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Research Article

Analysis of Crossing Behavior and Violations of Electric Bikers at Signalized Intersections

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This paper focuses on investigating electric bikers' (e-bikers) crossing behavior and violations based on survey data of 3,126 e-bikers collected at signalized intersections in Nantong, China. We first explore e-bikers' characteristics of late crossing, incomplete crossing, and violating crossing behaviors by frequency analysis and duration distribution, and examine a few influential factors for e-bikers' red-light running (RLR) behavior, including site type, crossing length and traffic signal countdown timers (TSCTs). E-bikers' RLR behavior is further divided into three categories, namely GR near-violations, RR violations, and RG violations. Second, we use a binary logistic regression model to identify the relationship between e-bikers' RLR behavior and potential influential factors, including demographic attributes, movement information, and infrastructure conditions. We not only make regression analysis for respective violation type, but also carry out an integrated regression of a census of all three types of violations. Some insightful findings are revealed: (i) the green signal time and site type are the most significant factors to GR near-violations, but with little impact on the other two violation types; (ii) the waiting time, waiting position, passing cars and crossing length exert considerable impact on RR violations; (iii) for RG violations, TSCTs, leading violators and gender are the most significant factors; (iv) it is also unveiled that site type, green signal time and TSCTs have negligible impact on the whole violations regardless of the violation types. Thus, it is more meaningful to investigate the impacts of these variables on e-bikers' RLR behavior according to different violation types; otherwise, the potential relationship between some crucial factors and e-bikers' RLR behavior might be ignored. These findings would help to improve intersection crossing safety for traffic management.

1. Introduction

The ownership and usage of electric bikes (e-bikes), a type of electric powered two-wheeled vehicle, have skyrocketed over the past decade in China. In 2016, over 200 million e-bikes were ridden on China's roads and three million more were sold in the same year compared to just a few thousand in 1998 [1, 2]. Due to its advantages of labor-saving, flexibility, and compatibility with the urban scale, e-bike constitutes a substantial proportion of the travel modes in China, especially in small-to-medium-sized cities. For example, in 2017, over 40% of trips in the downtown area of Nantong, Jiangsu Province, were made using e-bikes [3]. Similarly, in Nanning, Guangxi Province, e-bikes were used for 34% of trips in 2015 [4].

The number of e-bikes in China has been rapidly increasing, causing significant traffic safety issues. The total number of accidents and fatalities involving e-bikers has increased drastically in the past decade. Between 2013 and 2017, in China, e-bikers contributed to 56,200 traffic accidents, resulting in 8,431 fatalities, 63,400 injuries, and direct property losses of 111 million Yuan [5]. In Jiangsu Province, more than 50% of the e-bike-related traffic accidents and over 40% of the subsequent fatalities in 2018 were caused by e-bikers' traffic rule violating behavior [6]. Moreover, previous studies found that this violating behavior, especially red-light running (RLR) behavior at signalized intersections, partially contributed to the accidents and fatalities associated with e-bikers [7–11].

Most of the studies have focused on cyclists' RLR behavior at signalized intersections. Investigations have been performed on the influence of individual characteristics and psychological factors on cyclists' RLR behavior. For instance, Johnson et al. [12, 13] discovered the significant risk factors influencing cyclists' RLR behavior, such as gender, age, crash experience, and safety perception. Additionally, Wu et al. [14] revealed that gender, age, and conformity tendency significantly contributed to cyclists' red-light infringement. In another study, Pai and Jou [15] found that male or young cyclists were more prone to commit no-stopping RLR behavior. Similarly, Fraboni et al. [16] showed that male cyclists had a higher percentage of no-stopping crossings when the red light was on, whereas elderly cyclists (more than 50 years old) exhibited a stronger tendency to stop at a red light. A range of studies also discussed that the potential association of cyclists' RLR behavior was with other violations, such as unhelmeted riding [15], carrying passengers [15], using a phone [17], and listening to music [18, 19].

