PEDESTRIAN-VEHICLE INTERACTIONS AT UNCONTROLLED INTERSECTIONS UNDER MIXED TRAFFIC CONDITIONS

Submitted in partial fulfilment of the requirements

for the award of the degree of

Doctor of Philosophy

by

LALAM GOVINDA

717109

DEPARTMENT OF CIVIL ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY, WARANGAL

2022

PEDESTRIAN-VEHICLE INTERACTIONS AT UNCONTROLLED INTERSECTIONS UNDER MIXED TRAFFIC CONDITIONS

Submitted in partial fulfilment of the requirements

for the award of the degree of

Doctor of Philosophy

by

LALAM GOVINDA

717109

DEPARTMENT OF CIVIL ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY, WARANGAL

2022

NATIONAL INSTITUTE OF TECHNOLOGY
WARANGAL

CERTIFICATE

This is to certify that the thesis entitled **"Pedestrian-Vehicle Interactions at Uncontrolled Intersections under Mixed Traffic Conditions"** being submitted by **Mr. Lalam Govinda** for the award of the degree of **DOCTOR OF PHILOSOPHY** to the Department of **Civil Engineering** of **NATIONAL INSTITUTE OF TECHNOLOGY, WARANGAL** is a record of bonafide research work carried out by him under my supervision and it has not been submitted elsewhere for award of any degree.

Dr. K. V. R. RAVISHANKAR
Thesis Supervisor
Associate Professor
Department of Civil Engineering
National Institute of Technology, Warangal
Telangana, India

APPROVAL SHEET

This Thesis entitled "**PEDESTRIAN-VEHICLE INTERACTIONS AT UNCONTROLLED INTERSECTIONS UNDER MIXED TRAFFIC CONDITIONS**" by Mr. **LALAM GOVINDA** is approved for the degree of Doctor of Philosophy.

Examiners

____

____

____

Supervisor

____

Chairman

____

Date: ___________

DECLARATION

This is to certify that the work presented in the thesis entitled **“Pedestrian-Vehicle Interactions at Uncontrolled Intersections under Mixed Traffic Conditions”** is a bonafide work done by me under the supervision of **Dr. K. V. R. Ravishankar**, Associate Professor, Department of Civil Engineering, NIT, Warangal, Telangana, India and was not submitted elsewhere for the award of any degree. I declare that this written submission represents my ideas in my own words. I have adequately cited and referenced the original sources where others’ ideas or words have been included. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea /data/ fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

L. Govinda

Lalam Govinda

Roll No. 717109

Date: 03/11/2022

Dedicated to

AMMA, NANNA, AKKA, ANNA, GURUVU

ACKNOWLEDGEMENTS

I express my deep sense of gratitude and acknowledgement to **Dr. K.V.R. Ravishankar,** Associate Professor, Department of Civil Engineering, National Institute of Technology, Warangal, under whose guidance this research work was carried out. It was really a pleasure experience to work with him for his continuous guidance, valuable suggestions, encouragement and help with regard to research matters has helped me a lot. I consider it as a privilege to have worked with him.

I am highly indebted to my Doctoral Committee Members **Prof. C.S.R.K. Prasad**, Professor, Department of Civil Engineering, **Dr. Arpan Mehar**, Associate Professor, Department of Civil Engineering, **Prof. D.M. Vinod Kumar**, Professor, Department of Electrical Engineering, National Institute of Technology, Warangal for their assistance, encouragement, inspiration, and continuous monitoring of my work during the course of this research work.

I wish to take this opportunity to express my sincere thanks to **Prof. Venkaiah Chowdary**, Professor, Transportation Division, Department of Civil Engineering, National Institute of Technology, Warangal, **Dr. S. Shankar,** Associate Professor, Transportation Division, Department of Civil Engineering, National Institute of Technology, Warangal, **Dr. B. Raghuram Kadali**, Assistant Professor, Transportation Division, Department of Civil Engineering, National Institute of Technology, Warangal, **Dr. Vishnu. R,** Assistant Professor, Transportation Division, Department of Civil Engineering, National Institute of Technology, Warangal, for their valuable suggestions and encouragement throughout the course of my research work.

I am grateful to **Prof. N.V. Ramana Rao,** Director, National Institute of Technology, Warangal for extending every possible help during the course of the study.

I express my sincere acknowledgement for funding this research study by **Ministry of Human Resource and Development, Government of India**. I would like to thank the DataFromSky team for timely help in extracting video data and related academic agreement with the institute.

I extend my sincere acknowledgement to former M. Tech students Godumala Dharma Teja, M.R. Sai Kiran Raju and K. Vasanth Rao for their help in data collection.

I have been lucky to get so many wonderful friends in the Department of Civil Engineering: Dr. S. Eswar, Dr. D. Abhigna, Dr. J. Jaya Krishna, Dr. K. Mahaboob Peera, Dr. P. Yugender, Dr. L. Prasanth Sekhar, Dr. K. Aditya, Dr. Ustav Vishal, Dr. M. Anil, Dr. S. Srikanth, Dr. D. Harinder, T. Arjun Kumar, Dr. K. Srikanth, Ramakanth, Dr. S. Chakravarthy, Dr. R. Susmitha, J. Jithender, G. Shravan Kumar, Khalil, Ramesh Babu Kota, P. Sruthi Sekhar, Sudhir, Someswarao, Chiranjeevi, Ch. Lalitha Sri, Anirudh, Deep Chand, A. Nithin Kumar, Sagarika, Saraswathi, A. Aravind, Ayyappa Reddy Allu, Sudheekar Reddy, Aravind Goud, Mani Ratnam, Vikas, Kumarapu Kumar, M. Teja, Guru Prathap Reddy, and Sathish, M. Baburao. The dreary periods during research were enlivened up by the lighter moments we shared together.

I would like to thank Mr. Md. Abdul Gaffar and Mr. K. Ramesh, laboratory staff of Transportation Division.

Finally, I thank everyone, who contributed either directly or indirectly in successful completion of this work.

I wish to express my thanks to all the Research Scholars of Transportation Division, Department of Civil Engineering, NITW for their constant encouragement and timely help.

I express my deepest gratitude to my parents **Mr. L. Appanna** and **Smt. L. Satyavathi**, for their love, support, and encouragement without which this work would not have been possible. I would like to thank my brothers **L. Srirama Murthy, L. Appala Naidu** and sisters **Laxmi, Ratnam** for their support to continue my research work. Finally, I would like to thank many others whose names would be too numerous to mention here for their assistance, suggestions, friendship, and insightful discussions.

L. Govinda

LALAM GOVINDA

CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

Pedestrians are one of the vulnerable road users and their safety is utmost important. The pedestrian risk taking behaviour and driver yielding behaviour varies from person to person. There is a possibility of accidents between pedestrians and vehicles at pedestrian crossing locations due to the misunderstanding between pedestrians and drivers. Improvements in the pedestrian facilities and safety-related issues will help to reduce the number and severity of pedestrian-vehicle (P-V) accidents and improve the pedestrian safety. This can be possible only with better understanding of pedestrian road crossing behaviour and their interactions with vehicular traffic. The present study is intended to analyse and model the P-V interactions at uncontrolled intersections to know the various factors affecting the severity of P-V interactions. Also, intended to estimate and model the pedestrian dilemma zone (PDZ) at uncontrolled intersections to improve the gap acceptance behaviour of pedestrians.

Four 3-legged and four 4-legged uncontrolled intersections were selected from Warangal and Visakhapatnam cities in India. Video was recorded continuously for two hours in the morning (7:30AM to 9:30AM) and evening (4:30PM to 6:30PM) periods from each study location on a week day. Geometric details of all study locations were directly measured from the field. Required pedestrian, vehicle, and geometric parameters were extracted from the videos using MPC-HC media player, Kinovea and DataFromSky softwares. Risk indicator (RI) was defined using post encroachment time (PET) and approaching speeds of vehicles for each pedestrian-vehicle interaction.

The threshold limits of PET and RI were defined using support vector machine (SVM) technique in Python interface to define the severity levels of P-V interactions at uncontrolled intersections. The results showed that the severity of P-V interactions was inversely correlated with threshold limits of PET and threshold limits of RI directly correlated with RI. The severity level was higher at lower values of PET and higher values of RI. The threshold limits PET at three-legged intersections were found to be lower than that of four-legged intersections and threshold limits of RI at four-legged intersections were found to be lower than three-legged intersections.

An ordinal logistic regression models were developed at uncontrolled intersections to know the various parameters affecting the severity levels of P-V interactions. The model results showed that the probabilities of P-V interaction severity levels increase with the presence of

male pedestrians, crossing with luggage, usage of mobile phones while crossing, pedestrians crossing with lower crossing speeds, and pedestrians crossing at entry point of intersection. The probabilities of severity levels also increase with the increase in speed of the vehicle, left turning vehicles, and presence of young pedestrians. The probability of severity levels at three-legged intersections were found to be higher than that of four-legged intersections. The developed models were validated using various validation techniques.

The pedestrian dilemma zone (PDZ) at uncontrolled intersections was estimated using gap cumulative distribution (GCD) and support vector machine (SVM) methods and developed a binary logistic regression (BLR) model to estimate the PDZ boundary limits. The estimated lower and upper boundary limits of PDZ at three-legged intersections were 7.5 m and 24.0 m respectively using SVM method and 6.0 m and 18.5 m respectively at four-legged intersections. The boundary limits at three-legged intersections were found to be higher than that of four-legged intersections. The BLR model results showed that the PDZ boundary limits lies close to the intersection in case of male and young pedestrians. They shift away from the intersection when the pedestrians crossing at the entry point of intersection, increase in size and speed of vehicles. The developed models were validated using classification table, model fitting criteria, and likelihood ratio test.

The study results can be used for better understanding of P-V interactions at uncontrolled intersections under mixed traffic conditions. The proposed threshold limits of can be used to define the P-V interaction severity levels using pedestrian and vehicle characteristics at uncontrolled intersections. The proposed PDZ boundary limits can be used for the practical applications in the field to eliminate the dilemma behaviour of pedestrians while crossing the road at uncontrolled intersections.

Keywords – Pedestrians, Pedestrian-vehicle interactions, pedestrian dilemma zone, uncontrolled intersections, threshold limits, surrogate safety measures, support vector machine classification, gap cumulative distribution.

CHAPTER 1: INTRODUCTION

1.1 General

Transportation is a part in everyone's day to day life, whether it be walking or vehicular transportation or any other mode of transportation. Road transport provides mobility to people and goods. However, it exposes people to risk of road accidents. For shorter distances, walking is common across the world and it is the most preferable option in the developing countries like India. Walking helps in order to save fuel consumption and environment from the pollution. According to NHTS (National Household Travel Survey) national data 2001, the number of walking trips decrease as the distance to travel increases and most number of walking trips are possible at a distance of 0.26 miles to 0.50 miles. According to Census 2011 data, approximately 55.1% total worker trips in India are related to walking and approximately 70% of total workers choose to travel on foot when the work place or destination lies between 0-1 kilometres (Tiwari and Nishant, 2018). Figure 1.1 shows the distribution of trip length and mode of transportation in India. The number of walking trips decreases year by year not only due to increase in the vehicular volume but also due to neglecting importance of pedestrians and their safety.

In the process of travelling, sometimes they may have to cross the road to reach their destinations. Generally, pedestrians will cross the road at pedestrian crossing locations. Ideas, thinking, and perception of people varies from person to person. Pedestrians are one of the vulnerable road users and their safety is utmost important. The pedestrian risk taking behaviour and driver yielding behaviour varies from person to person. There is a possibility of accidents between the pedestrians and vehicles at these locations due to the misunderstanding between them. Number and severity of these accidents also influence the GDP of the country. Improvements in the pedestrian facilities and safety-related issues will help to reduce the number and severity of accidents and improve pedestrian safety. This can be possible only with better understanding of pedestrian road crossing behaviour and their interactions with vehicular traffic.

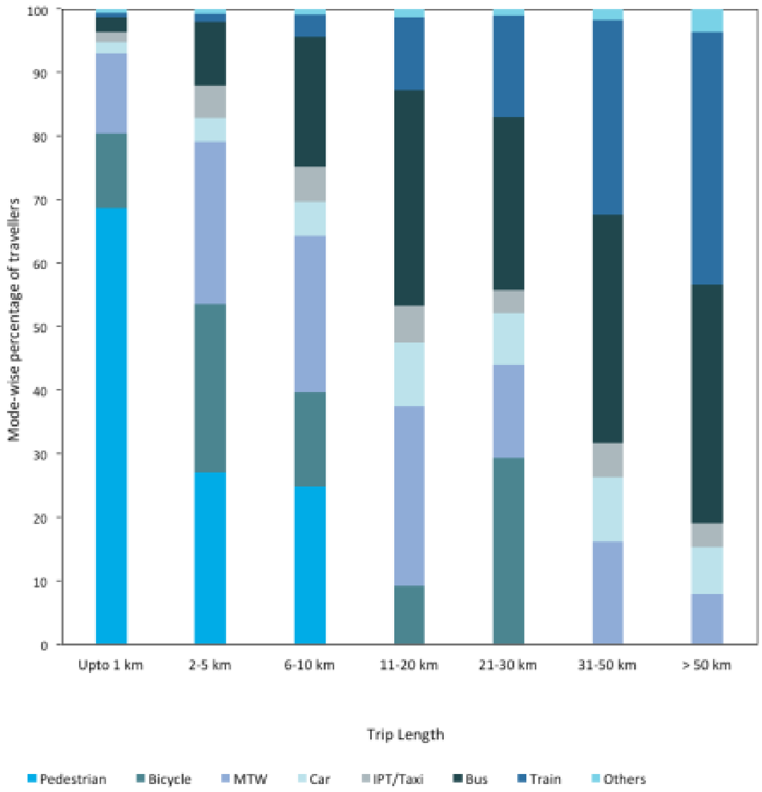


Figure 1.1: Distribution of trip length and mode of transport in India (Tiwari and Nishant, 2018).

1.2 Road accident statistics

Road accidents are one of the major reasons for loss of life or severe/minor injuries or property damage and these are not constrained to a particular location on the globe. Human errors are one of the major causes of road accidents and these errors include over speeding, distractions to drivers, drunken driving, avoiding safety gears and red light jumping etc. Not only human errors, other factors (weather conditions, road conditions etc.) also influence the road accidents and a lot of research is going on to identify the factors which causes the road accidents.

1.2.1 Global road accident statistics

According to World Health Organization (WHO) road accident report 2018, road traffic injury is the eighth leading cause of deaths for all age groups across the world and 1.35 million deaths occurring each year due to road accidents. Among these, more than half of the deaths are amongst pedestrians, cyclists, and motorcyclists who are the most neglecting part in road traffic system design in many countries and the distribution of road traffic deaths across the world by road user category are shown in figure 1.2. Across the world, the highest number of road accident deaths are related to the motorized two and three wheelers (29%) followed by passengers of four wheeled vehicles (28%), pedestrians (23%), others (17%), and cyclists (3%). Over the last 15 years, the rate of road traffic deaths has remained fairly constant at around 18 deaths per 1, 00,000 population. Over the last few years, the reduction in road traffic deaths varies significantly between the different countries of the world due to the variations in the income levels. The risk of traffic deaths in low and middle income countries is 3 times higher than that of high income countries.

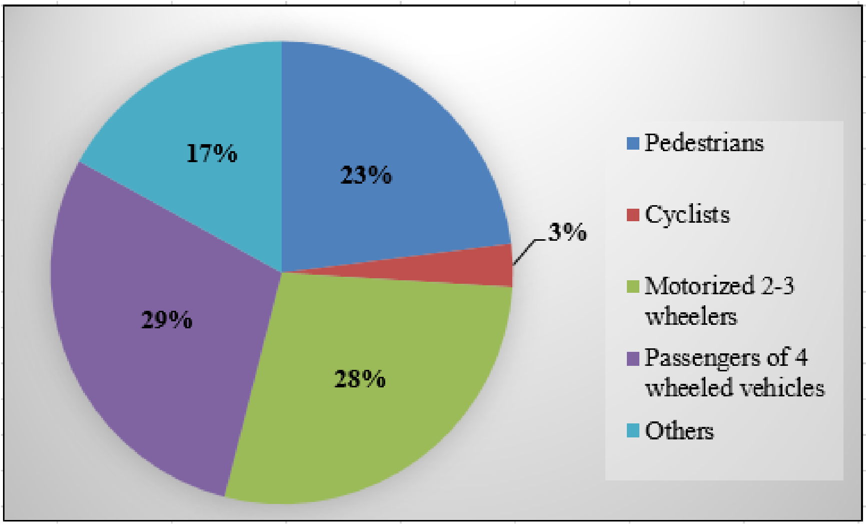


Figure 1.2: Distribution of deaths by road user type across the world (Source: World Health Organization Report, 2018).

1.2.2 Road accident statistics in India

India is the second largest country in the world in terms of both population and road network. With the growing number of vehicles and increase in road length, Indian roads are spattered with blood as accidents resulting in injuries and fatalities have been mounting over the past twenty years. There is one serious road accident occurs every minute and one death occurs every four minutes due to a road accident in India. The GDP of any country is highly influenced by the road accidents and India loses 3% of its GDP only due to the road accidents. As per the statistics of the Ministry of Road Transport and Highways-2020 (MoRTH-2020), total road accidents occurred, number of persons killed and number of persons injured over the last five decades were shown in figure 1.3. A drastic decrease in the total number of accidents and number of injuries, and almost equal number of road accident deaths every year from 2010 to 2020 was observed. This drastic change in the number of accidents and number of injuries is due to the improvements in the road traffic issues for smooth traffic flow. In 2020, a total of

3,66,138 accidents occurred on Indian roads, which claimed 1,31,714 lives and caused 3,48,279 injuries. The number of persons killed in 2020 due to road accidents 12.6 per cent less than the number of persons killed in road accidents during 2019.

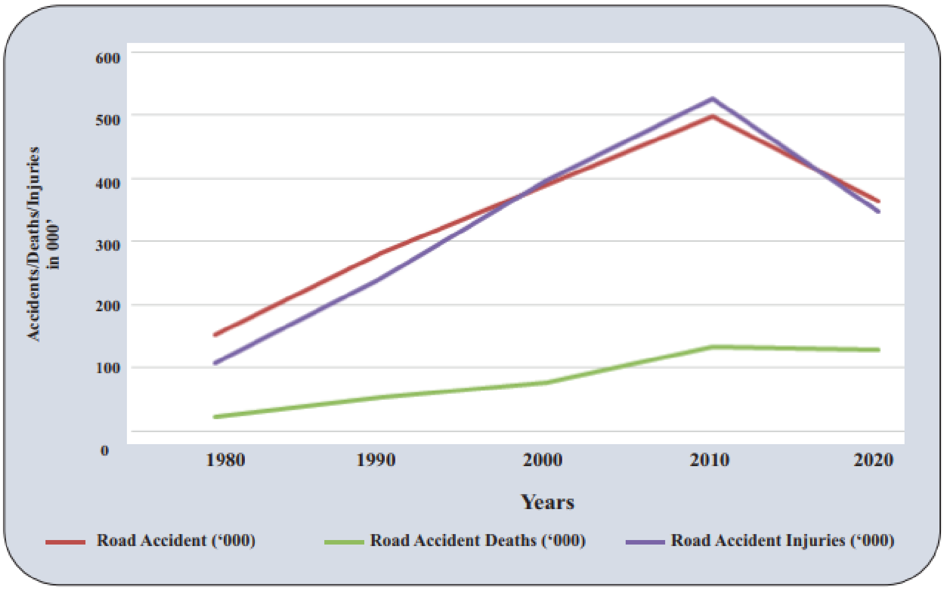


Figure 1.3: Decadal trend in the number of road accidents, deaths and injuries (Source: http://morth-roadsafety.nic.in)

1.2.3 Road accident statistics at pedestrian road crossing locations

Pedestrian crossings are the locations where the pedestrians will cross the road safely than other places. Generally, pedestrians will cross the road at intersections and mid-blocks crossings. Intersections are the locations where there is a possibility of merging and diverging of traffic and hence are prone to accidents. The share of road accidents by the type of traffic control in India from 2018 to 2020 was shown in table 1.1. The road accident statistics from 2018 to 2020 reveals that the share of number of accidents, number of persons killed and the number of persons injured at uncontrolled intersections were higher compared to other type of intersections. In 2020, approximately 20% of accidents occurred at uncontrolled intersections and around 8% of accidents occurred at other type of intersections. This large number of accidents and persons killed at uncontrolled intersections were due to the lack of understanding between the road users or lack of improvements in the crossing/diverging/merging facilities. The percentage of number of accidents, number of persons killed and number of persons injured in India from 2018 to 2020 with respect to type of intersection were shown in figures 1.4 to 1.6 respectively. According to the MoRTH (Ministry of Road Transport and Highways) road accident statistics-2020, among the different types of intersections, T-intersections accounted the highest number of accidents (10%), number of persons killed (8.4%) and number of persons injured (9.7%) followed by four arm intersections, Y-intersections, staggered intersections, and roundabouts respectively.

Table 1.1: Share of accidents at road intersections by type of traffic control in India: 2020 (Source: http://morth-roadsafety.nic.in)

Intersection type	Total accidents			Persons killed			Persons injured		
	2018	2019	2020	2018	2019	2020	2018	2019	2020
Uncontrolled	24.4	20.6	19.5	21.9	19	17.9	23.3	19.4	18.4
Flashing signal/Blinker	1.7	1.4	2	1.8	1.5	1.8	1.6	1.2	1.9
Stop sign	1.4	1.4	1.6	1.6	1.6	1.5	1.2	1.2	1.5
Police controlled	2.7	2.3	2	2.7	2.3	1.6	2.5	2.1	1.9
Traffic light signal	2.9	2.2	2.3	2.2	1.9	1.6	2.7	2	2.2
Others	66.8	72	72.6	69.7	73.7	75.6	68.8	74.2	74.1

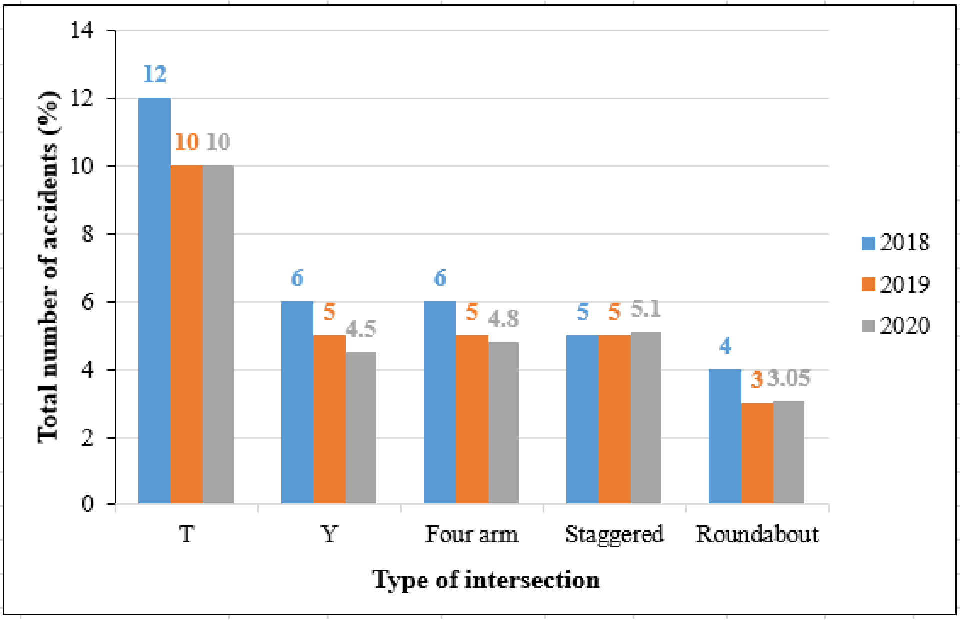


Figure 1.4: Number of accidents (%) in India from 2018 to 2020 at intersections

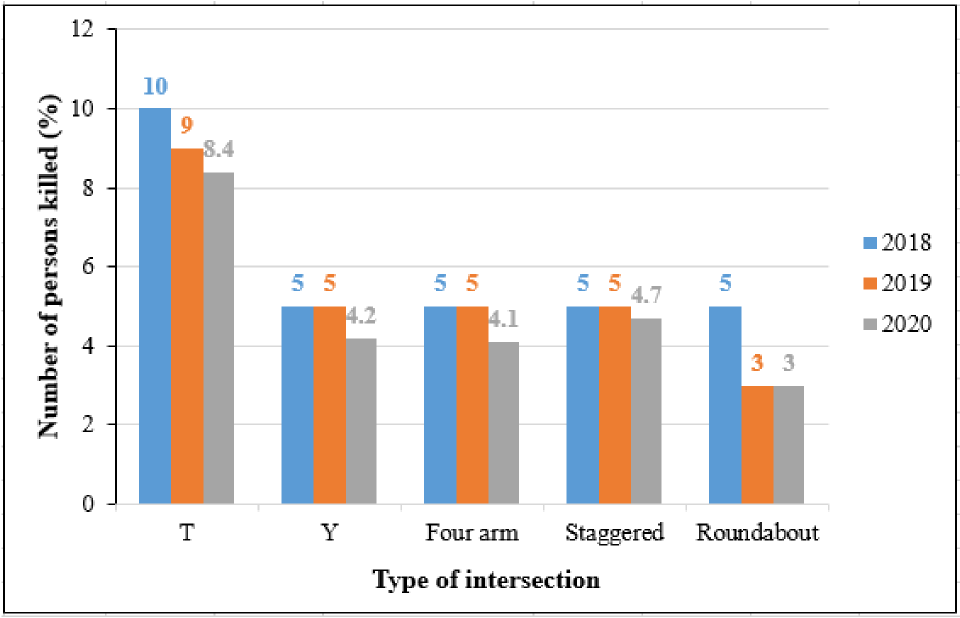


Figure 1.5: Number of persons killed (%) in India from 2018 to 2020 at intersections

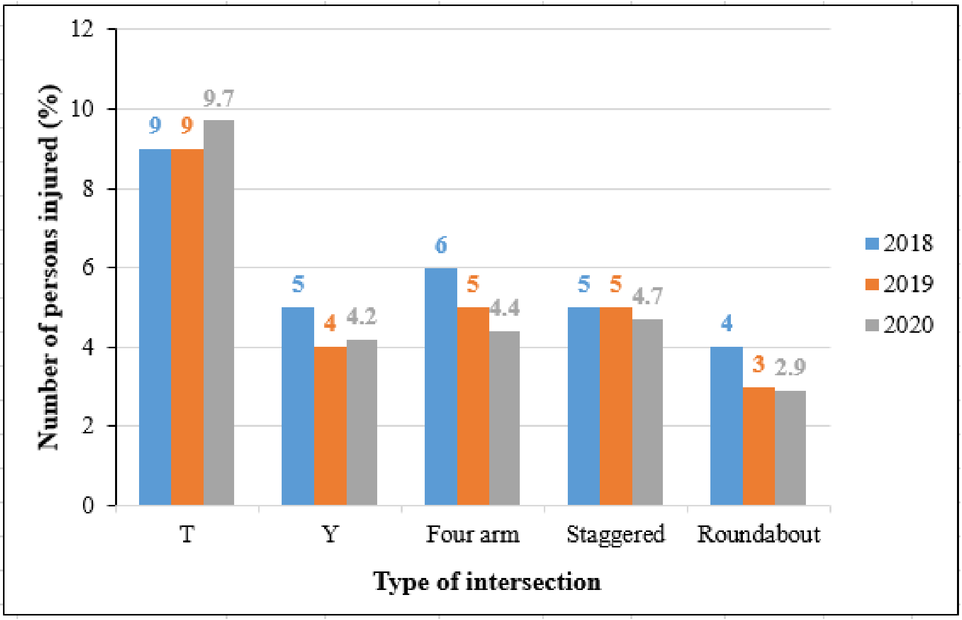


Figure 1.6: Number of persons injured (%) in India from 2018 to 2020 at intersections

The fatality rise is high for the pedestrians in the case of pedestrian-vehicle collisions compared to vehicle-vehicle collisions. This has high impact on the pedestrians compared to the vehicles. The share of pedestrian deaths due to pedestrian-vehicle accidents at pedestrian crossings in India were shown in table 1.2 below. Figure 1.7 shows the share of pedestrian deaths in India from 2013 to 2020. Despite some fluctuations, the pedestrian deaths are in increasing trend over the last 10 years. Even though the number of accidents, number of persons killed, and the number of persons injured were decreased over the years, the share of pedestrian deaths was not decrease. This clearly shows the importance given to the pedestrians.

Table 1.2: Share of pedestrian deaths at pedestrian crossings in India: 2013-2020 (Source: http://morth-roadsafety.nic.in)

Year	2020	2019	2018	2017	2016	2015	2014	2013
Pedestrians killed (%)	17.8	17	15	13.8	10.5	9.5	8.8	9.1

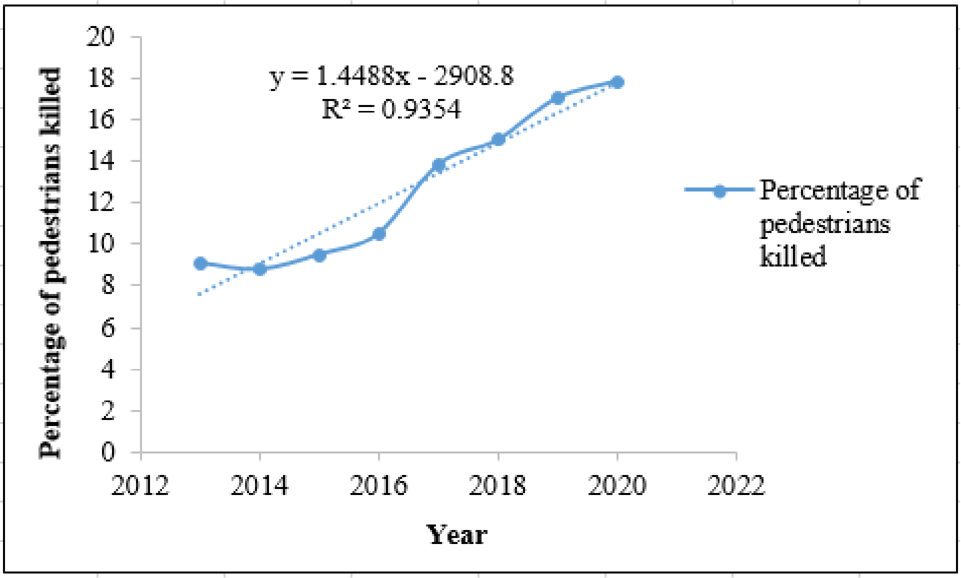


Figure 1.7: Share of pedestrian deaths in India from 2013 to 2020

1.3 Surrogate Safety Measures (SSMs)

Accident frequency and severity are direct measures of road safety and accident data used to measure the road safety. But the accidents are rare events and sometimes collection of sufficient accident data is not possible. In the absence of accident data, surrogate safety measures (SSMs) are used to predict and analyse the frequency and severity levels of possible potential traffic conflicts using videography data. SSMs are indirect and complementary safety measures and they don’t rely on the accident data. SSMs are more proactive, more accurate, more informative and more time-efficient (Hyden, 1987). The basic definitions of widely used SSMs to predict the frequency and severity levels of a possible potential traffic conflicts were discussed below.

i. **Time to collision (TTC):** It was introduced by Hayward in 1971. It is defined as the time to collision (seconds) when two vehicles continue their trajectory at the same speeds and the same angle without any kind of evasive behaviours (Hayward, 1971). Figure 1.8 shows the pictorial representation of TTC.

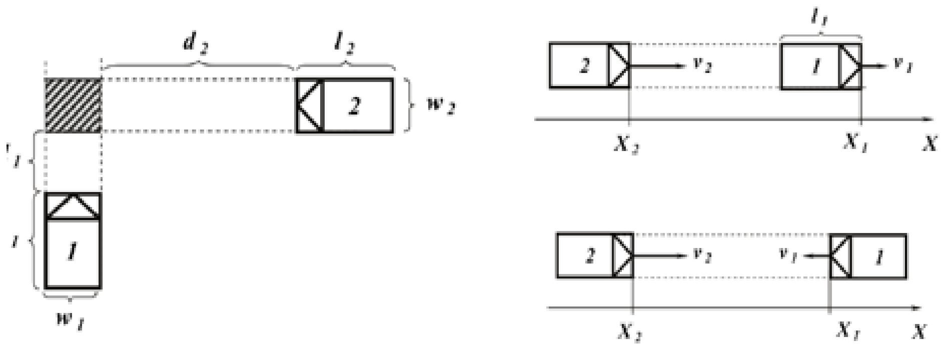


Figure 1.8: Pictorial representation of TTC definition (Hayward, 1971)

$$TTC = \frac{d_2}{v_2} \; if \; \frac{d_1}{v_1} < \frac{d_2}{v_2} < \frac{d_1 + l_1 + w_2}{v_1} \tag{1.1}$$

$$TTC = \frac{d_1}{v_1} \; if \; \frac{d_2}{v_2} < \frac{d_1}{v_1} < \frac{d_2 + l_2 + w_1}{v_2} \; (side) \tag{1.2}$$

$$TTC = \frac{X_1 - X_2 + l_1}{v_1 - v_2} \; if \; v_2 > v_1 \; (rear\ end) \tag{1.3}$$

$$TTC = \frac{X_1 - X_2}{v_1 + v_2} \; (head\ on) \tag{1.4}$$

Where, d_1, v_1, X_1, w_1 are the distance from conflict point, speed and width respectively for road user 1 and d_2, v_2, X_2, w_2 are the distance from conflict point, speed and width respectively for road user 2.

ii. **Post encroachment time (PET):** It is the time difference between the first road user leaving the conflict area and the second road user entering the conflict area (Allen 1978). Figure 1.9 shows the pictorial representation of PET.

