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Red Light Running Behavior of Bicyclists in Urban Area: Effects of Bicycle Type and Bicycle Group Size

ABSTRACT

Bicyclists are vulnerable to fatality and severe injury in road crashes. Red light running violation of bicyclists is the major contributory factors to the crash involvement of bicyclists worldwide. This study aims to identify the factors that affect the propensity of red light running of bicyclists. Effects of bicycle type and bicycle group size are considered. Video observation surveys were conducted at eight signalized intersections in the urban area of Nanjing City in China. Crossing behaviors of 6,930 bicyclists were recorded. Then, a random-parameter logit model was established to measure the association between the propensity of red light running of bicyclist and possible factors. Results indicated that the propensity of red light running of e-bike riders was significantly higher than that of conventional bicyclists. Additionally, factors including bicyclists' demographics, bicycle group size, traffic flow condition, road geometry and traffic control attributes also affected the propensity of red light running of bicyclists. Propensity of red light running of bicyclist decreased with the increase in the bicycle group size. Propensity increased with the increase in bicycle volume but declined when the opposing traffic volume increased. Presence of signal countdown display was correlated to the increase in the propensity of red light running. Furthermore, interaction effects between bike type and factors including bicyclists' age, bicycle group size and bicycle volume on the propensity of red light running were significant. These findings can enhance the understanding of red light running behaviors of bicyclists. Also, useful recommendations that can deter against red light running behaviors and enhance overall road safety were provided.

Keywords: bicycle safety; e-bike; red light running violation; signalized intersection, group size

1. INTRODUCTION

Cycling is increasingly recognized as a sustainable and efficient urban transport mode. It does not only alleviate the problem of traffic emission, but also enhance the well-being of people. In China, bicycles constitute the greatest mode share in a number of major cities. On average, the mode share of bicycles is about 35%, in accordance to the statistics from 51 cities in 2017 (Li et al., 2017). In some small to medium-sized cities, the bicycle mode shares can even be greater than 50%. In recent years, electric bicycles (e-bikes) have been increasingly popular in China. E-bikes refer to the bicycles that are either solely or partially electric-powered, while conventional bikes refer to those that can only operate with pedalling in China. The e-bike is equipped with a rechargeable battery and an electric motor to provide power assistance. E-bike can increase the mobility of the rider. Also, it is a good alternative to motorcycle as the ability to be pedaled by the riders can be retained. The annual average growth rate of mode share of e-bike in China was 2%. Number of e-bike riders in China could reach 290 million by the end of 2018 (Li et al., 2017).

However, bicycle safety has been of great concern. Bicyclists are more vulnerable to fatality and severe injury in road crashes, compared to other vehicle occupants (Du et al., 2014; Hu et al., 2014). In 2012, 10,707 bicyclists involved in fatal crashes and 43,901 involved in severely injured crashes respectively in China. For instances, e-bike riders accounted for 51.6% of all non-motorized traffic (i.e. pedestrian and bicyclists) fatalities and 64.2% of all non-motorized traffic injuries respectively (CRTASR, 2012, 2013). Risk-taking behaviors and traffic violations of bicyclists, including red light running violations, non-compliance of traffic signs and road markings, and riding on motorized traffic lanes, are major crash contributory factors (Ma et al., 2019). Red light running violation of bicyclists is the leading cause of traffic conflicts and collisions at signalized intersections worldwide (Bai et al, 2013; Jensupakarn and Kanitpong, 2018; Schleinitz et al., 2019). Therefore, it is of great importance to investigate the red light running behavior of bicyclists.

Studies have attempted the trends of red light running rate of bicyclists. Results of empirical surveys indicated that average red light running rate of bicyclists could range from 18% to 99% (Fraboni et al., 2018; Guo et al., 2014; Wu et al., 2012; Yan et al., 2015; Zhang and Wu, 2013). An online survey in Australia indicated that 37% of bicyclists surveyed had the experience of red light running violation (Johnson et al., 2013). An Irish survey even indicated that 88% of bicyclists surveyed had committed traffic violations (Lawson et al., 2013). The red light running rate of bicyclist was 97-99% at intersections with bicycle-specific traffic signals, and 17-21% at those with no bicycle-specific traffic signal respectively, according to a video observational survey in Dublin (Richardson and Caulfield, 2015). In China, the red light running rate of two-wheelers, including bicycles, e-bikes and scooters, varied remarkably across cities. Particularly, red light running rate was 18-25% in Nanjing City, 19% in Changsha City and 56% in Beijing City respectively (Wu et al., 2012; Guo et al., 2014; Yan et al., 2015).