Among several studies related to e-bikers, the findings showed that e-bikers had a stronger intention to violate a red light than regular cyclists [14, 20–30]. Yang et al. [23], with a hazard-based duration model, established that the prominent contributors to red-light infringement of cyclists and e-bikers were rider type, gender, waiting position, conformity tendency, and traffic volume. A recent study conducted by Yang et al. [10] reported the psychological factors (e.g., attitude, perceived behavioral control, moral norm, and self-identity) that significantly influenced e-bikers' RLR intention by using the theory of planned behavior. Also, the influence of infrastructure conditions on red-light infringement has been discussed. Zhang and Wu [22] found that installing sunshades at intersections could reduce the RLR rates of cyclists and e-bikers on sunny/cloudy days. Schleinitz et al. [24] investigated the impacts of lane types and intersection types on red-light infringement and found that cyclists and e-bikers riding on the carriageway had the lowest RLR rate, and the intersection type had a substantial effect on red-light infringement.

However, the role of infrastructure conditions contributing to e-bikers' RLR behavior in China remains unclear. Although Schleinitz et al. [24] have discussed the impact of the lane types and intersection types on red-light infringement of cyclists and e-bikers, their findings are not necessarily applicable elsewhere due to the considerably different definitions of e-bikes between China and the Western countries. Also, Zhang and Wu [22] only investigated one specific infrastructure condition (sunshades) while other infrastructure conditions which might influence e-bikers' RLR behavior in China were ignored. Among the infrastructure conditions of signalized intersections, traffic signal countdown timers (TSCTs) are attention-worthy, which assist motorists/riders/pedestrians in decision-making at signalized intersections by providing them with real-time signal duration information. In general, TSCTs are equipped with two types of countdown timers: green signal countdown timers (GSCTs) and red signal countdown timers (RSCTs). GSCTs and RSCTs display the remaining time of the green signal and of the red signal, respectively. E-bikers can decide to wait or cross based on the time displayed on GSCTs/RSCTs. Previous studies conducted by Islam et al. [31, 32] suggested that the presence of GSCTs/RSCTs contributed to an improvement in the crossing safety and efficiency of drivers at signalized intersections. However, no unified and consistent conclusion exists concerning the impact of TSCTs on pedestrians' crossing behavior at signalized pedestrian crossings [33–41]. To the best of our knowledge, few previous studies have discussed the effect of TSCTs on e-bikers' RLR behavior at signalized intersections. Furthermore, there is hardly any understanding on the influence of other infrastructure conditions, such as red/green signal time, intersection (site) type, crossing length, and crossing width, on e-bikers' crossing behavior and violations at signalized intersections.

To address these shortages, the first aim of this work is to provide an unobtrusive observation method to observe and analyze e-bikers' crossing behavior and violations. The second aim is to investigate the impact of various contributing factors, especially infrastructure conditions, on e-bikers' red-light infringement at signalized intersections. The possible contributing factors (independent variables) were classified into three broad categories, demographic attributes, movement information, and infrastructure conditions (Table 1). The final outputs obtained from this work might provide solutions for reducing the occurrence of accidents and fatalities involving e-bikers at signalized intersections, especially in developing countries with high e-bike ownership.

The remainder of the paper is organized into three parts. The first part describes the site testing, video recording, and video coding method. The second part presents the observation and analysis of e-bikers' crossing behavior and violations at signalized intersections, including late crossing, incomplete crossing, and violating crossing. The final part details the modeling of the influence of various contributing factors on e-bikers' RLR behavior.

2. Data

2.1. Site Testing. The purpose of this work was to investigate the crossing behavior and violations of e-bikers at signalized intersections. The observational site testing was based on two criteria. First, the sites had to be selected based on the research objectives. The site type had to include X-intersections (four-armed intersections) and T-intersections (three-armed intersections) (Figure 1), as well as intersections with/without TSCTs. Second, a high volume of e-bikes had to be available during the period of video recording. Before the final observational sites were confirmed, we had carried out a pilot observation and tested fourteen sites. Finally, eight signalized intersections were selected for further investigation in this study (Table 2). The study sites were geographically well located across the road network of Nantong, China (Figure 2).

