Hindawi
Journal of Advanced Transportation
Volume 2019, Article ID 2345903, 13 pages
https://doi.org/10.1155/2019/2345903

Research Article

A Random Parameter Logit Model of Immediate Red-Light Running Behavior of Pedestrians and Cyclists at Major-Major Intersections

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Received 10 December 2018; Revised 8 May 2019; Accepted 21 June 2019; Published 8 July 2019

Academic Editor: Richard S. Tay

It is a dangerous behaviour for pedestrians and nonmotorized vehicles to cross intersections without waiting when they arrive at intersections during the red-light period. This paper investigates three typical signalized major-major intersections in the center of Beijing, by collecting and analyzing 1368 samples of pedestrians and nonmotorized vehicles. A random parameter logit model (RPLM) is established, with immediate red-light running (IRLR) behaviour as the dependent variable. The results show that the number of people waiting upon arrival, number of people crossing upon arrival, traffic mode, motor vehicle phase upon arrival, and speed change upon arrival have significant effects on IRLR behaviour. Accordingly, we suggest enforcing education administration on cyclists to reduce cyclists' IRLR behaviour. Thus, people's red-light running (RLR) behaviour will further decrease with fewer cyclists' IRLR behaviour.

1. Introduction

Walking is an essential mode of transportation for citizens in all areas. Due to their convenience, low carbon, and environmental friendliness, traditional bicycles and electric ones are two important modes of transportation. In recent years, with the development of shared bicycles in China, the users number had reached 18,860,000 by the end of 2016. As efficient regulation and supervision are inadequate, however, illegal and unsafe behaviours are prevailing for all three modes of transportation. Consequently, the rate of traffic accidents related to the modes has been harrowingly high. In 2014, 15110 pedestrians and 11448 cyclists (in this paper, nonmotorized vehicles and cyclists are used to refer to bicycles and electric bicycles and their riders, respectively) died in traffic accidents in China, representing 25.82% and 19.56% of the total deaths, respectively [1].

In 2014, 34,065 pedestrians and 46,314 cyclists were injured in traffic accidents in China, representing 16.08% and 21.86%, respectively [1]. Some research findings indicated that the rate of red-light running (RLR) of pedestrians and cyclists was pretty high. In Italy, more than 60% riders were observed to run the red light [2]. Johnson et al. [3] investigated 2,061 cyclists and 37.3% of them were reported to have ever run a red light. Yang et al. [4, 5] found that the rate of RLR of pedestrians is 55.1% and that rate of cyclists is 61.1% in Beijing by field observational data. The previous studies showed that there was a strong correlation between RLR and traffic accident. It can be inferred that the reason for more than 60% of traffic accidents involved death of two-wheel vehicles is the behaviour of RLR [6]. In Canada, 11% of cyclist crashes were caused by disobeying a stop sign or a red light [7].

Accordingly, the safety of pedestrians and nonmotorized vehicles at signalized intersections has attracted the

increasing attention of researchers. To improve the safety level of signalized intersections in the city, there is a need to further analyze and summarize the RLR behaviour of pedestrians and cyclists and then propose suggestions on management and control strategy.

The RLR behaviour has been categorized by some scholars in the previous studies. Basically, there are three kinds of classification: (1) based on the cause of RLR behaviour [3]; (2) based on the length of waiting time [4]; (3) based on wait-or-not red light (this one can be viewed as the special situation of the second category) [8]. Like the research of Pai and Jou [8], this study first classifies the RLR behaviour into immediate red-light running (IRLR) behaviour whose waiting time is zero and delayed RLR behaviour whose waiting time is greater than zero. Then only the IRLR behaviour is analyzed. The primary objective of this study is to explore the factors affecting IRLR (in present research, if the road users (pedestrians, cyclist, or electric cyclist) are crossing the intersection against the red light without waiting, we define those people as having red-light running behavior.) behaviour of pedestrians and cyclists at signalized major-major intersections in Beijing, China. The random parameter logit model (RPLM) is undertaken to account for the unobserved heterogeneous effects among the intersections and individuals.

The rest of the paper is organized as follows. Section 2 provides a thorough literature review on RLR influential factors, frequency analysis, and data collection methods. Section 3 describes the process of data collection and gives a brief description of intersections; then RPLM is briefly introduced in Section 4. Section 5 presents the statistical descriptions of the samples of pedestrians and cyclists and develops the RPLM. Section 6 analyzes the estimation results of model. Last, we conclude this paper with several policy recommendations and some perspectives for future research.

2. Literature Review

Researchers have conducted a substantial number of studies to reduce the occurrence of RLR behaviour, analyzing the factors of pedestrians and cyclists' RLR behaviour using different statistic models based on data from different sources. The most common data source is field observational video, combined with questionnaires. It has been proved that logit regression model is an effective method to handle these problems.

Johnson et al. [9] investigated the RLR behaviour of bicycle commuters in Melbourne. Based on the analysis of the field data by using the binary logit regression model, they found that the main prediction factors of RLR behaviour are riding direction and existence of another road user (including bicyclists and pedestrians). This study demonstrated that the relative odds of infringement (*relative odds of infringement = Number of immediate red light running/Number of red light running*) when the riding direction is left turn is 28.3 times that ratio when the riding direction is straight. The study also showed that when there is another vehicle in the same direction the odds of infringement is 0.39, and when there is another bicycle in the same direction the odds of infringement is only 0.26.

Wu et al. [10] analyzed the RLR behaviour of both bicycles and electric bicycles. Their analysis of the field data on the basis of the binary logit regression model indicated that cyclists are more likely to run the red light when they have no accompanier, or fewer people are waiting, or some have been running the red light at the moment. RLR behaviour occurs more likely in the late stage of the red-light phase.