Let, t_1 be the time at which the first road used leaving the conflict area and t_2 be the time for second road user to reach the conflict area.

$$PET = t_2 - t_1 \tag{1.5}$$

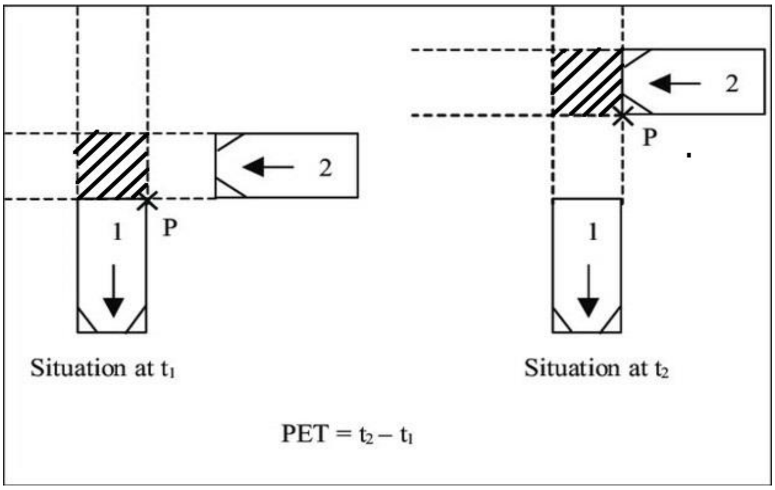


Figure 1.9: Pictorial representation of PET definition (Allen 1978)

iii. **Deceleration to safety time (DST):** It is the necessary deceleration to reach a nonnegative PET value if the movement of the conflicting road users remains unchanged (Hupfer 1997).

iv. **Gap time (GT):** It is the time lapse between the completion time of encroachment by one road user and the arrival time of the interacting road user if they continue with the same speed and path (Archer 2004).

v. **Risk indicator (RI):** It is derived using PET and approaching speeds of vehicles by Scholl et al. (2019). It is defined as the ratio of approaching vehicle speed over post encroachment time.

$$\text{Risk Indicator} = \frac{\text{Approaching Vehicle Speed}}{\text{Post Encroachment Time}} \tag{1.1}$$

1.4 Pedestrian Dilemma Zone (PDZ)

When a pedestrian is crossing the road, he/she may try to find a sufficient gap and the decision to stop/go depends on the available gap size. But sometimes pedestrian may get confused about whether the available gap is sufficient to cross the road or not. This situation is known as the dilemma of a pedestrian. This situation arises only when the vehicles are present within a certain section of a roadway and this section is known as the pedestrian dilemma zone (PDZ). Gap acceptance behaviour is the basic concept for dilemma zone analysis. PDZ is defined as "the section of a roadway where the presence of vehicles creates a stage of confusion for pedestrians while crossing the road" (Pawar et al., 2016). It consists of upper and lower boundary limits and the difference between these two limits is defined as the length of dilemma zone. Figure 1.10 shows the physical location of a pedestrian dilemma zone for one approach near an intersection. D_0 and D_1 are the lower and upper boundary limits respectively within which pedestrians are in a stage of confusion to judge whether the available gap is sufficient or not. There are several methods to estimate the dilemma zone using the filed data and the basic procedures of various methods to estimate PDZ boundary limits were briefly discussed below.

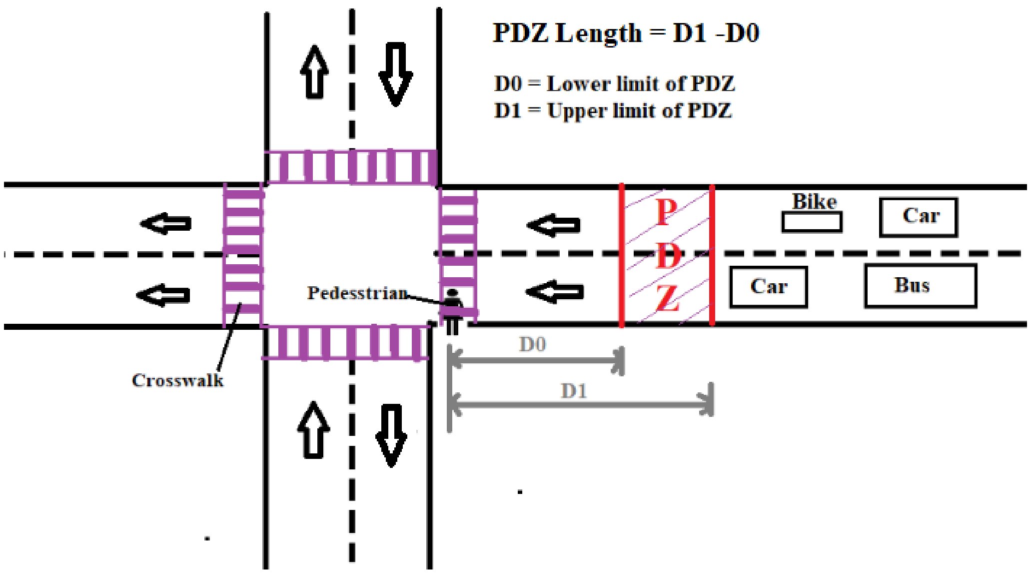


Figure 1.10: Location and length of pedestrian dilemma zone at an intersection

i. **Gap cumulative distribution (CGD) method:** This method is proposed by Zageer (1977) to estimate the dilemma zone boundary limits. In this method, a plot between the cumulative percentage gap accepted/rejected on y axis and distance on x-axis is plotted and then the distance on x-axis corresponding to 10 percentile accepted and 90 percentile rejected gaps on y-axis are taken as the lower and upper boundary limits of dilemma zone respectively.

ii. **Support vector machines (SVM) method:** Pawar et. al. (2016) used to SVM technique to find the dilemma zone boundaries at uncontrolled midblock crossing. In this method, a plot between speeds of vehicles or pedestrians on y-axis and distances of the vehicles from the pedestrian/vehicle trajectory paths on x-axis is plotted on a coordinated system. A hyperplane is constructed as a decision plan to separate the accepted and rejected gap sizes with maximum margin. The lower and upper limits of the dilemma zone are taken on the hyperplane corresponding to the plus or minus two standard deviations from the mean speed.

iii. **Binary logit method:** This method has two alternative outputs (accept/reject) as it is a discrete choice model. In this method, a binary logit model is developed using gap accept/reject as dependent variable and various independent variables and the lower and upper boundary limits of dilemma zone are estimated corresponding to the 0.1 and 0.9 probabilities.

iv. **Probabilistic method:** This method was proposed by Gazis et al. (1960) for estimating the dilemma zone boundaries. A detailed procedure to determine the boundary limits of dilemma zone is explained below.

a) **Classification of speed bands:** First the approaching speeds of vehicles or crossing speeds of pedestrians are classified into bands.

b) **Setting 10th percentile and 90th percentile boundaries classified speed bands:** Cumulative 10th percentile minimum accepted gaps and 90th percentile maximum rejected gaps are determined for various speed bands. After that, mark the midpoint of each speed band corresponding to the 10th percentile minimum accepted gaps and 90th percentile maximum rejected gaps.

c) **Plotting profile:** 10th and 90th percentile profiles for the midpoints are fitted and then lower and upper boundary limits of dilemma zone are taken on x-axis by projecting the average speed over the profiles.

1.5 Need for study

Intersections are one of the major causes of road accidents and around 25-30% of total road accidents in India are occurring at intersections only (MoRTH, 2020). According to the MoRTH road accident statistics 2020 report, approximately 70% of total accidents at intersections in India are occurring at uncontrolled intersections followed by signalized (10%), police controlled (8%), stop sign (6%) and flashing signal/blinker (6%) intersections. This high proportions of accidents at uncontrolled intersections in developing countries like India is mainly due to the heterogeneous traffic conditions and difficulty in correct judgment while crossing the road due to the large variations in vehicular speeds. 3-legged and 4-legged uncontrolled intersections are the major locations of road accidents and they accounted for more than 50% of total accidents at uncontrolled intersections. These road accident statistics tells the amount of research needs to be carried out at 3-legged and 4-legged uncontrolled intersections to explore the reasons behind these accidents.

Despite some fluctuations, pedestrian deaths are increasing every year (MoRTH, 2020). Intersections are one of the major pedestrian road crossing locations and they accounted for around 24% of total pedestrian deaths at intersections in United States (National Highway Traffic Safety Administration (NHTSA), 2020 report). This proportion may be higher in India where the traffic is heterogeneous and non-lane based behaviour followed by the drivers. This high proportions of pedestrian deaths at intersections are because of the higher severity levels in pedestrian-vehicle (P-V) accidents because of the misunderstanding between vehicles and pedestrians due to dilemma behaviour while crossing. A better understanding of P-V interactions is required to provide better pedestrian facilities at intersections to reduce the safety related issues.

In the past, the researchers identified various factors affecting the severity levels of P-V interactions using accident data and surrogate safety measures (SSMs). They also proposed the threshold limits for various severity levels of P-V interactions using either pedestrian or vehicle characteristics. But the severity depends on both pedestrian and vehicle characteristics. Determining the threshold limits for various P-V interaction severity levels using both pedestrian and vehicle characteristics will better correlate the actual severity in P-V interaction analysis and modelling.

The dilemma behaviour of pedestrians while crossing is also one of the major reasons for P-V accidents. Misjudgement due to the dilemma behaviour of pedestrians when the vehicle lies within a certain zone will cause the P-V accidents. Providing the lower limit (unsafe gap) and upper limit (safe gap) for this dilemma behaviour of pedestrians (known as pedestrian dilemma zone (PDZ)) will improve the gap acceptance behaviour and safety.

1.6 Objectives of the study

The objectives of the present research are:

1. To determine the threshold values of SSMs for various severity levels of pedestrian-vehicle (P-V) interactions at uncontrolled intersections under mixed traffic conditions.
2. To develop P-V interaction severity model at uncontrolled intersections under mixed traffic conditions.
3. To estimate and model the pedestrian dilemma zone (PDZ) boundaries at uncontrolled intersections under mixed traffic conditions.

1.7 Outline of the thesis

Chapter 1 details incudes with the global road accident statistics, road accident statistics in India, introduction on surrogate safety measures pedestrian dilemma zone, need, and objectives of the present study.

Chapter 2 presents the literature review of previous research carried out on pedestrian road crossing behaviour, P-V interaction analysis and modelling using SSMs and accident data, and pedestrian dilemma zone.

Chapter 3 presents a detailed methodology adopted for the present study with the help of a flow chart.

Chapter 4 presents the selection of study locations, and collection of traffic data from the field using video graphic method.

Chapter 5 deals with the extraction of required pedestrian and vehicular data from the video. This chapter also presents the field data analysis carried out on sample size of P-V interactions, pedestrians and vehicular speeds, and distances of vehicles from pedestrian trajectory paths at 3-legged and 4-legged uncontrolled intersections.

Chapter 6 presents the development of threshold values of surrogate safety measures to classify various severity levels of pedestrian-vehicle interactions at uncontrolled intersections.

Chapter 7 presents the development of pedestrian-vehicle interaction model at 3-legged and 4-legged uncontrolled intersections.

Chapter 8 presents the estimation, analysis, and modelling of pedestrian dilemma zone at uncontrolled intersections under mixed traffic conditions.

Chapter 9 deals with the summary, conclusions, major contributions, limitations and future scope of the present research

CHAPTER 2

LITERATURE REVIEW

2.1 General

In the present chapter, a detailed review of past research work carried out on the pedestrian risk analysis, interactions of pedestrians with vehicular traffic and dilemma zone estimation, analysis and modelling are presented. The review of earlier research work in the present study is helpful to understand the amount of research carried out in the past and to find the gaps in the earlier works related to pedestrian-vehicle interactions and dilemma zone analysis and modelling. In the light of the scope of the study, the literature review has been done under three heads, namely, (i) Studies on pedestrian road crossing behaviour and risk analysis, (ii) Studies on pedestrian-vehicle interactions analysis and modelling, and (iii) Studies on dilemma zone analysis and modelling.

2.2 Studies on pedestrian-vehicle interaction analysis and modelling

In the absence of crash data, SSMs are used to predict the severity levels of possible potential interactions between vehicle-vehicle and pedestrian-vehicle. There are several safety indicators to measure the severity levels and many of them are derived from similar concepts. This section deals with the previous studies which uses the SSMs to analyse and model the number and severity of P-V interactions. This section also, deals with the previous studies which analysed and modelled the P-V interactions using crash data.

Lord (1996) carried out an analysis on the interactions between left turning vehicles and pedestrians at intersections with aid of traffic conflict techniques and compared the traffic conflict rate between Cross intersections and T-intersections by collecting data from 8 locations in Canada. Surrogate safety indicators such as Time to Collision (TTC) and Post Encroachment Time (PET) were used to analyse pedestrian conflicts with traffic. TTC values < 1.5 seconds and PET values < 3.0 seconds were considered as severe conflicts. A multivariate accident prediction model was developed involving pedestrian and vehicle flows. It was concluded that T-intersections were more dangerous than Cross intersections due to high conflict rate.

Maki et al. (2002) analysed the P-V accidents and found that the risk of fatal accidents depends on the vehicle type (increases in the order of sedans, SUVs, and minivans). The number of fatalities per 1000 accidents were higher for pedestrians compared with bicyclists. The frequency of leg injuries was also higher in case of pedestrians. Also found that severity of bicycle head injuries greatly affected by front-end geometry of vehicles and the cause of fatal injuries in case of minivans were less compared to Bonnet-type vehicles for the same velocity.

Roudsari et al. (2004) compared the injury severity of pedestrian-light vehicle (P-LVT) crashes with pedestrian-passenger vehicles. Pedestrian crash data was collected from 1994 to 1998 in six cities in USA and carried out the analysis. The study results showed that adults struck by LTVs had higher risk of moderate injury than those struck by either van or passenger vehicle. The study observed that the severity of pedestrian injury drastically varies with vehicle design. The probability of death for pedestrians struck by passenger vehicles was significantly lower than for those struck by LTVs.

Salifu (2004) developed the flow-based accident prediction models for un-signalized urban intersections in Ghana. A three years accident data from 1996 to 1998 was collected at 91 un-signalized intersections in Ghana. Also, collected the traffic and road geometry data at each intersection and developed Negative Binomial models at X and T intersections separately to predict the accident frequency. This study observed that the most influential traffic exposure factors for X-intersection and T-intersection accidents were sum of crossing flow products and cross product of major and minor road traffic inflows respectively. The developed flow-based models for T-intersections better explained than that of X-intersections.

Lee and Abdel-Aty (2005) examined pedestrian-vehicle crashes based on crash data collected at intersections in Florida. Pedestrian-vehicle crash data was collected over four years (1999-2002) from Florida Department of Highway Safety and Motor Vehicles and carried out the frequency analysis. A second order log-linear model was developed to estimate the number of pedestrian crashes and the general form of developed model shown in equation 2.3 below. This study concluded that the frequency and injury severity of pedestrian crashes depends on traffic condition, road geometrics, environmental conditions and driver demographic factors. Middle aged pedestrians and drivers were subjected to more pedestrian crashes compared to other age and gender groups and trucks, vans, and buses have a smaller number of crashes than passenger cars. Pedestrian crashes were observed to increase with the increase in average traffic volume. On divided roads, a smaller number of crashes occurred with less number of lanes compared to undivided roads with more number of lanes.

Ismail et al. (2009) analysed the P-V conflicts using video data in Canada. The video data was collected from an intersection in British Columbia, Canada and extracted the conflict indicators (TTC, PET, GT, and DST) from the video. The study identified that a combination of indicators proved to be useful for identification of traffic conflicts.

Kaparias et al. (2010) proposed a new technique to analyse the P-V interactions. The proposed method can be used for conventional roads as well as shared space environments. The video data was collected using video graphic method. The conflicts were estimated using the newly developed Institute of Highways and Transportation Conflicts Technique (IHTCT) and the results were compared with the existing techniques to check the accuracy and functionality of the new technique. The study found that the newly developed technique estimated the similar results with the Swedish Traffic Conflicts Technique (STCT).

Amin et al. (2014) developed a pedestrian crossing behaviour model at uncontrolled intersection using adaptive neuro fuzzy inference system in India. Pedestrian age is the most significant parameter in crossing behaviour compared to other parameters and type of conflicting vehicle has the least effect on decision process.

Haleem et al. (2015) analysed the crash injury severity of pedestrians at non-signalized and signalized intersections. Three years (2008-2010) pedestrian crash data at intersections on state highways was collected in Florida and severity levels were collected intro five categories. Mixed logit models have been developed separately for non-signalized and signalized intersections using crash injury severity as dependent variable to know the various factors affecting the crash severity of pedestrians. The model results showed that speed limit, percentage of trucks, AADT (average annual daily traffic), lighting conditions, weather, and at-fault pedestrians were significantly affecting the crash injury severity of pedestrians at signalized intersections and pedestrian age, speed limit, pedestrian manoeuvre before crash, heavy vehicles, dark lightning conditions, crosswalk type and dry road surface condition significantly affect the crash injury severity at non-signalized intersections. The severity of pedestrian crash injury at signalized intersections increases with increase in percentage of trucks. The severity at both non-signalized and signalized intersections increases with the increase in speed limit.

Chen and Wang (2015) simulated the P-V interaction using cellular automata (CA) and found that the vehicle delay was not significantly affected by the small number of pedestrian flow because of the interruption to the vehicle flow is minimal. The average waiting time of the pedestrians was reduced at low vehicle flow which allows large gaps between the vehicles for pedestrian crossing and also decreases with the increase in the number of pedestrian crossings. The road way capacity for the vehicles decreases with the increase in the number of pedestrian crossings.

Zheng et al. (2015) developed a model for pedestrian-vehicle interaction outside the crosswalks using micro simulation in United States and found that presence of bus stations, pedestrian and vehicle volume, and crossing distance highly influence the jaywalking events. The number of jaywalkers were affected by the number of pedestrians along the sidewalk. The distance between the crosswalks shows the positive correlation with the number of jaywalking events. The average yielding rate to the pedestrians at permissible crossings were higher than that of jaywalkers.

Fu et al. (2016) evaluated pedestrian safety at un-signalized crossings during night time based on pedestrian-vehicle interaction data collected by thermal video systems mounted on an adjustable mast nearby to study location. Post Encroachment Time (PET) was taken as the surrogate safety measure to evaluate the pedestrian safety. It was concluded that the pedestrian crossing speeds and percentage of dangerous conflicts (PET < 1.5s) would be higher at night times compared to day times.

Gorrini et al. (2016) developed a model to analyse the P-V interactions at urban unsignalized intersections. Video data was collected from an urban unsignalized intersection in Italy and extracted the required data from the videos. The study observed that the elderly pedestrians walk slowly than adults due to the decline of locomotion and perceptive skills linked to aging.

Mejias et al. (2016) studied the relation between pedestrian-driver based factors and risk related to pedestrian collisions in Spain. Logistic Regression method was developed to determine the factors affecting pedestrian-vehicle crashes. It was identified that male, young (<18years) and old (>65 years) pedestrians were at pedestrians at higher risk and driving under the influence of alcohol, driving without a license and large sized vehicles were at higher risk among drivers.

Ni et al. (2016) evaluated the pedestrian safety at intersections using three interaction patterns approach in China. The video data was collected from four intersections in China and trajectory data was extracted from the videos using Traffic Analyzer. The analysis was carried out on P-V interactions using TTC (time to collision) and GT (gap time) as surrogate safety measures.

The interactions were classified in to hard interactions, no interactions, and soft interactions based on the trend of TTC and GT. The proposed method for P-V interactions is helpful to better understanding the safety from behavioural perspective.

Almodfer et al. (2017) developed a novel indicator in evaluating pedestrian-vehicle conflict analysis named as Lane based Post Encroachment Time (LPET). The study location was marked non signalised crosswalk in Wuhan, China. Based on the indicator LPET values, the conflicts were classified into three major categories namely serious, slight, and potential conflicts. From the analysis it was observed that the pedestrian-vehicle lane-based conflicts seemed to be not evenly distributed. The number and severity of conflicts increases with the pedestrian waiting time and position of lane (starting from the entry lane). The number and severity of conflicts would be higher in case of farther lanes compared to nearer lanes. Pedestrian walking speeds were dependent upon the lane position, and stages of crossing but not on the severity of the conflict.

Chen et al. (2017) analysed the P-V conflicts at intersections in China using unmanned aerial vehicle videos. The aerial video data was collected from the study location and the pedestrian and vehicle trajectory paths were extracted for 1494 pedestrians and 282 right turning vehicles. PET and RTTC (relative time to collision) were calculated for each P-V interaction and the results were compared between the pedestrian passing first (PPF) and vehicle passing first (VPF). This study found that the VPF was more dangerous than PPF. This is due to the no yielding behaviour of both pedestrians and vehicles to each other and the vehicle tries to accelerate to pass the conflict area first.

Ma et al. (2017) investigated the factors influencing the pedestrian injury severity (PIS) at intersections. 12 independent variables (pedestrian age, pedestrian gender, driver gender, vehicle type, number of vehicles, point of first contact, traffic type, road condition, divided type, weather condition, traffic control device condition, and hit-and-run related) were found significantly related to PIS in case of young driver model, 7 independent variables (pedestrian age, vehicle type, number of vehicles, point of first contact, traffic type, roadway geometry, and weather condition) were significantly related to PIS in case of middle age driver model and 10 independent variables(pedestrian age, driver license state, vehicle type, vehicle manoeuvre prior to the crash, point of first contact, lighting condition, divided type, intersection type, weather condition, and hit-and-run related) were significantly related to PIS in case of older driver model.

Shah and Vedagiri (2017) developed a surrogate safety methodology to assess the pedestrian safety based on post encroachment times (PET) of pedestrian-vehicle interactions. Data was collected from an uncontrolled intersection in Mumbai, India using video graphic method and required data extracted manually from the video. A Binary Support Vector Machine (SVM) algorithm was developed to find the threshold PET values based on three categories of conflict types as highly severe, severe and normal conflicts. Also, this study suggested the threshold PET values based on pedestrian gender and crossing speeds. The proposed threshold PET values for highly severe conflicts were 0.85 sec and 0.80 sec in case of male and female pedestrians respectively. The threshold PET values for normal conflicts were 1.7 sec and 1.65 sec in case of male and female pedestrians respectively.

Fu et al. (2018) evaluated the pedestrian safety at unsignalized intersections using a novel framework (distance-velocity (DV) model). Pedestrian and traffic data was collected using video graphic method and extracted trajectory data using tracker software. The study found that the proposed model better explains P-V interactions compared to other traffic conflict techniques. The performance of pedestrian safety at unprotected crosswalks was low due to the lowest yielding compliance. The proposed model can be used for simulation of P-V interactions, safety monitoring, and treatment evaluation. The study also found that the unprotected crosswalks perform worst for pedestrian safety than stop sign-controlled crosswalk.

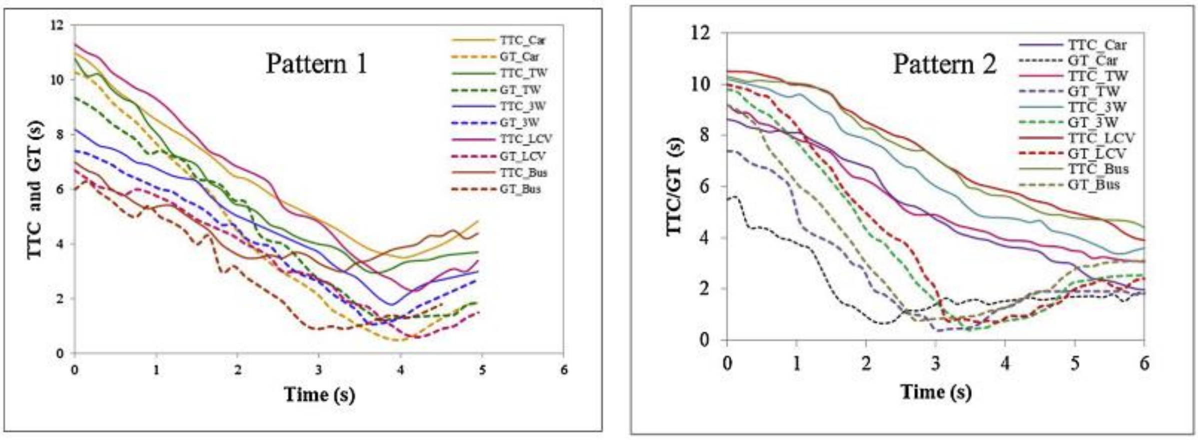
Hsu et al. (2018) proposed an MDP model to analyse the P-V interactions at unsignalized intersections in United States. A autonomous vehicle capable of a human controlled vehicle was created to simulate and developed the MDP model that needs to avoid collision. The pedestrian crossing behaviour model was compared between when there is some divergence and actually occurs. The study found that the safer interactions when pedestrians behaves similarly to the model assumed within the MDP.

Chen et al. (2019) analysed the right-turning pedestrian-vehicle interactions at intersections using microscopic simulation. Video data was collected from two urban intersections in China using unmanned aerial vehicle (UAV) and extracted the required data from the videos. Various models (vehicle maneuver model, path model, speed profile model, gap acceptance model, pedestrian behaviour model, desired direction model, and modified social force model) were developed and the validated the developed models. Post encroachment time (PET) was used as the surrogate safety measure. The study found that the safety at intersections was worst due to the larger dimensions and turning angles of intersections. For similar turning radii and crosswalk setback distances, 90-degree angle perform safer operations than 120-degree angle.

Scholl et al (2019) developed a surrogate video-based methodology for measurement and evaluation of pedestrian safety. Multiple Linear Regression model was developed by defining a novel surrogate safety measure termed as 'Risk Index' which is generated using Vehicle Speed and Post Encroachment Time (PET) for conditions of before and after applying traffic calming measures and the effectiveness of these measures were compared. This study concluded that motorcycles pose a serious threat to traffic safety compared to other vehicle types. Multilane roundabouts were most dangerous intersections across all safety indicators compared to all other intersection types.

Amado et al. (2020) reviewed the P-V interactions at unsignalized intersections. The study identified 381 studies and only nine studies were considered in this study. From each study, the type of methodology used for data collection, and typed of model used for the analysis were extracted and presented in this study. The review shows that videographic technique was mostly used for collecting the P-V interaction data using video cameras. The review observed that speed of vehicles, pedestrian attitude, adjacent yields, and the number of pedestrians waiting at crosswalk were mostly used in the micro simulation models. The review also observed that the heterogeneity of vehicles, pedestrians, drivers, and road environment were not considered in the modelling of P-V interactions.

Kathuria and Vedagiri (2020) evaluated the pedestrian-vehicle interaction dynamics at un-signalized intersections in India using SSMs (TTC, GT (gap time) and PET). Video data was collected from four un-signalized intersections in India and extracted the required data using Kinovia software. The analysis was carried out based on the evasive action taken by the pedestrian and vehicle. Two types of patterns were categorized using SSM indicators like TTC, GT and proposed a threshold value of SSMs for each pattern. The proposed threshold values of TTC_{min} and PET in this study were shown in table 2.1. The study observed that the number of critical interactions were higher in case of pattern 1 compared to pattern 2.



(a) (b)

Figure 2.1: TTC and GT profiles of (a) Pattern 1 (b) Pattern 2

Pattern 1: TTC_{min} and GT_{min} were occur simultaneously for all categories of vehicles. In this case, both or either pedestrian or vehicle take an evasive action.

Pattern 2: A clear distinction was observed between the occurrence of TTC_{min} and GT_{min}. In this case, neither pedestrian nor vehicle takes evasive action.

Table 2.1: Threshold values of TTC_{min} and PET for various P-V interaction severity levels

Pattern type	Safe passage		Mild interaction		Critical interaction	
	TTC_{min} (seconds)	PET (seconds)	TTC_{min} (seconds)	PET (seconds)	TTC_{min} (seconds)	PET (seconds)
Pattern 1	>2.5	-	1.2 to 2.5	-	<1.2	-
Pattern 2	>2.3	>2.6	1.3 to 2.3	1.0 to 2.6	<1.3	<1.0

Olszewski et al. (2020) proposed a novel surrogate safety indicator as a dangerous encounter index based on video graphic data collected from un-signalized pedestrian crossings. Pedestrian-vehicle encounters were classified into 4 categories. This study developed the relationship between dangerous encounter index and the severity of pedestrian-vehicle conflicts. The severity of conflicts increases with the increase in dangerous encounter index and the risk-taking behaviour of pedestrians also increases.

Santhosh et al. (2020) evaluated the pedestrian safety at intersections through comparing the frequency and severity of pedestrian conflicts. The study was conducted at T and X-intersections under mixed traffic conditions in India. Traffic data was collected from the study locations using videographic method and extracted the required data from the videos. Pedestrian vehicle conflict analysis (PVCA) method and VISSIM microsimulation were used to analyse the P-V interactions. The study found that the reduction in number of conflicts with the reduction in many pedestrian crossings to two crossings. The PVCA method showed that uncontrolled intersections were unsafe than controlled intersections.

Madigan et al. (2021) proposed a new methodology for understanding the P-V interactions of field and video data. On-site and video data were collected at an intersection in United Kingdom in weekdays. Intrerrater reliability was estimated using the index of concordance and compared between the two video coders before and after their joint analysis. The study found that the proposed observation protocol provided a consistent method for identifying interaction categories.

Muppa et al. (2022) analysed the P-V interactions at un-signalized intersections in India. The traffic data was collected at a four-legged uncontrolled intersection in Telangana, India using video-graphic method. The required data was extracted from the video using an automatic tracking software. TTC and GT were calculated for each interaction type and carried out the analysis for PPF and VPF cases. Higher values of TTC and GT were observed in case of PPF compared to VPF. This study found that the severity of P-V interactions were higher in case of VPF compared to PPF. Also, this study proposed the threshold values of TTC for various severity levels. The threshold TTC for critical, nominal, and safe P-V interactions at un-signalized intersections under mixed traffic conditions were <2.0 sec, 2.0 to 6.0 sec, and >6.0 sec respectively.

Table 2.1: Surrogate safety measures or indicators used in various studies.

S.No.	Indicator	Study used
1	Time to collision (TTC)	Jiang (2015); Hayward (1972); Hyden (1987); Fancher et al. (1998); Getmann et al. (2008); Ismail et al. (2009); Zhang et.al (2012); Patel et al. (2018); Nie et al. (2021)
2	Post encroachment time (PET)	Shah and Vedagiri (2017); Marisamynathan and Vedagiri (2020); Alhajyaseen (2015); Allen et al. (1978); Getmann et al. (2008); Ismail et al. (2009); Patel et al. (2018); Chandrappa et al. (2015); Fu et al. (2019); Goyani et al. (2019)

3	Deceleration to safety time (DST)	Ahmed and Tarek (2018); Hupfer (1997); Ismail et al. (2009); Ismail et al. (2010); Bagdadi & Varhelyi (2011); Zaki et al. (2014)
4	Gap time (GT)	Archer (2004); Ismail et al. (2009)
5	Time to zebra (TTZ)	Varhelyi (1998)
6	Time to vehicle (TTV)	Kumar et al. (2019)
7	Time to accident (TTA)	Kumar et al. (2019)
8	Pedestrian safety margin time (PSMT)	Almodfer et al. (2016); Hu et al. (2021)
9	Pedestrian risk indicator (PRI)	Cafiso et al. (2011)
10	Delta-V	Augenstein et al (2003); Ryb et al. (2007)
11	Extended Delta-V	Laureshyna (2017)
12	Time-to-Line crossing (TTLC)	Winsum et al. (2000)
13	Reciprocal of TTC	Chin et al. (1992)
14	T_2	Laureshyn et al. (2010)
15	Time Exposed Time-to-collision (TET)	Minderhoud and Bovy (2001)
16	Time Integrated Time-to-collision (TIT)	Minderhoud and Bovy (2001)
17	Relative time to collision (RTTC)	Zhang et.al. (2012); Chen et al. (2017)

2.3 Studies on pedestrian gap acceptance behaviour, dilemma zone analysis and modelling

Previous works conducted on pedestrian gap acceptance behaviour, and dilemma zone estimation and modelling are discussed in this section. Section 2.3.1 deals with the previous studies on pedestrian gap acceptance behaviour and section 2.3.2 deals with the dilemma zone estimation, analysis, and modelling.

2.3.1 Studies on Pedestrian gap acceptance behaviour

Harrel (1990) studied the factors influencing pedestrian cautiousness in crossing an intersection. Pedestrian cautiousness was measured based on distance measured from the stood pedestrian to the curb and pedestrian observation before crossing. It was concluded that older adults and women were observed to be more cautious. It was also observed that pedestrians were cautious at low traffic volumes as vehicles possess more speeds.

Keall (1995) studied the pedestrian exposure to risk of road accident in New Zealand. The information related to type of pedestrian activity was collected from the New Zealand Travel Survey and the analysis has been carried out. The study found that the pedestrian crossing time was higher for elder and young pedestrians compared to other age pedestrians. Female pedestrians spent higher crossing time than male pedestrians and the frequency of road crossing declines with increase in age. The risk of injury was significantly lower in case of pedestrian crossing at zebra crossings than crossing at other places.

Hamed (2001) analysed the behaviour of pedestrian while crossing the road. The pedestrian risk is higher as the pedestrian is closer to the central refuge island rather than near to the curb. Pedestrians, who involved in past traffic accidents tend to take less risk and take higher waiting time. Pedestrians waiting time and number of attempts to cross were affected by vehicle speeds and traffic volume.

Sun et al. (2003) developed the pedestrian-vehicle interaction model at uncontrolled midblock crosswalks in United States. Videography method was used to collect the data from uncontrolled midblock at the University of Illinois. For pedestrian gap acceptance behaviour fixed critical gap model, probability-based model, binary logit model and for motorist yielding behaviour discrete probability model, binary logit model were proposed. The results showed that pedestrian gap acceptance behaviour depends on group size, waiting time, and age of pedestrians and motorist yielding behaviour depends on vehicle type, number of pedestrians and age of motorist. PGA (pedestrian gap acceptance) binary logit model performs well for predicting gap acceptance of pedestrians compared to probability based model and critical gap model. Gap size, age of pedestrians and number of pedestrians waiting were used in PGA model and number of pedestrians waiting and type of vehicle were used in MOY (motorist to yield) model. In case of MOY model, binary logit model performs well compare to discrete probability model.

King et al. (2009) investigated the risk associated with illegal or noncompliance pedestrian crossing behaviour at intersections based on crash data in Australia. The analysis was carried out by comparing relative risks in different types of crossing patterns. It was concluded that the relative risk was 8 times higher in the case of illegally crossing pedestrians.

Yannis et al. (2010) carried out a study in Athens, Greece and developed a Multiple Linear Regression Model involving parameters such as the size of the vehicle, presence of illegally parked vehicles, space between the vehicle and the pedestrian. From the study results, it was observed that the pedestrian crossing decisions were much more influenced by the distance from the incoming vehicle than the vehicle speed. Among all vehicle types, the probability of rolling gap acceptance decreases in case of two wheelers is approaching vehicle.

Papadimitrou et al. (2012) studied pedestrian exposure to risk in relation to crossing behaviour by developing utility functions for pedestrian crossings at midblock, junction and no crossing conditions. Pedestrian behaviour, as well as pedestrian exposure to risk, was primarily influenced by parameters such as traffic volume, roadway width and walking speeds. It was observed that the microscopic approach of analysis was much effective than the macroscopic approach to evaluate pedestrian exposure to risk.

Jain et al. (2014) analysed the pedestrian crossing behaviour with respect to pedestrian demographics as well as pedestrian road crossing patterns. Crossing speeds, accepted gap sizes and safety margin for gaps were found from video graphic data collected from un-signalized intersections at Roorkee, Uttarakhand. This study observed that most of the pedestrians tend to take single stage perpendicular crossings. Female and older pedestrians have higher accepted gap time and safety margin compared to other pedestrian categories.

