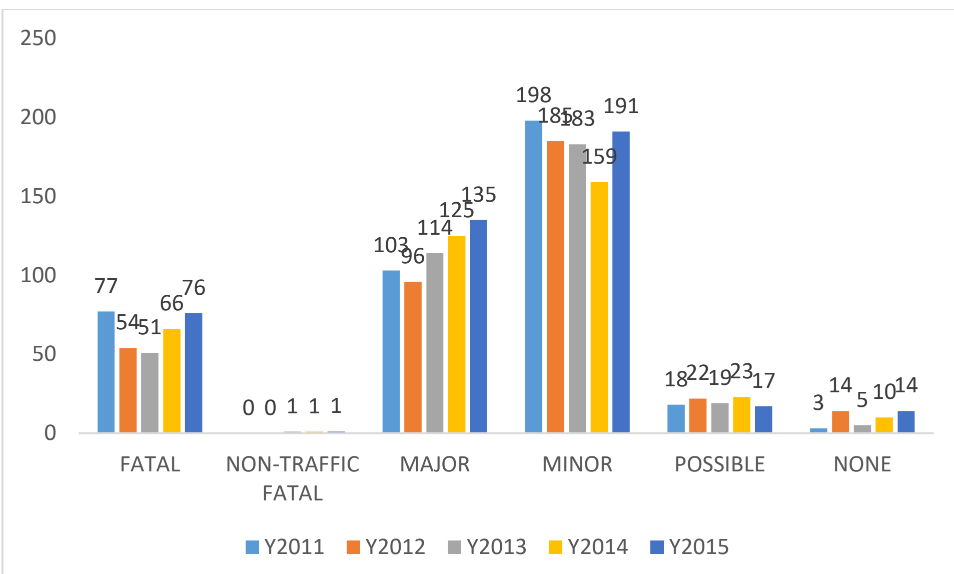

Figure 4: Total pedestrian crashes along roadways for five years (2011-2015)

3.3.3 Lighting

Pedestrian crashes at intersections occurred most frequently during daylight (56%) . In contrast, the majority of pedestrian crashes along roadway occurred during night time with or without street light (58%).

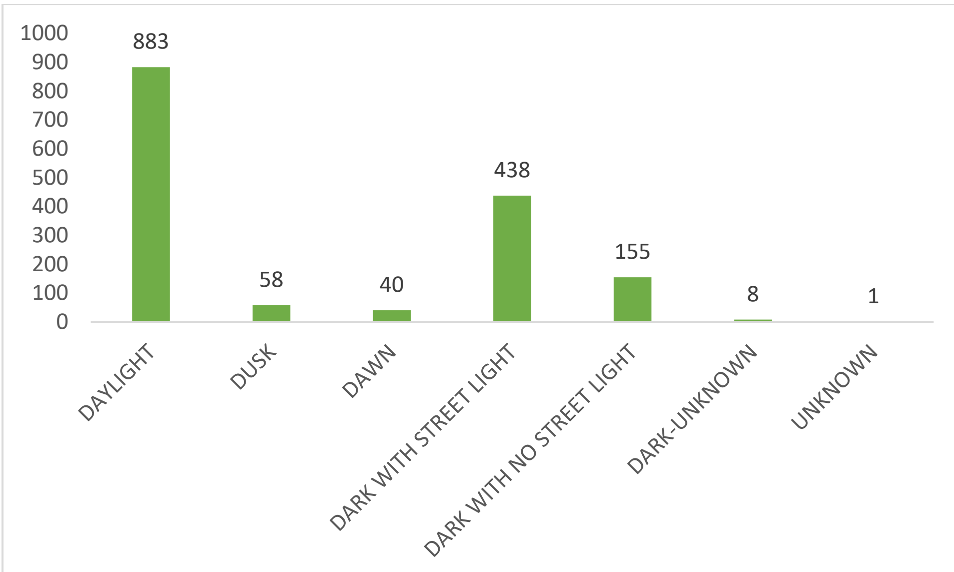

Figure 5 :Light condition for pedestrian crashes at intersections

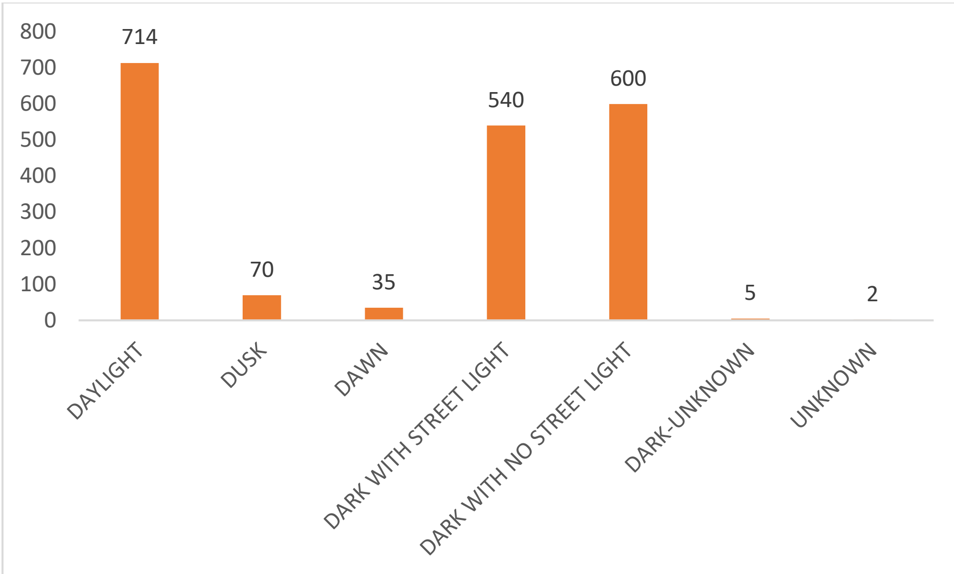

Figure 6 :Light condition for pedestrian crashes along roadway

3.3.4 Traffic control device

As it is illustrated in Figures (7) and (8), a higher number of pedestrian crashes were observed at intersections controlled by traffic light signal (47%), followed by uncontrolled intersections(28%).However,the majority of pedestrian crashes along roadways occurred at uncontrolled locations (82%).

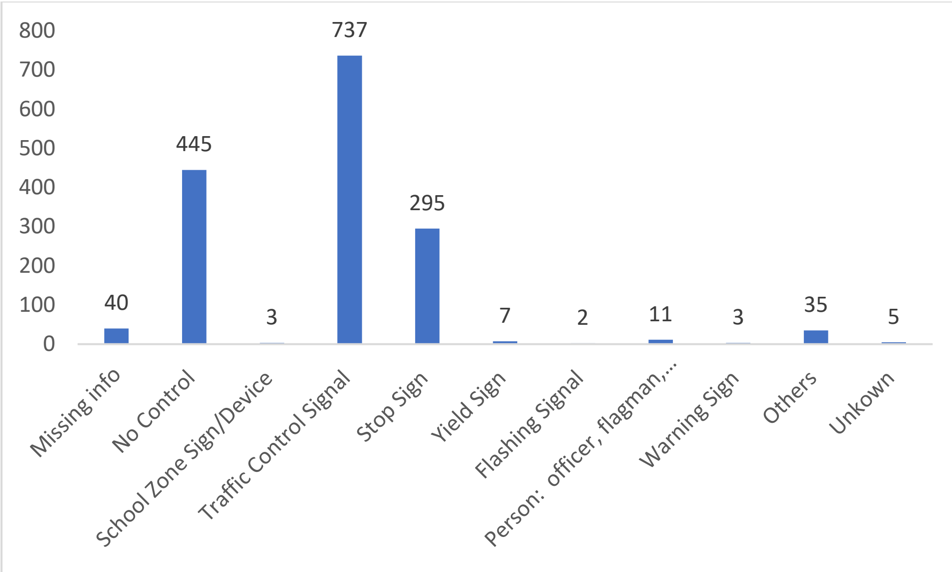

Figure 7: Traffic control device at intersections

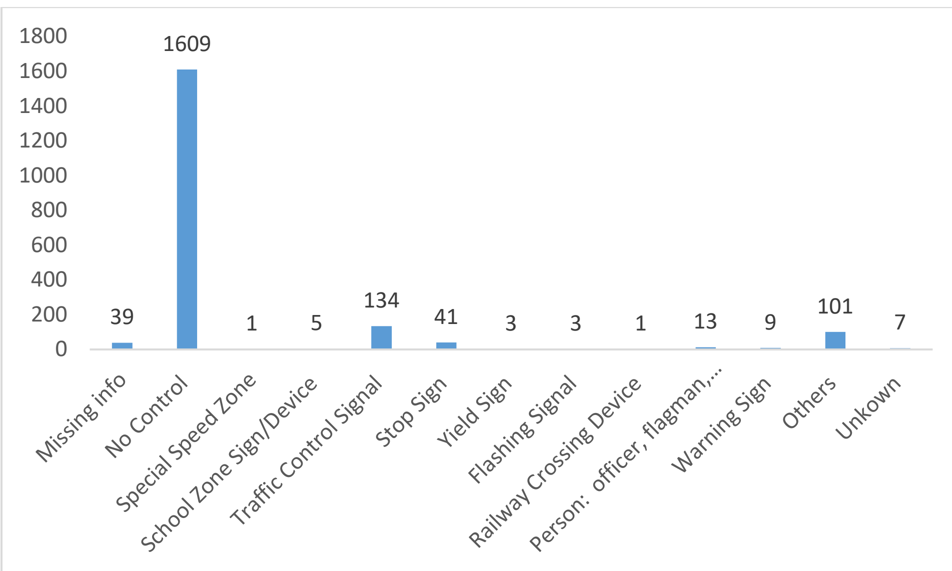

Figure 8: Traffic control device at roadways

3.3.5 Movement of the pedestrian at the time of the crash

As it is seen in Figure (9), the majority of crashes at intersections occurred while pedestrians were crossing (93%). Of those crossing crashes, about 57% occurred at daylight. Similarly, in figure (10), it can be noticed that about 63 and 25 percent of the crashes along roadways occurred while pedestrians were crossing and walking along roadway respectively. Of those crossing and walking along roadway crashes, 58 and 60 percent occurred during night time with or without street light.

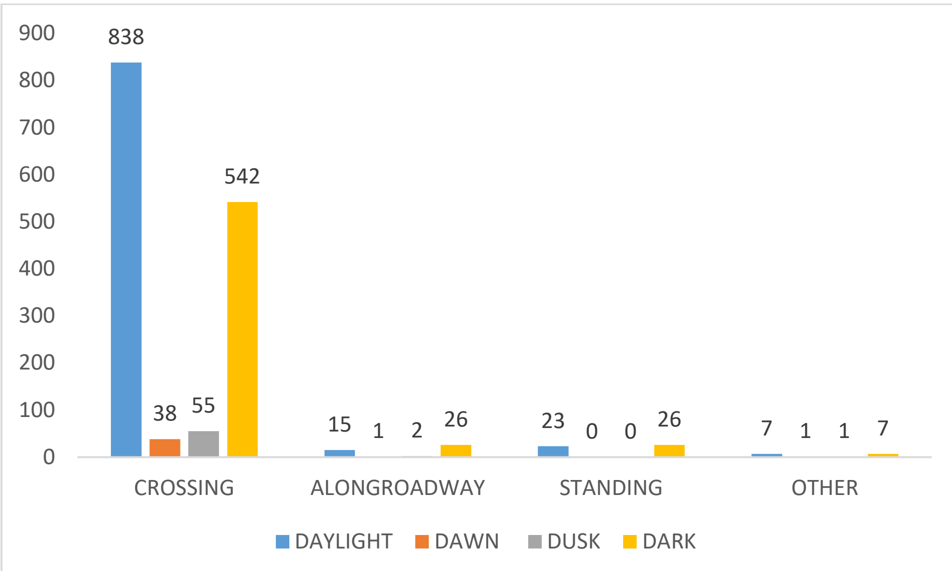

Figure 9: Number of Pedestrians movement by time of day of the crashes occurred at intersections

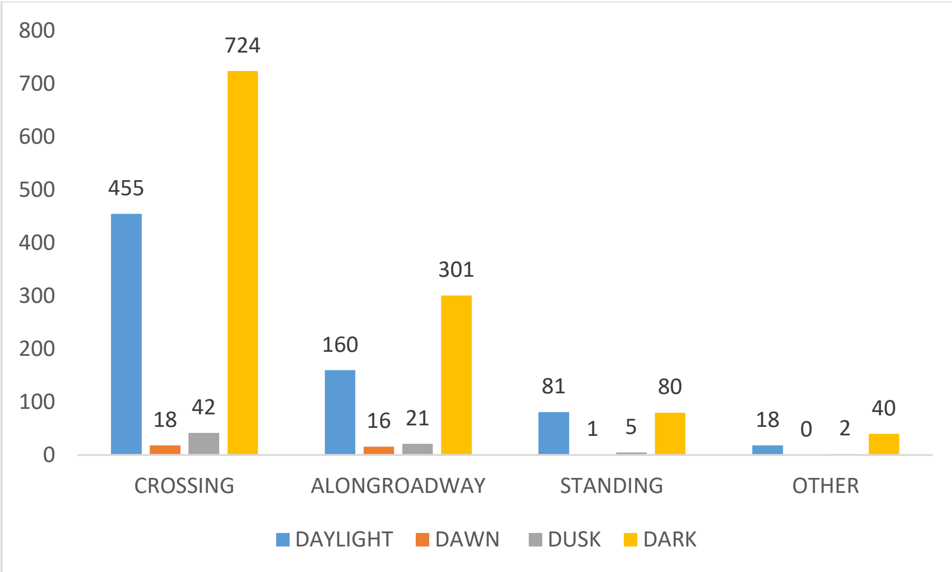

Figure 10: Number of Pedestrians movement by time of day of the crashes occurred at the roadway

3.3.6 Weather condition

The majority of crashes at both intersections and along roadways occurred during clear weather condition with 80% and 78% respectively..

