Binary Probabilistic Models for Pedestrians' Crossing Behaviour and Risk at the Free Left Turn: Delhi, India

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Abstract: Free left-turn lanes are common at major signalized intersections of Delhi to create additional capacity, and to facilitate continuous flow to left-turning traffic. The present study aims at examining the pedestrians' risk and road crossing behavior at free left-turns. Two most used binary probabilistic models, namely Logistic and Probit, were fitted to the data-set. Pedestrians cross the free left-turn when gaps are available within the traffic flow. Analysis of the data suggests that pedestrians' waiting time prior to the crossing of free left-turn is very less. Gap size is a significant parameter. Pedestrians' characteristics and type of conflicting vehicle do not influence their crossing behavior. Most of the pedestrians cross the free left turns with the gap size less than the adequate gap size. Both the univariate binary response Logistic and Probit regression models have been found to give similar results for the selected case.

Keywords: Pedestrian risk, Pedestrians' behaviour, Free left-turn, Logistic regression, Probit regression.

1. INTRODUCTION

Pedestrians are the most vulnerable group of road users. As per the police record of pedestrian fatality, the share of pedestrian fatalities in Delhi from 2001 to 2009 indicates that pedestrians have the largest share in total road fatalities. Moreover, the share remains the same over the years, which is about 50% of the total fatalities (Delhi Police, 2009). One of the important reasons for this may be the basic needs of pedestrians are not recognized as a part of the urban transport infrastructure improvement projects in Delhi.

Free left-turn lanes are commonly found at major signalized intersections of Delhi to create additional capacity, and to facilitate a continuous flow to the left-turning traffic. There are no specific rules which require motorists to yield for pedestrians at free left turns. Therefore, they generally do not give priority to pedestrians for crossing the turn. Pedestrians cross the road at these turns on the basis on his/her individual perception of speed and distance of the nearest conflicting vehicles. This essentially means that they have to cross the road at their own risk. Among various pedestrian facilities crosswalks are one of the most complex facilities, with high risk for pedestrians in congested urban areas. Pedestrians are exposed to risk while crossing a road in urban areas and non-crossing accidents generally represent a small proportion of pedestrian accidents (Lassarre et al., 2007; Duncan et al., 2002). While planning transport infrastructure of Delhi, priority has been accorded to uninterrupted flow of motorized vehicles. A common phenomenon that can often be witnessed in Delhi is that a pedestrian has to fight for space in the traffic system. In general, at an intersection that allows free turn to motorized traffic, a pedestrian waits for a suitable gap at the curbside/refuge to complete his/her crossing. A pedestrian who crosses the intersection at grade does not find any exclusive and safe crossing time because of the continuous flow of traffic at these turns. Pedestrians are therefore forced to cross in between the moving traffic. This makes the pedestrian crossing at these intersections susceptible to road crash.

Approximately one out of five accidents at signalized intersections involves a turning vehicle hitting a pedestrian (Robertson and Carter, 1984). Several researchers have studied the impact of the left turning vehicles on pedestrian crossing. Among them, Habib (1980) and Fruin (1973) examined pedestrian accidents at signalized intersections on one-way grid system. They discovered that a left-turn movement was approximately four times more dangerous to pedestrians than a through movement. Almuina (1989) examined accidents at one-way/one-way, one-way/two-way, and two-way/two-way intersections. Almuina's work demonstrated that with the exception of pedestrian accidents with straight-through vehicles, accidents involving left turning vehicles had the highest proportion of accidents for all types of intersections. Using the same database, Quaye et al. (1993) developed a prediction models for pedestrian accidents involving left turning vehicles for T-intersections and four-leg intersections. The models showed that T-intersections were generally more dangerous to pedestrians. Abdel-Aty and Keller (2005) found that the left turn crash has the highest risk for a severe injury crashes involving a pedestrian. Zador et al. (1980) have reported that free right turn on red (U.S. traffic drives on the right) increases pedestrian crashes at intersections. The effect of free left turns on intersections should be evaluated to understand the effect on pedestrian fatalities and the system should be changed if pedestrians are involved in disproportionate numbers at such intersections (Mohan and Bawa, 1985).