2.2. Video Recording. Video recording has been confirmed to be an effective field observation approach to studying traffic violation behavior at intersections [12, 22, 23, 33, 37]. In this study, video cameras (Sony HDR-CX680) were settled in the vantage and covert points to record footages of e-bikers' crossing behavior and violations. To obtain the required data, we had to ensure that the video recording covered the waiting area, the crossing process, the opposite lanes, and the light that was being displayed on at the traffic signals. The video data were recorded during the evening peak hours (5:00 p.m.–7:00 p.m.) on clear-weather weekdays (excluding Friday). As the

Table 1: Definitions of independent variables.

Categories	Variable	Variable type	Description
Demographic attributes	Gender	Categorical	0 = if female e-biker, 1 = if male e-biker
	Estimated age	Categorical	0 = if elderly e-biker (>50), 1 = if middle-aged e-biker (30–50), 2 = if young e-biker (<30)
	Waiting position[a]	Categorical	0 = if in designated area, 1 = if in nondesignated area (out of designated area, e.g., waiting beyond the stop line, occupying the motorized lanes or pavements)
Movement information	Waiting time	Continuous	Interval time between arrival time and begin-crossing time
	Leading violators	Continuous	Number of other violators in front of an e-biker who starts to cross
	Passing cars[b]	Continuous	Average number of motor vehicles passing path section per lane (flow) per min when an e-biker arrives
	Site	Categorical	0 = if site 1, 1 = if site 2, 2 = if site 3, 3 = if site 4, 4 = if site 5, 5 = if site 6, 6 = if site 7, 7 = if site 8
	Site type	Categorical	0 = if X-intersection, 1 = if T-intersection
	Red signal time	Continuous	Interval time of red signal phase
Infrastructure conditions	Green signal time	Continuous	Interval time of green signal phase
	Crossing length[c]	Continuous	Length of e-bikers crossing from stop line to opposite nonmotorized lanes
	Crossing width	Continuous	Width of straight crossing, represented by width of nonmotorized lane
	TSCTs	Categorical	0 = if TSCTs are uninstalled, 1 = if TSCTs are installed

[a]Refer to Figure 1 for illustration for waiting position. In video coding, if e-bikers perform a no-stopping crossing, waiting position is regarded as in designated area. [b]Refer to Figure 1 for illustration for passing car flows. [c]Refer to Figure 1 for illustration for crossing length.

