2017

Analysis of Pedestrian Safety Using Micro-simulation and Driving Simulator

Jiawei Wu
University of Central Florida

ANAYLSIS OF PEDESTRIAN SAFETY USING MICRO-SIMULATION AND DRIVING SIMULATOR

by

JIAWEI WU

B.S. Beijing Jiaotong University, 2012

M.S. University of Central Florida, 2014

A dissertation submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
in the Department of Civil, Environmental and Construction Engineering
in the College of Engineering and Computer Science
at the University of Central Florida
Orlando, Florida

Summer Term
2017

Major Professor: Essam Radwan

ABSTRACT

In recent years, traffic agencies have begun to place emphasis on the importance of pedestrian safety. In the United States, nearly 70,000 pedestrians were reported injured in 2015. Although the number only account for 3% of all the people injured in traffic crashes, the number of pedestrian fatalities is still around 15% of total traffic fatalities. Furthermore, the state of Florida has consistently ranked as one of the worst states in terms of pedestrian crashes, injuries and fatalities. Therefore, it is befitting to focus on the pedestrian safety. This dissertation mainly focused on pedestrian safety at both midblock crossings and intersections by using micro-simulation and driving simulator.

First, this study examined if the micro-simulation models (VISSIM and SSAM) could estimate pedestrian-vehicle conflicts at signalized intersections. A total of 42 video-hours were recorded at seven signalized intersections for field data collection. The observed conflicts from the field were used to calibrate VISSIM and replicate the conflicts. The calibrated and validated VISSIM model generated the pedestrian-vehicle conflicts from SSAM software using the vehicle trajectory data in VISSIM. The mean absolute percent error (MAPE) was used to determine the optimum TTC and PET thresholds for pedestrian-vehicle conflicts and linear regression analysis was used to study the correlation between the observed and simulated conflicts at the established thresholds. The results indicated the highest correlation between the simulated and observed conflicts when the TTC parameter was set at 2.7 and the PET was set at 8.

Second, the driving simulator experiment was designed to assess pedestrian safety under different potential risk factors at both midblock crossings and intersections. Four potential risk factors were selected and 67 subjects participated in this experiment. In order to analyze pedestrian safety, the surrogate safety measures were examined to evaluate these pedestrian-vehicle conflicts.

Third, by using the driving simulator data from the midblock crossing scenario, typical examples of drivers' deceleration rate and the distance to crosswalk were summarized, which exhibited a clear drivers' avoidance pattern during the vehicle pedestrian conflicts. This pattern was summarized into four stages, including the brake response stage, the deceleration adjustment stage, the maximum deceleration stage, and the brake release stage. In addition, the pedestrian-vehicle conflict prediction model was built to predict the minimum distance between vehicle and pedestrian.

Finally, this study summarized the three different kinds of data that were to evaluate the pedestrian safety, including field data, simulation data, and driving simulator data. The process of combining ~~of~~ field data, simulation data, and simulator data was proposed. The process would show how the researches could evaluate the pedestrian safety by using the field observations, micro-simulation, and driving simulator.

To my parents

Ruiming Wu and Jingli Bai

Who encourage me to realize my dream

To my wife, Wen

And my daughter, Ariella

Who awake up my spirit and responsibilities

ACKNOWLEDGMENTS

I would first sincerely express my gratitude to my advisor Dr. Essam Radwan. His support and guidance contributed greatly to the success of this work. What I learned from him during my Ph.D period is not only the special knowledge about transportation system, but also spirits of seriousness, honesty, modesty, and confidence as a dependent researcher.

I would like to thank my committee members, Dr. Essam Radwan, Dr. Mohammed Abdel-Aty, Dr. Hatem Abou-Senna, and Dr. Liqiang Ni for serving in my committee and for providing me with excellent course instructions and guidance.

In addition, I would like to thank my previous advisor, who is Dr. Xuedong Yan in China, for guiding me through emails and phones and encouraging me along the way.

Finally, thanks to my wife for her support to my whole graduate study. Without her encouragement, I cannot image the difficulty in finishing the Ph.D in transportation field.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER ONE: INTRODUCTION

1.1 Background

In recent years, traffic agencies have begun to place emphasis on the importance of pedestrian safety. Between 2006 and 2009, pedestrian fatalities in the United States declined from 4795 to 4109. However, the downward trend had halted and there were 4302 pedestrian deaths in 2010, increasing to 4457 in 2011 and 4743 in 2012 (Williams, 2013). Meanwhile, nearly 76,000 pedestrians were reported injured in 2012. Although the number only accounts for 3% percent of all the people injured in traffic crashes, the number of pedestrian fatalities is still around 14% of total traffic fatalities (National Highway Traffic Safety Administration, 2014). Furthermore, the state of Florida has consistently ranked as one of the worst states in terms of pedestrian crashes, injuries and fatalities (National Highway Traffic Safety Administration, 2012). Ernst (2011) also indicated that four metro areas in Florida (Orlando-Kissimmee, Tampa-St. Petersburg-Clearwater, Jacksonville, Miami-Fort Lauderdale-Pompano) were considered the most dangerous for pedestrians among all the United States. Therefore, pedestrian safety is of particular concern to Florida.

In order to better understand the causation of pedestrian crashes, some researchers have tried to assess pedestrian safety by using the field crash data, which is the traditional and frequent method (Haleem et al., 2015; Zhang et al., 2008; Jarrett and Saul, 1998; Lefler and Gabler, 2004). However, it often takes years to collect sufficient crash data to support statistically valid analyses, particularly for locations with infrequent crash events. In addition, the lack of complete reporting of pedestrian crashes also resulted in much smaller population of data to use. Therefore, traffic conflict analyses provided an alternative to investigate safety and develop prediction models for cases where crashes are infrequent (Zhang et al., 2014; Zhang et al., 2012; Alomodfer et al., 2015). A traffic conflict is defined as an event involving two or more road users, in which the action of one user causes the other user to make an evasive maneuver to avoid a collision (Parker and Zegger, 1989). Conflict analysis can be significant for evaluating roadway design alternatives, pedestrian safety, traffic signal control, freeway management options, and other designs that have not been widely implemented. However, there is little previous work that has developed prediction models for pedestrian conflicts. The micro-simulation model may be used to estimate the number of potential conflicts for alternative designs and permit the development of safety prediction models. The work completed thus far indicates that this approach is a valid surrogate measure to estimate safety and a promising method for predicting crashes (Gettman et al., 2008; Fan et al., 2013). However, there is no published literature that document the use of this method to assess the pedestrian crashes. Moreover, a driving simulator is also one of the effective tools that can also be used to identify pedestrian-vehicle conflicts and evaluate the pedestrian safety. In this dissertation, the purpose is to use both micro-simulation model and driving simulator to develop the pedestrian-vehicle conflict model and analyze the pedestrian safety.

1.2 Research Approaches

Firstly, a literature review of relevant domain information was conducted, including pedestrian safety issues, risk factors that related to pedestrian crashes, and simulation and simulator studies related to pedestrian safety.

Secondly, VISSIM and SSAM were used to estimate the number of potential conflicts between pedestrians and vehicles. In addition, several sites were selected to collect data from the field for the purpose of calibrating and validating VISSM and SSAM.

Thirdly, a series of scenarios were designed in the UCF driving simulator to collect data on drivers' behaviors that react to pedestrian crossing the street at both mid-block crossings and intersections. A total of 67 participants were selected to participate in the experiment. Several software packages including Microsoft EXCEL, SPSS, Minitab, and R were used to analyze the data and build statistical models to identify vehicle-pedestrian conflicts and estimate the pedestrian safety with different potential factors.

Fourthly, the driver's avoidance pattern was summarized based on the driving simulator experiment. In addition, the pedestrian-vehicle conflicts prediction model was developed to estimate the minimum distance between the pedestrian and the vehicle. The driver's characteristics, potential risk factors, and the basic vehicle information were included in the model.

Finally, the process of pedestrian safety evaluation based on the field data, micro-simulation data, and driving simulator data was summarized.

1.3 Research Objectives

The main objectives of this research are as follows:

(1) Use micro-simulation model to identify vehicle-pedestrian conflicts and assess the pedestrian safety. First, collect the field data at seven signalized intersections and develop the VISSIM simulation models, using the field data, to replicate similar conditions in a simulated environment. Then, the calibrated and validated VISSIM simulation models were used to obtain the pedestrian and vehicle trajectory files, and SSAM was then used to extract the pedestrian-vehicle conflicts.

(2) Use the driving simulator to design the pedestrian-vehicle conflict scenarios to evaluate the pedestrian safety with different risk factors. First, set up several scenarios in the driving simulator to test the drivers' behavior that react to the pedestrian crossing the street at both midblock crossings and signalized intersections and find out the potential risk factors that related to the pedestrian safety. Then, by processing the simulator data, selected surrogate safety measures for the pedestrian-vehicle conflict can be extracted and used to analyze the pedestrian safety with different risk factors.

(3) Use driving simulator data to explore the driver's avoidance pattern and build the pedestrian-vehicle conflict prediction model.

(4) Based on the analysis before, summarize the process of pedestrian safety evaluation based on the field data, micro-simulation data, and driving simulator data.

1.4 Proposal Organization

This chapter presents an introduction to the subject matter to be discussed as well as a description of the research approaches and objectives. Chapter 2 delves into literature to discuss the framing of the problem addressed by this research. Chapter 3 describes how to build the pedestrian-vehicle conflict model in VISSM and extract the data from SSAM. In addition, the data collected from the field will be used to calibrate and validate the VISSIM and SSAM model. Finally, the simulated conflicts generated by SSAM will be used to compare to the conflicts observed in the field to identify if the VISSIM and SSAM can be used to predict the pedestrian-vehicle conflicts. Chapter 4 describes the driving simulator study methodology, including experimental design, experiment procedure, subjects and data collection. Chapter 5 analyzes the midblock scenario and the intersection scenario by using simulator data and discuss the pedestrian safety measurements in each. Chapter 6 uses the driving simulator experiment data to explore the driver's avoidance pattern and develop the pedestrian-vehicle conflict prediction model. Chapter 7 summarizes three different kinds of data, including the field data, micro-simulation data, and driving simulator data. In addition, this Chapter proposes the process of pedestrian safety evaluation based on the field data, the micro-simulation data, and driving simulator data. Chapter 8 serves as the summary chapter.

CHAPTER TWO: LITERATURE REVIEW

In this chapter, a literature review of pedestrian safety was conducted, including pedestrian safety issues, potential risk factors that related to pedestrian crashes, microsimulation and driving simulator studies related to pedestrian safety. In addition, the UCF driving simulator was introduced at the end of this chapter.

2.1 Safety Issues Related to Pedestrian Crashes

A number of reports related to pedestrian safety issues have been released in the United States and all over the world in recent years. By analyzing the pedestrian crash data, governmental agencies addressed the pedestrian safety issues and determined the potential factors related to the pedestrian safety in order to provide useful information to guide countermeasure choices.

2.1.1 National Pedestrian Safety Reports

There have been numerous reports that were devoted to investigate and evaluate the pedestrian safety at the national level. The United State Department of Transportation (USDOT) produced the National Pedestrian Crash Report in 2008 using the fatal pedestrian crash data from Fatality Analysis Reporting System (FARS) and the other pedestrian crash data from the General Estimates System (GES) in the National Automotive Sampling System (Chang, 2008). The purpose of the report was to analyze the latest trends in pedestrian fatalities and to identify the probability of different contributing factors. The report mainly presented descriptive statistics and considered five potential factors, including long-term trends, crash locations, crash time, pedestrian characteristics and driver characteristics. Similar reports published by the USDOT also demonstrated the pedestrian safety in 2011(National Highway Traffic Safety Administration, 2013).

The National Highway Traffic Safety Administration (NHTSA) collected the pedestrian crash data for two years at six different sites in the United States (Chidester & Isenberg, 2001). By using the video camera recording and contour gauge techniques, a total of 521 pedestrian crashes were collected. The study provided pedestrian crash trends and summarize the scope and character of pedestrian accidents.

Governors Highway Safety Association (GHSA) addressed pedestrian safety by using the pedestrian fatality data (Williams, 2013). They also proposed some potential reasons for the increase in pedestrian deaths in 2010 through 2012. The possible explanations included the economic recession that might increase the walking, changes in demographics that led to pedestrians unfamiliar with road, and warmer weather pattern that might increase the pedestrian exposure.

The Federal Highway Administration (FHWA) provided a distance-based methodology to estimate annual pedestrian and bicyclist exposure in an urban environment (Molino et al., 2012). Pedestrian volume data was collected through personnel who observed pedestrian movements while standing on the sidewalk. The travel distances were measured with tape and remote distance-measuring equipment. By combining the two measurements, a linear regression model was developed to estimate annual pedestrian exposure.

The Transportation for America also examined the pedestrian fatalities for each state from 2000 to 2009 to identify the common thread on the roads (Ernst et al., 2011). The Pedestrian Danger Index (PDI) was used to rank the country's largest metropolitan areas according to their relative risk to walkers. The analysis concluded that Orlando tops the list of most dangerous places due to its high pedestrian fatality rate of 3 per 100,000 people, followed by Tampa, Jacksonville and Miami areas. They suggested that more funding should be used for the safer roads and a complete street policy should be adopted for pedestrians and bicyclists.

2.1.2 Statewide and Local Pedestrian Safety Reports

The New York Bicycling Coalition (NYBC) utilized two main databases to find pedestrian and bicyclist accident rates (Brustman, 1999). One of the databases was "Hospitalizations Due To Bicyclist and Pedestrian Injuries" from the Department of Health (DOH), which was more reflective of the actual injury situation. Another database was the "Summary of Bicycle and Pedestrian Accidents on State Highways" from the Department of Transportation (DOT), which looked for clusters of accidents on state highway routes. Through these two databases, researchers analyzed contributory factors in bicycle and pedestrian accidents. They employed a descriptive research method, which used the ratio of each factor to analyze bicycle and pedestrian accident rates. The report also provided suggestions for improving the local and statewide data collection, such as redefining bicycle accident reporting criteria and offering financial assistance for the data collection system upgrades.

Thomas et al. (2009) used five years of state crash data from Traffic Engineering Accident Analysis System (TEAAS) and the perception data from 400 intercept survey respondents to identify the general trends in pedestrian and drivers' characteristics in North Carolina. The kernel density analysis method was used to identify high risk locations in GIS and exploited Ripley's K-function test to decide whether crashes were clustered randomly.

Ballesteros et al. (2004) examined how pedestrian injury was associated with the vehicle type and integrated two pedestrian accident databases to reclassify pedestrian accidents. The severely injured pedestrian accident types were classified into life threatening, potentially life threatening and dead prior to arriving the hospital. The other type was considered as non-life threatening. It was concluded that the increased danger due to sport utility vehicles and pick-up trucks to pedestrians was explained by larger vehicle masses and faster speeds. Through calculations of the severity of the pedestrians' injury, it was found that the vehicle type might contribute to different injury patterns.

The City of Chicago (2011) published a summary report for pedestrian crash analysis for 2005-2009 crash data. The report provided descriptive analysis about the crash types, locations and severity. Pedestrian crash fatality rates per 100,000 residents were also used to compare with other US cities. In addition, crash maps were also provided to analyze where pedestrian crashes generally occurred in central business district and neighborhoods.

An overall technical guide for pedestrian safety assessments was introduced for California cities (Meghan et al., 2008). First, California cities were divided into several population groups based on the population size. Then, the rates of the different population groups were calculated per 10,000 populations to identify the high pedestrian accident cities.

Dumbaugh et al. (2012) mainly focused on the relationship between the environment and pedestrian crash accidents in Texas. Negative binomial regression models were used to fit the data and it was concluded that the environmental factors associated with pedestrian crashes were combination of traffic conflicts and the vehicle speed.

Oregon Department of Transportation (ODOT) utilized network screening methods, which complemented the crash frequency and severity screening by identifying risk factors, to identify locations for safety improvements where crashes had not been reported (Braughton and Griffin, 2014). A segment scoring system was also developed to estimate each risk factor and the GIS software summarized the pedestrian score of segments to identify the crash frequency and severity network for each Oregon region.

A pedestrian safety report published by Florida Department of Transportation pointed out why pedestrian fatality rates in Florida was higher than other states (Dewey et al., 2003). A multivariate regression model was used to analyze specific factors that related to the pedestrian fatality, including environmental factors and accidents locations. It was found that Florida residents walked more often in places that were exposed to traffic compared to other U.S. residents because of the warm winter, the natural timing of summer and winter sunlight. Besides, there were millions of tourists visiting Florida every year, which led to more exposure to traffic. Moreover, elderly residents, the interstate shortfall, and poverty rate explained over 70% of Florida's pedestrian fatalities. Another FDOT pedestrian safety report analyzed 6434 pedestrian crashes on roads during 2008-2010 in Florida (Alluri et al., 2013). A mixed logit model was developed to identify factors contributing to pedestrian injury severity at signalized and non-signalized locations. Statewide crash patterns, causes, and contributing factors were used to have a better understanding of pedestrian injury severity. Several countermeasures at both nonsignalized and signalized locations were suggested to reduce pedestrian crash frequency and severity.

2.2 Risk Factors Related to Pedestrian Crashes

There have been numerous studies that attempted to identify significant factors related to pedestrian accidents. The main factors discussed in this study include environmental factors, roadway characteristics factors, human factors, vehicle characteristics factors and special locations.

2.2.1 Environmental Factors

The environmental factors included time, weather, area type, and so on. First, the City of Chicago found that that 26% of pedestrian crashes occurred from 3 p.m. to 6 p.m. in Chicago, which was the period with most occurrences (Chang, 2008). However, NHTSA found that 24.7% percent of pedestrian deaths happened between 6 pm and 9 pm, which was the highest number of pedestrian deaths of the whole day (National Highway Traffic Safety Administration, 2013). Weather and lighting condition factors were also of common concern. Other studies showed that poor lighting conditions increased the likelihood of pedestrian injuries (Clifton et al., 2009; Mohamed et al, 2013). However, weather was not a significant factor in several studies (Clifton et al., 2009; Dai, 2012).

Noland and Quddus (2004) analyzed whether the different income areas were associated with pedestrian safety. They used the negative binomial model and found that areas with lower income were more prone to pedestrian crashes, which concurred with the study by Kravetz and Noland (Daniel & Noland, 2012). In addition, it was also found that areas with lower population density experienced more fatalities compared to those areas with higher population densities. Ukkusuri et al. (2012) showed that a greater fraction of residential land use decreased pedestrian crashes compared to the industrial, commercial and open land use type in New York City. Other related studies concluded that low density residential areas were more dangerous than compact residential areas (Cho et al., 2009; Zajac & Ivan, 2003).

Some research studied the factor of urban and rural areas as locations of interest. Zhu et al. (2008) gathered information on 35,732 pedestrian accidents and used Poisson distribution to calculate the 95% of confidence interval of an adjusted rate ratio (aRR) of pedestrian-vehicle crash and pedestrian injury according to resident years and miles walked in either urban or rural areas. Pedestrian crash rates were calculated per 100,000 person years and per million miles walked according to the region size. The analysis showed that hot accident spots were closer to urban areas, especially for small to mid-size.

2.2.2 Roadway Characteristics Factors

Several studies also focused on investigating roadway characteristics factors that impacted pedestrian safety. Turner et al. (2006) investigated roadway factors in an urban area in New Zealand. It was found that 56% of accidents occurred at mid-block locations, which were the highest among urban pedestrian accident locations. The second highest locations were at intersections which accounted for 38% of accidents. Brustman (1999) found that municipal streets had a higher probability of accidents involving a pedestrian compared to state roads, county roads, town roads and limited access highways.

Tarko and Azam (2011) developed the bivariate ordered probit model to identify how the roadway type affected the pedestrian injury severity by using the linked police-hospital data. It was found an increased likelihood of a pedestrian injury severity on rural roads and high-speed urban roads. Lee and Abdel-Aty (2005) used four years of vehicle-pedestrian crashes data from 1999 to 2002 in Florida to identify roadway characteristics that were correlated with high pedestrian crashes using a log-linear model. It was found that undivided roads with a greater number of lanes were more dangerous than divided roads with fewer lanes.

Ukkusuri et al. (2012) developed pedestrian accident frequency models for New York City and found that more pedestrian crashes were associated with larger road width and road width was related to operating speeds, length of crosswalks and traffic volume.

Hanson et al. (2013) also studied roadway characteristics which included the presence of sidewalks, buffers between the road and the sidewalk, number of travel lanes, the presence of medians, traffic control at intersections, and posted speed limits. The Google Street View imagery was used to collect data. The results showed that the presence of sidewalks could reduce the severity of pedestrian crashes. Lack of buffers between the road and the sidewalk and higher speed limits were found to be associated with higher pedestrian severe causalities and fatality rates. However, the number of travel lanes and presence of medians were not statistically significant for the pedestrian crashes. Moreover, crosswalks at traffic-controlled intersections was the only significant factor among the traffic control at intersections. Other related factors, like crosswalk at intersection, control only, control at intersection and control and crosswalk, appeared not to be significant.

2.2.3 Human Factors

There have been numerous studies that aimed at identifying significant human factors related to pedestrian crashes. Human factors included age, gender, race and alcohol involvement. According to different areas, crash distributions of different age groups were distinct. For example, an age-specific study of death rates due to pedestrian accidents in the city of Montreal was conducted in which the inner city was compared to the outer parts of the cities in four contiguous areas (Allard, 1982). It was found that the rates were the highest in downtown and decreased progressively in the outlying areas. In addition, since it was observed that older pedestrians had difficulty in crosswalk situations, the crossing time at signalized intersections should be extended, especially in areas with large population of elders.

In Chicago, crash rates of the ages between 15 and 18 was the highest among all age groups (City of Chicago, 2011). However, Lee and Abdel-Aty found that middle-age male drivers and pedestrians were more involved in pedestrian accidents than other groups when analyzing age and gender factors in Florida (Lee & Abdel-Aty, 2005). The similar findings were also observed by Eluru et al. (2008), Tarko and Azam (2011), LaScala et al. (2000), and Dai (2012).

Another study used walking exposure (kilometers walked per person-year), vehicle-pedestrian collision risk (number of collisions per kilometers walked) and vehicle-pedestrian collision case fatality rate (number of deaths per collision) to study the male-female discrepancy (Zhu et al., 2008). The results showed that the pedestrian death rate per person year for men was 2.3 times more than the women's and was attributed to a higher fatality per collision rate among male pedestrians.

Chang (2008) analyzed ethnic groups of pedestrian fatalities and found that nearly 60% of pedestrian fatalities were white, 15% were black, and 18% were Hispanic, which concurred with the study by Ukkusuri (2011).

Other studies claimed that pedestrian's alcohol involvement was an important human factor affecting pedestrian crashes. Noland and Quddus (2004) suggested that alcohol involvement increased the risk of a fatal crash, which was also proved by Mohamed et al. (2013) and Miles-Doan (1996). Zajac and Ivan (2003) stressed that both driver alcohol involvement and pedestrian alcohol involvement were found to significantly increase pedestrian injury severity.

In addition to these human factors, researchers recently started looking into the effects of pedestrian distraction when talking or texting on their cell phones. Nasar and Troyer (2013) used the National Electronic Injury Surveillance System (NEISS) database in hospital emergency rooms from 2004 to 2010. Pedestrian injuries were found to be higher in the case of distraction using cell phones compared to no distraction. Byington and Schwebel (2013) utilized virtual pedestrian streets to examine hazards for pedestrians while crossing a street and checked whether the distracted by cell phone influenced the pedestrian behaviors. It was found that pedestrian behavior was considered to be more dangerous using cell phones than crossing the street without distractions.

2.2.4 Vehicle Characteristic Factors

Several studies had investigated vehicle types in pedestrian crashes. In the NHTSA Pedestrian Crash Data Study (PCDS), 68% of the involved vehicles were passenger cars and 32% were other vehicles, including light trucks, vans, and utility vehicles (Chidester & Isenberg, 2001). However, although the truck was not the highest number in vehicle types, the influence of truck flow at intersections with high pedestrian activity was found to be one of the significant factors associated with the most severe injuries (Mohamed et al., 2013). Satiennam and Tanaboriboon (2003) used chi-square tests to study types of vehicles and ages of pedestrian fatalities in traffic accidents in Thailand. The results indicated that more than 60% of pedestrian fatalities were motorcycle crashes, which was the highest frequency of pedestrian accidents.

In recent years, many studies have focused on the vehicle speed for pedestrian crashes and pedestrian injury severities. Han et al. (2012) used two finite element pedestrian models and four finite element models for vehicles with different front-end shapes to evaluate pedestrian injury severities. It was found that vehicle speed was the significant factor in injury severity and the speed below 30 km/h could reduce all injury parameters, which was similar to the findings of Pitt et al. (1990).

2.2.5 Location Factors

Many researchers have attempted to perceive the pedestrian safety in some special locations, such as parking lots, school zones and highway-rail crossings. Boot et al. (2013) investigated pedestrian crash data for parking lots based on pedestrian age in West Central Florida. The data were collected from west central region between 2004 and 2008. They observed that pedestrian crashes in small parking lots and residential parking lots had a greater effect on crash rates than in large parking lots and other types of parking lots, such as retail and gas station. Moreover, older pedestrian group (age>75) were more involved in backward driving (cars in reverse) crashes while the younger pedestrian group (age<14) were more involved in forward driving crashes. However, parking space angle and attention patterns such as head turns and eye fixation while walking in crosswalks were found as non-significant factors when related to pedestrian crash frequency.