Attempts were also made to identify the factors affecting the propensity of red light running of bicyclists. Studies indicated that bicyclists' characteristics, traffic condition, road geometry, signal time plan, presence of bicycle facilities and e-bike licensing system all affected the incidence of red light running of bicyclists (Fraboni et al., 2018; Guo et al., 2014, 2017, 2018; Rosenbloom, 2009; Satiennam et al., 2018; Schleinitz et al., 2019; Zhou et al., 2017). In particular, propensity of red light running of male bicyclist was higher than that of female. Fear of accident and law obedience could be the possible reasons of non-aggressive behavior of female bicyclists (Bai et al, 2015). Also, propensities of red light running of young and mid-aged bicyclists were higher than that of their older counterparts (Wu et al., 2012). Additionally, students had higher likelihood to commit red light running offenses (Pai and Jou, 2014). For the effect of traffic condition, studies found that red light running rate of cyclists could decline with an increase in conflicting vehicular traffic volume (Guo et al., 2014, 2018). Presence of other bicyclists could also affect the propensity of red light running of bicyclists. Propensity could increase when there was no other bicyclist (Fraboni et al., 2018). For the road design, red light running rates of bicyclists at T-junctions and junctions with raised medians were higher (Schleinitz et al., 2019). For the traffic control, presence of signal countdown display increased the propensity of red light running of bicyclist (Guo et al., 2014). Also, waiting time had a significant effect on bicyclists' red light running behaviors (Zhou et al., 2017). Propensity of red light running increased remarkably when the red time was longer than 30 second, especially during the non-peak period (Pai and Jou, 2014). Furthermore, presence of sunshields (usually installed at the stop lines of signalized intersections) could reduce the propensity of red light running of bicyclists, especially on sunny days (Zhang and Wu, 2013).

Although attempts were made to examine the red light running behavior of bicyclists and possible explanatory factors, it was rare that the effects of bicycle type and presence of other bicycles on the propensity of red light running of bicyclists were considered. According to the Chinese Road Rule, e-bike is legally classified as bicycle and is required to be rode on the conventional bicycle lane. However, power of e-bike could be much higher than that of conventional bicycle. Average speed of e-bike can be of 8 km/h higher than that of conventional bicycle (Lin et al., 2008). Maximum operating speed of e-bike can reach 30 km/h (Cherry and Cervero, 2007; Lin et al., 2008). Thus, it can be expected that propensity of red light running of e-bike users be different from that of conventional bicycle. Additionally, it is very likely that the social norms can affect the propensity of red light running. Effect of social norms attributed to the presence of other bicyclists (as a group at the junction approach) on the red light running behavior can be moderated by the group size and bicycle type. Therefore, it is crucial to incorporate the factors including presence of bicycle group, group size and bicycle type when investigating the propensity of red light running of bicyclists. Then, effective traffic control, enforcement and publicity measures deterring against bicyclists' red light running behavior can be implemented.

In this study, we attempt to investigate the red light running behavior of bicyclists using a video observation survey at eight signal intersections in Nanjing City (one of the large Chinese cities with high bicycle use). Then, a random parameter logit model is established to measure the association between propensity of red light running of bicyclist and possible contributing factors, with which the effects of bicycle type and presence of bicycle group is considered.

The remainder of the paper is structured as follows: Section 2 describes the study design and method of data collection. Then, method of analysis is illustrated in Section 3. Furthermore, Section 4 will present the analysis results. Eventually, policy implications and recommendations are discussed in Section 5 and concluding remarks are provided in Section 6 respectively.

2. STUDY DESIGN

Video observation surveys were carried out at eight signal intersections in Nanjing City of China on selected days during the period from 1 May 2017 to 30 June 2017 that the weather conditions were fine. There was no rainfall, storm nor heat wave. As of the end of 2018, the total population of Nanjing was about 8.4 million. E-bikes constituted about a quarter of overall commuter trips in Nanjing. The eight selected sites were all regular cross-intersections. **Table 1** presented the characteristics of the selected sites. All of them were in the downtown area. **Figure 1** illustrated the locations of the eight selected sites. Layout and geometric design characteristics of the eight sites are similar. **Figure 2** illustrates the layout and configuration of one survey site. Of the eight intersections, five had signal countdown displays (both countdown to red and countdown to green).

Table 1. Characteristics of the selected sites

Site	Location	Signal Type	No. of Signal Phases	Cycle Length (sec)	Survey period (hr)
1	Zhongshan Road j/w Hankou Road	Flashing	4	140	4
2	Jinxianghe Road j/w Sipailou Street	Countdown	2	91	4
3	Zhongshan Road j/w Guangzhou Road	Countdown	4	140	4
4	Jinxianghe Road j/w Zhujiang Road	Countdown	4	140	4
5	Zhujiang Road j/w Taiping North Road	Flashing	4	140	4
6	Hongwu North Road j/w Beimen Bridge Road	Flashing	2	137	4
7	Hongwu North Road j/w Changjiang Road	Countdown	4	137	4
8	Hongwu Road j/w Huaihai Road	Countdown	4	137	4

Figure 1. Locations of the eight selected sites

Each site was surveyed for four hours, particularly two hours during the morning peak (i.e. 7:00 to 9:00 a.m.) and two hours during the evening peak time (i.e. 5:00 to 7:00 p.m.) respectively on a weekday. Therefore, a total of 32 hours of video were captured. Also, no (manual or automated) red light running enforcement was presence at all selected sites during the surveys. There was no law enforcement at all selected sites before the survey period or at other nearby intersections during the survey period. This was to eliminate the possible bias on the association attributed to the weather conditions and enforcement measures. In the survey, two video cameras were used. One was placed on the rooftop of a building nearby the intersection to capture the flow and turning movements of all motor vehicles, bicycles and pedestrian at the intersection. Another camera was placed at a high point nearby one intersection approach. Hence, information on bicyclists' characteristics, bicyclists' behaviors, traffic signal and signal time of the approach can be captured.