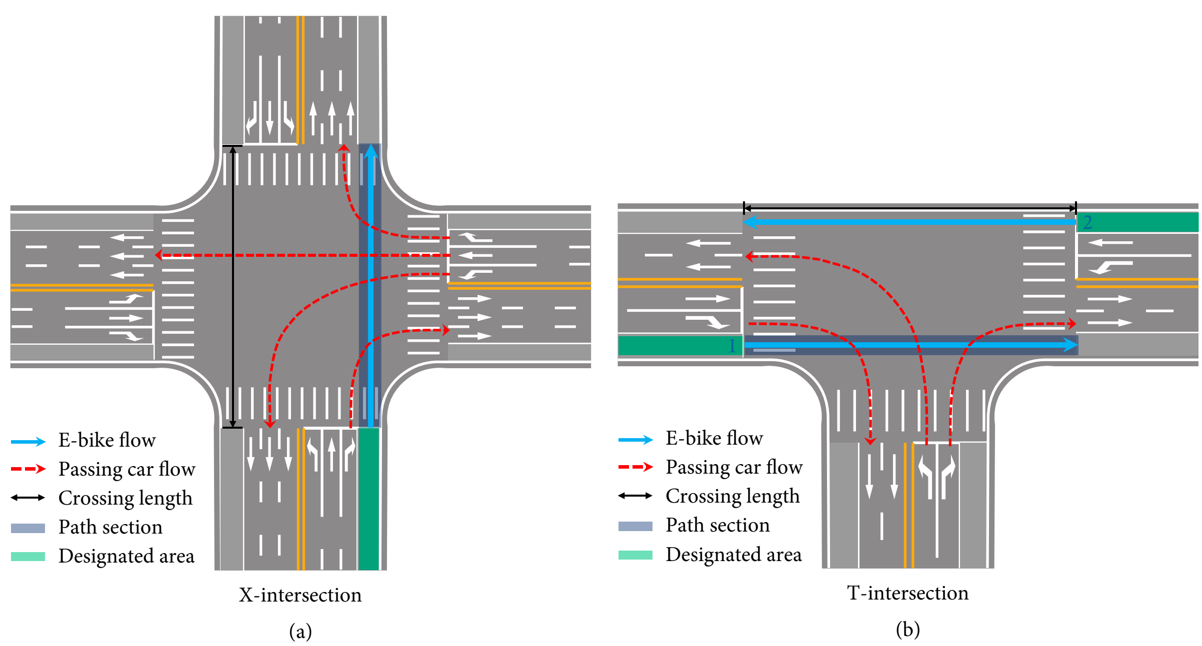


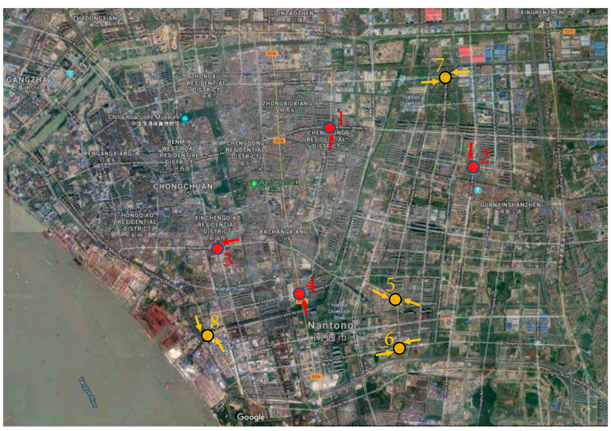
Figure 1: Illustrations of the intersections and variables.

approaching lanes had identical traits, we only recorded the data of one random direction of approaching lanes per one X-intersection (see the red arrows in Figure 2). According to the stipulation in the Chinese Road Traffic Safety Law, vehicles (motor and non-motor vehicles) are prohibited from passing when the red light is on. Hence, in the T-intersections (see in Figure 1(b)), the e-bike flows 1 and 2 were both subject to the red light, despite the e-bike flow 2 had no conflicts with passing car flows during the whole traffic signal cycle. Thus, considering the different traits of e-bike flows 1 and 2, we performed recording in two directions of approaching lanes which had straight-pass e-bikers (see yellow arrows in Figure 2). In addition, the recording time per site must reach at least one hour. To diminish the impacts of external factors on the crossing behavior, we had to ensure that no traffic police or wardens were regulating the traffic order during the observation.

Table 2: Descriptions of the selected signalized intersections.

Site	Site type	Width of nonmotorized lane (m)	Crossing length (m)	Green signal time (s)	Red signal time (s)	Yellow signal time (s)	All-red signal time (s)	TSCTs installation
1	X	3.0	54.8	27[a]	71	3	3	Uninstallation
2	X	4.5	63.8	52[a]	45	3	3	Uninstallation
3	X	4.5	51.4	34[a]	84	3	3	Installation
4	X	8.0	52.9	50[a]	47	3	3	Installation
5	T	3.5	25.1	22[b]	26	3	2	Installation
6	T	4.0	49.8	35[b]	44	3	3	Uninstallation
7	T	4.5	33.2	25[a]	34	3	2	Installation
8	T	3.5	37.5	20[a]	23	3	2	Uninstallation

[a]Straight green signal time; [b]Straight and left-turn green signal time.



● X-intersection
● T-intersection

Figure 2: Field data collection sites.

