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Modelling Pedestrian-Vehicle Conflict and Severity at Uncontrolled Midblock Crossings Inside Kathmandu Valley

Ashish Banstola [a], Pradeep Kumar Shrestha [b]

[a, b] *Department of Civil Engineering, Pulchowk Campus, IOE, Tribhuvan University, Nepal*
[a] 076mstre003.ashish@pcampus.edu.np, [b] pradeep.shrestha@pcampus.edu.np

Abstract

Pedestrian safety at uncontrolled urban midblock crossings is a critical prerequisite for sustainable urban transport. Evaluation of factors affecting pedestrian-vehicle conflict helps designers to proactively implement warrants to reduce the risk at such crossings. This study uses pedestrian safety margin(PSM),a surrogate safety measure, to further define scenarios of conflict and severity. The contributing factors for occurance of conflict were modelled and analyzed through binary logistic regression. In addition, an ordinal logit model was also developed to examine their influence on probability of occurance of 4 different levels of severity of conflict whose thresholds were defined on the basis of Pedestrian Vehicle Scaled Risk Indicator(PVSRI). Results show remarkable goodness of fit for conflict model ($AUC = 0.91, A = 84\%$) and ordinal sverity models ($A = 61\%$). Pedestrian speed,waiting time,vehicle type,pedestrian group size,accepted vehicular gap size,nature of crossing and lane position were found to have significantly impacted the odds of conflict and higher severity.

Keywords

Safety Margin, Pedestrian-Vehicle Conflict, Binary Logistic Regression, Ordinal Logistic Regression, Conflict Severity

1. Introduction

1.1 Background

Midblock pedestrian crossings are considered to be a critical component of transport facility as it involves direct interaction between vehicles and pedestrians with risk of failed crossing. Such interaction could be lessened by the use of signals, foot-over bridges and other traffic calming measures, however, fully controlling each and every such crossing simply is infeasible due to economic reasons and there is always a danger of pedestrian non-complying to these facilities, especially in developing countries where people often are inclined to take more risk. In addition, heterogeneous traffic and low yielding rate of drivers in developing countries has made pedestrians even more vulnerable.

A large proportion of pedestrian deaths are reported in urban areas in low and middle income countries [1]. Past researches and findings in Nepal highlighted that pedestrians were most vulnerable groups in road accidents because pedestrian safety had not been considered in design of transport system, which lead the Government of Nepal, in line with UN Global Action Plan for road safety, to introduce Road Safety Action Plan in 2013 envisioning the roles of various government bodies in reducing road crashes which amongst others includes proposition of activities and research work ensuring pedestrian safety at crossings [2]. Despite, in 2016, vulnerable road users (pedestrians, cyclists, and motorcyclists) accounted for approximately 72 percent of all road fatality victims, among the highest rates in the country, with pedestrians accounting for half of those [3].

A nationwide study conducted by Kumar and Suvash (2010) on injuries and violence found road traffic injuries as the most common injury type and nearly half (48.6 percent) of such injuries were borne by pedestrians [4]. And since the sidewalks in urban areas are relatively more safer than crosswalks, it can be reasonably concluded that such injuries occur as a result of unsuccessful crossing.Sustainable goals have envisioned pollution free and pedestrian friendly urban settings and as such, short trips on foot should be preferred compared to taking bus or taxi which can be achieved only through well designed pedestrian facilities [5].

The safety of pedestrians at crossings can be evaluated either by the use of historic crash data or through non crash measurements. Complete crash data could provide sound measurement of safety but in many cases they are either in inadequate form or not available at all, furthermore they only occur very few times and cannot be used to measure potential risk at a crossing where no such incidents has occured. Another form of measuring risk is through non-crash, often called proactive safety measurement, where surrogate measures of safety (SMOS) variables namely, Time to collision (TTC) and Post Encroachment Time(PET) or Safety Margin (SM) are observed. It involves identifying near-miss events (narrowly escaped collisions) and seeks the actual information about the events with driver as well as pedestrian behaviour under site conditions [6].