The increase in the number of free left-turns at signalized intersections in Delhi creates the need to assess their impact on pedestrians who cross the road at these turns. The objective of the present study is to analyze the impact of free left-turns on pedestrians crossing the road at these turns. This work aims to analyze the waiting time of pedestrian, and to develop probabilistic models to estimate the pedestrian risk and their crossing behaviour at free left-turns. It should be noted that at these turns no pedestrian crossing facilities are provided. As a consequence, there is no safe crossing time for pedestrian, rendering all such crossings unsafe.

2. SITE SELECTION AND DATA COLLECTION

To analyze the risk and road crossing behavior of pedestrians, data have been collected at a free left-turn of Indian Institute of Technology Delhi (IITD) intersection in New Delhi. The selected intersection has four legs that represent a typical Indian urban signalized intersection. In general, the intersection experiences very high and mix traffic volume flow. "Free left-turn" for vehicles is permissible on all the four approaches of the intersection (Figure 1). Some characteristics of the IITD intersection are: (1) Five phases comprise the signal cycle with the average length 260 seconds during the peak hour. (2) No special provisions (subway/foot-over bridge) for pedestrians except a green phase of all the directions for pedestrians at the zebra marking of intersections. (3) Intersection is almost at right angles. A free left-turn located underneath the flyover, has been chosen for the study and shown in Figure1.

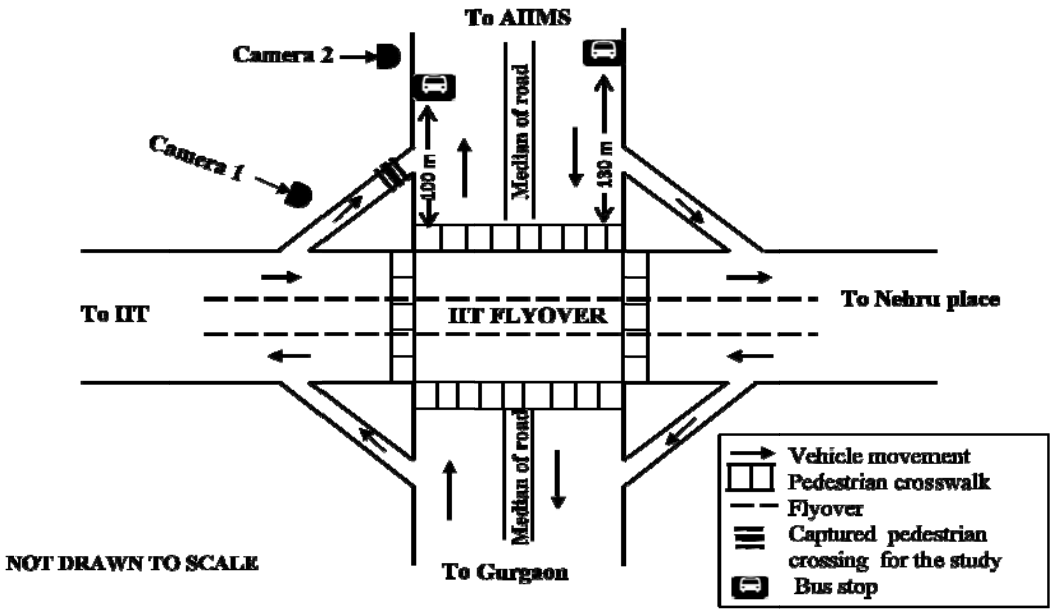

Figure 1. Schematic diagram of the selected intersection

Video recording was used to collect the data. This allowed continuous recording of the movement of vehicles and pedestrians within the screen range. A survey team collected the data in the morning peak hours (8:30 a.m. to 10:30 a.m.) on Wednesday, June 1, 2011. Before collecting the data, the site selection and survey planning was done. It was followed by a reconnaissance survey visit to the site to finalize and fix the methodology to carry out further survey work. Data have been collected for only one day and the selected day represented a typical working day. Because, it has been found that vehicular and pedestrian traffic is generally uniform throughout the weekdays (Monday -Friday). Total 268 pedestrians who cross the free left turn during the period of data collection were observed for the study. The crossing behavior of pedestrians was noted by reviewing the video footages. Two digital cameras were used to collect all the relevant information of pedestrian and vehicular traffic.