Liu and tung (2014) analysed the pedestrian road crossing decisions at uncontrolled intersections. Data was collected from the study locations using video graphic method and developed a logistic regression model to analysis the risk of pedestrians with respect to various dependent variables. This study observed that the pedestrian crossing decision depends on the distance between the pedestrian and the oncoming vehicle and vehicle speed. Pedestrian risk increases with the increase in vehicle speed. Young pedestrians cross the road safely compared to elder pedestrians. The time gap between two approaching vehicles also affects the pedestrian crossing decision.

Asaithambi et al. (2016) studied pedestrian road crossing behaviour under mixed traffic conditions. The study was carried out to compare the intersection performance after and before the implementation of control measures. The pedestrian and traffic data were collected from the uncontrolled intersections using videography method before and after installation of signals. The results showed that accepted pedestrian gap size mainly depends on pedestrian demographics (such as gender, age and crossing pattern) as well as traffic characteristics (such as vehicle speed, vehicle type, and traffic volume). A Multiple Linear Regression model (MLR) gap size model was developed for both before and after installation criteria of signals. The average crossing speed of pedestrians was decreased after the installation of signals. Installation of signals results in a decrease in accepted gaps in both male and female pedestrians.

Boroujerdian et al. (2016) developed a logit model for pedestrian gap acceptance at un-signalized crosswalk conflict zone. The results showed that the parameters like pedestrian distance to vehicle lane, vehicle speed change, pedestrian age, pedestrian speed, and vehicle position to the start point of pedestrian were affected the pedestrian gap acceptance behaviour. The parameters like waiting time, vehicle type, group size, and lag or gap were not effective in pedestrian gap acceptance behaviour.

Dutta and Vasudevan (2017) studied the pedestrian crossing behaviour and risk exposure due to heterogeneous vehicles and lack of lane discipline. Data was collected from the un-signalized intersections having different land use patterns. This study observed that the rolling behaviour was higher in case of male pedestrians compared to female pedestrians indicating the exhibition of more risk in case of male pedestrians.

Muley et al. (2017) analysed the pedestrian crossing behaviour at marked crosswalks on. Qatar using videographic method and extracted the headways of pedestrians and vehicles. The study found that the waiting behaviour of pedestrians was independent on pedestrian characteristics and depends only on traffic characteristics. The pedestrian crossing speed was significantly affected by the gender, group, and distraction. The yielding behaviour was affected by the crossing direction and not depends on gender. Pedestrians Crossing from the sidewalk to the intersection required additional waiting time, which led to greater yielding rates.

Sucha et al. (2017) analysed pedestrian-driver communication and decision strategies at crosswalks. The study made in homogenous traffic conditions. The study was conducted to get pedestrians and driver perceptions while crossing the intersection. Pedestrian behaviour and speed measurements were recorded with video graphic techniques. Data were extracted I pedestrian's parameters like vehicle distance from the crosswalk, age, gender, pedestrian densities. The questionnaire ware prepared to know the level of difficulty while crossing the zebra crossing. The decision of pedestrians to wait/go was influenced by the distance of vehicle from crosswalk, speed of vehicle, direction travel, and the presence of other pedestrians.

Ravishankar and Nair (2018) analysed the pedestrian risk at uncontrolled intersections under mixed traffic conditions in India. Data was collected from the study locations using video graphic method and extracted the pedestrian crossing behaviour data manually from the video. The study observed that the irregular crossings were more in case of middle age pedestrians compared to young and old age pedestrians. The statistical results showed that male and middle aged pedestrians have the least tendency to wait for suitable gaps and take more risks to cross the road. Pedestrians choose the rolling gap behaviour when there was a heavy traffic condition instead of waiting for suitable gaps.

Ramesh et al. (2018) developed a pedestrian gap acceptance model based on land use pattern and estimated the delay at midblock locations and intersections under mixed traffic conditions. The video data was collected from midblock locations and intersections using videographic method and extracted the required data using KM player. The study found that the pedestrian crossing speed was influenced by the pedestrian characteristics such as age and gender, traffic volume, number of traffic lanes, road geometry, and land use pattern. Female pedestrians exhibit lesser crossing speeds than male pedestrians.

Vasudevan et.al (2020) studied the gap acceptance behaviour at un-signalised intersections in India under heterogeneous traffic conditions. Data was collected from six intersections and extracted the required data. A binary logit model was developed to know the various factors affecting the gap acceptance behaviour of pedestrians. The study found that the size of critical gap reduces with the pedestrians accept the rolling gaps to cross the intersection. The pedestrian crossing behaviour was strongly affected by the peer pedestrians. The pedestrian gap acceptance behaviour was influenced by the presence of median, distractions, waiting time, and approaching vehicle composition.

2.3.2 Studies on pedestrian dilemma zone analysis and modelling

Gates et al. (2007) analysed the driver's behaviour in dilemma zone at intersections in USA. Video data was collected from six intersections and extracted the required data using Sony Vegas Video 6.0 software. This study concluded that the maximum breaking performance by the driver is not necessary when the vehicle lies within the dilemma zone. Also, this study found that the driver's decision to stop/go within the dilemma zone is depends on the presence of side-street vehicles, pedestrians, or presence of opposite left turning vehicles and the action of vehicles in adjacent lanes.

Oda et al. (2007) evaluated the driver's stopping behaviour in dilemma zone using KAKUMO traffic flow simulator and found that the vehicle's distance from the stop line heavily influence the driver's decision in dilemma zone. Also, observed that no significant difference in approaching speeds of passing and stopped vehicles.

Gates and Noyce (2010) studied the effect of vehicle type, platooning, and time of the day on the driver's behaviour in dilemma zone at intersections in USA. Video data was collected from six intersections and extracted the required data. From this study, it was concluded that the vehicle type and time of the day have a significant effect on the occurrence of red light running and deceleration rate but platooning has no significant effect on the red light running, break response, and deceleration rate. Passenger vehicles were 3.6 times less likely to commit red light running compared with tractor trailers and 2.5 times less likely to commit red light running compared with single unit trucks.

Pawar et al. (2016) estimated the pedestrian dilemma zone (PDZ) at high-speed uncontrolled midblock crossing locations under mixed traffic conditions. The video data was collected from two midblock locations in India and extracted 1107 pedestrian observations using AVS video editor. Lower and upper boundary limits of PDZ were estimated using various methods and the average values from all the methods were taken as the lower and upper boundary limits of PDZ. The observed lower and upper boundary limits of PDZ at high-speed uncontrolled midblock locations were 49.5m and 62.0m respectively.

Pawar and Patil (2017) estimated the boundary limits of minor-street vehicles while maneuvering at unsignalized intersections. The video data was collected from three four-legged medium speed (40km/h) unsignalized intersections and one three-legged high speed (60km/h) unsignalized intersection in India. A binary logit model has been developed to estimate the DZ boundary limits corresponding to 10% and 90% probabilities of stopping. The study results showed that the DZ location and length vary with the light condition, traffic, and geometric characteristics. The length of DZ varies from 74 to78 m for high-speed intersections and 22 to 26 m for medium-speed intersections. The study found that the length and location of DZ moves farther from the intersection as size and speed of vehicles increases. Table 2.2 shows the Proposed DZ boundary limits at three-legged and four-legged unsignalized intersections for various approaching speeds of vehicles.

Table 2.2: Dilemma zone boundary limits at unsignalized intersections

Intersection Type	Approach Speed (Km/h)	Probability of stopping	
		10%	90%
Four-legged	25	14	40
	35	23	48
	45	32	58
Three-legged	50	28	104
	70	50	124
	90	72	150

Pawar et al, (2020) modelled the dynamic distribution of dilemma zone at intersections in heterogenous traffic conditions in India. A total of 893 drivers' responses and vehicle trajectories were recorded using videographic method at three intersections. The recorded videos were processed using Advanced Video System (AVS) video editor. A binary logit model has been developed to find the probability of stopping and the boundary limits of DZ were estimated using the model corresponding to 10% and 90% stopping. McFadden's pseudo-R^2, sensitivity, and specificity were used as the performance measures of the developed model. The study found that the location of DZ shifts way from the intersection with increase in speed and size of vehicles and the length of DZ substantially vary with speed and size of vehicles. The dilemma zone on lane 2 shifts away from the intersection compared to DZ on lane 1 and the length of DZ was same on lane 1 and lane 2. Table 2.3 show the DZ boundary limits proposed in this study for various speeds of the vehicles.

Table 2.3: Dilemma zone boundary limits for different vehicular speeds at intersections.

Approach Speed (km/h)	TW		Car		Truck		Intersection	
	10%	90%	10%	90%	10%	90%	10%	90%
40	13	56	4	56	21	48	9	55
60	21	64	20	72	35	62	22	68
80	29	72	34	89	48	72	35	81

Pawar and Yadav (2022) developed the logit models to estimate the lower and upper boundary limits of PDZ at uncontrolled midblock sections in mixed traffic conditions. Field data was collected from two midblock locations in India and extracted the required data. PDZ boundary limits were estimated using cumulative gap distribution method and binary logistic regression model was developed to estimate the boundary limits using various characteristics of pedestrians and vehicles. This study observed that the type of vehicle, pedestrian type, and crossing speed were significantly affect the pedestrian gap acceptance behaviour. The binary logit model results reveals that the approaching speed of vehicle and distance between the vehicle and pedestrian trajectory path were the significantly affect the PDZ boundary limits and the length of PDZ. Boundary limits and the length of PDZ at uncontrolled midblock locations proposed in this study for various vehicular speeds and vehicle types were shown in the table 2.4.

Table 2.4: Lower, upper boundary limits and length of PDZ at uncontrolled mid-blocks

Approach speed (Kmph)	2-wheeler			Car			Truck		
	Lower boundary (m)	Upper boundary (m)	Length (m)	Lower boundary (m)	Upper boundary (m)	Length (m)	Lower boundary (m)	Upper boundary (m)	Length (m)
40	35	74	39	42	82	40	46	86	40
60	46	86	40	54	94	40	58	98	40
80	58	98	40	66	106	40	72	112	40

2.5 Summary

Researchers across the globe addressed the pedestrian-vehicle interactions, pedestrian gap acceptance behaviour, and pedestrian dilemma zone analysis and modelling at uncontrolled intersections. Analysis and modelling of P-V interactions in mixed traffic conditions is more difficult compared to homogeneous traffic conditions. Various methodologies, techniques, types of data used, models developed in various researches were discussed in this chapter. Each study used different methodologies, techniques, and models to analyse P-V interactions but most of the researchers used either TTC or PET as SSM to analyse and model the P-V interactions using video data. The previous studies (Thakur and Biswas, 2019; Amado et al., 2020) on P-V interactions were mainly concentrated on the discussion of various factors influencing their interaction severity levels. The use of PET or TTC alone is insufficient to measure the injury severity of a potential collision and inclusion of either pedestrian or vehicle parameters will better predict the potential possible collisions (Gyimah et al.. 2016).

Studies on MLR and logit models better explained pedestrian, vehicle, and traffic parameters whereas maximum likelihood and negative binomial models better explained pedestrian, vehicle, traffic, and geometric parameters. Most of the studies developed MLR and logistic regression models. The use of the latest advanced technologies like artificial intelligence and machine learning algorithms in P-V interaction modelling techniques will better predict the severity levels of possible P-V interactions. Pedestrian-vehicle interactions, pedestrian gap acceptance behaviour, and pedestrian dilemma zone depends on various characteristics of pedestrian, vehicle, geometric, environmental, and weather conditions.

A large number of parameters were used to analyse and model the pedestrian-vehicle interactions (Makia et al., 2002; Tay et al., 2011; Alhajyaseen, 2015; Fridman et al., 2020; Lee and Abdel-Aty, 2005; Roudsari et al. 2004; Ashton, 1977; Kloeden et al., 2001). However, additional parameters like the presence of median, stages of crossing, distance from the crosswalk, the gap between vehicles and pedestrian waiting time need to be considered for a better interaction modelling approach.

Next chapter deals with the detailed methodology of the present study with flow chart. Identification of the problem statement, selection of study locations, data collection and extraction, data analysis and modelling will be discussed briefly in the next chapter.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 General

The methodology adopted to work out the objectives of the pedestrian-vehicle analysis and modelling framed from the literature review is presented in this chapter. This chapter involves several stages including the problem statement, site selection, field data collection, analysis and modelling of the results. A detailed framework on defining the threshold values for surrogate safety measures (SSMs), analysis and modelling of pedestrian-vehicle interactions and pedestrian dilemma zone estimation and modelling is presented in this chapter.

3.2 Methodology

The proposed research methodology involves 5 stages/ to fulfil the objectives of the present research work. The first step involves the identification of the research problem and reviewing the previous literature to fix the objectives of the research. Second step consists of selection of the right study areas for the research and collecting the required data from the study locations using various data collection techniques. Third step involves the extraction of required data using some softwares and field data analysis. Fourth step involves defining the threshold values of SSMs, analysis and modelling of pedestrian-vehicle interactions and pedestrian dilemma zone estimation, analysis and modelling. Last step involves the conclusions of the present research. Figure 3.1 shows the flow chart of the proposed methodology for the present study.

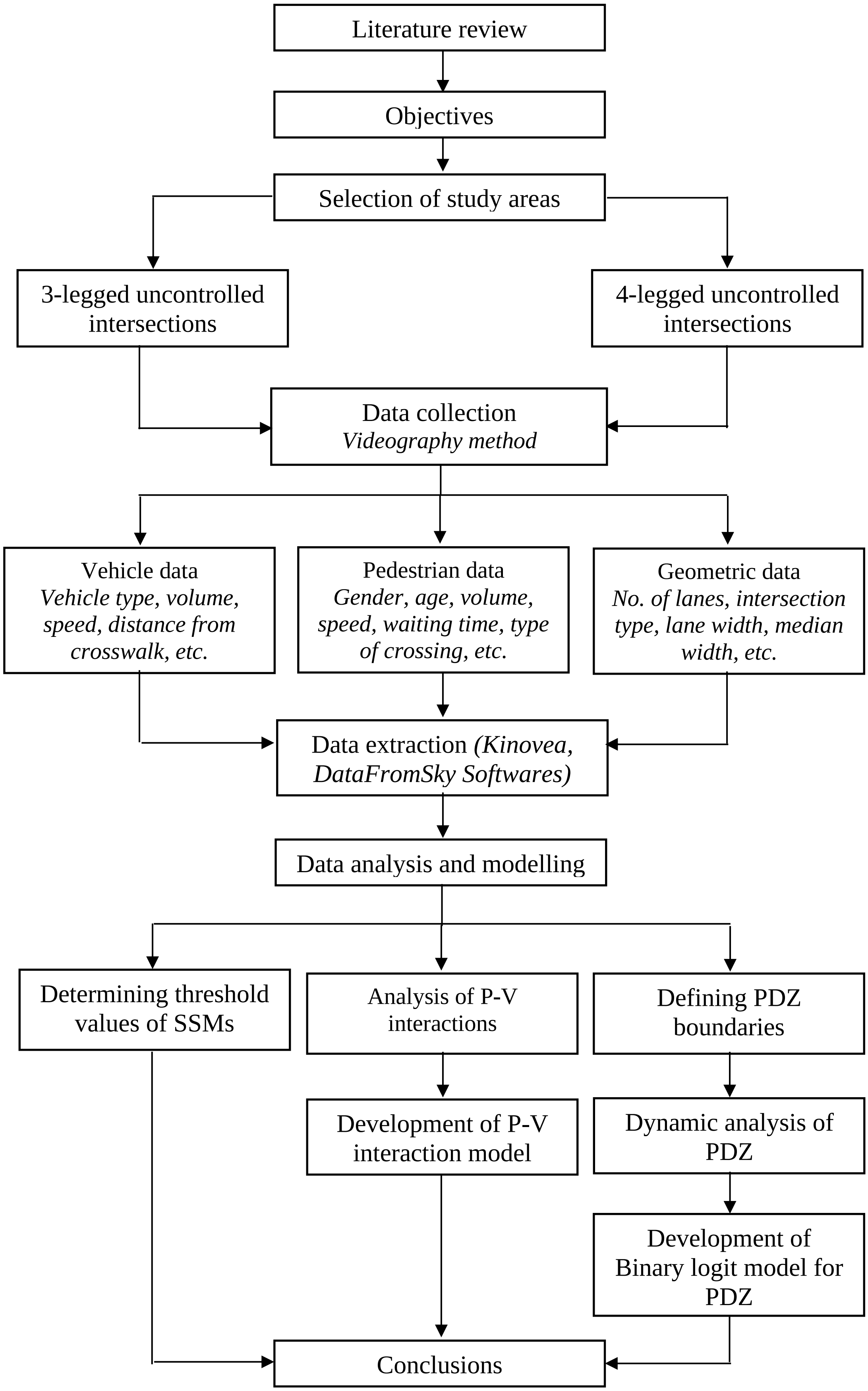


Figure 3.1: Flow chart for the proposed research methodology

3.2.1 Problem statement and literature review

The problem statement of the present research work is identified and the literature related to the problem statement is collected and reviewed. The objectives of the study are framed based on the previous literature review.

3.2.2 Selection of study areas and data collection

The study locations include 3-legged as well as the 4-legged uncontrolled intersections with reasonable proportion of pedestrian volume under mixed traffic condition in an urban area. The data collection from the study locations will be performed using a video graphic survey. Two high resolutions cameras will be used to collect the video data from each study location.

3.2.3 Data extraction

The required data from the video will be extracted using MPC-HC media player, Kinovia software, and DataFromSky software. The extracted data from the video includes pedestrian characteristics, vehicle characteristics, and geometric characteristics.

3.2.4 Data analysis and modelling

Extracted data will be used for the analysis and development of models related to the P-V interactions and PDZ. Also, the data will be used for defining the threshold values of SSMs for various P-V interaction severity levels. The below sub-sections explain how to define the threshold values and develop models for P-V interactions and PDZ.

3.2.4.1 Defining the threshold values of surrogate safety measures (SSMs)

The threshold values of SSMs for various pedestrian-vehicle interaction severity levels will be derived using machine learning algorithms (supported vector machine (SVM) method is used in the present study) for different combinations of pedestrian and vehicle characteristics. In SVM method, a plot between pedestrian speeds on y-axis and SSM on x-axis will be plotted on a coordinated system and the threshold value for various severity levels are taken corresponding to different pedestrian speeds.

3.2.4.2 P-V interaction analysis and modelling

The correlation analysis will be done to know the correlation between severity levels and other independent variables and the variables which shows the correlation with severity levels will be included in the modelling part. The variables with the significance level less than or equal to 5% from the regression analysis will be used for the development of models. The developed model will be validated using one of the validation techniques.

3.2.4.3 Pedestrian dilemma zone estimation, analysis and modelling

Lower and upper boundary limits and length of PDZ will be estimated using cumulative gap distribution method and SVM method. PDZ model will be developed to know whether the boundary limits lies close the intersection or shifts away from the intersection with various pedestrian and vehicle characteristics.

3.2.5 Conclusions

Finally, conclusions will be made from the results of P-V interaction analysis and modelling, threshold values of SSMs, and PDZ analysis and modelling.

3.3 Summary

In this chapter a detailed methodology of the research work to be done was explained using flow chart. Step by step approach adopted for conducting the study was explained in this chapter. Selection of study locations, data collection from study locations and data extraction will be explained in the next chapter.

CHAPTER 4: STUDY AREA AND DATA COLLECTION

4.1 General

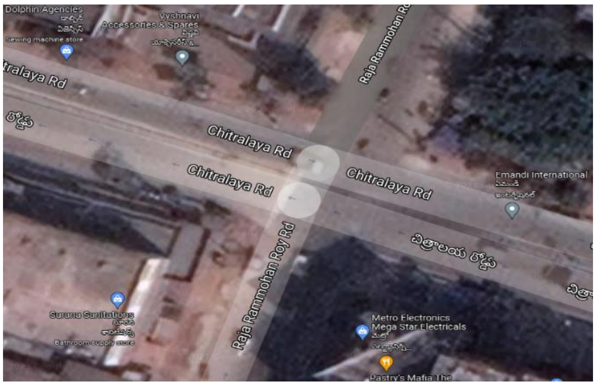
This chapter deals with the selection of study locations, land use characteristics of the study areas, data collection, time and period of data collection, and data extraction.

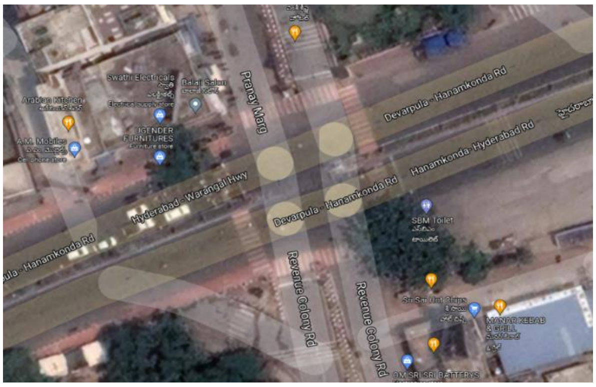
4.2 Study locations

Selection of study location is important for any research work. The present study was related to the pedestrian-vehicle interactions at uncontrolled intersections under mixed traffic condition in an urban area. Visakhapatnam and Warangal cities in India were selected for the present study and a rapid growth in population and traffic over the last two decades was observed in these two cities. The study location includes four 4-legged uncontrolled intersections and four 3-legged uncontrolled intersections.

4.2.1 Four-legged uncontrolled intersections

Jagadamba intersection is located near the Jagadamba theatre, Visakhapatnam, and Forest Office, Teacher's Colony, and SBH Colony intersections are located in Warangal in India. A two directional traffic flow with good proportions of vehicles and pedestrians was observed at all these study locations. Mixed type of traffic conditions were observed at all these four study locations. Jagadamba, Forest Office, and SBH Colony intersections have four lane divided highway on the major street but Teacher's Colony intersection has two lane road without divider on the major street. Forest Office intersection has the divider on the minor street road but Jagadamba, Teacher's Colony, and SBH Colony intersections does not have the divider for minor street road. Figures 4.1(a) - 4.1(d) shows the 4-legged uncontrolled intersections in Visakhapatnam and Warangal cities.





(a) (b)

(c) (d)

Figure 4.1: 4-legged uncontrolled intersection at (a) Jagadamba (b) Forest office (c) Teacher's colony (d) SBH colony

4.2.2 Three-legged uncontrolled intersections

Among the four 3-legged uncontrolled intersections, one location is selected from Visakhapatnam city and remaining three locations are selected from Warangal city in India. Marripalem intersection is located near to Marripalem market in Visakhapatnam city, and Ramanth Nagar, NIT Warangal, and KU X-Road intersections located near to Kazipet railway station, NIT Warangal, and Kakatiya University in Warangal city respectively. The traffic flow was observed to be two directional at all the study locations with reasonable proportions of vehicles and pedestrians. All the study locations have the similar land use characteristics (mixed type) and traffic conditions (mixed traffic conditions). Ramanth Nagar, NIT Warangal, and KU X-Road intersections have four lane divided highway on the major road while the Marripalem intersection has six lane divided highway on the major road. Ramanth Nagar, NIT Warangal, and KU X-Road intersections have median on the minor road while Marripalem intersection does not have median on the minor road. Figures 4.3(a) - 4.2(d) shows the three-legged uncontrolled intersections in Visakhapatnam and Warangal cities.

(a) (b)

(c) (d)

Figure 4.2: Three-legged uncontrolled intersection at (a) Ramanth Nagar (b) NIT Warangal (c) KU X-Road (d) Marripalem

4.3 Field data collection

The videography method was adopted to capture required pedestrian as well as vehicular data from the field. Video data was more appropriate to analyse the P-V interactions and dilemma zone. Two high resolution cameras were fixed to tripods and placed at an elevation in such a way that the movements of all pedestrians and vehicles are visible clearly for the entire intersection. Among the two cameras, one is used to cover the movement of vehicles for a distance of 50-60 meters from the zebra crossing line and the other is used to cover the entire intersection. Once the cameras fixed, the movements of pedestrians and vehicles were recorded continuously for two hours in the morning (7:30AM to 9:30AM) and evening (4:30PM to 6:30PM) on a typical weekday in clear weather conditions.

The geometric details of the study locations were directly measured from the field using tape and visual observations. Table 4.1 shows the geometric details of all the study locations. Except the Jagadamba intersection, all the study locations have a width of 3.5 meters for each lane on major as well as minor roads. Jagadamba intersection has 3.0 meters width per each lane on both minor and major roads.

Table 4.1: Geometric details of the study locations

S. No.	Location	Intersection type	Major road			Minor road		
			Lane width	No. of lanes	Median (Y/N)	Lane width	No. of lanes	Median (Y/N)
1	Jagadamba, (Visakhapatnam)	4-legged uncontrolled	3	4	Y	3	3	N
2	Forest office (Warangal)	4-legged uncontrolled	3.5	4	Y	3.5	4	Y
3	Teachers Colony (Warangal)	4-legged uncontrolled	3.5	2	N	3.5	2	N
4	SBH Colony (Warangal)	4-legged uncontrolled	3.5	4	Y	3.5	2	N
5	Ramanth Nagar (Warangal)	3-legged uncontrolled	3.5	4	Y	3.5	4	Y
6	NIT Warangal (Warangal)	3-legged uncontrolled	3.5	4	Y	3.5	4	Y
7	KU X-Road (Warangal)	3-legged uncontrolled	3.5	4	Y	3.5	4	Y
8	Marripalem (Visakhapatnam)	3-legged uncontrolled	3.5	6	Y	3.5	2	N

4.4 Summary

A brief description of the selected study locations for the present study is given in this chapter. The detailed process of data collection methods adopted for the present research work along with the geometric details of the study locations is presented. The extraction of required data from the video using various softwares and the field data analysis for the extracted data will be discussed in the next chapter.

CHAPTER 5: DATA EXTRACTION

5.1 General

This chapter deals with the various softwares used for extracting the required data from videos, the process of extracting pedestrian and vehicular parameters, field data analysis on pedestrian-vehicle (P-V) interactions sample size, crossing speeds of pedestrians, and approaching speeds of vehicles at three-legged and four-legged uncontrolled intersections.

5.2 Data extraction

MPC: HC 1.7 media player, Kinovea version 0.8.27, and DataFromSky (DFS) softwares were used in the present study to extract the required pedestrian, and vehicle parameters from the recorded videos at all the locations. MPC: HC 1.7 media player was used to extract parameters like pedestrian gender, age, crossing type, luggage carrying and/or mobile usage while crossing, vehicle type, gap accept/reject, vehicle enter or exit to the intersection, location, lane distribution, and severity levels of P-V interactions based on speed variations. DFS software was used to extract the parameters like distances of vehicles from pedestrian's trajectory paths, crossing speeds of pedestrians, approaching speeds of vehicles. Kinovea software was used to extract collision times of both pedestrians and vehicles to the conflict points.

Initially, the videos were imported into MPC: HC 1.7 media player and play backed the videos to extract the required parameters. The pedestrian gender was classified into male and female categories and pedestrian age was taken as children (<=15 years), young (15-30 years), middle age (30-60 years), and old age (>60 years) base on the physical appearance and visual observations (Patra et al., 2017). The crossing type, luggage, and mobile usage were classified as pedestrians crossing straight and rolling, with luggage and without luggage, and using mobile phones while crossing and not using mobile phones respectively. The type of conflicting vehicle was classified as two-wheeler (2W), three-wheeler (3W), car, light commercial vehicle (LCV), and heavy commercial vehicle (HCV). The severity levels of P-V interactions were classified into four categories (i.e. no interactions (NI), low severe interactions (LSI), moderately severe interactions (MSI), and severe interactions (SI)) on a scale of 0 to 3 based on the speed variations of both vehicles and pedestrians and extracted from the videos based on the visual observations. Table 5.1 shows description of classified P-V interaction severity levels based on visual observations.

Table 5.1: Description of P-V interactions severity levels classification based on visual observations

Scale	Severity Level	Description
0	No interactions	Both road users travel at their present speed to avoid collision
1	Low severe interactions	Both or one of the road users must change his/her speed to avoid collision
2	Moderately severe interactions	One road user must stop and other road user may or may not change his/her current speed to avoid collision
3	Severe interactions	Both road users must stop and proceed to avoid collision

The collected videos of each location were processed through online (https://datafromsky.com) and dot tlgx (.tlgx) files were opened in DFS viewer software. The calibration was done using four coordinates for each location and play backed the videos to extract the pedestrian and vehicle parameters. Figures 5.1 and 5.2 shows the calibration of DFS software and extraction of P-V trajectory data from software respectively. The distances of vehicles from pedestrian trajectory paths, crossing speeds of pedestrians, and approaching speeds of conflicting vehicles were extracted for all the P-V interaction samples. The accuracies of extracted speeds of pedestrians and vehicles were cross checked with manual extraction and observed more than 90% accuracy in all the cases.

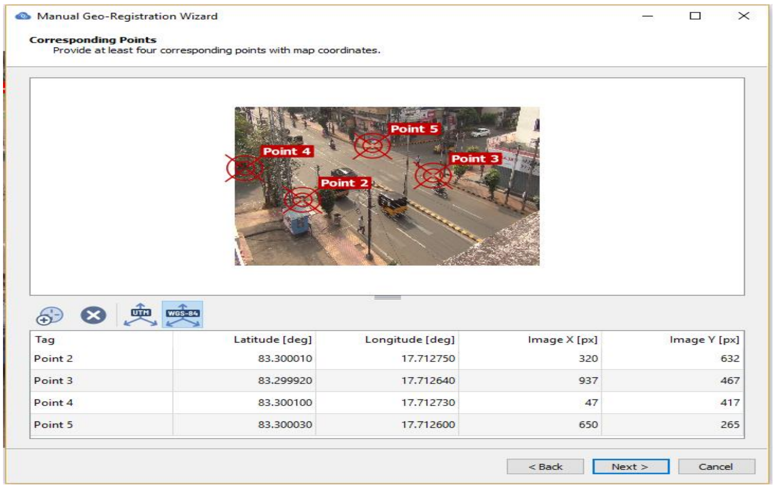


Figure 5.1: Calibration of DFS software using location coordinates

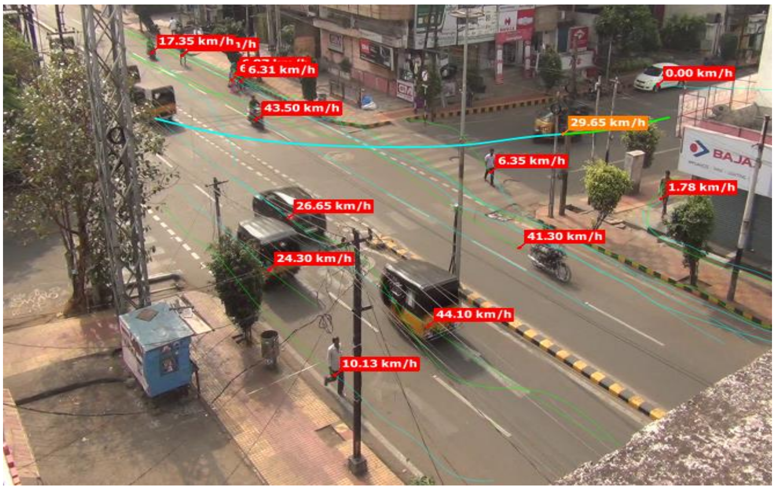


Figure 5.2: Extraction of P-V trajectory data from DFS software

To extract the collision times of pedestrians and vehicles, first videos were imported into the Kinovea software and plane calibration was done using perspective grid. Figure 5.3 shows the calibration video in Kinovea using perspective grid. A grid size of 0.9 m x 0.9 m was used as conflict area between the pedestrians and vehicles. The collision times were taken when the first road user leaving the conflict area and second road user arriving the conflict area. These collision times were used to calculate the post encroachment time (PET) for each P-V interaction.

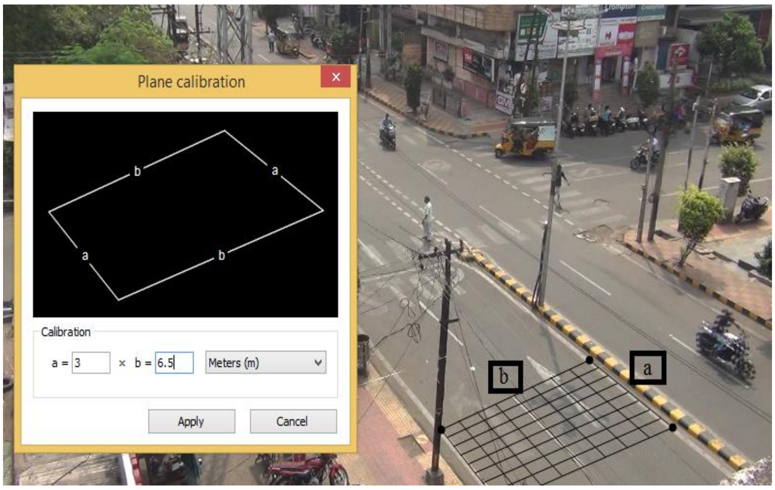


Figure 5.3: Calibration of the perspective grid in Kinovea software

5.2.1 Pedestrian-vehicle interactions sample size

Pedestrian-vehicle interactions data for 5416 samples at three-legged uncontrolled intersections and 5693 samples at four-legged uncontrolled intersections were extracted to define threshold limits of SSMs and development of P-V interaction models. Also, distances of vehicles from pedestrian trajectory paths were extracted for 4356 and 4758 samples at three-legged and four-legged intersections respectively to estimate the pedestrian dilemma zone (PDZ) boundary limits. Tables 5.1 and 5.2 shows the total number of samples extracted from each selected three-legged and four-legged uncontrolled intersections respectively.