Pedestrian-vehicle conflicts and crashes are random events whose occurances are influenced by various external factors such as traffic control, geometric design of road [7], behavioral and vehicular characteristics of the road users and so on.Anticipating the risk factors and evaluating pedestrian safety ,could help proactively change the design or policy for pedestrian friendly crossings.With this background, this study is an attempt towards assessing the influence of these elements on the probability of occurance of conflict and its severity, at midblock crossings of Kathmandu Valley using PSM values, one of the common surrogate safety measure of conflict.

1.2 Objectives

The prime objective of this study is to evaluate pedestrian safety at uncontrolled midblock crossings. Specific sub-objectives are:

1. To develop a Pedestrian-Vehicle conflict model to quantify the effects of pedestrian behavior, demographics, vehicular and road characteristics on occurance of conflict.
2. To formulate and analyze Pedestrian-Vehicle conflict severity model against the contributing factors.

2. Literature Review

Road crossing behaviour of pedestrians is inherently tied with their safety. Extensive research have been done on crossing behavior of pedestrians with factors like pedestrian perception, roadway and environmental characteristics taken into account. Earlier studies provide significant facts about pedestrian demographic characteristics (such as age, gender) and how these characteristics influence road crossing behaviour. Such studies have focused on detailed experiments to find out the effect of age on road crossing decisions with effect of vehicle distance or speed of vehicle [8, 9]. Road crossing behaviour with respect to gender has also been observed in various studies [10, 11]. Some studies have also addressed pedestrian road crossing behaviour by considering the effectiveness of educational training programs [12].

The concept of safety margin was first found to be introduced by Oxley et al.(1997) where study was done on differences in behavior of older and younger pedestrians while crossing a two lane undivided road to find out if the decline of cognitive, physical, sensory and perceptual abilities in older generation increases their vulnerability while crossing [8]. The result showed that younger slow walkers left a larger safety margin while the older slow walkers placed themselves at an increased risk of collision by keeping very less safety margin.

Kadali and Vedagiri(2015) conducted similar study at eight different midblock locations in India. In addition to MLR model, a binary logit model for Pedestrian vehicle non-conflict (PVNC) prediction was constructed to see the factors influencing probability of pedestrian-vehicle conflict[6]. Increase in age showed decrease in SM and thus, increase in probability of conflict (PC) while gender was not found significant to the model. Under pedestrian behavioral characteristics, rolling behavior was negatively correlated and platoon size was positively correlated with both SM and PC. Increase in accepted vehicular gap size also showed increase in SM. The results illustrated that pedestrians took more risk with two wheelers and 3 wheelers with less safety margin.

Kadali and Vedagiri (2016) assessed the severity of pedestrian vehicle conflict at unprotected midblock crossings in India. An ordered probit (OP) model was built in which the dependent variable was levels of severity of conflict based upon the distribution of safety margin values [13].

Zhang et al.(2017), unlike aforementioned studies safety margin observed for each lanes[14]. Number of conflicts was taken as an ordinal dependent variable influenced by traffic volume, presence of refuge, crossing strategy among others.Moreover, the study showed rolling crossing more dangerous in multilane crosswalks and also, increase in traffic volume, speed and absence of pedestrian refuge contributed to higher conflicts.

Govinda et.al.(2022) used a new indicator(Risk Indicator (RI)), the ratio of approaching vehicle speed and PET.MLR model was built considering RI as independent variable and pedestrian speed, gender, vehicle type as outcome variables [15].Later, using Support Vector Machine algorithm(SVM), threshold values of RI for pedestrian speed,gender and vehicle type was also generated. MLR results showed that pedestrian gender, age and speed, vehicle type and speed, interaction location and crossing position have a significant effect on RI.