Using questionnaire data, Johnson et al. [3] established models to examine the associations between cyclist characteristics and reasons for RLR behaviour. The study found that. (1) for RLR behaviour caused by left turn phase, gender, age, education, income, and cyclist crash involvement are statistically significant; (2) for RLR behaviour caused by the inductive detector loop failed to detect the cyclist, education and distance ridden in colder weather months are statistically significant; (3) for RLR behaviour caused by pedestrian crossing, age and driver red-light infringement in last 2 years are statistically significant; (4) for RLR behaviour caused by other reasons, gender and education are statistically significant.

Zhang et al. [11] applied logistic regression to analyze effects of intersection type (sun shield), weather type, type of cyclists, gender, age, and traffic volume on the RLR behaviour based on field observational data. The study results indicated that, except age, five other factors have significant effects on RLR behaviour. The study also analyzed the effect of type of intersection and type of weather on the RLR behaviour and safety margin with traffic volume as the covariate applying multivariate ANOVA.

Considering there are few researches on the RLR behaviour of pedestrians, Yang et al. [5] established a binary logit regression model to analyze factors on IRLR behaviour of pedestrians.

Except for the researches mentioned above, logistic regression method is widely used for analyzing the red-light violations of pedestrians and bicyclists in a lot of other previous studies [12–16].

The above researches provided many achievements on how factors affect the RLR behaviour of pedestrians and cyclists so that administrators can make more scientific decisions based on them. However, because of the inherent variability in the site conditions and other influential factors of specific intersections, there is likely a considerable amount of unobserved heterogeneity-variability that cannot be explained by the measurable data. Those previous studies failed to take the effects of unobserved heterogeneity into account [17]. In addition, the traditional logit regression methods are restricted to Independence of Irrelevant Alternatives (IIA), assuming that disturbances among the different crossing behaviours are independent, which may not always hold in the actual situations.

In the light of these two defects discussed above, there are some researchers who have improved their studies by using the approach of RPLM when investigating the effect of the factors on dependent variables in other traffic research areas. Anastaspopoulos et al. [18] investigated the effect of the related factors on the delay of highway project using the

Table 1: Characteristics of the three observed intersections.

Intersection	Zhongguancun East Rd. - Zhichun Rd.	Zhongguancun East Rd.- North third ring West Rd.	Zhongguancun South Rd. - Weigongcun Rd.
Intersection type	4-leg	4-leg	4-leg
Observed approaches	Zhongguancun East Rd.(North)	Zhongguancun East Rd.(North)	Zhongguancun South Rd.(South)
Crossing approaches	Zhichun Rd.	North third ring West Rd.	Weigongcun Rd.
Cycle length(s)	119	130	135
Number of motor vehicle lanes on the crossing streets in both directions	4(enter)+4(exit)	5(enter)+3(exit)	5(enter)+5(exit)
Crossing distance (m)	40	38.5	44
Area types	Urban	Urban	Urban
Separate signal for cyclists and pedestrians	No	No	No
Pedestrian signal type	Flashing	Flashing	Flashing

approach of the RPLM. Guo et al. [19] developed full Bayesian random parameters logistic regression to identify the key factors associated with bicyclists' RLR behaviour at two crossing facilities. Other studies have employed variations of random effects logistic regression model to analyze the relationship between traffic safety and factors [17, 20–24]. However, few researches apply RPLM to pedestrians' and (electric) bicyclists' IRLR behaviours at intersections. This study aims at RPLM to analyze the effects of the factors on IRLR behaviours of pedestrians and cyclists, and camera data are used.

3. Data

The field observational data were obtained by continuous recording using video camera in Beijing, China. This method of data gaining has been widely used in studies on RLR behaviour at intersections in the urban area [4, 5, 9–11, 25–27], by which high quality data are accessible [28].

3.1. Sites. Four criteria were used to select the signalized intersections for continuous recording in this study. First, the type of intersection selected is the typical major-major intersection type in the urban area, which have four characters: (1) it is a 4-leg intersection, (2) it has separate left-turn phases, (3) pedestrians and bicycles share the same light indicator, and (4) the light indicator is countdown type. Second, the geometry design and the individual traffic characteristics of the intersections are similar to each other. Third, the flow of pedestrians and cyclists is large enough. Fourth, motor vehicles volume is sufficient to ensure the observation of relationship between crossing road users (generally, road users include motor vehicle drivers, motorcyclists, bicyclists, and pedestrians; in the present research, road users refer to electric bicyclists, bicyclists, and pedestrians) and vehicles.

Three signalized major-major intersections in the central city of Beijing were selected based on the above criteria: Zhongguancun East Rd.-Zhichun Rd., Zhongguancun South Rd.-Weigongcun Rd., and Zhongguancun East Rd.-North Third Ring West Rd. To ensure that the data is more representative, this research only chooses one direction for shooting for each intersection. The chosen directions were westward, eastward, and eastward for Zhongguancun East Rd.-Zhichun Rd., Zhongguancun South Rd.-Weigongcun Rd., and Zhongguancun East Rd.-North Third Ring West Rd., respectively. The main characteristics and traffic light phase plans of the three selected intersections are listed in Table 1 and Figure 1 separately.

There are two criteria adopted to select the sites of cameras in this study: (1) the camera gets a complete view of all the road users (cyclists and pedestrians) with overlaps at the target groups; (2) the camera is not easy to be found by pedestrians and cyclists such as installed at the separation strip between motorized vehicles and nonmotorized vehicles close to the intersection to ensure that the behaviour of pedestrians and cyclists is not disturbed by the camera. The intersection layout, camera locations, and camera shooting directions at Zhongguancun East Rd.-Zhichun Rd. are shown in Figure 2.

3.2. Photograph. The dates of video shooting were weekdays in July 2014. The time periods of video shooting were 9:00~11:00 am and 14:00~16:00 pm to ensure the behaviour of pedestrians and cyclists was unaffected by traffic congestion. The weather was clear to ensure the behaviour of pedestrians and cyclists was unaffected by the inclement factors such as rain. Figure 3 displays the picture shot by Cameras 1, 2, and 3 at Zhongguancun East Rd.-Zhichun Rd. intersection.