Warsh et al. (2009) used five-year police-reported collision data and geographic information systems (GIS) to assess child pedestrian crashes in school zones. It was found that school zones were the most dangerous locations for child pedestrians and those crashes decreased as distance from school increase. Also, 37.3% of collisions happened among 10-14 years old.

Using the 2007-2010 highway-rail grade crossings (HRGC) crash data, Khattak (2013) employed the ordered probit model to investigate different variables that contributed to the severity level of pedestrian injuries. Model results showed that higher train speeds were associated with more severe injuries. Female pedestrians had higher injury severity when compared to others. Pedestrian crashes at HRGCs in commercial areas were more severe compared to other land uses (e.g., open space, residential, etc.) and lower crash severity levels at HRGCs with greater number of crossing highway lanes, with standard flashing light signals and in clear weather.

2.3 Simulation and Simulator Study Related to Pedestrian Safety

2.3.1 VISSIM

Many researchers have attempted to use VISSIM to evaluate and analyze pedestrian safety in the road network. Ishaque and Noland (2005) used the vehicle following model to simulate pedestrian flow characteristics in urban traffic networks and demonstrated that VISSIM could be used for multimodal network analysis by coding pedestrians as a vehicle, which was very important to allow full consideration of pedestrians in traffic policies by using traffic simulation software. Besides, they also set up a complex network in VISSIM to analyze pedestrian exposure to vehicle emissions and the role played by signal timings (Ishaque & Noland, 2008; Ishaque & Noland, 2009). The results showed that longer signal cycles could result in less vehicle emission, but cause longer pedestrian delay.

Boenisch and Kretz (2009) simulated pedestrians crossing a street with a lane for each direction in VISSIM. They found that a vehicle demand of 700 to 800 vehicles per hour and showed the maximum travel time for pedestrians. A study by Chen et al. (2010) attempted to develop a pedestrian delay estimation model for both signalized and unsignalized intersection considering vehicle-pedestrian conflicts. The pedestrian delay model was built by field data, but the effectiveness of the model was checked in VISSIM by simulating the two actual intersections.

In addition to the intersection, researchers recently started considering pedestrian behavior for roundabout by using VISSIM. Astrid et al. (2011) investigated how well the Rodegerdts and Blackwelder model could affect levels of service when pedestrians and bicycles crossed the exit of roundabout. Redegerdts and Blackwelder model calculated a percentage capacity loss for the approach situated closest to the exit being blocked, which was more suitable for analytical traffic model. By comparing the result from a microscopic simulation in VISSIM, it was found that the total travel time increased if the pedestrians and bicycles were included in the model. Besides, a high vehicle pedestrian flow seemed to be more affected by small changes in pedestrian flow according to the simulation results. Another study also used VISSIM to simulate roundabouts (Rouphail et al, 2005). First, they used observational data to validate the pedestrian gap parameter for blind and sighted pedestrians. And then, the pedestrian crossing treatment, which was the use of an upstream/downstream (midblock) pedestrian-activated signal and crosswalk, were proposed and tested in the simulation, indicating that it would guarantee a crossable gap and minimize any negative impact at roundabout.

2.3.2 Cellular Automata Micro Simulation

A cellular automata model is a discrete model studied in compatibility theory, mathematics, physics, complexity science, theoretical biology and microstructure modelling (Chopard, 1998). As the cellular automata model could characterize traffic flow's discreteness feature and easy to simulate in computer, it has been used to simulate traffic by many researches (Rickert et al., 1996; Maerivoet & De Moor, 2005; Meng & Weng, 2011).

In recent years, the cellular automata model has been applied to investigate pedestrian movements and behaviors. Blue and Adler (2001) used cellular automata model to simulate three modes of bi-directional pedestrian flow, including flows in directionally separated lanes, interspersed flow, and dynamic multilane flow. They found that the pedestrian emergent behavior from cellular automata model was consistent with the empirical data. Another study by Li et al. (2012) attempted to investigate pedestrian conflicts with vehicles at a crosswalk of a signalized intersection using cellular automata simulation. The simulation results showed the effects of different pedestrian signal timing and crosswalk widths on the crosswalk capacity, the number of traffic conflicts between pedestrians and vehicles, and pedestrian delay due to the conflicts. Besides, they also demonstrated that the cellular automata simulation could realistically capture the behaviors and characteristics of pedestrian-vehicle flows, which are similar to the findings of Zhang and Chang (2014) and Yue et al. (2010).

2.3.3 Driving Simulator

The driving simulator is another important tool for researchers to analyze traffic events. It can provide a well-controlled experimental condition and can collect the data, which are difficult to achieve in the real world as well. Mostly, driving simulators are used to analyze driving behaviors under different conditions (Kolisetty et al., 2006; Lee and Abdel-Aty, 2008; Wu et al., 2016; Yan et al., 2016). However, some studies also involve pedestrians in the driving simulator experiments in order to find out the interaction effects between pedestrians and vehicles.

Yuan et al. (2013) combined driving simulator and computer simulation to reconstruct the process of pedestrian-vehicle crash. The purpose of this study was to find out the relation between drivers' various emergency measures and pedestrians' injury severity. The findings indicated that the most effective way to reduce injury severity was steering with braking. Boot et al. (2013) invited 63 participants to do the driving simulator experiment in order to test the new pedestrian marking, which was called special emphasis marking. All the participants were divided into three different age groups and a 3D model of an intersection was created in the driving simulator. The results showed that drivers could recognize the special emphasis marking much more quickly than the normal crosswalk marking. Moreover, when there was a pedestrian crossing the street, drivers were not affected by the special emphasis marking.

2.4 Driving Simulator Issues

2.4.1 Advantages and Disadvantages of Driving Simulator Research

In recent years, the driving simulator have been widely used in the safety research. The modern driving simulator is usually built with the simulation software using a sophisticated driver environment which can give drivers on board impression that drivers feel that they drive in an actual vehicle. In addition, driving simulator usually include the visual system, audio system, and vibration system, which provide a realistic feel of all controls. Therefore, a driving simulator is one of the research tools which enables researchers to conduct multi-disciplinary investigations and analyses on a wide range of issues (Abdel-Aty et al., 2006; Godley et al., 2002; Zhang et al., 2015).

The use of a driving simulator for human factors research has many advantages. First, the driving simulator has controllability, reproducibility, and standardization compared to real vehicles (Yan, 2005). The behaviour of vehicles, pedestrian and other environmental conditions can be controlled based on the research purposes. Especially, the driving simulator has the ability to simulate dangerous driving situations in a safe environment, which makes researchers easier to test driving behaviors (Underwood et al., 2011; Tu et al., 2015; Yan et al., 2016; Chang et al., 2009). Second, the data can be collected accurately and efficiently (De Winter et al., 2009; Wu, 2014). It is difficult to collect the accurate data when a real vehicle is in the world. Compared to the real vehicle, the driving simulator could output the data less than a second. The researchers can get an accurate data up to 100 data points per second based on the different types of driving simulators.

Third, the driving simulator can test novel instructions and functions for feedback (Yan & Wu, 2014; Yan et al., 2015; Larue et al., 2015). Some new technologies and instructions cannot be easily tested in the real vehicles because of the safety issue. Therefore, the driving simulator is an alternative to achieve the feedback of new technologies and instructions.

However, there are also some disadvantages of driving simulator researches. First, the simulator fidelity is one of factors that impact the research result. Some researches pointed out that some low-fidelity simulators may evoke unrealistic driving behaviour so that the research outcomes may be invalid (De Winter et al., 2012). In order to reduce the fidelity impact, a high-fidelity simulator is used in this study. Another important disadvantage is simulator motion sickness (Kennedy et al., 1992; Frank et al., 1988; Brooks et al., 2010). The data collected from the simulator may be biased due to the sickness symptoms. Even worse, some participants could not complete the experiments because of the motion sickness, especially for the older participants. In this study, the participant takes less than 10 mins in each scenario and they also need to have a rest between scenarios in order to alleviate the sickness problem.

2.4.2 UCF Driving Simulator

This study used a driving simulator for the experiment and data collection, which was located in University of Central Florida, in the United States (see Fig. 1). This driving simulator is produced by NADS – the National Advanced Driving Simulator group from the University of Iowa, which provides a high fidelity driving testing environment. It includes a visual system (three 42” flat panel displays), a quarter-cab of actual vehicle hardware including a steering wheel, pedals, adjustable seat, and shifter from a real vehicle, a digital sound simulation system and the central console. The software, including Tile Mosaic Tool (TMT), Interactive Scenario Authoring Tool (ISAT) and Minisim, can be applied for researchers to create driving scenarios with the virtual traffic environments and the virtual road networks. The data sampling frequency is up to 60 Hz. In addition, a recording system was also installed. Five cameras were installed to ensure subjects' safety in the driving simulator and to capture the participants' performance while driving in the simulator.

Figure 1 :UCF driving simulator

CHAPTER THREE: MICRO-SIMULATION APPLICATION TO PEDESTRIAN-VEHICLE CONFLICTS

In this chapter, three main tasks are included. First, collect field data at seven signalized intersections. Second, develop calibrated and validated VISSIM simulation models at seven signalized intersections. Third, compare simulated conflicts generated by SSAM to the conflicts observed in the field and determine whether VISSIM and SSAM could provide reasonable estimates for pedestrian-vehicle conflicts at signalized intersections.

3.1 Field Data Collection

3.1.1 Experimental Sites

The data collection in the field was used to develop, calibrate, and validate the VISSIM and SSAM models. Seven intersections were selected from urban areas in Orlando, Florida. Four criteria were considered in the site selection process: (1) high pedestrian activity; (2) high traffic volume; (3) urbanized location, but outside the CBD or downtown area; (4) appropriate number of pedestrian crashes during the 5-year reporting period. The selected intersections are listed in Table 1. Orange Ave & Central Blvd is located in a downtown area where a large number of pedestrian activity occur during lunch hour. Sand Lake Rd & I-Drive is located in a tourist area where a high volume of pedestrian activity exists. Martin Luther King & US 92 is located near the university campus in Daytona Beach in Volusia County. Furthermore, selections of the remaining intersections were done according to the severity of pedestrian crashes. Silver Star & Hiawassee Rd had one fatality out of 20 pedestrian crashes as well as Kirkman Rd & Conroy Rd with two fatalities out of 13 pedestrian crashes.

Table 1: List of seven test intersections

No.	Intersection Name	5-year Ped Crashes[a]	Location	County
1	Primrose Dr & Colonial Dr	9	Orlando	Orange
2	Silver Star & Hiawassee Rd	20	Pine Hills	Orange
3	Sand Lake Rd & I-Drive	6	Orlando	Orange
4	Kirkman Rd & Conroy Rd	13	Orlando	Orange
5	Martin Luther King & US 92	7	Daytona Beach	Volusia
6	Orange Ave & Kaley St	8	Orlando	Orange
7	Semoran Blvd & Pershing Ave	8	Orlando	Orange

a. 5-year Ped Crashes are from June 2009 to May 2014.

3.1.2 Data Collection Procedures

Several steps were implemented in order to extract the data from the field. First Google Maps were utilized to extract the network geometry, such as link lengths, number of lanes, and connectors between links to model turning movements. Second, cameras were set up in each intersection to record the traffic volume, pedestrian volume, pedestrian crossing behavior, maximum queue length, and pedestrian-vehicle conflicts. One camera was set up on top of the roadside to achieve adequate viewing height to cover the functional area of the intersections. However, three intersections, Sand Lake Rd at I-Drive, Kirkman Rd at Conroy Rd, and Semoran Blvd at Pershing Ave were too large to cover the whole intersection with one camera. Therefore, two video cameras in opposite corners were set up for each of these intersections. Furthermore, field data collection was conducted during the weekday peak hours under dry weather condition. The data was collected from 9:00 am to 12:00 noon, and 3:00 pm-6:00 pm in the afternoon for each intersection. The data collection schedule is given in Table 2. In total, 6 hours of data were recorded for each signalized intersection.

Table 2: The data collection schedule

No.	Intersection Name	Days	Time	Hours
1	Primrose Dr & Colonial Dr	1	9am-12pm, 3pm-6pm	6
2	Silver Star & Hiawassee Rd	1	9am-12pm, 3pm-6pm	6
3	Sand Lake Rd & I-Drive	1	9am-12pm, 3pm-6pm	6
4	Kirkman Rd & Conroy Rd	1	9am-12pm, 3pm-6pm	6
5	Martin Luther King & US 92	1	9am-12pm, 3pm-6pm	6
6	Orange Ave & Kaley St	1	9am-12pm, 3pm-6pm	6
7	Semoran Blvd & Pershing Ave	1	9am-12pm, 3pm-6pm	6

The recorded videos were later reviewed for evaluation and analysis in the laboratory. For traffic volume and pedestrian volume, data was recorded in 15-min time intervals. Maximum queue length was recorded for further validation of driver behavior in the VISSIM model. Furthermore, the camera angles allowed only one or two approaches to capture the queue length of each intersection. Pedestrian behavior was collected to calibrate and validate VISSIM model for pedestrian behaviors. The parameters of pedestrian behavior observed included the directions, platoon number, waiting time, crossing time, and violation. Pedestrian conflicts between pedestrians and vehicles were recorded from the video by identifying pedestrian or vehicle evasive actions meaning the potential occurrence of a vehicle crashing into a pedestrian. Two trained observers were designated to review and analyze all the videotapes as well as record the information for each conflict.

The pedestrian-vehicle conflicts observed in the field are classified into two types, (a) vehicle-yield-pedestrian and (b) pedestrian-yield-vehicle, as shown in Figure 2. If the vehicle decelerates in order to avoid the crossing pedestrian, (which means the pedestrian arrives at the conflict point first), this is the type (a) conflict called vehicle-yield-pedestrian conflict. In contrast, if the vehicle arrives at the conflict point first and the immediate arrival of the pedestrian comes afterward, then this is the type (b) conflict called pedestrian-yield-vehicle. In practice, the vehicle-yield-pedestrian conflict is more dangerous than the pedestrian-yield-vehicle conflict. This is due to the fact that when the pedestrian yield to the vehicle at the signalized intersection, the pedestrian always stands still until the vehicle passes the potential conflict point. Under this condition, the TTC of pedestrian-yield-vehicle conflict is infinite. However, the TTC of vehicle-yield-pedestrian is always small so that it is a potential collision. Therefore, vehicle-yield-pedestrian conflict is more likely to lead to a traffic crash. In addition, the previous studies also defined the pedestrian-vehicle conflict, which only referred to the vehicle-yield-pedestrian conflict (Parker and Zegeer, 1989; Wu et al., 2106). Accordingly, this study only focuses on analyzing the vehicle-yield-pedestrian conflicts as the most hazardous.

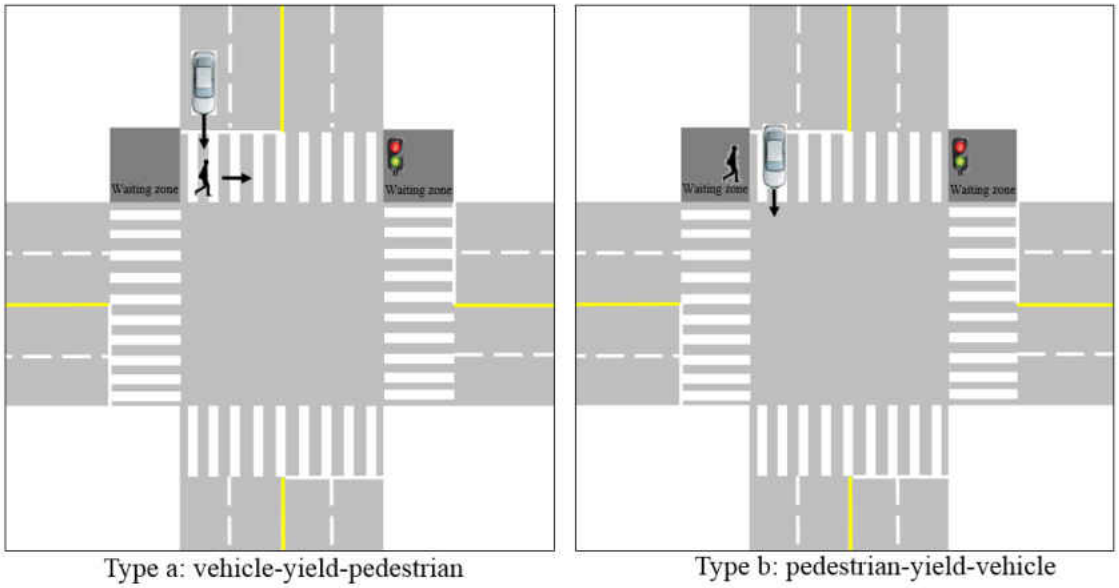


Figure 2: The pedestrian-vehicle conflict types observed in the field

3.1.3 Data Description

Table 3 summarizes the pedestrian crossing number recorded during the data collection period. As there are some pedestrians who did not use the crosswalk to cross the street, those pedestrian counts were disregarded and eliminated from the analysis. Therefore, the number of pedestrian volume in this section may slightly differ in comparison to the total pedestrian volume count. There were a total of 2610 pedestrian crossings at seven intersections observed in the field. 40.8% (1067 out of 2610) at intersections of the pedestrian crossing behaviors are single pedestrian crossing behaviors. The following subsections explained the pedestrian crossing behaviors for intersections in further details.

Table 3: Summary of pedestrian crossings at intersections

No.	Intersection Name	Total Crossings	Single	Two or More
1	Primrose Dr & Colonial Dr	214	152	28
2	Silver Star & Hiawassee Rd	305	148	65
3	Sand Lake Rd & I-Drive	1310	264	352
4	Kirkman Rd & Conroy Rd	299	192	46
5	Martin Luther King & US 92	140	107	16
6	Orange Ave & Kaley St	150	95	24
7	Semoran Blvd & Pershing Ave	192	109	32
	Total	2610	1067	563

The basic statistical descriptions of pedestrian crossing behavior at intersections are shown in Table 4. A total of 2863 pedestrian crossings were recorded at the seven signalized intersections. The average speed of all pedestrians was 1.62m/s (5.31 ft/sec). In addition, 8.8% of pedestrians have violation behaviors of which most of the violations were running the red light. 64% of pedestrians stopped on red and the average waiting time for all pedestrians were 51 seconds.

Table 4: Descriptive statistical results of pedestrian crossing behavior at intersections

No.	Intersection	Number of observations	Walking Speed (m/s)	Viola tion	Stop on Red	Waiting Time (Seconds)
1	Primrose Dr & Colonial Dr	180	1.70	19	53	47
2	Silver Star & Hiawassee Rd	213	1.65	43	138	44
3	Sand Lake Rd & I-Drive	616	1.57	9	484	66
4	Kirkman Rd & Conroy Rd	238	1.66	15	146	62
5	Martin Luther King & US 92	123	1.87	32	48	38
6	Orange Ave & Kaley St	119	1.42	12	67	41
7	Semoran Blvd & Pershing Ave	141	1.49	13	106	59

Table 5 shows the statistical results of observed conflicts at the seven signalized intersections. A total of 708 conflicts were observed at seven signalized intersections and the average post-encroachment time (PET) for each conflict was 4.05 seconds with a standard deviation of 1.56. The definition of PET is covered in section 3.3.

Table 5: Descriptive statistical results of pedestrian crossing behavior at intersections

No.	Intersection	Number of conflicts	PET (Seconds)
1	Primrose Dr & Colonial Dr	64	4.44
2	Silver Star & Hiawassee Rd	86	4.24
3	Sand Lake Rd & I-Drive	295	3.93
4	Kirkman Rd & Conroy Rd	94	3.81
5	Martin Luther King & US 92	34	3.59
6	Orange Ave & Kaley St	62	3.57
7	Semoran Blvd & Pershing Ave	73	5.00

3.2 Calibrated and Validated VISSIM Model

In this study, VISSIM version 7 was used to develop the vehicle/pedestrian simulation model at signalized intersections. Wiedemann 74 car-following model was used since it was recommended for urban traffic (PTV, 2011). The first step of developing the VISSIM model was to draw the network. Second, traffic volume and pedestrian volume for each direction were allocated to each lane group. In addition, the traffic volume also included 2% heavy vehicles on all approaches. Third, signal timing was coded in the VISSIM simulation model according to the field signal timing data. Last, conflict areas and priority rules were needed in the simulation model in order to simulate the vehicle and pedestrian movements more appropriately.

The VISSIM model cannot provide the necessary results until the model is calibrated and validated (Cunto and Saccomanno, 2008; Sun et.al, 2007; Li et al., 2011). VISSIM provides numerous calibration parameters that could be modified. In this study, average standstill distance (1,2,3,4,5), additive part of desired safety distance (2,3,4), multiple part of desired safety distance (2,3,4), the minimum headway (2,5,8) and the minimum gap time (2,3,4) were selected as the calibration parameters. The number of conflicts and the average TTC was used to calibrate these parameters. Finally, it was found that changing the calibration parameters didn't impact the number of conflicts and the average TTC. Therefore, in this case, the default value of parameters was used. In other words, average standstill distance was 2 meters, additive part of desired safety distance was 3 meters, multiple part of desired safety distance was 3 meters, the minimum ~~headway~~ gap was 5 meters, and the minimum gap time was 3 seconds. Then, the calibrated models were then validated with a new set of field data, including the pedestrian volumes, and the vehicle volumes. The average percent difference for all scenarios of pedestrian volume and vehicular traffic volume are 3.6% and 1.3%, respectively. Furthermore, animation of the VISSIM simulation models were checked for any unusual events. Finally, VISSIM was calibrated and validated. The intersection of Sand Lake Road and I Drive is shown in Figure 3.

Figure 3: VISSIM simulation model for Sand Lake Rd & I-Drive

Furthermore, the simulation was run for 3600 seconds (1 hour) with additional warm up period of 15 minutes in each scenario. A total of 10 runs with different seeding values for each one-hour time interval per intersection were completed for each scenario and the average of the runs was reported. For example, six hours of simulated data were collected at the seven intersections, then the VISSIM model was run for 10*6*7=420 times.

3.3 Surrogate Safety Assessment Model (SSAM) Calibration

SSAM software can automate conflict analysis by directly processing vehicle trajectory data from VISSIM. It can provide a summary of the total number of conflicts broken down by type of conflict. In addition, SSAM could also calculate some surrogate safety measures for each event (Radwan et al., 2016). Five measures were relevant to evaluate the traffic safety, which are TTC, PET, MaxS, DeltaS, DR and MaxD. Each surrogate safety measure is defined as follows:

- TTC (Time to collision): the time distance to a collision of two road users if they keep their directions and velocities. The shorter the TTC, the more dangerous the situation.
- PET (Post-encroachment time): the period of time from the moment when the first road user is leaving the conflict area until the second road user reaches it.
- MaxS: the maximum speed of either vehicle throughout the conflict measured in meter per second.
- DeltaS: is the difference in vehicle speeds as observed at the simulation time where the minimum TTC value for this conflict was observed measured in meter per second.
- DR: the initial deceleration of the second vehicle measured in meter per square second.
- MaxD: the maximum deceleration of the second vehicle measured in meter per square second.

SSAM software can automate conflict analysis by directly processing vehicle trajectory data from VISSIM. However, SSAM was not explicitly designed for pedestrian conflict analysis, so there is no vehicle or entity type available in the trajectory file format by which to identify pedestrian conflicts. In other words, SSAM cannot estimate the pedestrian-to-vehicle conflicts without simulating the pedestrian as vehicles in VISSIM (Wu et al., 2017). Therefore, to identify pedestrian-to-vehicle conflicts from all kinds of conflicts, the csv file exported by SSAM can be of help. From the csv file, the pedestrian-vehicle conflict can be filtered based on the “vehicle” length. The length of pedestrian is usually defined between 0.3 and 0.5 meter. In comparison, the length of vehicle is usually defined over 3.5 meters.

At the time this research was conducted the current version of SSAM only permitted vehicle to vehicle conflicts yet VISSIM allowed the vehicle to pedestrian interactions. An alternative approach to the one described above was to use VISSIM for simulating the vehicle-pedestrian activities, store the trajectory files, then produce video of the simulation activities. Playing the video back and manually observe the TTC and PET using the internal clock of the video would produce the needed data.

Two threshold values for surrogate measures of safety were used in SSAM to detect the conflicts, which are maximum TTC and maximum PET. TTC is defined as the time distance to a collision of two road users if they keep their directions and velocities. PET is defined as the period of time from the moment when the first road user is leaving the conflict area until the second road user reaches it. For example, if the maximum TTC is set as 1.5, then SSAM will only generate the conflict data that contains TTC value less than 1.5. In general, SSAM utilizes a default maximum TTC value of 1.5 seconds and maximum PET value of 5 seconds to delineate the vehicle-vehicle conflicts. However, the pedestrian-vehicle conflict is totally different from the vehicle-vehicle conflicts. That's why the maximum TTC and PET thresholds need to be established for pedestrian-vehicle conflicts.