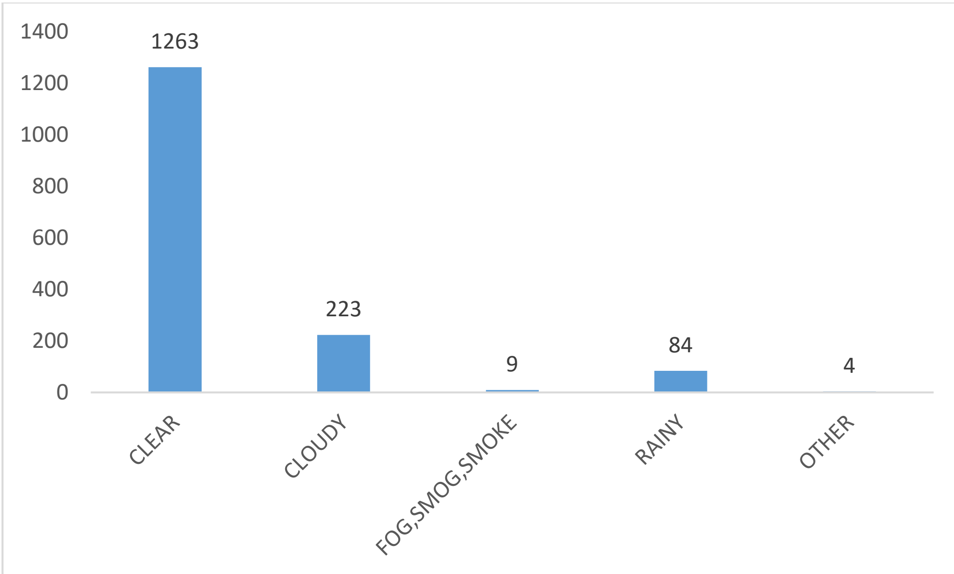

Figure 11: Prevailing weather condition of crashes occurred at intersections

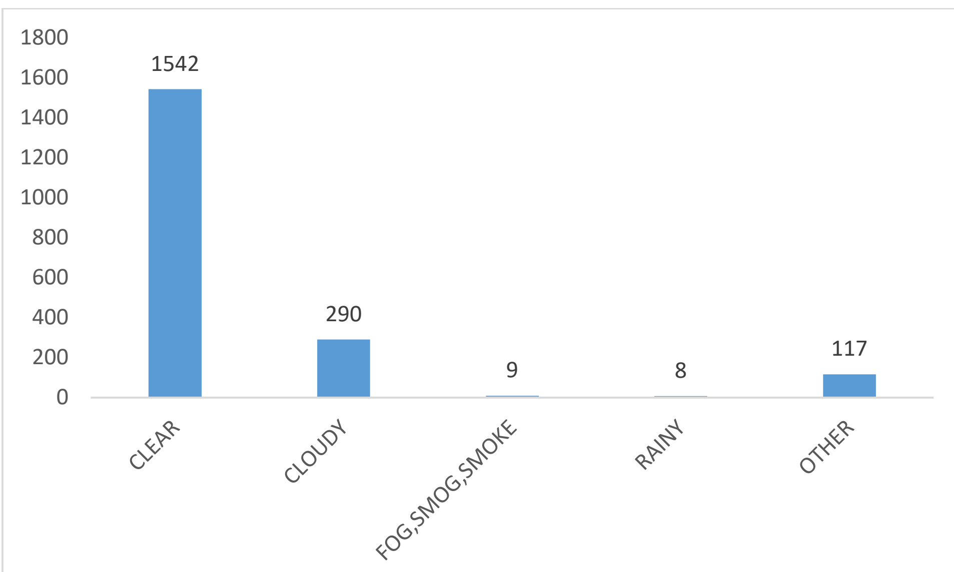

Figure 12: Prevailing weather condition of crashes occurred at the roadway

3.3.7 Road surface condition

Figures(13) and (14) show that about 90, 88 % of the crashes occurred on dry road surface at intersections and along roadways respectively.

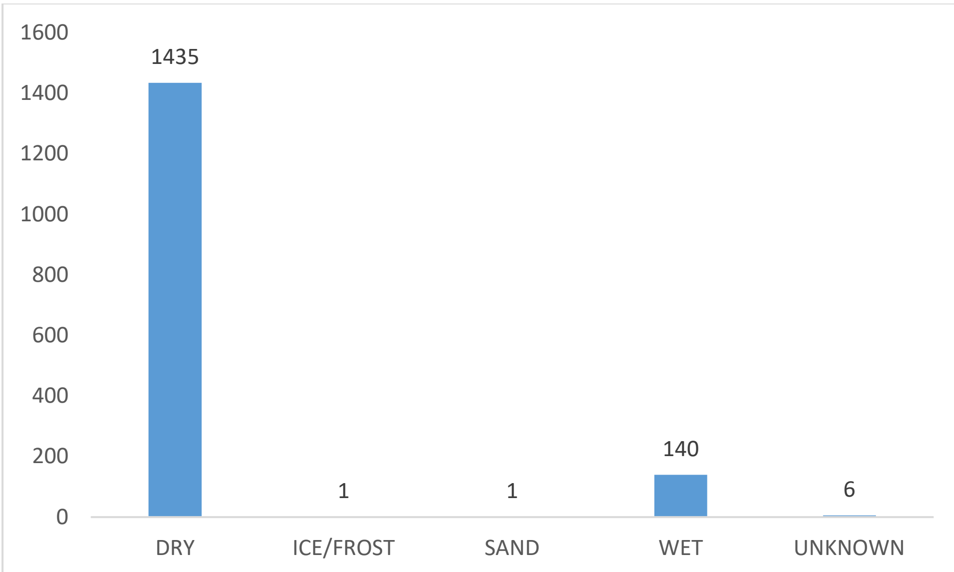

Figure 13: Prevailing road surface condition of crashes occurred at intersections

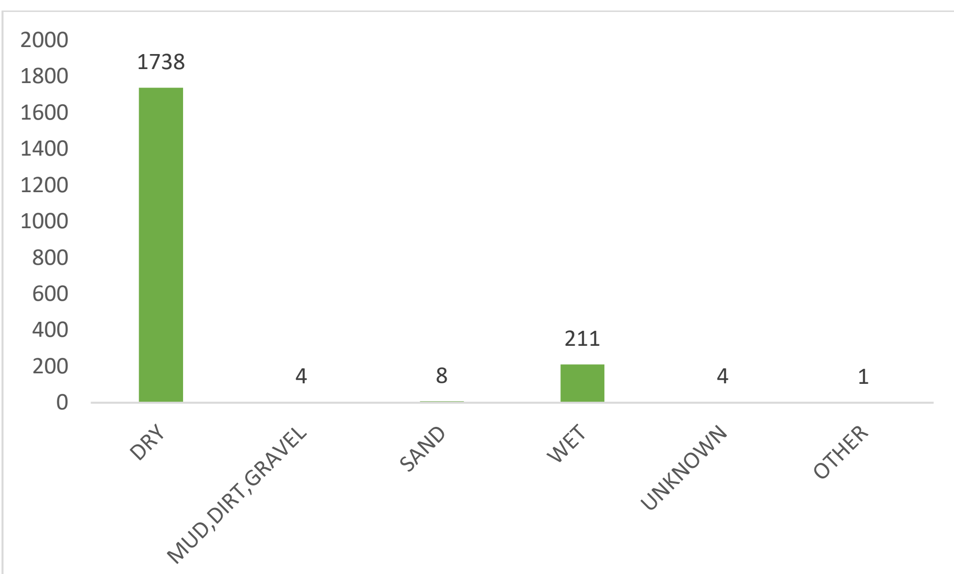

Figure 14: Prevailing road surface condition of crashes occurred at roadway

3.3.8 At fault road user

As it is shown in figure(15), about 51% of crashes occurring at the intersctions were due to the driver's fault.In contrast, in figure(16) pedestrians were found to be at fault at 68 % of total crashes occurring along the roadways.

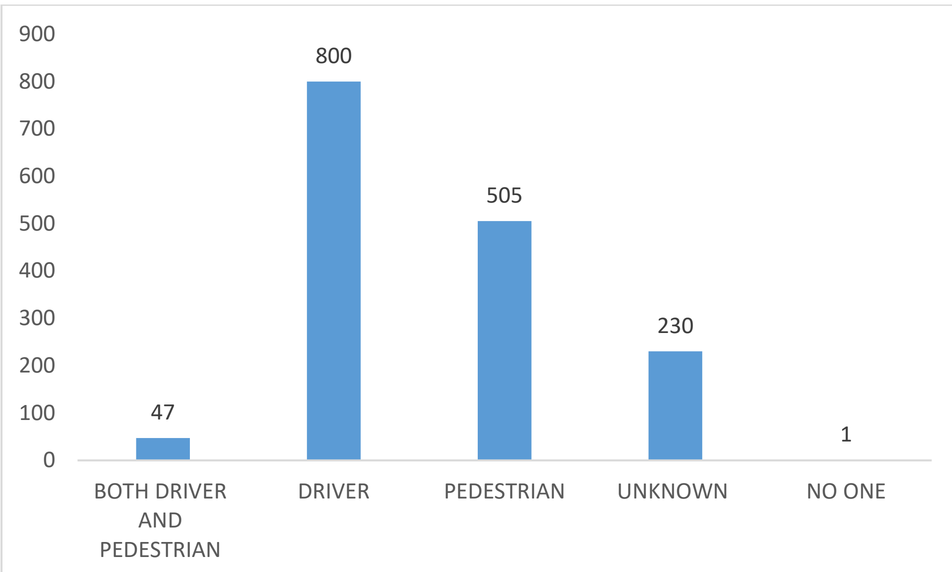

Figure 15: At fault road user of crashes occurred at intersection

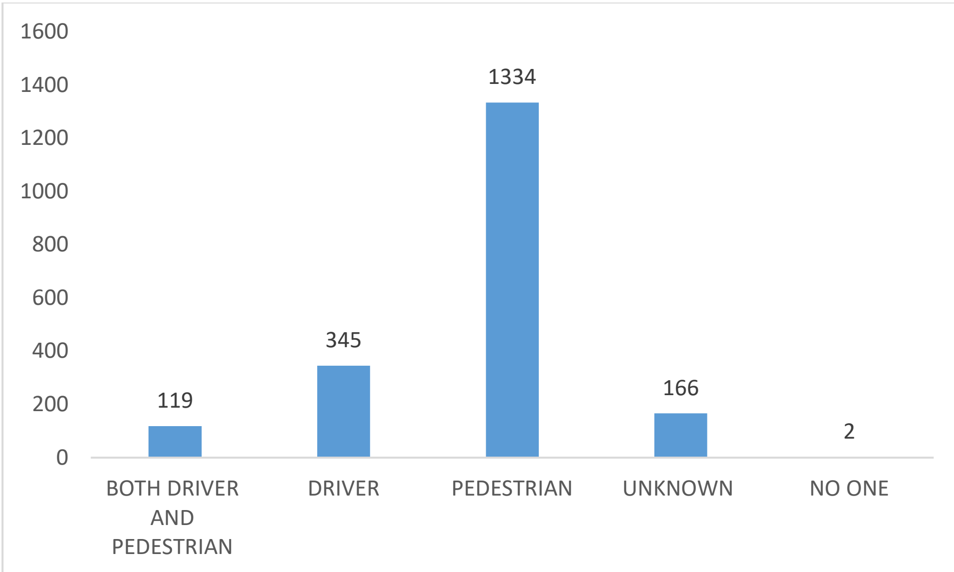

Figure 16: At fault road user of crashes occurred at roadway

3.3.9 Presence of crosswalks and sidewalks

Regardless who was at fault for crashes, at the vicinity of the intersections, about 63 percent of crashes occurred while pedestrians were crossing at a marked crosswalk. On the other hand, the majority of pedestrian crashes along roadways occurred while the pedestrians were crossing at locations with no crosswalk (94 percent). Similarly, about 72 percent of crashes occurred while pedestrians were walking along roadway without sidewalk.

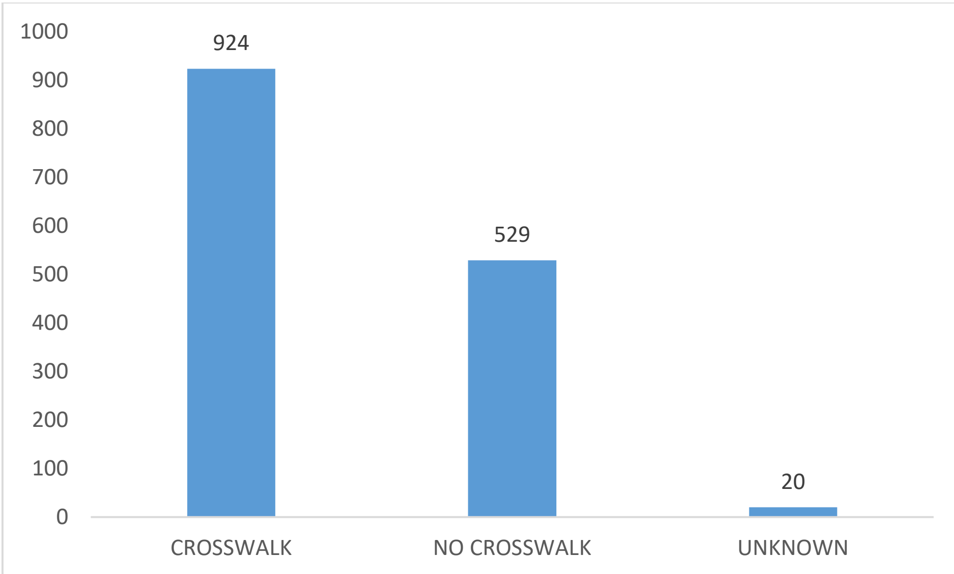

Figure 17: Presence of crosswalks for crashes occurred at intersections

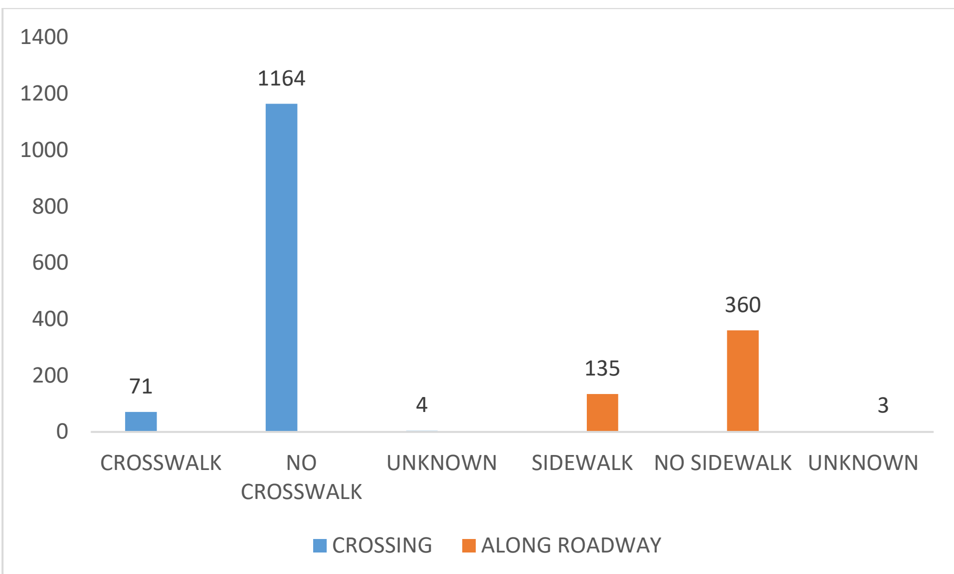

Figure 18: Presence of crosswalks and sidewalks for crashes occurred at roadway

3.3.10 Handicapped involvement

Crashes that involved Handicapped pedestrians were found to be about 5% at intersections and 1% along roadways.