Table 5.1: Total number of P-V interactions samples extracted at three-legged uncontrolled intersections

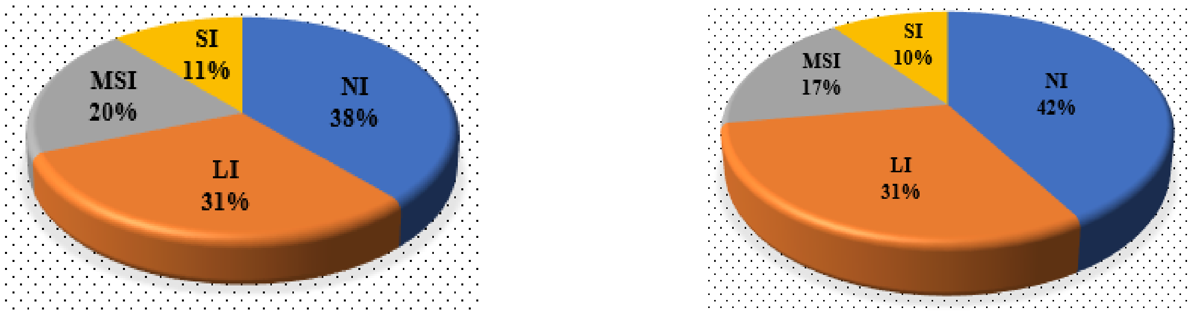
Purpose of extraction	Total number of P-V interaction samples extracted				
	Ramanth Nagar (Warangal)	NIT Warangal (Warangal)	KU X-Road (Warangal)	Marripalem (Visakhapatnam)	Total
Threshold limits of SSMs	1289	1617	1029	1481	5416
P-V interactions model	1289	1617	1029	1481	5416
Pedestrian dilemma zone estimation	1016	1379	836	1125	4356

Table 5.2: Total number of P-V interactions samples extracted at four-legged uncontrolled intersections

Purpose of extraction	Total number of P-V interaction samples extracted				
	Forest office (Warangal)	Teacher's Colony Road (Warangal)	SBH Colony (Warangal)	Jagadamba (Visakhapa tnam	Total
Threshold limits of SSMs	1581	972	1376	1764	5693
P-V interaction model	1581	972	1376	1764	5693
Pedestrian dilemma zone estimation	1371	726	1178	1483	4758

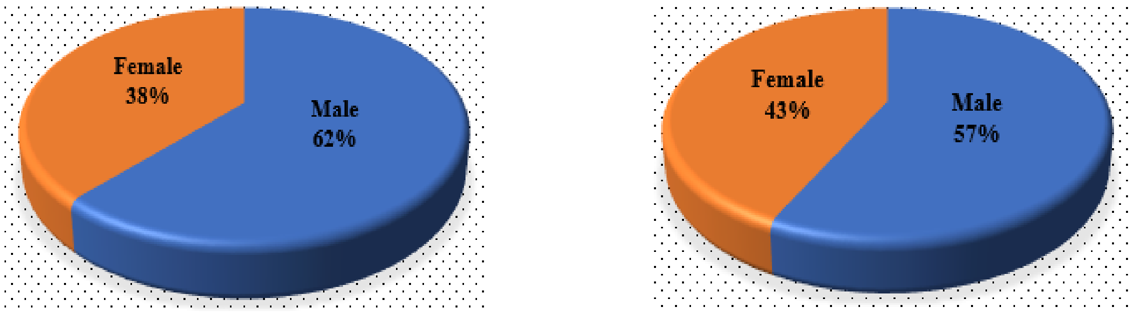
Figures 5.4 to 5.7 shows the percentage distribution of P-V interaction samples data based on severity level type, pedestrian gender, pedestrian age, and vehicle type respectively. Approximately 38% and 42% of total extracted P-V interactions at three-legged and four-legged uncontrolled intersections respectively were related to no interactions type. Approximately 31%, 20%, and 11% of total extracted interactions at three-legged intersections were related to LSI, MSI, and SI respectively. Approximately 31%, 17%, and 10% of total extracted interactions at four-legged intersections were related to LSI, MSI, and SI respectively. The extracted percentage of P-V interactions were observed to be more in case of male pedestrians (62% at three-legged intersections and 57% at four-legged intersections) compared to female pedestrians (38% at three-legged intersections and 43% at four-legged

intersections) at both the type of intersections. Approximately 12%, 33%, 39%, and 16% P-V interactions were related to children, young, middle age, and old age pedestrians respectively at three-legged intersections. The percentage of interactions were observed to be more in case of middle age pedestrians compared to other age group pedestrians at both the type of intersections. Two-wheelers have the highest percentage of interactions data (45% at three-legged intersections and 43% four-legged intersections) compared to other vehicle types.



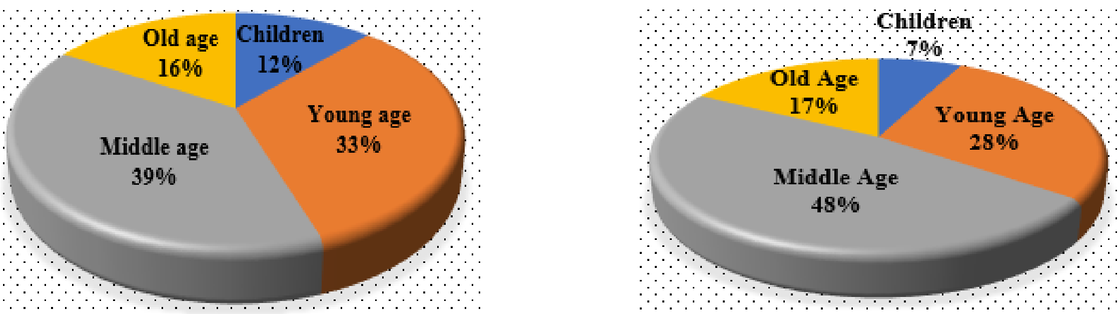
(a) (b)

Figure 5.4: Percentage of P-V interactions samples based on severity levels at (a) three-legged intersections (b) four-legged intersections



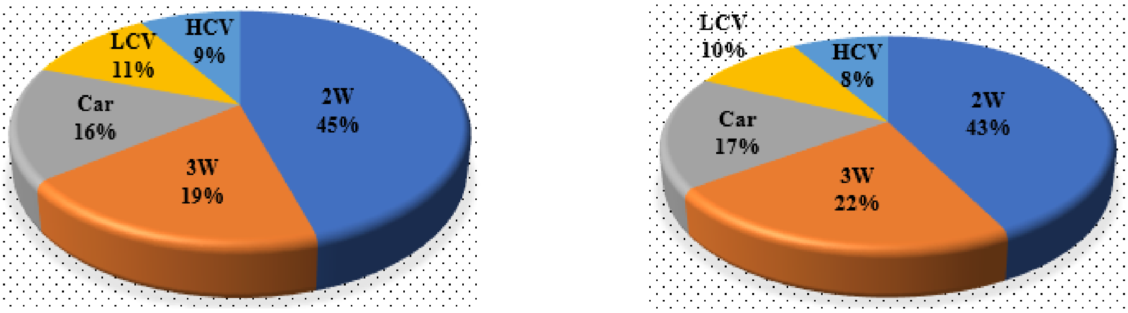
(a) (b)

Figure 5.5: Percentage of P-V interactions samples based on pedestrian gender at (a) three-legged intersections (b) four-legged intersections



(a) (b)

Figure 5.6: Percentage of P-V interactions samples based on pedestrian age at (a) three-legged intersections (b) four-legged intersections



(a) (b)

Figure 5.7: Percentage of P-V interactions samples based on vehicle type at (a) three-legged intersections (b) four-legged intersections

5.2.2 Pedestrian crossing speeds

The pedestrian crossing speeds for all P-V interactions were extracted using DFS software at three-legged and four-legged uncontrolled intersections. Tables 5.3 and 5.4 shows the descriptive statistics of extracted pedestrian crossing speeds with respect to gender and age at three-legged and four-legged intersections respectively. Figures 5.8 and 5.9 shows the box plots of pedestrian crossing speeds variation with respect to gender and age respectively.

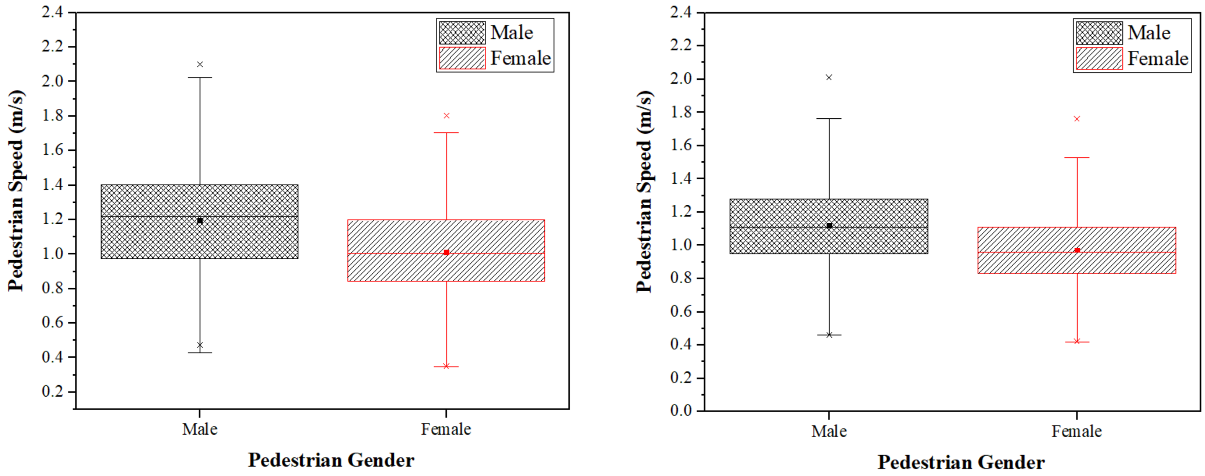
A one-way Analysis of Variance (ANOVA) at 95% significance level was carried out in Statistical Package for the Social Sciences (SPSS) software to mathematically analyse whether there is a significant difference in pedestrian crossing speeds with respect to gender and age of pedestrians. From ANOVA results, it was observed that there was a significant difference between the crossing speed of pedestrians with respect to pedestrian gender ($p = 0.014$) and age ($p = 0.003$). Also, observed that there was a significant difference in pedestrian crossing speeds at three-legged and four-legged uncontrolled intersections ($p = 0.001$).

Table 5.3: Descriptive statistics of pedestrian crossing speeds at three-legged intersections

Crossing speed (m/s)	Male	Female	Children	Young	Middle	Old
Minimum	0.43	0.35	0.54	0.45	0.39	0.32
Maximum	2.15	1.89	1.83	2.26	2.06	1.97
Average	1.20	1.01	1.15	1.29	1.06	0.99

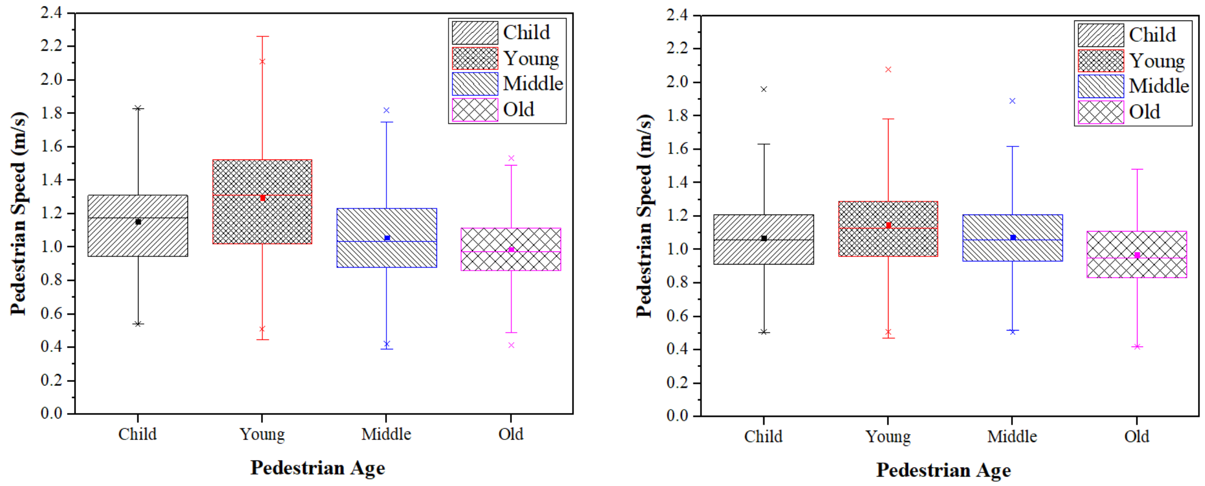
Table 5.4: Descriptive statistics of pedestrian crossing speeds at four-legged intersections

Crossing speeds (m/s)	Male	Female	Children	Young	Middle	Old
Minimum	0.37	0.28	0.50	0.41	0.32	0.28
maximum	2.13	1.91	1.96	2.13	1.94	1.86
average	1.12	0.97	1.07	1.15	1.08	0.97



(a) (b)

Figure 5.8: Variation of pedestrian crossing speeds with respect to gender at (a) three-legged intersections (b) four-legged intersections



(a) (b)

Figure 5.9: Variation of pedestrian crossing speeds with respect to age at (a) three-legged intersections (b) four-legged intersections

The following observations were made from the tables 5.3 and 5.4, and figures 5.8 and 5.9 at three-legged and four-legged uncontrolled intersections,

- The minimum pedestrian crossing speed was observed to be lower in female pedestrians.
- The maximum crossing speed of pedestrians was observed to be higher in male pedestrians.
- The average crossing speed of male pedestrians was observed to be higher compared to female pedestrians. Similar findings were observed by Montufar et al. (2007), Huang and Ma (2010), Marisamynathan and Perumal (2014), and Varsha et al. (2016)
- Young pedestrians have higher crossing speeds compared to children, middle age, and old age pedestrians respectively.
- The crossing speeds of pedestrians were higher at three-legged intersections compared to four-legged intersections.

5.2.3 Vehicular approaching speeds

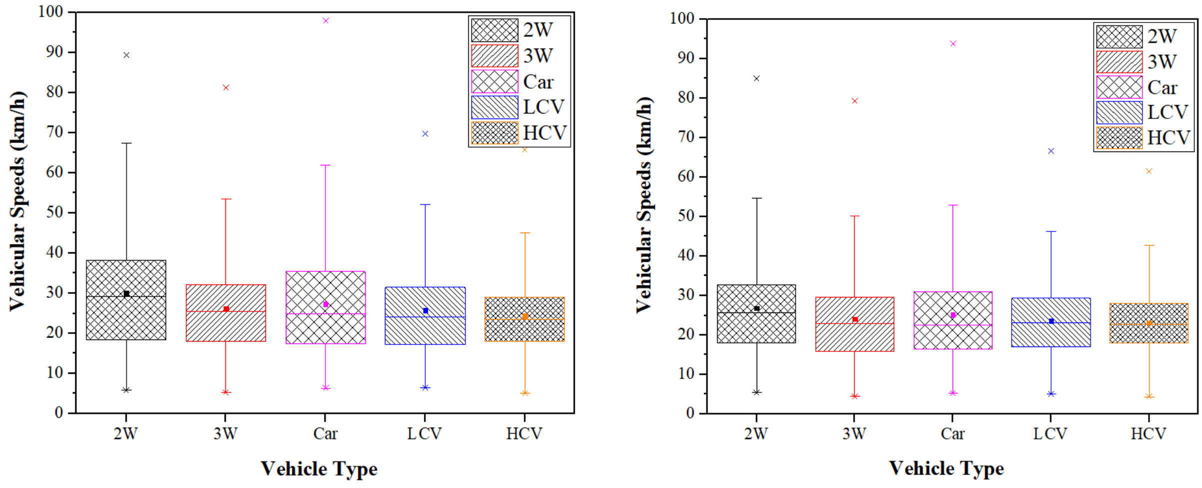
The approaching speeds of vehicles were extracted for each P-V interaction sample using DFS software and analysed the variation of speeds with respect to type of vehicle. Tables 5.5 and 5.6 shows the descriptive statistics of extracted vehicular speeds at three-legged and four-legged intersections respectively and figure 5.10 shows the variation of vehicular speeds with respect to type of vehicle.

Table 5.5: Descriptive statistics of vehicular approaching speeds at three-legged intersections

Approaching speeds (km/h)	2W	3W	Car	LCV	HCV
Minimum	5.81	5.30	6.34	6.51	5.10
maximum	89.35	81.28	97.85	69.67	65.68
average	30.04	26.10	27.37	25.73	24.43

Table 5.6: Descriptive statistics of vehicular approaching speeds at four-legged intersections

Approaching speeds (km/h)	2W	3W	Car	LCV	HCV
Minimum	5.40	4.47	5.30	5.10	4.40
maximum	84.91	79.30	93.79	66.59	61.44
average	26.83	24.06	25.16	23.69	23.19



(a) (b)

Figure 5.10: Variation of vehicular approaching speeds with respect to type of vehicle at (a) three-legged intersections (b) four-legged intersections

The following observations were made from the tables 5.5 and 5.6, and figure 5.10,

- The minimum approaching speed of vehicles was observed to be lower in HCVs at three-legged as well as four-legged intersections
- The maximum approaching speed of vehicles was observed to be higher in cars at three-legged and four-legged intersections.
- The average approaching speed of 2Ws was higher than that of cars, 3Ws, LCVs, and HCVs respectively at three-legged and four-legged uncontrolled intersections.

5.3 Summary

In the present chapter, the required data of pedestrians and vehicles related to P-V interactions were extracted using MPC: HC media player, Kinovea, and DFS softwares. The percentage distribution of extracted interactions with respect to severity type, pedestrian gender, age, and vehicle type at three-legged and four-legged uncontrolled intersections were presented in the present chapter. Also, the crossing speeds of pedestrians with respect of gender and age, and approaching speeds of vehicles with respect to type of vehicle were compared at three-legged and four-legged intersections.

In the next chapter, defining the threshold limits of SSMs using machine learning algorithms at three-legged and four-legged uncontrolled intersections are presented.

CHAPTER 6: DEFINING THE THRESHOLD LIMITS OF SURROGAGE SAFETY MEASURES

6.1 General

The severity levels of P-V interactions can be predicted using the threshold limits of surrogate safety measures (SSMs). The present chapter is intended to propose the threshold limits of SSMs (PET and RI) using machine learning algorithms at uncontrolled intersections in mixed traffic conditions. The comparison of P-V interaction severity levels at three-legged and four-legged uncontrolled intersections is also presented in the present chapter.

6.2 Support vector machines (SVM) algorithm for classification

Machine learning (ML) is one of the most popular words and it is used for a wide range of applications in the recent decades which predicts the outcomes of an event more accurately without being explicitly programmed to do so. Machine learning algorithms can be used for both classification and regression purposes, and they use input data to predict a new output values. Machine learning is often categorized into four approaches (i.e., supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning) based on how an algorithm learns to become more accurate in its predictions. The algorithm in the supervised machine learning is trained with both labelled inputs and desired outputs and mostly they are used for classification, regression modelling and ensembling purposes. Classification algorithms use the input training data to predict the likelihood of output data will fell into one of the predetermined categories. Mostly Logistic Regression, Naive Bayes, K-Nearest Neighbors (KNN), Decision Tree and Support Vector Machine (SVM) algorithms in machine learning are used for classification purposes.

Logistic regression is a very basic classification algorithm which predicts the outcome of an event based on one or more independent variables. To estimate discrete values from a set of independent variables, logistic regression is used. By adjusting the data to a logit function, it aids in predicting the likelihood of an event. The best fitting of this algorithm looks like S-shape. Even though it is efficient and simple algorithm, can’t handle a larger number of categorical variables.

The Naive Bayes classifier assumes that a certain feature's presence in a class is unrelated to the presence of any other feature. When determining the likelihood of a specific result, a Naive Bayes classifier would consider each of these characteristics independently, even if these features are related to one another. It is an effective tool for large datasets and simple to construct.

KNN is a straightforward algorithm that classifies any new cases by getting the consent of at least k of its neighbours and then saves all the existing cases. KNN can be easily comprehended by using an analogy to everyday life. It is computationally expansive, and variables should be normalized.

SVM algorithm is one of the supervised machine learning methods, mostly used for classification (binary and multiclass) and regression purposes. This algorithm is more effective in high dimensional spaces and where the number of samples are less than number of dimensions. The probability estimates cannot be directly measured using this algorithm. In this method, the data points are plotted in n-dimensional space to perform classification by fitting a best hyperplane to separate the two classes with largest margin. For non-linearly separable data kernelized SVM is used to transform the one-dimensional data into two dimensions. The transformed data in two dimensions will become linearly separable. Kernel function measures the similarity between the data points in the newly transformed space. Important parameters of kernelized support vector classifier (SVC) are given below,

i) Kernel function: Kernel function is a technique for transforming data from its input form into the format needed for processing it. The term "Kernel" is used because SVM uses a collection of mathematical operations to provide the window through which the data can be manipulated. The various kernel functions are;
   a) Gaussian kernel: When there is no prior knowledge of the data, transformation is performed using the Gaussian Kernel.
   b) Radial basic function (RBF) kernel: It is same as gaussian kernel function but basic method added in this function to improve the transformation.
   c) Sigmoid kernel: The sigmoid kernel function, which serves as an activation function for artificial neurons, is equivalent to a two-layer perceptron model of the neural network.
   d) Polynomial kernel: It is used in image processing. It displays the similarity of the vectors in the training set of data in a feature space over the polynomials of the initial variables used.
   e) Linear kernel: It is used when the data is linearly separable.

ii) Gamma: The distance of a single training point is influenced by the gamma parameter. More points being together if the gamma parameter is low, and the points must be closed to each other in case of higher gamma parameter. Gamma parameter is useful for anon-separable data.

iii) Cost (C) parameter: C parameter incurs the penatly for any misclassified data. The penalty is low for misclassified data, if the C is minimal and due to the high penalty SVM aims to reduce the number of misclassified examples if the C is big.

6.3 Defining the threshold limits for various severity levels of P-V interactions

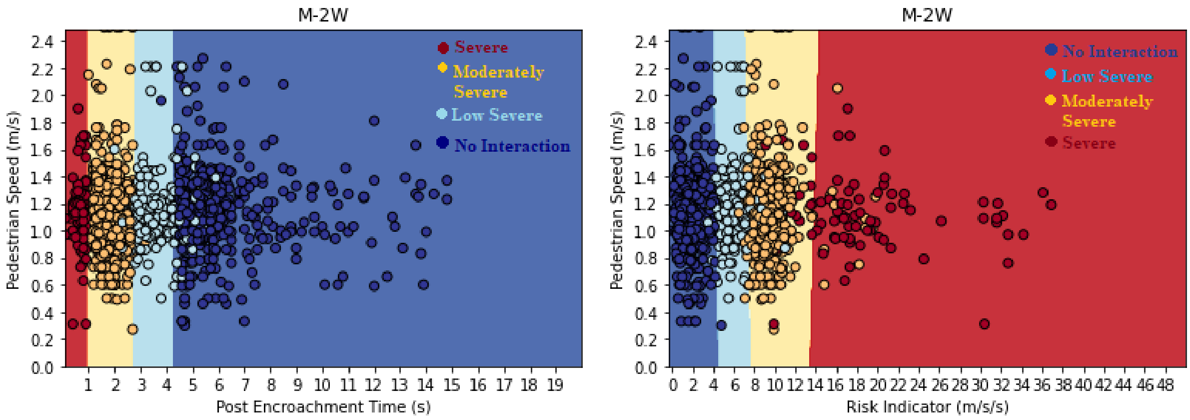
Support vector machine (SVM) classification code in Python interface was used in the present study to determine the threshold limits of SSMs for various P-V interaction severity levels at three-legged as well as four-legged uncontrolled intersections. For the present study, 70% data was used as training data for algorithm and the remaining 30% as testing data for validation purpose. A plot between pedestrian crossing speeds on y-axis and Post Encroachment Time (PET) or Risk Indicator (RI) on x-axis were plotted for various categories of pedestrians and vehicles and the threshold limits were defined corresponding to mean pedestrian crossing speed. Figure 6.1 shows the SVM code in Python interface used in the present study for classification purpose. Linear kernel function was used in the present study as the data is two-dimensional and linearly separable. Gamma function was set as ‘auto’ and used maximum cost (C) parameter. The code was run for three-legged and four-legged intersections and the classification plots were used to define the threshold limits.