A number of trials were investigated to get the optimum thresholds for TTC and PET that would define a vehicle-pedestrian conflict. Finally, it was found that when the TTC threshold ranged from 2 to 3 and the PET ranged from 5 to 9, SSAM provided a better estimate of the number of conflicts that matched the field data. Therefore, further analysis was needed to determine the exact value of

TTC and PET for pedestrian-vehicle conflicts. Consequently, the TTC threshold was set at 2.0, 2.3, 2.5, 2.7, 3 for 5 levels, and the PET threshold was set at 5, 6, 7, 8, 9 for additional five levels and 5*5=25 combinations of pedestrian-vehicle conflicts were generated by SSAM. The mean absolute percent error (MAPE) was used to measure the differences between the mean PET observed in the field and the mean PET simulated in VISSIM and SSAM. The lower MAPE, the smaller the difference between the simulated conflicts and observed conflicts. The MAPE value can be calculated by the following equation:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \left| \frac{c_s^i - c_o^i}{c_o^i} \right|$$

Where n represents the number of intersections, c_s^i represents the mean PET of the simulated conflicts for one intersection, and c_o^i represents the mean PET of the observed conflicts for one intersection.

MAPE value with different maximum TTC and PET thresholds is shown in Table 6. The MAPE value for the total conflicts varied from 12.7% to 73.2% for different maximum TTC and PET thresholds. In addition, the contour plot for MAPE is shown in Figure 4. It is found that when the TTC ranges from 2.6 to 2.8 seconds and PET threshold ranges from 8 to 9, the best goodness-of-fit between the observed and the simulated conflict of mean PET is achieved with MAPE value under 13%. Therefore, the maximum TTC and PET thresholds for pedestrian-vehicle conflicts were identified at 2.7 and 8, respectively. The following analysis is based on the maximum TTC threshold set as 2.7 and the maximum PET threshold set as 8.

Table 6: MAPE with different maximum TTC and PET thresholds

Maximum PET threshold	Maximum TTC threshold				
	2	2.3	2.5	2.7	3
5	0.1473	0.1365	0.1438	0.1256	0.2885
6	0.1402	0.1382	0.1439	0.1394	0.1549
7	0.1475	0.1409	0.1421	0.1420	0.1551
8	0.1678	0.1399	0.1344	0.1273	0.1399
9	0.1922	0.1410	0.1378	0.1301	0.1467

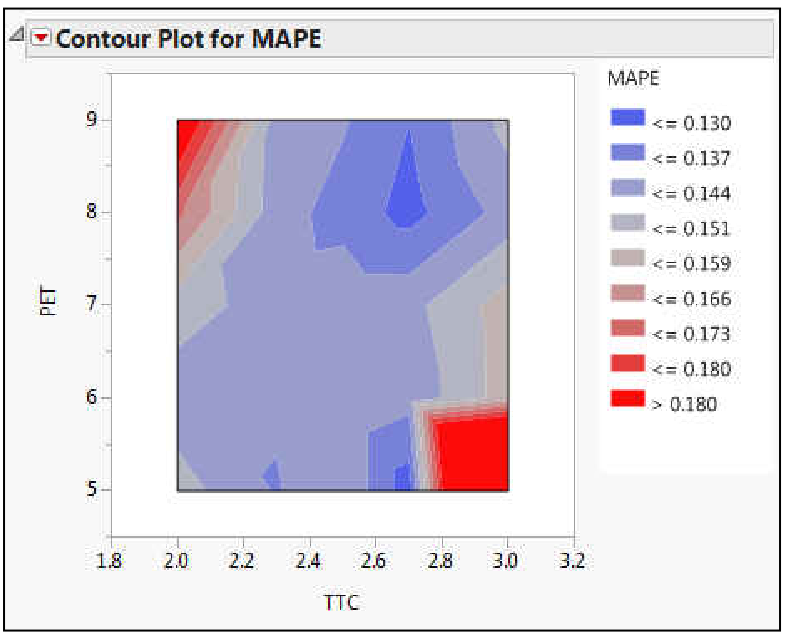


Figure 4: Contour plot for MAPE value with different TTC and PET threshold

3.4 Relationship between Simulated Conflicts and Observed Conflicts

After both VISSIM and SSAM were calibrated, the conflicts were generated and identified by SSAM at the maximum TTC threshold of 2.7 and the maximum PET threshold of 8. The average number of simulated conflicts for each three-hour interval (am hours or pm hours) was summarized and compared to the observed conflicts in the field, as shown in Table 7. A linear regression model was developed to study the relationship between simulated and observed conflicts. Figure 5 shows the regression analysis results of the linear regression model between observed conflicts and simulated conflicts.

Table 7: The number of simulated conflicts and observed conflicts

No.	Intersection Name	Time	Simulated Conflicts	Observed Conflicts
1	Primrose Dr & Colonial Dr	am	7	23
		pm	12	41
2	Silver Star & Hiawassee Rd	am	36	35
		pm	53	51
3	Sand Lake Rd & I-Drive	am	116	139
		pm	174	156
4	Kirkman Rd & Conroy Rd	am	14	32
		pm	39	62
5	Martin Luther King & US 92	am	13	13
		pm	35	21
6	Orange Ave & Kaley St	am	33	33
		pm	50	29
7	Semoran Blvd & Pershing Ave	am	16	35
		pm	30	38

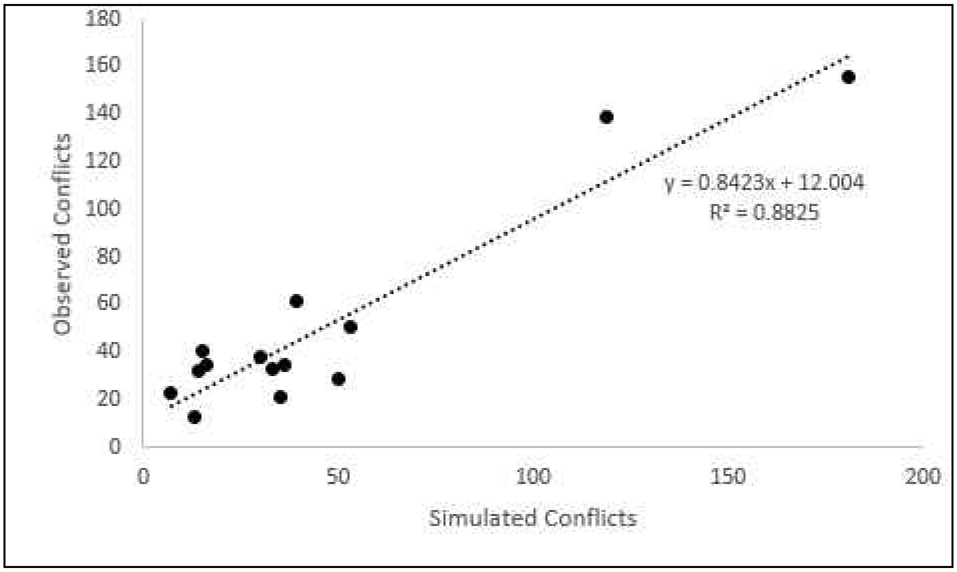


Figure 5: Relationship between simulated conflicts and observed conflicts

According to the linear regression results, it is found that the p-value of independent variable is 0.00, indicating that number of simulated conflicts is significantly correlated with the number of observed conflicts. In addition, the R^2 value for the model was 0.8825, which means that 88.25% of the variability in the observed conflicts can be explained by the variation in the simulated conflicts. For each one additional unit increase in the number of simulated conflicts, the mean of the observed conflicts is estimated to increase by 0.84. Although there is a significant statistical relationship between simulated conflicts and observed conflicts, at some locations, the number of simulated conflicts estimated by the VISSIM model and SSAM is less than the number of conflicts observed in the field. This was attributed to the fact that pedestrians don't always adhere to the rules of the traffic signals in the field and the analysis showed that 8.77% of the pedestrians had illegal behavior while crossing the intersection such as jay walking and pedestrian signal violation which cannot be simulated in VISSIM. This illegal behavior may increase the conflicts between pedestrians and vehicles thus resulting in the simulated conflicts being lower than the observed conflicts in the field.

CHAPTER FOUR: DRIVING SIMULATOR EXPERIMENT METHODOLOGY FOR ESTIMATING PEDESTRIAN SAFETY

According to the literature, there is no related research that focuses on investigating the potential risk factors of pedestrian conflicts from the drivers' point of view in driving simulator. In order to test driver's behavior against pedestrian conflicts with different potential factors, this chapter documented an experiment study based on the UCF driving simulator. The purposes are to build the vehicle-pedestrian conflicts for both midblock crossings and intersections in driving simulator and to evaluate the pedestrian safety with different potential risk factors by using the traffic conflict analysis.

4.1 Midblock Crossing Experimental Design

According to the literature, there are several factors that affect pedestrian safety at midblock crossings. In this section, the midblock crossing scenario is designed in driving simulator to test the different potential risk factors at midblock crossings and to estimate pedestrian safety using these factors.

4.1.1 Factors Description

This experiment utilized a within-subjects repeated measures full factorial design to test potential risk factors that related to pedestrian safety at midblock crossing (Wu et at., 2016). Four experimental factors are selected from the literature, including time of day, crosswalk marking, number of lanes, and pedestrian visibility factors, described in Table 8. Each factor has two levels. First, crash data show 77.2% (392 out of 508) of the pedestrians' fatalities happened during the dark time in Florida District 5 area. Only 19.1% of the pedestrians' fatalities happened during the daylight time. Therefore, time of day is one of the most important factors included in this study. The two levels of this factor are daytime and night. Second, Zegeer et al. (2001) pointed out that the crosswalk marking was very important to the pedestrian. Those who cross the street without the marking have a higher crash rate than those who cross the street using the marking. Therefore, pedestrian crossing the street with or without the marking should be one of the potential factors. Third, almost 38% of fatal pedestrian crashes occurred on four-lane roadways and 22% of fatal pedestrian crashes occurred on two-lane roadway in Florida (Florida Department of Highway Safety and Motor Vehicles, 2010). Drivers have varying sight based on different type of roads, so gathering drivers' response with different numbers of lanes is important. In this study, two-lane road for each direction and one-lane road with one parking lane are two levels of this factor. Last, the pedestrian visibility represents the pedestrian dressing color. The literature showed that pedestrian in dark clothing were more likely to be struck. Therefore, two levels of pedestrian visibility factor are pedestrian dressing in dark color or in bright color. Finally, the factorial manipulation of the four factors described above resulted in 16 unique midblock crossings.

Table 8: List of factors used in the midblock crossing scenario

Factor	Description	Levels	
		Low Value (-1)	**High Value (+1)**
Time of day	The time in the scenario	Night	Daytime
Crosswalk marking	Whether the pedestrian uses crosswalk to cross the street	No	Yes
Roadway type	The roadway type when participants meet the pedestrian	One traveling lane with one parking lane for each direction	Two lanes for each direction
Pedestrian visibility	The color of the pedestrian clothes	Dark	Bright

4.1.2 Experimental Design

The midblock crossing scenario was designed to investigate drivers' behaviors when drivers reacted to a potential conflict between the simulator and a pedestrian at midblock crossings, as illustrated in Figure 6. In order to create a potential conflict between pedestrian and simulator, a road trigger was used in this scenario. First, a roadside pedestrian was designed to walk across the street at a speed of 3.5 ft/s, which was based on Manual on Uniform Traffic Control Devices (MUTCD). The distance between pedestrian and potential conflict point was 30 ft. Then the pedestrian walking time (t_{ped}) was calculated during this period:

$$t_{ped} = \frac{30ft}{3.5ft/s} = 8.57s$$

The speed limits were set at 40 mph in all roads. Therefore, the estimate distance between the road trigger and the potential conflict point (L_v) was calculated as follows:

$L_v = t_{ped} * V = 8.57s * 40\ mph = 503\ ft$

Therefore, the roadside pedestrian was activated to cross the street when the simulator vehicle was 503 ft way from the path of the crossing pedestrian. Meanwhile, there were no other vehicles before the simulator vehicle to interfere with the drivers' behavior and judgement. Thus, if participants kept 40 mph speed along their presumed path to the potential conflict point, there would be a pedestrian-vehicle crash. If participants noticed the pedestrian and made a deceleration, there would be a pedestrian-vehicle conflict.

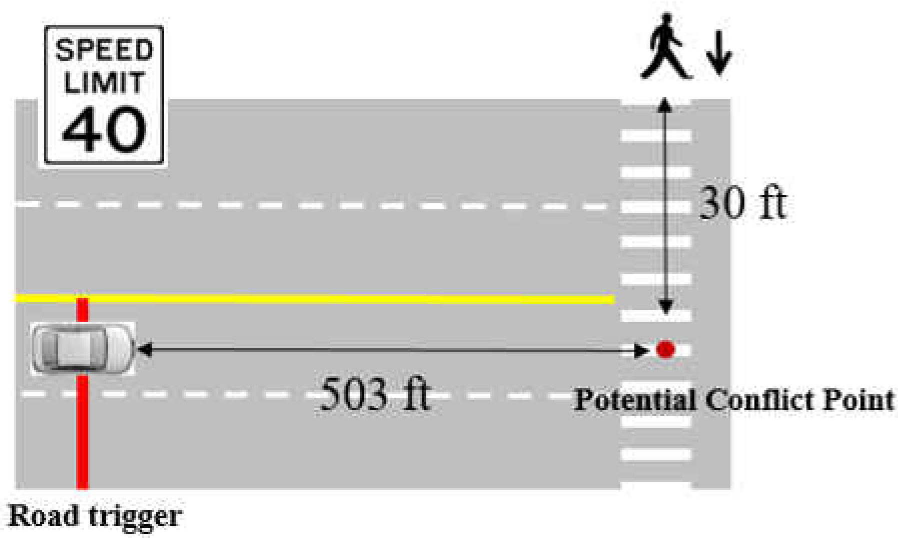


Figure 6: The midblock crossing scenario design for pedestrian-vehicle conflict

With different factors, a total of 16 test midblock crossings were added in the driving simulator. Among those, half of the midblock crossings were in the daytime sub-scenario and the other 8 midblock crossings were in the night sub-scenario. In each sub-scenario, the midblock crossing with different factors was randomly assigned to the scenario. In addition, there were additional midblock crossings, intermingled with the test midblock crossings. The total length of each scenario is around 3.5 miles, and participants need to drive around 10 mins to finish each sub-scenario.

4.2 Intersection Scenario Design

Based on the literature, there are several factors that affect pedestrian safety at intersections. In this section, the experiment was designed to test the different potential risk factors at intersections and to estimate pedestrian safety using these factors.

4.2.1 Factors Description

This experiment utilized a within-subjects repeated measures full factorial design to test potential risk factors that related to pedestrian safety at intersections. Four experimental factors are selected from the literature, including time of day, vehicle movement, pedestrian movement, and pedestrian visibility factors, described in Table 9. Each factor has two levels. First, the literature pointed out that vehicle movement directions impact the pedestrian safety (Hubbard et al., 2009). Pedestrian crossing the signalized intersections may have two potential conflicts with turning vehicles: right turn on green (RTOG), and permitted left turns on green (LTOG). These potential conflicts between pedestrians and vehicles are difficult to address. In order to mitigate the pedestrian safety risk, enforcement of pedestrian right-of-way laws was applied. However, some research proved that the enforcement of pedestrian right-of-way was useless in many circumstances. Second, the pedestrian movement is also every important. Varying the side of approach provided natural variation in the angular size of the pedestrian. Different directions of pedestrian movement may affect the driver perception. Therefore, gathering driver response data with different pedestrian movement is important.

Table 9: List of factors used in the intersection scenario

Factor	Description	Levels	
		Low Value (-1)	High Value (+1)
Time of day	The time in the scenario	Night	Daytime
Vehicle movement	Whether the vehicle makes left turn or right turn	Left	Right
Pedestrian movement	Pedestrian cross the intersection from the right side or the left side	Left	Right
Pedestrian visibility	The color of the pedestrian clothes	Dark	Bright

4.2.2 Experimental Design

The intersection scenario was designed to investigate drivers' behaviors when drivers reacted to a potential conflict between the simulator vehicle and the pedestrian at intersections, as illustrated in Figure 7. The traffic light in this intersection has permitted left-turn signal. When the driver arrived at the intersection, the traffic light on the driver's side is always green. A pedestrian was designed to walk across the intersection at a speed of 3.5 ft/s. When the driver arrived at the stop line, a road trigger was activated. Then, the pedestrian start to cross the intersection. Meanwhile, there were no other vehicles before the simulator vehicle to interfere with the drivers' behavior and judgement.

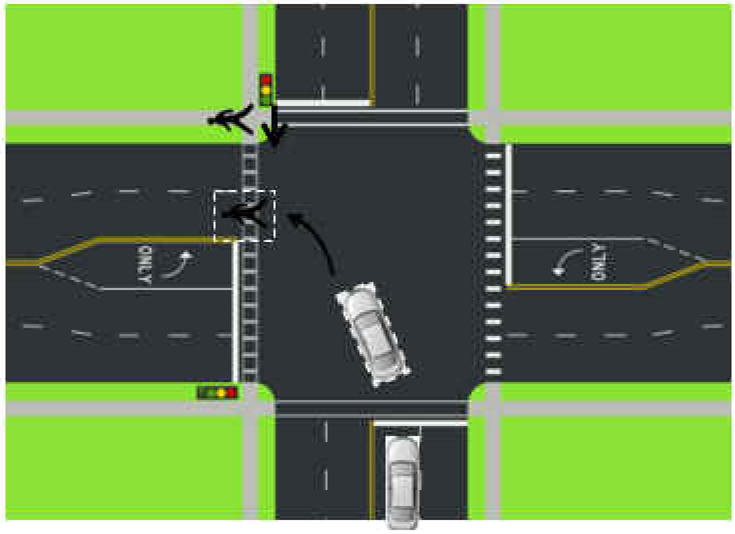


Figure 7: The intersection scenario design for pedestrian-vehicle conflict

With different factors, a total of 16 test intersections were added in this scenario. Among those, half of the intersections were in the daytime sub-scenario and the other 8 intersections were in the night sub-scenario. In each sub-scenario, the intersection with different factors was randomly assigned to the scenario. In addition, there were two additional intersections, intermingled with the test intersections. The total length of each scenario is around 3.5 miles, and participants need to drive around 10 mins to finish each sub-scenario.

4.3 Subjects

A total of 67 subjects, who had regular driver licenses, were selected to participate in this experiment. They were chosen from students, faculty, and staff of the University of Central Florida and volunteers from outside of the university. Since 8 subjects could not complete the experiment because of the motion sickness, finally, 59 subjects (28 Males and 31 females) finished the experiment successfully. In addition, all the participants were divided into two age groups. The age of the younger group ranges from 20 to 40 years. The age of the older group ranges from 40 to 60 years. Finally, 36 participants are in the younger group and 23 participants are in the older group. The distribution of the participants is shown in Table 10.

Table 10: The ideal number of participants recruited in the formal experiment

Age	**Gender**		**Total**
	Male	**Female**	
Under 40	20	16	36
Over 40	11	12	23
Total	31	28	59

4.4 Experiment Procedure

Upon arrival, all participants were asked to read and sign an informed consent form (per IRB protocol), which is shown in Appendix A. Each participant was asked to take short survey before and after the experiment. The survey is shown in Appendix B. Before starting the experiment, each participant was asked to take a short training session, including the Traffic Regulation Education, the Safety Notice, and the Familiarity Training. In the Traffic Regulation Education session, all participants were advised to drive and behave as they normally do and follow traffic rules as they do in real-life situations. In the Safety Notice session, each participant was told that they could quit the experiment at any time if they had any motion sickness symptoms or any kind of discomfort. In the Familiarity Training session, each participant was given at least 10 minutes training to familiarize them with the driving simulator operation, such as straight driving, acceleration, deceleration, left/right turn turning, and other basic driving behaviors.

After completing the short training course, participants would start the formal experiment and test two scenarios in a random sequence so as to eliminate the time order effect. In addition, all participants were recommended to rest at least 15 minutes between the scenarios.

4.5 Data Collection

4.5.1 Simulator Data Collection Procedure

The driving simulator data included the experiment sampling time, vehicle speed, acceleration, vehicle position, steering angle and many other related parameters. The data sampling frequency is up to 60 Hz, and the collected raw data was stored in DAQ type file. The DAQ file could only be opened through Nadstools in Matlab, which was developed by NADS. First of all, DAQ files could be read through Nadstools in Matlab and then output to the EXCEL type files. In order to organize and easily process the raw data generated from the experiments, a program was developed to automatically extract the experiment data from the EXCEL files (See Appendix C).

4.5.2 Midblock Crossing Scenario Data Collection

To assess the pedestrian-vehicle conflicts at midblock crossings, the data were recorded starting from 500 ft in advance of each midblock crossing. However, the drivers sometimes did not yield to the pedestrian and they accelerated to pass the conflict point before the pedestrian arrived at the conflict point. Since the previous studies defined the pedestrian-vehicle conflict, which only referred to the vehicle-yield-pedestrian conflict (Parker and Zegger, 1989), the cases illustrated above were excluded in the following analysis. Finally, 59 participants resulted in 908 experiments records. Among those, only 53 collisions were observed. A value of $P<0.05$ is adopted as the level for significance. The related dependent measures were defined as follows:

- Maximum Deceleration (ft/s^2): The maximum deceleration during the pedestrian-vehicle conflict period.
- Maximum Deceleration Location (ft): The distance between the conflict point and the point where the driver has the maximum deceleration during the pedestrian-vehicle conflict period.
- Minimum Distance (ft): The minimum distance between the driver and the pedestrian during the pedestrian-vehicle conflict period.
- PET (s): Post-encroachment time for the pedestrian-vehicle conflict.
- Minimum TTC (s): The minimum TTC during the pedestrian-vehicle conflict period.

4.5.3 Intersection Scenario Data Collection

To assess the pedestrian-vehicle conflicts at intersections, the data were recorded starting from stop line of each intersection. However, the drivers sometimes did not yield to the pedestrian and they accelerated to pass the conflict point before the pedestrian arrived at the conflict point. Therefore, the cases illustrated above were excluded in the following analysis. Finally, 59 participants resulted in 884 experiments records. Among those, only 21 collisions were observed.

A value of $P<0.05$ is adopted as the level for significance. The related dependent measures were defined as follows:

- Entrance Speed (mph): The vehicle’s operating speed when the vehicle arrives at the stop line.
- Minimum Distance (ft): The minimum distance between the driver and the pedestrian during the pedestrian-vehicle conflict period.
- PET (s): Post-encroachment time for the pedestrian-vehicle conflict.
- Minimum TTC (s): The minimum TTC during the pedestrian-vehicle conflict period.

CHAPTER FIVE: DRIVING SIMULATOR EXPERIMENT RESULTS AND DATA ANALYSES

This chapter is to analyze the pedestrian-vehicle conflicts based on the driving simulator experiment at both midblock crossings and intersections. Several surrogate measures were extracted to evaluate the pedestrian-vehicle conflicts with potential risk factors, such as maximum deceleration, time-to-collision, and post-encroachment time.

5.1 Midblock Crossing Scenario Data Analyses

5.1.1 Maximum Deceleration

The mixed model was used to analyze whether the potential risk factors impacted the maximum deceleration during the pedestrian-vehicle conflict period. A mixed model is a typically statistical model, which usually contains fixed effects and random effects (Little et al., 2006). Fixed factors are the primary interests of the model and would be used again for the multiple observations per subject. Random effects are not the primary intersects, however, they are thought of as a random selection from the dataset, such as subject effect. In general, ANOVA is the common statistical models to analyze the differences among group means and their associated procedures. However, multiple measurements per subject generally result in the correlated errors that are explicitly forbidden by the assumptions of ANOVA and regression models. Mixed models could handle these correlated errors by adding the fixed effects and random effects. In addition, ANOVA cannot be used when any subject has missing values, while the mixed model allows the missing values in the dataset. Therefore, the mixed model was used to analyze the relationship between independent variables and dependent variables in this study.

Four potential risk factors and two driver characteristic factors are chosen as independent variables. The four risk factors include time of day, crosswalk marking, number of lanes, and pedestrian visibility factors. Two driver characteristic factors include gender and age group. The maximum deceleration is chosen as the dependent variables. The basic statistical descriptions of experiment results are shown in Table 11. Table 12 shows final mixed model of the maximum deceleration. Hypothesis test with a 0.05 significance level is used to decide on the significant factors for the models.

Table 11: Descriptive statistics of the maximum deceleration for the midblock crossings scenario

Factors		The maximum deceleration (ft/s2)				
		Count	Mean	Standard Deviation	Percentile 05	Percentile 95
Age group	Under 40	555	-16.87	8.39	-34.03	-5.32
	Over 40	353	-19.35	9.07	-34.16	-7.68
Gender	Male	473	-16.70	8.40	-34.10	-7.37
	Female	435	-19.07	8.94	-34.11	-5.09
Time of day	Night	452	-19.01	9.23	-34.14	-5.35
	Daytime	456	-16.67	8.06	-34.03	-7.37
Crosswalk marking	Yes	455	-17.30	8.13	-33.99	-7.92
	No	453	-18.37	9.29	-34.13	-4.50
Roadway type	One lane	447	-17.38	8.12	-34.10	-7.98
	Two lanes	461	-18.27	9.29	-34.09	-3.86
Pedestrian visibility	Dark	456	-19.67	9.56	-34.16	-3.33
	Bright	452	-15.97	7.38	-33.94	-8.00

Table 12: Summary of the mixed model of the maximum deceleration for the midblock crossings scenario

Term	Estimate	Std. Error	DF	t Ratio	Prob>|t|
Intercept	-18.11	0.53	56.1	-33.62	<0.0001
Age	1.17	0.54	56.2	2.17	0.0339
Gender	1.07	0.53	56.1	2.04	0.0465
Time of day	-1.18	0.25	848.9	-4.69	<0.0001
Pedestrian visibility	-1.85	0.25	848.3	-7.35	<0.0001

According to the results, age, gender, time of day and pedestrian visibility are significantly related to the maximum deceleration. Since there is no two-way interaction effect found between each factor for the maximum deceleration. Female drivers have a larger maximum deceleration than male drivers and drivers who are over 40 years old also have a larger maximum deceleration than drivers who are under 40 years old. The maximum deceleration of driving at night is larger than that of driving in the daytime (t=-4.69, p-value<0.0001). The possible reason is that drivers have low visibility when driving at night. Therefore, when they notice a pedestrian crossing the street at night, they would have a harder brake than the daytime. Moreover, the average maximum deceleration of pedestrian dressing the dark color clothes is 19.67 ft/s^2, whereas the average maximum deceleration of pedestrian dressing the bright color clothes is 15.97 ft/s^2. The final mixed model indicates that there is a significant difference between the dark color clothes and bright color clothes of the pedestrian clothes in average maximum deceleration (t=-7.35, p-value<0.0001). When pedestrians have the dark clothes, drivers usually have a harder brake. However, there is no interaction effect found between time of day and pedestrian visibility, indicating that pedestrians with bright color clothes contribute to the maximum deceleration no matter it is at night or in the daytime.