Each pedestrian was viewed in slow motion by progressing the tape one frame (30 frames per second) at a time with "Adobe After Effects" a digital motion graphics and compositing software. Many rewinding and viewing of the tape was needed to extract all of the relevant information for pedestrians and vehicles.

3. PREDICTOR VARIABLES

To analyze the road crossing behavior of pedestrians, predictor variables were extracted from the recorded videos. Waiting time of pedestrian prior to the road crossing is observed from the recorded data. Predictor variable Gap size (in second) faced by pedestrian is estimated as.

- The length of the first Gap size faced by the pedestrians is calculated by $t_{v_1} - t_a$, where t_a is the time when pedestrian arrives at the crossing and t_{v_1} is the time when first conflicting vehicle enters at the crosswalk.
- The other Gap sizes faced by the pedestrians are calculated by $t_{v_i} - t_{v_{i-1}} (i = 2,3,..,n)$, where t_{v_i} is the time when i^{th} conflicting vehicle enters at the crosswalk and n is the number of gap sizes faced by the pedestrian.

If a pedestrian accepts that available gap (i.e., crosses the road within that gap), then it was considered as an *accepted gap*; otherwise it was considered as a *rejected gap* (Khatoon *et al.*, 2013).

The following variables were categorized manually into broad groups from their appearance by the data analysts: (1) Gender of pedestrian: "male" and "female" (2) Age group of pedestrian: "child", "young adult", "middle-aged" and "old-aged" (3) Type of pedestrian: "crossing alone" and "crossing in a group", (4) Type of conflicting vehicle: "Heavy vehicle", "Light commercial vehicle (LCV)", "Car", "Motorized two wheeler (M2W)" and "Motorized three wheeler (M3W)".

4. METHODOLOGY

As a first step, frequencies are compared for the waiting time of pedestrians. Afterwards, the probability of road crossing by a pedestrian (with the predictor variables gap size available to pedestrian, gender, age and type of pedestrian and type of conflicting vehicle) is modeled by two mostly used binary probabilistic regression models: Logistic and Probit. The results obtained from the two models are compared to find the model that fits better. Adequate gap size to cross the left turn is determined. Pedestrian risk is defined as the probability of gap size accepted by pedestrians which is less than the adequate gapsize.

Under the binary discrete choice framework, the probability of pedestrians' road crossing decision is seen as a choice between two alternatives: the pedestrian starts crossing, or the pedestrian decides not to cross.

To obtain the Logistic and Probit models, first we write z as the linear sum of β_0 and $\beta_i X_i$ $(i = 1,2,..,5)$ where the $X_i s$ are the predictor variables (discussed in Section 3), $\beta_0$is the intercept (the value of the criterion when the predictor is equal to zero); and the independent variables weighted by their parameters, $\beta_i's$.

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5, \tag{1}$$

Let P be the probability of the road crossing by a pedestrian. In the binary Logistic regression, P is related to predictor variables $X_1, X_2\, X_3\, X_4$ and X_5 in a non-linear way and specified as:

$$P = \frac{1}{1+e^{-z}} = \frac{1}{1+e^{-(\beta_0+\sum_{i=1}^{5}\beta_i X_i)}} \tag{2}$$

In the binary Probit regression, P is the cumulative distribution function (CDF) of the unit-normal distribution and specified as:

$$P = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{Z} e^{-\frac{1}{2}Z^2}\, dZ$$
$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\beta_0 + \sum_{i=1}^{5} \beta_i X_i} e^{-\frac{1}{2}Z^2}\, dZ \quad (3)$$

5. ANALYSIS AND DISCUSSION

5.1 Waiting Time Analysis

Waiting time of the pedestrians prior to the road crossing is an important measure of pedestrian risk taking behaviour. The mean and standard deviation of the waiting time of the pedestrians as observed from the data are 1.4 sec and 1.7 sec, respectively. Waiting time analysis has been done by taking a sample of 268 pedestrian who cross the free left-turn. The findings are summarized in the Table1.