It is a challenge to extract pedestrian and cyclist attributes from videos. To ensure the validity of these data, the following efforts were made:

(1) The video cameras were well hidden behind roadside fixed objects such as trees or telegraph poles to avoid being seen by the individuals and consequently causing a change in crossing behaviours.

(2) Three synchronized high-resolution video cameras were used to collect data of road users crossing behaviours. To make sure the whole crossing process can be recorded clearly, Camera 1 and Camera 3 were

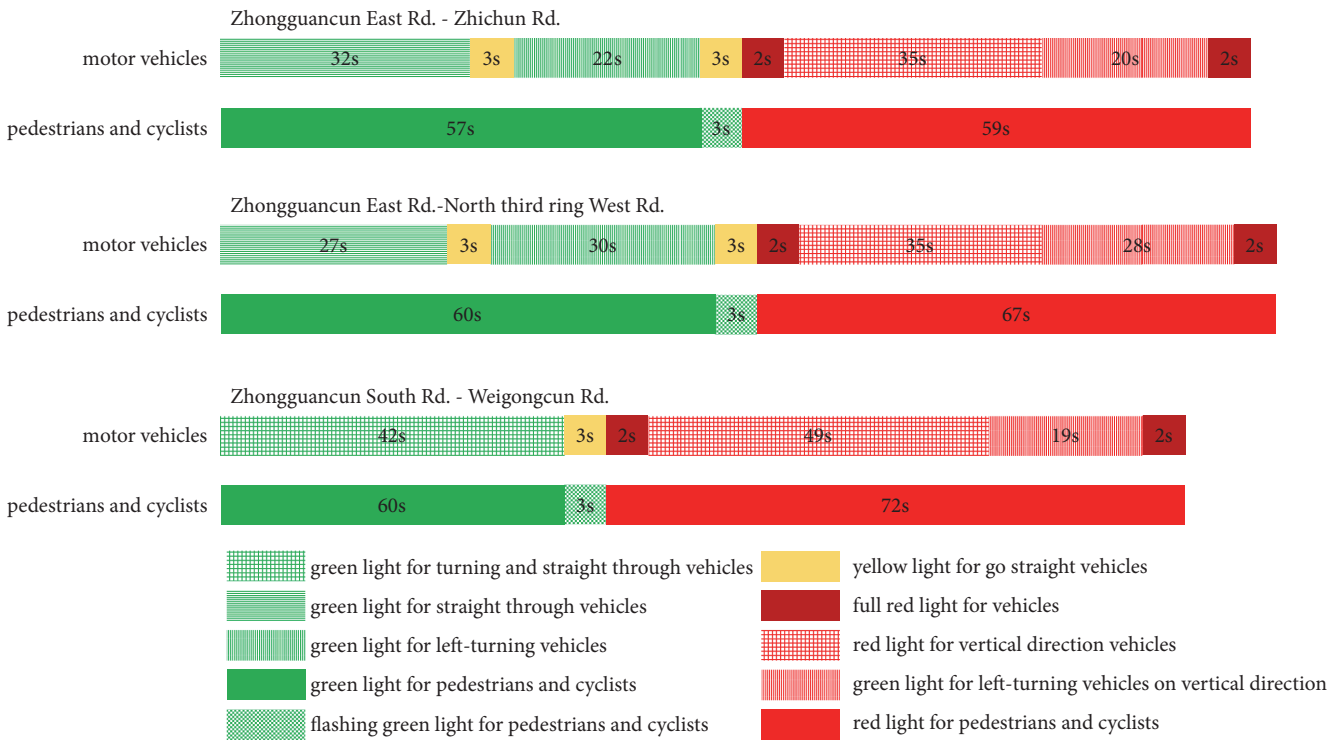

Figure 1: The traffic light phase plan of motor vehicles, pedestrians, and cyclists at three observed intersections.

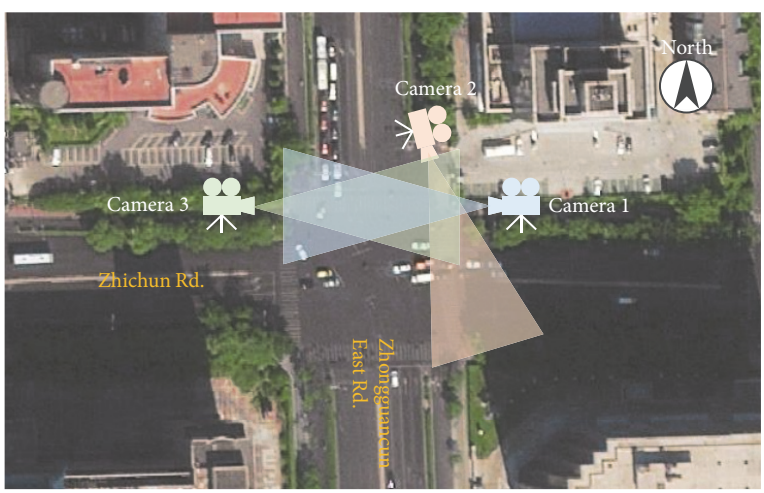

Figure 2: The intersection layout, camera locations, and camera shooting directions at Zhongguancun East Rd.-Zhichun Rd. intersection.

positioned on the opposite side of crosswalk to shoot the same road user group. Camera 2 was placed on the vertical direction with Camera 1 and Camera 3 as supplement.

(3) Since the road users arrive one by one, we can distinctly see and identify the road user attributes (e.g., hairstyle/dress preference/gender) and bicycle attribute (ordinary bike/electric bike).

(4) The data extraction process was performed by two researchers (Yanting Liu and Wencheng Wang) who have received training on the requirements of extraction and judgement of road user attributes. Yanting Liu was in charge of those videos recorded by Camera 1 whose shooting direction was the same as the road users' heading direction. Wencheng Wang was in charge of those videos recorded by Camera 2 whose shooting direction was opposite to the road users' heading direction. Two researchers identified road users' attributes separately, and then their records were matched. If the information of the same road user matched successfully, this information was

Figure 3: Photographs from Cameras 1, 2, and 3 at Zhongguancun East Rd.-Zhichun Rd. intersection.

accepted as the final dataset. If the same road user has different record or judgement, the third researcher (Xiaobao Yang) makes the final decision to decide which one was closer to the truth by combining Cameras 1, 2, and 3.