5.1.2 Maximum Deceleration Location

The maximum deceleration location is another measurement that can reflect the pedestrian safety. The maximum deceleration is measured as the distance between the conflict point and the point where the driver has the maximum deceleration during the pedestrian-vehicle conflict period. Four factors are chosen as the potential factor that might impact the maximum deceleration location, including time of day, crosswalk marking, number of lanes, and pedestrian visibility factors. The basic statistical descriptions of experiment results are shown in Table 13. Table 14 shows final mixed model of the maximum deceleration location. Finally, all parameters' P-values are less than 0.05.

Table 13: Descriptive statistics of the maximum deceleration location for the midblock crossings scenario

Factors		Maximum deceleration location (ft)				
		Count	Mean	Standard Deviation	Percentile 05	Percentile 95
Age group	Under 40	555	179.70	92.81	57.45	355.80
	Over 40	353	219.19	103.88	66.66	427.30
Gender	Male	473	172.50	91.70	52.30	355.80
	Female	435	219.57	101.09	67.24	412.37
Time of day	Night	452	172.28	85.33	51.88	286.57
	Daytime	456	217.62	106.45	71.68	424.43
Crosswalk marking	Yes	455	206.38	93.80	78.30	377.21
	No	453	183.67	103.00	47.31	420.31
Roadway type	One lane	447	185.07	85.90	68.64	344.64
	Two lanes	461	204.73	109.62	51.59	420.31
Pedestrian visibility	Dark	456	157.78	85.50	45.49	312.56
	Bright	452	232.65	97.73	88.40	424.43

Table 14: Summary of the mixed model of the maximum deceleration location for the midblock crossings scenario

Term	Estimate	Std. Error	DF	t Ratio	Prob>|t|
Intercept	200.96	4.75	54.2	42.28	<0.0001
Age group	-17.54	4.76	54.3	-3.68	0.0005
Gender	-21.69	4.65	54.2	-4.66	<0.0001
Time of day	-23.31	2.51	841.4	-9.27	<0.0001
Crosswalk marking	10.69	2.51	840.6	4.26	<0.0001
Roadway type	-10.17	2.51	840.0	-4.05	<0.0001
Pedestrian visibility	-37.44	2.51	840.7	-14.90	<0.0001

The final results show that all of the main effects are significant factors. First, it is found that the maximum deceleration location of male drivers usually is nearer to the conflict point compared to female drivers (t=-4.66, p-value<0.0001). Also, younger drivers tend to brake late than older drivers. Figure 8 shows the comparison of four potential risk factors. It indicates that distance between the conflict point and the maximum deceleration location for drivers driving in the daytime is far more than that for drivers driving at night, indicating that the drivers' maximum deceleration location is near to the pedestrian at night (t=-9.27, p-value<0.0001). The crosswalk with pavement marking have a larger value of the maximum deceleration locations, indicating that the marked crosswalk could alert the drivers to brake earlier (t=4.26, p-value<0.0001). The maximum deceleration location of one-lane road is 185.07 ft far from the conflict point, whereas the maximum deceleration location of two-lane road is 204.73 ft. This finding indicates that one lane road may lead to higher pedestrian crash risk based on the maximum deceleration location. In addition, pedestrian visibility also exhibits a statistically significant effect on the maximum deceleration location (t=-14.90, p-value<0.0001). Not surprisingly, pedestrian with the dark color clothes leads to the shorter distance between the maximum deceleration location and the conflict point, which may increase the risk of the pedestrian crash.

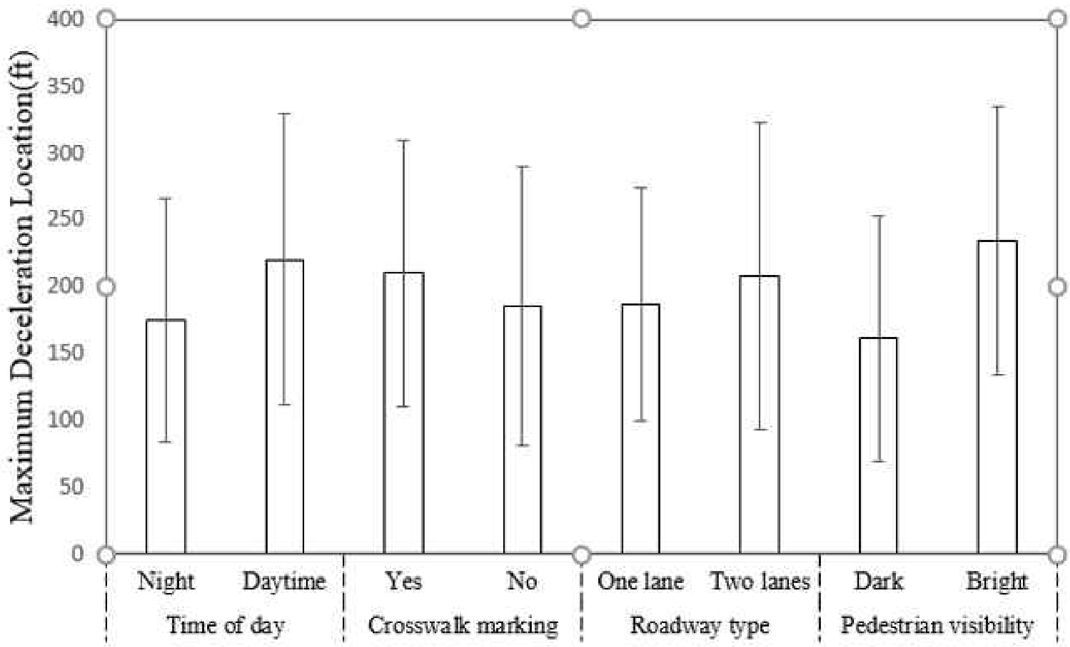


Figure 8: Comparison of maximum deceleration location of time of day, crosswalk marking, roadway type, and pedestrian visibility for the midblock crossings scenario

Moreover, four two-way interaction terms are found to be significantly related to the maximum deceleration location, which is shown in Table 15. Figure 9 shows the plots of interaction terms. First, the time of day has interaction effects with crosswalk marking and roadway type. For the night time, the maximum deceleration location of marked crosswalk is almost the same as no marked crosswalk. However, in the daytime, the marked crosswalk would increase the distance between the maximum deceleration location and the conflict point. In addition, for the night time, the maximum deceleration location for one lane roadway is almost the same as two lanes roadway. However, when the pedestrian-vehicle conflicts happen in the daytime, the maximum deceleration location of the one lane roadway is significantly lower than that of the two lanes roadway. Second, pedestrian visibility has interaction effects with crosswalk marking and roadway type. If the pedestrian wears the bright color clothes, there is no significant difference in crosswalk marking. However, if the pedestrian wears the dark color clothes, the marked crosswalk would help drivers to brake earlier than unmarked crosswalk. In addition, if pedestrian wears dark color clothes, roadway type is not related to the maximum deceleration location. However, if pedestrian wears bright color clothes, there is a significant difference in roadway type. As shown in Figure 5, it is found that drivers would make the maximum deceleration earlier on the two lanes road than one lane road.

Table 15: Summary of the interaction effects of the maximum deceleration location for the midblock crossings scenario

Term	Estimate	Std. Error	DF	t Ratio	Prob>|t|
Time of day* Crosswalk marking	-5.81	2.51	840	-2.31	0.0209
Time of day* Roadway type	11.66	2.51	841.7	4.64	<0.0001
Crosswalk marking* Pedestrian visibility	11.41	2.51	840.6	4.54	<0.0001
Roadway type*Pedestrian visibility	8.24	2.51	840.0	3.28	0.0011

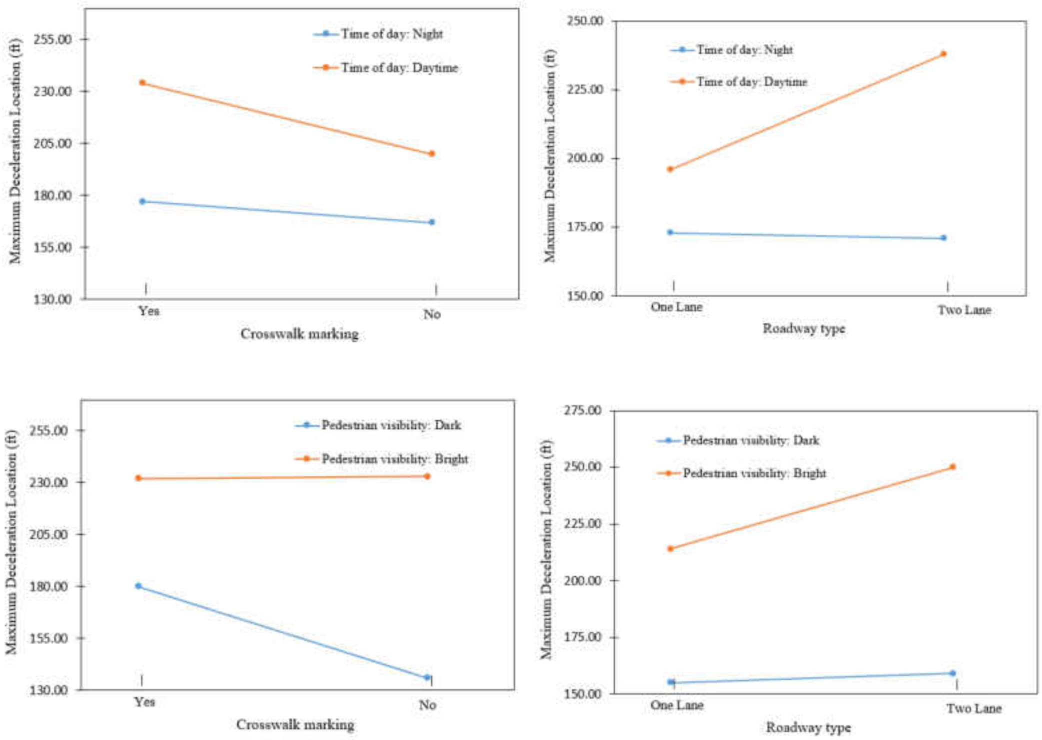


Figure 9: Plot of interactions of the maximum deceleration location for the midblock crossings scenario

5.1.3 Minimum Distance

The distance between the driver and the pedestrian changes during the pedestrian-vehicle conflict period and a minimum distance exists during this process. The minimum distance is not only used to estimate the occurrence of a collision between the driver and the pedestrian, but also used as a safety threshold reflecting the temporal buffer that drivers allow themselves for interaction with the pedestrian. Four potential risk factors (time of day, crosswalk marking, number of lanes, and pedestrian visibility factors) and two driver characteristic factors (gender and age group) are chosen as the independent variables and the minimum distance is chosen as the dependent variables. The basic statistical descriptions of experiment results are shown in Table 16. Table 17 shows final mixed model of the maximum deceleration location. Finally, roadway type and pedestrian visibility are the only significant factors. There is no interaction found in the final model.

Table 16: Descriptive statistics of the minimum distance for the midblock crossings scenario

Factors		Minimum distance (ft)				
		Count	Mean	Standard Deviation	Percentile 05	Percentile 95
Age group	Under 40	555	23.60	5.41	14.33	32.52
	Over 40	353	24.00	5.91	15.64	33.05
Gender	Male	473	23.61	5.42	14.55	32.46
	Female	435	23.91	5.81	14.49	33.68
Time of day	Night	452	23.81	6.03	13.06	32.79
	Daytime	456	23.70	5.16	15.71	33.03
Crosswalk marking	Yes	455	23.55	4.89	15.74	31.60
	No	453	23.96	6.24	13.43	34.53
Roadway type	One lane	447	23.11	4.87	15.25	31.30
	Two lanes	461	24.38	6.18	14.30	33.68
Pedestrian visibility	Dark	456	22.77	5.79	12.56	31.71
	Bright	452	24.75	5.24	16.59	33.68

Table 17: Summary of the mixed model of the minimum distance for the midblock crossings scenario

Term	Estimate	Std. Error	DF	t Ratio	Prob>|t|
Intercept	23.81	0.47	58.1	49.64	<0.0001
Roadway type	-0.63	0.13	846.3	-4.64	<0.0001
Pedestrian visibility	-0.99	0.13	846.5	-7.32	<0.0001
Roadway type* Pedestrian visibility	0.98	0.13	846.3	7.22	<0.0001

According to the results, the minimum distance between the driver and the pedestrian for one lane road and two lanes road are 23.11 ft and 24.38 ft, respectively. This result shows the significant difference in roadway type (t=-4.64, p-value<0.0001). The possible reason is that when drivers drive in the wide road, they are more cautious and notice the pedestrian more easily. In comparison, it is hard for them to notice the pedestrian in the narrow road, especially there is a parking lane beside the traveling lane. Therefore, the minimum distance is shorter for one lane road. Similarly, the pedestrian wearing bright color clothes have a positive impact on the minimum distance. When pedestrians wear the bright color clothes, it is much easier for drivers to notice them and take action to avoid the collision. However, when pedestrians wear dark color clothes, the minimum distance is significant shorter, which increases the risk of pedestrian crashes.

5.1.4 Post encroachment time

Post encroachment time (PET) is the time between the departure of the encroaching vehicle or pedestrian from the conflict point and the arrival of the vehicle or pedestrian. In this case, vehicles need to yield to the crossing pedestrian, so the pedestrian usually cross the street first and then drivers pass the conflict point. The basic statistical descriptions of experiment results are shown in Table 18. The average PET of all the pedestrian-vehicle conflicts is 6.98 seconds with a standard deviation of 2.64. The mixed model is used to check the difference between each group in PET. The results show that time of day and pedestrian visibility have significant impact on PET, which is shown in Table 19. For the night time, the mean of PET is 6.65 seconds with a standard deviation of 2.62; for the daytime, the mean of PET is 7.18 seconds with a standard deviation of 2.57. There is a significant difference between nighttime and daytime ($t=-4.29$, $p\text{-value}<0.0001$). In addition, pedestrian visibility also has significant influence on PET ($t=-6.27$, $p\text{-value}<0.0001$). The average PET of pedestrians with dark color clothes is significantly smaller than that of pedestrians with bright color clothes, which also indicates that pedestrians wearing dark color clothes have a higher risk of crash.

Table 18: Descriptive statistics of PET for the midblock crossings scenario

Factors		PET (sec)				
		Count	Mean	Standard Deviation	Percentile 05	Percentile 95
Age group	Under 40	555	6.85	2.52	0.00	10.68
	Over 40	353	7.02	2.73	0.00	11.38
Gender	Male	473	6.81	2.49	0.00	10.67
	Female	435	7.03	2.72	0.00	11.38
Time of day	Night	452	6.65	2.62	0.00	10.68
	Daytime	456	7.18	2.57	2.80	11.22
Crosswalk marking	Yes	455	7.04	2.34	3.85	10.87
	No	453	6.79	2.84	0.00	11.38
Roadway type	One lane	447	7.00	2.29	3.97	10.67
	Two lanes	461	6.84	2.88	0.00	11.28
Pedestrian visibility	Dark	456	6.54	2.77	0.00	10.68
	Bright	452	7.29	2.37	4.13	11.08

Table 19: Summary of the mixed model of PET for the midblock crossings scenario

Term	Estimate	Std. Error	DF	t Ratio	Prob>|t|
Intercept	6.95	0.23	58	29.17	<0.0001
Time of day	-0.26	0.06	847.6	-4.29	<0.0001
Pedestrian visibility	-0.39	0.06	847.4	-6.27	<0.0001

5.1.5 Minimum TTC

Time to collision (TTC) has been widely used to evaluate the traffic environment in terms of safety in recent researches (Vogel, 2003; Ward et al., 2015; Shahdah et al., 2015). In this case, the minimum TTC is measured during the pedestrian-vehicle conflict. Table 20 shows the descriptive statistics of the minimum TTC. The mixed model is also used to analyze the potential risk factors, including time of day, crosswalk marking, roadway type, and pedestrian visibility. The model results show in Table 21.

Table 20: Descriptive statistics of TTC for the midblock crossings scenario

Factors		Minimum TTC (sec)				
		Count	Mean	Standard Deviation	Percentile 05	Percentile 95
Age group	Under 40	555	4.31	1.93	0.00	7.57
	Over 40	353	5.10	2.27	0.00	9.13
Gender	Male	473	4.20	1.90	0.00	7.57
	Female	435	5.07	2.21	0.00	8.92
Time of day	Night	452	4.06	1.89	0.00	7.58
	Daytime	456	5.17	2.15	1.65	9.03
Crosswalk marking	Yes	455	4.79	1.89	1.77	8.30
	No	453	4.44	2.28	0.00	8.95
Roadway type	One lane	447	4.52	1.84	1.80	7.80
	Two lanes	461	4.71	2.33	0.00	8.75
Pedestrian visibility	Dark	456	3.90	1.99	0.00	7.23
	Bright	452	5.33	1.97	2.78	8.93

Table 21: Summary of the mixed model of the minimum TTC for the midblock crossings scenario

Term	Estimate	Std. Error	DF	t Ratio	Prob>|t|
Intercept	4.75	0.15	55.3	31.58	<0.0001
Age group	-0.35	0.15	55.3	-2.35	0.0224
Gender	-0.39	0.15	55.3	-2.65	0.0105
Time of day	-0.57	0.05	838	-12.04	<0.0001
Crosswalk marking	0.14	0.05	837.8	2.84	0.0046
Roadway type	-0.09	0.05	837.5	-2.09	0.0373
Pedestrian visibility	-0.74	0.05	837.8	-15.42	<0.0001

First, age and gender have significant influence on the minimum TTC. The average of the minimum TTC of female drivers is 5.07 seconds, and the average of the minimum TTC of male drivers is 4.2 seconds. Based on the mixed model results, the minimum TTC of female drivers is significantly larger than that of male drivers, indicating that females have a lower crash risk. Similarly, the minimum TTC of drivers who are under 40 years old is significantly smaller than that of drivers who are over 40 years old. The time of day is also one of the significant factors that affect the minimum TTC. When driving at night, the average minimum TTC is 4.06 seconds with a standard deviation of 1.89. In comparison, the daytime driving increases the average minimum TTC, which is statistical significantly larger than night time (t=-12.04, p-value<0.0001). The marked crosswalk has a larger minimum TTC than unmarked crosswalk and two lanes road also has a larger minimum TTC than one lane road. Moreover, the pedestrian visibility is also associated with the minimum TTC. Pedestrians wearing dark clothes reduce the minimum TTC during the pedestrian-vehicle conflict compared to pedestrians with bright color clothes. This reduction implies that pedestrian wearing dark clothes may affect the drivers' avoidance performance and lead to the more dangerous situations.

Moreover, seven two-way interaction terms are found to be significantly related to the minimum TTC, which is shown in Table 22. Figure 10 illustrates the relationship of interaction terms.

Table 22: Summary of the interaction effects of the mixed model for the minimum TTC for the midblock crossings scenario

Term	Estimate	Std. Error	DF	t Ratio	Prob>|t|
Age Group* Crosswalk marking	0.11	0.04	837.8	2.25	0.0249
Age Group * Pedestrian visibility	0.11	0.04	837.8	2.3	0.0217
Gender* Time of day	0.14	0.04	838	3.06	0.0023
Time of day* Roadway type	0.28	0.04	838.2	6.06	<0.0001
Crosswalk marking* Roadway type	0.14	0.04	837.7	3.06	0.0023
Crosswalk marking* Pedestrian visibility	0.23	0.04	837.8	4.96	<0.0001
Roadway type* Pedestrian visibility	0.18	0.04	837.5	3.88	0.0001

Age group shows interaction effects with crosswalk marking and pedestrian visibility. For the drivers who are over 40 years old, it seems that marked crosswalk doesn't affect the minimum TTC. However, if the drivers are under 40 years old, the marked crosswalk would increase the minimum TTC. The pedestrian with bright color clothes increases the minimum TTC for both younger drivers and older drivers compared to the pedestrian with the dark color clothes. The slope of the older driver group is larger than the younger driver group, indicating that bright color clothes have more effects on the older driver. For the interaction between gender and time of day, it is found that time of day have more effect on female than male, although both drivers have a larger minimum TTC in the daytime than night time. As for the interaction between time of day and roadway type, two different tendencies are found. One lane road decreases the minimum TTC than two lanes road in the daytime, however, it increases the minimum TTC than two lanes road in the night time. Moreover, there is almost no difference in the minimum TTC between marked crosswalk and unmarked crosswalk for the two lanes road. But for the one lane road, the marked crosswalk significantly increases the minimum TTC than the unmarked crosswalk. If the pedestrian wears bright color clothes, it seems that there is no difference in the minimum TTC between marked crosswalk and unmarked crosswalk. However, the marked crosswalk significantly increases the minimum TTC than the unmarked crosswalk when the pedestrian wears dark clothes. The similar finding for the roadway type and pedestrian visibility. When the pedestrian wears dark clothes, there is almost no difference in the minimum TTC between one lane road and two lanes road. However, when the pedestrian wears bright color clothes, two lanes road have a larger minimum TTC than one lane road.

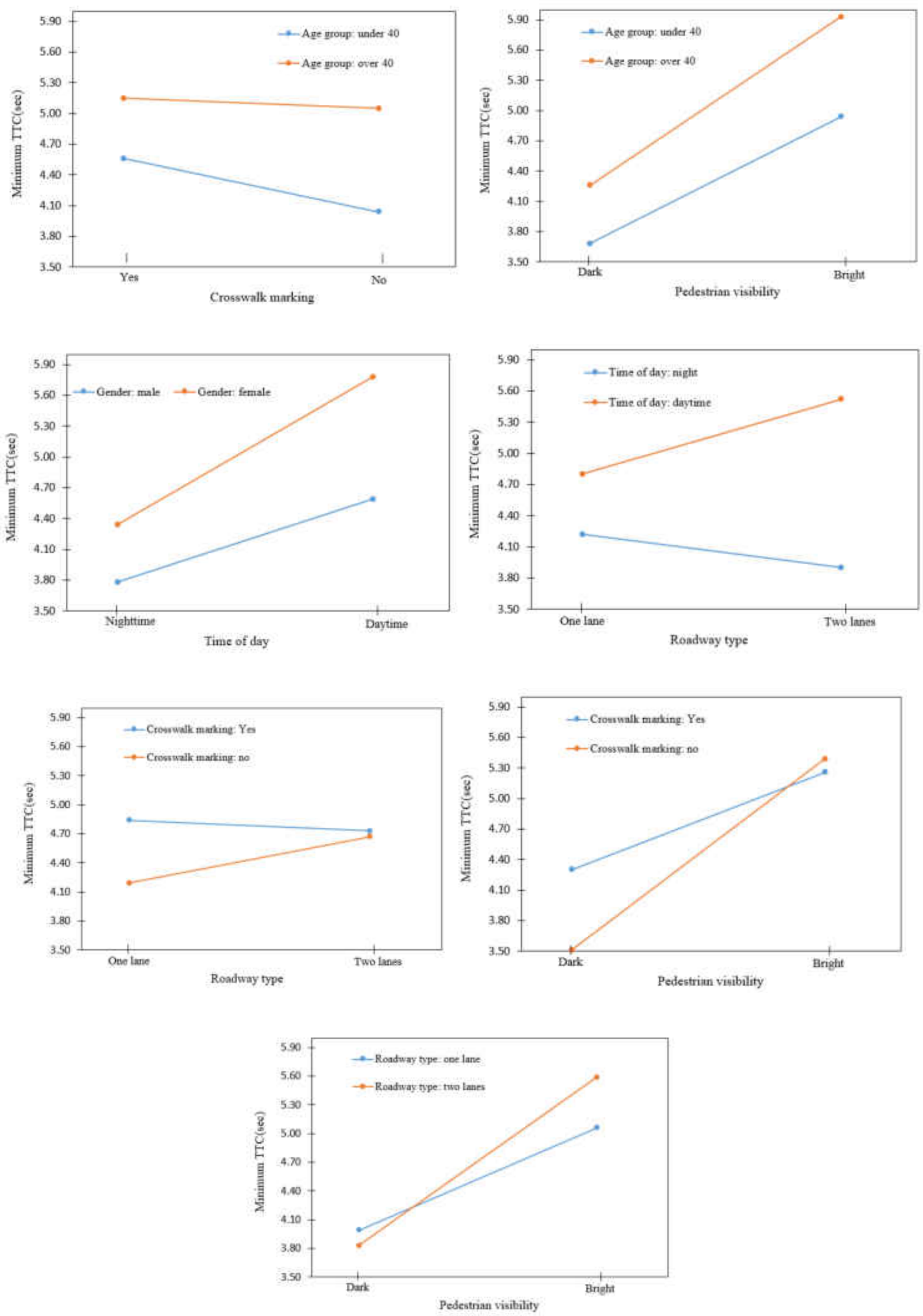
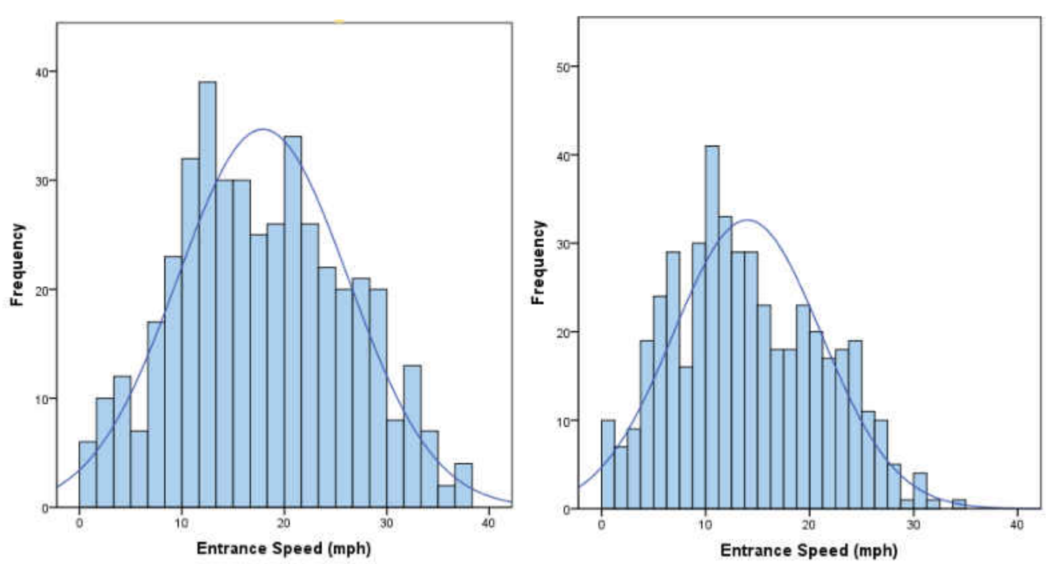


Figure 10: Plot of interactions of the maximum deceleration location for the midblock crossings scenario

5.2 Intersection Scenario Data Analyses

5.2.1 Entrance Speed

Entrance speed is measured when the vehicle arrives at the stop line. For the left turns, the mean of speed is 17.90 mph with a standard deviation of 8.32; for the right turns, the mean of the speed is 14.00 mph with a standard deviation of 7.10. The histograms of the entrance speed for both left turns and right turns appear very close to normal distribution as shown in Figure 11. The average entrance speeds of left turns tend to be higher than that of right turns, presumably because the left turn has a larger radius than the right turn. The driver could have a higher speed to make left turns than right turns.