2.3. Video Coding. In this work, only e-bikers who went right across the signalized intersection were coded. Right-turn e-bikers were not coded as they were not subject to the traffic light following the Chinese Road Traffic Safety Law; left-turn e-bikers were also excluded due to the limited field of view of the video cameras [22, 23]. To improve the efficiency of the video coding, all coders received extensive training on the coding scheme, and video data were coded simultaneously by two groups of coders. One group extracted the data related to e-bikers, and the other group extracted the data of motor vehicles which may conflict with e-bikers. The data of e-bikers include gender, estimated age, waiting position, waiting time, and leading violators. The data of motor vehicles include the number of passing cars when the e-biker arrived. The two groups of data were matched based on the arrival time of each e-biker and the signal cycle containing e-bikers' arrival time. To avoid potential bias in video coding, two independent coders performed the same coding task. One-way intraclass correlations (for continuous variables) and Cohen's kappa (for categorical variables) were used to validate the coding reliability. The calculated coefficients ranged from 0.85 to 0.97, indicating that the video coding was reliable.

3. Results and Discussion

To clarify the signal phase of e-bikers' arriving, waiting, starting crossing, and completing crossing, the traffic signal status was divided into four phases: steady green signal (SGS), last 10 s green signal (LGS), yellow signal (YS), and red signal (RS). SGS and LGS phases are referred to as the green signal (GS) phase (Figure 3). The reason for adding an LGS phase is that a high proportion (79%) of the e-bikers who arrived during the last 10 s of the GS phase were unable to complete the crossing before the initiation of the RS phase (Table 3). Thus, the application of four signal phases is beneficial for the discussion on the crossing behavior and violations.

3.1. General Observations. The data of the total number of 3,126 eligible subjects were obtained by video coding. Among the subjects, 59.4% ($n = 1,857$) were male and the proportions of young, middle-aged, and elderly e-bikers were 40.5% ($n = 1,266$), 49.2% ($n = 1,538$) and 10.3% ($n = 322$). The statistics showed that 26%, 17%, 5%, and 52% of e-bikers arrived at the study sites within the SGS, LGS, YS, and RS phases, respectively (Table 3).

3.1.1. Late Crossing. The late crossing is defined as a crossing behavior in which e-bikers start to cross after they have arrived during the LGS/YS phase. The time left to the RS onset that e-bikers started crossing is listed in Table 4, in which we summarized the minimum, maximum, mean, ratio, 15th percentile, and 85th percentile values by sites. The minimum values showed that e-bikers made a decision to cross even during the last seconds (from 0 to 2 s) to the RS onset. That is, some e-bikers chose to cross even when they arrived within the YS phase (generally 2-3 s in China). The maximum values indicated the total time before the RS onset, which was the sum of the SGS, LGS, and YS phases. The 15th percentile values showed the time (left to RS onset) that most of the observed e-bikers started to cross was more than that shown in Table 4. Considering the difference of the maximum time left to RS onset among the sites, the ratio of the mean time divided by the maximum time was used to compare the relative mean time when starting crossing on the same scale. The results showed that ratios of the mean time left to RS onset at Sites 5, 7, and 8 were lower than those of the other sites. Likewise, the

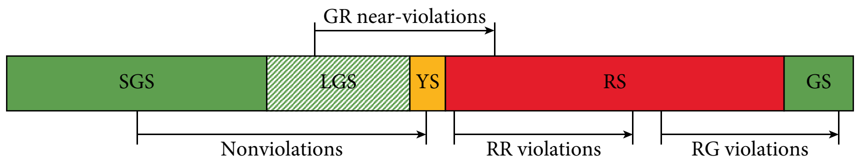


FIGURE 3: Signal phases and violation types.

TABLE 3: Statistics of signal phase upon arrival, crossing decision and incomplete crossing.

Signal phase	Arrival number		Decision			Incomplete crossing before RS/GS onset	
	Freq.	Per.	Wait	Cross	Cross Per.	Freq.	Per.
SGS	819	26%	3	816	100%	6[a]	1%[a]
LGS	547	17%	82	465	85%	369[a]	79%[a]
YS	141	5%	59	82	58%	82[a]	100%[a]
RS	1,619	52%	626	993	61%	569[b]	57%[b]
Total	3,126	100%	770	2,356	-	-	-

[a]Frequency and percent of e-bikers who started to cross during SGS/LGS/YS phases and unfinished it before RS onset. [b]Frequency and percent of e-bikers who started to cross during RS phase and unfinished it before GS onset.