(5) The first researcher judged road users' age by their dress preference, hairstyle, and gesture, while the second researcher judged that by road users' countenance.

(6) The researchers marked on the screen to make it easier to identify the speed of the pedestrians, bicycles, and electric bicycles.

(7) Since batteries provided a key clue to isolating electric bicycles from ordinary ones, identification of bicycle type was thought to be less of a problem. Furthermore, the stopping cyclists at red lights that were observed not to propel their bicycles by pedaling (i.e., instead, by using the throttle) were identified as the users of electric bicycles [8].

3.3. Coding. The main research object is the behaviour of pedestrians and cyclists who infringe the red light. Thus, only the pedestrians and cyclists who arrive at the intersection at the red phase were taken as samples. When the pedestrians and cyclists arrive at the intersection, if the signal is green, these persons' behaviour was not coded to analyze because they have no probability of running the red light. When the pedestrians and cyclists arrive at the intersection at a red light, they have to make decision on whether to wait with some behaviours as the decision basis. To ensure the observation is clear and accurate, only those samples whose direction is the same as the video shooting direction were selected with left-turn road users neglected.

The video data should be converted to data applicable to the statistical package. Before analysing in the statistical package, all needed information and variables are coded into an EXCEL by a certain set of rules. In total, variables including basic information, behaviours, and environment conditions when arriving and behaviour and environment conditions when awaiting are coded and defined. The detailed contents are shown in Table 2.

The concepts of close left turn and far left turn are shown in Figure 4. For Camera 1, close left turn refers to the trajectory of vehicle 1. Far left turn is the trajectory of vehicle 2.

4. Methodology

This paper studied IRLR behaviour of pedestrians and cyclists crossing the street immediately after arrival at a signalized intersection by the method of RPLM.

4.1. Logit Model. The logistic regression is used to identify fitting, defensible models that describe the relationship between a binary dependent variable and explanatory variables [29]. It has been applied to model a wide variety of transportation data: accident-injury severities modelling [30, 31]; commuters' valuation of travel time analysis [32]; airport risk and accidents models development [33]; examination of risk factors associated with RLR behaviour at signalized intersections [34, 35].

In this study, $Y = 1$ denotes IRLR behaviour and $Y = 0$ denotes other behaviours. The equation of the logit model can be shown as

$$L_n(Y = 1) = \ln\left(\frac{P_n(Y = 1)}{1 - P_n(Y = 1)}\right) = \boldsymbol{\beta X}_n \tag{1}$$

The probability that the nth observation runs the red light immediately is

$$P_n(Y = 1) = \frac{\exp(\boldsymbol{\beta X}_n)}{1 + \exp(\boldsymbol{\beta X}_n)} \tag{2}$$

where $P_n(Y{=}1)$ is the probability of observation n running the red light immediately. $\boldsymbol{\beta}$ is a vector of estimable parameters for IRLR and $\boldsymbol{X}_n$ is a vector of the observable characteristics (covariates) that may have an effect on the IRLR behaviour for observation n.

4.2. Random Parameter Logit Model. As mentioned above, the logit model is suitable for many applications. However, it also has limitations, which may result in erroneous parameter estimates if the basic assumptions are not satisfied. The RPLM addresses several weaknesses of the traditional logit model by allowing parameter values to vary across observations [29].

Table 2: Definitions of variables coded.

Variables	Descriptions
Personal characteristics	
Gender	Male, 0; Female, 1
Age	Estimated age group: young (<30), 1; middle-aged (30-50), 2; elderly (>50), 3
Mode of transportation	Pedestrian, 1; bicycle, 2; electric bicycle, 3
Direction	The direction which the people come from when the people arrives at the intersection: left, 1; right, 2; back, 3
Arriving behaviour & environmental conditions	
Arrival phase	The phase of motor vehicles: the left-turn light of the approach whose direction is same as the direction of observation group is green (close left turn), 1; the go straight light of the approach whose direction is vertical to the direction of observation group is green, 2; the left-turn light of the approach whose direction is vertical to the direction of observation group is green (far left turn), 3
Speed change upon arrival	The people's speed change when the people arrive at the intersection: slower, 1; faster, 2; unchanged, 3
Cross traffic volume*	Average volume crossing motor vehicles per lane per minute during the red-light phase of pedestrians and cyclists when the people arrive at the intersection (rank from small to large): low (0-25%), 1; medium (26%-75%), 2; high (76%-100%), 3
No. of people waiting upon arrival	The number of other pedestrians who are waiting for the green light when the people arrive at the intersection
No. of people crossing upon arrival	The number of other pedestrians who are crossing against the red light when the people arrive at the intersection
IRLR behaviour	Whether to run the red light immediately when the people arrive at the intersection: no, 0; yes, 1
RLR behaviour	Whether to run the red light: no, 0; yes, 1

* Cross traffic volume definition of low to high: the quartiles of cross traffic volume are selected as the threshold for low, medium, and high (upper quartile for high and medium; lower quartile for medium and low). The actual values ar: low (0-25%) (volume ≤ 85v/15min), 1; medium (26%-75%) (85v/15min ≤ volume ≤ 103v/15min), 2; high (volume ≥ 103v/15min 76%-100%), 3.

As presented in articles of McFadden and Train [36], Train [37], and Hensher et al. [38], a function that determines observations' IRLR behaviours is defined as

$$T_n = \boldsymbol{\beta}\mathbf{X}_n + \varepsilon_n \tag{3}$$

where T_n is the propensity function that determines the probability of observation n's IRLR behaviours. The disturbance term ε_n is assumed to be extreme value Type I distributed [29]. All other terms are as previously defined.