Figure 2. Illustration of a video observation site

The video data was coded manually in the laboratory by several well-trained graduate research assistants. Prior to the actual data coding, each research assistant was given a 30-minute training video for practicing. Consistency and accuracy of the trials would be assessed by the senior graduate research assistant. Additionally, the senior graduate research assistant was stationed in the laboratory for random checking and answering of queries from the research assistants throughout the process of data coding.

Additionally, a video processing software - VideoStudio - was used to facilitate the frame-by-frame (25 frames per second) search of the observers. Therefore, the time when a bicyclist crossed the stop line can be captured. Note that a bicyclist would be considered as running the red light whenever he or she crossed the stop line during the red indication, regardless of whether one completed the crossing or not. Information on bicyclists' demographics (i.e. age and gender), presence of other bicycles as a group and group size, bicycle type, bicycle movement, vehicular traffic volume, geometric design, traffic control and signal time was collected. Information on bicyclists' demographics were obtained based on the facial appearance in the video. Bicyclists' age was stratified into three classes: (i) youngsters, who appeared to be younger than 25 years; (ii) elderly, who appeared to be older than 60 years; and (iii) others. Thresholds of 25 years old for youngster and 60 years old for elderly are commonly used in safety literatures (Ma and Yan, 2014; Bai and Kattan, 2014; Singleton and Wang, 2014).

For the traffic condition, number of bicycles arrived at the concerned intersection approach per cycle, and vehicular traffic volume of opposing traffic streams per cycle were recorded. For the traffic control attributes, presence of signal countdown display, cycle time, green time and red time are considered. According to the Chinese Road Rule, bicyclists are required to obey the pedestrian signal. For the geometric design, factors including crossing length and presence of raised median are considered.

For the presence of bicycle group, whether two or more bicycles arrived at the junction approach is considered as a group depends on the time headway of following bicycles. Considered that threshold distance of constraint status of two or more bicycles was 9 meter and average operating speed of bicycle was 14 to 26 km/h (Lin et al., 2008; Mohammed et al., 2019), the threshold time headway for bicycle group would be set at 2 second (Hoogendoorn and Daamen, 2016). As shown in **Figure 3**, to avoid the interference by bicycles crowded at the stop lines, a 'reference line' for estimating the time headway of approaching bicycles was set at 10 meters upstream of the stop line. Let t_i and t_j denote the times at which bicycle i and j passing through the reference line respectively. If time differential Δt_{ij} ($\Delta t_{ij} = t_j - t_i$) is less than two seconds, then bicycle i and bicycle j would be considered to be in the same group.

Figure 4 illustrates the distributions of bicycle group size. In the proposed analysis, group size is stratified into four categories: (i) Category I – 1 bicycle (i.e. no group, constitutes to 9.8% of overall); (ii) Category II – 2 to 4 bicycles (41.2%); (iii) Category III – 5 to 8 bicycles (26.0%); and (iv) Category IV – more than 8 bicycles (23.0%). Except for Category I, as shown in Figure 3, the categories are set out in accordance to the second and third quartiles of bicycle group size. In the proposed video observation surveys, characteristics and behaviors of 6,930 bicyclists were captured. **Table 2** presents the summary statistics of the 6,930 observations. In particular, 4,410 (63.6%) were e-bike riders and 2,520 (36.4%) were conventional bicyclists respectively.