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix, accuracy_score
import numpy as np
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
data_clear = pd.read_csv('SVM.csv')
Gender = 'm'
veh_type = 'HCV'
data_clear_copy = data_clear[(data_clear['Gender'] == Gender) & (data_clear['veh cat'] == veh_type)]
y = data_clear_copy.pop('sev code')
data = data_clear_copy[['Ped speed', 'pet']].copy()
X = data.copy()
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 23)
le = LabelEncoder()
y_train = le.fit_transform(y_train)
y_test = le.transform(y_test)
model = SVC(kernel = 'linear', gamma ='auto', C=1000)
model.fit(X_train, y_train)
predict = model.predict(X_test)
confusion_matrix(y_test, predict)
print('Accuracy Score', accuracy_score(y_test, predict))
print('confusion matrix', confusion_matrix(y_test, predict))
X_train = np.array(X_train)
x_min, x_max = X_train[:, 1].min() - 0, 20
y_min, y_max = 0, 2.5
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.02),
                     np.arange(y_min, y_max, 0.02))
Z = model.predict(np.c_[yy.ravel(), xx.ravel()])
Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, cmap = 'RdYlBu_r', alpha = 0.9)
plt.scatter(X_train[:, 1], X_train[:, 0], c = y_train, cmap = 'RdYlBu_r', edgecolors = 'black')
plt.xlabel('Post Encroachment Time (s)')
plt.ylabel('Pedestrian Speed (m/s)')
plt.yticks(np.arange(0, 2.5, 0.2))
plt.xticks(np.arange(0, 20, 1))
plt.xlim(xx.min(), xx.max())
plt.ylim(yy.min(), yy.max())
plt.title(Gender.upper() + '-' + veh_type.upper())
plt.show()
```

Figure 6.1: SVM classification code in Python interface

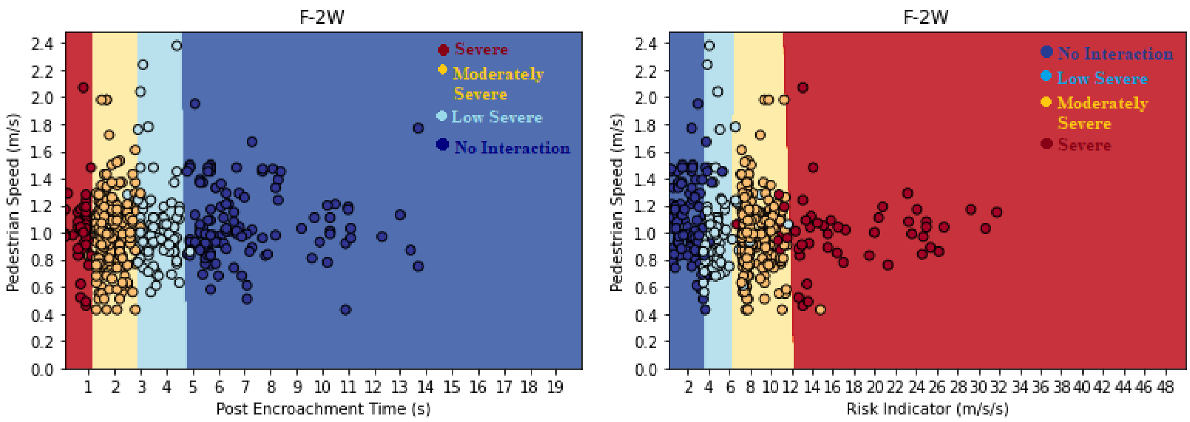
6.3.1 Three-legged uncontrolled intersections

SVM code was run for various categories of pedestrians and vehicles at three-legged uncontrolled intersections and the classification plots were taken to determine the threshold limits. Figures 6.2 to 6.11 shows the classification plots at three-legged intersections for various categories of pedestrians and vehicles to determine the threshold limits of PET and RI. Red colour dots in the classification plots indicates that the severe interactions, yellow colour dots indicate the moderately severe interactions, light blue colour dots indicate the low severe interactions, and dark blue colour dots indicates the no interactions between the pedestrians and vehicles. The boundary between two severity levels was separated by hyperplane.



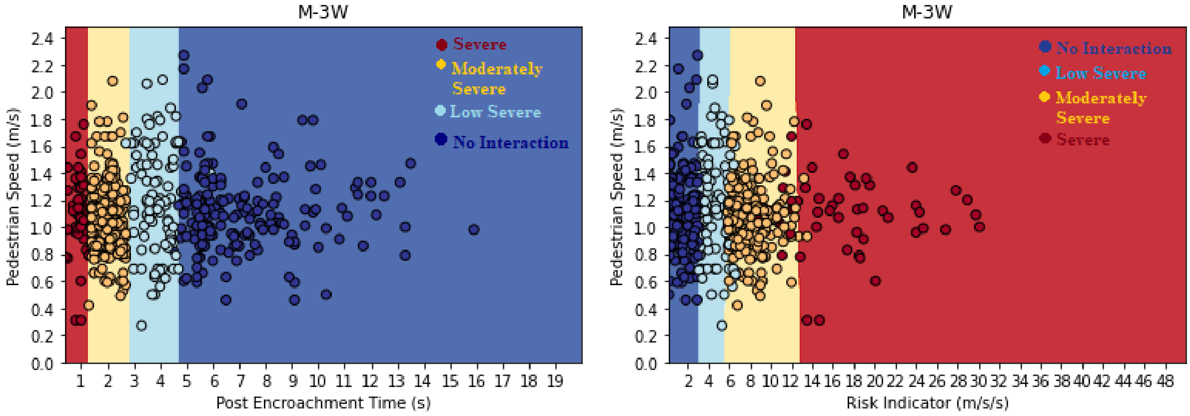
(a) (b)

Figure 6.2: SVM plots for P_M-V_{2W} category to define threshold limits of (a) PET (b) RI



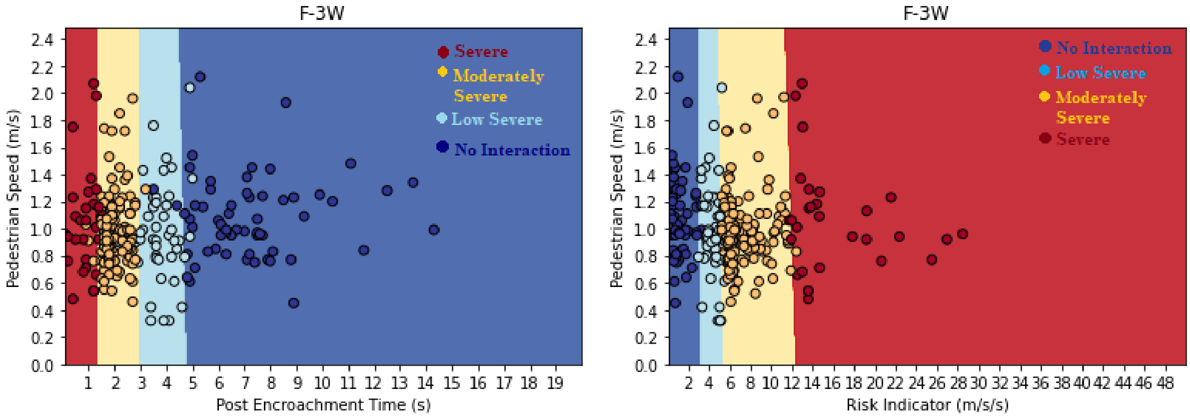
(a) (b)

Figure 6.3: SVM plots for P_F-V_{2W} category to define threshold limits of (a) PET (b) RI



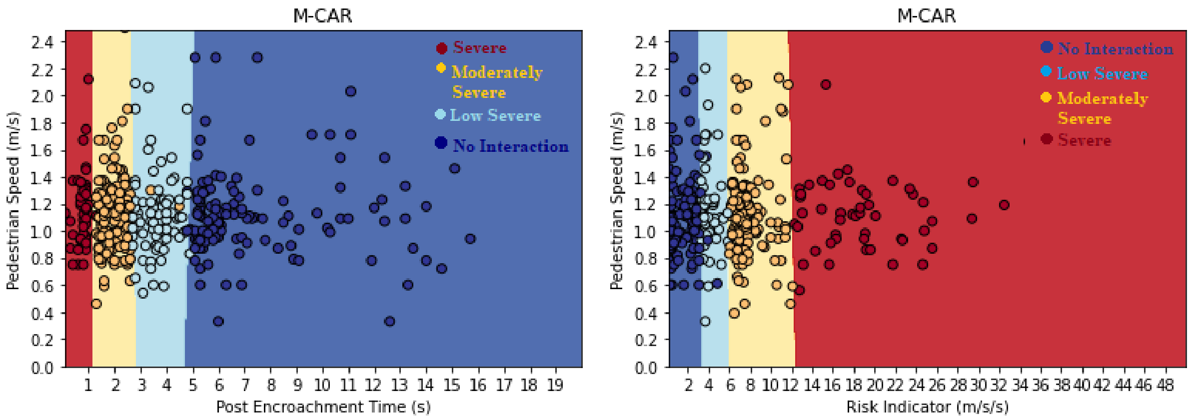
(a) (b)

Figure 6.4: SVM plots for P_M-V_{3W} category to define threshold limits of (a) PET (b) RI



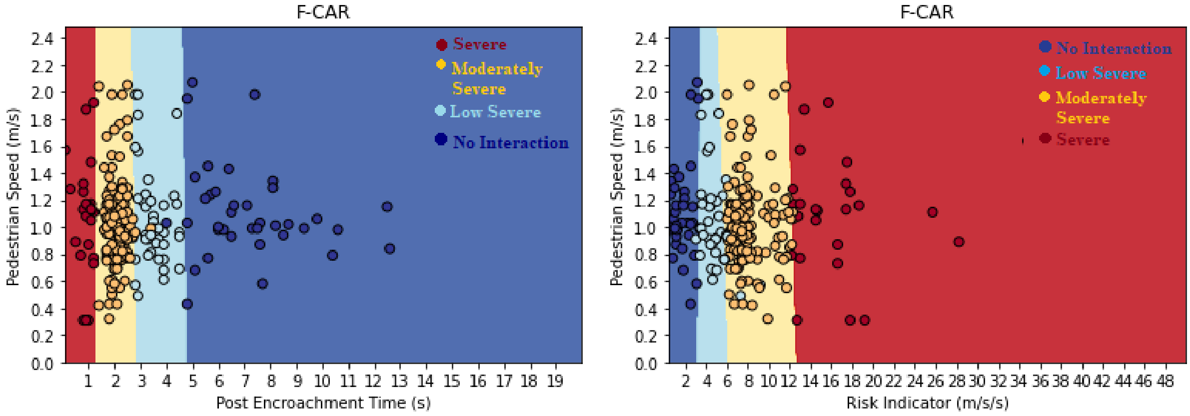
(a) (b)

Figure 6.5: SVM plots for P_F-V_{3W} category to define threshold limits of (a) PET (b) RI



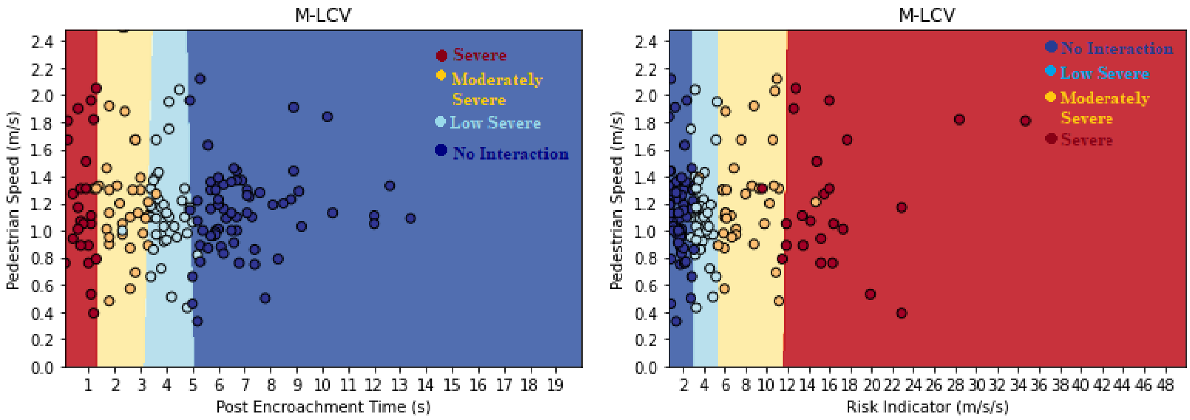
(a) (b)

Figure 6.6: SVM plots for P_M-V_{Car} category to define threshold limits of (a) PET (b) RI



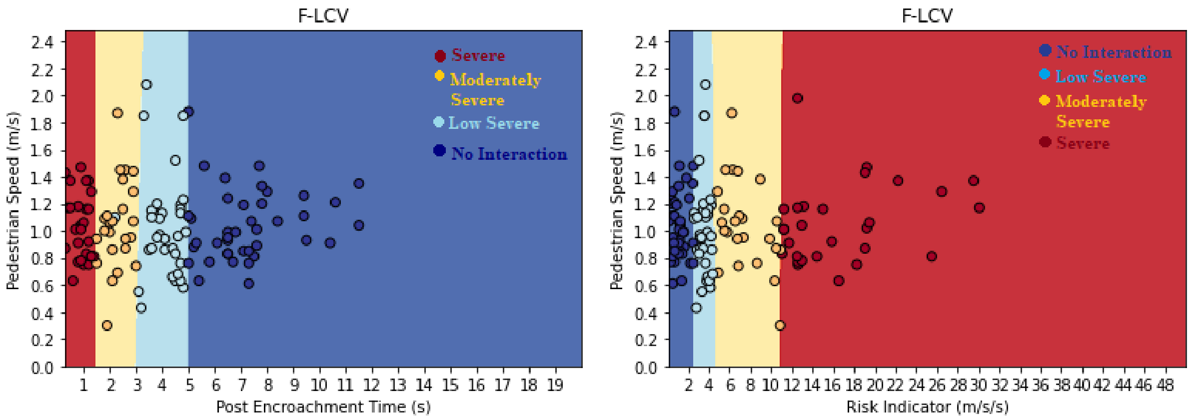
(a) (b)

Figure 6.7: SVM plots for P_F-V_{car} category to define threshold limits of (a) PET (b) RI



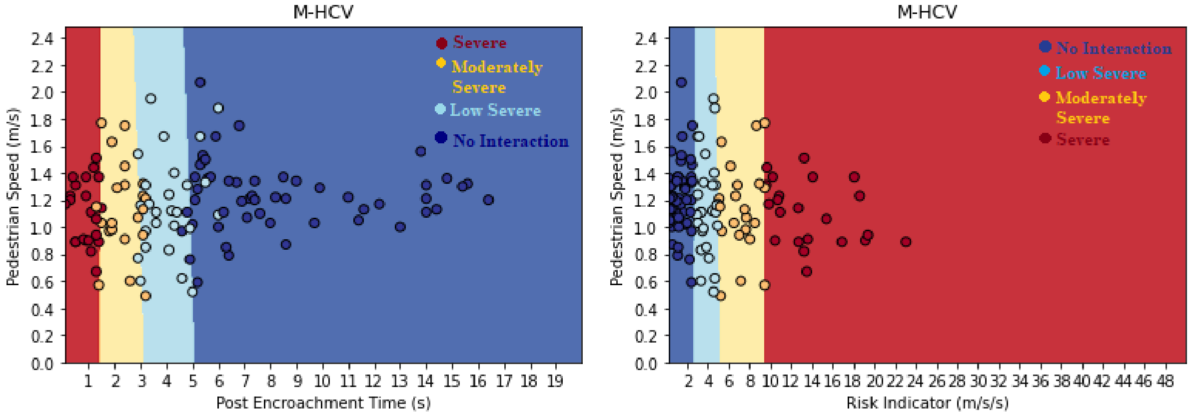
(a) (b)

Figure 6.8: SVM plots for P_M-V_{LCV} category to define threshold limits of (a) PET (b) RI



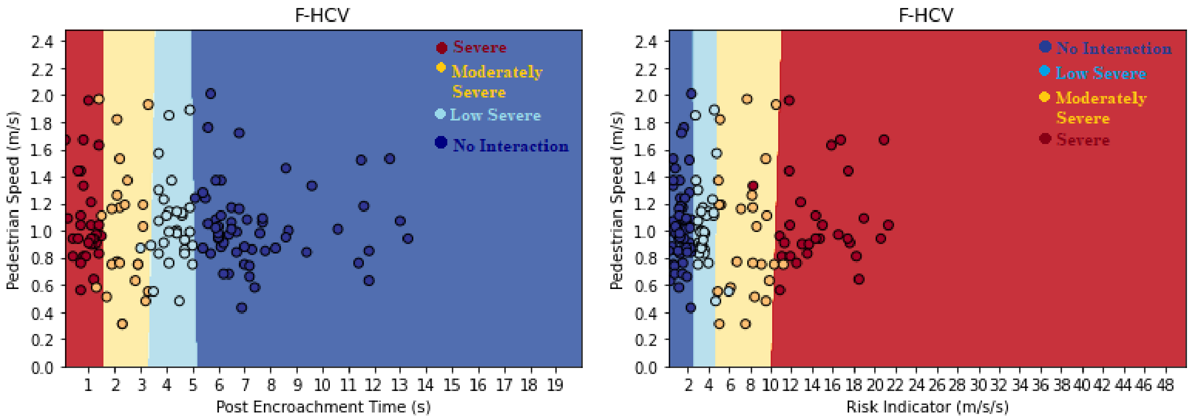
(a) (b)

Figure 6.9: SVM plots for P_F-V_{LCV} category to define threshold limits of (a) PET (b) RI



(a) (b)

Figure 6.10: SVM plots for P_M-V_{HCV} category to define threshold limits of (a) PET (b) RI



(a) (b)

Figure 6.11: SVM plots for P_F-V_{HCV} category to define threshold limits of (a) PET (b) RI

The threshold limits of PET and RI for various P-V interaction severity levels for different combinations of pedestrians and vehicles were defined using the figures 6.2 to 6.11. The proposed threshold limits of PET and RI for various severity levels were shown in table 6.1 and 6.2 respectively. From table 6.1, it can say that P-V interactions that occur in case of male pedestrians and two-wheelers (P_M-V_{2W}) at three-legged uncontrolled intersections were severe interactions if the PET is less than or equal to 0.9s. The interactions those occur in case of P_M-V_{2W} were moderately severe if the PET lies between 0.9s to 2.7s, low severe if the PET lies between 2.7s to 4.4s, and no interactions if the PET more than 4.3s. P-V interactions that occur in case of male pedestrians and three-wheelers (P_M-V_{3W}) at three-legged uncontrolled intersections was severe interactions if the PET is less than or equal to 1.2s. The interactions those occur in case of P_M-V_{3W} were moderately severe if the PET lies between 1.2s to 2.8s, low severe if the PET lies between 2.8s to 4.8s, and no interactions if the PET more than 4.8s. Similarly, P-V interaction severity levels can be estimated using the threshold limits of PET for other combinations of pedestrians and vehicles (P_M-V_{Car}, P_M-V_{LCV}, P_M-V_{LCV}, P_M-V_{HCV}, P_F-V_{2W}, P_F-V_{3W}, P_F-V_{Car}, P_F-V_{LCV}, and P_F-V_{HCV}) from table 6.1.

From table 6.2, it can say that P-V interactions those occur in case of female pedestrians and two-wheelers (P_F-V_{2W}) at three-legged uncontrolled intersections were severe interactions if the RI is more than 12.2 m/s/s. The interactions those occur in case of P_F-V_{2W} were moderately severe interactions if RI lies between 6.3 m/s/s to 12.2 m/s/s, low severe interactions if RI lies between 3.5 m/s/s to 6.3 m/s/s, and no interactions if RI less than or equal to 3.5 m/s/s. Similarly, the interactions in case of P_F-V_{3W} were severe, moderately severe, low severe, and no interactions if RI more than 12.0 m/s/s, lies between 5.2 m/s/s to 12.0 m/s/s, lies between 3.0 m/s/s to 5.2 m/s/s, and less than or equal to 3.0 m/s/s respectively.

Table 6.1: Threshold limits of PET for various severity levels at thee-legged intersections.

Pedestrian & Vehicle Type	Threshold PET values (s)			
	No interaction	Low severe interaction	Moderately severe interaction	Severe interaction
P_M-V_{2W}	>4.3	4.4-2.7	2.7-0.9	<=0.9
P_M-V_{3W}	>4.8	4.8-2.8	2.8-1.2	<=1.2
P_M-V_{Car}	>4.7	4.7-2.8	2.8-1.1	<=1.1
P_M-V_{LCV}	>5.1	5.0-3.1	3.1-1.3	<=1.3
P_M-V_{HCV}	>5.1	5.1-3.2	3.2-1.4	<=1.4
P_F-V_{2W}	>4.7	4.7-2.8	2.8-1.1	<=1.1
P_F-V_{3W}	>4.8	4.8-2.9	2.9-1.3	<=1.3
P_F-V_{car}	>4.7	4.7-2.8	2.8-1.2	<=1.2
P_F-V_{LCV}	>5.0	5.0-2.9	2.9-1.4	<=1.4
P_F-V_{HCV}	>5.2	5.2-3.3	3.3-1.5	<=1.5

Table 6.2: Threshold limits of RI for various severity levels at three-legged intersections.

Pedestrian & Vehicle Type	Threshold RI values (m/s/s)			
	No interaction	Low severe interaction	Moderately severe interaction	Severe interaction
P_M-V_{2W}	<=4.4	4.4-7.6	7.6-13.3	>13.3
P_M-V_{3W}	<=3.0	3.0-5.5	5.5-12.7	>12.7
P_M-V_{Car}	<=3.2	3.2-5.9	5.9-12.2	>12.2
P_M-V_{LCV}	<=3.0	3.0-5.3	5.3-11.5	>11.5

P_M-V_{HCV}	<=2.5	2.5-5.1	5.1-9.4	>9.4
P_F-V_{2W}	<=3.5	3.5-6.3	6.3-12.2	>12.2
P_F-V_{3W}	<=3.0	3.0-5.2	5.2-12.0	>12.0
P_F-V_{car}	<=3.1	3.1-5.9	5.9-12.4	>12.4
P_F-V_{LCV}	<=2.4	2.4-4.6	4.6-10.8	>10.8
P_F-V_{HCV}	<=2.5	2.5-4.6	4.6-10.0	>10.0

The performance of the classified data was described using confusion matrix and accuracies. The accuracy of the classified data was estimated using true positives, true negatives, false positives, and false negatives from the confusion matrix. The mathematical form of accuracy definition was shown in equation 6.1. More than 85% accuracies of classified data were observed for both PET and RI in all the cases of pedestrian and vehicle combinations and the table 6.1 shows the accuracies of classified data for PET and RI at three-legged uncontrolled intersections.

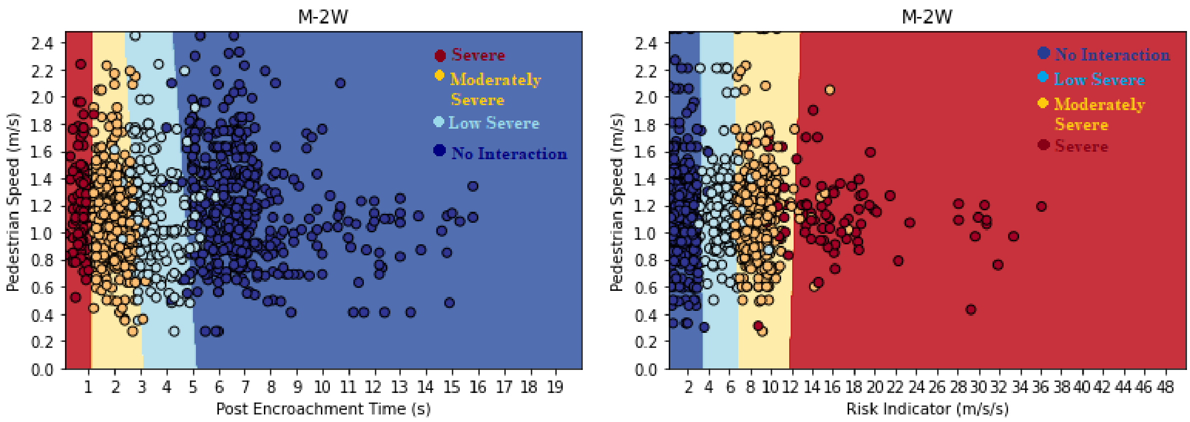
$$Accurary = \frac{true\ positives + true\ negatives}{true\ positivs + true\ negatives + false\ positives + false\ negatives} \qquad (6.1)$$

Table 6.3: Accuracies of classified data in SVM as three-legged intersections

Pedestrian & Vehicle Type	PET (%)	RI (%)
P_M-V_{2W}	92.95	90.34
P_M-V_{3W}	94.8	88.08
P_M-V_{Car}	95.27	94.12
P_M-V_{LCV}	87.09	92.18
P_M-V_{HCV}	89.56	93.34
P_F-V_{2W}	94.69	88.97
P_F-V_{3W}	93.44	95.91
P_F-V_{car}	93.22	93.17
P_F-V_{LCV}	90.59	91.83
PF-VHCV	88.84	90.67

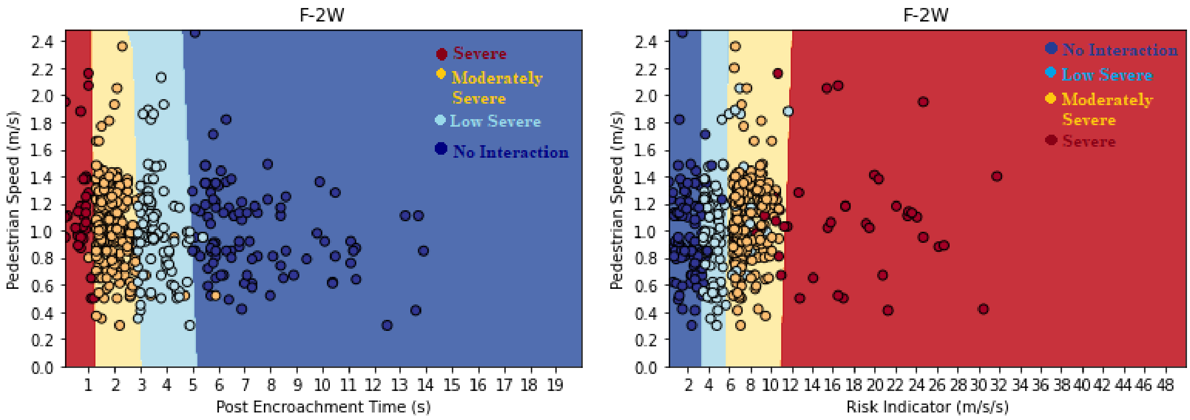
6.3.2 Four-legged uncontrolled intersections

SVM code in python interface was run for different combinations of pedestrians and vehicles at four-legged uncontrolled intersections and the classification plots were taken to determine the threshold limits. Figures 6.12 to 6.21 shows the classification plots at four-legged intersections for various combinations of pedestrians and vehicles to determine the threshold limits of PET and RI.



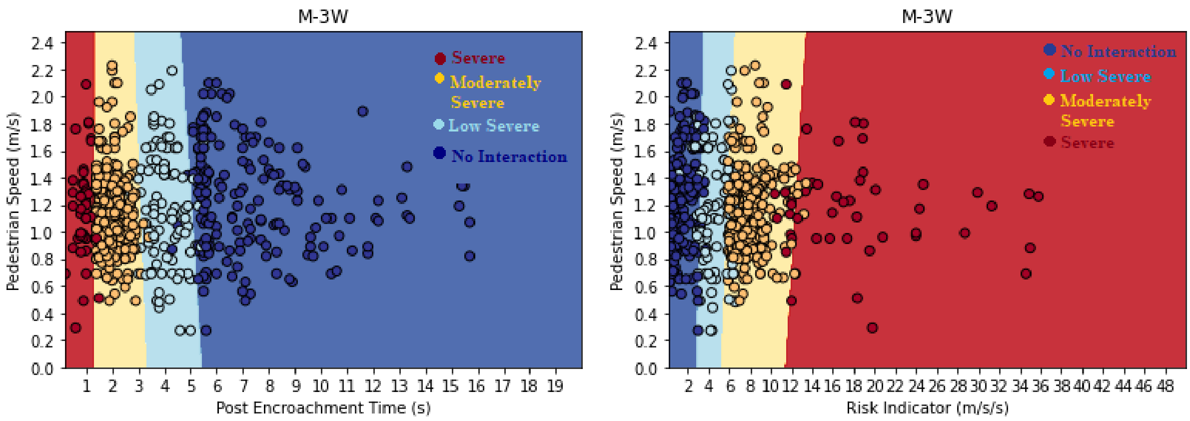
(a) (b)

Figure 6.12: SVM plots for P_M-V_{2W} category to define threshold limits of (a) PET (b) RI



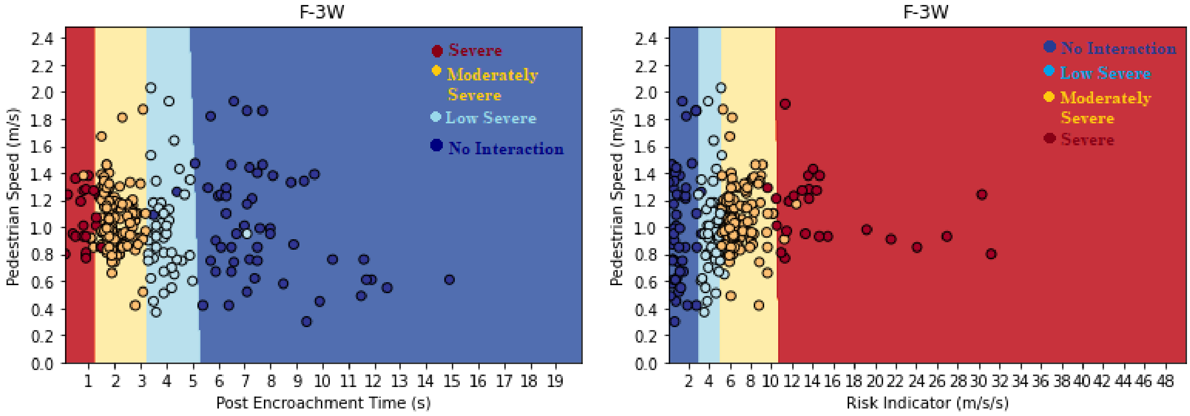
(a) (b)

Figure 6.13: SVM plots for P_F-V_{2W} category to define threshold limits of (a) PET (b) RI



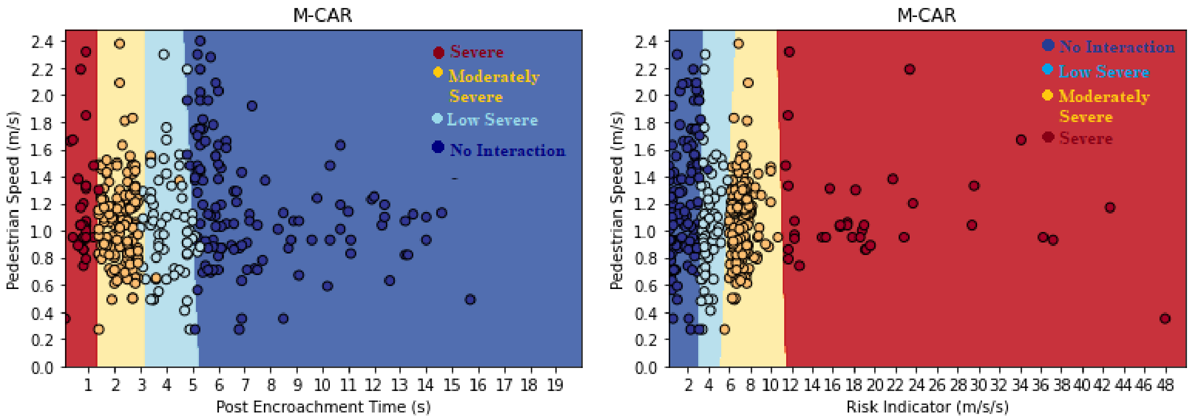
(a) (b)

Figure 6.14: SVM plots for P_M-V_{3W} category to define threshold limits of (a) PET (b) RI



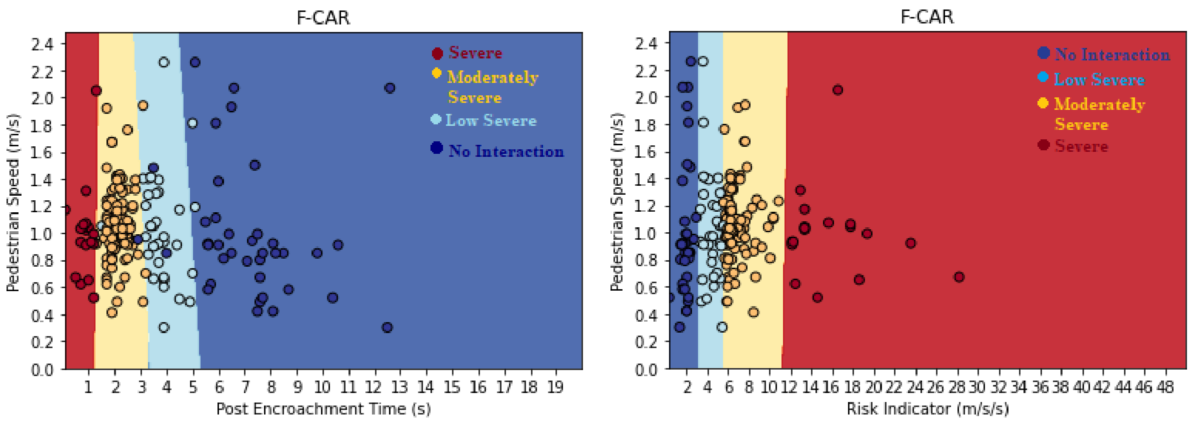
(a) (b)

Figure 6.15: SVM plots for P_F-V_{3W} category to define threshold limits of (a) PET (b) RI



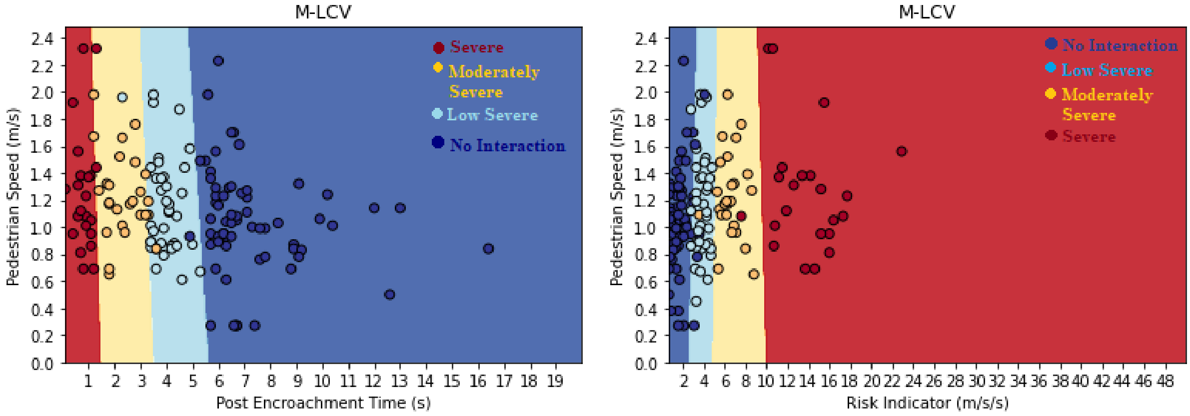
(a) (b)

Figure 6.16: SVM plots for P_M-V_{Car} category to define threshold limits of (a) PET (b) RI



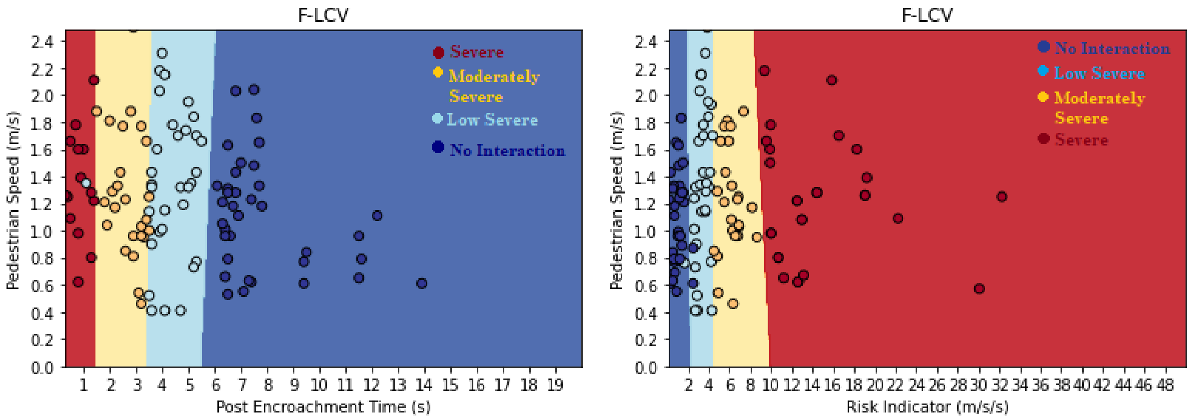
(a) (b)

Figure 6.17: SVM plots for P_F-V_{Car} category to define threshold limits of (a) PET (b) RI



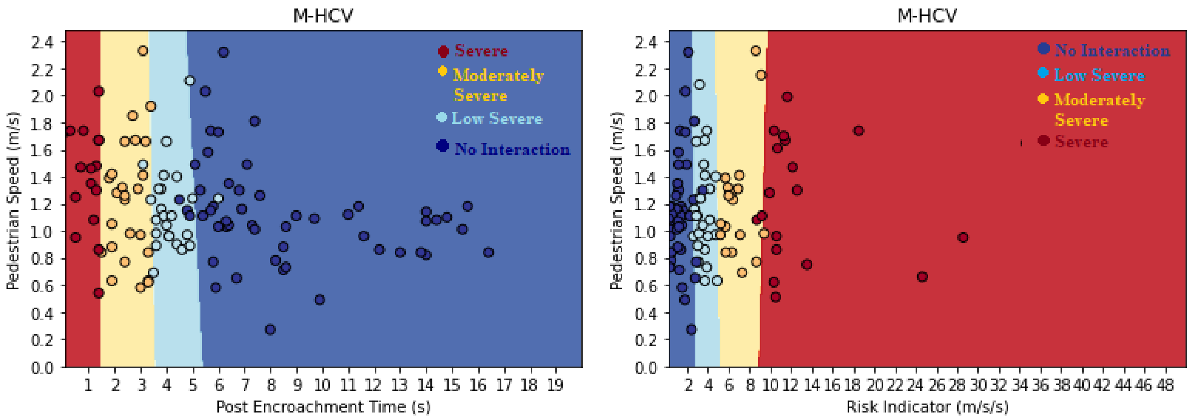
(a) (b)

Figure 6.18: SVM plots for P_M-V_{LCV} category to define threshold limits of (a) PET (b) RI



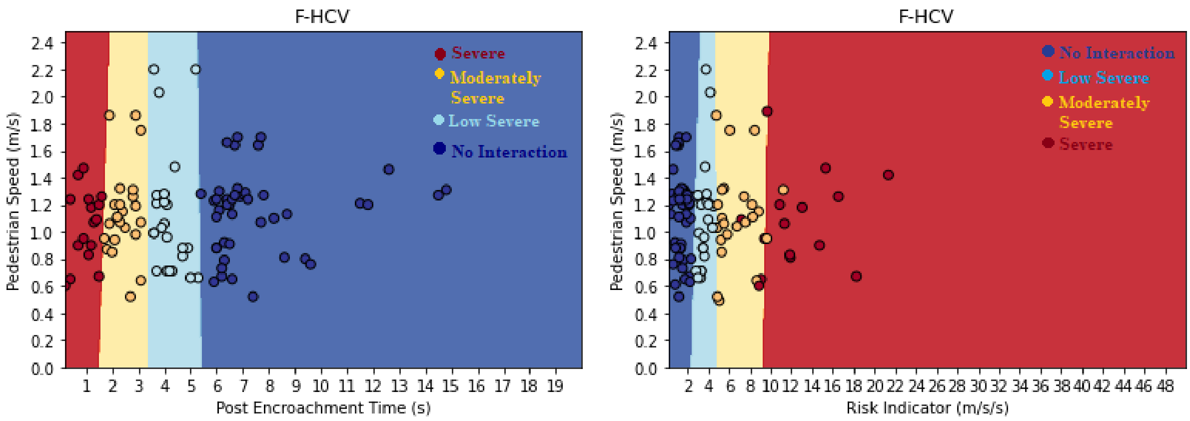
(a) (b)

Figure 6.19: SVM plots for P_F-V_{LCV} category to define threshold limits of (a) PET (b) RI



(a) (b)

Figure 6.20: SVM plots for P_M-V_{HCV} category to define threshold limits of (a) PET (b) RI



(a) (b)

Figure 6.21: SVM plots for P_F-V_{HCV} category to define threshold limits of (a) PET (b) RI

The threshold limits of PET and RI for various P-V interaction severity levels for different combinations of pedestrians and vehicles at four-legged uncontrolled intersections were defined using the figures 6.12 to 6.21. The proposed threshold limits of PET and RI for various severity levels were shown in table 6.4 and 6.5 respectively. From table 6.4, it can say that P-V interactions that occur in case of male pedestrians and two-wheelers (P_M-V_{2W}) at four-legged uncontrolled intersections were severe interactions if the PET is less than or equal to 1.1s. The interactions those occur in case of P_M-V_{2W} were moderately severe if the PET lies between 1.1s to 3.1s, low severe if the PET lies between 3.1s to 5.1s, and no interactions if the PET more than 5.1s. Similarly, P-V interaction severity levels can be estimated using the threshold limits of PET for other combinations of pedestrians and vehicles (P_M-V_{3W}, P_M-V_{Car}, P_M-V_{LCV}, P_M-V_{LCV}, P_M-V_{HCV}, P_F-V_{2W}, P_F-V_{3W}, P_F-V_{Car}, P_F-V_{LCV}, and P_F-V_{HCV}) from table 6.4.

From table 6.5, it can say that P-V interactions those occur in case of male pedestrians and two-wheelers (P_M-V_{2W}) at four-legged uncontrolled intersections were severe interactions if the RI is more than 11.7 m/s/s. The interactions those occur in case of P_M-V_{2W} were moderately severe interactions if RI lies between 6.8 m/s/s to 11.7 m/s/s, low severe interactions if RI lies between 3.2 m/s/s to 6.8 m/s/s, and no interactions if RI less than or equal to 3.2 m/s/s. Similarly, the interactions in case of P_M-V_{3W} were severe, moderately severe, low severe, and no interactions if RI more than 11.2 m/s/s, lies between 5.2 m/s/s to 11.2 m/s/s, lies between 2.8m/s/s to 5.2 m/s/s, and less than or equal to 2.8 m/s/s respectively.

Table 6.4: Threshold limits of PET for various severity levels at four-legged intersections.

Pedestrian & Vehicle Type	Threshold PET values (s)			
	No interaction	Low severe interaction	Moderately severe interaction	Severe interaction
P_M-V_{2W}	>5.1	5.1-3.1	3.1-1.1	<=1.1
P_M-V_{3W}	>5.3	5.3-3.2	3.2-1.2	<=1.2
P_M-V_{Car}	>5.2	5.2-3.2	3.2-1.3	<=1.3
P_M-V_{LCV}	>5.4	5.4-3.5	3.5-1.4	<=1.4
P_M-V_{HCV}	>5.5	5.4-3.6	3.6-1.5	<=1.5
P_F-V_{2W}	>5.2	5.2-3.1	3.1-1.2	<=1.2
P_F-V_{3W}	>5.3	5.3-3.2	3.2-1.3	<=1.3
P_F-V_{car}	>5.3	5.3-3.2	3.2-1.2	<=1.2
P_F-V_{LCV}	>5.4	5.4-3.3	3.3-1.4	<=1.4
P_F-V_{HCV}	>5.4	5.4-3.3	3.3-1.6	<=1.6

Table 6.5: Threshold limits of RI for various severity levels at four-legged intersections.

Pedestrian & Vehicle Type	Threshold RI values (m/s/s)			
	No interaction	Low severe interaction	Moderately severe interaction	Severe interaction
P_M-V_{2W}	<=3.2	3.2-6.8	6.8-11.7	>11.7
P_M-V_{3W}	<=2.8	2.8-5.2	5.2-11.2	>11.2
P_M-V_{Car}	<=3.1	3.1-5.5	5.5-11.5	>11.5
P_M-V_{LCV}	>2.7	2.7-5.0	5.0-10.0	>10.0
P_M-V_{HCV}	>2.6	2.6-4.8	4.8-9.5	>9.5
P_F-V_{2W}	<=3.2	3.2-5.6	5.6-11.4	>11.4
P_F-V_{3W}	<=2.9	2.9-4.8	4.8-10.7	>10.7
P_F-V_{car}	<=3.1	3.1-5.4	5.4-11.3	>11.3
P_F-V_{LCV}	<=2.1	2.1-4.5	4.5-10.6	>10.6
P_F-V_{HCV}	<=2.2	2.2-4.6	4.6-9.2	>9.2

The performance of the classified data was described using confusion matrix and accuracies. The accuracy of the classified data was estimated using true positives, true negatives, false positives, and false negatives from the confusion matrix. More than 80% accuracies of classified data were observed for both PET and RI in all the cases of pedestrian and vehicle combinations and the table 6.6 shows the accuracies of classified data for PET and RI at four-legged uncontrolled intersections.

Table 6.6: Accuracies of classified data in SVM as four-legged intersections.

Pedestrian & Vehicle Type	PET	RI
P_M-V_{2W}	88.28	90.09
P_M-V_{3W}	89.21	87.66
P_M-V_{Car}	91.81	87.31
P_M-V_{LCV}	92.31	90.77
P_M-V_{HCV}	90.00	89.53
P_F-V_{2W}	88.56	86.35
P_F-V_{3W}	93.96	84.35
P_F-V_{car}	92.12	88.61
P_F-V_{LCV}	90.13	83.82
P_F-V_{HCV}	95.68	82.61

6.3.3 Comparison of threshold limits of PET and RI

The threshold limits of PET and RI for various severity levels of P-V interactions were given in tables 6.2 and 6.3 respectively for three-legged uncontrolled intersections and tables 6.5 and 6.6 for four-legged uncontrolled intersections. From tables 6.2 to 6.5, it was observed that the threshold limits of PET for male pedestrians were lower compared to female pedestrians and 2Ws have lower threshold limits of PET compared to Cars, 3Ws, LCVs, and HCVs respectively. The threshold limits of PET at three-legged uncontrolled intersections were observed to be lower than that of four-legged uncontrolled intersections. The threshold limits of PET were lower at higher severity levels of P-V interactions.

From tables 6.3 to 6.6, it was observed that the threshold limits of RI for male pedestrians were higher compared with female pedestrians and 2Ws have higher threshold limits of RI compared to Cars, 3Ws, LCVs, and HCVs respectively. The threshold limits of RI were higher at higher severity levels of P-V interactions. The threshold limits of RI at three-legged uncontrolled intersections were observed to be higher than that of four-legged uncontrolled intersections.

6.4 Summary

In the present chapter, the threshold limits of PET and RI of various P-V interactions severity levels were defined for different categories of pedestrians and vehicles using SVM algorithms in Python interface at three-legged and four-legged uncontrolled intersections. The severity of

P-V interactions was inversely correlated with PET and direct correlated with RI. The threshold limits of PET were lower for severe interactions and higher of no interactions. The threshold limits of RI were lower for no interactions and higher for severe interactions. Lower threshold PET and higher threshold RI limits were observed for M-2W interaction category compared to other interaction categories.

Next chapter deals with the development of P-V interactions severity models at three-legged and four-legged uncontrolled intersections and the validation of developed models. Also, it deals with the comparison of P-V interactions severity levels at three-legged and four-legged uncontrolled intersections.

CHAPTER 7: MODELLING OF PEDESTRIAN-VEHICLE INTERACTIONS

7.1 General

Pedestrian-vehicle (P-V) accidents are one of the major reasons for fatalities and the severity of these accidents vary with various parameters of pedestrian, vehicle, geometry, weather, and environment. An accident is a rare event and it is difficult to collect accident data during an accident. Many parameters are not possible to collect during an accident and their effect on severity is unknown. Surrogate safety measures (SSMs) are an indirect safety measures which measure the severity of a near miss traffic events. Analysis and modelling of P-V interactions using SSMs will help to know the various factors affecting the severity of a potential possible interaction. In the present chapter, an attempt is made to develop pedestrian-vehicle (P-V) interaction severity model separately at three-legged and four-legged uncontrolled intersections to know the various factors affecting the severity level. The present chapter also, deals with the comparison of P-V interaction severities at these intersections.

7.2 Modelling of P-V interaction severities at uncontrolled intersections

The severities of P-V interactions can be modelled using various modelling techniques. Binary logit (BL) models are used for categorical variables with two categories in the dependent variable. Ordinal logit (OL) and multinomial logit (MNL) models are used for categorical variables with more than two categories in the dependent variable. OL model prefers over the MNL model when the order of the dependent variable is important. In OL, slopes are constant across categories but intercepts are different for each category due to the parallel lines assumption. In the present study, ordinal logit model (OLM) is used to predict the probabilities of P-V interaction severity levels.

The probabilities of P-V interaction severity levels can be predicted in order logit model using the following equations,

$$Logit\big(P(Y \leq j)\big) = \beta_{0j} + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{1}$$

$$P(Y = 0) = \frac{\exp\,(\alpha_0 + X\beta)}{1 + \exp\,(\alpha_0 + X\beta)} \tag{2}$$

$$P(Y = 1) = \frac{\exp\,(\alpha_1 + X\beta)}{1 + \exp\,(\alpha_1 + X\beta)} - \frac{\exp\,(\alpha_0 + X\beta)}{1 + \exp\,(\alpha_0 + X\beta)} \tag{3}$$

$$P(Y=2) = \frac{\exp(\alpha_2 + X\beta)}{1+\exp(\alpha_2 + X\beta)} - \frac{\exp(\alpha_1 + X\beta)}{1+\exp(\alpha_1 + X\beta)} \tag{4}$$

$$P(Y=3) = \frac{\exp(\alpha_3 + X\beta)}{1+\exp(\alpha_3 + X\beta)} - \frac{\exp(\alpha_2 + X\beta)}{1+\exp(\alpha_2 + X\beta)} \tag{5}$$

Y = Observed P-V interaction severity level on ordinal scale (j = 0, 1, 2, 3)

β_{0j} = Intercept corresponding to j^{th} severity level

$X_1, X_2, \ldots, X_n$ = Independent variables used in the model

$\beta_1, \beta_2, \ldots, \beta_n$ = Coefficients corresponding to each independent variable

Table 7.1 shows the description of the dependent and independent variables used in the analysis and separate code/number is assigned for each. The severity level, which is defined from the threshold limits for each P-V interaction sample was taken as the dependent variable and pedestrian, vehicle, and geometric parameters were taken as the independent variables for the development of OLM.

Table 7.1: Description of the variables used in the regression analysis

S. No.	Variable	Category/Units/Code
1	Severity	Dependent variable: No interaction – 0, Low severe interaction – 1, Moderately severe interaction – 2, Severe interaction – 3
2	Pedestrian gender (PG)	Male –1, Female – 2
3	Pedestrian age (PA)	Child-1, Young age-2, Middle age-3, Old age-4
4	Pedestrian speed (PS)	1 – <=0.5m/s, 2 – 0.5-1.5m/s, 3 – 1.0-1.5m/s, 4 – >1.5m/s
5	Luggage (Lug)	0 – No, 1 – Yes
6	Mobile usage (MU)	0 – No, 1 – Yes
7	Crossing Type (CT)	1 – Straight, 2 – Rolling
8	Pedestrian Platoon (PP)	1 – One, 2 – Two, 3 – More than two
9	Vehicle type (VT)	Two-wheeler-1, Three-wheeler-2, Car-3, LCV-4, HCV-5
10	Vehicle speed (VS)	1 – <=15km/h, 2 – 15-30km/h, 3 – 30-45km/h, 4 – >45km/h
11	Vehicle direction (VD)	1 – Through, 2 – Right turn, 3 – Left turn
12	Interaction location (IL)	1 – Entry, 2- Exit
13	Lane distribution (LD)	1 – Lane one, 2 – Lane two, 3 – Lane three, 4 – Lane four

Before doing the OLR, a Chi-square test has been performed in Statistical Package for Social Sciences (SPSS) software between the dependent variable and each independent variable at three-legged as well as four-legged uncontrolled intersections to identify the most insignificant variables with P-V interactions severity levels. Table 7.2 shows the Chi-square test results at three-legged and four-legged intersections. From the table 7.2, the variables with low Chi-square value and high p- value (p>0.05) were identified to exclude from the regression analysis. From the Chi-square test, it was observed that pedestrian platoon, and lane distribution were the most insignificant variables with P-V interactions severity levels at three-legged as well as four-legged intersections. The pedestrian crossing types was significant at 90% confidence interval at four-legged intersections and not significant at three-legged intersections. Hence, pedestrian crossing type was included in the regression analysis.

Table 7.2: Chi-square test results at three-legged and four-legged uncontrolled intersections.

S.No.	Variable type	3-legged intersections			4-legged intersections		
		Chi-Square value	df	p-value	Chi-Square value	df	p-value
1	Pedestrian gender	133.414	3	0.000	19.516	3	0.000
2	Pedestrian age	193.689	9	0.000	135.374	9	0.000
3	Pedestrian speed	158.84	9	0.000	243.416	9	0.000
4	Luggage	17.443	3	0.011	116.887	3	0.000
5	Mobile usage	89.222	3	0.000	37.752	3	0.001
6	Crossing type	4.587	3	0.135	6.388	3	0.094
7	Pedestrian platoon	8.653	6	0.386	5.775	6	0.449
8	Vehicle type	250.967	12	0.000	231.027	12	0.000
9	Vehicle speed	133.728	9	0.000	29.681	9	0.005
10	Vehicle direction	187.781	6	0.000	119.834	6	0.000
11	Interaction location	254.755	3	0.000	199.823	3	0.000
12	Lane distribution	7.879	9	0.325	9.342	9	0.274

Table 7.3 shows the descriptive statistics of the variables used in the OLR. A total of 5416 and 5693 P-V interactions at three-legged and four-legged uncontrolled intersections respectively were used for the OLR. 70% of total data was used for the development of OLM and remaining 30% data was used for the validation of developed models.

Table 7.3: Descriptive statistics of variables used in the ordinal logistic regression.

Parameter type		Three-legged intersections		Four-legged intersections	
		Percentage of samples	Number of samples	Percentage of samples	Number of samples
Severity	No interaction	38.2	2069	41.6	2368
	Low severe	31.0	1679	30.8	1753
	Moderately severe	19.4	1051	17.4	991
	Severe	11.4	617	10.2	581
Gender	Male	61.8	3347	57.3	3262
	Female	38.2	2069	42.7	2431
Age	Child	11.9	644	7.2	410
	Young	32.9	1783	28	1597
	Middle	39	2110	47.7	2716
	Old	16.2	880	17.1	971