As discussed above, the RPLM assumes the vector of estimable parameter $\boldsymbol{\beta}$ varies across the observed individuals. Define RPLM with

$$P_n^r(Y=1) = \int_X P_n(Y=1)\, f(\boldsymbol{\beta} \mid \boldsymbol{\varphi})\, d\boldsymbol{\beta} \tag{4}$$

where $P_n^r(Y=1)$ is the probability of running the red light immediately of observation n. $f(\boldsymbol{\beta} \mid \boldsymbol{\varphi})$ is the probability density function of $\boldsymbol{\beta}$, which is usually specified to be continuously distributed in most applications, such as normal, lognormal, triangular, and uniform function (for more details see Hensher et al. [38]). In the present research, random parameters are assumed to be normally distributed, which is a widely used assumption in previous studies [22, 24]. $\boldsymbol{\varphi}$ is the vector of parameters of the density function (such as mean and variance). Substituting (2) into (4) gives the RPLM

$$P_n^r(Y=1) = \int_X \frac{\exp(\boldsymbol{\beta}\mathbf{X}_n)}{1+\exp(\boldsymbol{\beta}\mathbf{X}_n)} f(\boldsymbol{\beta} \mid \boldsymbol{\varphi})\, d\boldsymbol{\beta} \tag{5}$$

All terms are as previously defined. Only the numerical solution of the equation can be obtained because the expression of the probability is not explicit in formula (5). The integral operation will become very complex when the dimension of $\boldsymbol{X}_n$ is more than 2. Therefore, it should be solved by the simulation algorithm.

Since there is no prior knowledge for random parameters, all parameters are assumed random and then evaluate their estimated standard deviations according to t-test of each parameter [8]. Train [37] and Bhat [39] claimed that the Halton sequence method is an effective method in the previous studies. It has also been proved that it is sufficient to obtain accurate estimation of the parameter when the Halton draws are 200 by many studies [20, 39–41]. In addition, the computation time is not too long when the Halton draws are 200, while it appears relatively time-consuming when the number of draws is more than 200 [8]. Therefore, it is assumed that all parameters of the explanatory variables are subjected to normal distribution and the Halton draws are 200.

Since it is almost impossible to interpret the effect of a variable only based on the direct observation of the parameters, marginal effects should also be computed. The marginal effect can offer an overview of the effect caused by a one-unit variation in an explanatory variable on the probabilities of IRLR behaviour [29]. If the explanatory variable x_k is continuous variable, the marginal effect of x_k is

$$ME(x_k) = \frac{\partial P_n^r(Y=1)}{\partial x_k}$$

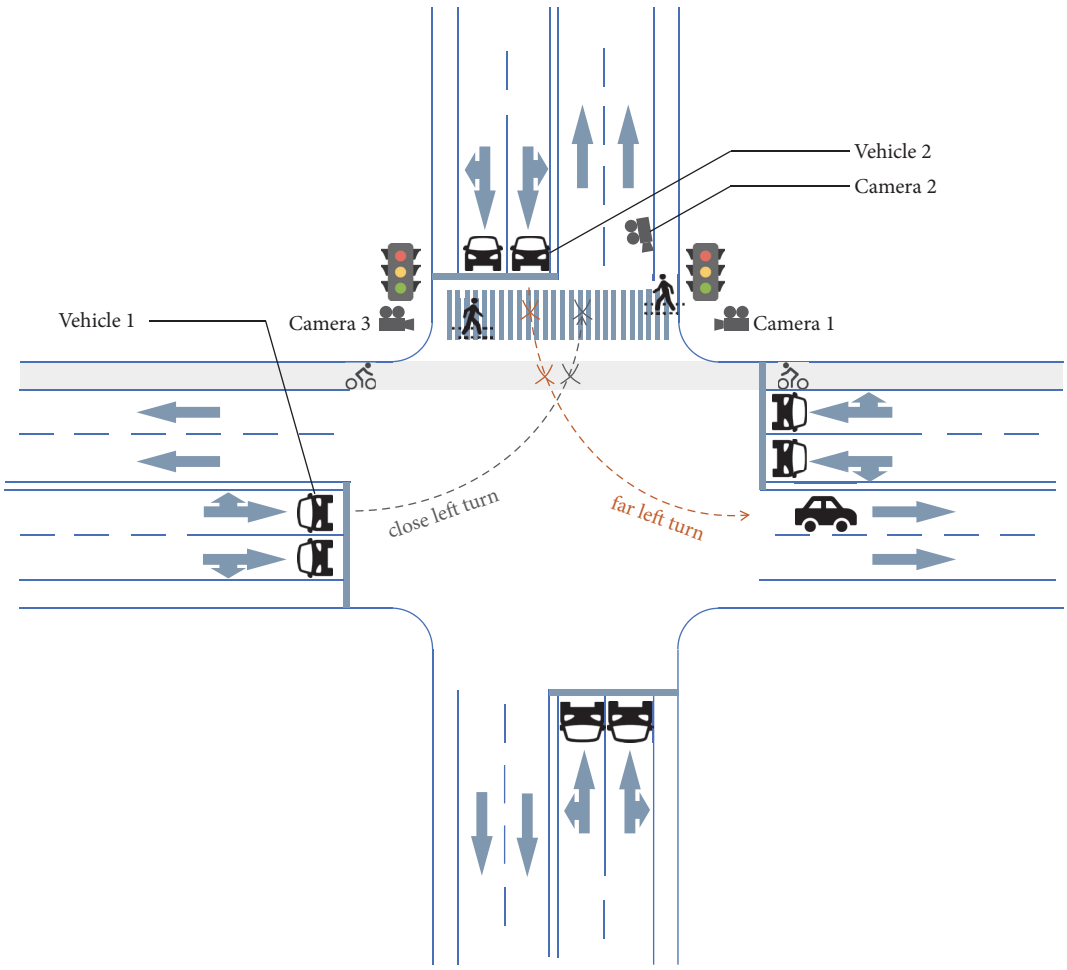

Figure 4: Illustration of the concepts of close left turn and far left turn.