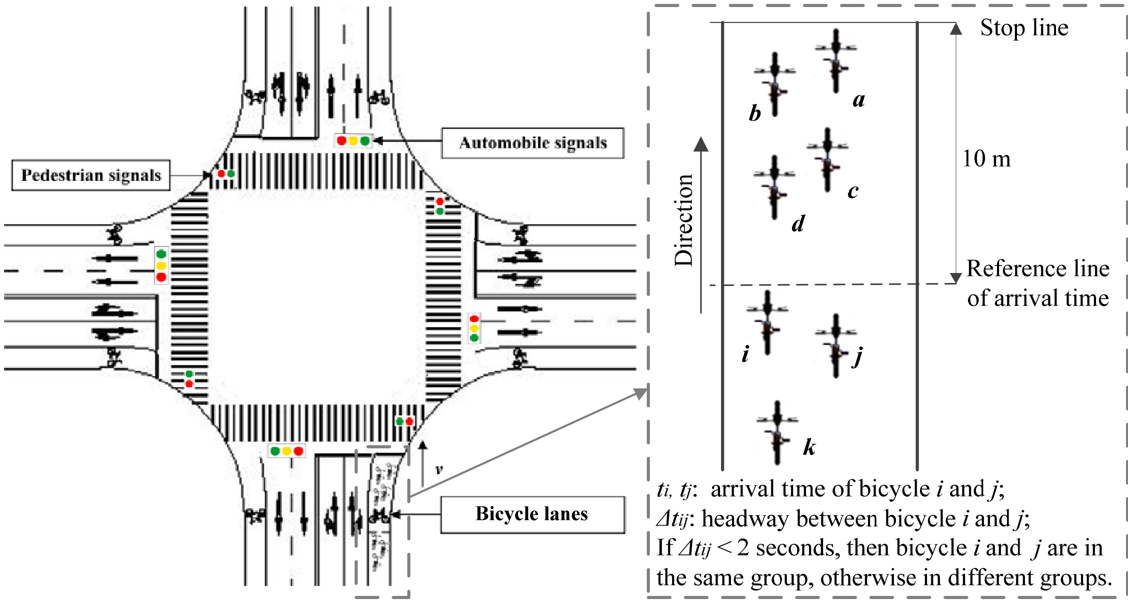

Figure 3. Definition of bicycle group

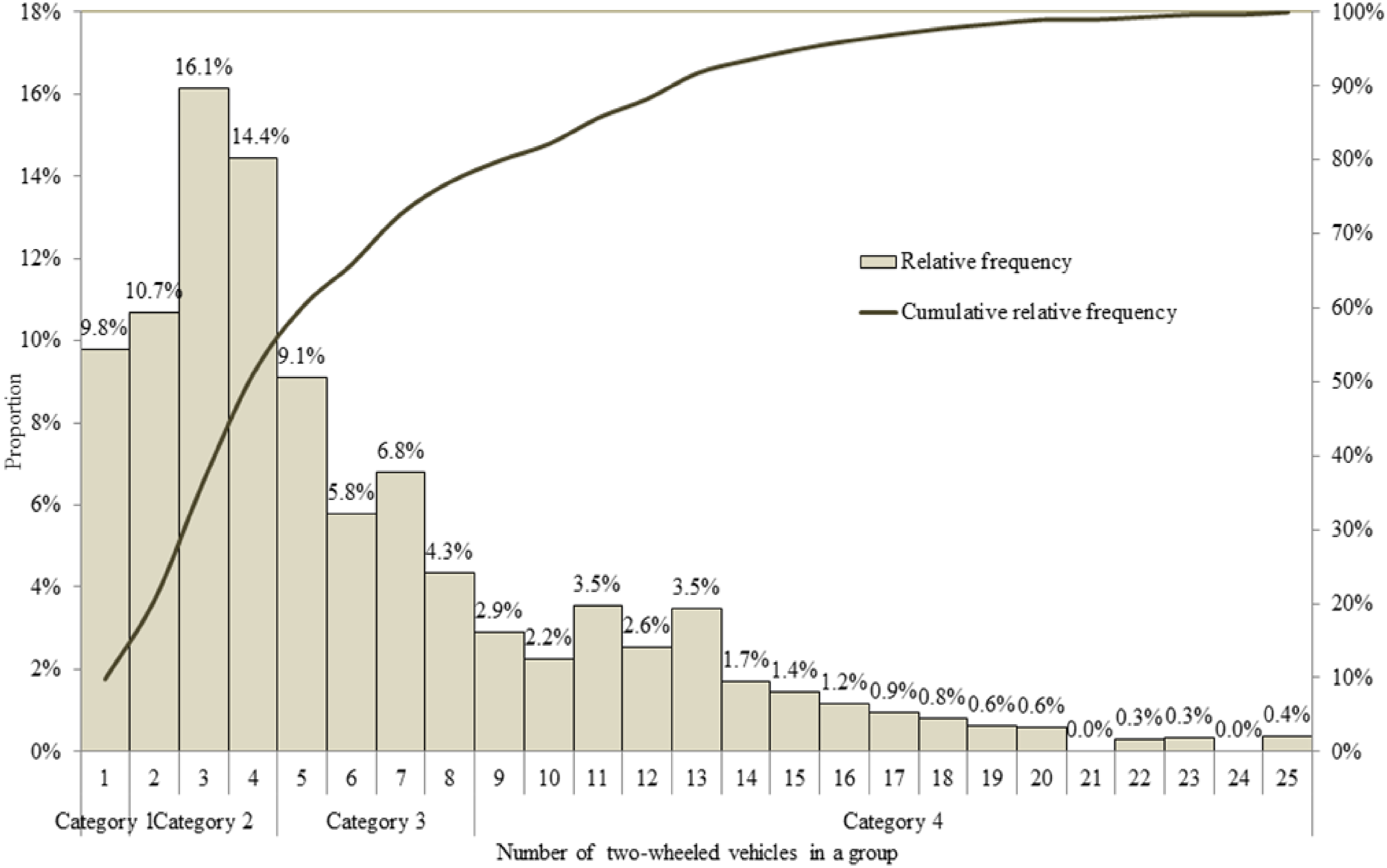

Figure 4. Distribution of bicycle group size

Table 2. Summary of the sample (number of observations = 6,930)