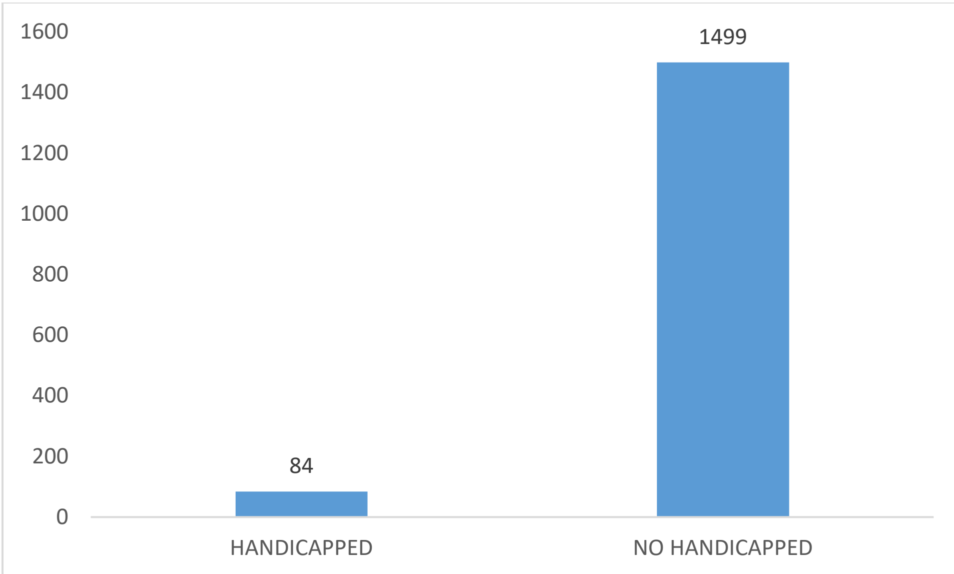

Figure 19: Involvement of handicapped pedestrians in crashes occurred at intersections

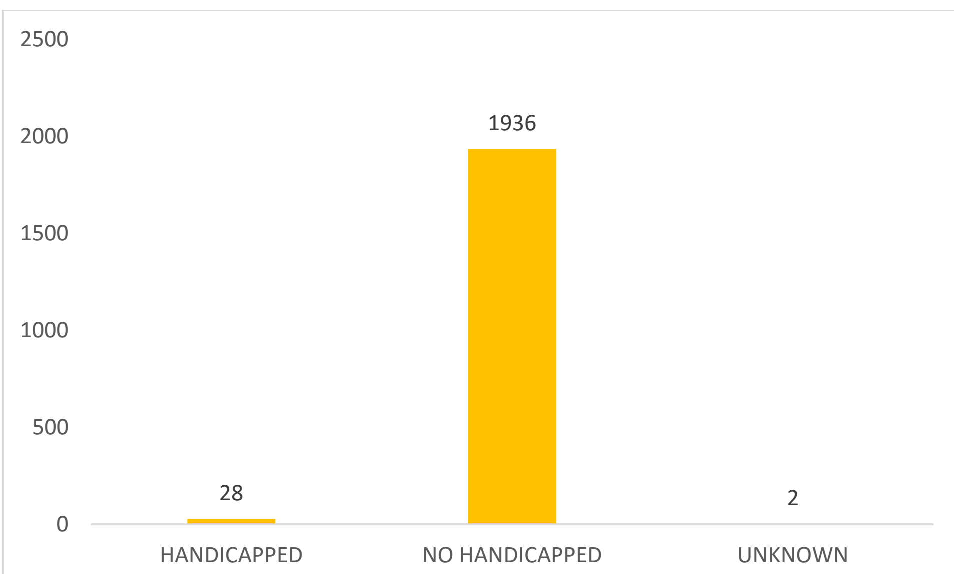

Figure 20: Involvement of handicapped pedestrians in crashes occurred at roadway

3.4 Types of pedestrian crashes at Intersections and Along Roadways

3.4.1 Pedestrian crashes at intersection

Three main types of crashes were analyzed,

Crashes that involve right-turning vehicles.

And they account for 24 percent of all analyzed crashes at intersections.

Crashes that involve left-turning vehicles.

And they account for 28 percent of all analyzed crashes

Crashes that involved through traffic

And they are about 47 percent of all crashes that occurred at intersections.

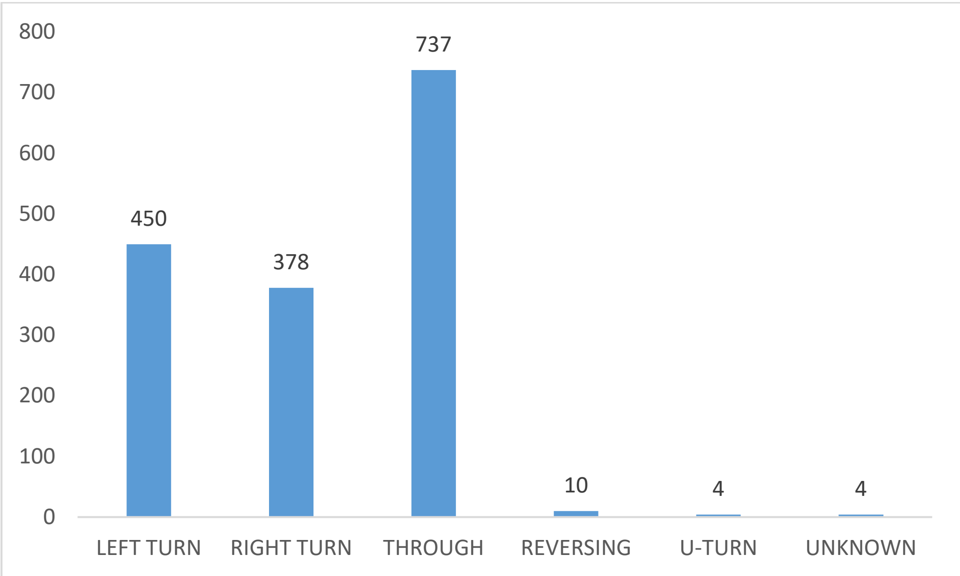

Figure 21: Types of pedestrian crashes at the intersections

3.4.2 Pedestrian crashes at roadway

Based on pedestrian movement, there are three types of pedestrian crashes at roadway,

Crashes involved crossing pedestrian

The majority of crashes at roadway occurred while pedestrians were crossing either at crosswalk or without crosswalk .They account for 63 percent of all analyzed crashes at roadway.

Pedestrian walking along roadway

These types of crashes are common. They involved a pedestrian walking along the shoulder of the road due to absence of sidewalk or the pedestrian not using available sidewalk. Walkig in the direction of traffic increases the crash risk (Lauma and Peltona (2013) . Figure (18) shows that walking along roadway either with or against traffic direction accounted fo r 25 percent of all analyzed pedestrian crashes at roadway.

Pedestrians being in roadway, standing or Other

These crash types include standing in roadway,walking in roadway, lying in roadway, working in roadway, playing in roadway, and play vehicle-related (i.e., pedestrian was struck while riding a play vehicle (e.g., skates, scooter, etc.)). In total, 12 percent of all pedestrian crashes analyzed were resulting from pedestrians being in the roadway .

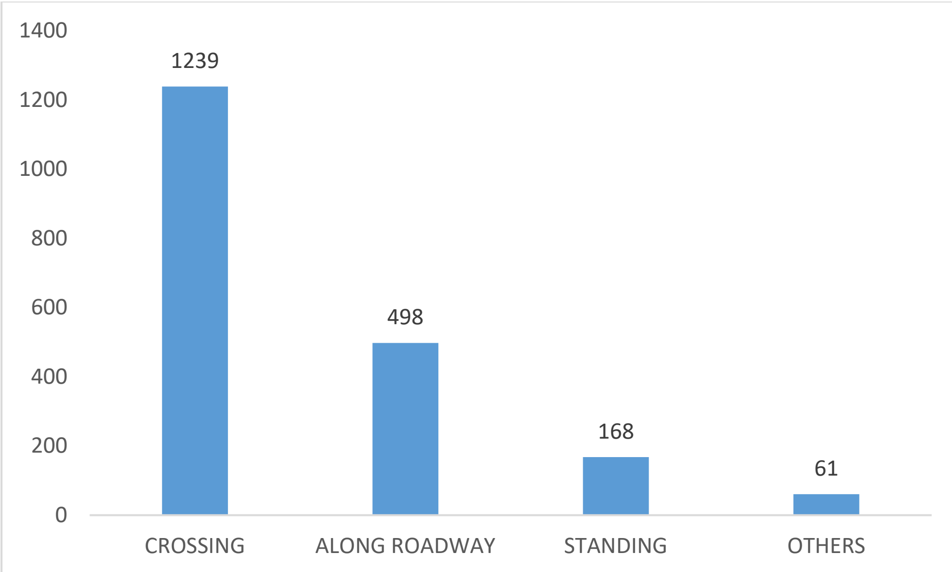

Figure 22: Types of pedestrian crashes at roadway

3.5 Risk behaviors and causes of pedestrian crashes

Several reasons were identified based on specific behaviors committed by either motorist or pedestrian or both of them. Following are some risk behaviors and crash causes for pedestrian crashes :

3.5.1 Pedestrian at fault

As it was illustrated in figures (15,16), the crashes in which pedestrian being at fault accounted for 32, and 68 percent (505, and 1334 crashes) of total crashes that occurred at the vicinity of intersections (1583) and roadway (1966).However, in some crashes, pedestrians were found at fault for more than one cause.

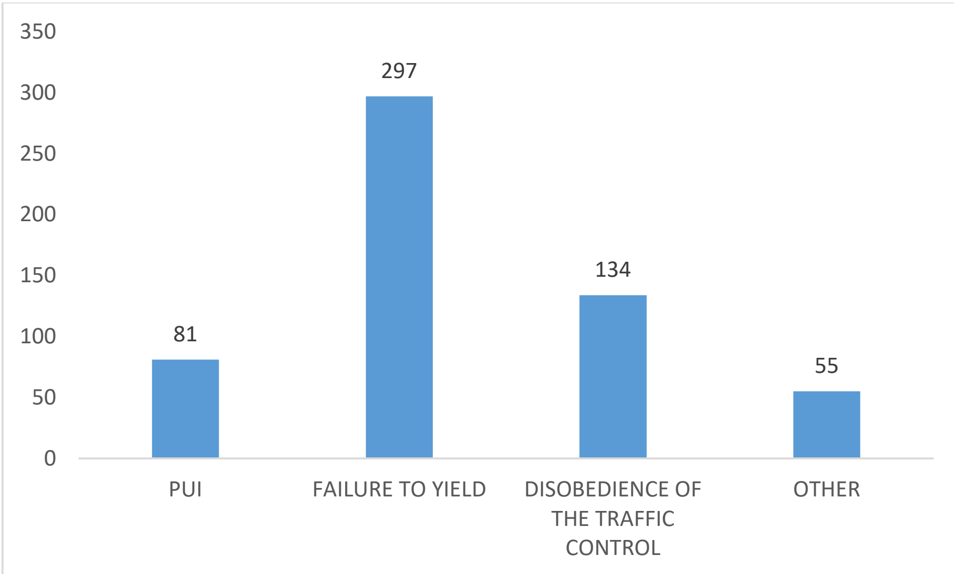

Figure 23: Causes of pedestrian crashes at intersection when pedestrian being at fault

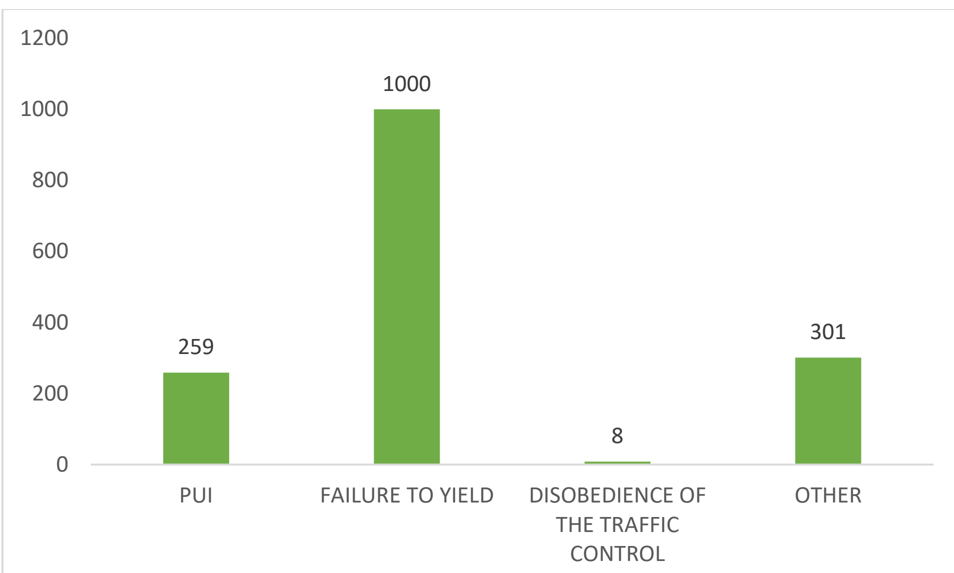

Figure 24: Causes of pedestrian crashes at roadway when pedestrian being at fault

3.5.1.1 Failing to yield

This risk behavior was found to be committed by both pedestrians and motorists. The crashes that involve pedestrians failed to yield to the right of way include pedestrian failure to yield to the right of way for right and left turning vehicles,dash, crossing an expressway, dart-out, mailbox-related, trapped, walking in roadway, lying in roadway, standing in roadway, working in roadway, playing in roadway,dancing in roadway, and play vehicle-related . Overall, 19 percent of analyzed pedestrian crashes at intersections and 51 percent of analyzed pedestrian crashes at roadway were a result of this risk behavior .

3.5.1.2 Pedestrians disregarding traffic control sign, signal, or officer

These crashes resulted from pedestrian failing to obey traffic sign ,signal, or officer. In total, 8 percent of all pedestrian crashes analyzed at intersections ,and 0.4 percent of all pedestrian crashes analyzed at roadway resulted from pedestrians' disobedience to traffic control devices.

3.5.1.3 Pedestrian being under the influence of alcohol or drugs (PUI)

At Intersections, about 5 percent of analyzed crashes resulted from pedestrian being under the influence of alcohol or drugs, while they account for 13 percent at roadway.

3.5.1.4 Other

Crashes within this group include some other reasons ,such as failing to use sidewalks, wrong walking direction, disabled vehicle-related, entering / exiting parked vehicle, school bus-related, and other unusual circumstances. Overall, other causes comprised nearly 3% and 15% of all analyzed crashes occurred at intersections and roadway respectively.

3.5.2 Driver at fault

As it was illustrated in figutures (15,16), the crashes in which motorist being at fault accounted for 51, and 18 percent (800, and 345 crashes) of total crashes occurred at vicinity of intersections and roadway (1583,1966).However, in some crashes, motorists were found at fault for more than one cause.