Table 1. Pedestrians' waiting time analysis

Waiting time (in sec)	No of pedestrian crosses	Frequencies (%)
0−1	170	63.3
1−2	52	19.3
2−3	27	10.1
> 3	20	7.3

Table 1 shows that at the selected location: 63.3% pedestrians crossed the road within one second of waiting, 19.3% pedestrians crossed within two seconds of waiting, 10.1% pedestrians crossed within three seconds of waiting, and only 7.3% pedestrians crossed after more than three seconds of waiting. This shows that pedestrians' waiting time is very less at the selected free left turn. Most of the pedestrians cross the road without waiting. This may because of the continuous flow of motorized traffic even after certain time of waiting they do not find a safe crossing time to cross the turn. In this work we have not analyzed the waiting time in detail because pedestrians' waiting time at the selected free left turn is very low (93% pedestrian cross the turn within 3 sec of waiting). Thus only frequency analysis has been done for pedestrians' waiting time.

5.2 Crossing Behavior

In discrete choice modeling Logistic and Probit are the two most used binary probabilistic regression models. Therefore, to achieve higher prediction accuracy, both Binary Logistic and Probit regression analyses have been used in the study. The models consider that probability of road crossing by a pedestrian is dependent on the Gap-size, gender, age, whether they are alone or in a group, and the type of the conflicting vehicle. The distribution of the categorical predictor variables in the dataset is shown in Table2.

Table2: Distribution of predictor variables

Gender Of Pedestrian				
Male: 78.2%			Female:21.8%	
Age Group of pedestrian				
Child: 2.1%	Young Adult: 47.4%		Middle aged: 40.3%	Old aged: 10.2%
Type of pedestrian				
Crossing alone: 43.5%			Crossing in a group: 56.5%	
Type of conflicting vehicle				
Heavy vehicle: 9.0%	LCV: 0.3%	Car: 46.8%	M2W: 32.9%	M3W: 11%

The predictor variables in the models are a mix of continuous and categorical. SPSS statistical software has been used for the analysis. Dummy coding method is used to code categorical predictor variables. Dummy coding is the comparisons in relation to the omitted reference category. The following categories are taken as a reference for the categorical predictor variables: (1) female for the gender of pedestrian, (2) old aged for the age group of pedestrian, (3) crossing in a group for the type of pedestrian and, (4) M3W for the type of conflicting vehicle.

Gap sizes longer than 40 seconds i.e. the visibility range of the pedestrian, were eliminated from the data set because pedestrians did not consider them while making the decision regarding crossing.

Due to insufficient sample size (as shown in Table 2), the following categories of the predictor variables were excluded from the data set: children from the age category, and light commercial vehicle from the type of conflicting vehicle category.

The regression coefficients and p-values of predictor variables obtained from the Logistic and Probit regression models are mentioned in the Table 3. A positive coefficient means that an increase in the predictor leads to an increase in the predicted probability. A negative coefficient means that an increase in the predictor leads to a decrease in the predicted probability.