$$= \frac{\partial \int_X \left(\exp\left(\boldsymbol{\beta}\mathbf{X}_n\right) / \left(1 + \exp\left(\boldsymbol{\beta}\mathbf{X}_n\right)\right)\right) f\left(\boldsymbol{\beta} \mid \boldsymbol{\varphi}\right) d\boldsymbol{\beta}}{\partial x_k} \tag{6}$$

If the explanatory variable x_k is an indicator variable, when its value changes from zero to one, marginal effect is denoted as

$$\begin{aligned} ME\left(x_k\right) = {} & P_n^r\left(Y = 1 \mid \text{given } x_k = 1\right) \\ & - P_n^r\left(Y = 1 \mid \text{given } x_k = 0\right) \end{aligned} \tag{7}$$

More detailed descriptions can be found in the papers of DeMaris and Morgan, Roncek, and Hanushek and Jackson [42–44]

5. Results

5.1. Descriptions. In total, 1368 samples were collected. The samples of pedestrians, bicycle riders, and electric bicycles riders are 503, 339, and 526, respectively. The proportion of sample who run the red light immediately is 19.3% (264). It can be seen from Table 3 that the rate of IRLR behaviour of male (20%) is greater than that of female (17%). And the rates of IRLR behaviour of the middle-age and the old (24% and 21%, respectively) are also greater than the young (15%). It is also shown in Table 3 that the IRLR behaviour proportion differences take different values for the three transportation modes. The difference between male and female for electric bicycle riders is greater than those for pedestrians and bicycle riders. It is also true that the IRLR behaviour proportion differences are distinct among three transportation modes. The proportion of IRLR behaviour of the old is 30% in the group of pedestrians, greater than those of the middle-age and the young. The rate of IRLR behaviour of the middle-age and old (23% and 15%, respectively) in the group of bicycle riders is greater than that of the young (9%). The rate of IRLR behaviour of the young and the middle-age (20% and 27%, respectively) in the group of electric bicycle riders is greater than that of the old (17%).

In addition, both the proportion of RLR behaviour and the proportion of IRLR behaviour for different transportation modes are different. The proportion of the RLR behaviour of electric bicycle riders (63%) is obviously greater than that of pedestrians (48%) and bicycle riders (47%). The proportion of IRLR behaviour of electric bicycle riders (24%) is obviously greater than that of pedestrians and bicycle riders (both

Table 3: Descriptive statistic and proportions of observation value with different attribute.

	Mode of transportation			Total
	Pedestrian	Bicycle	Electric bicycle	
(a) Contingence table of proportions of IRLR behaviour				
Gender				
Female	15%	20%	18%	17%
Male	18%	15%	25%	20%
Age				
Young	13%	9%	20%	15%
Middle-aged	18%	23%	27%	24%
Elderly	30%	15%	17%	21%
(b) Proportions of different infringements				
RLR*	48%	47%	63%	54%
IRLR	17%	17%	24%	19%
(c) Descriptive statistic of continuous variables				
	Min	Max	Mean	Std. Dev
No. of people waiting upon arrival	0	35	5.9	6.201
No. of people crossing upon arrival	0	21	1.14	2.339

*Including IRLR.

are 17%). The proportions of IRLR behaviour for different transportation modes are similar when only accounting for the samples who have the RLR behaviour.

5.2. The Results of Random Parameter Logit Model. The results of comparison between RPLM and the fixed parameter logit model (FPLM) are shown in Table 4. RPLM fits better than FPLM in terms of the AIC value. Therefore, the following analysis is mainly based on the RPLM results.

When the coefficient is positive, IRLR behaviour occurrence takes a higher probability with the rising value of the variable. When the corresponding p-value is less than 0.05, the effect of the variable on the sample is statistically significant. The coefficient of standard deviation means the estimation of the standard deviation of the normal distribution that the parameters of variables follow. If the corresponding p-value is less than 0.05, the standard deviation is not statistically equal to zero. That means the parameter of the variable follows the normal distribution whose mean value is the estimation of the coefficient of the variable and whose standard deviation is the estimation of the coefficient of standard deviation.

Table 5 provides the likelihood-ratio test results for the random and fixed parameter logit models, which shows that the random parameter models have a statistically superior fit relative to the traditional fixed-parameter model.

Interpreting the effects of the explanatory variables would be difficult because the coefficient of more than one variable passed the test of normal distribution. Thus, the marginal effect of these variables is also estimated. The change of the probability of the IRLR behaviour when a variable's value from 0 changes into 1 was calculated to reveal the marginal effect of these variables.

6. Discussion

No. of people waiting upon arrival, no. of people crossing upon arrival, mode of transportation, and arrival phase passed the test according to Table 4. These four variables' parameters are normally distributed. The change of speed when arriving did not pass the test so its parameter is fixed.

6.1. No. of People Waiting upon Arrival. The effect of no. of people waiting upon arrival on the IRLR behaviour is significantly negative (-0.946). The parameter is subjected to a normal distribution whose mean value is -0.946 and whose standard deviation is 0.893. Therefore, the parameters of 85.5% of samples are less than 0 while 14.5% of samples are greater than 0. This demonstrates that effect of no. of people waiting upon arrival on 85.5% of samples is negative, and the probability of the IRLR behaviour decreases. That effect on 14.5% of samples is positive, and the probability of the IRLR behaviour increases. The results of marginal effect indicated that the mean of the probability of the IRLR behaviour for each sample will decrease 0.3% when no. of people waiting upon arrival increases one unit. The result is consistent with the previous studies [42–44]. For example, Yang et al. [4] have shown that the odds of the IRLR behaviour of bicycle riders and electric bicycle riders decrease 12.8% when no. of people waiting upon arrival increases one unit [4]. The results may be caused by the conformity tendency of road users, which has been mentioned in the researches of Rosenbloom and Zhou et al. [12, 45]. The effect of no. of people waiting upon arrival on the IRLR behaviour of pedestrians and cyclists should not be neglected.