3.5.2.1 Failing to yield

As noted earlier, this risk behavior was committed by both pedestrians and motorists. The crashes caused by drivers that failed to yield to the right of way include right and left turning vehicles failed to yield to pedstrians at intersections in marked or unmarked crosswalk, drivers failed to slow down before reaching the intersection in the absence of a crosswalk at an intersection, motorists failed to fully stop at yield sign or stop sign, backing vehicle – roadway failed to yield to the right of way to crossing pedestrians and motor vehicles failed to yeild to pedestrians at midblock crosswalk.

. Overall, 31, and 3 percent of analyzed pedestrian crashes occurred at intersections and roadway respectively were a result of this risk behavior.

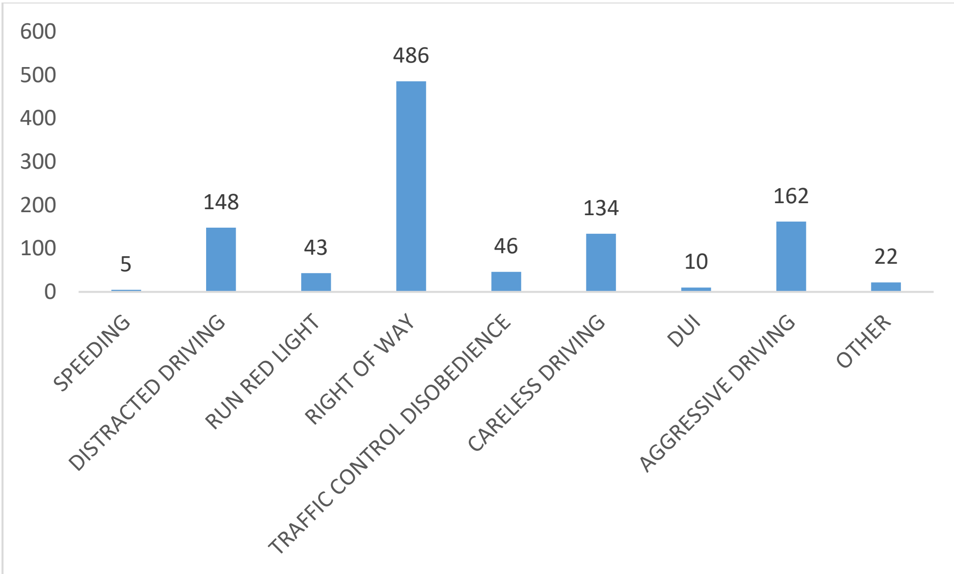

Figure 25: Causes of pedestrian crashes at intersection when motorist being at fault

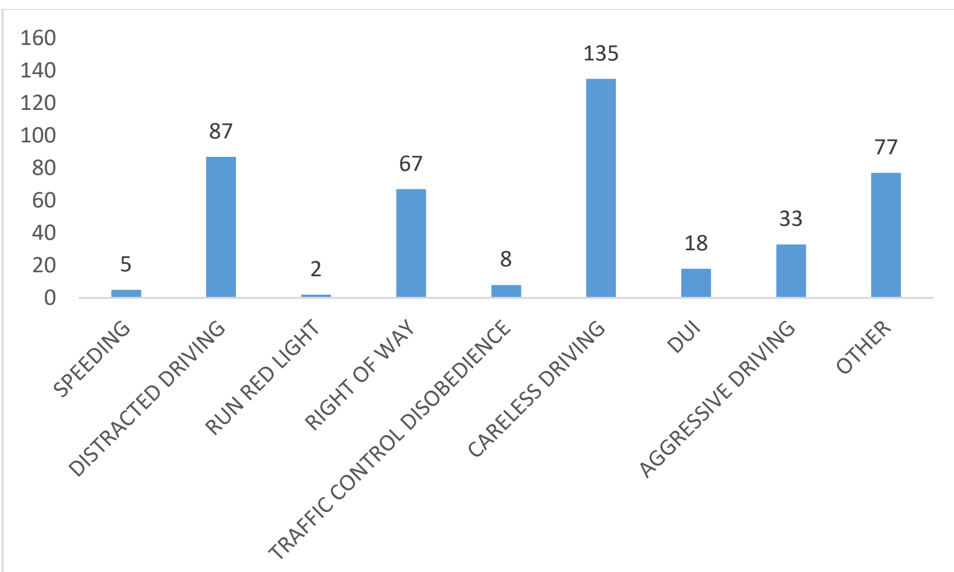

Figure 26: Causes of pedestrian crashes at roadway when motorist being at fault

3.5.2.2 Disregarding traffic control sign, signal, or officer

These crashes resulted from drivers' failure to obey traffic sign ,signal, or officer. In total, 3 percent of all pedestrian crashes analyzed at intersections were resulting from drivers' disobedience to traffic control.

3.5.2.3 Driver being under the influence of alcohol or drugs (DUI)

These include all crashes associated with the presence of alcohol, such as motor vehicle loss of control,and drove off roadway. At both Intersections and roadway, about 1 percent of analyzed crashes resulted from driver being under the influence of alcohol or drugs.

3.5.2.4 Speeding

Speeding accounts for less than 1 percent of all analyzed crashes at intersection or roadway.

3.5.2.5 Distracted driving

Distracted driving constituted 9 and 4 percent respectively of all pedestrian crashes analyzed at intersections and roadway.

3.5.2.6 Running red light

It constituted 3 percent of all pedestrian crashes analyzed at intersections and less than 1 percent of all analyzed crahes at roadway.

3.5.2.7 Careless driving

Careless driving caused about 8, and 7 percent of all crashes occurred at intersections and roadway respectively.

3.5.2.8 Aggressive driving

It resulted in 10, and 2 percent of all crashes occurred at intersections and roadway respectively.

3.5.2.9 Other

Crashes within this group include driver having medical emergency, being in wrong lane, being in wrong direction, improper passing, improper turn, failure to leave enough clearance . They constituted nearly 1 and 4 percent of all analyzed crashes at intersections and roadway.

CHAPTER FOUR: MODELING APPROACH

4.1 Data Source:

As mentioned earlier, data from the Signal 4 Analytics database was used in this study. It included all the pedestrian crashes that occurred in Central Florida over a 5 year-period (2011-2015). The analysis included the pedestrian crashes that occurred at intersections and along roadway segments at mid-block locations. In the analysis, pedestrian crash frequencies are used instead of crash rates for three reasons, First, pedestrian volumes are expensive and difficult to collect, so it is a hard task to determine the pedestrian exposure since it depends on both pedestrian and vehicles volume. Second, there is a lack of surrogate data and accuracy for estimating pedestrian volumes. Third, pedestrian crashes happen rarely compared to vehicle crashes, thus it can fluctuate from the random nature of crash occurrences.

The focus in this study was on pedestrian, driver, location and environmental related factors. Those factors were identified as risk factors that involved pedestrian crashes. It should be noted that pedestrian and driver characteristics such as gender or age were not included in the analysis.

4.2 Crash types Classification:

4.2.1 Pedestrian crashes at intersections:

The three major types of crashes at intersections were through moving vehicles, left turning, and right turning vehicles crashes colliding with crossing pedestrian. Since the crashes that occurred while pedestrians were crossing accounted for 93% of total crashes at intersections, the other crash types were not included in the analysis.

The other types included pedestrians struck while walking along roadways, standing, lying, etc. Therefore, considering only crossing pedestrians, the three common crashes at intersection (TH, LT, RT) were used as categorical outcomes for the response of the multinomial model that predicts the likelihood of the crash types at intersection and mid-block locations.

4.2.2 Pedestrian crashes at mid-block locations:

A similar approach was adopted for the mid-block locations. Crossing and walking along roadways struck by through moving vehicles were observed to be the most common crashes at midblock locations. For a multinomial model that predicts the likelihood of the crash types at intersection and mid-block locations, through vehicle crashes was a possible categorical outcome for the response of mid-block locations.

4.3 Independent variables

Several pedestrian, driver, location and environmental characteristics were identified as variables that influence the type and severity of pedestrian crashes. Pedestrian characteristics include the actions that the reporting officer reported in the crash report as pedestrian contributing actions regardless if the pedestrian was issued a citation or not. The most common actions were failure to yield to the right of way to driver, and disobedience of traffic signs, signals, or officers. Pedestrians under the influence also were included in the data even though it was not as common as the other two previous pedestrian characteristics based on the descriptive statistics. The involvement of handicapped pedestrians was considered within the pedestrian characteristics.

Like pedestrian characteristics, driver characteristics include all the actions concluded by reporting officers as a driver's contributing action that caused the crash. Those characteristics encompass drivers' alcohol/ drug use, failure to yield to the right of way to pedestrians, disobedience of traffic control, speeding, running red light, distracted, aggressive, and careless driving.

Environmental characteristics contain weather condition, road surface, and time of day. Finally, location characteristics comprise crash location, type of traffic control, presence of crosswalk, and presence of sidewalk.

4.4 Data Analysis and Models background

Discrete or nominal data is widely common in the transportation field. Mode of travel (auto-mobile, bus, rail transit), and type of vehicles accident (run-off-road, rear-end, head-on, etc.) are examples of discrete data in transportation. The approach to statistically model the discrete outcomes is identical even though it differs in the theories used to derive these models. Two popular modeling approaches are utilized; probit and logit.

In the analysis, since the dependent variables (pedestrian crash type, signalized VS un-signalized intersections, and injury severity) are categorical in nature, models of discrete data were used. Three different models were chosen based on the level of the outcome.

A multinomial logit model was developed to predict the likelihood that a pedestrian will be involved into one of the common crash types. A binary regression model was developed to understand the significant factors contributing to the occurrence of crashes at each intersection type whether at signalized intersections or unsignalized ones. Lastly, ordinal regression model was developed to identify the significant factors affecting the level of injury severity sustained by pedestrians at both intersections and mid-block locations. Statistical analysis was initially conducted for all intersection and roadway crashes combined in general models, however, due to the difference in the crash characteristics and contributing factors in terms of the location for intersections and roadways, it was imperative to separate the intersection crashes from the roadway crashes and develop separate models as will be shown in chapter 5.

4.4.1 Multinomial Logit Model to Predict the Crash Type

It is a proper statistical model to use when the outcome variable is nominal with three or more levels. The categorical independent variables are used to predict the probabilities of unordered categorical outcomes. The results of the model are used to estimate the odds that the response, which is the pedestrian crash type in this study, will be in one category as compared to another category. To overcome the problem that the analysis may end up with the total probability of choosing all possible outcome categories greater than 1, one of the outcomes is set to be a baseline or reference outcome category, and the result is illustrated to compare the odds of the other outcomes to the reference outcome.

Two Multinomial Logit models were developed. Initially, a general Multinomial Logit Model was developed to predict the probability of the pedestrian crash types at intersections and mid-block locations combined because the dependent variable has three level outcomes (through, left turn, and right turn crashes). Left turn crash was set to be the baseline. However, due to the difference in the crash characteristics and contributing factors in terms of the location for intersections and roadways, it was imperative to separate the intersection crashes from the roadway crashes and develop separate Multinomial Logit model for intersection crashes. A Multinomial model could not be used to predict the crash types of mid-block locations because the common crashes that occurred at mid-block locations are less than three. Following is the standard multinomial logit (MNL) formulation.

$$P_n(i) = \frac{EXP[\beta_i X_{in}]}{\sum_{\forall I} EXP(\beta_I X_{In})} \quad (1)$$

Where $P_n(i)$ is the probability of observation n having discrete outcome (i ∈ I), I denoting all possible outcomes for observation n, β_i is a vector of estimable parameters for discrete outcome i and X_{in} is a vector of observable characteristic (covariates) that determine discrete outcome for observation n.

Statistical Evaluation

The more general and appropriate test is the likelihood ratio test. It assesses the significance of individual parameters. The likelihood ratio test follows a chi-square distribution. The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The likelihood ratio test statistic is

$$X^2 = -2[LL(\beta_R) - LL(\beta_U)] \quad (2)$$

T-statistics is also commonly used and practically reliable to assess the variables' significance although it assumes normality which is not strictly true due to the assumption that the MNL is derived from extreme value distribution not from a normal distribution.

4.4.2 Binary regression Model to predict the crash location

It is used when the outcome variable is discrete with two levels. Binary regression model is distinguished from multinomial models by assuming the disturbance term is normally distributed.

$$P_n(1) = P(\beta_1 X_{1n} - \beta_2 X_{2n} > \varepsilon_{2n} - \varepsilon_{1n}) \quad (3)$$

Where $P_n(1)$ is the probability of outcome 1 occurring for observation n, $\varepsilon_{2n}, \varepsilon_{1n}$ are the random disturbance terms. β_1, β_2 are vectors of estimable parameters for discrete outcome 1 and 2 respectively.

A binary regression model was utilized to model the significant factors contributing to the main causes at each intersection type due to the consideration of two level outcomes (at signalized intersections or unsignalized intersections).

4.4.3 Ordinal regression (Ordered Logit) model for injury severity

It is widely used to predict the probability of ordinal discrete outcomes. Ordered probability models are derived by defining an unobserved variable z that is used as a basis for modeling the ordinal ranking of data.

$$Z = \beta X + \varepsilon \qquad (4)$$

This unobserved variable is typically a linear function for each observation.

where X is a vector of variables determining the discrete ordering for observation n, β is a vector of estimable parameters, and ε is a random disturbance.

The observed ordinal data, y, is related to Z for each observation as defined :

$y = 1$ if $z \leq \mu0$

$y = 2$ if $\mu0 < z \leq \mu1$

$y = 3$ if $\mu1 < z \leq \mu2$ (14.2) (5)

$y = . . .$

$y = I$ if $z \geq \mu I–1$

where μ are estimable parameters (referred to as thresholds) that define y, which corresponds to integer ordering,

By assuming that ε is normally distributed across observations with mean = 0 and variance = 1 (probit models' assumption), the probabilities of the ordered outcomes is:

$$P(y = i) = \emptyset(\mu_i - \beta X) - \emptyset(\mu_{i+1} - \beta X) \qquad (6)$$

where μi and μi+1 represent the upper and lower thresholds for outcome I, and Φ(·) is the cumulative normal distribution

Three Ordinal Regression models were developed. One general model to identify the contributing factors affecting the level of injury severity sustained by pedestrians for the intersections and mid-block locations combined, and two models identifying the significant factors affecting the level of injury severity sustained by pedestrians at intersections and mid-block locations separately.

CHAPTER FIVE: ANALYSIS AND RESULTS

5.1 Background

The data obtained from the Signal 4 Analytics database contained 6,789 crashes that have occurred in Central Florida over a 5 year-period (2011-2015). After conducting the crash screening criteria, which was explained in chapter 3, a total of 3,549 crashes at intersections and along roadway segments at mid-block locations was determined. Of these crashes, 1,583 occurred at intersections, and 1,966 occurred along roadway segments (between intersections).