3. Methodology

3.1 Study Area

For the proposed study, an ideal site is an uncontrolled unsignalized midblock crossing (legal/illegal) where the pedestrians cross perpendicular to the direction of movement of vehicles with no or very little amount of side friction and intersection effects. The factors influencing pedestrian-vehicle interaction like crossing decision, increasing/ decreasing speed, how much time to wait in curb, whether to yield vehicle or not, should not be guided by external control factors like YIELD, STOP signs, or traffic signals. Considering these criteria,two midblock crossings, one located at main road of Baneshwor(in front of Everest hospital, about 260 m west of main intersection) (legal) and the other at ring road section of Ekantakuna(illegal) were selected, shown in Figure 1.

(a) 1 **(b)** 2

Figure 1: Site locations

The north side and the south side of both sections are specially designed for public vehicles to pick and drop passenger along the curb. Stoppage (Deceleration and acceleration) of these vehicles affected the speed of other vehicles (following) and also disrupted ideal pedestrian cross flow scenario. On contrary, middle section of four lanes, was found to have no such side friction obstructions and met all other basic site selection criteria. Thus, observation was initiated/terminated once pedestrian reached the one of the two shelters (median like structure separating the two parts).

3.2 Data Collection and Extraction

Videographic survey was conducted at both both locations using a Hero Go-Pro camera. The camera was placed at suitable height to capture the range of all pedestrian vehicle interaction throughout the crossings and, reference marks such that the vehicle speed could be calculated from the video. Recording was later played on VLC media player for frame by frame extraction of data. Survey was done on the month of July 2022 during day time 9:30-11:00 am hours and 4:00pm to 5:00pm hours on weekdays under normal weather condition. Time for survey was chosen from pilot study such that high volume of pedestrian-vehicle interactions could be obtained. About 800 datasets was collected for further statistical analysis.

3.3 Variables Description

Pedestrian and driver behaviour/demographics, roadway and vehicular characteristics are taken into account in an attempt to explain the conflicting behavior of pedestrian. For explaining the influence of demographics, pedestrian gender and age are observed visually from the video. Age groups were categorized into three groups:below 20,between 20 and 40 and above 40 on the basis of pilot survey. Pedestrian group size, waiting time, pedestrian crossing speed are observed to describe pedestrian behavior. Group size is taken as a continuous variable whereas for ordinal logistic regression, it is divided into three categories. Pedestrian speed is calculated

Table 1: Description of Variables

S.N.	Variable names	Variable Type	Proportions
1	Age	Categorical	
	Age <20		108 (19%)
	Age 20-40		373 (64%)
	Age >40		100 (17%)
2	Gen	Categorical	
	F		212 (36%)
	M		369 (64%)
3	GR_Size	Categorical	
	Gr_Size 1		263 (32%)
	Gr_Size (2)		232 (28%)
	Gr_Size(3-4)		206 (25%)
	Gr_Size(5-7)		128 (15%)
4	LE_ILLE	Categorical	
	Illegal		192 (33%)
	Legal		389 (67%)
5	Dry	Continuous	
	0		394 (68%)
	1		103 (18%)
	2		84 (14%)
6	Lan_No	Categorical	
	1		146 (25%)
	2		145 (25%)
	3		145 (25%)
	4		145 (25%)
7	Wait_Time	Continuous	4 (1, 9)
8	Ped_Speed	Continuous	1.09 (0.90, 1.34)
9	Veh_gap	Continuous	4.8 (3.5, 7.1)
10	Safety Margin	Continuous	1.7 (0.5, 3.8)
11	Veh_typ	Categorical	
	Two Wheeler		409 (70%)
	Car_JS		143 (25%)
	VAN_BUS		21 (3.6%)
	Heavy		8 (1.4%)
12	Veh_Speed	Continuous	10.0 (7.8, 13.4)

on a lane by lane basis (for each lane). Vehicle speed was obtained from the time taken by vehicle to cross 25m average trap length. The time of arrival of first vehicle and conflicting vehicle after acceptance of gap at crossing, was noted down for computing vehicle gap. Description of all variables is shown in Table 1.