TABLE 4: Time left to the RS onset.

Site	Min. (s)	Max. (s)	Mean (s)	Ratio	15th Percentile	85th Percentile
1	1	30	26	0.87	19	28
2	2	55	45	0.82	34	51
3	1	37	32	0.87	26	35
4	2	53	42	0.79	31	48
5	0	25	18	0.70	9	24
6	1	38	29	0.77	20	36
7	1	28	20	0.71	12	26
8	0	23	16	0.70	9	21

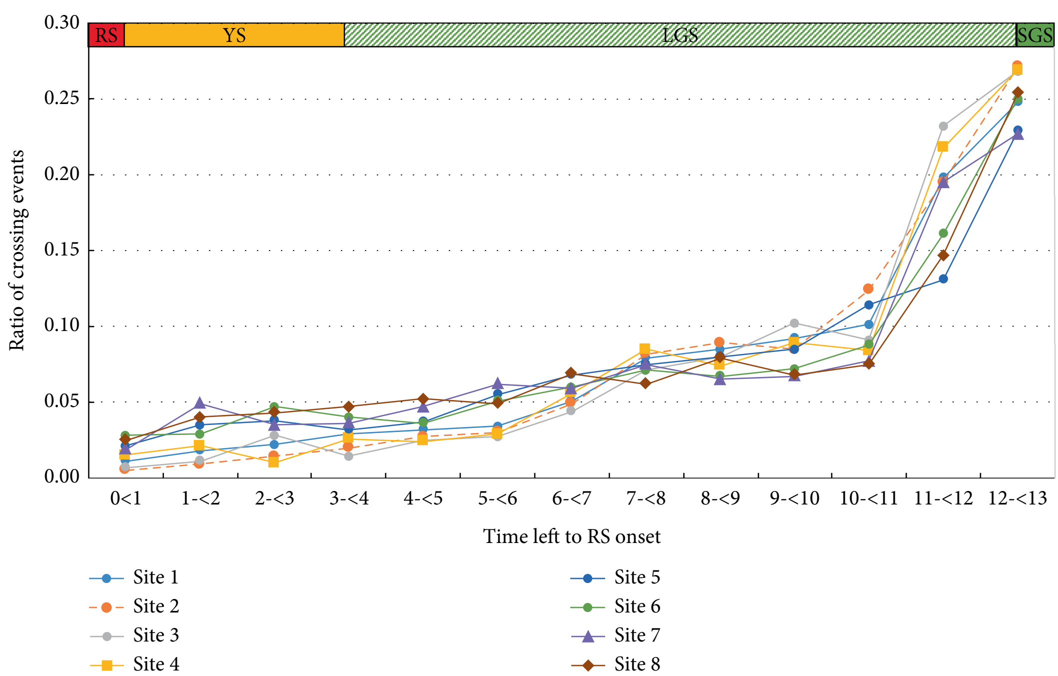


FIGURE 4: Ratio of crossing events during the time left to the RS onset (LGS and YS phases) in each site.

crossing lengths of Site 5, 7, and 8 were found to be shorter than the ones of the other sites. Inferentially, the shorter crossing length made e-bikers perceive that they might have the ability to complete the crossing safely even during the last few seconds. Therefore, we can consider crossing length as a possible contributing factor.

Next, we compared different sites using the same scale by a ratio of the crossing events. The ratio of the crossing events is defined as the number of the crossing events at each time left to RS onset divided by the total number of crossing events during LGS/YS phases. As shown in Figure 4, the ratios of the crossing events at Sites 5, 6, 7, and 8 were higher than those at Sites 1, 2, 3, and 4 during the last seconds to RS onset (time left to RS onset ranged from 0 to 6 s). Since the crossing length of Site 6 is longer than the average crossing length of all sites (49.8 m vs. 46.1 m), this result cannot be explained by the

Table 5: Descriptive statistics of violations in study sites.