Factor	Attributes	Frequency	Mean	%	Std. dev.
Bicycle type	E-bike	4410		63.6%	
	Conventional bicycle	2520		36.4%	
Bicycle group size	Category I: 1	680		9.8%	
	Category II: 2 - 4	2857		41.2%	
	Category III: 5 - 8	1797		25.9%	
	Category IV: >8	1596		23.0%	
Gender	Male	4095		59.1%	
	Female	2835		40.9%	
Age group	Youngster	390		5.7%	
	Others	6119		88.3%	
	Elderly	421		6.1%	
Bicyclist behavior	Carrying passenger or good	1512		21.8%	
	No	5418		78.2%	
Bicycle volume per cycle	Min. = 3; Max. = 69		24.8		13.5
Opposing traffic per cycle	Min. = 4; Max. = 79		51.5		20.9
Presence of raised median	Yes	1078		15.6%	
	No	5852		84.4%	
Crossing length	Min. = 17; Max. = 40		30.6		6.2
Presence of signal countdown display	Yes	4177		60.3%	
	No	2753		39.7%	
Ratio of green to cycle time	Min. = 0.2; Max. = 0.5		0.3		0.1

3. METHOD OF ANALYSIS

In conventional studies, logit regression approach has been applied to model the propensity of traffic violations (Wong et al., 2008; Zhang and Wu, 2013; Guo et al., 2014; Li et al., 2014). However, classical logit models assumed the parameters of possible factors to be fixed across observations. They could not address the problem of unobserved location-specific heterogeneity (Xu et al., 2015). Red light running propensity among the bicyclists of the same characteristics (e.g. gender and age group) may vary with unobserved (and not measurable in observational survey) factors including safety perception and attitudes. Additionally, the complexity of the interaction effects among the factors including road design, traffic conditions and bicyclists' behaviors may also result in heterogeneity. Such heterogeneity was unlikely accounted for using the explanatory variables at the location level (Xiong and Mannering, 2013).

To account for the effect of unobserved heterogeneity, the random-parameter approach should be applied. Formulation of classical binary logit model is given by,

$$P(y_i = 1 | X_i) = \frac{\exp(\boldsymbol{\beta}' X_i)}{1 + \exp(\boldsymbol{\beta}' X_i)} \tag{1}$$

where $P(.)$ is the probability distribution function, y_i is the indicating variable for red light running (1 denotes red light running, and 0 otherwise) of the i^{th} observation; $i=1,2, \ldots, N$, $\boldsymbol{X_i}$ is the vector of explanatory variables, $\boldsymbol{\beta}$ is the vector of the means of parameters.

For the random-parameter logit model, a random component is added to the parameter using the formulation given as follows,

$$\beta_j = \beta + \omega_j \tag{2}$$

where ω_j is the randomly distributed error term for factor attribute j (normally distributed with mean 0 and the variance Σ_j). Log-likelihood of the random-parameter logit model is given by,

$$LL = \sum_{n=1}^{N} \left[y_i Ln \frac{\exp(\beta_j' x_i)}{1 + \exp(\beta_j' x_i)} + (1 - y_i) Ln \frac{1}{1 + \exp(\beta_j' x_i)} \right] \tag{3}$$

To indicate the impact of possible contributing factor on the propensity of red light running, given that other variables remain constant, elasticities are estimated using the formulation given as follows (Washington et al., 2010),

$$E_{x_{ik}}^{P(i)} = \frac{\partial p(i)}{\partial x_{ik}} \times \frac{x_{ik}}{P(i)} = [1 - P(i)] \boldsymbol{\beta}_{ik} x_{ik} \tag{4}$$

where $E_{xik}^{P(i)}$ is the elasticity of the k^{th} independent variable; x_{ik} is the value of k^{th} independent variable for i^{th} observation; β_{ik} is the coefficient of x_{ik}; $P(i)$ is the propensity of red light running of the i^{th} observation.

In this study, the proposed random-parameter logit model is set out using software package *NLOGIT 5.0*. For the detailed steps and algorithm, readers may refer to the Reference Guide of NLOGIT 5.0 (Greene, 2012)

4 RESULTS

Figure 5 illustrates the distribution of bicyclists who violated the red light by bicycle type and decile of red time. Of the 6,930 bicyclists captured in the observation survey, 1,464 violated the red light. Hence, the overall red light running rate was 21.1%. Of the 1,464 red-light runners, two-third were observed in the first and last deciles of red time. This indicated that late stop and early start of bicycles can be prevalent. For instances, late stop could be attributed to the perception of bicyclists that opposing vehicular traffic may take some time to reach the conflict point upon the onset of red indication, while the early start could be attributed to the early cut-off or red clearance interval for vehicular traffic respectively. The remaining one third of red-light runners were evenly distributed across other portions of red time.

Additionally, distribution of red-light runners by red time was dependent to the bicycle type at the 5% level. The overall red light running rate of e-bike (26.5%) was remarkably higher than that of conventional bicycle (11.7%). However, red light running rate of conventional bicycle (46.3%) was noticeably higher than that of e-bike (38.5%) in the first decile of red time (Red light running rate of conventional bicycle was also higher than that of e-bike in the last decile despite the difference was marginal).