Safety margin is defined as the time difference between a pedestrian reaching the end of each lane/curb and vehicle arriving at middle of the respective lane. Higher values of SM indicate non conflicting behaviour while lower values indicate conflicting behaviour of pedestrians. Here, conflict has been defined as the case where the SM value is less than 1 second ; so every pedestrian crossing a lane has two outputs, either he/she shows conflicting behavior (SM less than 1) or non-conflicting behaviour (SM more than 1). Threshold of 1 sec has been used by many literatures [6, 16, 17, 14], notion being that pedestrian and driver need at least 1 second for reaction time.

Risk Indicator(RI), dependent variable for ordinal logistic regression is a concept which arises from the inadequacy of safety margin to define the severity of conflict because of latters relation with vehicle speed; safety margin of 2s against 50km/h vehicle speed is a severe case than against 20km/h vehicle speed. It has been defined as the ratio of vehicle speed to safety margin. However,since SM contained negative values there was a need to rescale it to positive values greater than zero which was done by shifting the minimum negative value of SM to zero and others accordingly. This new indicator has been termed as Pedestrian Vehicle Scaled Risk Indicator (PVSRI).

$$\text{PVSRI} = \frac{\text{Vehicle Speed}}{\text{SM}_{\text{Scaled}}}$$

Cumulative distribution function(CDF) of PVSRI at 25%,50%,75% and 100% were used to obtain following levels of severity:

1. Low Risk : $PVSRI < 5.38$
2. Slight Risk : $5.38 < PVSRI < 6.8$
3. Fair Risk : $6.8 < PVSRI < 8.23$
4. High Risk : $PVSRI > 8.23$

Kernel density plot of PVSRI showed drastic rise and fall at these thresholds indicating clear distinction between the levels. The CDF division also prevents class imbalance. To test further, whether the levels defined are different from each other or not, Kruskal Wallis test was performed against 5 independent numeric variables one by one. Results shown in Table 2 allows to reject null hypothesis that the population median of the variables of 4 severity levels are same. ANOVA test could not be performed owing to the categorical nature of dependent variable.

Table 2: Kruskal-Wallis Test Results

S.N	Variables	Chi-Squared	P value
1	Vehicle Gap	629.12	0.00
2	Vehicle Speed	467.75	0.00
3	Safety Margin	612.5	0.00
4	Waiting Time	297.13	0.00
5	Pedestrian Speed	485.44	0.00

3.4 Binary Logistic Regression

When the outcome is a binary variable,specially in a behavioural model, it is often preferred to portray it in the form of binary logistic model. Two cases,namely conflict and non-conflict is assumed to depend upon variables describing pedestrian demographics,their behaviour,vehicle characteristics,crossing type, and yielding behaviour of drivers. Log of odds of conflict relates with the independent variables in a manner as stated in following equation:

$$y^* = \beta_0 + X_1\beta_1 + X_2\beta_2 + X_3\beta_3.... + \epsilon$$

$$\epsilon \sim N(0, \sigma^2)$$

where,
$y^* = \log\left(\frac{P(C)}{1-P(C)}\right)$,
$P(C)$ = Probability of Conflict,
β_0 = constant,
X = Matrix of independent variables,
β = Coefficients of respective independent varibles

The parameter β is estimated by maximum loglikelihood method and is computed through *glm()* function in R.