Table 3. Regression coefficient and p-value of predictor variables

Predictor variable	Logistic regression		Probit regression	
	Estimate	p-value	Estimate	p-value
Gap size	1.72	0*	0.8	0*
Male	0.72	0.37	0.32	0.41
Children	0.17	0.95	0.21	0.86
Young Adult	2.56	0.29	1.15	0.22
Middle age	1.95	0.42	0.79	0.4
Crossing Alone	-0.36	0.56	-0.25	0.43
Car	-0.87	0.37	-0.54	0.2
Heavy vehicles	-5.31	0.54	-9.43	0.9
2 Wheeler	-1.687	0.09	-0.84	0.07

* Significant at 99% CI

Table 3 shows the effect of different predictor parameters on pedestrians' road crossing behaviour at free left-turn. The findings can be summarized as follows:

Gap size parameter is highly significant (significant value 0.00) for both Logistic and Probit regression models. All other parameters (pedestrians' characteristic and type of conflicting vehicle) are insignificant (at 99% CI) in determining the probability of road crossing of pedestrian at the selected free left-turn. Thus with the gap sizes of the same length the risk taking behaviour of all type of pedestrians with different conflicting vehicle is similar. At free left-turn, traffic signals have not been provided. As a consequence, there is no safe signal for pedestrians, rendering all crossings unsafe. The absence of signals and continuous flow of traffic make pedestrians behave independently, leading to increased variability in their road crossing behavior.

5.3 Pedestrian Risk

Section 7.2 shows that the road crossing behaviour of pedestrian statistically depends only on the gap size parameter at the selected free left-turn. Thus Gap size available to pedestrian is considered to estimate risk to the pedestrian crosswalks. In our earlier work (Khatoon et al., 2013), risk to pedestrian is defined as a function of "accepted gap size" (T) which is the measure of time to collision. When the accepted gap size increases, risk decreases. The probability of risk would be 1 as the gap asymptotically goes towards zero i.e. the situation of serious conflicts. Hence

$$Risk \propto 1/T \tag{4}$$

In this study, adequate gap size (t) to accommodate safe crossing for pedestrian is determined as:

$$t = \frac{d}{v} + s \tag{5}$$

Where,

d	:Width of the free left-turn crosswalk (3.9 m)
v	:Average walking speed of pedestrian (assumed as 1 m/s),
S	: Pedestrians' start-up time before crossing, seconds (standard value = 2 sec).

The value of adequate gap size (t) by the equation (1) is obtained 5.9 sec.

Dewar (1992) established the standard of walking speed of pedestrians at 1.22 m/sec for the purpose of intersection design. However, many researchers found that 1.22 m/sec is too fast crossing speed for intersection. Asher et al. (2012) stated that an assumed normal walking speed for pedestrian crossings of 1.22 m/s is inappropriate for all type of pedestrians. They found that the mean walking speed for men was 0.9 m/s and 0.8 m/s for women. Fruin (1971) found that nearly half of pedestrians walk below 1.22 m/sec. Knoblauch et al. (1996) studied of walking speeds at 16 crosswalks and found that the 15^{th} percentile walking speed of younger pedestrians (ages of 14 to 64) and older pedestrians (ages of 65 and above) were 1.25 m/sec and 0.97 m/sec respectively. Thus, the average pedestrian walking speed for this study is assumed as 1 m/s.

Furthermore, to improve the models, all the insignificant parameters are removed. Thereafter Logistic and Probit regression models have been fitted with only the "gap size" as the predictor variable i.e. assuming that probability of road crossing by a pedestrian depends on the gap size and the effects other predictor variables are negligible. From Logistic and Probit model the values of Intercept (β_0) were obtained 5.14 and 2.48 respectively; values of Logistic and Probit regression coefficient (β_1) were 1.59 and 0.74 respectively; and both the models and gap size parameters were highly significant.

To check the adequacy of the fitted Logistic and Probit regression model, the final models are validated using within sample tests (Omnibus test and ROC plots).

5.3.1 Omnibus tests

Omnibus tests are used for testing whether the explained variance by the model in a set of data is significantly greater than the unexplained variance.

To assess whether a model fits the data we compare the observed and predicted values of the outcome. In the Logistic regression, the measure is the Log-likelihood.

$$\text{Log-Likelihood}=\sum_{i=1}^{N}\{Y_i ln\big(P(Y_i)\big)+(1-Y_i)\}ln[1-P(Y_i)] \tag{6}$$

where,

Y_i: the observed output (cross or not cross) for the i^{th} case.