Prior to the establishment of refined model, the possible correlations between candidate variables should be estimated using Pearson coefficients. Candidate variables that were highly correlated to other variables would not be considered in subsequent analysis. Additionally, stepwise approach was applied to identify significant variables of the proposed model. **Table 3** presents the results of parameter estimation of confined random-parameter logit model.

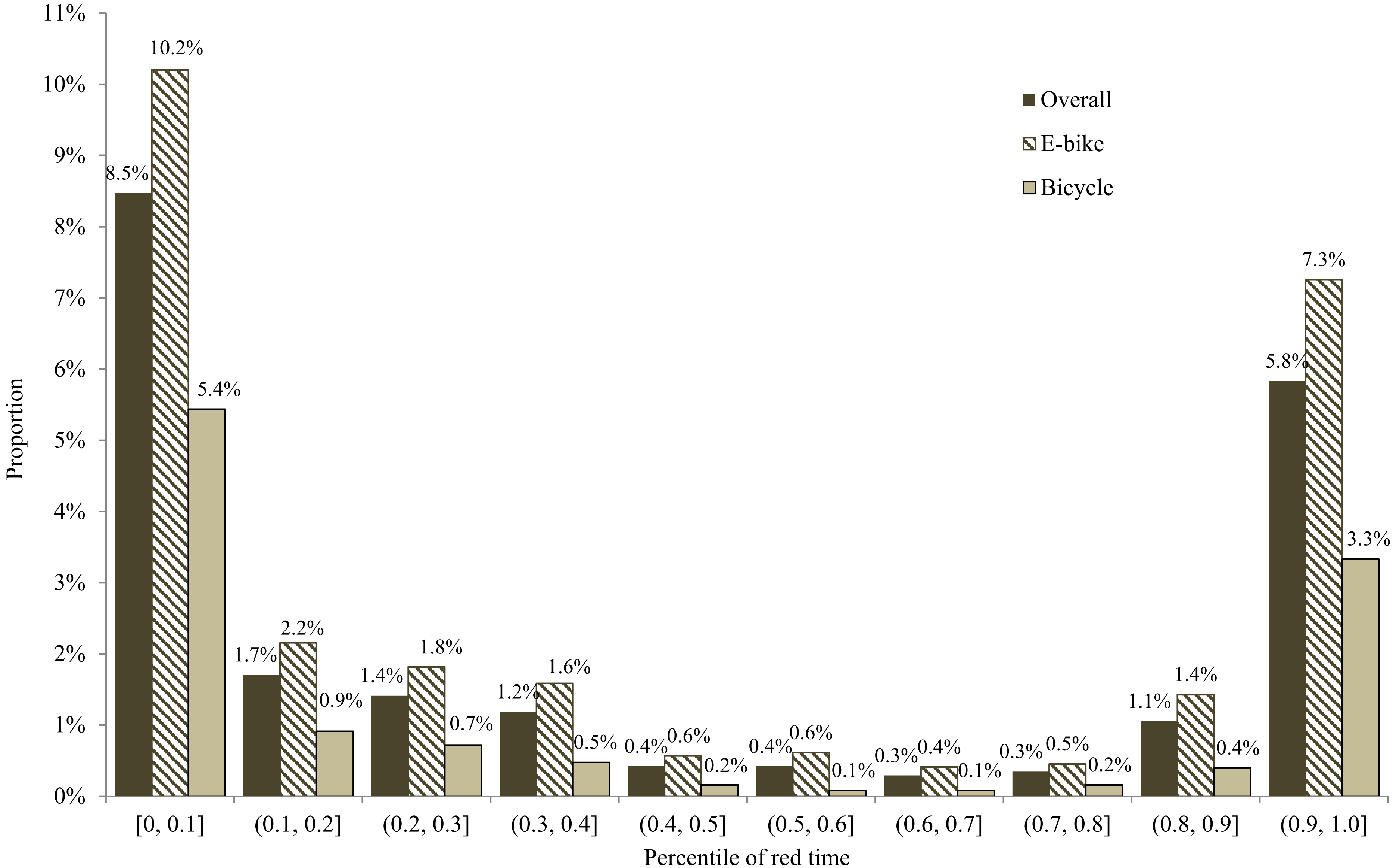

Figure 5. Distribution of bicyclists who violated the red light by bicycle type and decile of red time

Table 3. Results of random-parameter logit model for red light running propensity