6.2. No. of People Crossing upon Arrival. The effect of no. of people crossing upon arrival on the IRLR behaviour is

Table 4: Summary of random and fixed parameter logit models estimation results for IRLR behaviour.

	RPLM		FPLM	
	Coefficient	z	Coefficient	z
Intercept	1.739***	5.3	-0.492	-0.23
No. of people waiting upon arrival	-0.946***	-9.79	-0.121***	-6.31
Std. Dev[a]	0.893***	10.04		
No. of people crossing upon arrival	1.054***	9.02	0.219***	5.85
Std. Dev[a]	3.064***	9.91		
Mode of transportation				
Pedestrian VS. Electric bicycle	-2.629***	-6.9	-0.759***	-4.04
Std. Dev[a]	3.995***	8.08		
Bicycle VS. Electric bicycle	-0.327		-0.327	-1.63
Std. Dev[a]	2.005***			
Arrival phase				
Arriv_phs_1[d] VS. Arriv_phs_3[e]	-1.908***	-5.67	-0.586**	-2.44
Std. Dev[a]	0.275	1.12		
Arriv_phs_2[f] VS. Arriv_phs_3[e]	-3.754***	-8.84	-1.833***	-8.25
Std. Dev[a]	2.19***	6.41		
Speed change upon arrival				
Slower VS. Unchanged	-1.295***	-4.56	-0.402**	-2.1
Std. Dev[a]	0.517	1.57		
Faster VS. Unchanged	11.359***	6.51	3.641***	4.97
Std. Dev[a]	2.501	1.3		
Sample size	1368		1368	
$LL(0)$[b]	-522.5		-521.152	
$LL(\beta)$[c]	-496.72		-671.030	
AIC	1015.3		1060.3	

** Significant at 0.95 level of confidence.
*** Significant at 0.99 level of confidence.
[a] Standard deviation of normally distributed parameter.
[b] Initial log-likelihood.
[c] Log-likelihood at convergence.
[d] The left-turn light of the approach whose direction is same as the shooting direction is green.
[e] The left-turn light of the approach whose direction is vertical to the shooting direction is green.
[f] The go straight light of the approach whose direction is vertical to the shooting direction is green.

Table 5: Goodness-of-fit measures for the random and fixed parameter logit models.

	RPLM	FPLM
Number of parameters	8	7
$LL(0)$	-522.5	-521.152
$LL(\beta)$	-496.72	-671.03
$\chi^2 = -2[LL(\beta)_{\text{random}} - LL(\beta)_{\text{fixed}}]$	348.62	
Degrees of freedom	1	
Critical χ^2	7.88(0.995 level of confidence)	
Number of observations	1368	1368

significantly positive (1.054). The parameter follows a normal distribution whose mean value is 1.054 and whose standard deviation is 3.064. Therefore, the parameters of 63.3% of samples are greater than 0 while 36.7% of samples are less than 0. This demonstrates that effect of no. of people crossing upon arrival on 63.3% of samples is positive, and the probability of the IRLR behaviour increases. That effect on 36.7% of samples is negative, and the probability of the IRLR behaviour decreases. The difference of this variable among different individuals is greater than that of no. of people waiting upon arrival. The results of marginal effect indicated that the mean of the probability of the IRLR behaviour for each sample will increase 0.3% when no. of people crossing upon arrival increases one. These results are similar to previous research, in which the odds of the IRLR behaviour of bicycle riders and electric bicycle riders

increase with increasing no. of people crossing upon arrival [4].

Together with the result above, this result indicates that IRLR behaviour is influenced by other road users' behaviour. The more the road users crossing against red light are, the more likely the road users run the red light. This conformity tendency was confirmed in many previous studies on road users' street-crossing behaviour [10, 12, 45]. The effect of no. of people crossing upon arrival on the IRLR behaviour of pedestrians and cyclists should not be neglected.

6.3. Mode of Transportation. The mode of transportation is a three-category variable. Two dummy variables are set by the model. The first dummy variable is expressed by pedestrians vs. electric bicycle riders with 0 denoting electric bicycle riders and 1 denoting pedestrians. The second dummy variable is expressed by bicycle riders vs. electric bicycle riders with 0 denoting electric bicycle riders and 1 denoting bicycle riders.

Only the first dummy variable has significantly decreasing effect (-2.629). The parameter follows a normal distribution and is estimated with a mean of -2.629 with a standard deviation of 3.995, which shows that 74.5% of this distribution is below zero and 25.5% is above zero. This implies that most pedestrians (74.5%) are less likely to have IRLR behaviour, and 25.5% of pedestrians have a higher probability of the IRLR behaviour. The results of marginal effect indicated that the mean of the probability of the IRLR behaviour for each sample will decrease 0.8% when the sample from an electric bicycle rider changes into a pedestrian. These results are confirmed by previous study [10], in which the violation rates of bicyclist and e-bicycle are slightly higher than that of pedestrian in Changsha, China.

The second dummy variable's effect on the IRLR behaviour is not significant. The rate of the IRLR behaviour of bicycle riders is 17% and that rate of electric bicycle riders is 24%. Although the difference of the rate of the IRLR behaviour between bicycle riders and electric bicycle riders is 7%, these two rates are not significantly different. This may be due to the same operation environment the bicyclist and e-bicyclist have. For instance, bicycles and e-bikes are operated in the same lane with fixed width which is commonly separated from motor-vehicle lanes. This may be the reason why they are able to influence each other in the mixed traffic and show similar behaviours as a result [10].

In addition, bicycles and electric bicycles are classified as nonmotor vehicles according to the traffic law in China, which makes them subject to the same traffic rules; in turn, they have similar performances. These results are similar to previous researches [10, 11].

6.4. Arrival Phase. Arrival phase is also a three-category variable. Two dummy variables are set by the model. The first dummy variable is expressed by close left turn vs. far left turn with 0 denoting far left turn and 1 denoting close left turn. The second dummy variable is expressed by straight vehicle in road vs. far left turn with 0 denoting far left turn and 1 denoting straight vehicle in road.