Ped speed	<0.5m/s	3.4	184	2.7	154
	0.5-1.0m/s	39.6	2145	37.0	2105
	1.0-1.5m/s	48.1	2605	47.6	2713
	>1.5m/s	8.9	482	12.7	722
Luggage	No	81.8	4430	85.5	4865
	Yes	18.2	986	14.5	828
Mobile usage	No	85.9	4654	90.3	5141
	Yes	14.1	762	9.7	552
Crossing type	Straight	35.4	1917	28.0	1593
	Rolling	64.6	3499	72.0	4100
Vehicle type	2W	45.9	2486	42.6	2425
	3W	19.3	1045	22.3	1270
	Car	16.1	872	17.3	983
	LCV	11.0	596	9.5	541
	HCV	8.7	471	8.3	473
Vehicle speed	<15km/h	15.7	850	17.3	982
	15-30km/h	50.0	2708	53.0	3017
	30-45km/h	23.4	1268	21.5	1226
	>45km/h	10.9	591	8.2	468
Vehicle direction	Through	74.3	4024	78.3	4458
	Right turn	14.4	780	12.9	734
	Left turn	11.3	612	8.8	501
Interaction Location	Entry	49.6	2688	46.2	2630
	Exit	50.4	2728	53.8	3063
Total		100.0	5416	100.0	5693

7.2.1 P-V interaction severity model for three-legged uncontrolled intersections

An ordinal logistic regression (OLR) was performed in Statistical Package for Social Sciences

(SPSS) software between the dependent and independent variables at 95% significance interval to predict the probabilities of P-V interaction severity levels at three-legged uncontrolled intersections. Table 7.4 shows the results of OLR from SPSS software at three-legged intersections and the variables from table with $p<0.05$ were included in the developed ordinal logit model (OLM) to estimate the probabilities of severity levels. From logistic regression results, pedestrian gender, age, crossing speed, luggage, mobile usage, vehicle type, speed, direction, and location of P-V interaction were found to have significant effect ($p<0.05$) on severity levels of P-V interactions. Pedestrian crossing type has no significant effect ($p>0.05$) on severities of P-V interactions. The probability of severity of an interaction increases with the increase in independent variable, if the sign of the estimate (B) is positive and decreases with increase in independent variable, if the sign of estimate (B) is negative.

Table 7.4: Ordinal logistic regression results for three-legged uncontrolled intersections.

Parameter type		Estimate	p-value	Odds ratio
Severity	No interaction	-1.83	0.000	0.16
	Low severe interaction	-0.913	0.000	0.401
	Moderately severe interaction	-0.519	0.026	0.595
Gender	Male	0.403	0.000	1.496
	Female	0[a]	-	-
Age	Child	-0.763	0.000	0.466
	Young	0.358	0.000	1.43
	Middle	0.189	0.037	1.184
	Old	0[a]	-	-
Pedestrian speed	<=0.5 m/s	-1.014	0.000	0.363
	0.5-1.0 m/s	-0.756	0.000	0.469
	1.0-1.5 m/s	-0.252	0.021	0.777
	>1.5 m/s	0[a]	-	-
Luggage	No	-0.345	0.000	0.708
	Yes	0[a]	-	-
Mobile usage	No	-0.395	0.000	0.674
	Yes	0[a]	-	-
Crossing type	Straight	0.091	0.126	1.09
	Rolling	0[a]	-	-
Vehicle type	2W	1.088	0.000	2.968
	3W	0.718	0.000	2.05
	Car	0.942	0.000	2.565
	LCV	0.394	0.009	1.483
	HCV	0[a]	-	-
Vehicle speed	<=15 km/h	-0.463	0.001	0.629
	15-30 km/h	-0.315	0.005	0.73

	30-45 km/h	-0.266	0.009	0.766
	>45 km/h	0[a]	-	-
Vehicle direction	Right turn	-1.31	0.000	0.27
	Through	-1.023	0.000	0.359
	Left turn	0[a]	-	-
Interaction location	Entry	0.816	0.000	2.261
	Exit	0[a]	-	-
a. This parameter is set to zero because it is redundant.				

7.2.1.1 Effect of pedestrian, vehicle, and geometric parameters on severity of P-V interactions at three-legged uncontrolled intersections

The effect of pedestrian, vehicle, and geometric parameters on P-V interaction severity levels were quantified using odds ratio (OR), which is defined as the ratio of probability of an event to the probability of a non-event. For continuous predictors, OR>1.0 indicates that the event is more likely to occur as the predictor increases. For categorical predictors, OR compares the odds of the event occurring at 2 different levels of predictors. OR>1.0 indicates that the event is more likely to occur at level 1 and OR<1.0 indicates that the event is less likely to occur at level 1. For positive estimates (OR>1), the severities (Y = 0 or 1 or 2) are increased by (OR-1) percent for one unit increase in the variable X. For negative estimates (OR<1), the severities (Y = 0 or 1 or 2) are decreased by (1-OR) percent for one unit increase in the variable X.

The OR of 1.496 for male pedestrians indicate that one unit increase in male pedestrians increase the probability of P-V interaction severity level by 49.6% (i.e. (1.496-1) *100). The probabilities of severity levels were increased by 43.0% (OR = 1.430) and 18.4% (OR = 1.184) in case of young and middle age pedestrians respectively. These higher probabilities of severity levels in male and young pedestrians are because of higher risk-taking behaviour due to the higher crossing speeds. The probabilities of severity levels were observed to be lower when the pedestrians crossing without luggage (29.2% less severe) and mobile usage (32.6% less severe). Also, the probabilities of P-V interaction severity levels were decreased by 63.7%, 53.1%, and 22.3% when the pedestrians crossing at less than or equal to 0.5 m/s, 0.5-1.0 m/s, and 1.0-1.5 m/s respectively. The pedestrians crossing at higher speeds will take more risk than the pedestrians crossing at lower speeds is the reason for lower probabilities of severity levels when crossing at lesser speeds.

Vehicle type was found to be the most influencing parameters of P-V interaction severity levels as the OR of vehicle types were observed to be the highest. The OR of 2.968, 2.050, 2.565, and

1.483 indicate that the probability of P-V interaction severity levels were increased by 196.8%, 105.0%, 156.5%, and 48.3% for 2Ws, 3Ws, cars, and LCVs respectively. Further, the probability of P-V interaction severity levels were decreased by 37.1%, 27.0%, and 23.4% for the one unit increase in vehicles approaching the intersection with less than or equal to 15 km/h, 15-30 km/h, and 30-45 km/h respectively. The probability of severity of an interaction was lower for right turning vehicles (73.0%) followed by through vehicles (64.15%). Also, the probability increased by 126.1% for one unit increase in the interactions which occurs at entry point of the intersection.

7.2.2 P-V interaction severity model for four-legged uncontrolled intersections

An ordinal logistic regression was performed in SPSS software for four-legged uncontrolled intersections and the variables with $p<0.05$ are included in the developed OLM. Table 7.5 shows the results of OLR performed in SPSS software at four-legged intersections. From logistic regression results, pedestrian gender, age, crossing speed, luggage, mobile usage, vehicle type, speed, direction, and location of P-V interaction were found to have significant effect ($p<0.05$) on severity levels of P-V interactions.

Table 7.5: Ordinal logistic regression results for four-legged uncontrolled intersections.

Parameter type		Estimate	p-value	Odds ratio
Severity	No interaction	-2.535	0.000	0.079
	Low severe interaction	-1.785	0.000	0.168
	Moderately severe interaction	-0.461	0.038	0.631
Gender	Male	0.377	0.000	1.458
	Female	0^a	-	-
Age	Child	-0.697	0.000	0.498
	Young	0.494	0.000	1.638
	Middle	0.176	0.017	1.193
	Old	0^a	-	-
Pedestrian speed	<=0.5 m/s	-1.084	0.000	0.338
	0.5-1.0 m/s	-0.797	0.000	0.45
	1.0-1.5 m/s	-0.176	0.037	0.839
	>1.5 m/s	0^a	-	-
Luggage	No	-0.447	0.000	0.639
	Yes	0^a	-	-
Mobile usage	No	-0.561	0.000	0.571
	Yes	0^a	-	-
Crossing type	Straight	0.087	0.193	1.09
	Rolling	0^a	-	-

Vehicle type	2W	1.027	0.000	2.793
	3W	0.778	0.000	2.178
	Car	0.904	0.000	2.47
	LCV	0.358	0.028	1.43
	HCV	0[a]	-	-
Vehicle speed	<=15km/h	-0.596	0.000	0.551
	15-30km/h	-0.249	0.012	0.78
	30-45km/h	-0.264	0.014	0.768
	>45km/h	0[a]	-	-
Vehicle direction	Right turn	-1.152	0.000	0.316
	Through	-0.792	0.000	0.453
	Left turn	0[a]	-	-
Interaction location	Entry	0.7	0.000	2.014
	Exit	0[a]	-	-
a. This parameter is set to zero because it is redundant.				

The effect of pedestrian, vehicle, and geometric parameters on P-V interaction severity levels were quantified using odds ratio (OR). From the table 7.5, the OR of 1.458 in case of male pedestrians indicate that the odds of P-V interaction severity levels in male pedestrians were 1.458 times higher than the odds of the severity levels in female pedestrians. The OR of 1.638, and 1.193 indicate that the odds of the severity levels were 1.638 times, and 1.193 times higher in young, and middle age pedestrians respectively than the odds of severity levels in old age pedestrians. The higher risk taking behaviour due to higher crossing speeds in male and young pedestrians is the reason for higher odds of severity levels. The odds of P-V interaction severities were lower when the pedestrians crossing at less than or equal to 0.5 m/s (0.338 times), 0.5-1.0 m/s (0.450 times), and 1.0-1.5 m/s (0.839 times) respectively than the odds of severities when pedestrians crossing at more than 1.5 m/s. Further, the odds of severity levels were lower when the pedestrians crossing without luggage (0.639 times), and mobile usage (0.571 times) than the odds of severity levels in pedestrians crossing with luggage, and mobile usage.

Vehicle type was found to be the most influencing parameters of P-V interaction severity levels as the OR of vehicle types were observed to be the highest at four-legged intersections. The OR of 2.793, 2.178, 2.470, and 1.430 indicate that the odds of the severity levels were 179.3%, 117.8%, 147.0% and 43.0% higher for 2Ws, 3Ws, cars, and LCVs respectively than the odds of severity levels for HCVs. Further, the odds of severity levels were 44.9%, 22.0%, and 23.2% lower for the vehicles approaching the intersection with less than or equal to 15 km/h, 15-30 km/h, and 30-45 km/h respectively than the odds of severities for vehicles approaching at more than 45 km/h. The odds of severities were lower for right turning vehicles (68.4%) followed by through vehicles (54.7%) than the odds of severities for left turning vehicles. Also, the odds P-V interaction severities were higher in the interactions which occurs at entry point of the intersection (101.4% higher) than the odds of severities in the interactions which occurs at exit point of intersection.

7.3 Validation of OL models at three-legged and four-legged intersections

In logistic regression models, log likelihood ratio test, pseudo R-square, AIC (Akaike's Information Criteria), and BIC (Bayesian Information Criteria) are used to measure the goodness of fit. Deviance is a measure of lack of fit to the data and it is computed using the log likelihood values of saturated model and fitted model. The difference between the deviance of null model and final model gives the chi-square value. The predictors significantly improve the model fit if the final model deviance is smaller than that of null model deviance. The equation 7.1 shows the difference in deviances of null model and final model.

$$D_{null} - D_{final} = -2ln\frac{likelihood\ of\ the\ null\ model}{likelihood\ of\ the\ final\ model} \tag{7.1}$$

Pseudo R-square values are also used in logistic regression to measure the goodness of fit. McFadden's pseudo R-square is most widely used and it is calculated using equation 7.2. Tabachinick & Fidell (2007) suggested that the McFadden pseudo R^2 values ranging from 0.2 to 0.4 are highly satisfactory.

$$McFadden\ pseudo\ R^2 = 1 - \frac{log\ likelihood\ of\ final\ model}{log\ likelihood\ of\ null\ model} \tag{7.2}$$

AIC and BIC are computed using the following equations,

$$AIC = \frac{2}{N}(-\log likelihood + k) \tag{7.3}$$

$$BIC = -2\log likelihood + \log(N) \times k \tag{7.4}$$

Where, N is the number of points in the training data set, and k is the number of parameters in the model.

Tables 7.6 and 7.7 shows the model fitting information of the developed ordinal logit models at three-legged and four-legged uncontrolled intersections respectively. The McFadden pseudo

R-square values at three-legged and four-legged intersections were 0.115 and 0.106 respectively. The deviance values of intercept only model and final were 7125.939 and 6131.676 respectively at three-legged intersections, 6306.854 and 5455.059 respectively at four-legged intersections. The AIC values of intercept only model and final were 8654.068 and 7799.806 respectively at three-legged intersections, 8056.341 and 7344.546 respectively at four-legged intersections. The BIC values of intercept only model and final were 8673.225 and 7346.677 respectively at three-legged intersections, 8075.997 and 7495.086 respectively at four-legged intersections. The lower values of McFadden pseudo R-square values indicates that the developed models were somewhat week. But, the lower deviance, AIC and BIC values of final model compared to intercept only model indicates the good fit of the developed models at three-legged and four-legged intersections.

Table 7.6: Model fitting information of OLM at three-legged intersections

Model	Model fitting criteria			Likelihood ratio test		
	AIC	BIC	-2 log likelihood	Chi-square	df	sig.
Intercept only model	8654.068	8673.225	8648.068	-	-	-
Final model	7799.806	7946.677	7653.806	994.262	20	0.000
McFadden pseudo R^2	0.115					

Table 7.7: Model fitting information of OLM at four-legged intersections

Model	Model fitting criteria			Likelihood ratio test		
	AIC	BIC	-2 log likelihood	Chi-square	df	sig.
Intercept only model	8056.341	8075.997	8050.341	-	-	-
Final model	7344.546	7495.086	7198.546	851.795	20	0.000
McFadden pseudo R^2	0.106					

7.4 Comparison of P-V interaction severity levels at three-legged and four-legged uncontrolled intersections

Odds ratio (OR) of a variable is used to compare the probability of severity levels of P-V interactions between three-legged and four-legged intersections. The probability of severity of an interaction is higher, if the OR of a variable is higher and vice versa. The OR of male pedestrians at three-legged intersections (OR = 1.496) was higher than OR of male pedestrians at four-legged intersections (OR = 1.458). This means that one unit increase in male pedestrians at three-legged intersections increase the probability of P-V interaction severity level by 3.8% compared to one unit increase in male pedestrians at four-legged intersections (the severity level at three-legged intersections was 3.8% higher compared to four-legged intersections when male pedestrian involves in an interaction at both locations). Further, the probability severity level was increased by 17.5% at three-legged intersections for one unit increase in 2Ws compared to one unit increase at four-legged intersections. Similarly, the probabilities of severity levels were increased by 2.5%, 6.9%, 10.3%, 7.8%, and 24.7% at three legged intersections for one unit increase in pedestrians crossing at less than or equal to 0.5m/s, crossing without luggage, mobile usage, vehicle approaching at less than or equal to 15 km/h, and interaction occurs at the entry point of intersection respectively compared to one unit increase at four-legged intersections. The higher OR values of variables at three-legged intersections indicates that the probability of P-V interaction severity was higher at three-legged intersections compared to four-legged intersections. Hence, it was concluded that the severity levels of P-V interactions at three-legged intersections were higher compared to four-legged intersections. The higher approaching speeds of vehicles at three-legged intersections is the reason for higher P-V interaction severity levels compared to four-legged intersections. Lord (1996) also found that T-intersections were more dangerous than X-intersections.

7.5 Summary

In the present chapter, the OL models were developed to predict the severity levels of P-V interactions at three-legged and four-legged uncontrolled intersections. The OL regression results confirmed that the P-V interaction severity levels depends various factors of pedestrian, vehicle, geometry at three-legged and four-legged intersections. The developed OL models were validated using log likelihood ratio test, pseudo R-square, AIC, and BIC values and the validation results indicate the good fit of the developed models. The severities of P-V interactions were compared between three-legged and four-legged intersections using OR of variables and found the higher severity levels at three-legged intersections compared to four-legged intersections.

In the next chapter, estimation of pedestrian dilemma zone boundary limits using various methods, modelling of PDZ boundary limits, and validation of developed models at three-legged and four-legged uncontrolled intersections are presented.

CHAPTER 8: PEDESTRIAN DILEMMA ZONE ESTIMATION AND MODELLING

8.1 General

Pedestrian gap acceptance theory is the basic concept for pedestrian dilemma zone (PDZ) analysis and modelling. PDZ is formed by the moving vehicles on the road which creates a stage of confusion to the pedestrians while finding a suitable gap to cross the road. There is a possibility of an interaction between the pedestrian and vehicle due to the incorrect decision taken by the pedestrian when the vehicle lies within the limits of PDZ. The lower limit (below which the available gap is unsafe to cross) and upper limit (above this limit the available gap is safe to cross) of PDZ will help the pedestrians to judge whether the available gap is sufficient or not to cross the road to avoid interactions with vehicles. Modelling of PDZ will help to know the effect of various pedestrian and vehicle characteristics on these PDZ limits. In this chapter, an attempt is made to estimate the boundary limits, and length of PDZ (spatial PDZ boundaries and length) at 3-legged and 4-legged uncontrolled intersections. Also, this chapter deals with the development of PDZ model at 3-legged and 4-legged uncontrolled intersections separately to determine the PDZ boundary limits.

8.2 Pedestrian dilemma zone (PDZ) estimation

PDZ boundaries can be estimated using cumulative gap distribution (CGD) method, support vector machine (SVM) method, binary logistic (BL) method, and probabilistic distribution method. A brief explanation of estimating PDZ boundary limits using these methods is given in section 1.4 of chapter 1. In the present study, cumulative gap distribution and support vector machine methods were used to estimate the PDZ boundary limits.

8.2.1 PDZ estimation using gap cumulative distribution (GCD) method

This method was proposed by Zegeer (1977) for measuring dilemma zone boundaries of vehicles corresponding to more than 10% and less than 90% of vehicles would choose to stop at signalized intersections. Later, this method was used by Pawar et al. (2016) to estimate the PDZ boundary limits at uncontrolled midblock crossings. In this method, a plot between distance of vehicle from the pedestrian trajectory path when he/she accept/reject the gap on x-axis and cumulative percentage gap accepted on y-axis is plotted and the distances corresponding to 10% and 90% cumulative percentage accepted gaps were taken as the lower and upper boundaries of the PDZ.

In the present study, the GCD plots were plotted separately for 3-legged and 4-legged uncontrolled intersections as the statistical results showed significant difference in accepted/rejected gaps (distance) between the 3-legged and 4-legged intersections. Figures 8.1 below shows the GCD plots for estimating the PDZ boundary limits at 3-legged intersections. The estimated lower and upper boundary limits of PDZ at 3-legged intersections corresponding to more than 10% cumulative accepted gaps and less than 90% cumulative rejected gaps were 9.5m and 19.5m respectively. The length of PDZ (difference between upper boundary limit and lower boundary limit) was 10.0m.

Figures 8.2 shows the GCD plots for estimating the PDZ boundary limits at 4-legged intersections. The estimated lower and upper boundary limits of PDZ at 4-legged intersections corresponding to more than 10% cumulative accepted gaps and less than 90% cumulative rejected gaps were 9.0m and 16.5m respectively. The length of PDZ (difference between upper boundary limit and lower boundary limit) was 7.5m.

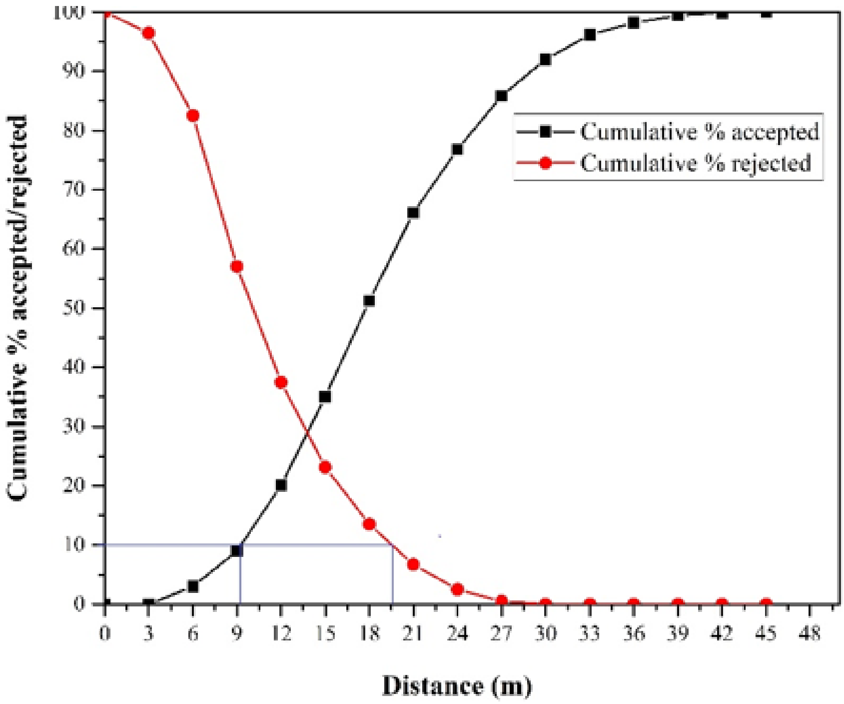


Figure 8.1: PDZ boundary limits estimation using GCD method at 3-legged uncontrolled intersections.

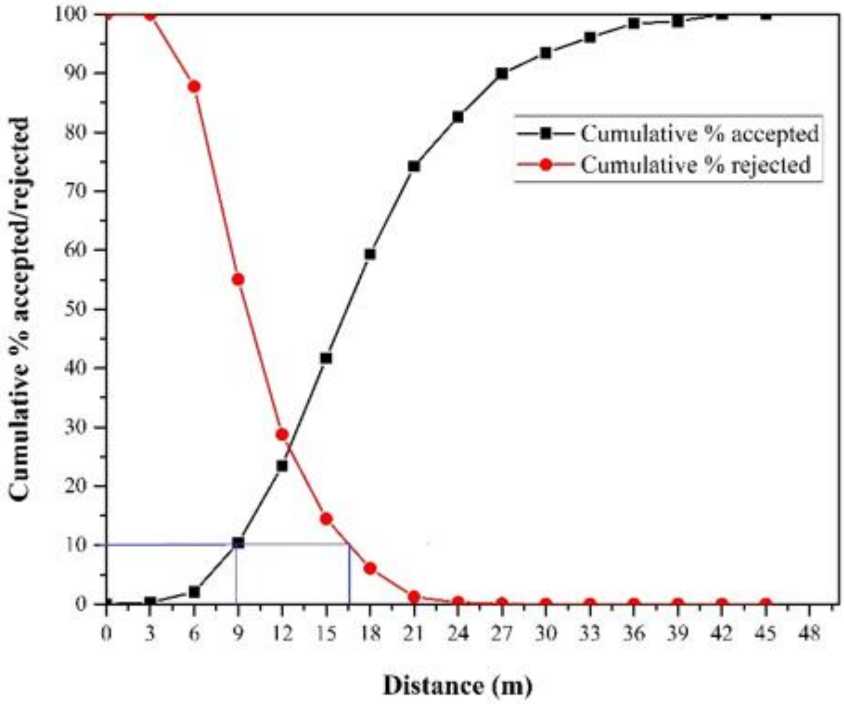


Figure 8.2: PDZ boundary limits estimation using GCD method at 4-legged uncontrolled intersections.

8.2.2 PDZ estimation using support vector machine (SVM) method

The basic rules, various kernel functions used in the classification techniques, and use of SVM technique for multilevel classification of various P-V interaction severity levels were discussed in the section 6.1 of chapter 6. In the present study, SVM code in python interface was used for the binary classification of accepted and rejected pedestrian gaps. P-V trajectory data were plotted on a coordinated system with the approaching speeds of the vehicles on y-axis and the distance of vehicles from pedestrian trajectory paths on x-axis for both accepted and rejected gaps. SVM construct a hyperplane as a decision plane to separate both accepted and rejected gaps with the maximum margin. In the present case, linear kernel function was used as the data sets were observed to be linearly non-separable. SVM code in python interface to determine the PDZ boundary limits is shown in figure 8.3. Figures 8.4 and 8.5 shows the profiles of both accepted and rejected gaps at 3-legged and 4-legged uncontrolled intersections respectively. In these figures, red profiles indicate all rejected gaps and blue profiles indicate all accepted gaps. The overlapping profile of both accepted and rejected gaps is the best optimal hyperplane and the distances on this plane corresponding to various vehicle speed ranges were taken as the boundary limits of PDZ. The lower and upper boundary limits of PDZ were taken corresponding to the two standard deviation from the mean speed (from the normal distribution curve about 95% values lies within limits of two standard deviation from mean).

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix, accuracy_score
import numpy as np
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
data_clear = pd.read_csv('SVM.csv')
y = data_clear.pop('AR')
data = data_clear[['speed', 'distance']].copy()
X = data.copy()
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 4)
le = LabelEncoder()
y_train = le.fit_transform(y_train)
y_test = le.transform(y_test)
model = SVC(kernel = 'linear', gamma ='auto', C=10000)
model.fit(X_train, y_train)
predict = model.predict(X_test)
confusion_matrix(y_test, predict)
print('Accuracy Score', accuracy_score(y_test, predict))
print('Confusion Matrix', confusion_matrix(y_test, predict))
X_train = np.array(X_train)
x_min, x_max = X_train[:, 1].min() - 2, 50
y_min, y_max = 0, 100
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.02),
                     np.arange(y_min, y_max, 0.02))
Z = model.predict(np.c_[yy.ravel(), xx.ravel()])
Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, cmap = 'RdYlBu_r', alpha = 0.9)
plt.scatter(X_train[:, 1], X_train[:, 0], c = y_train, cmap = 'RdYlBu_r', edgecolors = 'black')
plt.xlabel('Distance (m)')
plt.ylabel('Speed (Kmph)')
plt.xticks(np.arange(0, 50, 2))
plt.yticks(np.arange(0, 100, 5))
plt.xlim(xx.min(), xx.max())
plt.ylim(yy.min(), yy.max())
plt.show()
```