Site	Site type	Violation type			Total violations	Total crossing	Violation ratio
		GR near-violations	RR violations	RG violations			
1	X	41	62	53	156	476	32.8%
2	X	33	41	40	114	317	36.0%
3	X	97	82	128	307	612	50.2%
4	X	79	51	99	229	544	42.1%
5	T	63	46	71	180	319	56.4%
6	T	42	47	53	142	277	51.3%
7	T	72	55	90	217	356	61.0%
8	T	30	40	35	105	225	46.7%
Total		457	424	569	1,450	3,126	46.4%

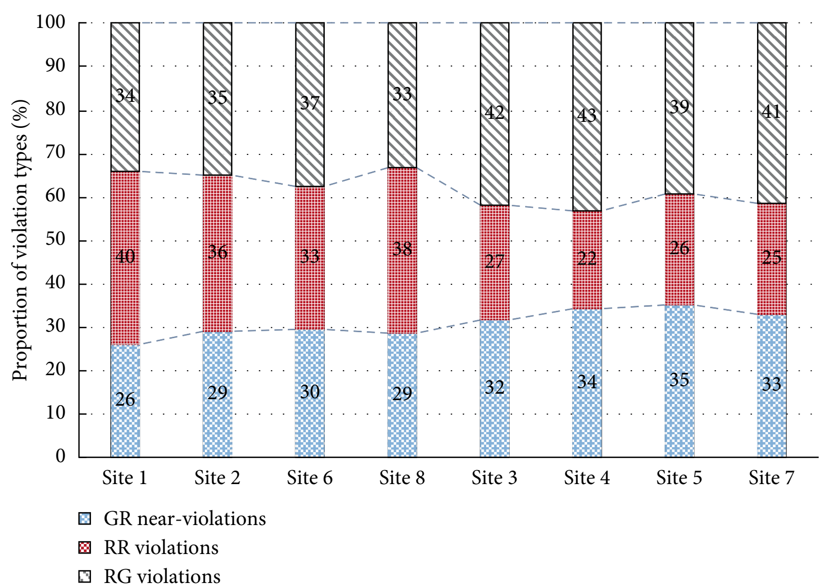


Figure 5: Proportion of violation types for each site.

influence of the crossing length and could have been caused by the specific site type. As seen in Figure 1(a), e-bikers experienced possible conflicts with right-turn vehicles (which are not generally subject to the traffic signal lights in China) in each approaching lane at X-intersections (Sites 1, 2, 3, and 4), which may deter the crossing events within the last few seconds to RS onset. Figure 1(b) showed that the e-bike flow 1 could experience the same conflicts with right-turn vehicles at the T-intersections as those at the X-intersections before the RS onset. However, since the e-bike flow 2 had no direct conflicts with the passing car flows during the whole traffic signal cycle, the e-bikers would perceive that completing the crossing was safe enough, and they made a faster decision to cross at Sites 5, 6, 7, and 8. Accordingly, the site type was also considered as a possible influencing factor in this study. Moreover, the ratios of crossing events dramatically increased after the interval from 10 to 11 s, subsequently reaching relatively high ratios of crossing events (from 0.227 to 0.271) within the interval of 12–13 s. On the whole, the curve trend in Figure 4 indicated that the ratios of crossing events were higher as the time left to RS onset was prolonged. This trend was due to the more time available to e-bikers to complete the crossing before the RS onset regardless of whether they had to wait for the next GS phase with the increased time left to the RS onset.