The first dummy variable has significantly decreasing effect (-1.908). The estimation of the standard deviation is 0.275. However, it did not pass the test, showing that the first dummy variable is a fixed variable. Therefore, the odds of IRLR during close left-turn phase is 14.8% ($1 - e^{-1.908}$) lower than that during far left turn when other variables are controlled. (Note: the close left-turn phase and the far left-turn here are referring to phase of motor vehicles. This is also applicable to the following two paragraphs.)

The second dummy variable has significantly decreasing effect (-3.754). The parameter is found to be normally distributed with a mean of -3.754 and a standard deviation of 2.19, showing 95.6% of this distribution is below zero and 4.4% is above zero. This implies that, compared with far left-turn phase, most road users (95.6%) are less likely to have IRLR behaviour during straight phase. The results of marginal effect indicated that the mean of the probability of the IRLR behaviour for each sample will decrease 1.1% when the phase of motor vehicles changes from straight into far left turn.

The result is consistent with the previous study by Yang et al. [4]: it is more likely to run the red light immediately for the bicycle rider and electric bicycle rider during the left-turn phase of motor vehicles. The reason is that there are no crossing motor vehicles at one half of the road near road users during the far left-turn phase. In turn, there are more opportunities for road users to operate twice-crossing street and wait at the median line of the road.

6.5. Speed Change upon Arrival. Speed change upon arrival is also a three-category variable. Two dummy variables were set by the model. The first dummy variable is expressed by slower vs. unchanged with 0 denoting unchanged and 1 denoting slower. The second dummy variable is expressed by faster vs. unchanged with 0 denoting unchanged and 1 denoting faster. Both dummy variables are fixed coefficients based on the results of the model.

The first dummy variable has significantly decreasing effect (-1.295). The estimation of the standard deviation is 0.517. However, it did not pass the test showing that the first dummy variable is a fixed variable. Therefore, the odds of the IRLR of those samples whose arriving speed has slowed down are 27.4% ($1 - e^{-1.295}$), lower than that of those samples whose arriving speed has not changed when other variables are controlled.

The second dummy variable has significantly increasing effect (-11.360). The estimation of the standard deviation is 2.501. However, it did not pass the test showing that the first dummy variable is a fixed variable. Therefore, the odds of the IRLR of those samples whose arriving speed has accelerated is 85819.37($e^{11.360}$) times higher than that of those samples whose arriving speed has not changed when other variables are controlled. This result indicates that those road users who speed up when arriving at the intersection are very likely to cross the intersection against the red light. Similar results of crossing speed change were reported in many researches [46, 47]. Pedestrians tend to change their walking speed while crossing to adjust to the traffic conditions for safe crossing, and more than half of them accelerated.

7. Conclusions and Future Work

1368 samples including pedestrians, bicycle riders, and electric bicycle riders were collected in this study. A RPLM of IRLR behaviour of pedestrian and cyclists at the signalized intersection in the urban was developed. The results indicate that no. of people waiting upon arrival, no. of people crossing upon arrival, pedestrians vs. electric bicycle riders, arrival phase, and speed change upon arrival have significant effects on the IRLR behaviour. Four variables, no. of people waiting upon arrival, no. of people crossing upon arrival, pedestrians vs. electric bicycle riders, and straight vehicles in road vs. far left turn, produce statistically significant random parameters. Two variables, close left turn vs. far left turn and speed change upon arrival, result in fixed parameters.

The present outcomes might be helpful for the proposal of traffic management countermeasures to decrease intersection-crossing risk behaviours:

(1) A random parameter with a normal distribution is found statistically significant for numbers of people crossing or waiting upon arrival. The result indicates that the presence and action of different road users can influence each other's crossing decision because of conformity tendency [10, 48]. So, conformity tendency of road users can be used to guide safety education or mandatory requirements. For instance, red-light infringement education can be first taken among the groups which are more likely to obey the traffic rules (e.g., students); in turn, other groups of road users would be influenced positively.

(2) The discussion demonstrates that the electric bicycle riders are more likely to run the red light immediately. So, related enforcement should be conducted on the electric bicycle riders. For example, a license system could be imposed because the licenses are not required for e-bicycle and regular bicycle at that time, which makes it a challenge to penalize those RLR riders. The benign and healthy sequence results would occur. First, it would directly decrease the IRLR behaviour and the RLR behaviour of the electric bicycle riders. Then no. of people waiting upon arrival would increase and no. of people crossing upon arrival would decrease. Then it would reduce the IRLR behaviour of pedestrians, bicycle riders, and electric bicycle riders.

(3) Arrival phase is significantly associated with IRLR behaviours. This suggests a greater risk-taking propensity for the road users arriving during far left turn. As previous research discussed [3], it may be appropriate in some situations to permit pedestrians and cyclists to continue through an intersection against a red traffic light. And, improvements are needed to existing road infrastructure to ensure safety for second-crossing.

In conclusion, the findings of this research would be useful for transportation engineers to better understand the behaviour of pedestrians to find related solutions for the problem. And it is also helpful in developing more accurate and reliable pedestrian and cyclist simulation models. There are still several limitations in the present study which should be addressed in future work. First, data from three intersections makes it difficult to be representative of most intersections and this may limit the transferability of the research. Modeling with an increased sample size should have a better transferability. Second, the phasing and timing variables of the intersctions may be also important to road users' behaviours, which are not considered in present research. Future studies including the phasing and timing variables are needed to better understand how those factors influence IRLR behaviours. Third, only the factors' effects on the behaviour of IRLR have been analyzed in this study. There is need for a further study on the rule and factors of waiting time of the waited pedestrians and cyclists.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This research was jointly supported by the Fundamental Research Funds for the Central Universities [No. 2018JBM023] and National Natural Science Foundation of China [Grants Nos. 91746201 and 71621001], China Scholarship Council [201707090042], and Center of Cooperative Innovation for Beijing Metropolitan Transportation.

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