The Log-likelihood is therefore based on summing the probabilities associated with the predicted and actual outcomes. The Log-likelihood statistic indicates that how much unexplained information is there after the model has been fitted. It follows, the large values of the log-likelihood statistic indicate the poorly fitting statistical models, because the larger the value of log-likelihood, the more unexplained observations there. Table 4 shows the Omnibus tests of model coefficients and model summary.

Table 4. Omnibus Tests of model

	-2 Log-likelihood	R square	Chi-Square	Degrees of freedom	Sig Value
Intercept only	405.4				
Logistic regression	106.5	0.85	298.8	1	0
Probit regression	114.7	0.83	290.5	1	0

Table 4 shows that when only constants are included, -2LL is 405.4, but when the predictor variable Gap size has been included the values of -2LL have been reduced to 106.5 and 114.7 with the Binary Logistic and Probit regression respectively. This reduction shows that both the models are better at predicting the pedestrian road crossing behaviour at the selected free left-turn than they were before predictor variable gap size was added in the models. The value of -2LL is reduced more with the Logistic regression in comparison with Probit regression

The efficiency of the model is assessed using the model chi-square statistics, which measures the difference between the model as it currently stands and the model when only the constant is included. We could assess the significance of the change in a model by taking the log-likelihood of the new model and subtracting the Log-likelihood (LL) of the baseline model from it.

$$\chi^2 = 2[LL(New) - LL(Baseline)] \quad (7)$$
$$df = k_{new} - k_{baseline}$$

The chi-square distribution used in Logistic and Probit regression, has degrees of freedom equal to the number of parameter in the new model (k_{new}) minus the number of parameters in the baseline model ($k_{baseline}$). The value of $k_{baseline}$ is always equal to 1, because the constant is the only parameter to estimated in the baseline model. The chi-square statistics in Table 4 indicate that both the models are statistically significant (sig value is 0.00). Thus, overall the models predict the probability of road crossing significantly better than the model with only the constant included.

The values of R square are obtained 0.85 and 0.83 with Logistic and Probit regression respectively, indicating that both the models are good enough to predict the outcome variables. Larger value of R-square is obtained with Logistic regression.

5.3.2 Receiver operating characteristic (ROC) curves

A measure of goodness-of-fit often used to evaluate the fit of a Logistic regression model is based on the simultaneous measure of sensitivity (True positive) and specificity (True negative) for all possible cutoff points. First, we calculate sensitivity and specificity pairs for each possible cutoff point and plot sensitivity on the y axis by (1-specificity) on the x axis. This curve is called the receiver operating characteristic (ROC) curve. The area under the ROC curve ranges from 0.5 and 1.0 with larger values indicative of better fit. ROC curves have been plotted by the SPSS statistical software and shown in Figure 2.

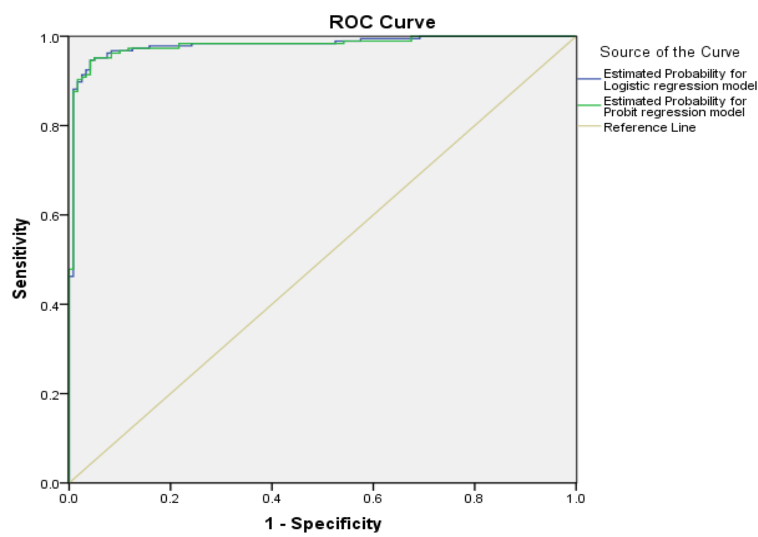

Figure 2. ROC curves for Estimated Probability by Logistic and Probit model

The test results for ROC curve for estimated probability by Logistic and Probit model are summarized in Table 5.