Figure 8.3: SVM code in Python interface to estimate PDZ boundary limits.

In the present study, 3.91 km/h and 50.63 km/h were plus or minus two standard deviation values from mean speed (27.27 km/h) at 3-legged intersections and 4.06 km/h and 46.17 km/h were the plus or minus two standard deviation values from mean speed (25.11 km/h) at 4-legged intersections. The classification plots for the PDZ boundary limits estimation using SVM method at three-legged and four-legged intersections were shown in figure 8.4 and 8.5 respectively. The estimated lower and upper boundary limits of PDZ using SVM method were 7.5m and 24.0m respectively at 3-legged uncontrolled intersections and 6.0 and 18.5 respectively at 4-legged uncontrolled intersections. The estimated length of PDZ using SVM method was 16.5 m at 3-legged intersections and 12.5 m at 4-legged intersections.

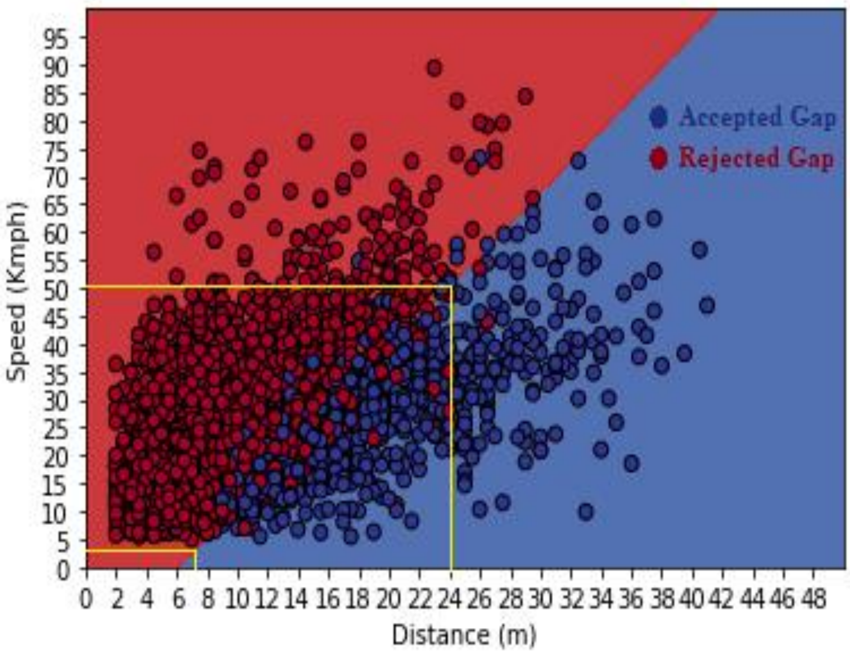


Figure 8.4: PDZ boundary limits estimation using SVM method at 3-legged uncontrolled intersections.

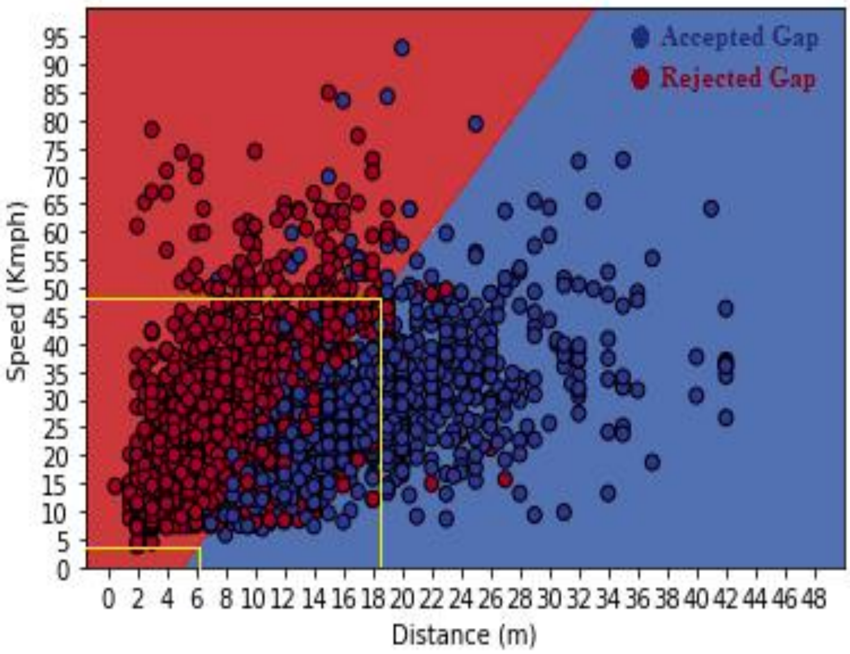


Figure 8.5: PDZ boundary limits estimation using SVM method at 4-legged uncontrolled intersections.

The performance of SVM classified data was described using confusion matrix and the accuracy of SVM classified data was estimated using true positives, true negatives, false positives, and false negatives. The mathematical form of accuracy definition is shown in equation 8.1 and the estimated accuracy for classified data at 3-legged and 4-legged intersections given in table 8.1. In the present case, the test results predict with a good accuracy of 87.3% and 89.0% at 3-legged and 4-legged intersections respectively.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{True Positives} + \text{False Positives} + \text{True Negatives} + \text{False Negatives}} \tag{8.1}$$

Table 8.1: Confusion matrices and accuracy of testing data in SVM at three-legged and four-legged intersections.

<table>
<tr><td rowspan="3" colspan="2"></td><td colspan="4">Predicted</td></tr>
<tr><td colspan="2">three-legged intersection</td><td colspan="2">four-legged intersection</td></tr>
<tr><td>Accepted</td><td>Rejected</td><td>Accepted</td><td>Rejected</td></tr>
<tr><td rowspan="2">Actual</td><td>Accepted</td><td>207</td><td>85</td><td>302</td><td>83</td></tr>
<tr><td>Rejected</td><td>50</td><td>767</td><td>36</td><td>680</td></tr>
<tr><td colspan="2">Accuracy</td><td colspan="2">87.3%</td><td colspan="2">89.0%</td></tr>
</table>

The estimated boundary limits of PDZ using GCD and SVM methods were shown in table 8.2. The estimated lower limit of PDZ using GCD method was higher than that of estimated limit using SVM method at three-legged and four-legged intersections. The estimated upper limit of PDZ at three-legged and four-legged intersections was lower in case of GCD method compared to SVM method. GCD method overestimated the lower limit and under estimated the upper limit compared with SVM method. SVM better estimated the PDZ boundary limits with largest margin compared to GCD method. Figure 8.6 shows the physical location and length of PDZ at three-legged and four-legged uncontrolled intersections estimated from SVM method. The lower and upper boundary limits of PDZ at three-legged intersections shifts way from the intersection or crosswalk or pedestrian trajectory path compared to four-legged intersections. The length of PDZ at three-legged intersections was higher than that of four-legged intersections. The higher approaching vehicular speeds due to the smaller number of conflicting points at three-legged intersections is the reason for shifting the boundary limits away from the intersection.

Table 8.2: PDZ boundary limits at three-legged and four-legged intersections.

S.No.	Intersection type	Method used	PDZ Limits(m)		
			Lower limit	Upper limit	Length
1	Three-legged uncontrolled	GCD	9.0	19.5	10.5
		SVM	7.5	24	16.5
2	Four-legged uncontrolled	GCD	9.0	16.5	7.5
		SVM	6.0	18.5	12.5

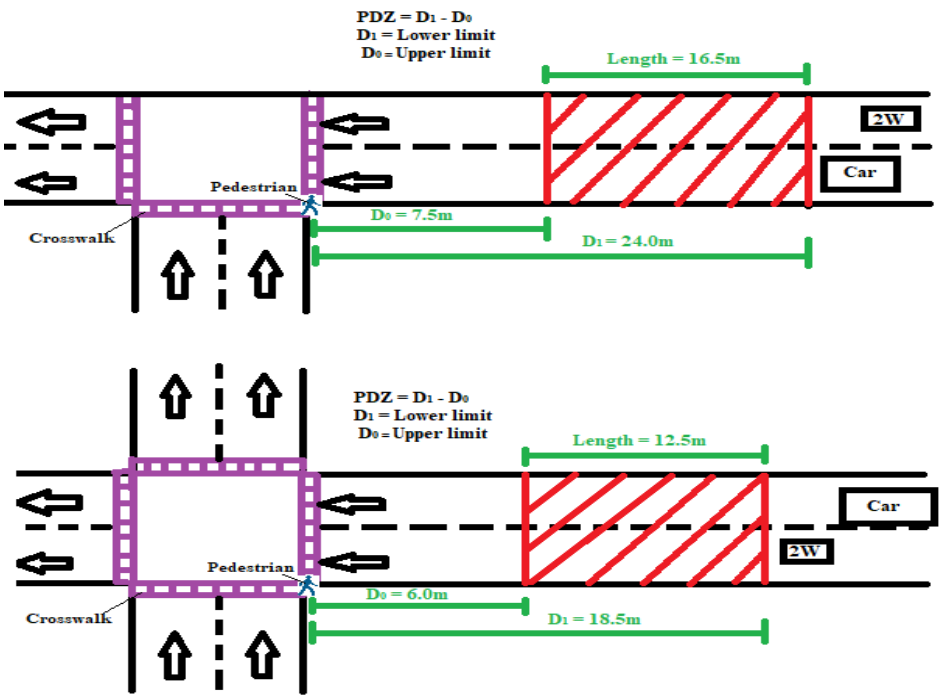


Figure 8.6: Physical location PDZ boundaries at three-legged and four-legged intersections.

8.3 Modelling of pedestrian dilemma zone (PDZ) boundaries

Logistic models can be used to model the probability of one event taking place by having the log-odds of one or more independent variables. Multinomial and order logit models can be used to model the categorical dependent variables of more than two categories. Binary logit model is preferred in case of categorical dependent variables with two categories. A pedestrian perception of accepting the gap is a binary event where the probability of choosing the gap lies between 0 and 1. In the present case, binary logit model is useful to capture the pedestrian behaviour in accepting and rejecting the gap to cross the road.

$$y_k = \begin{cases} 0, & if\ k^{th}\ pedestrian\ reject\ the\ gap \\ 1, & else \end{cases}$$

The probability of accepting a given gap i for the pedestrian k is given by,

$$P_k(i) = \frac{1}{1+e^{-U_i}} \quad (8.1)$$

$$U_i = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_n X_n \quad (8.2)$$

Where, U_i is the utility of gap i,

α is the intercept used in the model

X_1, X_2, X_3, …, X_n are the independent variables

$\beta_1, \beta_2, \beta_3, \dots, \beta_n$ are the coefficients of independent variables.

Logistic loss (log loss) is used to measure the goodness of fit in case of logistic regression. As the respondents are independent of one another, maximum likelihood is given by the product of the probabilities and log transformation is given is equation 8.3.

$$lnL = \sum y_A \ln(P_A) + (1 - y_A)(1 - P_A) \quad (8.3)$$

Where, P_A is the probability of accepting the given gap

Pedestrian has to decide whether the available gap is sufficient or not to cross the road. Sometimes this decision making is difficult when the vehicles are within a certain region on the road. This region is known as pedestrian dilemma zone and it can be estimated by developing a binary logistic regression model between dependent (gap accept/reject) and independent variables (pedestrian age (PA), pedestrian gender (PG), pedestrian speed (PS), location of pedestrian crossing (LPC), vehicle type (VT), vehicle distance (VD) and vehicle approaching speed (VS)). Description of variables used in the binary logistic regression analysis were shown in table 8.3.

Table 8.3: Description of variables used in the binary logistic regression

S. No.	Variable	Description	Category/Code
1	Gap accept/reject	Whether a pedestrian accepted or rejected the available gap	Reject-0, Accept-1
2	Pedestrian gender (PG)	Based on visual appearance classified as male and female	Male-1, Female-2
3	Pedestrian age (PA)	Based on visual appearance classified as child (<15 years), young age (15-30 years), middle age (30-60 years) and old age (>60	Children-1, Young age-2, Middle age-3, Old age-4
4	Pedestrian speed (PS)	Crossing speeds of pedestrians	Pedestrian speed (m/s)
5	Vehicle type (VT)	Classified based on visual appearance as Two-wheeler (2W), Three-wheeler (3W), Car, Light commercial vehicle (LCV) or Heavy commercial vehicle (HCV)	2W-1, 3W-2, Car-3, LCV-4, HCV-5
6	Vehicle speed (VS)	Approaching speeds of the vehicles	Speed in kmph
7	Vehicle distance (VD)	The distance of the vehicle from the pedestrian trajectory path when he/she accept/reject the gap	Distance in meters
8	Location of pedestrian crossing (LPC)	Whether the pedestrian crossing at entry or exit of the intersection	Entry-1, Exit-2

8.3.1 PDZ model for three-legged uncontrolled intersections

A binary logistic regression (BLR) was performed in Statistical Package for Social Sciences (SPSS) software between the dependent and independent variables at 95% significance interval to estimate the probability of gap acceptance by pedestrians at three-legged uncontrolled intersections. Table 8.4 shows the results of the BLR for three-legged uncontrolled intersections and the variables from the table with $p<0.05$ were included in the developed binary logit model (BLM) to estimate the PDZ boundary limits. The logistic regression results confirmed that pedestrian gender (PG), age (PA), crossing speed (PS), vehicle type (VT), approaching speed (VS), distance of vehicle from pedestrian trajectory path, and location of pedestrian crossing (LPC) have significant effect ($p<0.05$) on the gap acceptance behaviour of pedestrians. The positive sign of the estimate (B) indicates that with an increase in the independent variable, the probability of accepting of a give gap by the pedestrian also increase. The negative estimate (B) indicates that the probability of gap acceptance by pedestrians decreases with the increase in independent variable.

Table 8.4: BLR results for three-legged uncontrolled intersections

Variable type		Estimate (B)	p-value	Odds Ratio (OR)
Constant		-2.853	0.000	0.058
Distance (D)		0.376	0.000	1.456
Pedestrian gender	Male (P_M)	0.637	0.000	1.891
Pedestrian age	Child (P_C)	-0.388	0.046	0.678
	Young (P_Y)	0.590	0.000	1.804
	Middle (P_{Mid})	0.304	0.042	1.355
Pedestrian speed (PS)		0.615	0.000	1.850
Vehicle type	2W (V_{2W})	-0.368	0.026	0.692
	3W (V_{3W})	-0.965	0.000	0.380
	Car (V_{Car})	-1.074	0.000	0.341
	LCV (V_{LCV})	-1.302	0.000	0.272
Vehicle speed (VS)		-0.128	0.000	0.880
LPC	Entry	-0.203	0.037	0.816

Odd ratio (OR) was used to quantify the impact of significant factors on choosing the gap accepted versus gap rejected. For positive coefficients, the odds of Y = 1 are increased by (OR-1) percent for one unit increase in the variable X. The OR of distance was 1.456 indicates that one unit increase in vehicle distance from P-V interaction point results in 45.6% (i.e. (1.456-1)*100) increase in the probability of gap acceptance by the pedestrian. One unit increase in pedestrian crossing speed (OR = 1.850) results in 85.0% increase in the probability of gap acceptance. Further, one unit increase in vehicular speed (OR = 0.880) results in 12.0% decrease in the probability of gap acceptance. The probability of gap acceptance was also higher in case of male (1.891 times), and young (1.804 times) pedestrians compared to female and old age pedestrians respectively. Further, it was also lower when the interaction occurs at entry point of intersection (0.816 times) compared to exit point. The probability of gap acceptance was also higher in case of 2Ws compared to 3Ws, Cars, and LCVs respectively.

The utility equation from table 8.4 can be expressed as,

$$U_i = -2.853 + (0.376 \times D) + (0.637 \times P_M) - (0.388 \times P_C) + (0.590 \times P_Y) + (0.304 \times P_{Mid}) + (0.615 \times PS) - (0.368 \times V_{2W}) - (0.965 \times V_{3W}) - (1.074 \times V_{Car}) - (1.302 \times V_{LCV}) - (0.128 \times VS) - (0.203 \times LPC_{Entry}) \quad (8.4)$$

Female, old age pedestrians, HCVs, and exit point of pedestrian crossing were taken as the reference variables in the BLR. These variables are redundant and the estimates set as zero.

The equations to estimate lower and upper boundary limits of PDZ were developed using utility and probability equations corresponding to 0.9 and 0.1 probabilities respectively. After substituting the utility equation and probability of 0.1 in equation 8.1, the obtained equation for estimating lower boundary limit PDZ (D_0) at three-legged intersections is as follows:

$$D_0 = 1.74 - (1.69 \times P_M) + (1.03 \times P_C) - (1.57 \times P_Y) - (0.81 \times P_{Mid}) - (1.64 \times PS) + (0.98 \times V_{2W}) + (2.57 \times V_{3W}) + (2.86 \times V_{Car}) + (3.46 \times V_{LCV}) + (0.34 \times VS) + (0.54 \times LPC_{Entry}) \quad (8.5)$$

After substituting the utility equation and probability of 0.9 in equation 8.1, the obtained equation for estimating upper boundary limit PDZ (D_1) at three-legged intersections is as follows:

$$D_1 = 4.39 - (1.69 \times P_M) + (1.03 \times P_C) - (1.57 \times P_Y) - (0.81 \times P_{Mid}) - (1.64 \times PS) + (0.98 \times V_{2W}) + (2.57 \times V_{3W}) + (2.86 \times V_{Car}) + (3.46 \times V_{LCV}) + (0.34 \times VS) + (0.54 \times LPC_{Entry}) \quad (8.6)$$

8.3.1.1 Effect of pedestrian parameters on PDZ boundaries

The equations 8.5 and 8.6 are used to estimate the lower and upper boundary limits of PDZ respectively at three-legged uncontrolled intersections. The initial observation from the binary logistic regression confirmed that the boundary limits of PDZ significantly affected by the pedestrian parameters like gender, age, crossing speed, and location of crossing. Pedestrian gender and age (except children) have negative impact on the PDZ boundaries and the boundary limits lies close to the intersection or crosswalk or pedestrian trajectory path in case of male pedestrians compared to female pedestrians. PDZ boundary limits lies close to the intersection in case of young pedestrians compared to old age pedestrians and they shift away from the intersection in case of children. The boundary limits shift away from the intersection with an increase in pedestrian age. The higher risk-taking behaviour of male and young age pedestrians is the reason for dilemma behaviour at lesser boundary limits. The PDZ boundary limits lies close to the intersection at higher crossing speeds of pedestrians and shifts away from the intersection when the pedestrians crossing at the entry point of the intersection compared to exit point.

8.3.1.2 Effect of vehicle parameters on PDZ boundaries

The initial observations from binary logistic regression and equations 8.5 and 8.6 conformed that the PDZ boundary limits depends on vehicle parameters like type and speed. The positive sign of the coefficients of vehicle types and speeds in the equations 8.5 and 8.6 indicates that the PDZ boundary limits were positively correlated with the vehicle type and speed. The boundary limits shift away from the intersection or crosswalk or pedestrian trajectory path with increase in the size of vehicles. Thus, the lower and upper limits of PDZ lies close to the intersection in case of 2Ws compared to 3Ws, cars, LCVs, and HCVs respectively. Therefore, it is concluded that the pedestrians have less dilemma with 2Ws at comparatively shorter distances with 3Ws, cars, LCVs and HCVs respectively. Similar findings were reported by Pawar and Yadav (2022) for midblock locations. The boundary limits of PDZ (location from the intersection or crosswalk or pedestrian trajectory path) shifts away from the intersection with the increase in approaching speeds of conflicting vehicles. Pedestrians will have more dilemma at longer distances when the vehicle approaching the intersection with higher speeds. Pawar and Patil (2017) were also observed the similar finding for minor street vehicles dilemma zone.

8.3.1.3 Validation of BL model

The prediction success table (confusion matrix) was used to evaluate the performance of the developed model with 0.5 as threshold value of classification. The sensitivity and specificity, which measures the proportion of positives and negatives respectively that are correctly identified were used to evaluate the performance of binary classification test. Table 8.5 shows the prediction success table for the developed binary logit model at three-legged uncontrolled intersections. From the table 8.5, the sensitivity and specificity were found to be 93.1% and 70.2% respectively. The overall prediction success rate for the developed model was 86.4%. Overall, the developed model predicts the correct values with an accuracy of 86.4%.

The model fitting information of the developed binary logit model at three-legged intersections was shown in table 8.6. The model fitting was assessed using a Likelihood ratio test and McFadden's pseudo R^2 value was calculated using -2log likelihoods of final model and intercept only model (McFadden pseudo R^2 = 1-((-2log likelihood of final model)/(-2log likelihood of intercept model only))). The McFadden pseudo R^2 value calculated in the present study was 0.419 (i.e. 1-(2734.760/4706.760)), which would suggest that the developed model is highly satisfactory. Tabachinick & Fidell (2007) suggested that the McFadden pseudo R^2 values ranging from 0.2 to 0.4 are highly satisfactory. Also, lower values of Akaike's Information Criteria (AIC), Bayesian Information Criterion (BIC), and -2log likelihood values of the final model when compared with intercept only model indicates the good fit of the developed model.

Table 8.5: Prediction success table for developed model at three-legged intersections

Observed		Predicted		
		Gap		Percentage Correct
		Reject	Accept	
Gap	Reject	2567	190	93.1%
	Accept	339	800	70.2%
Overall Percentage		86.4%		

Table 8.6: Model fitting information of binary logit model at three-legged intersections

Model	Model fitting criteria			Likelihood ratio test		
	AIC	BIC	-2 log likelihood	Chi-square	df	sig.
Intercept only model	4708.880	4715.146	4706.878			
Final model	2760.760	2842.240	2734.760	1972.118	12	0.000
McFadden pseudo R^2	0.419					

8.3.2 Four-legged uncontrolled intersections

A binary logistic regression was performed in SPSS software at 95% significance interval to estimate the probability of gap acceptance by pedestrians at four-legged uncontrolled intersections. Table 8.7 shows the results of BLR for four-legged uncontrolled intersections and the variables from the table with $p<0.05$ were included in the developed BLM to estimate the PDZ boundary limits. The logistic regression results confirmed that PG, PA, PS, VT, VS, distance of vehicle from pedestrian trajectory path (VD), and LPC have significant effect ($p<0.05$) on the gap acceptance behaviour of pedestrians at four-legged intersections.

Table 8.7: Binary logistic regression results for four-legged uncontrolled intersections

Variable type		Estimate (B)	p-value	Odds Ratio (OR)
Constant		-4.102	0.000	0.016
Distance (D)		0.608	0.000	1.837
Pedestrian gender	Male (P_M)	0.441	0.002	1.554
Pedestrian age	Child (P_C)	-1.084	0.010	0.338
	Young (P_Y)	0.664	0.002	1.942
	Middle (P_{Mid})	0.438	0.025	1.550
Pedestrian speed (PS)		0.710	0.000	2.034
Vehicle type	2W (V_{2W})	-0.508	0.035	0.602
	3W (V_{3W})	-0.821	0.004	0.439
	Car (V_{Car})	-0.974	0.001	0.378
	LCV (V_{LCV})	-1.304	0.003	0.271
Vehicle speed (VS)		-0.155	0.000	0.891
LPC	Entry	-0.296	0.016	0.744

The impact of significant factors on choosing the gap accepted versus gap rejected was quantified using odd ratio (OR). The OR of distance was 1.837 indicates that one unit increase in distance of the vehicle from pedestrian trajectory path results in 83.7% (i.e. (1.837-1)*100) increase in the probability of gap acceptance by the pedestrian at four-legged uncontrolled intersections. One unit increase in pedestrian crossing speed (OR = 2.034) results in 103.4% increase in the probability of gap acceptance. Further, one unit increase in vehicular speed (OR = 0.891) results in 10.9% decrease in the probability of gap acceptance. The probability of gap acceptance was also higher in case of male (1.554 times), and young (1.942 times) pedestrians compared to female and old age pedestrians respectively. Further, it was also lower when the interaction occurs at entry point of intersection (0.744 times) compared to exit point. The probability of gap acceptance was also higher in case of 2Ws compared to 3Ws, Cars, and LCVs respectively. The higher OR values of variables in case of four-legged intersections increase the probability of gap acceptance compared to three-legged intersections and the lower values decreases the probability of gap acceptance.

The utility equation from table 8.7 can be written as,

$$U_i = -4.102 + (0.608 \times D) + (0.441 \times P_M) - (1.084 \times P_C) + (0.664 \times P_Y) + (0.438 \times P_{Mid}) + (0.710 \times PS) - (0.508 \times V_{2W}) - (0.821 \times V_{3W}) - (0.974 \times V_{Car}) - (1.304 \times V_{LCV}) - (0.115 \times VS) - \left(0.296 \times LPC_{Entry}\right) \quad (8.7)$$

Female, old age pedestrians, HCVs, and exit point of pedestrian crossing were taken as the reference variables in the BLR. These variables are redundant and the estimates set as zero.

The equations to estimate lower and upper boundary limits of PDZ at four-legged uncontrolled intersections were developed using utility and probability equations corresponding to 0.9 and 0.1 probabilities respectively. After substituting the utility equation and probability of 0.1 in equation 8.1, the developed equation for estimating lower boundary limit PDZ (D_0) at four-legged intersections is as follows:

$$D_0 = 3.13 - (0.73 \times P_M) + (1.78 \times P_C) - (1.09 \times P_Y) - (0.64 \times P_{Mid}) - (1.17 \times PS) + (0.83 \times V_{2W}) + (1.35 \times V_{3W}) + (1.60 \times V_{Car}) + (2.14 \times V_{LCV}) + (0.19 \times VS) + \left(0.49 \times LPC_{Entry}\right) \quad (8.8)$$

After substituting the utility equation and probability of 0.9 in equation 8.1, the developed equation for estimating upper boundary limit PDZ (D_1) at four-legged intersections is as follows:

$$D_1 = 10.36 - (0.73 \times P_M) + (1.78 \times P_C) - (1.09 \times P_Y) - (0.64 \times P_{Mid}) - (1.17 \times PS) + (0.83 \times V_{2W}) + (1.35 \times V_{3W}) + (1.60 \times V_{Car}) + (2.14 \times V_{LCV}) + (0.19 \times VS) + \left(0.49 \times LPC_{Entry}\right) \quad (8.9)$$

8.3.2.1 Effect of pedestrian and vehicle parameters on PDZ boundaries

The equations 8.8 and 8.9 are used to estimate the lower and upper boundary limits of PDZ respectively at four-legged uncontrolled intersections. From the equations, it was observed that the boundary limits of PDZ significantly affected by the pedestrian parameters like gender, age, crossing speed and location of crossing, and vehicle parameters like type and speed. The PDZ boundary limits lies close to the intersection in case of male and young pedestrians compared to female and old age pedestrians respectively. They shift away from the intersection with the increase in pedestrian age (except children). For children, the boundary limits were higher and shifts away from the intersection compared to old age pedestrians. The boundary limits were higher and shifts away from the intersection when the pedestrians crossing at lower speeds compared to pedestrians crossing at higher speeds. Also, they shift away from the intersection when the pedestrian crossing at the entry point of the intersection compared to exit point.

The boundary limits of PDZ shifts away from the intersection with the increase in size of vehicles. LCVs have higher boundary limits and they shift away from the intersection compared to 2Ws. Therefore, it is concluded that the pedestrians have more dilemma with LCVs at comparatively longer distances with 2Ws. The boundary limits of PDZ (location from the intersection or crosswalk or pedestrian trajectory path) at four-legged intersections shifts away from the intersection with the increase in approaching speeds of conflicting vehicles. Pedestrians will have more dilemma at longer distances when the vehicle approaching the intersection with higher speeds

8.3.2.2 Validation of BL model

The prediction success table (confusion matrix) was used to evaluate the performance of the developed model at four-legged intersections with 0.5 as threshold value of classification. Table 8.8 shows the prediction success table for the developed BLM at four-legged uncontrolled intersections. From the table 8.5, the sensitivity and specificity were found to be 90.2% and 70.1% respectively. The overall prediction success rate for the developed model was 83.5%. Overall, the developed model predict the correct values with an accuracy of 83.5%.

The model fitting information of the developed BLM at four-legged intersections was shown in table 8.9. The McFadden pseudo R^2 value calculated in the present study was 0.595 (i.e., 1-(1895.86/4686.346)), which would suggest that the developed model is highly satisfactory. Also, lower values of Akaike's Information Criteria (AIC), Bayesian Information Criterion (BIC), and -2log likelihood values of the final model when compared with intercept only model indicates the good fit of the developed model for four-legged intersections.

Table 8.8: Prediction success table for developed model at four-legged intersections

<table>
<tr><td colspan="2" rowspan="3">Observed</td><td colspan="3">Predicted</td></tr>
<tr><td colspan="2">Gap</td><td rowspan="2">Percentage Correct</td></tr>
<tr><td>Reject</td><td>Accept</td></tr>
<tr><td rowspan="2">Gap</td><td>Reject</td><td>2209</td><td>240</td><td>90.2%</td></tr>
<tr><td>Accept</td><td>368</td><td>861</td><td>70.1%</td></tr>
<tr><td colspan="2">Overall Percentage</td><td colspan="3">83.5%</td></tr>
</table>

Table 8.9: Model fitting information of binary logit model at four-legged intersections

Model	Model fitting criteria			Likelihood ratio test		
	AIC	BIC	-2 log likelihood	Chi-square	df	sig.
Intercept only model	4688.346	4694.556	4686.346			
Final model	1921.860	2002.591	1895.86	2790.486	12	0.000
McFadden pseudo R^2	0.595					

8.4 Summary

In the present chapter, estimated the boundary limits and length of PDZ at uncontrolled intersections using GCD and SVM methods. SVM better predicted the boundary limits with largest margin compared to GCD method. The PDZ boundary limits at three-legged intersections were higher and shifts away from the intersection or crosswalk or pedestrian trajectory path compared to four-legged intersections.

Binary logit models were developed separately for three-legged and four-legged uncontrolled intersections to estimate the lower and upper boundary limits of PDZ corresponding to 0.1 and 0.9 probabilities of gap acceptance respectively. Pedestrian (gender, age, and crossing speed), vehicle (type, approaching speed, distance from pedestrian trajectory path), and geometric (location of crossing) parameters were found to be statistically significant with the gap acceptance behaviour of pedestrians at uncontrolled intersections and influence the boundary limits of PDZ. The developed models were validated using classification table, and Nagelkerke's pseudo R-square value.

In the next chapter, summary of the present research work and conclusions drawn from the study are presented. Limitations of the present study, scope of future work, and the contributions are also presented in the next chapter.

CHAPTER 9: SUMMARY AND CONCLUSIONS

9.1 General

This chapter deals with the overall summary of the present research work, conclusions drawn from the present research, major contributions of the present study, limitations of this study, and future scope of the present research.

9.2 Summary of the study

Four 3-legged and four 4-legged uncontrolled intersections were selected from Warangal and Visakhapatnam districts in India. Video graphic method was used to collect the traffic data from all study locations. Cameras were fixed at an elevation in such a way that traffic coming and leaving from each leg of the intersection is clearly visible. Video was recorded continuously for two hours in the morning (7:30AM to 9:30AM) and evening (4:30PM to 6:30PM) periods from each study location on a week day. Geometric details of all study locations were directly measured from the field. MPC-HC media player, Kinovea and DataFromSky softwares were used to extract the pedestrian (gender, age, crossing speed, presence of luggage and mobile phones, crossing type, and collision time) and vehicle (type, approaching speed, distance from pedestrian trajectory path, and collision time) parameters. Severity of P-V interactions also extracted from the video using visual observations. Pedestrians are classified based on the characteristics of age: children (<15 years), young (15-30 years), middle age (30-60 years) and old age (>60 years), gender: male and female, luggage: crossing with luggage and crossing without luggage, mobile phones: using mobile phones while crossing and crossing without using mobile phones. Severity of P-V interactions is classified as no interaction (both road users travel at their present speed to avoid collision), low severe interaction (both or one of the road users must change his/her speed to avoid collision), moderately severe interaction (one road user must stop and other road user may or may not change his/her current speed to avoid collision) and severe interaction (both road users must stop and proceed to avoid collision). Risk indicator (RI) was calculated using approaching speed of vehicle and post encroachment time (PET). Statistical tests were carried out on the crossing speeds of pedestrians with respect to gender and age, and approaching speeds of vehicles with respect to type of vehicle to know the variations in the speeds.

Threshold limits of PET and RI were defined for different categories of pedestrians (gender) and vehicles (type) using SVM multiclass classification algorithm in Python interface at 3-

legged and 4-legged uncontrolled intersections. The performance of classified data was described with confusion matrix and measured the accuracy of classified data using true positives, true negatives, false positives, and false negatives. The results showed that there is difference in threshold limits of PET and RI at 3-legged and 4-legged intersections.

P-V interaction severity levels were classified using threshold RI limits, pedestrian gender, and vehicle type for all the extracted samples. Chi-square test has been carried out in Statistical Package for the Social Sciences (SPSS) software between the dependent (severity of P-V interactions) and independent variables and the variables with p-value less than 0.05 and lesser Chi-square value were not included in the ordinal logistic regression (OLR). OLR has been performed in SPSS for 95% confidence interval and estimates of variables with $p<0.05$ were included in the model. Odds ratios (OR) of other variables were compared with odds ratio of reference variable (OR of reference variable is one). The severity of a variable was higher than that of reference variable if the OR>1.0. The severity of P-V interactions at 3-legged and 4-legged intersections were compared using OR. The developed mode was validated using log likelihood ratio, chi-square value, and McFadden's pseudo R^2 value.

Gap cumulative distribution (GCD) and support vector machine (SVM) methods were used to estimate the boundary limits of pedestrian dilemma zone (PDZ) at 3-legged and 4-legged uncontrolled intersections. In GCD method, a plot between cumulative % gap accepted/rejected on y-axis and distance on x-axis was plotted and the distances corresponding to 10% accepted gaps and 90% rejected gaps were taken as the lower and upper boundary limits of the PDZ. In SVM method, distances of the vehicles from the pedestrian trajectory paths and pedestrian crossing speeds for both accepted and rejected gaps were plotted on a coordinated system. The distances on the optimal hyperplane corresponding to -2σ and $+2\sigma$ from the mean speed were taken as the lower and upper boundary limits of PDZ. The performance of classified data in SVM was described with confusion matrix and measured the accuracy of classified data using true positives, true negatives, false positives, and false negatives. Boundary limits and length of PDZ at 3-legged and 4-legged intersections were compared.