(a) The histograms of entrance speed for left turns (b) The histograms of entrance speed for right turns

Figure 11: Distribution of entrance speed for the intersection scenario

5.2.2 Minimum Distance

The minimum distance is still checked in the intersection scenarios. Six independent variables (age group, gender, time of day, vehicle movement, pedestrian movement, and pedestrian visibility) are chosen as potential factors that might be associated with the minimum distance of the pedestrian-vehicle conflicts and the descriptive statistics are shown in Table 23.

Table 23: Descriptive statistics of the minimum distance for the intersection scenario

Factors		Minimum distance (ft)				
		Count	Mean	Standard Deviation	Percentile 05	Percentile 95
Age group	Under 40	539	25.57	10.17	14.65	45.21
	Over 40	345	26.08	10.51	14.93	46.24
Gender	Male	458	25.50	10.41	15.19	45.26
	Female	426	26.07	10.18	14.25	46.14
Time of day	Night	445	25.23	10.25	14.12	45.41
	Daytime	439	26.31	10.33	15.23	46.14
Vehicle movement	Left	430	26.54	12.04	15.08	51.89
	Right	454	24.96	8.00	14.12	38.41
Pedestrian movement	Far	452	28.66	11.86	15.64	52.56
	Near	432	23.00	7.59	14.04	36.68
Pedestrian visibility	Dark	440	23.49	7.94	14.91	37.53
	Bright	444	28.04	11.78	14.90	51.89

Running all of six given factors, Table 24 lists the mixed model results for the minimum distance. The significant main effects include the time of day, vehicle movement, pedestrian movement and pedestrian visibility. First, the results show that the minimum distance for night time is significantly smaller than that for the daytime (t=-3.05, p-value=0.0024). This tendency is in accordance with the findings in the midblock crossing scenarios. Second, the average of the minimum distance between the pedestrian and the driver for left turns is 26.54 ft, while the average of the minimum distance for right turns is 24.96 ft. The test also indicates that the minimum distance for left turns is statistically larger than that for right turns. Third, the pedestrian crossing the street from the far side has a larger minimum distance than the pedestrian crossing the street from the near side. This finding indicates that it is more dangerous for the pedestrian crossing the street from the near side than the far side. Last but not the least, the pedestrian with the bright color clothes also increases the minimum distance compared to the pedestrian with the dark color clothes. In addition, the two-way interaction vehicle movement and pedestrian visibility is also significant. Figure 12 shows the interaction effect of pedestrian visibility on vehicle movement for the minimum distance. It is found that the minimum distance for left turns are the almost the same with different pedestrian dressing color. In comparison, the pedestrian with the dark color clothes reduces the minimum distance for the right turns. The possible explanation is that it is easier for left turns to notice the crossing pedestrians because of the wider driver's view. However, for the right turns, it is hard for drivers to notice the pedestrian with dark color clothes.

Table 24: Summary of the mixed model of the minimum distance for the intersection scenario

Term	Estimate	Std. Error	DF	t Ratio	Prob>|t|
Intercept	25.80	0.64	54.6	40.31	<0.0001
Time of day	0.61	0.20	817.5	-3.05	0.0024
Vehicle movement	-0.73	0.20	816.5	3.66	0.0003
Pedestrian movement	-2.8	0.20	815.6	13.90	<0.0001
Pedestrian visibility	-2.19	0.20	815.1	-10.89	<0.0001
Vehicle movement* Pedestrian visibility	3.78	0.20	815.5	18.75	<0.0001

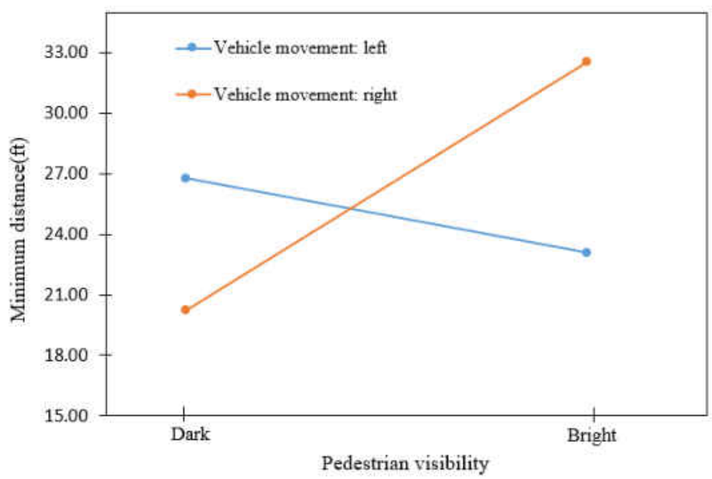


Figure 12: Interaction effect of pedestrian visibility on time of day for the minimum distance

5.2.3 Post encroachment time

The descriptive statistics of PET is shown in Table 25 and the summary of the mixed model for PET is shown in Table 26. The time of day and the pedestrian visibility are the only significant factors that affect PET in the intersection scenario. For the night time, the mean of PET is 6.47 seconds with a standard deviation of 4.29; for the daytime, the mean of PET is 6.05 seconds with a standard deviation of 4.10. There is a significant difference between the night time and daytime ($t=1.97$, p-value=0.0487). In addition, the pedestrian visibility also impacts the PET. Based on the results, it is found that the average PET of the pedestrian wearing the dark clothes is smaller than that of the pedestrian wearing the bright, indicating that drivers wait more time if the pedestrian wears the bright clothes.

Table 25: Descriptive statistics of PET for the intersection scenario

Factors		PET (sec)				
		Count	Mean	Standard Deviation	Percentile 05	Percentile 95
Age group	Under 40	539	6.10	4.10	1.57	13.88
	Over 40	345	6.51	4.34	1.80	14.57
Gender	Male	458	5.97	4.19	1.57	13.88
	Female	426	6.57	4.18	1.67	14.40
Time of day	Night	445	6.47	4.29	1.60	14.35
	Daytime	439	6.05	4.10	1.63	13.88
Vehicle movement	Left	430	6.34	3.47	1.98	12.65
	Right	454	6.19	4.79	1.53	15.82
Pedestrian movement	Far	452	6.18	3.49	0.80	12.45
	Near	432	6.34	4.83	1.65	15.98
Pedestrian visibility	Dark	440	5.26	3.53	1.65	11.89
	Bright	444	7.25	4.56	1.13	15.98

Table 26: Summary of the mixed model of PET for the intersection scenario

Term	Estimate	Std. Error	DF	t Ratio	Prob>|t|
Intercept	6.34	0.28	53.4	22.41	<0.0001
Time of day	0.24	0.12	823.6	1.97	0.0487
Pedestrian visibility	-1.00	0.12	819.4	-8.20	<0.0001

5.2.4 Minimum TTC

The descriptive statistics of the minimum TTC for the intersection scenario is shown in Table 27. The mixed model is still used to analyze the four potential risk factors, including age group, gender, time of day, vehicle movement, pedestrian movement, and pedestrian visibility. The results list in Table 28.

Table 27: Descriptive statistics of the minimum TTC for the intersection scenario

Factors		Minimum TTC (sec)				
		Count	Mean	Standard Deviation	Percentile 05	Percentile 95
Age group	Under 40	539	5.52	2.63	0.72	9.99
	Over 40	345	5.74	2.53	1.52	9.92
Gender	Male	458	5.50	2.59	0.65	9.99
	Female	426	5.72	2.59	1.47	9.95
Time of day	Night	445	5.30	2.56	0.82	9.65
	Daytime	439	5.91	2.59	1.02	10.40
Vehicle movement	Left	430	5.09	2.16	1.24	8.75
	Right	454	6.09	2.86	0.82	10.63
Pedestrian movement	Far	452	6.18	2.76	0.50	10.47
	Near	432	5.00	2.26	1.01	8.56
Pedestrian visibility	Dark	440	5.74	2.68	1.56	10.42
	Bright	444	5.47	2.49	0.63	9.62

Table 28: Summary of the mixed model of the minimum TTC for the intersection scenario

Term	Estimate	Std. Error	DF	t Ratio	Prob>|t|
Intercept	5.58	0.09	57.2	57.13	<0.0001
Time of day	-0.30	0.08	823.1	-3.74	0.0002
Vehicle movement	-0.50	0.08	829.5	-6.26	<0.0001
Pedestrian movement	0.59	0.08	826.5	7.32	<0.0001
Vehicle movement*pedestrian movement	-0.32	0.08	830.5	-4.06	<0.0001

Based on the results, it is found that time of day, vehicle movement, and pedestrian movement are significant factor that impact the minimum TTC. First, the minimum TTC of night time is 5.30 seconds with a standard deviation of 2.56, while the minimum TTC of daytime is 5.91 seconds with a standard deviation of 2.59 seconds. When driving at night, the average minimum TTC is significantly smaller compared to the daytime period (t=-3.74, p-value=0.0002). It implies that it is dangerous when the pedestrian-vehicle conflict happens at night. Second, the minimum TTC of left turns is significantly smaller than that of right turns, indicating that drivers need to pay more attention to pedestrians when they make left turns than right turns. Moreover, the pedestrian movement is also associated with the minimum TTC, which means drivers reaction to pedestrians who appear from the near side is different to pedestrians who appear from the far side. It seems that pedestrians who appear from the near side is more dangerous than pedestrians who appear from the far side. Last but not the least, the interaction effect of vehicle movement on pedestrian movement for the minimum distance is shown in Figure 13. It is found that the minimum TTCs for pedestrian-vehicle conflict of left turns are the almost the same with different pedestrian movements. In comparison, when the vehicle makes right turn, the pedestrian showing on the left side increases the minimum distance compared to the pedestrian showing on the right side. The possible explanation is that it is easier for drivers to notice the pedestrian showing on the left side other than right side.

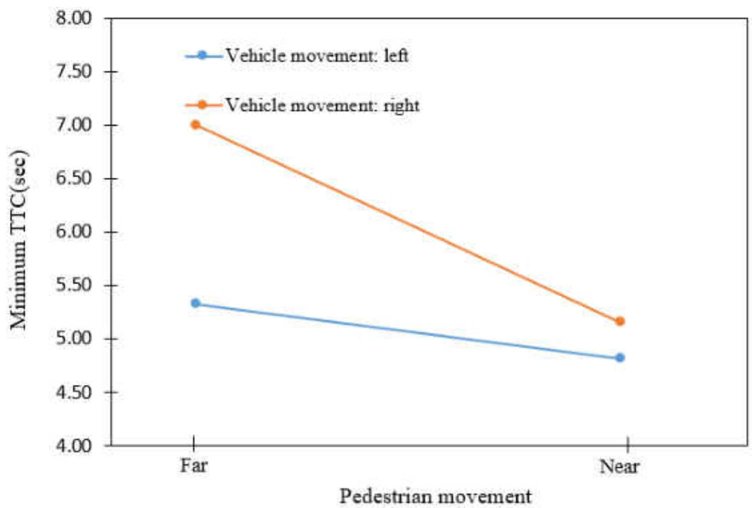


Figure 13: Plot of interactions between vehicle movement and pedestrian movement of the minimum TTC for intersection scenario

CHAPTER SIX: DRIVER'S AVOIDANCE PATTERN AND PEDESTRIAN-VEHICLE CONFLICTS MODEL

In this chapter, analysis of variance (ANOVA) was used to analyse the drivers' behavior during the pedestrian-vehicle conflicts period. Two driver's characteristic (age and gender) and four potential risk factors were selected as the independent variables and four key variables summarized above are chosen as the dependent variables. The hypothesis testing in the following analyses are based on a 0.05 significance level. In addition, the pedestrian-vehicle conflicts model was built based on the dataset. The minimum distance between the pedestrian and the vehicle was selected as the independent variable.

6.1 Driver's avoidance pattern

During the pedestrian-vehicle conflict period, drivers adjust their speed by changing the deceleration rate to avoid the crash (Li et at., 2016). Figure 14 shows the typical examples of drivers' deceleration rate and the location changes. These examples exhibited a clear avoidance pattern which can be summarized into four stages, as shown in Figure 15. The red line represents the deceleration rate and the blue curve represents the vehicle's speed.

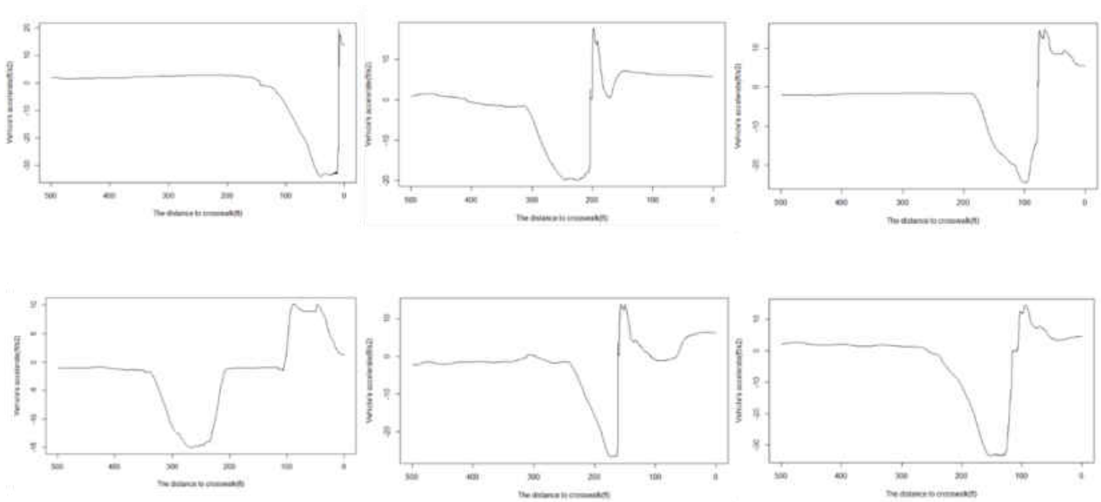
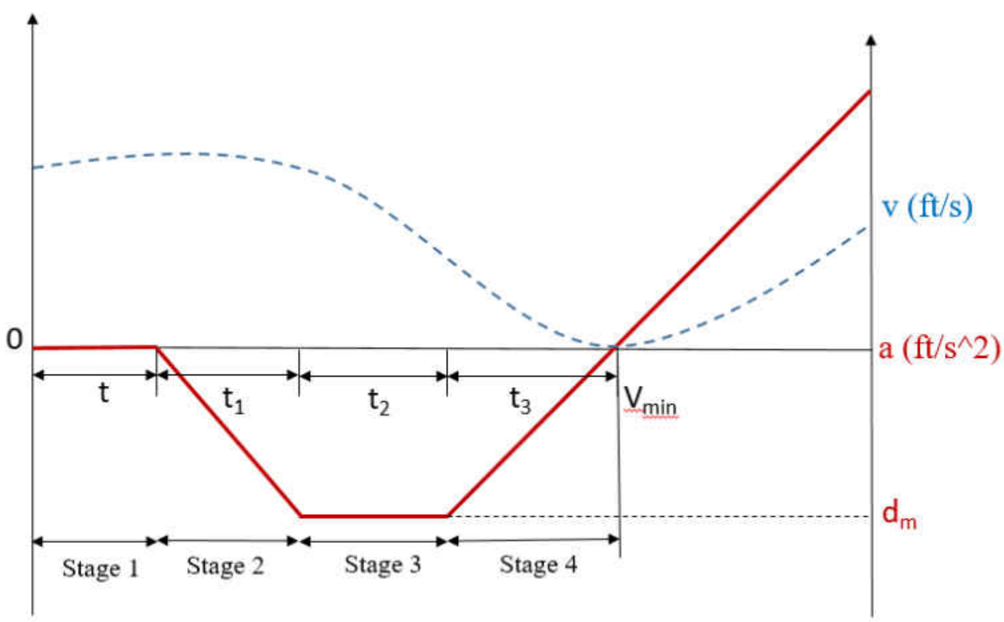


Figure 14: Drivers' deceleration rate and the distance to crosswalk during the avoidance period



Stage 1: Brake reaction stage

Stage 2: Deceleration adjustment stage

Stage 3: Maximum deceleration stage

Stage 4: Brake release stage

Figure 15: Drivers' avoidance pattern during the pedestrian-vehicle conflict

Stage 1: Brake reaction stage.

This stage starts from the time when drivers noticed the pedestrian crossing the street, and ended as the driver start to brake. The time duration of this stage was t_1, which was also called brake reaction time. The driver usually kept a constant initial speed during this stage. In order to get t_1, the eye tracker was usually needed. However, because of the equipment limitation, t_1 is not discussed in this study.

Stage 2: Deceleration adjustment stage

In this stage, drivers perceived the crash risk because of the sudden pedestrian appearance and then start to brake until the maximum deceleration. The time duration of this stage was t_2. In addition, the deceleration rate was assumed to be linearly increased.

Stage 3: Maximum deceleration stage

In this stage, drivers reached the maximum deceleration and stayed for a while. Drivers would release the brake until they could make sure that they won't hit the pedestrian. The duration time of this stage was t_3 and the maximum deceleration rate was d_m.

Stage 4: Break release stage

In this stage, drivers started to release the break. Finally, drivers completely stopped the car or drivers started to accelerate. The duration time of this stage was t_4.

Based on the drivers' avoidance pattern, the key variables during the pedestrian-vehicle conflict period were summarized, which include t_2 (deceleration adjustment time), t_3 (maximum deceleration time), d_m (maximum deceleration rate), and t_4 (brake release time).

6.2 Driver's behavior analysis

6.2.1 Deceleration adjustment time (t_2)

The ANOVA results of deceleration adjustment time are listed in Table 29. The AVOVA results show that four variables are significant, including age, gender, roadway type, and dressing color. Time of day and marking are not significant factors. The difference of age, gender, roadway type, and dressing color on deceleration adjustment time are shown in Figure 16. Based on the results, drivers who are under 40 years old (M = 1.44s, S.D.=1.28) had a higher deceleration adjustment time than drivers who are over 40 years old (M = 1.22s, S.D.=1.17). It seems that drivers under 40 years old are more aggressive than those over 40 years, that's why they need more deceleration time. For the gender, it appears that the mean of deceleration adjustment time for male drivers (M = 1.42s, S.D.=1.37) is higher than that for female drivers (M = 1.28s, S.D.=1.08). In other words, females drive an increased proclivity of quickly braking than male drivers. The reason is that female drivers react late in urgent situations than male drivers so that the deceleration adjustment time of female drivers become smaller than male drivers (Li et al., 2016). As for the potential risk factors, roadway type and dressing color are found to be significant with deceleration adjustment time. The deceleration adjustment time of one travelling lane with one parking lane (M = 1.39s, S.D.=1.27) is significantly higher than that of two travelling lanes (M = 1.32s, S.D.=1.22). The possible explanation is that two travelling lanes road provide the driver with more space to react than one lane road with one parking lane. Similarly, dark color clothes (M = 1.44s, S.D.=1.05) increased the deceleration adjustment time than the bright color (M = 1.27s, S.D.=1.40). When pedestrians wear the dark color clothes, drivers are difficult to find the pedestrians. Therefore, drivers need more time at the deceleration adjustment stage when pedestrian wear dark color clothes.

Table 29: Analysis of variance (ANOVA) results of deceleration adjustment time (t_2)

Variables	Df	Mean Square	F-Value	Sig.
Age	1	6.7	7.986	0.00483
Gender	1	3.8	4.534	0.03352
Time of day	1	0.3	0.382	0.53671
Marking	1	1.2	1.465	0.22650
Roadway Type	1	3.4	4.091	0.04342
Dressing Color	1	7.5	8.967	0.00283

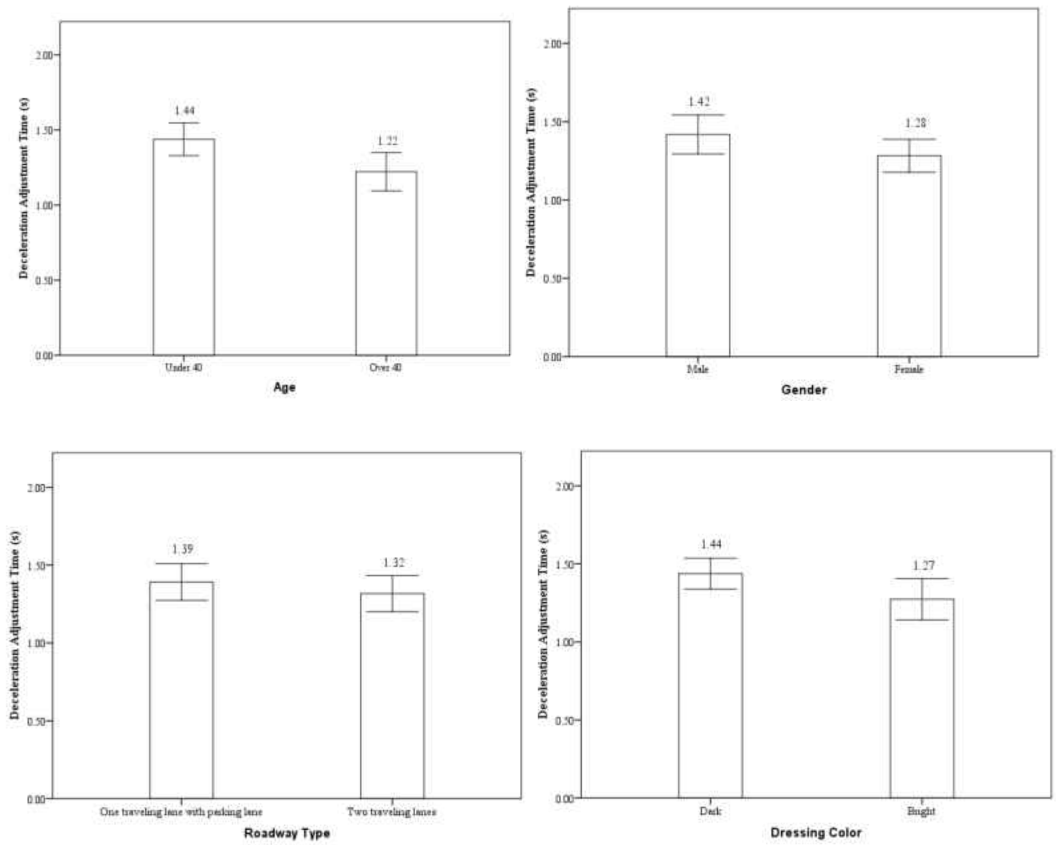


Figure 16: Relationship between deceleration adjustment time and significant factors

6.2.2 Maximum deceleration time (t_3) and maximum deceleration rate (d_m)

The basic statistical descriptions of independent variables for t_3 and d_m are listed in Table 30. Table 31 shows the ANOVA results for the maximum deceleration time and maximum deceleration rate. The ANOVA results indicate that age, gender, time of day, crosswalk marking, and dressing color have significant effect on the maximum deceleration time. However, all factors are found to be significantly associated with the maximum deceleration rate. From Table 30, it is found that if one group has a higher maximum deceleration rate, this group have a lower maximum deceleration time. For example, drivers who are over 40 years old has a higher maximum deceleration rate than drivers who are under 40 years old. However, drivers who are over 40 years old has a lower maximum deceleration time than drivers who are under 40 years old. This finding is appropriate for all variables. The lower t_3 and higher d_m implies that drivers have a relatively hard brake so that they don't need to keep the maximum deceleration for a long time. For male drivers, t_3 is 2.05 seconds and d_m is 17.04 ft/s^2. For female drivers, t_3 is 1.61 seconds and d_m is 20.00 ft/s^2. In addition, night time driving has a lower t_3 and a higher d_m than the day time driving, which indicates that drivers driving at night are more likely to have a hard brake than driving in the daytime. For the crosswalk marking, t_3 has a higher value with the marking and a lower value without a marking. Similarly, d_m has higher value without the marking and lower value with the marking. Roadway type only affects d_m, but it didn't affect t_3. Based on the results, drivers on the two lanes road have a higher maximum deceleration rate than those on the one lane with one parking lane. As for the dressing color, pedestrian with dark color clothes has a lower maximum deceleration time and a higher maximum deceleration rate. The possible reason is that when pedestrians wear bright color clothes, drivers are much easier to notice them. Therefore, they are more likely to have a hard brake, but keep a shorter period of maximum deceleration time.