The explanatory and dependent variables were identified and extracted to an Excel sheet to be used in the analysis. Crash types identified earlier were considered for the analysis. For intersection-related crashes, left turn, right turn and through moving vehicles striking crossing pedestrians were the three major crash types. At midblock locations, major crash types were through moving vehicles hitting pedestrians crossing and walking along the roadway. A "dark clothes" variable was eliminated before the model being carried out due to insufficiency of the data in the crash reports. The variable of "Roadway condition" was also eliminated from the analysis due to the collinearity with the "Weather condition" variable. Not all crash records had complete information. Records missing key information were excluded before the analysis.

The final full dataset for intersection and mid-block locations included 2,608 crashes. Of these crashes, 1,171 occurred at intersections, and 1,437 occurred along roadway segments (between intersections). Since all the dependent variables were categorical; therefore, Discrete Outcome Models were utilized in the analysis of the crashes. Each model was selected based on the level of the dependent variable to be predicted. Table (1) illustrates all the variables used in the analysis with their subcategories.

Table 1: Variables Considered for the Analysis

Set	Factor	Variable	Code	Measure
Pedestrian Characteristics	Pedestrian-related Causes	Pedestrian under influence (PUI), Pedestrian failed to yield right of way PFYROW, Pedestrian disobeyed traffic control PFYTCD, handicapped Pedestrian, Pedestrian walking along roadway, Pedestrian crossing	1	Nominal
			2	
Driver characteristics	Driver-related Causes	Driver under influence (DUI), Driver failed to yield to right of way DFTYRW, Driver disobeyed traffic control DFYTCD, Run red light, Distracted driving, Careless driving, Speeding, Aggressive Driving	1	Nominal
			2	
Environmental Characteristics	Weather	Clear	1	Nominal
		Reverse	2	
	Time of Day	Daytime	1	Nominal
		Nighttime lightened	2	
		Nighttime-not lightened	3	
Location Characteristics	Presence of Crosswalk	No	1	Nominal
		NA (Along roadway crash)	2	
		Yes	3	
	Presence of Sidewalk	No	1	Nominal
		NA (Crossing crash)	2	
		Yes	3	
	Type of Control	No control	1	Nominal
		Control sign	2	
		Signal Control	3	
	Crash Location	Intersection	1	Nominal

Set	Factor	Variable	Code	Measure
Crash Characteristics		Midblock	2	
	Crash Type	LEFT TURN	1	Nominal
		RIGHT TURN	2	
		THROUGH	3	
	At Fault Party	Driver	1	Nominal
		Pedestrian	2	
	Injury Severity	None	1	Ordinal
		Possible	2	
		Minor	3	
		Major	4	
		Fatal (within 30 days)	5	

For “Presence of Crosswalk” and “Presence of Sidewalk” variables, when the presence of either a sidewalk or crosswalk was not mentioned in the report, Google Maps was used to investigate whether they were present or not. The subcategory “NA” was used with the “Presence of Crosswalk” when the crash involved a walking pedestrian along the roadway. Similarly, it was used with the explanatory variable of “Presence of Sidewalk” when the crash involved a crossing pedestrian.

5.2 Analysis Process

SPSS statistical software package was used to develop the regression models. A backward Stepwise Regression procedure was used. The criteria used for variables inclusion was significance level (α=0.05 used in the study). The first step in developing the model started with including all the variables and sequentially removing one independent variable at each step. The variable removed was the one that showed no significance ($P>0.05$). The procedure iterates until a good fit regression model was obtained in the final step, in which all the included explanatory variables were significant ($P<=0.05$). Any independent variable that had at least one significant subcategory variable was retained.

5.3 Models Analysis and Results

5.3.1 Multinomial Logistic Regression Model

All the aforementioned explanatory variables in Table 1 were used in the initial model, however, 8 of them showed a statistical significance and were retained, as shown in Table 2. For all the three crash types, left turn crash was set as baseline. The estimated coefficient (B) and the odd ratio (EXP(B)) were used to predict the odds that the crash type will be in one category (right turn or through crash) as compared to the left turn crash.

Table 2: The final Multinomial Logit Model for Intersections and mid-block locations crashes

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	408.257[a]	.000	0	.
TypeofControl	691.955	283.698	4	.000
AtFaultParty	885.571	477.314	2	.000
DRIVERFTYTCD	414.302	6.045	2	.049
RunRedLight	422.186	13.929	2	.001
Carelessdriving	439.947	31.690	2	.000
AggressiveDriving	414.140	5.883	2	.053
HandicapedPed	414.982	6.725	2	.035
TOD	430.539	22.282	4	.000

Table 3: Parameter Estimates for Crash Type at intersections and mid- block locations

VEH MOV[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
RT	Intercept	-.571	.916	.388	1	.533			
	[TypeofControl=No Cntrl]	-.444	.244	3.316	1	.069	.642	.398	1.034
	[TypeofControl=Sign]	.344	.198	3.022	1	.082	1.411	.957	2.080
	[TypeofControl=Signal]	0[b]	.	.	0	.	.	.	.
	[AtFaultParty=Driver]	.704	.259	7.385	1	.007	2.022	1.217	3.359
	[AtFaultParty=Ped]	0[b]	.	.	0	.	.	.	.
	[DRIVERFTYTCD=No]	-.169	.472	.128	1	.720	.844	.335	2.129
	[DRIVERFTYTCD=Yes]	0[b]	.	.	0	.	.	.	.
	[RunRedLight=No]	-.608	.496	1.504	1	.220	.544	.206	1.439
	[RunRedLight=Yes]	0[b]	.	.	0	.	.	.	.
	[Carelessdriving=No]	.523	.277	3.566	1	.059	1.687	.980	2.902
	[Carelessdriving=Yes]	0[b]	.	.	0	.	.	.	.
	[AggressiveDriving=No]	.530	.222	5.696	1	.017	1.698	1.099	2.624
	[AggressiveDriving=Yes]	0[b]	.	.	0	.	.	.	.
	[HandicapedPed=N]	-.776	.346	5.024	1	.025	.460	.234	.907
	[HandicapedPed=Y]	0[b]	.	.	0	.	.	.	.
	[TOD=Daytime]	.400	.266	2.256	1	.133	1.492	.885	2.513
	[TOD=Night-L]	.245	.306	.640	1	.424	1.277	.702	2.325
	[TOD=Night-NL]	0[b]	.	.	0	.	.	.	.
TH	Intercept	6.101	.866	49.626	1	.000			
	[TypeofControl=No Cntrl]	2.262	.175	166.112	1	.000	9.599	6.805	13.539
	[TypeofControl=Sign]	1.523	.198	59.328	1	.000	4.585	3.112	6.756

VEH MOV[a]	B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
							Lower Bound	Upper Bound
[TypeofControl=Signal]	0[b]	.	.	0	.	.	.	.
[AtFaultParty=Driver]	-2.940	.187	246.425	1	.000	.053	.037	.076
[AtFaultParty=Ped]	0[b]	.	.	0	.	.	.	.
[DRIVERFTYTCD=No]	-.909	.444	4.202	1	.040	.403	.169	.961
[DRIVERFTYTCD=Yes]	0[b]	.	.	0	.	.	.	.
[RunRedLight=No]	-1.636	.479	11.651	1	.001	.195	.076	.498
[RunRedLight=Yes]	0[b]	.	.	0	.	.	.	.
[Carelessdriving=No]	-.847	.232	13.364	1	.000	.429	.272	.675
[Carelessdriving=Yes]	0[b]	.	.	0	.	.	.	.
[AggressiveDriving=No]	.170	.229	.554	1	.457	1.186	.757	1.858
[AggressiveDriving=Yes]	0[b]	.	.	0	.	.	.	.
[HandicapedPed=N]	-.768	.354	4.699	1	.030	.464	.232	.929
[HandicapedPed=Y]	0[b]	.	.	0	.	.	.	.
[TOD=Daytime]	-.549	.198	7.668	1	.006	.577	.391	.852
[TOD=Night-L]	-.128	.225	.324	1	.569	.880	.566	1.367
[TOD=Night-NL]	0[b]	.	.	0	.	.	.	.

a. The reference category is: LT.

b. This parameter is set to zero because it is redundant.

Type of control, at fault party, driver's disobedience of traffic control device (signal, sign, officer), running the red light, careless driving, aggressive driving, involvement of handicapped pedestrian, and time of the day were found to have a significant impact on the type of pedestrian crashes at intersections and midblock location. Many other independent variables (e.g., at crosswalk, speeding and distracted driving, pedestrian being under influence of drugs or alcohol, pedestrian's failure to yield right of way, driver's failure to yield right of way, pedestrian disobedience of traffic control (sign, signal, officer), driving under influence, and weather condition were tried but none of them showed a strong statistical evidence of association with pedestrians' crash type.

Left turn variable was defined as the reference category. "Type of control" variable was significant for the through moving vehicles. The results show a higher probability of crash occurrence associated with through moving vehicles at non-signalized locations or locations controlled with traffic signs when compared to left turn crashes. The probability of through moving vehicle crashes at locations with no traffic control device was 9.599 times (OR) of left turn crashes.

Drivers were found (2.022) times more likely to be at fault in right turn crashes (which is mainly at intersections) compared to left turn crashes. In contrast, drivers were less likely (0.053) to be the main cause for the through crashes compared to left turn crashes. "Driver Failed to Yield to Traffic Control ", "Run Red Light" and " Careless Driving" variables were significant for through moving crashes. Driver running the red light , disobeying traffic control device, or driving carelessly increase the odds of through crash when compared to left turn crashes.

However, left turn crashes were more likely to occur with aggressive driving compared to right turn crashes. The chance of right turn crashes not caused by aggressive driving is 1.698

times when compared to left turn crashes. The probability of right turn and through crashes are higher when a handicapped pedestrian is involved. Most right turn movements are allowed on red signals at intersections compared to left turn movements while thru movement crashes involving a handicapped pedestrian are found to be at midblock crossings which are rarely controlled.

Finally, "Time of Day" variable is significant for through moving vehicles crashes. Through crashes are less likely to occur at daytime compared to left turn crashes. Left turn crashes were 1.79 times more likely to be associated with day time when compared to through crashes.

5.3.2 Binary Model

As it was mentioned, SPSS statistical software package was used to carry out the model. All the explanatory variables of the intersections dataset that was mentioned in Table 1 were used in the initial model. A backward stepwise regression procedure was used until the final model was achieved, in which all included independent variables were significant (at 95% CI). 5 of the variables showed a statistical significance and were retained, as shown in Table 6. While developing the model, a sub-category variable should be defined as a reference for every independent variable that has more than one category. The parameters are estimated taking this sub-category as reference. Table 5 shows the coding for the significant independent variables of the final binary model to be used for the result inference. Overall, the outcome measures predict the probability for crashes that occurred at un-signalized intersections for each variable compared to the reference variable. Un- signalized intersections include all intersections that do not have any type of control or un-signalized intersections but have some type of sign control, such as special speed zone, school zone sign/device, stop sign, yield sign, person (officer, flagman, guard) and Warning sign.

Table 4 : Dependent Variables Encoding

Original Value	Internal Value
Signalized	0
Unsignalized	1

Table 5: Categorical Variables Codings

		Frequency	Parameter coding	
			(1)	(2)
VEH MOV	LT	345	1.000	.000
	RT	281	.000	1.000
	TH	545	.000	.000
PED FTY TCD	No	1039	1.000	
	Yes	132	.000	
At Fault Party	Driver	708	1.000	
	Ped	463	.000	
Run Red Light	No	1128	1.000	
	Yes	43	.000	
At Crosswalk	N	425	1.000	
	Y	746	.000	

Table 6 : Estimated Parameters for Un-signalized intersections crashes

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	AtCrosswalk (1)	2.751	.222	153.888	1	.000	15.657
	AtFaultParty (1)	1.744	.254	47.180	1	.000	5.722
	RunRedLight (1)	1.381	.401	11.879	1	.001	3.977
	VEHMOV			33.108	2	.000	
	VEHMOV (1)	-1.030	.188	29.905	1	.000	.357
	VEHMOV (2)	-.911	.201	20.456	1	.000	.402
	PEDFTYTCD (1)	1.741	.393	19.659	1	.000	5.703
	Constant	-4.480	.547	67.159	1	.000	.011

a. Variable(s) entered on step 1: AtCrosswalk, AtFaultParty, RunRedLight, VEHMOV, PEDFTYTCD.

Result of the Binary Model:

The existence of crosswalk, at fault party, run red light, vehicle movement, and pedestrian's failure to obey the traffic control device showed a statistical significance in the model at a 95% confidence level ($P<0.05$). The Categorical Variables Codings in the Table 5 illustrates the coding system defined by the SPSS program. As mentioned earlier, for each variable, there was a sub-category defined to be a reference, in which the results were compared to it. For existence of crosswalk variable, the "crosswalk exists" sub-category was set to be the reference. Similarly, the sub-categories Pedestrian at Fault, Driver Run Red Light, Pedestrian disobeys Traffic Control Device, and Vehicles proceeding through were defined as references for their relevant independent variables.

The results revealed that the sub-category (1) for the "At Crosswalk" variable was significant at a 95% confidence level ($P=0<0.05$). In the categorical coding table, AtCrosswalk (1) refers to no crosswalk presents. The coefficient of AtCrosswalk(1) is 2.751. The positive sign indicates that the crashes are more likely to occur at un-signalized intersections if crosswalks do not exist. The chance of crashes at un-signalized intersections is 15.657 times higher in the absence of crosswalks compared to locations in which crosswalks are present.

The results also showed that the sub-category (1) for the "At fault party" variable was significant at a 95% confidence level ($P=0<0.05$). In the categorical coding table, (1) refers to driver being at fault. The coefficient of At Fault Party (1) is 1.744. The likelihood of crashes at un-signalized intersections was higher when the driver is at fault. The probability of crashes at un-signalized intersections in which the drivers were the contributing factors of the crash is 5.722 times higher compared to when the pedestrians were the at fault party. A higher chance of crashes at signalized intersections were associated with running the red light.

Furthermore, the probability of crashes at un-signalized intersections is lower when the vehicle turns either right or left. The likelihoods of crashes at un-signalized intersections are 0.357 and 0.402 times lower when the vehicle maneuvers left or right respectively compared to proceeding through vehicle.

Finally, the results illustrate a lower chance of crash occurrence at signalized intersections when pedestrians obey the traffic control device compared when pedestrians disobey. That agrees with the Multinomial Model which showed a higher likelihood of frequency of through crashes associated with running the red light, drivers' disobedience of traffic control, and careless driving when compared to left turn crashes, which confirms that a higher likelihood of crashes that occurred near the intersections were a result of a drivers' fault.

5.3.3 Ordinal Regression Model

Similar to the previous process used in developing the binary model, all the independent variables mentioned in Table1 were used in the initial model, however, 8 of them showed a statistical significance and were kept in the final model shown in Table 7. The sub-category Fatal was the reference, so positive estimated coefficients in the model imply increasing likelihood of fatalities and decreasing likelihood of no injuries.