Variable			**Coefficient**	**Standard error**	**Elasticity**
Constant		Mean	-0.81	0.52	*N/A*
		S.D.	*0.19***	*0.06*	*N/A*
Bicycle type (Control: conventional)	E-bike		0.92**	0.30	0.57
Bicycle group size (Control: 5- 8 bicycles)	1 bicycle		2.29**	0.14	0.22
	2 - 4 bicycles	Mean	1.55**	0.18	0.63
		S.D.	*5.70***	*0.22*	*N/A*
	2 - 4 bicycles x E-bike		0.61**	0.18	0.12
	> 8 bicycles	Mean	-1.41**	0.12	-0.32
		S.D.	*1.22***	*0.10*	*N/A*
Gender (Control: female)	Male		1.13**	0.17	0.66
Age group (Control: others)	Youngster		0.78**	0.25	0.04
	Youngster x E-bike		2.31**	0.32	0.04
	Elderly		-1.96**	0.36	-0.12
	Elderly x E-bike		1.04*	0.51	0.02
Carrying passenger or good			-0.52**	0.13	-0.11
Bicycle volume per cycle			0.03**	0.01	0.80
Bicycle volume x E-bike			-0.01^	0.01	-0.17
Opposing traffic per cycle		Mean	-0.08**	0.01	-4.24
		S.D.	*0.14***	*0.01*	*N/A*
Opposing traffic x E-bike			0.02**	0.01	0.65
Crossing length			-0.15**	0.01	-4.56
Presence of raised median			1.94**	0.15	0.30
Presence of signal countdown display			4.19**	0.20	2.50
Log likelihood			-1985.03		
McFadden pseudo R-squared			0.27		
Chi squared			1480.47		

^ Marginal significance at the 10% level
** Statistical significance at the 5% level*
*** Statistical significance at the 1% level*

As shown in **Table 3**, bicycle type and group size significantly affected the propensity of red light running, both at the 1% level. Propensity of red light running of e-bike riders was 57% higher than that of conventional bicyclists. Increase in the bicycle group size was correlated to the reduction in the propensity of red light running. In particular, propensity of red light running increased when bicycle group size was less than five. Such increase in the propensity was more prevalent among the e-bike riders. Propensity of red light running when there was no other bicycle present was 22% higher than that when there were 5 to 8 bicycles in a group. Additionally, the propensity when there were 2 to 4 bicycles in a group was 63% higher (the propensity of e-bike rider in such a group further increased by 12%). In contrast, propensity of red light running when there were more than 8 bicycles in a group was 32% lower than that when there were 5 to 8 bicycles in a group.

For the bicyclists' attributes, gender, age group and presence of passenger or goods were found correlated to the propensity of red light running, all at the 1% level. In particular, propensity of male bicyclists was 66% higher than that of female bicyclists. Additionally, propensity of younger bicyclists was 4% higher than that of the normal adult (such increase was more remarkable for e-bike riders). However, propensity of older bicyclists was 12% lower than that of the normal adult (such reduction was slightly weaker for e-bike riders). Furthermore, propensity of red light running when passenger or goods was present was 11% lower than that of the counterpart, at the 1% level of significance.

For the effect of traffic condition, propensity of red light running increased with the increase in bicycle volume, but decreased with the increase in opposing vehicular traffic, both at the 1% level of significance. 1% increase in bicycle flow was correlated to 0.8% increase in the propensity. However, 1% increase in opposing vehicular traffic was correlated to 4.2% reduction in the propensity. Propensity of red light running of e-bike rider was less sensitive to the changes in bicycle volume and opposing vehicular traffic.

For the effects of road geometry and traffic control attributes, increase in the crossing length was correlated to the reduction in propensity. However, presence of raised median and signal countdown display was correlated to the increase in propensity, both at 1% level of significance.

5. DISCUSSION

5.1. Bicycle Type

This study examined the red light running behaviors of bicyclists (both e-bike and conventional bicycle) using video observation survey. A random-parameter model was established to measure the relationship between propensity and possible contributing factors. Propensity of red light running of e-bike riders was found higher than that of conventional bicyclists. This could be attributed to the increase in the power of e-bike. Indeed, the average operating speed of e-bikes could be of 8 km/h higher than that of conventional bicycles (Lin et al., 2008). Because of the increased mobility, e-bike riders tended to be more aggressive. This finding is consistent with previous studies that the e-bike riders were more likely to engage in risky behaviors than bike riders (Bai et al., 2013, 2015, 2017; Guo et al., 2014). Yet, it is worth exploring the relationship between riders' characteristics, aggressiveness and operating speed, when more comprehensive information on the safety perception of bicyclist is available from the attitudinal survey. E-bike is increasingly popular in major Chinese cities despite that findings on the effect of bicycle type on red light running maybe controversial (Bai et al., 2013, 2015; Guo et al., 2014; Schleinitz et al., 2019; Wu et al., 2012). Mode share of e-bike was 150% higher than that of conventional bicycle in Nanjing City (Cheng et al., 2019). Findings of this study should be indicative to the planning and implementation of enforcement and road safety publicity measures targeted to the bicyclists, especially for the e-bike riders (Guo et al, 2014).