Table 30: Descriptive statistics of six factors related to the t_3 and d_m

Variables		t_3		d_m	
		Mean	**Std.Deviation**	**Mean**	**Std.Deviation**
Age	Under 40	1.98	1.82	-17.37	8.02
	Over 40	1.64	1.51	-20.10	8.37
Gender	Male	2.05	1.84	-17.04	7.98
	Female	1.61	1.54	-20.00	8.52
Time of day	Night	1.64	1.43	-19.47	8.76
	Day	2.07	1.95	-17.32	7.79
Marking	Yes	1.95	1.69	-17.81	7.81
	No	1.74	1.74	-19.06	8.87
Roadway Type	One lane with one parking lane	1.89	1.68	-17.65	7.97
	Two lanes	1.80	1.75	-19.23	8.70
Dressing Color	Dark	1.53	1.35	-20.55	8.84
	Bright	2.16	1.97	-16.29	7.27

Table 31: Analysis of variance (ANOVA) results of maximum deceleration time (t_3) and maximum deceleration rate (d_m)

	Variables	Df	Mean Square	F-Value	Sig.
t_3	Age	1	25.47	12.806	0.0003
	Gender	1	41.63	20.824	0.0001
	Time of day	1	24.75	12.439	0.0004
	Marking	1	17.39	8.744	0.0032
	Roadway Type	1	1.57	0.787	0.3751
	Dressing Color	1	72.46	36.426	0.0001
d_m	Age	1	1493	25.283	0.0001
	Gender	1	1643	27.819	0.0001
	Time of day	1	712	12.064	0.00054
	Marking	1	462	7.816	0.00530
	Roadway Type	1	510	8.629	0.00340
	Dressing Color	1	4052	68.623	0.0001

6.2.3 Brake Release Time (t_4)

The brake release time is the time between starting to release the break and the time the driver completely stops or starts to accelerate for normal driving. Table 32 represents the ANOVA results of the deceleration adjustment time. The ANOVA results show that age and dressing color are the only two factors that affect the brake release time (t_4). The difference of age and dressing color on t_4 is shown in Figure 17. Drivers who are under 40 years old have an average of 1.50s t_4 with a standard deviation of 1.23. In comparison, drivers who are over 40 years old have an average of 1.29s t_4 with a standard deviation of 0.91. It indicates that younger drivers are more likely to release the brake faster than older drivers. Moreover, dressing color is also a significant factor that influence the t_4. From Figure 17, it is found that pedestrians with dark color clothes has an average of 1.27s t_4, which is significantly lower than pedestrian with bright color.

Table 32: Analysis of variance (ANOVA) results of deceleration adjustment time (t_4)

Variables	Df	Mean Square	F-Value	Sig.
Age	1	8.827	7.198	0.007
Gender	1	3.460	2.821	0.093
Time of day	1	0.018	0.015	0.903
Marking	1	1.772	1.445	0.230
Roadway Type	1	2.403	1.959	0.162
Dressing Color	1	18.883	15.398	0.000

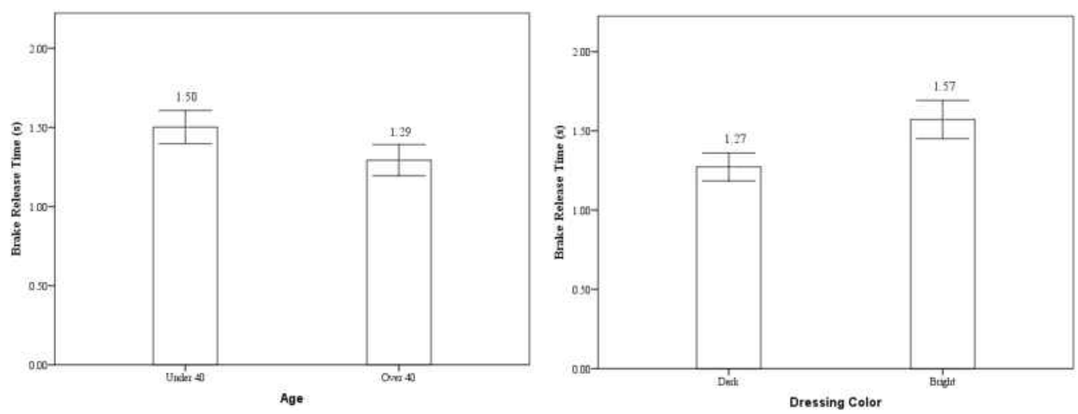


Figure 17: Relationship between brake release time and significant factors

6.3 Pedestrian-vehicle conflict prediction model

In the process of driver's avoidance pattern, drivers change their speeds by changing the deceleration rate in response to the pedestrian's behavior. Thus, the distance between the pedestrian and the vehicle becomes shorter as the vehicle approaches the pedestrian. In order to evaluate each conflict, the minimum distance between the pedestrian and the vehicle is used. The minimum distance is defined as the distance between the pedestrian and the vehicle when the vehicle completely stops or the vehicle is at the lowest speed. The minimum distance can not only estimate the occurrence of a collision between the vehicle and the pedestrian, but also can be used as a safety threshold reflecting the pedestrian safety.

In order to predict the minimum distance between the pedestrian and the vehicle, the linear regression model is used qualify the relationships between the dependent variable and the explanatory variables. The dependent variable is the minimum distance between the pedestrian and the vehicle. The independent variables include three different aspects: driver's characteristics, potential risk factors, and real-time vehicle information. The driver's characteristics include age and gender. Potential risk factors include time of day, marking, roadway type, and dressing color. The real-time vehicle information includes the initial speed when the driver starts to decelerate, the initial location when the driver starts to decelerate, the deceleration adjustment time, the maximum deceleration time, and the maximum deceleration rate. The hypothesis test with a 0.05 significance level is used to decide on the significant factors.

Table 33 lists the linear regression results of main effects. The significant independent variables include age, gender, dressing color, initial speed, initial location, t_2, d_m, and t_3. Marking, roadway type, and time of day are not significant.

Table 33: Linear regression results between dependent variable and independent variables

Variables	Estimate	Std.Error	t	p-value
Intercept	54.25	5.61	9.655	0.00
Age	8.46	1.62	5.226	0.00
Gender	9.60	1.59	6.037	0.00
Dressing color	-3.01	1.67	-1.798	0.0725
Initial speed	-4.73	0.15	-31.223	0.00
Initial location	0.90	0.01	71.038	0.00
t_2	-17.80	0.88	-20.140	0.00
d_m	-2.67	0.14	-19.083	0.00
t_3	-12.11	0.65	-18.502	0.00

The model equation is shown as follows:

$$\mathrm{D}_{min} = 54.24 + 8.46 * Age + 9.60 * Gender - 3.01 * Dressing\ color - 4.73 * Initial\ speed + 0.90 * Initial\ location - 17.80 * \mathrm{t}_2 - 2.67 * \mathrm{d}_m - 12.11 * \mathrm{t}_3$$

Figure 18 shows the relationship between age, gender and the minimum distance. The drivers who are over 40 years old has a larger minimum distance than the drivers who are under 40 years old. The finding indicates that older drivers are more conservative than younger drivers. In addition, the average minimum distance of male drivers is 112 ft, and the average minimum distance of female drivers is 155ft. It is obvious that female drivers are more likely to have a longer minimum distance than male drivers. In other words, female drivers are more likely to stop the vehicle earlier than male drivers and keeps a longer distance.

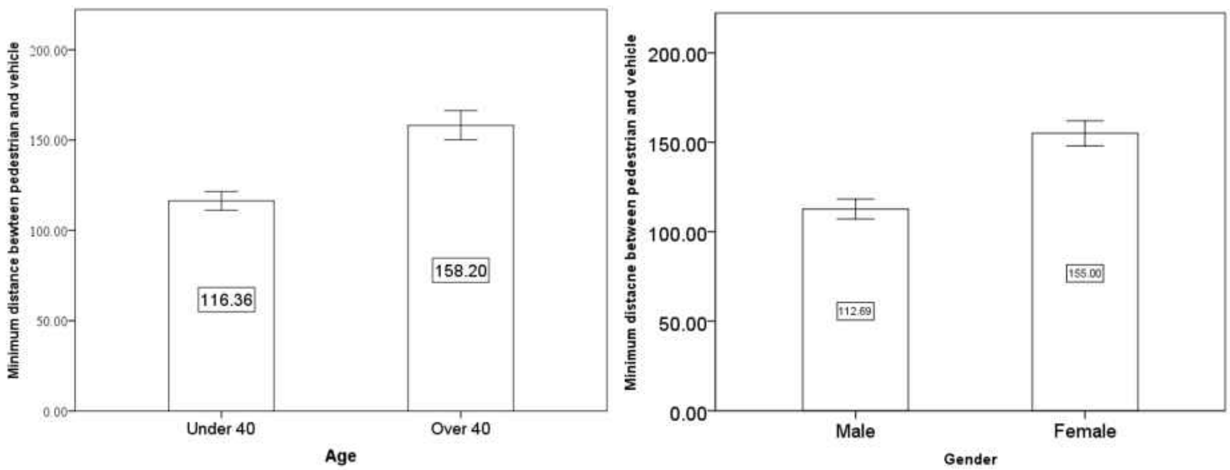


Figure 18: Relationship between the minimum distance and age, gender

As for the potential risk factors, dressing color is the only significant factor that affects the minimum distance. Figure 19 shows relationship between the minimum distance and the dressing color. If the pedestrian wears the dark color clothes, the minimum distance between pedestrian and vehicle is 114.39 ft on average, which is smaller than the pedestrian with the bright color clothes. This significant difference implies that pedestrian wearing dark clothes may affect the drivers' avoidance performance and lead to the pedestrian to be a more dangerous situation.

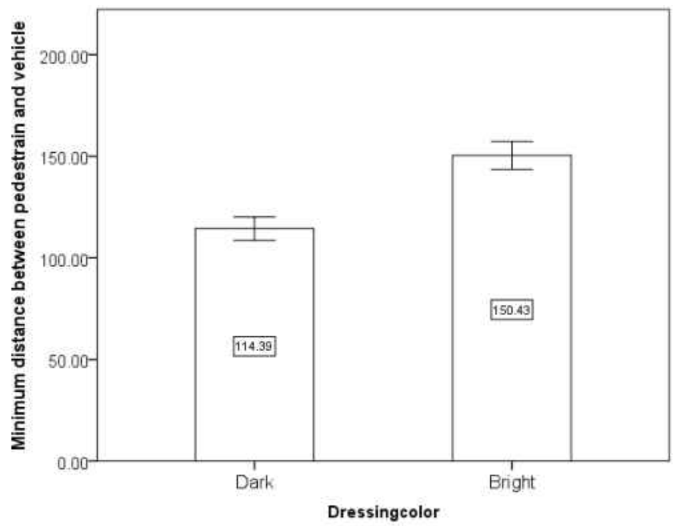


Figure 19: Relationship between the minimum distance and color

All the real-time vehicle information is significantly associated with the minimum distance between the pedestrian and the vehicle. As the initial speed increases or the initial location decreases, the minimum distance between the pedestrian and the vehicle decreases. In other words, if the vehicle has a higher speed, or the driver are closer to the crosswalk when he or she start to brake, it is more likely to be a crash.

After the driver starts to brake, t_2, t_3 and d_m is changing all the time. As the driver approaches the crosswalk, the pedestrian-vehicle conflict model could predict the minimum distance between the pedestrian and the vehicle. If the result is reliable, the model could be used in the vehicle alert system. When the vehicle has detected the crossing pedestrian, the alert system will be activated. If the estimate minimum distance between the pedestrian and the vehicle is smaller than the safety threshold, the alert system could give the driver alert to remind the driver. According to the results, R square of the model was 0.9015, which indicated that 90.15% of the variation in the minimum distance could be explained a linear relationship with these predictors. The average of the predicted minimum distance by the regression model is 132.41 ft, which is the same as the average of the obtained minimum distance by the experiment data (as shown in Table 34). In addition, the relative absolute error (RSE) is used to validate the model. RSE is to measure the difference between the minimum distance predicted by the model and the minimum distance obtained by the experiment data. The equation is shown as follows:

$$\mathrm{RSE} = \frac{1}{n}\sum_{i=1}^{n}\left|D_{\min(E)}^{i} - D_{\min(M)}^{i}\right|$$

Based on the results, the average RSE is 15.91 ft, which means that the average difference between predicted minimum distance and the obtained minimum distance is 15.91 ft. In addition, another regression model relates the minimum distance predicted by the model to the minimum distance obtained by the experiment data. Figure 20 shows the relationship between the experiment data and the prediction model. The results indicate that the minimum distance predicted by the model is significantly associated with the minimum distance obtained by the experiment. In addition, the R square for the model is 0.902, indicating that 90.2% of the variability in the experiment data could be explained by the variation in the prediction results. Accordingly, the results indicated that the pedestrian-vehicle conflict prediction model had a good prediction performance.

Table 34: Comparison of the minimum distance from the experiment data and model results

		Experiment data		Model results		RSE
		Mean	S.D.	Mean	S.D.	
Age	Under 40	116.358	5.011	116.358	5.011	16.500
	Over 40	158.200	8.517	158.200	8.517	14.934
Gender	Male	112.695	5.265	112.695	5.265	16.910
	Female	155.004	7.509	155.004	7.509	14.742
Total		132.41	4.453	132.41	4.453	4.453

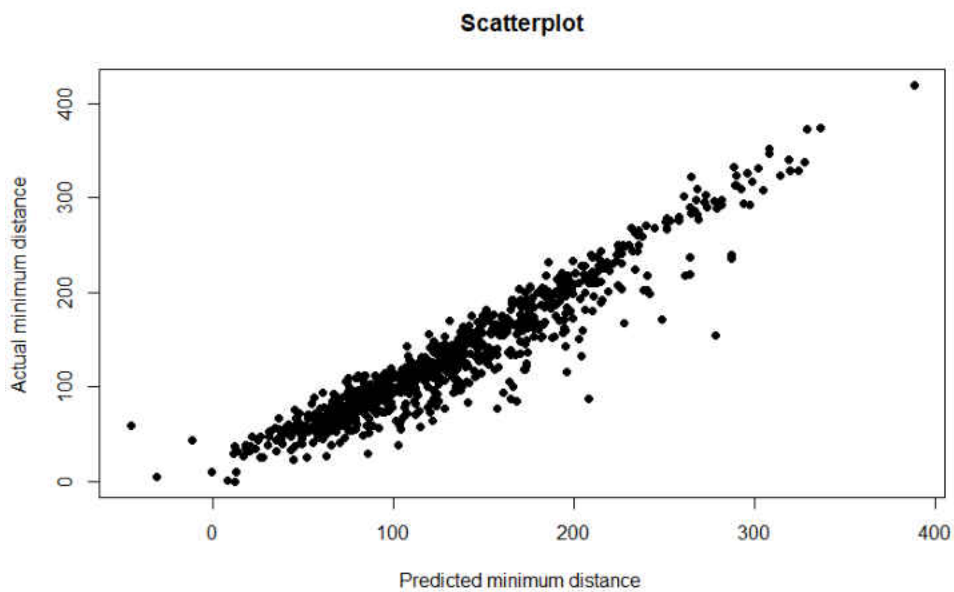


Figure 20: The relationship between the experiment data and the prediction results

CHAPTER SEVEN: THE PROCESS OF PEDESTRIAN SAFETY EVALUATION BY USING FIELD DATA, MICRO-SIMULATION DATA AND DRIVING SIMULATOR DATA

The objective of this chapter is to summarize three different types of data, including field data, micro-simulation data, and driving simulator data. In addition, the process of evaluation of pedestrian safety by combination field data, micro-simulation data and driving simulator data is proposed.

7.1 Field data collection for pedestrian safety

The field data collection is very important for the pedestrian safety analysis. First, the crash report can be used to determine if the location has the pedestrian safety problem for the long term. The crash report is usually generated by the police when there is a traffic accident. From the report, the crashes that involve the pedestrian can be picked up. If one location has more pedestrian involved crashes than usual, the traffic engineer should pay attention to it. Second, the field data collection also includes pedestrian volumes, traffic volumes, pedestrian violation rate, and vehicle's queue length. In addition, the roadway characteristics, signal timing, and other environmental factors are also the important data that could be collected from the field. Third, as technological advance of computer and video processing technology has been developed over a decade, the pedestrian-vehicle conflicts data could also be collected from the field. Ismail et al. (2009) developed the automated analysis for pedestrian-vehicle conflicts using the video data. This method could capture TTC and PET for each conflict between the pedestrian and the vehicle. Therefore, Table 35 summarizes the data that could be collected from the field.

Table 35: Summary of field data collection

Field data collection	
Crash report	The number of crashes that involve the pedestrian
Traffic data	Pedestrian volumes, vehicle volumes, queue length, signal timing, pedestrian violation rate, ……
Conflict data	The number of conflicts, PET, TTC, ……
Others	Environmental factors, road characteristics, ……

7.2 Micro-simulation data collection for pedestrian safety

Several simulation tools were reviewed including Synchro, aaSIDRA, Paramics, and VISSIM. Since the focus of this study is on pedestrian-vehicle interaction, VISSIM is the best tool to achieve the study objectives. Other simulation models didn't have the ability to simulate the pedestrian movements, or require extensive coding to incorporate necessary pedestrian performance attributes (Rouhail et al., 2002; Rouhail et al., 2005). To simulate the pedestrian in VISSIM, the data collected in the field are used to build, calibrate, and validate the VISSIM model. Another simulation model, which is used to extract the pedestrian and vehicle trajectory from VISSIM, is called Surrogate Safety Assessment Model (SSAM). Combination of VISSIM and SSAM could obtain the number of pedestrian-vehicle conflicts, TTC, PET, maximum speed, and maximum deceleration for each conflict. By using these data, the pedestrian safety could be evaluated.

7.3 Driving simulator data collection for pedestrian safety

Driving simulator data are different from field data and micro-simulation data. The driving simulator data are usually based on the experiment. As for the experiment, the pedestrian's behavior is usually controlled by the experimenter. Therefore, the pedestrian behavior is not same as the field observation and microsimulation model. In general, the driving simulator experiment is to find out the potential risk factors that relate to the road characteristic, driver's behavior, and environmental factors. After several subjects finish the driving simulator experiment, the pedestrian-vehicle conflicts under different conditions could be evaluated through the experiment data. The data output includes maximum deceleration, maximum deceleration location, minimum distance, PET, and TTC. Based on these information, the potential factors could be found out.

7.4 Comparison of TTC and PET for Field Data, Simulation Data, and Driving Simulator Data

To compare TTC and PET of field data, simulation data, and driving simulator data, the intersection data of field, simulation, and driving simulator were used. First, 708 pedestrian-vehicle conflicts were observed in the field. There were also 628 pedestrian-vehicle conflicts that were obtained from VISSIM. For the driving simulator experiment, 884 pedestrian-vehicle conflicts were collected. Second, the mean of PET for field data is 4.06 seconds. For the simulation data, the average PET is 4.12 seconds, which is close to the PET of field data. However, the PET of the simulator data is much higher than that of field data and simulation data. The reason is that the experiment is designed and the pedestrian is crossing the street ignoring the vehicle. Therefore, there is not an interaction between pedestrians and vehicles. The purpose is to test driver's reactions. But the pedestrian and vehicle are interacted in the field and simulation. Therefore, the PET of driving simulator is different with field data and simulation data. Third, TTCs are not collected in the field for pedestrian-vehicle conflicts since it is difficult to collect TTC by observing the videos. The average TTC of simulation data is 1.75 seconds with a standard deviation of 0.41. However, the average TTC of driving simulator data is 5.61 seconds with a standard deviation of 2.59. The reason is similar to the PET difference between simulation data and driving simulator data. The driving simulator experiment is designed and the pedestrian-vehicle conflicts are not collected randomly. It is better to compare the different groups within driving simulator data.

Table 36: Comparison of TTC and PET of Field Data, Simulation Data, and Driving Simulator Data

	TTC			PET		
	Count	**Mean**	**S.D.**	**Count**	**Mean**	**S.D.**
Field Data	708	-	-	708	4.06	1.23
Simulation Data	628	1.75	0.41	628	4.12	0.88
Driving Simulator Data	884	5.61	2.59	884	6.26	4.22

7.5 The process of pedestrian safety evaluation

By combining the field data, micro-simulation data, and driving simulator data, the process of evaluation of pedestrian safety is summarized in Figure 21. First, based on the crash report, the pedestrian safety at certain location could be evaluated to determine if this location need to improve the pedestrian safety. After that, the field data collection could be processed. The field data collection includes traffic volume, pedestrian volume, signal timing, roadway characteristics, and so on. Then, based on the field data, the micro simulation model is built and driving simulator experiment is designed. As for the micro-simulation, VISSIM and SSAM are the best tools to simulate the pedestrian-vehicle interactions. After VISSIM simulation model is calibrated and validated, SSAM could output the conflicts between pedestrians and vehicles. In terms of driving simulator experiment, the design should involve the conflict between the pedestrian and the driver. After several subjects finish the experiment, the data could be collected. Therefore, the potential factors that may affect pedestrian safety could be found out through the analysis of micro-simulation data and driving simulator data. Based on the potential factors, several countermeasures are proposed to improve the pedestrian safety. Then, these countermeasures could apply to the microsimulation and driving simulator first. After evaluating the pedestrian-vehicle conflicts that are obtained from micro-simulation and driving simulator, the effective countermeasures could be applied to field. Finally, over a few years, the crash report could be checked again and the engineers could go through the process again.

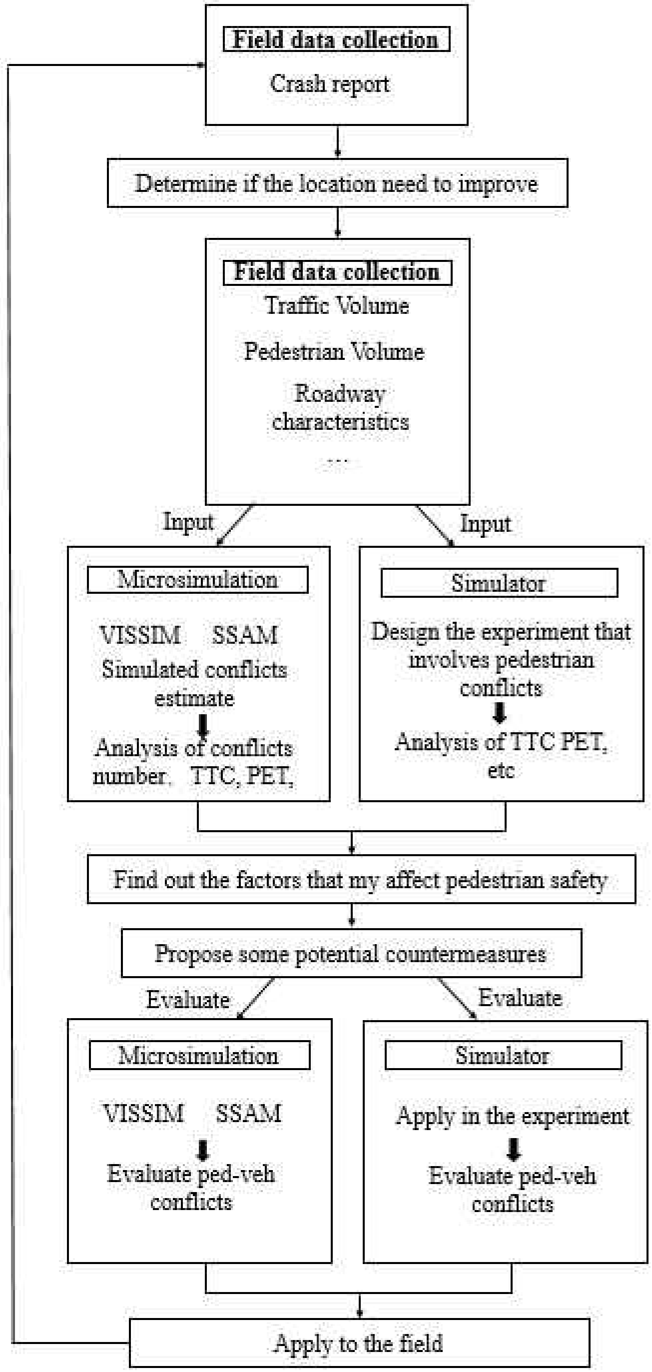


Figure 21: The process of evaluation of pedestrian safety

CHAPTER EIGHT: SUMMARY

Pedestrian safety has become more prevalent for governmental agencies to address the safety of public. This dissertation mainly focused on how to evaluate the pedestrian safety by using the micro-simulation and driving simulator through the pedestrian-vehicle conflicts. Firstly, this study examines the optimum values of post encroachment time (PET) and time-to-collision (TTC) parameters that would define a pedestrian-to-vehicle conflict at signalized intersections using a simulation model (VISSIM) and a Surrogate Safety Assessment Model (SSAM). Then, the results of the regression analysis indicate the highest correlation between the simulated and observed conflicts. Secondly, this study aimed to assess pedestrian-vehicle conflicts under different potential risk factors at both midblock crossings and signalized intersections. A full factorial experiment is designed in the driving simulator to study the pedestrian-vehicle conflicts, using four potential risk factors which included time of day, crosswalk marking, roadway type, and pedestrian dressing color. Thirdly, the driver's avoidance pattern is summarized based on the driving simulator data and the pedestrian-vehicle conflict prediction model is built to evaluate the pedestrian safety at midblock crossings.