Binary logistic regression (BLR) has been performed in SPSS software at 95% confidence interval for 3-legged and 4-legged intersections using gap accept/reject as dependent variable and pedestrian, vehicle, and geometric characteristics as independent variables to determine the probability of gap acceptance. The estimates of the variables from regression analysis with $p<0.05$ were used for the models development. The boundary limits of PDZ were estimated from the BL models corresponding to 0.1 and 0.9 probabilities of pedestrian gap acceptance. The model fitting of the developed BL models were validated with classification table, log likelihood test, chi-square value, and Nagelkerke pseudo R^2.

9.3 Conclusions

The following conclusions were drawn from the present study,

1. Average crossing speeds of male pedestrians are higher than female pedestrians. Young pedestrians have higher crossing speeds compared to children, middle age and old age pedestrians respectively. Higher risk-taking behaviour in case of male and young pedestrians is the reason for higher crossing speeds. Pedestrian crossing speeds are higher at 3-legged uncontrolled intersections compared to 4-legged uncontrolled intersections.
2. Approaching speeds of 2Ws are higher than cars, 3Ws, LCVs, and HCVs respectively. Easy manoeuvre at higher speeds due to the size benefit is the reason for higher approaching speeds in case of 2Ws. Three-legged intersections have higher approaching vehicular speeds than four-legged intersections. Less number of conflicting points at 3-legged intersections is the reason for higher vehicular speeds.
3. Severity of P-V interactions has inverse correlation with PET and direct correlation with RI. Severity of P-V interactions increases with the increase in RI values and decrease in PET values.
4. Two-wheelers have lower threshold PET limits and higher RI limits compared to cars, 3Ws, LCVs, and HCVs. Male pedestrians have lower threshold PET limits and higher threshold RI limits than female pedestrians. Higher approaching speeds and crossing speeds in case of 2Ws and male pedestrians is the reason for lower PET values. 3-legged intersections have lower threshold PET values and higher threshold RI values compared to 4-legged intersections.
5. The statistical test (Chi-square test) results reveals that pedestrian platoon size, crossing type, and lane on which P-V interaction occurs don’t have significant effect on the severity of P-V interactions. The severity of P-V interactions is significantly influenced by pedestrian gender, age, crossing speed, presence of luggage and mobile phones, vehicle type, approaching speeds, direction of vehicle travel, and location of an interaction.
6. The severity of P-V interactions is higher for male and young pedestrians compared to female and other age groups respectively. Presence of luggage and usage of mobile phones

while crossing increase the severity of interactions. Increase in pedestrian crossing speed also increases the severity of P-V interactions.

7. The severity of P-V interactions is higher for 2Ws compared to cars, 3Ws, LCVs, and HCVs respectively. The increase in vehicular speeds increase the severity of P-V interactions.
8. Three-legged uncontrolled intersections have higher severity levels of P-V interactions compared with four-legged uncontrolled intersections.
9. Pedestrian dilemma zone boundaries shift away from the crosswalk or intersection with the increase in pedestrian age (except for children), vehicle size, and vehicular speeds and lies close to the intersection with the increase in pedestrian crossing speed. Also, lies close to the intersection in case of male pedestrians and interaction occurs at the exit point of the intersection.
10. The boundary limits and length of PDZ at 3-legged intersections are higher and shifts away from the crosswalk or intersection compared with 4-legged intersections.

9.4 Contributions of the study

The major contributions of the present study are:

1. The present study proposed the threshold limits of SSMs (for both PET and RI) using pedestrian (gender and speed) and vehicle (type and speed) characteristics to classify the severity levels of P-V interactions at 3-legged and 4-legged uncontrolled intersections. One of the advanced machine learning algorithms was used in the present study for multiclass classification purpose. The proposed threshold values can be used to predict the severity of an interaction based on interacting pedestrian gender, vehicle type and either PET or RI. This predicted severity levels will help to know the pedestrian safety at an uncontrolled intersection.
2. This study developed the ordinal logistic regression (OLR) models for P-V interactions at 3-legged and 4-legged uncontrolled intersections to know the effect of various parameters on severity of interactions. This study considered two new variables i.e. location of P-V interaction (whether pedestrian is crossing at entry or exit of the intersection) and lane distribution (lane on which P-V interaction occurs) in the OLR analysis to know their effect on the severity of interactions. This study also considered the other less explored variables like presence of luggage, mobile phones, pedestrian crossing type and direction of vehicle traveling in the OLR analysis to know their effect on the severity of interactions. The OLR

model results can be used for predicting the severity of a possible P-V interactions at uncontrolled intersections. The predicted severities will help to know the pedestrian safety at uncontrolled intersections more precisely.

3. This study proposed upper and lower boundary limits of PDZ at uncontrolled intersections that helps the pedestrians to eliminate the dilemma behaviour. Also, this study developed the PDZ models at uncontrolled intersections to know the effect of various pedestrian, vehicle, and geometric characteristics on boundary limits of PDZ. A possible policy direction towards the practical field applications of PDZ boundary limits proposed in the present study will help to eliminate the dilemma behaviour of pedestrians and improve their safety at uncontrolled intersections. The proposed PDZ boundary limits in this study can be used for better understanding of P-V interactions using simulation tools.

9.5 Limitations of the study and future research

There are some limitations in the present study even though it addressed the majority of parameters which affects P-V interaction severity levels and PDZ.

1. The present study didn't consider the pedestrian age to define the threshold limits of SSMs. But the OLR models proved that the severity of P-V interactions depends on pedestrian age. In future, the researchers can extend their work to define the threshold limits of SSMs using pedestrian age also. For example, the present study proposed the threshold PET limits of M-2W category for various severity levels. In future, it can be extended to define the threshold PET limits of M-Age-2W category for various severity levels.
2. The present study was conducted in a clear weather condition. This study omitted the effect of weather and environmental conditions on severity of P-V interactions in developing the OL models. In future, the researchers can be extended their work to develop P-V interactions severity models using pedestrian, vehicle, geometric, weather, and environmental characteristics.
3. This study estimated the spatial PDZ boundary limits at 3-legged and 4-legged uncontrolled intersections only. In future, this research can be extended to estimate the PDZ boundary limits at other pedestrian crossing locations also. This study didn't estimate the dynamic variations of the PDZ boundary limits with respect to various pedestrian, vehicle and geometric characteristics.

4. The present study is limited to 3-legged and 4-legged uncontrolled intersections but a detailed study of P-V interactions at various pedestrian crossing locations will help for better understanding of P-V interaction severity levels.

APPENDIX A

Support Vector Machine Code to determine threshold values of SSMs

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix, accuracy_score
import numpy as np
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
data_clear = pd.read_csv('SVM.csv')
Gender = 'm'
veh_type = '2W'
data_clear_copy = data_clear[(data_clear['Gender'] == Gender) & (data_clear['veh cat'] ==
veh_type)]
y = data_clear_copy.pop('sev code')
data = data_clear_copy[['Ped speed', 'speed/pet']].copy()
X = data.copy()
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 23)
le = LabelEncoder()
y_train = le.fit_transform(y_train)
y_test = le.transform(y_test)
model = SVC(kernel = 'linear', gamma ='auto', C=10000)
model.fit(X_train, y_train)
predict = model.predict(X_test)
confusion_matrix(y_test, predict)
print('Accuracy Score', accuracy_score(y_test, predict))
X_train = np.array(X_train)
x_min, x_max = X_train[:, 1].min() - 1, 20
y_min, y_max = 0, 3.0
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.02),
                     np.arange(y_min, y_max, 0.02))
Z = model.predict(np.c_[yy.ravel(), xx.ravel()])
Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, cmap = 'RdYlBu_r', alpha = 0.9)
plt.scatter(X_train[:, 1], X_train[:, 0], c = y_train, cmap = 'RdYlBu_r', edgecolors = 'black')
```

```
plt.xlabel('Risk Indicator')
plt.ylabel('Pedestrian Speed (m/s)')
plt.xticks(np.arange(0, 20, 1))
plt.xlim(xx.min(), xx.max())
plt.ylim(yy.min(), yy.max())
plt.title(Gender.upper() + '-' + veh_type.upper())
plt.show()
```

REFERENCES

1. Ahmed, T., and Tarek, S. (2018). "Models to evaluate the severity of pedestrian vehicle conflicts in five cities." *Transportmetrica A: Transport Science: 15(2),* 354-375.
2. Alhajyaseen, W.K.M. (2015). "The Integration of Conflict Probability and Severity for the Safety Assessment of Intersections." *Arabian Journal for Science and Engineering*, 421-430.
3. Allen, B.L., Shin, B.T., Cooper, D.J. (1978). "Analysis of traffic conflicts and collision." *Transportation Research Record: 667*, 67–74.
4. Almodfer, R., Xiong, S., Fang, Z., Kong, X., and Zheng, S. (2016). "Quantitative analysis of lane-based pedestrian-vehicle conflict at a non-signalized marked crosswalk." *Transportation Research Part F: 42*, 468-478.
5. Amado, H., Ferriera, S., Tavares, J.P., Ribeiro, P., and Freitas, E. (2020). "Pedestrian-Vehicle Interaction at Unsignalized Crosswalks: A Systematic Review." *Sustainability: 12*, 1-23. doi:10.3390/su12072805
6. Amin, H.J., Desai, R.N., and Patel, P.S. (2014). "Modelling the crossing behavior of pedestrian at uncontrolled intersection in case of mixed traffic using adaptive neuro fuzzy inference system." *Journal Traffic Logistic Engineering: 2(4),* 263-270.
7. Archer, J. (2004). "Methods for the Assessment and Prediction of Traffic Safety at Urban Intersections and Their Application in Micro Simulation Modelling." *Academic Thesis, Royal Institute of Technology, Stockholm,* Sweden.
8. Asaithambi, G., Kuttan, M.O., and Chandra, S. (2016). "Pedestrian Road Crossing Behavior under Mixed Traffic Conditions: A Comparative Study of an Intersection before and after Implementing Control Measures." *Transportation in Developing Economies: 2(14),* 1-12.
9. Ashton, S.J., Pedder, J.B., and Mackay, G.M. (1977). "The Bumper and Other Front Structures." *International IRCOBI Conference on the Biomechanics of Impact*.
10. Augenstein, J., Perdeck, E., Stratton, J., Digges, K., Bahouth, G. (2003). "Characteristics of crashes that increase the risk of serious injuries." Assoc. Adv. Automot. Med. Ann. Proc., 561–576.
11. Bagdadi, O., and Varhelyi, A. (2011). "Jerky driving-An indicator of accident proneness?" *Accident Analysis & Prevention: 43(4),* 1359–1363.
12. Cafiso, S., Garcia, A., Cavarra, R., Romero, M.A. (2011). "Crosswalk Safety evaluation using a Pedestrian Risk Index as Traffic Conflict Measure." *3rd International Conference on Road Safety and Simulation, Indianapolis, USA*, 1-15.

13. Chandrappa, A.K., Bhattacharyya, K., and Maitra, B. (2015). “Estimation of PET and Threshold Wait Time for Pedestrians on Busy Urban Corridor in Heterogeneous Traffic Environment: An Experience in Kolkata.” *Conference on Eastern Asian Society for Transportation Studies*, Philippines, 1-10.
14. Chen, P., Wu, C., and Zhu, S. (2016). “Interaction between vehicles and pedestrians at uncontrolled mid-block crosswalks.” *Safety Science 82*, 68-76.
15. Chen, P., Zeng, W., Yu, G., and Wang, Y. (2017). “Surrogate Safety Analysis of Pedestrian-Vehicle Conflict at Intersections Using Unmanned Aerial Vehicle Videos.” *Journal of Advanced Transportation*, 1-12.
16. Chen, P., Zeng, W., and Yu, G. (2019). “Assessing right-turning vehicle-pedestrian conflicts at intersections using an integrated microscopic simulation model.” *Accident Analysis and Prevention: 129*, 211-224. https://doi.org/10.1016/j.aap.2019.05.018
17. Dutta, B., and Vasudevan, V. (2017). “Study on Pedestrian Risk Exposure at Unsignalized Intersection in a Country with Extreme Vehicle Heterogeneity and Poor Lane Discipline.” *Transportation Research Record Journal of the Transportation Research Board: 2634(1)*, 69-77. 10.3141/2634-11
18. Fancher, P.S., Branchet, Z. (1998). “Evolving model for studying driver and vehicle system performance in longitudinal control of headway.” *77th Annual Meeting of the Transportation Research Board*, Washington D.C., USA.
19. Fridman, L., Ling, R., Rothman, L., Cloutier, M.S., Macarthur, C., Hagel, B. and Howard, A. (2020). “Effect of reducing the posted speed limit to 30 km per hour on pedestrian motor vehicle collisions in Toronto, Canada - a quasi-experimental, pre-post study.” *BMC Public Health*, 1-8.
20. Fu, T., Moreno, L.M., and Saunier, N. (2016). “Measuring crosswalk safety at non signalized crossings during night time based on surrogate measures of safety: Case study in montreal, Canada.” *Transportation Research Record Journal of the Transportation Research Board: 2586(1)*, 90-99. 10.3141/2586-10.
21. Fu, T., Moreno, L.M., and Saunier, N. (2018). “A novel framework to evaluate the pedestrian safety at non-signalized locations.” *Accident Analysis and Prevention: 111*, 23-33. https://doi.org/10.1016/j.aap.2017.11.015
22. Fu, T., Hu, W., Moreno, L.M., and Saunier, N. (2019). “Investigating secondary pedestrian-vehicle interactions at non-signalized intersections using vision-based trajectory data.” *Transportation Research Part C: 105*, 222-240.

23. Gates, T.J., Noyce, D.A., Laracuente, L., and Nordheim E.V. (2007). "Analysis of Driver Behaviour in Dilemma Zones at Signalized Intersections." *Transportation Research Record: Journal of the Transportation Research Board*, 29-39. DOI: 10.3141/2030-05
24. Gates, T.J., and Noyce, D.A. (2010). "Dilemma Zone Driver Behaviour as a Function of Vehicle Type, Time of Day, and Platooning." *Transportation Research Record: Journal of the Transportation Research Board*, 84-93. DOI: 10.3141/2149-10.
25. Getman, D., Pu, L., Sayed, T., and Shelby, S.G. (2008). "Surrogate Safety Assessment Model and Validation: Final Report." *FHWA-HRT*, 08-051.
26. Gorrini, A., Vizzari, G., and Bandini, S. (2016). "Towards Modelling Pedestrian-Vehicle Interactions: Empirical Study on Urban Unsignalized Intersection." *Proceedings of the 8th International Conference on Pedestrian and Evacuation Dynamics*, 1-10.
27. Gyimah, R.A., Saberi, M., and Sarvi, M. (2016). "Macroscopic modeling of pedestrian and bicycle crashes: Across-comparison of estimation methods." *Accident Analysis and Prevention*, 147-159.
28. Goyani, J., Pawar, N., Gore, N., Jain, M., and Arkatkar, S. (2019). "Investigation of traffic conflicts at un-signalized intersection for reckoning crash probability under mixed traffic conditions." *Journal of the Eastern Asia Society for Transportation Studies*, 2091–2110.
29. Hamed, M.M. (2001). "Analysis of pedestrians' behavior at pedestrian crossings." *Safety Science: 38(1)*, 63-82. 10.1016/S0925-7535(00)00058-8
30. Haleem, K., Alluri, P., Gan, A. (2015). "Analyzing pedestrian crash injury severity at signalized and non-signalized locations." *Accident Analysis and Prevention 81*, 14-23. http://dx.doi.org/10.1016/j.aap.2015.04.025
31. Harrel, W.A. (1990). "Factors Influencing Pedestrian Cautiousness in Crossing Streets" *The Journal of Social Psychology: 131(3)*, Psychology: 131(3), 67-372. 10.1080/00224545.1991.9713863
32. Haung, C., and Ma, W. (2010). "A Statistical Analysis of Pedestrian Speed on Signalized Intersection Crosswalk." *Tenth International Conference of Chinese Transportation Professionals (ICCTP), Beijing, China*.
33. Hayward, J.C. (1972). "Near-miss determination through use of a scale of danger." *Highway Research Record: 384*, 24-34.
34. Hsu, Y.C., Gopalswamy, S., Saripalli, S., and Shell, D.A. (2018). "An MDP Model of Vehicle-Pedestrian Interaction at an Unsignalized Intersection." *2018 IEEE 88th Vehicular Technology Conference (VTC-Fall)*, 1-6. doi: 10.1109/VTCFall.2018.8690813

35. Hu, L., Ou, J., Huang, J., Wang, F., Wang, Y., Ren, B., Peng H., and Zhou L. (2021). “Safety evaluation of pedestrian-vehicle interaction at signalized intersections in Changsha, China.” *Journal of Transportation Safety & Security*, 1-26.
36. Hupfer, C. (1997). “Deceleration to safety time (DST)-a useful figure to evaluate traffic safety.” *Proceeding of the ICTCT Conference Proceedings of Seminar 3, Department of Traffic Planning and Engineering, Lund University*, Lund, Sweden.
37. Hyden, C. (1987). “The development of a method for traffic safety evaluation: The Swedish Traffic Conflicts Technique.” *Doctoral dissertation, Lund University*, Lund, Sweden.
38. Ismail, K., Sayed, T., Saunier, N., and Lim, C. (2009) “Automated Analysis of Pedestrian–Vehicle Conflicts Using Video Data.” *Transportation Research Record: Journal of the Transportation Research Board: 2140*, 44-54. DOI: 10.3141/2140-05
39. Ismail, K., Sayed, T., and Saunier, N. (2010) “Automated analysis of pedestrian-vehicle conflicts: Context for before-and-after studies.” *Transportation Research Record: 2198*, 52-64.
40. Ismail K, Sayed T, and Saunier N (2011) “Methodologies for Aggregating Indicators of Traffic Conflict”, *Transportation Research Record: Journal of the Transportation Research Board: 2237*, 10–19.
41. Jain, A., Gupta, A., Rastogi, R. (2014). “Pedestrian crossing behavior analysis at intersections.” *Journal of Traffic and Transportation Engineering: 4(1)*, 103-116. 10.7708/ijtte.2014.4(1).08
42. Jiang, J. (2015). “Intercultural Analyses of Time-to Collision in Vehicle–Pedestrian Conflict on an Urban Midblock Crosswalk.” *IEEE transactions on intelligent transportation systems: 16(2)*,1-15.
43. Kaparias, I., Bell, M.G.H., Greensted, J., Cheng, S., Miri, M., Taylor, C., and Mount, B. (2010). “Development and Implementation of a Vehicle-Pedestrian Conflict Analysis Method.” *Transportation Research Record: Journal of the Transportation Research Board: 2198*, 75-82. DOI: 10.3141/2198-09
44. Kathuria, A., and Vedagiri, P. (2020). “Evaluating pedestrian vehicle interaction dynamics at un-signalized intersections: A proactive approach for safety analysis.” *Accident Analysis and Prevention: 134*, 1-15. https://doi.org/10.1016/j.aap.2019.105316
45. Keall, M.D. (1995). “Pedestrian exposure to risk of road accident in New Zealand.” *Accident Analysis and Prevention: 27(5)*, 279-740. 10.1016/0001-4575(95)00019-v
46. Kelly, J.C., and Kevin, J.K. (2004). “The Utility of the NHTS in Understanding Bicycle and Pedestrian Travel.” *National Household Travel Survey Conference, Washington*, 1-18.

47. Kloeden, C.N., Ponte, G. and McLean, A.J. (2001). "Travelling speed and the risk of crash involvement on rural roads." *Report CR 204*, Australian Transport Safety Bureau, Canberra, ACT.
48. Kumar, A., Paul, M., and Ghosh, I. (2019). "Analysis of Pedestrian Conflict with Right-Turning Vehicles at Signalized Intersections in India." *Journal of Transportation Engineering, Part A: Systems: 145(6)*, 1-12.
49. Laureshyn, A., Svensson, A., and Hyden, C. (2010). "Evaluation of traffic safety, based on micro-level behavioural data: Theoretical framework and first implementation." *Accident Analysis and Prevention: 42*, 1637-1646.
50. Laureshyn, A., Ceunynck, T.D., Karlsson, C., Svensson, S., Daniels, S. (2017). "In search of the severity dimension of traffic events: Extended Delta-Vas a traffic conflict indicator." *Accident Analysis and Prevention: 98*, 46-56. http://dx.doi.org/10.1016/j.aap.2016.09.026
51. Lee, C., Abdel-Aty, M. (2005). "Comprehensive analysis of vehicle–pedestrian crashes at intersections in Florida." *Accident Analysis and Prevention*, 775-786.
52. Liu, Y.C., and Tung, Y.C. (2014). "Risk Analysis of Pedestrians' Road-Crossing Decisions: Effects of Age, Time Gap, Time of Day, and Vehicle Speed." Safety Science: 63, 77-82. https://doi.org/10.1016/j.ssci.2013.11.002
53. Lord, D. (1996). "Analysis of Pedestrian Conflicts with Left-Turning Traffic." *Transportation Research Record: 1538*, 61-67.
54. Ma, Z., Lu, X., Chien, S.I., and Hu, D. (2017). "Investigating factors influencing pedestrian injury severity at intersections." *Traffic Injury Prevention*, 1-9.
55. Madigan, R., Lee, Y.M., and Merat, N. (2021). "Validating a methodology for understanding pedestrian –vehicle interactions: A comparison of video and field observations." *Transportation Research Part F: 81*, 101-114. https://doi.org/10.1016/j.trf.2021.05.006
56. Mejas, E.J., Ruiz, V.M., Prieto, C.A., and Requena, R.O. (2016). "Pedestrian- and driver-related factors associated with the risk of causing collisions involving pedestrians in Spain." *Accident Analysis and Prevention: 92*, 211-218. 10.1016/j.aap.2016.03.021
57. Makia, T., Kajzer, J., Mizunoc, K., and Sekine, Y. (2002). "Comparative analysis of vehicle–bicyclist and vehicle–pedestrian accidents in Japan." *Accident Analysis and Prevention: 35*, 927-940.
58. Marisamynathan, S., and Perumal, V. (2014). "Study on Pedestrian Crossing Behavior at Signalized Intersections." *Journal of Traffic and Transportation Engineering: 1(2)*, 103-110.

59. Marisamynathan, S., and Vedagiri, P. (2020). "Pedestrian Safety Evaluation of Signalized Intersections using Surrogate Safety Measures." *Transport 35(1)*, 48-56.
60. Minderhoud, M.M., and Bovy, P.H.L. (2001). "Extended time-to-collision measures for road traffic safety assessment." *Accident Analysis and Prevention*, 89-97.
61. Montufar, J., Arango, J., Porter, M., and Nakagawa, S. (2007). "Pedestrians' Normal Walking Speed and Speed When Crossing a Street." *Journal of the Transportation Research Board*, 90-97.
62. MoRTH (2020). "Road Accidents in India: 2020." *Ministry of Road Transport and Highways*, New Delhi, 1-267.
63. Muley, D., Kharbeche, M., Alhajyaseen, W., and Al-Salem, M. (2017). "Pedestrians' Crossing Behavior at Marked Crosswalks on Channelized Right-Turn Lanes at Intersections." *Procedia Computer Science: 109C*, 233-240.
64. Muppa, K.R., Kumar, C.N., and Tallam, T. (2022). "Vehicle-Pedestrian Interaction Analysis at Un-signalized Intersection using Trajectory Data." *Earth and Environmental Science: 982*, 1-11. doi:10.1088/1755-1315/982/1/01205
65. Neal-Sturgess, C.E., Coley, G. and Oliveira, D.P. (2002). "Pedestrian Injuries: Effects of Impact Speed and Contact Stiffness." *Conference on IMechE Vehicle Safety*.
66. Ni, Y., Wang, M., Sun, J., Li, K. (2016). "Evaluation of pedestrian safety at intersections: A theoretical framework based on pedestrian-vehicle interaction patterns." *Accident Analysis and Prevention: 96*, 118-129. http://dx.doi.org/10.1016/j.aap.2016.07.030
67. Nie, B., Li, Q., Gan, S., Xing, B., Huang, Y., and Li, S.B. (2021). "Safety envelope of pedestrians upon motor vehicle conflicts identified via active avoidance behaviour." *Scientific Reports*, 1-10.
68. Oda, T., Suda, Y., Tanaka, S., and Yamaguchi, D. (2007). "Evaluation of Stopping Behaviour of Drivers in Dilemma Zone Using Driving Simulator." *International Journal of ITS Research: 5(1)*, 47-54.
69. Olszewski, P., Buttler, I., Czajewski, W., Dabkowski, P., Kraskiewicz, C., Szagala, P., and Zielinska, A. (2016). "Pedestrian safety assessment with video analysis." *Transportation Research Procedia*, 2044 – 2053.
70. Papadimitriou, E., Yannis, G., and Golias J. (2012). "Analysis of Pedestrian Exposure to Risk in Relation to Crossing Behavior." *Transportation Research Record: Journal of the Transportation Research Board*, 79-90.

71. Patel, A.V., Hildebrand, J.S., Leach, C.R., Campbell, P.T., Doyle, C., Shuval, K., Wang, Y., and Gapstur, S.M. (2018). “Walking in relation to mortality in a large prospective cohort of older U.S. adults.” *American Journal of Preventive Medicine: 54*, 10-19.
72. Pathivada, B.K., and Perumal, V. (2019). “Analysing dilemma driver behaviour at signalized intersection under mixed traffic conditions.” *Transportation Research Part C: 60*, 111-120. https://doi.org/10.1016/j.trf.2018.10.010
73. Patra, M., Sala, E., Ravishankar, K.V.R. (2017). “Evaluation of pedestrian flow characteristics across different facilities inside a railway station.” Transportation Research Procedia 25, 4767-4774. 10.1016/j.trpro.2017.05.488
74. Pawar, D.S., Kumar, V., Singh, N., and Patil, G.P. (2016). “Analysis of dilemma zone for pedestrians at high-speed uncontrolled midblock crossing.” *Transportation Research Part C: 70*, 42-52. http://dx.doi.org/10.1016/j.trc.2016.04.012
75. Pawar, D.S., and Yadav, A.K. (2022). “Modelling the pedestrian dilemma zone at uncontrolled midblock sections.” *Journal of Safety Research: 80*, 87-96. https://doi.org/10.1016/j.jsr.2021.11.006
76. Pawar, D.S., Pathak, D., and Patil. G.R. (2020). “Modelling Dynamic Distribution of Dilemma Zone at Signalized Intersections for Developing Traffic World.” *Journal of Transportation Safety & Security: 14(5)*, 886-904. https://doi.org/10.1080/19439962.2020.1852464
77. Pawar, D.S., and Patil. G.R. (2022). “Minor-Street Vehicle Dilemma While Maneuvering at Unsignalized Intersections.” *Journal of Transportation Engineering, Part A: Systems, 143(8)*, 1-11. 10.1061/JTEPBS.0000066
78. Ramesh, A., Ashritha, K., and Kumar, M. (2018). “Development of Model for Pedestrian Gap Based on Land Use Pattern at Midblock Location and Estimation of Delay at Intersections.” *Journal of Institute of Engineers: India Series A: 99(3)*, 413-422.
79. Ravishankar, K.V.R., and Nair, P.M. (2018). “Pedestrian risk analysis at uncontrolled midblock and unsignalised intersections.” *Journal of traffic and transportation engineering: 5(2)*, 137-147.
80. Roudsari, B.S., Mock, C.N., Kaufman, R., Grossman, D., Henary, B.Y., and Crandall, J. (2004). “Pedestrian crashes: higher injury severity and mortality rate for light truck vehicles compared with passenger vehicles.” *Injury Prevention: 10*, 154–158.
81. Ryb, G.E., Dischinger, P.C., Kufera, J.A., Burch, C.A. (2007). “Delta V, principal direction of force, and restraint use contributions to motor vehicle crash mortality.” J. Trauma: Inj. Infect. Crit. Care: 63 (5), 1000–1005.

82. Salifu, M. (2004). "Accident Prediction Models for Un-signalized Urban Junctions in Ghana." *IATSS Research: 28*, 68-81.
83. Sandt, L., and Zegeer, C.V. (2006). "Characteristics Related to Midblock Pedestrian–Vehicle Crashes and Potential Treatments." *Transportation Research Record: Journal of the Transportation Research Board, Washington*, 113–121.
84. Santhosh, D., Bindhu, B.K., Koshy, B.I. (2020). "Evaluation of pedestrian safety in unsignalized T and X – Intersections through comparison of the frequency and severity of pedestrian conflicts." *Case Studies in Transport Policy: 8*, 1352-1359. https://doi.org/10.1016/j.cstp.2020.09.006
85. Scholl, L., Elagaty, M., Navarro. B.L., Zamora, E., and Moreno, L.M. (2019). "A Surrogate Video-Based Safety Methodology for Diagnosis and Evaluation of Low-Cost Pedestrian-Safety Countermeasures: The Case of Cochabamba, Bolivia." *Sustainability: 11(17)*, 1-22.
86. Shah, H., and Vedagiri P. (2017). "Evaluation of Pedestrian Safety at Un-signalized Intersection under Mix Traffic Condition Using Surrogate Safety Measures." *15th International Conference on Computers in Urban Planning and Urban Management (CUPUM 2017)*, University of South Australia, Adelaide, 1-20.
87. Sucha, M., Dostal, D., Rissera, R. (2017). "Pedestrian-driver communication and decision strategies at marked crossings." *Accident Analysis and Prevention: 102*, 41–50. https://doi.org/10.1016/j.aap.2017.02.018
88. Sun, D., Ukkusuri, S.V.S.K., Benekohal R.F.,and Waller, S.T. (2003). "Modeling of Motorist-Pedestrian Interaction at Uncontrolled Mid-block Crosswalks." *Paper presented at Annual Meeting of the Transportation Research Board*, Washington: 1-35.
89. Tay, R., Choi, J., Kattan, L., and Khan, A. (2011). "A Multinomial Logit Model of Pedestrian–Vehicle Crash Severity." *International Journal of Sustainable Transportation*, 233-249.
90. Thakur, S., and Biswas, S. (2019). "Assessment of Pedestrian-Vehicle Interaction on Urban Roads: A Critical Review." *Archives of Transport: 51(3)*, 49-63.
91. Tiwari, G., and Nishant (2018). "Travel to Work in India: Current Patterns and Future Concerns." Transport Research & Injury Prevention Programme (TRIPP-PR-18-01), Indian Institute of Technology Delhi, New Delhi.
92. Varhelyi, A. (1998). "Drivers' speed behaviour at a zebra crossing: A case study." Accident Analysis and Prevention: 30(6), 731–743.
93. Varsha, V., and Bindhu, B.K. (2016). "Effect of Pedestrian Characteristics at Signalized Intersection." *International Journal of Engineering Research & Technology*, 1-6.

94. Vasudevan, V., Mehta, M., and Dutta, B. (2020). "Pedestrian temporal gap acceptance behaviour at unsignalized intersections in Kanpur, India." *Transportation Research Part F: 74*, 95-103. https://doi.org/10.1016/j.trf.2020.08.010
95. WHO (2018). "Global status report on road safety: 2018." *World health organization,* 1-20.
96. Winsum, V.W., Martens, M., and Herland, L. (1999). "The effects of speech versus tactile driver support messages on workload, driver behaviour and user acceptance." *Report TNO Human Factors Research Institute*, Soesterberg, Netherlands.
97. Yannis, G., Papadimitriou, E., and Theofilatos, A.A. (2010). "Pedestrian Gap Acceptance for Mid-Block Street Crossing." *World Conference on Transportation Research, Libson, Portugal*.
98. Zaki, M., Sayed, T., and Shaaban, K. (2014). "Using Drivers' Jerk Profiles in Computer Vision based Traffic Safety Evaluations." *Proceedings of the 93rd Annual Meeting of the Transportation Research Board,* Washington D.C., USA.
99. Zegeer, C. (1977). "Effectiveness of Green-extension Systems at High-speed Intersections." *Kentucky Department of Transportation (Research Report 472)*.
100. Zheng, Y., Chase, R.T., Elefteriadou, L., and Schroeder, B.J. (2015). "Modeling vehicle–pedestrian interactions outside of crosswalks." Simulation Modelling Practice and Theory 59, 89-101. 10.1016/j.simpat.2015.08.005
101. Zhang, Y., Yao, D., Qiu, T.Z., Peng, L., and Zhang, Y. (2012). "Pedestrian safety analysis in mixed traffic conditions using video data." *IEEE Transactions on Intelligent Transportation Systems: 13(4),* 1832–1844.

Publications

Journals

1. **Lalam Govinda**, M.R. Sai Kiran Raju and K.V.R. Ravishankar (2022) "Pedestrian-Vehicle Interaction Severity Level Assessment at Uncontrolled Intersections using Machine Learning Algorithms", *Safety Science*, Vol. 153, pp. 01-09. (**SCI, IF: 6.392**)
2. **Lalam Govinda** and K.V.R. Ravishankar (2022) "A critical review on Pedestrian Road Crossing Behaviour and Pedestrian-Vehicle Interactions", *Innovative Infrastructure Solutions: 7:313*, pp. 1-14. https://doi.ord/10.1007/s41062-022-00917-6 (**Scopus**)
3. **Govinda Lalam** and Ravishankar K.V.R. (2022) "Pedestrian Gap Acceptance Behavioural Modelling at Midblock and Uncontrolled Intersections", *U. Porto Journal of Engineering*. (**Accepted, Scopus**)
4. **Lalam Govinda**, Doddapaneni Abhigna, Parvathy M Nair, and K.V.R. Ravi Shankar (2020) "Comparative Study of Pedestrian Crossing Behaviour at Uncontrolled Intersection and Midblock Locations", **Transportation Research Proceedings**, Vol. 48, pp. 698-706. (**Scopus**)

Conferences

1. **L. Govinda**, G. Dharma Teja, K.V.R Ravi Shankar (2020) "Analysis of Pedestrian-Vehicle Interactions at Uncontrolled Intersections under Mixed Traffic Conditions", Second ASCE India Conference (CRSIDE2020), Kolkata, India.
2. **L. Govinda**, D. Abhigna, S. Eswar, K.V.R Ravi Shankar (2019) "Effect of Pedestrian Characteristics on Traffic Performance at Uncontrolled Intersections using Microsimulation", International Conference on Innovative Trends in Civil Engineering for Sustainable Development (ITCSD-2019), NIT Warangal, India.
3. **L. Govinda**, D. Abhigna, P.M. Nair, and K.V.R. Ravi Shankar (2019) "Comparative Study of Pedestrian Crossing Behaviour at Uncontrolled Intersection and Midblock Locations", World Conference on Transport Research (WCTR-2019), Mumbai, India.