Results of the Ordinal Regression Model

Table 7: Parameter Estimates for Injury Severity

Factors		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[INJURYSEV_A = 1]	-6.594	.412	256.751	1	.000	-7.401	-5.788
	[INJURYSEV_A = 2]	-5.373	.402	178.566	1	.000	-6.161	-4.585
	[INJURYSEV_A = 3]	-2.539	.388	42.919	1	.000	-3.299	-1.779
	[INJURYSEV_A = 4]	-.780	.387	4.064	1	.044	-1.538	-.022
Location	[TypeofControl=No Cntrl]	-.111	.099	1.245	1	.264	-.305	.084
	[TypeofControl=Sign]	-.428	.126	11.622	1	.001	-.675	-.182
	[TypeofControl=Signal]	0[a]	.	.	0	.	.	.
	[AtFaultParty=Driver]	-1.017	.135	56.364	1	.000	-1.283	-.752
	[AtFaultParty=Ped]	0[a]	.	.	0	.	.	.
	[RunRedLight=No]	-.690	.308	5.016	1	.025	-1.294	-.086
	[RunRedLight=Yes]	0[a]	.	.	0	.	.	.
	[AggressiveDriving=No]	-.617	.166	13.842	1	.000	-.942	-.292
	[AggressiveDriving=Yes]	0[a]	.	.	0	.	.	.
	[VEHMOV=LT]	-.408	.135	9.208	1	.002	-.672	-.145
	[VEHMOV=RT]	-.515	.148	12.124	1	.000	-.805	-.225
	[VEHMOV=TH]	0[a]	.	.	0	.	.	.
	[PedFTYROW=No]	-.332	.105	9.957	1	.002	-.539	-.126
	[PedFTYROW=Yes]	0[a]	.	.	0	.	.	.
	[PUI=NO]	-.671	.117	32.692	1	.000	-.900	-.441
	[PUI=Yes]	0[a]	.	.	0	.	.	.
	[TOD=Daytime]	-.847	.097	76.651	1	.000	-1.036	-.657
	[TOD=Night-L]	-.297	.100	8.865	1	.003	-.492	-.101
	[TOD=Night-NL]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Type of control device, at fault party, pedestrians/drivers' failure to yield right of way, running the red light, aggressive driving, vehicle movement, pedestrian being under influence, time of the day variables were found to be significantly affecting the level of injury severity sustained by pedestrian struck by a vehicle.

The sub category traffic sign control was significant (P=0.01). Its negative coefficient indicates a lower likelihood of severe injuries associated with locations controlled by traffic signs compared to crashes occurring at signalized locations. Severity at signalized locations is probably due to red light running for thru vehicles and crossing pedestrians. Estimated coefficients for at fault party was negative and statistically significant (at 95% confidence level), implying a lower probability of severe injuries for crashes caused by drivers at fault compared to crashes caused by pedestrians' fault.

Crashes that are not resulting from running the red light were associated with lower likelihood of severe injuries compared to running red light crashes. similarly, crashes resulted in aggressive driving increased the likelihood of severity. Furthermore, crashes caused by vehicles turning left or right, which are mainly intersections-related crashes, are associated with less severe injuries than crashes associated with through moving vehicles due to the lower turning speed. A previous study done by Schneider et al (2013) found an increase in fatal probability when crossing between intersections. Chu (2006) indicated a higher chance of fatality risk was associated with mid-block crashes.

A higher likelihood of severe injury was significant for pedestrians failing to yield to the right of way. Similar to Chu's (2006) observation, the likelihood of severe injuries was significantly higher for pedestrians under influence of drugs or alcohol compared to sober pedestrian.

Finally, the likelihood of less severe injury was associated with crashes occurring during daylight time and nighttime but with street lighting compared to crashes that occurred during nighttime conditions and without street lighting, which agrees with findings of Aty and Lee(2005), Doan (1966), Schneider et al(2013), Haleem et al (2013), and Chu (2006).

5.3.4 Separated Models for Intersections and Mid-Block Locations

As it was mentioned earlier in Chapter 4, in order to get more detailed results and the contributing factors for each location, separate models for each location were also developed as shown in the following sections.

5.3.4.1 Multinomial Logistic Regression for Intersections

A Multinomial Regression Model was developed to predict the crash types at the intersections since the most common crashes were left, right, and through moving vehicles striking crossing pedestrians. A similar process in section 5.3.1 was used. Tables 8 and 9 illustrate the output of the Multinomial Regression model that was developed for intersections-related crashes.

Table 8: The final Multinomial Logit Model for Intersections crashes

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	224.966[a]	.000	0	.
TypeofControl	278.804	53.838	4	.000
AtFaultParty	539.928	314.962	2	.000
DRIVERFTYTCD	230.604	5.639	2	.060
RunRedLight	248.660	23.694	2	.000
Carelessdriving	240.426	15.460	2	.000
AggressiveDriving	229.908	4.942	2	.085
HandicapedPed	232.366	7.400	2	.025

Table 9: Parameter Estimates for Crash Type at intersections

VEH MOV[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
RT	Intercept	-.195	.891	.048	1	.827			
	[TypeofControl=No Cntrl]	-.509	.242	4.438	1	.035	.601	.374	.965
	[TypeofControl=Sign]	.350	.198	3.123	1	.077	1.419	.963	2.093
	[TypeofControl=Signal]	0[b]	.	.	0	.	.	.	.
	[AtFaultParty=Driver]	.753	.258	8.503	1	.004	2.123	1.280	3.522
	[AtFaultParty=Ped]	0[b]	.	.	0	.	.	.	.
	[DRIVERFTYTCD=No]	-.200	.469	.181	1	.670	.819	.327	2.053
	[DRIVERFTYTCD=Yes]	0[b]	.	.	0	.	.	.	.
	[RunRedLight=No]	-.626	.490	1.633	1	.201	.535	.205	1.397
	[RunRedLight=Yes]	0[b]	.	.	0	.	.	.	.
	[Carelessdriving=No]	.552	.277	3.982	1	.046	1.737	1.010	2.987
	[Carelessdriving=Yes]	0[b]	.	.	0	.	.	.	.
	[AggressiveDriving=No]	.487	.221	4.840	1	.028	1.627	1.055	2.511
	[AggressiveDriving=Yes]	0[b]	.	.	0	.	.	.	.
	[HandicapedPed=N]	-.810	.345	5.501	1	.019	.445	.226	.875
	[HandicapedPed=Y]	0[b]	.	.	0	.	.	.	.
TH	Intercept	5.535	.913	36.737	1	.000			
	[TypeofControl=No Cntrl]	.891	.197	20.548	1	.000	2.437	1.658	3.583
	[TypeofControl=Sign]	1.024	.216	22.574	1	.000	2.785	1.825	4.250
	[TypeofControl=Signal]	0[b]	.	.	0	.	.	.	.
	[AtFaultParty=Driver]	-2.620	.208	158.633	1	.000	.073	.048	.109
	[AtFaultParty=Ped]	0[b]	.	.	0	.	.	.	.
	[DRIVERFTYTCD=No]	-.959	.461	4.318	1	.038	.383	.155	.947
	[DRIVERFTYTCD=Yes]	0[b]	.	.	0	.	.	.	.
	[RunRedLight=No]	-2.015	.468	18.532	1	.000	.133	.053	.334
	[RunRedLight=Yes]	0[b]	.	.	0	.	.	.	.
	[Carelessdriving=No]	-.593	.270	4.829	1	.028	.553	.326	.938
	[Carelessdriving=Yes]	0[b]	.	.	0	.	.	.	.
	[AggressiveDriving=No]	.179	.266	.452	1	.501	1.196	.710	2.015
	[AggressiveDriving=Yes]	0[b]	.	.	0	.	.	.	.
	[HandicapedPed=N]	-.837	.373	5.037	1	.025	.433	.209	.899
	[HandicapedPed=Y]	0[b]	.	.	0	.	.	.	.

a. The reference category is: LT

b. This parameter is set to zero because it is redundant.

Results of Multinomial Regression Model for Intersection Crashes:

Type of control, at fault party, driver's disobedience of traffic control device (signal, sign, officer) , running red light, careless driving, aggressive driving, and involvement of handicapped pedestrians were all found to have a significant impact on the type of pedestrian crashes at intersections.

Left turn variable was defined as the reference category. "Type of control" variable was significant at a 95% confidence level ($P<0.05$). The results show that the left turn crashes were more likely to occur at un-signalized intersections compared to right turn crashes. However, through moving crashes at non-signalized intersections (OR=2.437) or un-signalized intersections which have some type of sign control, such as special speed zone, school zone sign/device, stop sign, yield sign, person: officer, flagman, guard, and Warning Sign (OR=2.785) have a higher likelihood of occurrence when compared to left turn crashes.

Drivers were found (2.123) times more likely to be at fault in right turn crashes when compared to left turn crashes. In contrast, drivers were less likely (0.073) to be the main cause for the through crashes compared to left turn crashes. "Run Red Light" and "Driver Failed to yield to Traffic Control "variables were significant for through moving crashes. Drivers running the red light or disobeying traffic control device increase the odds of through crashes when compared to left turn crashes.

Left turn crashes were more likely to occur with careless driving compared to right turn crashes. The chance of right turn crashes not caused by careless driving is 1.737 compared to left turn crashes. However, careless driving related crashes are more likely to be associated with through crashes when compared to left turn crashes. Similarly, left turn crashes were more likely to occur due to aggressive driving compared to right turn crashes.

The odds of right turn and through crashes were higher when a handicapped pedestrian is involved. That could be attributed to the fact that the majority of right turn movements are allowed on red signals at intersections compared to left turn movements while thru movement crashes are more likely to be associated with careless driving and running the red light as mentioned earlier.

5.3.4.2 Ordinal Regression Model for Injury Severity Level at intersections

Similar process in section 5.3.3 was used. All the independent variables mentioned in Table1 were used in the initial model, however, 6 of them showed a statistical significance and were kept in the final model shown in Table 10. The sub-category Fatal was the reference, so positive estimated coefficients in the model imply increasing likelihood of severe injuries and decreasing likelihood of less severe injuries.

Results of the Ordinal Regression Model for Intersection crashes:

Table 10: Parameter Estimates for Injury Severity at Intersections

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[INJURYSEV_A = 1]	-7.113	.574	153.695	1	.000	-8.237	-5.988
	[INJURYSEV_A = 2]	-5.749	.561	104.932	1	.000	-6.849	-4.649
	[INJURYSEV_A = 3]	-3.047	.538	32.042	1	.000	-4.102	-1.992
	[INJURYSEV_A = 4]	-1.064	.539	3.907	1	.048	-2.120	-.009
Location	[TypeofControl=No Cntrl]	.130	.136	.903	1	.342	-.138	.397
	[TypeofControl=Sign]	-.477	.146	10.646	1	.001	-.764	-.191
	[TypeofControl=Signal]	0[a]	.	.	0	.	.	.
	[AtFaultParty=Driver]	-1.664	.151	121.264	1	.000	-1.960	-1.368
	[AtFaultParty=Ped]	0[a]	.	.	0	.	.	.
	[RunRedLight=No]	-.942	.313	9.056	1	.003	-1.555	-.328
	[RunRedLight=Yes]	0[a]	.	.	0	.	.	.
	[Carelessdriving=No]	-.468	.210	4.942	1	.026	-.880	-.055
	[Carelessdriving=Yes]	0[a]	.	.	0	.	.	.
	[AggressiveDriving=No]	-.600	.186	10.408	1	.001	-.965	-.236
	[AggressiveDriving=Yes]	0[a]	.	.	0	.	.	.
	[PUI=NO]	-.668	.223	9.009	1	.003	-1.104	-.232
	[PUI=Yes]	0[a]	.	.	0	.	.	.
	[TOD=Daytime]	-.795	.164	23.430	1	.000	-1.117	-.473
	[TOD=Night-L]	-.262	.177	2.191	1	.139	-.609	.085
	[TOD=Night-NL]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Type of control device, at fault party, running the red light, careless and aggressive driving, pedestrian under influence, and time of the day variables were found to be significantly affecting the level of injury severity sustained by pedestrian struck by a vehicle at intersections.

The sub category traffic sign control was significant (P=0.01). Its negative coefficient indicates a lower likelihood of higher injury associated with intersections controlled by traffic signs compared to crashes occurring at signalized intersections. Severity of injuries at signalized location is probably due to red light running for thru vehicles and crossing pedestrians." At both signalized and un-signalized intersections, pedestrian crashes involving at-fault pedestrians are associated with an increase in the injury severity compared to crashes when drivers were at fault or both pedestrians and drivers were at fault (Haleem et al. 2015). Likely, estimated coefficients for at fault party was negative and statistically significant (at 95% confidence level), implying a lower probability of severe injury for crashes caused by drivers at fault compared to crashes caused by pedestrians' fault. Crashes that are resulting from running the red light were associated with higher likelihood of higher injuries compared to not running red light related crashes. Similarly, crashes associated with both aggressive and careless driving increased the likelihood of severe injuries.

Furthermore, a higher likelihood of severe injury was significant for pedestrians under influence of drugs or alcohol compared to sober pedestrians. Finally, the likelihood of less severe injury was associated with crashes occurring during daylight time when compared to crashes occurred during nighttime conditions without street lighting.

5.3.4.3 Ordinal Regression Model for Injury Severity Level at Mid-block Locations

All the explanatory variables mentioned in Table 1 were used in the initial model. Similar process in section 5.3.3 was used until the final model was achieved, in which all included independent variables were significant (at 95% CI). 6 of the variables showed a statistical significance and were retained, as shown in Table 11.

Table 11: Parameter Estimates for Injury Severity at Mid-Block Locations

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[INJURYSEV_A = 1]	-8.451	.788	115.027	1	.000	-9.995	-6.906
	[INJURYSEV_A = 2]	-7.475	.776	92.891	1	.000	-8.996	-5.955
	[INJURYSEV_A = 3]	-4.425	.753	34.538	1	.000	-5.901	-2.949
	[INJURYSEV_A = 4]	-2.760	.749	13.577	1	.000	-4.228	-1.292
Location	[AtFaultParty=Driver]	-.858	.199	18.664	1	.000	-1.247	-.469
	[AtFaultParty=Ped]	0[a]	.	.	0	.	.	.
	[AggressiveDriving=No]	-1.331	.396	11.285	1	.001	-2.108	-.555
	[AggressiveDriving=Yes]	0[a]	.	.	0	.	.	.
	[DUI=No]	-1.961	.582	11.368	1	.001	-3.101	-.821
	[DUI=Yes]	0[a]	.	.	0	.	.	.
	[PedFTYROW=No]	-.482	.135	12.682	1	.000	-.748	-.217
	[PedFTYROW=Yes]	0[a]	.	.	0	.	.	.
	[PUI=NO]	-.701	.139	25.451	1	.000	-.974	-.429
	[PUI=Yes]	0[a]	.	.	0	.	.	.
	[TOD=Daytime]	-.919	.125	53.916	1	.000	-1.164	-.674
	[TOD=Night-L]	-.352	.125	7.955	1	.005	-.597	-.107
	[TOD=Night-NL]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

At fault party, aggressive driving, drivers /pedestrians under influence, pedestrian failure to yield right of way, and time of the day variables were found to be significantly affecting the level of injury severity sustained by pedestrians struck by a vehicle at midblock locations.