8.1 Micro-simulation application to pedestrian-vehicle conflicts

In this study, field data was collected to obtain pedestrian volume, traffic volume, pedestrian crossing behavior, and pedestrian-vehicle conflicts at seven signalized intersections in Orlando, Florida. Then, the field data was used to calibrate and validate the VISSIM model for the seven signalized intersections. SSAM was used to extract the pedestrian-vehicle conflicts by processing the vehicle trajectory data from the calibrated and validated VISSIM model. The mean absolute percent error (MAPE) was used to get the suitable maximum TTC and PET thresholds for pedestrian-vehicle conflicts. The simulated conflicts generated by VISSIM and identified by SSAM were compared to the observed conflicts in the field to determine whether VISSIM and SSAM could provide reasonable results for safety assessment at signalized intersections.

There were two major findings in this study. First, the suitable maximum TTC and PET thresholds for pedestrian-vehicle conflicts were identified through measuring the differences between the mean PET observed in the field and the mean PET simulated in VISSIM and SSAM using the MAPE. According to the results, it was found that when the maximum TTC and PET threshold were at 2.7 and 8 seconds, respectively, the MAPE was the lowest, indicating the highest correlation and best goodness-of-fit between simulated conflicts and observed conflicts. Second, although it was concluded that the number of simulated conflicts was significantly related to the number of observed conflicts according to the linear regression results, the number of simulated conflicts estimated by VISSIM model and SSAM was less than the number of conflicts observed in the field, which reflects that VISSIM might underestimate the pedestrian-vehicle conflicts.

8.2 Assessment of pedestrian-vehicle conflicts at midblock crossings based on driving simulator experiment

One of the objective in this study was to assess pedestrian-vehicle conflicts under different potential risk factors at midblock crossings. The scenarios were specifically designed for the pedestrian-vehicle conflicts in the driving simulator. The driving simulator data were extracted and analyzed. Finally, the results addressed several aspects of this objective.

Time of day is an important factor that affects the drivers' behaviors. According to the results, the night time driving not only increases the maximum deceleration, but also decreases the PET and the minimum TTC compared to daytime driving. All of the findings imply that the night time driving is more dangerous than the daytime driving for the pedestrian-vehicle conflicts, which is in accordance with the findings of the literature [26,27]. The reason is that drivers have low visibility when they drive at night. Therefore, it is hard to notice pedestrians at night. When they notice the pedestrian, it is usually late compared to the daytime, which results in the dangerous situation. The marked crosswalk is also associated with the pedestrian safety. Although the marked crosswalk has nothing to do with the PET, it reduces the maximum deceleration and increases the minimum TTC. This finding indicates that those who cross the street without the marking have more risk than those who cross the street using the marking. Furthermore, the pedestrian safety is related to the roadway type. In this study, only two roadway types are tested in the experiment and it is found that different roadway types lead to different driving behavior for the pedestrian-vehicle conflicts. Finally, the pedestrian dressing color is examined to investigate the effects on the drivers' behavior. It is found that when pedestrians dress dark clothes, drivers usually have a larger maximum deceleration. In addition, PET and the minimum TTC of the pedestrian with the dark color are also smaller than that of the pedestrian with the bright color. This implies that it is very important for pedestrians wearing the bright color, especially in the nighttime.

8.3 Assessment of pedestrian-vehicle conflicts at signalized intersections with a concurrent pedestrian phasing based on driving simulator experiment

This study was designed to assess pedestrian-vehicle conflicts under different potential risk factors at signalized intersections with a concurrent pedestrian phasing. The scenarios were specifically designed for the pedestrian-vehicle conflicts in the driving simulator. The driving simulator data were extracted and analyzed. Finally, the results addressed several aspects of this objective.

First, time of day is an important factor that affects the drivers' behavior. According to the results, the night time driving decreases the minimum distance and the minimum TTC, indicating that the day time driving has lower risks than night time driving. Vehicle movement and pedestrian movement only have effects on the minimum distance and the minimum TTC. Moreover, the pedestrian visibility is examined to investigate the effects on the drivers' behavior. It is found that when pedestrians dress dark clothes, drivers usually have a smaller minimum distance and a small PET. This implies that it is very important for pedestrians to wear the bright color clothes, especially at night time. However, the age and gender didn't affect three surrogate measures based on the analysis.

8.4 Driver's avoidance pattern and pedestrian-vehicle conflicts prediction model

First, driver's avoidance behavior pattern was summarized during the pedestrian-vehicle conflict. There are four stages showing that how drivers react to the pedestrian conflict, including brake reaction stage, deceleration adjustment stage, maximum deceleration stage, and brake release stage.

Based on the driver's avoidance behavior pattern, four key variables are extract from the data, which include deceleration adjustment time, maximum deceleration rate, maximum deceleration time, and brake release time. Then, driver's characteristics variables (age and gender) and potential risk factors (time of day, marking, roadway type, and dressing color) are associated with the four key variables by using the ANOVA. The results indicate that age, gender, roadway type, and dressing color are the significant factors that affect the deceleration adjustment time. Time of day, and marking has no effects on the deceleration adjustment time. In addition, age, gender, time of day, marking, and dressing color impact the maximum deceleration time. Among those, under 40 years old group, male drivers, daylight driving, crosswalk with marking, and bright color clothes increase the maximum deceleration time. On the contrary, under 40 years old group, male drivers, daylight driving, crosswalk with marking, and bright color clothes decreased the maximum deceleration rate. However, the roadway type only affects the maximum deceleration rate, and doesn't influence the maximum deceleration time. One lane with parking lane road has a higher deceleration rate than two lanes road. Last, age and dressing color are found to be significantly associated with the release brake time. Drivers who are over 40 years old have a lower brake release time than drivers who are under 40 years old. In addition, pedestrians with dark color clothes increased the brake release time than pedestrian with bright color clothes.

Finally, the pedestrian-vehicle conflict prediction model is developed based on the midblock crossing experiment data. The results identify the significant effects of age, gender, dressing color, initial speed, initial location, t_2, d_m, and t_3 on the minimum distance between the pedestrian and the vehicle. The model has a good performance, which could be tested as the vehicle alert system in the future.

8.5 Summary of the process of the pedestrian safety evaluation

At the end of the dissertation, the process of the pedestrian safety evaluation was summarized based on the field data, micro-simulation data, and driving simulator data. First, based on the crash data, the location could be determined if it has the pedestrian safety issues. And the field data are collected to provide the traffic information, roadway characteristics, and so on. Then the micro-simulation and driving simulator experiment can be used to find out the factors that may impact the pedestrian safety. Next, the proposed countermeasures based on the micro-simulation and driving simulator results could be tested in the microsimulation and driving simulator again. Finally, the effective countermeasures could be applied to the field.

APPENDIX A: IRB APPROVAL LETTER

University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

Approval of Human Research

From: **UCF Institutional Review Board #1**
FWA00000351, IRB00001138

To: **Ahmed E. Radwan and Co-PI: Hatem Ahmed Yassin Abou-Senna, Jiawei Wu**

Date: **February 22, 2016**

Dear Researcher:

On 02/22/2016, the IRB approved the following human participant research until 02/21/2017 inclusive:

Type of Review:	UCF Initial Review Submission Form
Project Title:	Evaluating Pedestrian-vehicle Conflict Using Driving Simulation
Investigator:	Ahmed E Radwan
IRB Number:	SBE-16-12032
Funding Agency:	
Grant Title:	N/A
Research ID:	1057178

The scientific merit of the research was considered during the IRB review. The Continuing Review Application must be submitted 30days prior to the expiration date for studies that were previously expedited, and 60 days prior to the expiration date for research that was previously reviewed at a convened meeting. Do not make changes to the study (i.e., protocol, methodology, consent form, personnel, site, etc.) before obtaining IRB approval. A Modification Form **cannot** be used to extend the approval period of a study. All forms may be completed and submitted online at https://iris.research.ucf.edu .

If continuing review approval is not granted before the expiration date of 02/21/2017, approval of this research expires on that date. When you have completed your research, please submit a Study Closure request in iRIS so that IRB records will be accurate.

Use of the approved, stamped consent document(s) is required. The new form supersedes all previous versions, which are now invalid for further use. Only approved investigators (or other approved key study personnel) may solicit consent for research participation. Participants or their representatives must receive a copy of the consent form(s).

All data, including signed consent forms if applicable, must be retained and secured per protocol for a minimum of five years (six if HIPAA applies) past the completion of this research. Any links to the identification of participants should be maintained and secured per protocol. Additional requirements may be imposed by your funding agency, your department, or other entities. Access to data is limited to authorized individuals listed as key study personnel.

In the conduct of this research, you are responsible to follow the requirements of the Investigator Manual.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Joanne Muratori

Signature applied by Joanne Muratori on 02/22/2016 04:56:10 PM EST

IRB Manager

APPENDIX B: DRIVING SIMULATOR SURVEY

Name: ________Gender: ___________Age:__________No.:______

SIMULATOR QUESTIONNAIRE

Before scenarios

1. How long have you had a Florida driver's license?
   a. Less than 5 years
   b. 5-10 years
   c. 11-15 years
   d. 16-20 years
   e. 21+
2. How old are you?
   a. 18-24
   b. 25-40
   c. 40-64
   d. 65+
3. How far do you typically drive in one year?
   a. 0-5000 miles
   b. 5,000-10,000 miles
   c. 10,000-15,000 miles
   d. 15,000-20,000 miles
   e. 20,000 miles+
4. What is your highest level of education?
   a. High school
   b. College
   c. Bachelor's Degree
   d. Graduate School
5. What is your range of income?
   a. 0-10,000
   b. 10,000-25000

c. 25,000-40,000

d. 40,000-55,000

e. 55,000-70,000

f. 70,000+

6. Have you been in any accidents that involved pedestrian(s) in the last 3 years?

   a. Yes

   b. No

If so, how many pedestrians were involved? Where did the crash occur (e.g. intersection, highway, freeway, mid-block, etc.)?

7. What vehicle do you normally drive?

   a. Sedan

   b. Pickup Truck or Van

   c. Motorcycle or Moped

   d. Professional Vehicle (Large Truck or Taxi)

   e. Other

8. Are you a professional driver, like taxi driver, truck driver?

   a. Yes

   b. No

9. Do you have a history of severe motion sickness or seizures?

   a. Yes

   b. No

10. Do you have an experience about virtual reality games (such as simulator)?

    a. Yes

    b. No

Name: ________Gender: ____________Age:___________No.:______

SIMULATOR QUESTIONNAIRE

After scenarios

1. Did you feel sick or nauseous during the experiment?
   a. Yes
   b. No
2. Did you notice each pedestrian crossing the street?
   a. Yes
   b. No
3. What factor do you think affect the potential pedestrian-vehicle crash?
   a. Day vs. night
   b. 4-lane road vs. 2-lane road with one parking lane
   c. Pedestrian dressing color: dark vs. bright
   d. Marking vs. no marking
   e. Intersections vs. mid block crossings
   f. Pedestrian direction of traveling: right side vs. left side
   g. Right turn vs. left turn at the signalized intersections
   h. Others ________________________________
4. Do you have any suggestions or feedback on how to improve the simulation or have any complaints in regards to the scenarios you ran?

5. Do you think the scenarios were logical and true to a real life situation?

6. What did you like and dislike about the simulation?

APPENDIX C: R PROGRAM TO PROCESS EXPERIMENT DATA

The following code for the midblock scenario as an example show how to find key parameters from the experiment output file:

1. Midblock crossings scenario coding example:

```
#Select txt

data1 = read.delim(file.choose())

#calculate the accelerate of the driver

data1$negsign = ifelse(data1$Accelerate.x.feet.sec2. > 0, 1, -1)

data1$accelerate=
sqrt(data1$Accelerate.x.feet.sec2.^2+data1$Accelerate.y.feet.sec2.^2+data1$Accelerate.z.feet.
sec2.^2)*data1$negsign

#add the timestep in the data

Time = c(seq(from=0, to=(nrow(data1)-1)*(1/60), by=1/60))

data1$Time = Time

#subset the No.1 midblock

midblock1 = subset(data1, {X<14584 & X>13922 & Y < (-33973.9) & Y > (-34473.72)} )

#manange the No.1 midblock


speed<-midblock1[,8:27] ## column for speed

position<-midblock1[,28:87] ## column for position

c <- 1:ncol(position) ##set the

position.x<-position[,c%%3==1]  ## position of x

position.z<-position[,c%%3==0]  ## position of z

position.y<-position[,c%%3==2]  ## position of y

columnNumber<-apply(speed, 1, function(x) match(TRUE,{x>1 & x<=5}))

columnNumber<-as.numeric(columnNumber)

## Retrieve the value of speed

index2D<-function(v=columnNumber,DF=speed){
```

```
sapply(1:length(v),function(x){
  DF[x,v[x]]})
}
obj.speed<-index2D()##Output speed
obj.x<-index2D(DF=position.x)##Output position.x
obj.y<-index2D(DF=position.y)##Output speed
obj.z<-index2D(DF=position.z)##Output speed


newmidblock1<-
cbind(obj.speed,obj.x,obj.y,obj.z,midblock1$Vehicle.Speed.mph.,midblock1$Y,midblock1$X,mid
block1$Z,midblock1$Time,midblock1$accelerate)
newmidblock1<-data.frame(newmidblock1)
names(newmidblock1)<- c("obj.speed", "object.x","object.y","object.z","Vehicle.Speed.mph.",
"Y", "X","Z","Time","accelerate")
#calculate the minimum distance
newmidblock1$distance=sqrt((newmidblock1$X-newmidblock1$object.x)^2+(newmidblock1$Y-
newmidblock1$object.y)^2)
minimum.distance1 = min(newmidblock1$distance)
#calculate the PET
pettimerow = which(abs(newmidblock1$object.x-14195.71)==min(abs(newmidblock1$object.x-
14195.71)))
pettimecol = which(names(newmidblock1)=="Time")
pettime = newmidblock1[pettimerow,pettimecol]
PET1 = newmidblock1[nrow(newmidblock1),pettimecol]-pettime
#calculate TTC


newmidblock1$diff.y<-c(diff(newmidblock1$Y),0)
newmidblock1$diff.x<-c(diff(newmidblock1$X),0)
```

```
newmidblock1$diff.abs<-sqrt(newmidblock1$diff.y^2+newmidblock1$diff.x^2)

newmidblock1$revse.abs<-rev(newmidblock1$diff.abs)

newmidblock1$revse.cul<-cumsum(newmidblock1$revse.abs)

newmidblock1$d1ft<-rev(newmidblock1$revse.cul)#calculate cumulative distance for vehicle

newmidblock1$d1m<-newmidblock1$d1ft*0.3048

subsetofttc1<-subset(newmidblock1,{newmidblock1$object.x<14195.71&
newmidblock1$object.x>14165.63 } )#subset the newmidblock1

subsetofttc1$diff.object.y<-c(diff(subsetofttc1$object.y),0)

subsetofttc1$diff.object.x<-c(diff(subsetofttc1$object.x),0)

subsetofttc1$diff.object.abs<-sqrt(subsetofttc1$diff.object.y^2+subsetofttc1$diff.object.x^2)

subsetofttc1$revse.object.abs<-rev(subsetofttc1$diff.object.abs)

subsetofttc1$revse.object.cul<-cumsum(subsetofttc1$revse.object.abs)

subsetofttc1$d2ft<-rev(subsetofttc1$revse.object.cul)#calculate cumulative distance for
pedestrian

subsetofttc1$d2m<-subsetofttc1$d2ft*0.3048

subsetofttc1$Vehicle.Speed.ms<-subsetofttc1$Vehicle.Speed.mph.*0.44704


subsetofttc1$vehicle.ttc.head<-(subsetofttc1$d1m-2.32)/subsetofttc1$Vehicle.Speed.ms

subsetofttc1$vehicle.ttc.tail<-(subsetofttc1$d1m+2.32)/subsetofttc1$Vehicle.Speed.ms

subsetofttc1$pedestrian.ttc<-subsetofttc1$d2m/subsetofttc1$obj.speed#condition 1

subsetofttc1$pedestrian.ttc.head<-subsetofttc1$d2m/subsetofttc1$obj.speed

subsetofttc1$pedestrian.ttc.tail<-(subsetofttc1$d2m+2.08)/subsetofttc1$obj.speed

subsetofttc1$vehicle.ttc<-(subsetofttc1$d1m-2.32)/subsetofttc1$Vehicle.Speed.ms#condition 2

subsetofttc1$ttc <- ifelse
((subsetofttc1$vehicle.ttc.head<subsetofttc1$pedestrian.ttc)&(subsetofttc1$vehicle.ttc.tail>su
bsetofttc1$pedestrian.ttc), subsetofttc1$pedestrian.ttc,
ifelse((subsetofttc1$pedestrian.ttc.head<subsetofttc1$vehicle.ttc)&(subsetofttc1$pedestrian.tt
c.tail>subsetofttc1$vehicle.ttc),subsetofttc1$vehicle.ttc,100))

#Calculate TTC and related distance
```

```
minimum.ttc1 = min(subsetofttc1$ttc)

minittcrown = which(grepl(minimum.ttc1, subsetofttc1$ttc))

minittccoln = which(names(subsetofttc1)=="d1ft")

miniposition1 = subsetofttc1[minittcrown, minittccoln]


#calculate the maximum deceleration and related position

maxdec1 = min(newmidblock1$accelerate)

maxdecrown = which(grepl(maxdec1, newmidblock1$accelerate))

maxdeccoln = which(names(newmidblock1)=="d1ft")

maxposition1 = newmidblock1[maxdecrown, maxdeccoln]

#writing results

DF.result<-
data.frame(Daylight=rep(NA),Marking=rep(NA),Roadwaytype=rep(NA),Dressingcolor=rep(NA),
Maximum.Deceleration=rep(NA),     Max.Deceleration.Location=rep(NA),Min.Distance=rep(NA),
PET=rep(NA),Min.TTC=rep(NA),Min.TTC.Location=rep(NA),  # as many cols as you need

            stringsAsFactors=FALSE)

#Daylight (0=dark, 1= daytime); Marking(0=no, 1=yes);Roadwaytype(0=2lane with parking, 1= 4
lanes); Dressing Color(0=Black, 1=Bright)

DF.result[1,]<-
c(NA,1,1,0,maxdec1,maxposition1,minimum.distance1,PET1,minimum.ttc1,miniposition1)
```

2. Intersections scenario coding example:

```
#Select txt

data1 = read.delim(file.choose())

#calculate the accelerate of the driver


data1$negsign = ifelse(data1$Accelerate.x.feet.sec2. > 0, 1, -1)
```

```
data1$accelerate                                                                    =
sqrt(data1$Accelerate.x.feet.sec2.^2+data1$Accelerate.y.feet.sec2.^2+data1$Accelerate.z.feet.
sec2.^2)*data1$negsign


#add the timestep in the data

Time = c(seq(from=0, to=(nrow(data1)-1)*(1/60), by=1/60))

data1$Time = Time


#subset the No.1 intersection

intersection1 = subset(data1, {X<(-8176.31) & X>(-8390) & Y < (2437) & Y > (2226.17)} )


#manange the No.1 intersection

speed<-intersection1[,8:27] ## column for speed

position<-intersection1[,28:87] ## column for position

c <- 1:ncol(position) ##set the

position.x<-position[,c%%3==1]  ## position of x

position.z<-position[,c%%3==0]  ## position of z

position.y<-position[,c%%3==2]  ## position of y

columnNumber<-apply(speed, 1, function(x) match(TRUE,{x>1 & x<=5}))

columnNumber<-as.numeric(columnNumber)


## Retrieve the value of speed

index2D<-function(v=columnNumber,DF=speed){

  sapply(1:length(v),function(x){

    DF[x,v[x]]})

}
```

```
obj.speed<-index2D()##Output speed

obj.x<-index2D(DF=position.x)##Output position.x

obj.y<-index2D(DF=position.y)##Output speed

obj.z<-index2D(DF=position.z)##Output speed

newintersection1<-
cbind(obj.speed,obj.x,obj.y,obj.z,intersection1$Vehicle.Speed.mph.,intersection1$Y,intersectio
n1$X,intersection1$Z,intersection1$Time,intersection1$accelerate)

newintersection1<-data.frame(newintersection1)

names(newintersection1)<-                                                    c("obj.speed",
"object.x","object.y","object.z","Vehicle.Speed.mph.", "Y", "X","Z","Time","accelerate")


#calculate the minimum distance

newintersection1$distance                    =                    sqrt((newintersection1$X-
newintersection1$object.x)^2+(newintersection1$Y-newintersection1$object.y)^2)

minimum.distance1 = min(newintersection1$distance)


#calculate the PET

pettimerow                    =                    which(abs(newintersection1$object.y-
2288.64)==min(abs(newintersection1$object.y-2288.64)))

pettimecol = which(names(newintersection1)=="Time")

pettime = newintersection1[pettimerow,pettimecol]

PET1 = newintersection1[nrow(newintersection1),pettimecol]-pettime


#calculate TTC

newintersection1$diff.y<-c(diff(newintersection1$Y),0)

newintersection1$diff.x<-c(diff(newintersection1$X),0)

newintersection1$diff.abs<-sqrt(newintersection1$diff.y^2+newintersection1$diff.x^2)

newintersection1$revse.abs<-rev(newintersection1$diff.abs)
```

```
newintersection1$revse.cul<-cumsum(newintersection1$revse.abs)

newintersection1$d1ft<-rev(newintersection1$revse.cul)#calculate cumulative distance for vehicle

newintersection1$d1m<-newintersection1$d1ft*0.3048


subsetofttc1 <- subset(newintersection1, {newintersection1$object.y<2337.22 & newintersection1$object.y>2288.64 } )#subset the newintersection1

subsetofttc1$diff.object.y<-c(diff(subsetofttc1$object.y),0)

subsetofttc1$diff.object.x<-c(diff(subsetofttc1$object.x),0)

subsetofttc1$diff.object.abs<-sqrt(subsetofttc1$diff.object.y^2+subsetofttc1$diff.object.x^2)

subsetofttc1$revse.object.abs<-rev(subsetofttc1$diff.object.abs)

subsetofttc1$revse.object.cul<-cumsum(subsetofttc1$revse.object.abs)

subsetofttc1$d2ft<-rev(subsetofttc1$revse.object.cul)#calculate cumulative distance for pedestrian

subsetofttc1$d2m<-subsetofttc1$d2ft*0.3048

subsetofttc1$Vehicle.Speed.ms<-subsetofttc1$Vehicle.Speed.mph.*0.44704


subsetofttc1$vehicle.ttc.head<-(subsetofttc1$d1m-2.32)/subsetofttc1$Vehicle.Speed.ms

subsetofttc1$vehicle.ttc.tail<-(subsetofttc1$d1m+2.32)/subsetofttc1$Vehicle.Speed.ms

subsetofttc1$pedestrian.ttc<-subsetofttc1$d2m/subsetofttc1$obj.speed#condition 1


subsetofttc1$pedestrian.ttc.head<-subsetofttc1$d2m/subsetofttc1$obj.speed

subsetofttc1$pedestrian.ttc.tail<-(subsetofttc1$d2m+2.08)/subsetofttc1$obj.speed

subsetofttc1$vehicle.ttc<-(subsetofttc1$d1m-2.32)/subsetofttc1$Vehicle.Speed.ms#condition 2


subsetofttc1$ttc <- ifelse
((subsetofttc1$vehicle.ttc.head<subsetofttc1$pedestrian.ttc)&(subsetofttc1$vehicle.ttc.tail>su
bsetofttc1$pedestrian.ttc), subsetofttc1$pedestrian.ttc,
```

```
ifelse((subsetofttc1$pedestrian.ttc.head<subsetofttc1$vehicle.ttc)&(subsetofttc1$pedestrian.tt
c.tail>subsetofttc1$vehicle.ttc),subsetofttc1$vehicle.ttc,100))


#Calculate TTC

minimum.ttc1 = min(subsetofttc1$ttc)


#Calculate Entrance Speed

EntSpeed1 = newintersection1[1,5]


#Calculate Totaltime

Totaltime1 = abs(newintersection1[1,9]-newintersection1[nrow(newintersection1),9])


#No.1 intersection writing results

DF.result <- data.frame(Daylight=rep(NA), Turning=rep(NA),
Ped_movement=rep(NA),Dressingcolor=rep(NA),minimum.distance=rep(NA),
PET=rep(NA),minimum.ttc=rep(NA), EntSpeed=rep(NA),Totaltime=rep(NA),  # as many cols as
you need

                stringsAsFactors=FALSE)


#Daylight (0=dark, 1= daytime); Turning(0=left, 1=right); Pedestrian Movement (0=left, 1= right);
Dressing Color(0=Black, 1=Bright)

DF.result[1, ] <- c(NA,1,0,1,minimum.distance1,PET1,minimum.ttc1,EntSpeed1,Totaltime1)
```

APPENDIX D: PRESENTATION AND PUBLICATION

Wu, J., Abou-senna, H., Radwan, E., & Darius, B. (2015). Micro-Simulation Application to Pedestrian Safety at Mid Block Crossing. In *2015 Road Safety & Simulation International Conference*, Orlando, Florida USA, 6-8 October 2015.