3.5 Ordinal Logistic Regression

Ordinal logistic regression is a statistical analysis method that can be used to model the relationship between an ordinal response variable and one or more explanatory variables. An ordinal variable is a categorical variable for which there is a clear ordering of the category levels. In this research, the level of severity of conflict is taken as an ordinal dependent variable of 4 levels. The basic equation of the model is:

$$y^* = \beta_0 + X_1\beta_1 + X_2\beta_2 + X_3\beta_3.... + \epsilon$$

where,
y^* = latent variable defining thresholds of severity,
β_0 = Constant,
X = Matrix of independent variables,
β = Coefficients of respective independent variables

Classification of risk levels was based on the threshold values (α) of latent variable y^*

$$\text{Decision} = \begin{cases} \text{No Risk} & y^* < \alpha_1 \\ \text{Slight Severity} & \alpha_2 > y^* > \alpha_1 \\ \text{Fair Severity} & \alpha_3 > y^* > \alpha_2 \\ \text{High Severity} & y^* > \alpha_3 \end{cases}$$

4. Results and Discussions

4.1 Correlation Matrix

Pearsons correlation and Cramers V tests were performed for continuous and categorical datatypes respectively before model training. Table 3 and 4 are the results of separate tests which shows no strong correlation(> 0.5) between independent variables which allows to proceed with all variables for model development.

Table 3: Pearson Results:Numeric datatypes

	GR_Size	Wait_Time	Ped_Speed	Veh_gap	Veh_Speed
GR_Size	1	0.05	-0.01	-0.02	-0.19
Wait_Time	0.05	1	0.02	-0.07	-0.03
Ped_Speed	-0.01	0.02	1	0.00	0.04
Veh_gap	-0.02	-0.07	0.00	1	0.28
Veh_Speed	-0.19	-0.03	0.04	0.28	1

Table 4: Cramers V Results: Categorical datatypes

	Age	Gen	Veh_Typ	lane	LE_ILLE	Dry
Age	1	0.11	0.07	0.00	0.22	0.15
Gen	0.11	1	0.04	0.00	0.22	0.05
Veh_Typ	0.07	0.04	1	0.17	0.08	0.09
lane	0.00	0.00	0.17	1	0.00	0.08
LE_ILLE	0.22	0.22	0.08	0.00	1	0.36
Dry	0.15	0.05	0.09	0.08	0.36	1

4.2 Pedestrian Vehicle Conflict Model

Randomnly selected 75% of data from the original dataset was used to build the model considering all variables in R-4.3.3. The primary model had many insignificant variables which were later removed through stepwise regression method to find the best combination set of variables. This final model is presented in Table 5 below.*Values in brackets show standard error of the variable.*

Table 5: PV Conflict Model

	Dependent variable:
	Conflict
GR_Size2	0.81^{**}
	(0.34)
GR_Size(3-4)	0.78^{**}
	(0.37)
GR_Size(5-7)	0.04^{**}
	(0.3)
lane2	1.97^{***}
	(0.41)
lane3	1.09^{***}
	(0.41)
lane4	2.29^{***}
	(0.40)
Veh_gap	-0.80^{***}
	(0.08)
Ped_Speed	-1.93^{***}
	(0.44)
Wait_Time	-0.05^{**}
	(0.02)
Constant	4.28^{***}
	(0.68)
Observations	499
Log Likelihood	−188.74
Akaike Inf. Crit.	397.47
Residual Deviance	377.47 (df = 489)
Null Deviance	658.03 (df = 498)
Note:	*p<0.1; **p<0.05; ***p<0.01

From the results it can be seen that, pedestrians have higher chances of conflict while crossing second lane and fourth lane compared to first lane (reference category). The odds of probability of such a conflict increases nearly by 1.97 times in second lane and even more, by 2.29 times in fourth lane (last lane), while for the third lane the odds increases but by a lesser amount, nearly 0.95 times. Availability of shelters at the beginning of crossings provided comfortable waiting zones for pedestrians. Also, although pedestrians didnot wait that much at the middle of the road; they did it much frequently and much longer than at the ending of the first and third lanes. Thus,it can be seen that if the pedestrians get comfortable waiting shelters, they are less inclined to show conflicting behaviour. This also highlights the risk pedestrians faces at wide crossings of multiple lanes with no proper resting place.