Estimated coefficients for at fault party was negative and statistically significant (at 95% confidence level), implying a lower likelihood of higher injuries for crashes caused by drivers at fault compared to crashes caused by pedestrians' fault. That was consistent with the findings of Mohamed et al (2012) that crossing at intersections reduces the severity of the crash. From the preliminary statistics, it was shown that pedestrians were more likely to be the main contributing cause of the crashes that occurred at mid-block locations while drivers were the main contributing cause at intersections.

Aggressive driving crashes were associated with higher likelihood of more severe injuries compared to not aggressive driving related crashes. A higher likelihood of severe injury was significant for pedestrians failing to yield to the right of way. The model revealed that the likelihood of severe injury was significantly higher for pedestrians under the influence of drugs or alcohol compared to sober pedestrians.

In addition, crashes that occurred while drivers were under the influence had a greater likelihood of severe injuries compared with crashes involved sober drivers. Finally, the likelihood of less severe injury was associated with crashes occurring during daylight time and nighttime but with street lighting compared to crashes occurred during nighttime conditions and without street lighting.

CHAPTER SIX: CONCLUSION

This research investigates the main reasons leading the State of Florida to be ranked among the worst states in terms of pedestrian safety. The study analyzes the characteristics and causation of pedestrian crashes that occurred in Central Florida over a 5 year-period (2011-2015) at intersections and along roadway segments at mid-block locations using the data obtained from the Signal 4 Analytics database. All pedestrian related crashes were compiled and all the 6,789 crash reports were studied thoroughly. Intersection and roadway pedestrian related crashes were identified along with all the parameters and conditions related to the high crash risk of pedestrians. However, a screening criteria was developed and crashes that did not meet this criterion were excluded from the analysis.

Preliminary descriptive statistics revealed the most common types of crashes at each location. For intersection-related crashes, it was found that left turn, right turn and through moving vehicles struck crossing pedestrians. At midblock locations, major crash types were through moving vehicles hitting pedestrians crossing and walking along the roadway.

The evaluated factors affecting pedestrian crashes were classified into four main categories; location characteristics (e.g. intersection, midblock, type of control, presence of crosswalk, presence of sidewalk), pedestrian factors (e.g. pedestrian under influence, failed to yield to the right of way), driver/vehicle characteristics (e.g. driving under influence, failed to yield to traffic control device, aggressive driving), and environmental-related factors (e.g. weather conditions, road surface conditions and time of day) were among the factors studied.

Three different models were utilized in the analysis using the SPSS statistical software package. A multinomial logit model was developed to predict the likelihood that a pedestrian will be involved into one of the common crash types. A binary regression model was developed to understand the significant factors contributing to the main causes at each intersection type whether at signalized or un-signalized intersections. Lastly, an ordinal regression model was developed to identify the significant factors affecting the level of injury severity sustained by pedestrians.

Statistical analysis was initially conducted for all intersection and roadway crashes combined in a general model, however due to the different crash characteristics and contributing factors in terms of the location for intersections and roadways, it was imperative to separate the intersection crashes from the roadway crashes and develop separate models.

The results of the multinomial logit model for intersection crashes revealed a high probability of right turn crashes associated with drivers at fault with no aggressive driving related crashes compared to left turn crashes. The results also showed that the probability of through moving vehicle crashes with no traffic control device was 2.437 times higher than left turn crashes. These results confirmed the results of the binary model that a lower likelihood of left or right turn crashes was associated with un-signalized intersections when compared to through crashes. Lastly, a greater probability of through crashes was associated with running the red light when compared to left turn crashes.

The results of the binary model revealed that the majority of the un-signalized intersection crashes were attributed to drivers at fault. Among other contributing factors was crossing at un-signalized intersections not equipped with the crosswalks. The chance of crashes at unsignalized intersections is 15.657 times higher in the absence of crosswalks compared to unsignalized intersections in which crosswalks are present. Conversely, signalized intersections related crashes were attributed to running the red light and pedestrians failing to obey traffic control devices.

For the ordinal models for crashes at either intersections or mid-block locations , the results revealed that a reduction in the likelihood of severe injuries was associated with drivers being at fault, daytime, no aggressive driving related crashes and sober pedestrians . However, red light running related to intersection crashes, as well as pedestrians failing to yield to the right of way, and drivers under influence related to midblock crashes were associated with high injury severity and an increase in the likelihood of severe injuries.

The findings of this research and examination of the factors affecting pedestrians' crash likelihood and injury severity can lead traffic engineers and other transportation professionals to better crash mitigation strategies, countermeasures and policies that would alleviate this growing problem in Central Florida. The following are some proposed countermeasures:

- At mid-block crossings segmentation, increase the number of crosswalks with pedestrian control signs , signals , or advanced yield markings.
- Increase the lighting along roadways and intersections or install high-visibility crosswalks.
- Installing sidewalks or paved shoulders to avoid along roadway crashes.
- At intersections, improving signal indication to drivers to yield to pedestrians such as adding blank out signs with flashing yellow arrow signals.

- At the high crash frequency intersections, prohibiting turn on red and/or prohibiting permissive left turns can be a countermeasure option.
- Local and state police enforcement of the existing traffic rules.
- Public education campaigns to increase the road users' awareness. For example, providing information to pedestrians reminding them to be visible when walking or running along roads at night.
- Erecting barriers to direct pedestrians to cross-walks.
- Adopting some innovative technologies such as installing flashing crosswalk to notify the pedestrians to cross once they have the right to cross.
- Equipping the future connected vehicles with a new function that could alert drivers of entering pedestrians.

APPENDIX A: SAMPLE OF DATA SET

Report #	Crash Location	Type of Control	At Crosswalk	Sidewalk Exists	At Fault Party	Driver FTY ROW	DRIVER FTY TCD	Speeding	Distracted Driving	Run Red Light	Careless driving	Aggressive Driving	DUI	VEH MOV	Ped FTY ROW	PED FTY TCD	PED MOV	Road_Surf_Cond
8331780	Int	Signal	Y	NA	Ped	No	No	No	No	No	No	No	No	TH	No	Yes	CR	Dry
8722343	Int	Signal	Y	NA	Driver	No	No	No	No	No	No	Yes	No	RT	No	No	CR	Dry
10118913	Int	Signal	Y	NA	Driver	No	No	No	No	No	Yes	No	No	LT	No	No	CR	Dry
10122519	Int	No Cntrl	Y	NA	Driver	Yes	No	No	No	No	No	No	No	LT	No	No	CR	Dry
11046813	Int	Signal	Y	NA	Driver	No	No	No	No	No	No	No	No	RT	No	No	CR	Dry
11047833	Int	Signal	Y	NA	Ped	No	No	No	No	No	No	No	No	TH	No	Yes	CR	Dry
11377777	Int	Sign	Y	NA	Driver	No	No	No	No	No	Yes	No	No	RT	No	No	CR	Dry
11939132	Int	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
12161457	Int	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
12161817	Int	Signal	Y	NA	Driver	No	No	No	No	No	No	No	No	LT	No	No	CR	Dry
12240527	Int	Signal	Y	NA	Driver	Yes	No	No	No	No	No	No	No	LT	No	No	CR	Dry
12245080	Int	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
12639611	Int	Signal	Y	NA	Ped	No	No	No	No	No	No	No	No	LT	No	Yes	CR	Dry
12640698	Int	Signal	Y	NA	Driver	No	No	No	No	No	No	Yes	No	RT	No	No	CR	Dry
70822967	Int	Signal	Y	NA	Driver	Yes	No	No	No	No	No	No	No	LT	No	No	CR	Wet
71672248	Int	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
71672538	Int	Signal	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
71672948	Int	Signal	Y	NA	Driver	No	No	No	No	No	No	No	No	RT	No	No	CR	Dry
71673094	Int	Sign	N	NA	Driver	No	No	No	No	No	No	No	No	RT	No	No	CR	Dry
71973707	Int	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	RT	Yes	No	CR	Dry
71673875	Int	Signal	N	NA	Ped	No	No	No	No	No	No	No	No	LT	Yes	No	CR	Dry
72797922	Int	Signal	Y	NA	Ped	No	No	No	No	No	No	No	No	LT	Yes	No	CR	Dry
73480005	Int	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
73480601	Int	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	No	No	CR	Dry
73480642	Int	Signal	Y	NA	Driver	No	No	No	No	No	No	Yes	No	RT	No	No	CR	Dry
73480732	Int	No Cntrl	N	NA	Driver	Yes	No	No	No	No	No	No	No	LT	No	No	CR	Dry
73480973	Int	Signal	Y	NA	Driver	No	No	No	No	No	No	Yes	No	LT	No	No	CR	Wet
73481458	Int	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
73481770	Int	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	No	No	CR	Dry
73482327	Int	Signal	Y	NA	Ped	No	No	No	No	No	No	No	No	TH	No	Yes	CR	Dry
73482405	Int	Signal	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
73482832	Int	Signal	Y	NA	Driver	No	No	No	No	No	No	No	No	LT	No	No	CR	Dry
73483303	Int	Signal	Y	NA	Ped	No	No	No	No	No	No	No	No	TH	No	Yes	CR	Dry
73483871	Int	Signal	Y	NA	Driver	No	No	No	No	No	Yes	No	No	TH	No	No	CR	Dry
73700053	Int	Sign	N	NA	Driver	No	No	No	No	No	No	Yes	No	RT	No	No	CR	Dry
73700571	Int	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	No	No	CR	Dry
73700634	Int	Signal	Y	NA	Driver	Yes	No	No	Yes	No	No	Yes	No	LT	No	No	CR	Dry
73700669	Int	Signal	Y	NA	Driver	Yes	No	No	No	No	No	Yes	No	LT	No	No	CR	Dry
73700806	Int	No Cntrl	N	NA	Driver	No	No	No	No	No	Yes	No	No	LT	No	No	CR	Wet
73701653	Int	Signal	Y	NA	Driver	Yes	No	No	No	No	No	No	No	RT	No	No	CR	Dry
73701828	Int	Signal	Y	NA	Ped	No	No	No	No	No	No	No	No	TH	No	Yes	CR	Dry
73710799	Int	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	No	No	CR	Dry
73713136	Int	No Cntrl	Y	NA	Driver	No	No	No	No	Yes	No	No	No	TH	No	No	CR	Dry
73713508	Int	Sign	N	NA	Driver	Yes	No	No	No	No	No	No	No	LT	No	No	CR	Wet
73713610	Int	Sign	Y	NA	Driver	No	No	No	Yes	No	No	Yes	No	TH	No	No	CR	Dry
73714901	Int	Signal	Y	NA	Ped	No	No	No	No	No	No	No	No	RT	No	Yes	CR	Dry
73738663	Int	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	No	No	CR	Dry
73986845	Int	Sign	Y	NA	Driver	Yes	No	No	No	No	No	No	No	TH	No	No	CR	Dry
73988320	Int	No Cntrl	Y	NA	Driver	Yes	No	No	No	No	No	No	No	RT	No	No	CR	Dry
74220592	Int	Sign	N	NA	Driver	Yes	No	No	No	No	No	Yes	No	TH	No	No	CR	Dry
74655875	Int	Signal	Y	NA	Driver	No	No	No	Yes	No	Yes	No	No	TH	No	No	CR	Dry
74769281	Int	No Cntrl	Y	NA	Ped	No	No	No	No	No	No	No	No	TH	No	Yes	CR	Dry
75211444	Int	Sign	Y	NA	Driver	Yes	No	No	No	No	No	No	No	TH	No	No	CR	Dry
75506778	Int	Signal	Y	NA	Driver	No	No	No	No	No	No	Yes	No	LT	No	No	CR	Dry
75509750	Int	Signal	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
75902155	Int	Signal	Y	NA	Ped	No	No	No	No	No	No	No	No	RT	No	Yes	CR	Dry
76401115	Int	Signal	N	NA	Ped	No	No	No	No	No	No	No	No	TH	No	No	CR	Dry
76780587	Int	Signal	Y	NA	Driver	No	No	No	Yes	No	No	Yes	No	LT	No	No	CR	Dry
76781133	Int	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
76781564	Int	Signal	Y	NA	Driver	Yes	No	No	No	No	No	No	No	LT	No	No	CR	Dry
76782576	Int	Signal	N	NA	Ped	No	No	No	No	No	No	No	No	LT	Yes	No	CR	Dry
76783321	Int	Sign	Y	NA	Driver	No	No	No	No	Yes	Yes	No	No	TH	No	No	CR	Dry
76783458	Int	Sign	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
80144671	Int	Signal	Y	NA	Ped	No	No	No	No	No	No	No	No	LT	No	Yes	CR	Dry
80194466	Int	Signal	Y	NA	Driver	Yes	No	No	No	No	No	No	No	LT	No	No	CR	Dry
80194806	Int	Signal	Y	NA	Driver	No	No	No	No	No	No	Yes	No	LT	No	No	CR	Dry
80236389	Int	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Wet
80302933	Int	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	No	No	CR	Dry
80822630	Int	Signal	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry

83125163	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	No	Yes	CR	Dry
83125205	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83125733	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83126371	MidBlk	No Cntrl	NA	N	Driver	No	No	No	No	No	Yes	No	No	TH	No	No	AL	Dry
83139728	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	No	No	CR	Wet
83140947	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83146129	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Wet
83148349	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83149565	MidBlk	No Cntrl	NA	Y	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	AL	Dry
83149939	MidBlk	No Cntrl	NA	Y	Driver	No	No	No	Yes	No	Yes	No	No	TH	No	No	AL	Dry
83150303	MidBlk	Signal	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83154441	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83154655	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83159773	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Wet
83160168	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83162085	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	No	No	CR	Dry
83162586	MidBlk	No Cntrl	NA	N	Driver	No	No	No	No	No	No	No	No	TH	No	No	AL	Dry
83162775	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Wet
83162891	MidBlk	Signal	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83163628	MidBlk	Signal	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83163818	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83165865	MidBlk	Signal	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83166228	MidBlk	No Cntrl	NA	N	Ped	No	No	No	No	No	No	No	No	TH	No	No	AL	Dry
83168054	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83169581	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83170151	MidBlk	No Cntrl	NA	N	Driver	No	No	No	Yes	No	No	No	No	TH	No	No	AL	Dry
83171410	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83171552	MidBlk	No Cntrl	NA	Y	Ped	No	No	No	No	No	No	No	No	TH	No	No	AL	Dry
83171560	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83171801	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83172179	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83172205	MidBlk	No Cntrl	NA	N	Driver	No	No	No	Yes	No	No	Yes	No	TH	No	No	AL	Dry
83172374	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	No	No	CR	Dry
83172394	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83172415	MidBlk	No Cntrl	NA	N	Driver	No	No	No	No	No	Yes	No	No	TH	No	No	AL	Dry
83175271	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Wet
83175656	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83175771	MidBlk	Sign	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83176528	MidBlk	Signal	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83177209	MidBlk	No Cntrl	NA	N	Driver	No	No	No	Yes	No	Yes	No	No	TH	No	No	AL	Dry
83177268	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83183131	MidBlk	Sign	N	NA	Driver	No	No	No	No	No	Yes	No	No	TH	No	No	CR	Dry
83185400	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83185408	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Wet
83186302	MidBlk	No Cntrl	NA	N	Ped	No	No	No	No	No	No	No	No	TH	No	No	AL	Dry
83186348	MidBlk	No Cntrl	NA	N	Driver	No	No	No	No	No	Yes	No	No	TH	No	No	AL	Dry
83186945	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83187047	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83187216	MidBlk	No Cntrl	NA	Y	Driver	No	No	No	No	No	No	No	No	TH	No	No	AL	Dry
83187933	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Wet
83187970	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83188296	MidBlk	Sign	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83188656	MidBlk	No Cntrl	NA	N	Ped	No	No	No	No	No	No	No	No	TH	No	No	AL	Dry
83189127	MidBlk	Sign	N	NA	Driver	No	No	No	Yes	No	Yes	No	No	TH	No	No	CR	Dry
83189130	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83189315	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83190962	MidBlk	Signal	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83191277	MidBlk	No Cntrl	NA	N	Driver	No	No	No	No	No	Yes	No	No	TH	No	No	AL	Dry
83191303	MidBlk	No Cntrl	NA	N	Ped	No	No	No	No	No	No	No	No	TH	No	No	AL	Dry
83196023	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83197059	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83197460	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83198075	MidBlk	Sign	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83198614	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83203653	MidBlk	No Cntrl	NA	N	Driver	No	No	No	No	No	No	No	No	TH	No	No	AL	Dry
83203657	MidBlk	No Cntrl	NA	N	Ped	No	No	No	No	No	No	No	No	TH	No	No	AL	Dry
83204385	MidBlk	No Cntrl	NA	N	Driver	No	No	No	No	No	No	Yes	No	TH	No	No	AL	Dry
83206814	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83207152	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83207434	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83207632	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83216392	MidBlk	No Cntrl	N	NA	Ped	No	No	No	No	No	No	No	No	TH	Yes	No	CR	Dry
83226603	MidBlk	No Cntrl	NA	N	Driver	No	No	No	Yes	No	No	Yes	No	TH	No	No	AL	Dry

APPENDIX B: PRELIMINARY MODELS

Preliminary Model Considering all the Independent Variables for the Multinomial Regression Model for Intersections and Mid-Block Locations

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	956.456[a]	.000	0	.
CrashLocation	1274.337[b]	317.881	2	.000
TypeofControl	1003.263[b]	46.806	4	.000
AtCrosswalk	957.510[b]	1.054	2	.590
SidewalkExists	956.456[b]	.000	2	1.000
AtFaultParty	1001.095[b]	44.639	2	.000
DriverFTYROW	956.909[b]	.453	2	.797
DRIVERFTYTCD	962.041[b]	5.585	2	.061
Speeding	958.960	2.504	2	.286
DistractedDriving	958.111[b]	1.655	2	.437
RunRedLight	975.028[b]	18.572	2	.000
Carelessdriving	963.804[b]	7.348	2	.025
AggressiveDriving	962.228[b]	5.772	2	.056
DUI	958.727[b]	2.271	2	.321
PedFTYROW	956.543[b]	.087	2	.957
PEDFTYTCD	956.538[b]	.082	2	.960
PUI	957.915[b]	1.459	2	.482
PEDMOV	956.456[a]	.000	0	.
HandicapedPed	963.516[b]	7.060	2	.029
WeatherCondition	957.351[b]	.895	2	.639
TOD	968.649[b]	12.193	4	.016

Preliminary Model Considering all the Independent Variables for the Multinomial Regression Model for Intersections

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	956.455[a]	.000	0	.
TypeofControl	1003.261	46.807	4	.000
AtCrosswalk	957.509	1.054	2	.590
AtFaultParty	1001.093	44.639	2	.000
DRIVERFTYTCD	962.040	5.585	2	.061
Speeding	958.960	2.505	2	.286
DistractedDriving	958.110	1.655	2	.437
RunRedLight	975.027	18.572	2	.000
Carelessdriving	963.802	7.348	2	.025
AggressiveDriving	962.226	5.772	2	.056
DUI	958.726	2.271	2	.321
PEDFTYTCD	956.537	.082	2	.960
PUI	957.913	1.459	2	.482
HandicapedPed	963.514	7.060	2	.029
WeatherCondition	957.349	.895	2	.639
TOD	968.648	12.193	4	.016
DriverFTYROW	956.907	.453	2	.797
PedFTYROW	956.542	.087	2	.957

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

Preliminary Model Considering all the Independent Variables for the Binary Regression Model

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	AtCrosswalk(1)	2.798	.227	151.949	1	.000	16.407
	AtFaultParty(1)	1.445	.487	8.792	1	.003	4.241
	DriverFTYROW(1)	.340	.269	1.602	1	.206	1.405
	DRIVERFTYTCD(1)	-.398	.469	.719	1	.396	.672
	Speeding(1)	.373	1.819	.042	1	.837	1.452
	DistractedDriving(1)	.210	.231	.827	1	.363	1.234
	RunRedLight(1)	1.667	.431	14.953	1	.000	5.294
	Carelessdriving(1)	.705	.343	4.230	1	.040	2.023
	AggressiveDriving(1)	.050	.213	.056	1	.814	1.051
	DUI(1)	.054	.849	.004	1	.949	1.056
	VEHMOV			33.569	2	.000	
	VEHMOV(1)	-1.049	.192	29.832	1	.000	.350
	VEHMOV(2)	-.961	.206	21.649	1	.000	.383
	PedFTYROW(1)	.789	.392	4.056	1	.044	2.201
	PEDFTYTCD(1)	2.340	.503	21.662	1	.000	10.379
	PUI(1)	.269	.317	.721	1	.396	1.309
	HandicapedPed(1)	.163	.293	.310	1	.578	1.178
	WeatherCondition(1)	-.092	.176	.274	1	.601	.912
	TOD			1.164	2	.559	
	TOD(1)	.071	.212	.113	1	.736	1.074
	TOD(2)	-.127	.236	.292	1	.589	.880
	Constant	-7.159	2.366	9.152	1	.002	.001

a. Variable(s) entered on step 1: AtCrosswalk, AtFaultParty, DriverFTYROW, DRIVERFTYTCD, Speeding, DistractedDriving, RunRedLight, Carelessdriving, AggressiveDriving, DUI, VEHMOV, PedFTYROW, PEDFTYTCD, PUI, HandicapedPed, WeatherCondition, TOD.

Preliminary Model Considering all the Explanatory Variables For the Ordinal Regression Model for Intersections

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[INJURYSEV_A = 1]	-7.337	1.681	19.058	1	.000	-10.631	-4.043
	[INJURYSEV_A = 2]	-5.971	1.677	12.679	1	.000	-9.258	-2.684
	[INJURYSEV_A = 3]	-3.253	1.670	3.797	1	.051	-6.525	.019
	[INJURYSEV_A = 4]	-1.252	1.668	.563	1	.453	-4.522	2.018
Location	[TypeofControl=No Cntrl]	-.032	.158	.042	1	.838	-.342	.277
	[TypeofControl=Sign]	-.624	.163	14.600	1	.000	-.945	-.304
	[TypeofControl=Signal]	0[a]	.	.	0	.	.	.
	[AtCrosswalk=N]	.189	.158	1.438	1	.230	-.120	.498
	[AtCrosswalk=Y]	0[a]	.	.	0	.	.	.
	[AtFaultParty=Driver]	-1.335	.356	14.081	1	.000	-2.032	-.638
	[AtFaultParty=Ped]	0[a]	.	.	0	.	.	.
	[DriverFTYROW=No]	.174	.226	.591	1	.442	-.270	.617
	[DriverFTYROW=Yes]	0[a]	.	.	0	.	.	.
	[DRIVERFTYTCD=No]	.193	.364	.280	1	.597	-.521	.906
	[DRIVERFTYTCD=Yes]	0[a]	.	.	0	.	.	.
	[Speeding=No]	-1.239	1.115	1.234	1	.267	-3.424	.947
	[Speeding=yes]	0[a]	.	.	0	.	.	.
	[DistractedDriving=No]	-.134	.193	.478	1	.489	-.512	.245
	[DistractedDriving=Yes]	0[a]	.	.	0	.	.	.
	[RunRedLight=No]	-.814	.330	6.088	1	.014	-1.460	-.167
	[RunRedLight=Yes]	0[a]	.	.	0	.	.	.
	[Carelessdriving=No]	-.232	.282	.677	1	.411	-.785	.321
	[Carelessdriving=Yes]	0[a]	.	.	0	.	.	.
	[AggressiveDriving=No]	-.596	.191	9.764	1	.002	-.969	-.222
	[AggressiveDriving=Yes]	0[a]	.	.	0	.	.	.
	[DUI=No]	.572	.722	.626	1	.429	-.844	1.988
	[DUI=Yes]	0[a]	.	.	0	.	.	.
	[VEHMOV=LT]	-.280	.153	3.369	1	.066	-.580	.019
	[VEHMOV=RT]	-.301	.167	3.269	1	.071	-.628	.025
	[VEHMOV=TH]	0[a]	.	.	0	.	.	.
	[PedFTYROW=No]	-.024	.264	.008	1	.929	-.541	.493
	[PedFTYROW=Yes]	0[a]	.	.	0	.	.	.
	[PEDFTYTCD=No]	.084	.304	.076	1	.783	-.513	.680
	[PEDFTYTCD=Yes]	0[a]	.	.	0	.	.	.

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
	[PUI=NO]	-.630	.234	7.228	1	.007	-1.090	-.171
	[PUI=Yes]	0[a]	.	.	0	.	.	.
	[HandicapedPed=N]	-.182	.248	.536	1	.464	-.668	.305
	[HandicapedPed=Y]	0[a]	.	.	0	.	.	.
	[WeatherCondition=Clear]	-.056	.141	.158	1	.691	-.332	.220
	[WeatherCondition=Diverse]	0[a]	.	.	0	.	.	.
	[TOD=Daytime]	-.755	.166	20.617	1	.000	-1.081	-.429
	[TOD=Night-L]	-.227	.180	1.591	1	.207	-.579	.125
	[TOD=Night-NL]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Preliminary Model Considering all the Explanatory Variables for the Ordinal Regression Model for Mid-Block Locations

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[INJURYSEV_A = 1]	-8.276	2.776	8.890	1	.003	-13.716	-2.836
	[INJURYSEV_A = 2]	-7.296	2.773	6.925	1	.009	-12.731	-1.862
	[INJURYSEV_A = 3]	-4.227	2.769	2.331	1	.127	-9.653	1.200
	[INJURYSEV_A = 4]	-2.555	2.767	.853	1	.356	-7.979	2.868
Location	[AtFaultParty=Driver]	-.541	.278	3.792	1	.051	-1.085	.004
	[AtFaultParty=Ped]	0[a]	.	.	0	.	.	.
	[AggressiveDriving=No]	-1.289	.426	9.163	1	.002	-2.124	-.454
	[AggressiveDriving=Yes]	0[a]	.	.	0	.	.	.
	[DUI=No]	-1.888	.589	10.277	1	.001	-3.042	-.734
	[DUI=Yes]	0[a]	.	.	0	.	.	.
	[PedFTYROW=No]	-.433	.178	5.929	1	.015	-.781	-.084
	[PedFTYROW=Yes]	0[a]	.	.	0	.	.	.
	[PUI=NO]	-.687	.140	24.119	1	.000	-.962	-.413
	[PUI=Yes]	0[a]	.	.	0	.	.	.
	[TOD=Daytime]	-.944	.128	54.283	1	.000	-1.195	-.693
	[TOD=Night-L]	-.381	.128	8.838	1	.003	-.632	-.130
	[TOD=Night-NL]	0[a]	.	.	0	.	.	.
	[TypeofControl=No Cntrl]	-.124	.188	.436	1	.509	-.492	.244
	[TypeofControl=Sign]	-.126	.259	.238	1	.626	-.634	.381

	Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
[TypeofControl=Signal]	0[a]	.	.	0	.	.	.
[AtCrosswalk=N]	-.064	.348	.034	1	.854	-.746	.618
[AtCrosswalk=NA]	-.027	.407	.005	1	.946	-.826	.771
[AtCrosswalk=Y]	0[a]	.	.	0	.	.	.
[SidewalkExists=N]	-.211	.251	.704	1	.401	-.703	.282
[SidewalkExists=NA]	0[a]	.	.	0	.	.	.
[SidewalkExists=Y]	0[a]	.	.	0	.	.	.
[AtFaultParty_A=1]	0[a]	.	.	0	.	.	.
[AtFaultParty_A=2]	0[a]	.	.	0	.	.	.
[DriverFTYROW=No]	.630	.404	2.424	1	.119	-.163	1.422
[DriverFTYROW=Yes]	0[a]	.	.	0	.	.	.
[DRIVERFTYTCD=No]	-.014	.926	.000	1	.988	-1.829	1.801
[DRIVERFTYTCD=Yes]	0[a]	.	.	0	.	.	.
[Speeding=No]	.073	2.057	.001	1	.972	-3.958	4.104
[Speeding=yes]	0[a]	.	.	0	.	.	.
[DistractedDriving=No]	-.216	.316	.470	1	.493	-.835	.402
[DistractedDriving=Yes]	0[a]	.	.	0	.	.	.
[Carelessdriving=No]	.551	.319	2.989	1	.084	-.074	1.177
[Carelessdriving=Yes]	0[a]	.	.	0	.	.	.
[PEDFTYTCD=No]	-.802	.723	1.230	1	.267	-2.220	.616
[PEDFTYTCD=Yes]	0[a]	.	.	0	.	.	.
[PEDMOV=AL]	0[a]	.	.	0	.	.	.
[PEDMOV=CR]	0[a]	.	.	0	.	.	.
[HandicapedPed=N]	.155	.459	.114	1	.736	-.745	1.055
[HandicapedPed=Y]	0[a]	.	.	0	.	.	.
[WeatherCondition=Clear]	-.132	.124	1.141	1	.285	-.375	.110
[WeatherCondition=Diverse]	0[a]	.	.	0	.	.	.

Link function: Logit.
a. This parameter is set to zero because it is redundant.

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