Wu, J., Radwan, E., & Abou-Senna, H. (2016). Pedestrian-vehicle conflict analysis at signalized intersections using micro-simulation. In 1*7th International Conference Road Safety On Five Continents (RS5C 2016)*, Rio de Janeiro, Brazil, 17-19 May 2016.

Wu, J., Radwan, E., & Abou-Senna, H. (2016). Assessment of Pedestrian-Vehicle Conflicts with Different Potential Risk Factors at Midblock Crossings Based on Driving Simulator Data. Transportation Research Board 96th Annual Meeing, 2017.

Yan, X., & Wu, J. (2014). Effectiveness of variable message signs on driving behavior based on a driving simulation experiment. Discrete dynamics in nature and society, 2014.

Wu, J., Yan, X., & Radwan, E. (2016). Discrepancy analysis of driving performance of taxi drivers and non-professional drivers for red-light running violation and crash avoidance at intersections. Accident Analysis & Prevention, 91, 1-9.

Li, X., Yan, X., Wu, J., Radwan, E., & Zhang, Y. (2016). A rear-end collision risk assessment model based on drivers' collision avoidance process under influences of cell phone use and gender—A driving simulator based study. Accident Analysis & Prevention, 97, 1-18.

Yan, X., Wang, J., & Wu, J. (2016). Effect of In-Vehicle Audio Warning System on Driver's Speed Control Performance in Transition Zones from Rural Areas to Urban Areas. International journal of environmental research and public health, 13(7), 634.

Liu, Y., Yan, X., Wang, Y., Yang, Z., & Wu, J. (2017). Grid Mapping for Spatial Pattern Analyses of Recurrent Urban Traffic Congestion Based on Taxi GPS Sensing Data. Sustainability, 9(4), 533.

Determine if VISSIM and SSAM could estimate pedestrian-vehicle conflicts at signalized intersections. Potential presentation and publication.

Assessment of pedestrian-vehicle conflicts with different potential risk factors at midblock crossings based on driving simulator experiment. Potential presentation and publication.

Assess pedestrian-vehicle conflicts at signalized intersection with a concurrent pedestrian phasing - A driving simulator study. Potential presentation and publication.

REFERENCES

1. Abdel-Aty, M., Yan, X., Radwan, E., Harris, G., & Klee, H. (2006). Using the UCF Driving Simulator as a Test Bed for High Risk Locations.
2. Allard, R. (1982). Excess mortality from traffic accidents among elderly pedestrians living in the inner city. American Journal of Public Health, 72(8), 853-854.
3. Alluri, P., Haleem, K., Gan, A., Lavasani, M., & Saha, D. (2013). Comprehensive Study to Reduce Pedestrian Crashes in Florida.
4. Almodfer, R., Xiong, S., Fang, Z., Kong, X., & Zheng, S. (2015). Quantitative analysis of lane-based pedestrian-vehicle conflict at a non-signalized marked crosswalk. Transportation Research Part F: Traffic Psychology and Behaviour.
5. Archer, J. (2004). Methods for the assessment and prediction of traffic safety at urban intersections and their application in micro-simulation modelling. Royal Institute of Technology.
6. Astrid, B., Johan, O., and Andreas, A. (2011). Analytical traffic models for roundabouts with pedestrian crossings. Procedia Social and Behavioral Sciences, Vol. 16, pp.697-708.
7. Ballesteros, M. F., Dischinger, P. C., & Langenberg, P. (2004). Pedestrian injuries and vehicle type in Maryland, 1995–1999. Accident Analysis & Prevention, 36(1), 73-81.
8. Boenisch, C., & Kretz, T. (2009). Simulation of pedestrians crossing a street.
9. Blue, V. J., & Adler, J. L. (2001). Cellular automata microsimulation for modeling bi-directional pedestrian walkways. Transportation Research Part B: Methodological, 35(3), 293-312.
10. Boot, W., Charness, N., Stothart, C., Fox, M., Mitchum, A., Lupton, H., & Landbeck, R. (2013). Final Report: Aging Road User, Bicyclist, and Pedestrian Safety: Effective Bicycling Signs and Preventing Left-Turn Crashes BDK83 977-15.
11. Boot, W., Charness, N., Mitchum, A., Landbeck, R., & Stothart, C. (2014). Aging Road User Studies of Intersection Safety.
12. Braughton, M., & Griffin, A. (2014). SafeTREC-UCTC Seminar: ODOT Pedestrian and Bicycle Safety Implementation Plan. Institute of Transportation Studies, UC Berkeley.

13. Brooks, J. O., Goodenough, R. R., Crisler, M. C., Klein, N. D., Alley, R. L., Koon, B. L., ... & Wills, R. F. (2010). Simulator sickness during driving simulation studies. Accident Analysis & Prevention, 42(3), 788-796.

14. Brustman, R. (1999). An analysis of available bicycle and pedestrian accident data. New York Bicycling Coalition, Albany, NY.

15. Byington, K. W., & Schwebel, D. C. (2013). Effects of mobile Internet use on college student pedestrian injury risk. Accident Analysis & Prevention, 51, 78-83.

16. Chang, C. Y., & Chou, Y. R. (2009). Development of fuzzy-based bus rear-end collision warning thresholds using a driving simulator. IEEE Transactions on Intelligent Transportation Systems, 10(2), 360-365.

17. Chang, D. (2008). National pedestrian crash report (No. HS-810 968).

18. Chen Kuan-min, Luo Xiao-qiang, Ji Hai, and Zhao Yang-dong. (2010). Towards the pedestrian delay estimation at intersections under vehicular platoon caused conflicts. Scientific Research and Essays Vol. 5(9), pp.941-947.

19. Chidester, A. B., & Isenberg, R. A. (2001). Final report: The pedestrian crash data study. Society of Automotive Engineers.

20. Cho, G., Rodríguez, D. A., & Khattak, A. J. (2009). The role of the built environment in explaining relationships between perceived and actual pedestrian and bicyclist safety. Accident Analysis & Prevention, 41(4), 692-702.

21. Chopard, B., & Droz, M. (1998). Cellular automata. Springer.

22. Clifton, K. J., Burnier, C. V., & Akar, G. (2009). Severity of injury resulting from pedestrian–vehicle crashes: What can we learn from examining the built environment?. Transportation research part D: transport and environment,14(6), 425-436.

23. City of Chicago. (2011). Pedestrian Crash Analysis (2005-2009 Crash Data). Chicago Dep.

24. Cunto, F., & Saccomanno, F. F. (2008). Calibration and validation of simulated vehicle safety performance at signalized intersections. Accident analysis & prevention, 40(3), 1171-1179.

25. Dai, D. (2012). Identifying clusters and risk factors of injuries in pedestrian–vehicle crashes in a GIS environment. Journal of Transport Geography, 24, 206-214.

26. De Winter, J. C. F., De Groot, S., Mulder, M., Wieringa, P. A., Dankelman, J., & Mulder, J. A. (2009). Relationships between driving simulator performance and driving test results. Ergonomics, 52(2), 137-153.

27. De Winter, J., Van Leuween, P., & Happee, P. (2012, August). Advantages and disadvantages of driving simulators: A discussion. In Proceedings of Measuring Behavior (pp. 47-50).

28. Dewey, J. F., Denslow, D., Lenze, D., Holt, L., & Lotfinia, B. (2003). Transportation Issues: Pedestrian Safety.

29. Dumbaugh, E., Li, W., & Joh, K. (2012). Examining the Design and Developmental Factors Associated with Crashes Involving Pedestrians, Cyclists, and Motorists in Urban Environments (No. SWUTC/12/161107-1). Southwest Region University Transportation Center, Texas Transportation Institute, Texas A & M University System.

30. Eluru, N., Bhat, C. R., & Hensher, D. A. (2008). A mixed generalized ordered response model for examining pedestrian and bicyclist injury severity level in traffic crashes. Accident Analysis & Prevention, 40(3), 1033-1054.

31. Ernst, M., Lang, M., & Davis, S. (2011). Dangerous by design: Solving the epidemic of preventable pedestrian deaths.

32. Fan, R., Yu, H., Liu, P., & Wang, W. (2013). Using VISSIM simulation model and Surrogate Safety Assessment Model for estimating field measured traffic conflicts at freeway merge areas. IET Intelligent Transport Systems,7(1), 68-77.

33. Frank, L. H., Casali, J. G., & Wierwille, W. W. (1988). Effects of visual display and motion system delays on operator performance and uneasiness in a driving simulator. Human Factors: The Journal of the Human Factors and Ergonomics Society, 30(2), 201-217.

34. Florida Department of Highway Safety and Motor Vehicles. (2010). Traffic Safety Facts: October 2010·Pedestrian.

35. Gettman, D., Pu, L., Sayed, T., & Shelby, S. G. (2008). Surrogate safety assessment model and validation: Final report (No. FHWA-HRT-08-051).

36. Godley, S. T., Triggs, T. J., & Fildes, B. N. (2002). Driving simulator validation for speed research. Accident analysis & prevention, 34(5), 589-600.

37. Haleem, K., Alluri, P., & Gan, A. (2015). Analyzing pedestrian crash injury severity at signalized and non-signalized locations. Accident Analysis & Prevention, 81, 14-23.

38. Hanson, C. S., Noland, R. B., & Brown, C. (2013). The severity of pedestrian crashes: an analysis using Google Street View imagery. Journal of transport geography, 33, 42-53.

39. Han, Y., Yang, J., Mizuno, K., & Matsui, Y. (2012). Effects of vehicle impact velocity, vehicle front-end shapes on pedestrian injury risk. Traffic Injury Prevention, 13(5), 507-518.

40. Hubbard, S. M., Bullock, D. M., & Mannering, F. L. (2009). Right turns on green and pedestrian level of service: Statistical assessment. Journal of Transportation Engineering, 135(4), 153-159.

41. Ismail, K., Sayed, T., Saunier, N., & Lim, C. (2009). Automated analysis of pedestrian-vehicle conflicts using video data. Transportation Research Record: Journal of the Transportation Research Board, (2140), 44-54.

42. Ishaque, M. M., & Noland, R. B. (2005). Pedestrian modeling in urban road networks: issues, limitations and opportunities offered by micro-simulation.9th Annual Computers in Urban Planning and Urban Management, London, 9.

43. Ishaque, M. M., & Noland, R. B. (2008). Simulated pedestrian travel and exposure to vehicle emissions. Transportation Research Part D: Transport and Environment, 13(1), 27-46.

44. Ishaque, M. M., & Noland, R. B. (2009). Pedestrian and vehicle flow calibration in multimodal traffic microsimulation. Journal of Transportation Engineering, 135(6), 338-348.

45. Jarrett, K. L., & Saul, R. (1998, June). Pedestrian injury-analysis of the PCDS field collision data. In 16th International Technical Conference on the Enhanced Safety of Vehicles (Vol. 2, No. DOT HS 808 759).

46. Kennedy, R. S., Fowlkes, J. E., Berbaum, K. S., & Lilienthal, M. G. (1992). Use of a motion

sickness history questionnaire for prediction of simulator sickness. Aviation, Space, and Environmental Medicine, 63(7), 588-593.

47. Khattak, A., & Tung, L. W. (2015). Severity of pedestrian crashes at highway-rail grade crossings. A Message from the JTRF Co-General Editors 3, 54(2), 91.
48. Kolisetty, V., Iryo, T., Asakura, Y., & Kuroda, K. (2006). Effect of variable message signs on driver speed behavior on a section of expressway under adverse fog conditions—a driving simulator approach. Journal of advanced transportation, 40(1), 47-74.
49. Kravetz, D., & Noland, R. (2012). Spatial analysis of income disparities in pedestrian safety in northern New Jersey: is there an environmental justice issue? Transportation Research Record: Journal of the Transportation Research Board, (2320), 10-17.
50. Larue, G. S., Kim, I., Rakotonirainy, A., Haworth, N. L., & Ferreira, L. (2015). Driver's behavioural changes with new intelligent transport system interventions at railway level crossings—A driving simulator study. Accident Analysis & Prevention, 81, 74-85.
51. LaScala, E. A., Gerber, D., & Gruenewald, P. J. (2000). Demographic and environmental correlates of pedestrian injury collisions: a spatial analysis.Accident Analysis & Prevention, 32(5), 651-658.
52. Lee, C., & Abdel-Aty, M. (2005). Comprehensive analysis of vehicle–pedestrian crashes at intersections in Florida. Accident Analysis & Prevention, 37(4), 775-786.
53. Lee, C., and Abdel-Aty, M. (2008). Testing effects of warning messages and variable speed limits on driver behavior using driving simulator. Transportation Research Record, no. 1069, pp. 1743-1748.
54. Lefler, D. E., & Gabler, H. C. (2004). The fatality and injury risk of light truck impacts with pedestrians in the United States. Accident Analysis & Prevention, 36(2), 295-304.
55. Li, H., Li, J., Yang, Z., Wu, J., & Chen, X. (2011, October). Micro-simulation study on capacity of roundabout. In 2011 14th International IEEE Conference on Intelligent Transportation Systems (ITSC) (pp. 852-857). IEEE.

56. Littell, R. C., Stroup, W. W., Milliken, G. A., Wolfinger, R. D., & Schabenberger, O. (2006). SAS for mixed models. SAS institute.

57. Li, X., Yan, X., Li, X., and Wang, J. (2012). Using cellular automata to investigate pedestrian conflicts with vehicles in crosswalk at signalized intersection. Discrete Dynamics in Nature and Society, 2012.

58. Li, X., Yan, X., Wu, J., Radwan, E., & Zhang, Y. (2016). A rear-end collision risk assessment model based on drivers' collision avoidance process under influences of cell phone use and gender—A driving simulator based study. Accident Analysis & Prevention, 97, 1-18.

59. Maerivoet, S., & De Moor, B. (2005). Cellular automata models of road traffic. Physics Reports, 419(1), 1-64.

60. Meghan Mitman, Matthew Ridgway, & Chira-Chavala, T. (2008). A Technical Guide for Conducting Pedestrian Safety Assessments for California Cities.

61. Meng, Q., & Weng, J. (2011). An improved cellular automata model for heterogeneous work zone traffic. Transportation research part C: emerging technologies, 19(6), 1263-1275.

62. Miles-Doan, R. (1996). Alcohol use among pedestrians and the odds of surviving an injury: evidence from Florida law enforcement data. Accident Analysis & Prevention, 28(1), 23-31.

63. Mohamed, M. G., Saunier, N., Miranda-Moreno, L. F., & Ukkusuri, S. V. (2013). A clustering regression approach: A comprehensive injury severity analysis of pedestrian–vehicle crashes in New York, US and Montreal, Canada. Safety science, 54, 27-37.

64. Molino, J. A., Kennedy, J. F., Inge, P. J., Bertola, M. A., Beuse, P. A., Fowler, N. L., ... & Do, A. (2012). A Distance-Based Method to Estimate Annual Pedestrian and Bicyclist Exposure in an Urban Environment (No. FHWA-HRT-11-043).

65. Nasar, J. L., & Troyer, D. (2013). Pedestrian injuries due to mobile phone use in public places. Accident Analysis & Prevention, 57, 91-95.

66. National Highway Traffic Safety Administration. (2012). Fatality analysis reporting system.

67. National Highway Traffic Safety Administration. (2013). Traffic safety facts 2011 data--

pedestrians. Annals of emergency medicine, 62(6), 612.

68. National Highway Traffic Safety Administration. (2014). Traffic safety facts 2012 data--pedestrians.
69. Noland, R. B., & Quddus, M. A. (2004). A spatially disaggregate analysis of road casualties in England. Accident Analysis & Prevention, 36(6), 973-984.
70. Parker Jr, M. R., & Zegeer, C. V. (1989). Traffic Conflict Techniques for Safety and Operations. Observers Manual (No. FHWA-IP-88-027).
71. PTV, A. (2011). VISSIM 5.40 user manual. Karlsruhe, Germany.
72. Radwan, E., Darius, B., Wu, J., & Abou-Senna, H. (2016, November). Simulation of pedestrian safety surrogate measures. In ARRB Conference, 27th, 2016, Melbourne, Victoria, Australia.
73. Rickert, M., Nagel, K., Schreckenberg, M., & Latour, A. (1996). Two lane traffic simulations using cellular automata. Physica A: Statistical Mechanics and its Applications, 231(4), 534-550.
74. Robert Pitt, Bernard Guyer, Chung-Cheng Hsieh, & Malekt, M. (1990). The severity of pedestrian injuries in children: an analysis of the pedestrian injury causation study. Accident Analysis and Prevention, 22(6), 549-560.
75. Rouphail, N., Wan, B., Chae, K., Hughes, R., and Harkey, D. (2002). Evaluation and Application of Pedestrian Modeling Capabilities Using Computer Simulation. University of North Carolina at Chapel Hill and NC State University, Prepared for Western Michigan University and National Institutes of Health/National Eye Institute.
76. Rouphail, N., Hughes, R., and Chae, K. (2005). Exploratory simulation of pedestrian crossings at roundabouts. Journal of Transportation Engineering, 131(2), pp.211-218.
77. Satiennam, T., & Tanaboriboon, Y. (2003). A Study on pedestrian accidents and investigation of pedestrian’s unsafe conditions in Khon Kaen municipality, Thailand. Journal of the Eastern Asia Society for Transportation Studies, 5.
78. Shahdah, U., Saccomanno, F., & Persaud, B. (2015). Application of traffic microsimulation for evaluating safety performance of urban signalized intersections. Transportation Research Part C:

Emerging Technologies, 60, 96-104.

79. Sun, J., Yang, X. G., & Liu, H. D. (2007). Study on Microscopic traffic simulation model systematic parameter calibration . Journal of System Simulation, 1, 10-14.

80. Tarko, A., & Azam, M. S. (2011). Pedestrian injury analysis with consideration of the selectivity bias in linked police-hospital data. Accident Analysis & Prevention, 43(5), 1689-1695.

81. Thomas, L., Hamlett, C., Hunter, W., Gelinne, D., Raborn, C., Stutts, J., & Zegeer, C. (2009). Identifying Locations for Pedestrian and Bicyclist Safety Improvements in Chapel Hill and Carrboro, North Carolina. University of North Carolina: Highway Safety Research Center.

82. Tu, H., Li, Z., Li, H., Zhang, K., & Sun, L. (2015). Driving Simulator Fidelity and Emergency Driving Behavior. Transportation Research Record: Journal of the Transportation Research Board, (2518), 113-121.

83. Turner, S., Francis, T., & Roozenburg, A. (2006). Predicting accident rates for cyclists and pedestrians. Land Transport New Zealand.

84. Ukkusuri, S., Miranda-Moreno, L. F., Ramadurai, G., & Isa-Tavarez, J. (2012). The role of built environment on pedestrian crash frequency. Safety Science, 50(4), 1141-1151.

85. Underwood, G., Crundall, D., & Chapman, P. (2011). Driving simulator validation with hazard perception. Transportation research part F: traffic psychology and behaviour, 14(6), 435-446.

86. Vogel, K. (2003). A comparison of headway and time to collision as safety indicators. Accident analysis & prevention, 35(3), 427-433.

87. Ward, J. R., Agamennoni, G., Worrall, S., Bender, A., & Nebot, E. (2015). Extending Time to Collision for probabilistic reasoning in general traffic scenarios. Transportation Research Part C: Emerging Technologies, 51, 66-82.

88. Warsh, J., Rothman, L., Slater, M., Steverango, C., & Howard, A. (2009). Are school zones effective? An examination of motor vehicle versus child pedestrian crashes near schools. Injury prevention, 15(4), 226-229.

89. Williams, A. (2013). Pedestrian Traffic Fatalities by State. Washington, DC: Governors Highway

Safety Association.

90. Wu, J. (2014). Analysis of taxi drivers' driving behavior based on a driving simulator experiment. University of Central Florida, Orlando, FL.

91. Wu, J., Radwan, E., & Abou-Senna, H. (2017). Determine if VISSIM and SSAM could estimate pedestrian-vehicle conflicts at signalized intersections. Journal of Transportation Safety & Security, (just-accepted).

92. Wu, J., Radwan, E., & Abou-Senna, H. (2016). Assessment of Pedestrian-Vehicle Conflicts with Different Potential Risk Factors at Midblock Crossings Based on Driving Simulator Data. In Transportation Research Board 96th Annual Meeting.

93. Wu, J., Radwan, E., & Abou-Senna, H. (2016). Pedestrian-vehicle conflict analysis at signalized intersections using micro-simulation. In 17th International Conference Road Safety On Five Continents (RS5C 2016), Rio de Janeiro, Brazil, 17-19 May 2016.

94. Wu, J., Yan, X., & Radwan, E. (2016). Discrepancy analysis of driving performance of taxi drivers and non-professional drivers for red-light running violation and crash avoidance at intersections. Accident Analysis & Prevention, 91, 1-9.

95. Yan, X. (2005). Safety issues of red-light running and unprotected left-turn at signalized intersections (Doctoral dissertation, University of Central Florida Orlando, Florida).

96. Yan, X., Liu, Y., & Xu, Y. (2015). Effect of Audio In-vehicle Red Light–Running Warning Message on Driving Behavior Based on a Driving Simulator Experiment. Traffic injury prevention, 16(1), 48-54.

97. Yan, X., Li, X., He, S., Weng, J., Wong, S. C., & Pang, H. (2016). Effects of intersection field of view on emergent collision avoidance performance at unsignalized intersections: analysis based on driving simulator experiments.Journal of Advanced Transportation.

98. Yan, X., Wang, J., & Wu, J. (2016). Effect of In-Vehicle Audio Warning System on Driver's Speed Control Performance in Transition Zones from Rural Areas to Urban Areas. International Journal of Environmental Research and Public Health, 13(7), 634.

99. Yan, X., & Wu, J. (2014). Effectiveness of variable message signs on driving behavior based on a driving simulation experiment. Discrete dynamics in nature and society, 2014.

100. Yuan, Q., Li, Y., Liao, Y., & Tang, S. (2013). Study of Correlation between Driver Emergency Measures and Pedestrian Injury Based on Combined Driving Simulator and Computer Simulation. Advances in Mechanical Engineering, 5, 171479.

101. Yue, H., Guan, H., Zhang, J., & Shao, C. (2010). Study on bi-direction pedestrian flow using cellular automata simulation. Physica A: Statistical Mechanics and its Applications, 389(3), 527-539.

102. Zajac, S. S., & Ivan, J. N. (2003). Factors influencing injury severity of motor vehicle–crossing pedestrian crashes in rural Connecticut. Accident Analysis & Prevention, 35(3), 369-379.

103. Zegeer, C., Stewart, J., Huang, H., & Lagerwey, P. (2001). Safety effects of marked versus unmarked crosswalks at uncontrolled locations: analysis of pedestrian crashes in 30 cities. Transportation Research Record: Journal of the Transportation Research Board, (1773), 56-68.

104. Zhang, G., Cao, L., Hu, J., & Yang, K. H. (2008). A field data analysis of risk factors affecting the injury risks in vehicle-to-pedestrian crashes. Annals of advances in automotive medicine, 52, 199-214.

105. Zhang, X., and Chang, G. (2014). A mixed-flow simulation model for congested intersections with high pedestrian-vehicle traffic flows. Simulation: Transactions of the Society for Modeling and Simulation International, Vol. 90(5), pp.570-590.

106. Zhang, Y., Liu, S., Qiu, Z., Yao, D., & Peng, L. (2012). Pedestiran-vehicle Conflict Parameter Analysis and Safety Evaluation. Journal of Harbin Institute of Technology, Vol. 44, No. 12, pp. 123-128.

107. Zhang, Y., Yan, X., & Yang, Z. (2015). Discrimination of effects between directional and nondirectional information of auditory warning on driving behavior. Discrete Dynamics in Nature

and Society, 2015.

108. Zhang, Y., Yao, D., Qiu, T. Z., & Peng, L. (2014). Scene-based Pedestrian Safety Performance Model in Mixed Traffic Situation. IET Intelligent Transport Systems, Vol. 8, No. 3, pp. 209-218.

109. Zhu, M., Cummings, P., Chu, H., & Xiang, H. (2008). Urban and rural variation in walking patterns and pedestrian crashes. Injury prevention, 14(6), 377-380.