Acceptance of a unit large vehicular gaps is shown to decrease the odds of probability of conflict by 0.8 times. Similarly, increase in one unit of pedestrian speed decreases the odds nearly by two times. Furthermore, pedestrians who spend more time at the road and the shelter (waiting time) are found to have less conflicting chances. Waiting time is negatively correlated with conflict by 0.05.

As pedestrian cross in groups, they tend to show more conflicting behaviour than crossing alone. When the group size is 2 the odds increases by 0.81 times compared to single crossing pedestrians(reference category). Likewise, when the group size if 3-4 such odds is found to increase but by a lesser amount 0.78. However,for larger crossing groups of 5-7, the coefficient is near zero.

4.3 Ordinal Logistic Regression Model for Severity of Conflict

Vehicle speed was not considered as a predicting variable due to its predefined relation with PVSRI. In addition,variables namely age,gender,group size and yielding behaviour of driver are not found to be significant at 95% level of significance for explaining the relationship with Scaled RI(PVSRI) in the initial model. After multiple trials, the final model generated using *clm()* function in R-4.3.3 ,is displayed in Table 6 and 7. Since the independent variable is ordinal multiclass, unlike multinomial, base model is not required.

Results show that the probability of higher severity of conflict is positively correlated with type of crossing. The log of odds of increase in severity rises by 1.21 in illegal crossings compared to legal ones(reference category) with proper zebra and lane markings.

Models show that pedestrians take more severe risk while crossing second and final lanes. The result is consistent with the conflict model result in terms of the location of more conflicting lanes; odds of severe risk increases 1.64 times at the second lane, by 1.01 after pedestrian rests at the middle of the road, at the third lane and by 1.54 times at the final lane relative to first lane(reference category). This shows that pedestrians are likely to take more severe risk as number of lanes increases without availability of proper waiting shelters.

Availability of unit more gap is found to decrease the odds by 0.41 times. Similarly, increase in pedestrian speed and wait time are also found to decrease the odds by 0.69 and 0.03 times respectively. This shows pedestrians who wait more before crossing the road and spend more time on the road while crossing are found to have lesser risk of severe conflict. Also, the coefficients highlight that pedestrian who cross the road slowly are more vulnerable.

Table 6: Conflict Severity Model

	Dependent variable:
	PVSRI
lane2	1.64^{***}
	(0.26)
lane3	1.01^{***}
	(0.26)
lane4	1.54^{***}
	(0.26)
Veh_gap	-0.41^{***}
	(0.04)
LE_ILLEIllegal	1.21^{***}
	(0.20)
Ped_Speed	-0.69^{**}
	(0.29)
Veh_typCar_Jeep_VAN	-1.07^{***}
	(0.21)
Veh_typHeavy	-1.38^{***}
	(0.46)
Wait_Time	-0.03^{**}
	(0.01)
Observations	492
Log Likelihood	−575.73
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 7: Threshold Coefficients

	Estimate	Std.Error	z value
No risk/Slight risk	-3.49	0.43	-8.19
Slight risk/Fair risk	-2.14	0.41	-5.24
Fair risk/High Risk	-0.62	0.40	-1.58

As for vehicle type, two wheelers(reference category) are found to be riskiest; the odds decreased by 1.07 and 1.38 times for cars,jeep,van and heavy vehicles like buses and trucks respectively. This may be because pedestrians perceived the threat of bigger vehicle size and kept more safety margin against heavy vehicles compared to the other two and in contrast, felt more safe and showed least risking behavior against cars, jeeps and vans.

5. Model Validation

Both the models were validated using random 25% of the dataset(testing set). While for binary logit conflict model, parameters were computed through confusion matrix and ROC curve, the multilevel severity model was validated through confusion matrix only.