5.2. Bicycle Group

To the best of our knowledge, it is rare that the effect of presence of other bicycle as a group and group size on the propensity of red light running is examined. As revealed in the current study, propensity of red light running of bicyclist declines when the bicycle group size increases. **Table 4** presents the distribution of red light running rate of bicyclist by bicycle type and group size. As shown in Table 3, overall red light running rate decreases monotonically from 33.2% for 1 bicycle to 9.3% for more than 8 bicycles. Similar observation can be revealed for e-bike rider (even more remarkable reduction from 45.9% for 1 bicycle to 10.8% for more than 8 bicycles). This could be attributed to the effect of social norms (Abadi et al, 2019; Harrell, 1991; Rosenbloom, 2009; Sun, 1993). In particular, the bicyclist could be less conscious (against the criticism from others) when there is no other bicycle at the junction approach. Therefore, the rider may have higher tendency to commit traffic violations (e.g. red light running violation, and violations of traffic sign and road marking) (Abadi et al, 2019; Rosenbloom, 2009). Again, the unfavorable effect of the absence of other bicycles on red light running propensity was more profound for e-bike (as shown in Table 3, red light running rate of conventional bicycle first increases moderately from 7.9% for 1 bicycle to 12.9% for 2 to 4 bicycles, but gradually declines to 6.1% for more than 8 bicycles) because of the increase in the power and operating speed. Nevertheless, presence of manual enforcement might be effective in deterring against red light running violation, in relation to the influence of social norms (Chen et al., 2020). Yet, it is worth exploring the effect of speed differential across bicycle type on the red light running propensity, when more detailed information on bicycle movement and speed are available in the extended study.

Table 4. Red light running rates by bicycle type and group size

Bicycle type	**Group size**			
	1 bicycle	**2 to 4 bicycles**	**5 to 8 bicycles**	**More than 8 bicycles**
Overall	33.2%	25.8%	19.5%	9.3%
E-bike	45.9%	40.1%	22.6%	10.8%
Conventional bicycle	7.9%	12.9%	9.7%	6.1%

5.3 Traffic Condition

Both bicycle volume and opposing vehicular traffic volume significantly affected the propensity of red light running. In particular, propensity increases with the increase in bicycle volume, but declines when the opposing traffic volume increases. This could be because bicyclists tend to be more cautious under high traffic flow condition, given the higher risk of crash involvement and severe injury. Such effect could diminish when bicycle volume increases. To mitigate the problem, green time for bicycle could be extended (adaptively) when bicycle volume increases. Indeed, it could reduce the traffic delay of bicyclist at the junctions and reduce the tendency of red light running (Wong et al., 2007; Sze et al., 2011a). Yet, it is worth exploring the effect of safety perception (attributed to the variation in opposing vehicular traffic volume) on the propensity of red light running when the relevant data is available from the attitudinal survey (Chen et al., 2020; Wong et al., 2008).

5.4. Traffic Control

Presence of signal countdown display was correlated to the increase in the propensity of red light running. In particular, average red light running rate at the intersections with signal countdown displays was 74% higher than that with no signal countdown display (such increase was even more obvious for conventional bicyclists). As shown in **Figure 3**, red light running was prevalent during the first and last deciles of the red period. Indeed, presence of signal countdown display can magnify the level of anxiety of the bicyclists. Then, the possible late stop and early start are more prevalent. Therefore, installation of signal countdown display should be proceeded with great caution. Nevertheless, it is worth investigating the bicyclists' responses to the signal countdown display using the driving simulator approach (Chen et al., 2019).

6 CONCLUSIONS

This study investigates the red light running behavior of bicyclist using the video observation survey. A random-parameter logit model is established to measure the association between the propensity and factors including bicyclists' characteristics, traffic condition, road geometry and traffic control attributes. Additionally, effects of bicycle type (e-bike versus conventional bicycle) and presence of other bicycles as a group (and group size) are considered. Results indicate that propensity of red light running of e-bike riders is higher than that of conventional bicyclists. Also, bicycle type can moderate the effects of bicycle group size, age of bicyclist, bicycle volume and opposing vehicular traffic volume. Bicycle has been promoted as a sustainable transport mode (where e-bike is increasingly popular in recent years) despite that it is vulnerable to road fatality and severe injury (Sze et al., 2011b). Findings of this study should improve the understanding of red light running behaviors of bicyclists. Then, it should be indicative to the effective enforcement and road safety publicity measures that could deter against the red light running of targeted bicyclist group (Sze et al., 2011a). Stricter penalties and more enforcement, such as e-bike licensing system and manual police enforcement, could be imposed to combat the red light running behavior of e-bike riders (Guo et al, 2017). Moreover, safety education and promotion programs could enhance the safety awareness and modify the obedience behaviors of individuals and community (Chen et al., 2020). Hence, the overall bicycle safety can be enhanced. Yet, it is worth exploring the moderating effect of bicyclists' characteristics on the safety perceptions and red light running behaviors under different traffic conditions, with respect to traffic speed and traffic composition, when more comprehensive information is available from the attitudinal survey in the future (Wong et al., 2008; Li et al., 2014).

Consider the limit of video resolution, data on bicyclists' age was categorical, i.e. youngster, mid-aged and elderly, based on the rider's facial appearance in the video. Attributes like presence of helmet, hat and sunglasses were not recorded in this study. Additionally, effect of emerging technology including bike-sharing, that was yet to be introduced at the time of survey, on the red light running behaviors could have been investigated. Nevertheless, it is worth exploring the feasibility of automated video coding approach in the extended study. On the other hand, this study is limited to the behaviors of bicyclists during the peak periods on weekdays. In the extended study, difference in red light running behaviors of bicyclists between peak and non-peak periods should be examined.

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