Table 5. Test results for ROC curve

Test Result Variable(s)	Area	Std. Error	Significant value	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
Estimated Probability by Logistic regression	0.981	0.007	0	0.966	0.995
Estimated Probability by Probit regression	0.98	0.008	0	0.965	0.995

Table 5 shows that the area under the curve is 0.981 and 0.980 by the Logistic and Probit regression models respectively with 95% confidence interval. Also, the area under the curves are significantly different from 0.5 since significant value is 0.00 i.e. both Logistic and Probit regression classifies the group significantly better than by chance.

Our findings from the experiments can be summarized as follows:

- Slightly reduced value of Log-likelihood statistic from the Logistic regression model
- Slightly larger value of R square from the Logistic regression model
- Slightly larger area under the ROC curve from the Logistic regression model

Thus we conclude that Logistic regression model is marginally better in depicting the pedestrian road crossing behaviour for the selected case.

However, from both the univariate regression models, the difference in the results obtained is not very significant. We can also state that both the univariate binary response Logistic and Probit regression models provide similar results for our case of study. This corroborates the findings of Hahn and Soyer (2005) that the Logistic and Probit links give essentially similar results for univariate binary response models.

After models validation the probabilities of road crossing at different gap sizes were calculated by the obtained value of intercept and coefficients and shown in the Table 6.

Table 6. Probability of road crossing at different gap sizes (in %)

Gap size (sec)		2	4	5.9*
Predicted Probabilities (%)	Logistic Regression	14	78	99
	Probit Regression	18	69	97

* Adequate gap size

Table 6 shows that at the free left-turn, the predicted probabilities of road crossing by a pedestrian with the gap size less than the adequate gap size (5.9 second) are 99% and 97% by Logistic and Probit regression models, respectively.

6. CONCLUSIONS

Free left-turns provide very less waiting time but results in high risk to a pedestrian who crosses at the intersection. About 63% pedestrians crossed a free left-turn within one second of waiting. All the parameters (pedestrians' characteristic and type of conflicting vehicle) except the gap size available to pedestrian, are not contributing significantly in pedestrians' road crossing behaviour. The univariate Logistic and Probit regression models give comparable results to estimate pedestrian road crossing behavior at the selected free left-turn. Adequate gap size to cross the selected free left-turn obtained is 5.9 sec. Logistic regression model predicted that about 99% pedestrians crossed the free left-turn with a gap size less than the adequate gap size. Whereas, Probit regression model predicted that about 97% pedestrians crossed the free left-turn with a gap size less than the adequate gap size.

Free left-turns are often introduced to reduce traffic congestion. However, the study shows the negative impact of free left turns on pedestrians. Therefore free left turns either should be controlled by traffic light or with speed control measures which ensures lower speed of turning vehicles, reducing the risk to pedestrians. Thus, a pedestrian actuated signal, traffic-calming devices such as raised pedestrian crossing to reduce vehicle speeds, synchronization within signal system or other crossing facility must be provided to ensure safe and convenient pedestrian crossings at these turns.

7. LIMITATION OF THE STUDY

The data used for statistical analysis was from a video camera placed at a place where the maximum number of pedestrians is found to be crossing the road. However, there are still a number of pedestrians who are engaged in risk taking crossing at other points. This data was not captured by the video camera, and is therefore not within the scope of this analysis. This study does not correlate the observed risk to the actual crashes. To conduct such an analysis we need to rely on police data over a much longer period of time. The study could be extended to include actual crash data.

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