5.1 PV Conflict Model Validation

The confusion matrix and corresponding performance metrics for binary model are as follows:

Table 8: Conflict Model Confusion Matrix

		Actual	
		No Conflict	Conflict
Predicted	No Conflict	96	17
	Conflict	9	45

i) Accuracy = $\frac{96+45}{96+45+17+9}$ = 84.43%

ii) Sensitivity = 91.43%

iii) Specificity = 72%

iv) Positive Prediction Value = 84.96%

ROC curve obtained by plotting true positive rate (TPR) vs false positive rate(FPR) at thresholds ranging from 0 to 1 is shown in figure 2 below. Area under the ROC curve (AUC) provides insight into the power of separatibility of the binary classifier. The value of $AUC = 0.91$ was acquired, which shows excellent classification capability of the model.

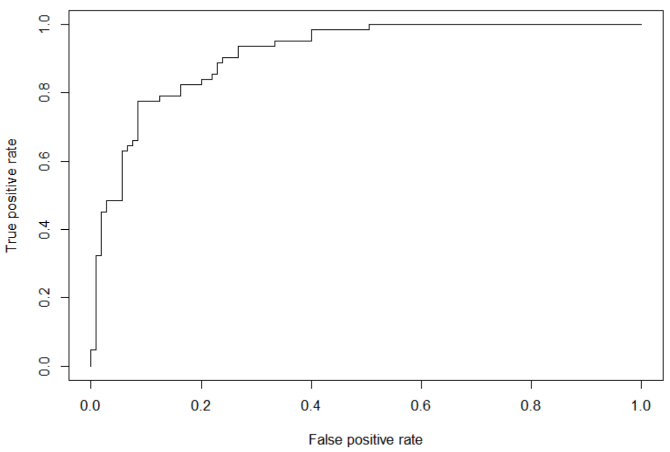

Figure 2: ROC Curve

5.2 PV Severity Model Validation

Table 9: Severity Model Confusion Matrix

		Actual			
		No risk	Slight Risk	Fair Risk	High Risk
Predicted	No risk	27	7	6	3
	Slight Risk	3	15	3	4
	Fair Risk	5	8	28	11
	High Risk	3	6	7	31

From the confusion matrix shown in Table 9,

$$\text{Accuracy of Severity model} = \frac{\sum \text{diag}}{\sum \text{all}} = \frac{101}{167} = 60.7\%$$

The classification accuracy of this ordinal multiclass model 60.7%, suggests that the model performs satisfactorily.

6. Conclusion and Recommendation

6.1 Conclusion

Pedestrian safety was evaluated at two uncontrolled midblock crossings based on Safety margin(SM) values. Conflict model for predicting probability of conflict and ordinal logistic model for levels of severity of conflict were developed and validated. The contributing factors explaining pedestrian behaviour,vehicle and roadway characterstics were taken as independent variables.

The findings quantified how much severe a conflict would be if occured at illegal crossings compared to legal crossings. Lane position,vehicle gap,pedestrian speed,wait time,group size significantly affected odds of both conflict and severity. In addition,pedestrian crossing in groups of 2 showed most conflicting behaviour. Similarly,the severity was highest for two wheelers and minimal for heavy vehicles.One notable observation in relation to pedestrian speed and wait time is that pedestrians who cross the road with increased speed but spend longer time waiting at the beginning and at the end of lanes are exposed to less severe conflict.

6.2 Recommendation

This study proposes a modified indicator for pedetsrian-vehicle severity evaluation at midblock crossings under mixed traffic conditions. It underscores the importance of waiting shelters for pedestrians while crossing multiple lanes. In addition, research highlights the importance of proper lane and zebra markings at places of high pedestrian crossflow,high volume of two wheelers and low vehicle gap. All contributing factors have been quantifed with respect to risk so that it would become helpful for planners and designers in developing various levels of warrants and safety guidelines to improve pedestrian safety by assessing the severity of conflict. However,the findings of this study is limited to four lanes without median barrier, it also doesnot assess the effect of land use type,is not validated by actual crash data and doesnot include many other minute behavioral characteristics of pedestrians and driver.

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