3.1.2. Incomplete Crossing. There are two types of the incomplete crossing. One incomplete crossing is defined as a crossing behavior in which e-bikers start crossing during the SGS/LGS/YS phases and cannot complete the crossing before the RS onset. Table 3 showed that the proportions of the incomplete crossing were 1%, 79%, and 100% during the SGS, LGS, and YS phases, correspondingly. The likelihood of e-bikers' crossing during the LGS phase was considerably higher than those during the YS phase (85% vs. 58%). Generally, the e-bikers who arrived during the SGS phase could complete the crossing before the RS onset, among which 1% incomplete crossing was due to faulty e-bikes or insufficient electricity supply. It was observed that about 79% of the e-bikers who started crossing during the LGS phase could not complete the crossing before the RS onset, while all of those who started crossing during the YS phase could not complete it. Accordingly, if the late-entry e-bikers

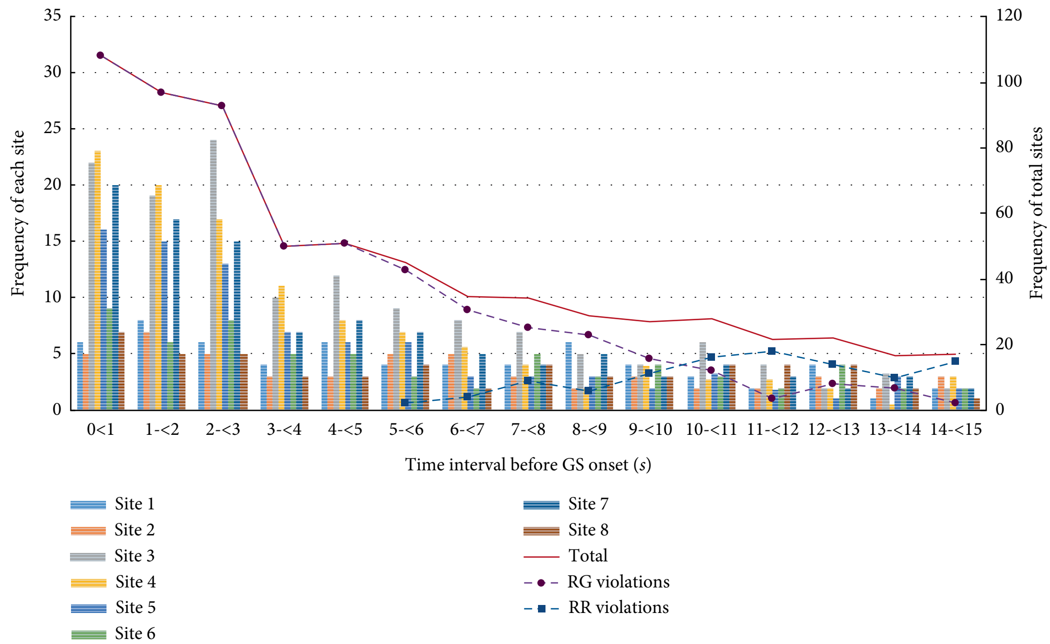


Figure 6: Crossing time distribution of RG/RR violations before GS onset.

Table 6: Results of the univariate analysis.

Variable	GR near-violations −2log likelihood C_1	C_2	ΔC	$Pr > \chi^2$	RR violations −2log likelihood C_1	C_2	ΔC	$Pr > \chi^2$	RG violations −2log likelihood C_1	C_2	ΔC	$Pr > \chi^2$
Gender	1,682.15	1,625.81	56.34	<0.0001	1,984.26	1,970.34	13.92	0.00	1,845.62	1,832.97	12.65	0.00
Estimated age	1,675.64	1,664.49	11.15	0.00	1,546.33	1,537.38	8.95	0.00	2,014.65	1,954.83	59.82	<0.0001
Waiting position	1,513.46	1,511.9	1.56	0.21	2,182.47	1,995.16	187.31	<0.0001	2,111.79	1,830.12	281.67	<0.0001
Waiting time	1,559.23	1,558.22	1.01	0.29	2,067.51	1,772.89	294.62	<0.0001	2,202.43	2,069.7	132.73	<0.0001
Leading violators	2,154.47	2,057.08	97.39	<0.0001	2,077.68	1,935.57	142.11	<0.0001	2,134.97	1,857.72	277.25	<0.0001
Passing cars	2,057.11	2,025.49	31.62	<0.0001	1,675.24	1,395.58	279.66	<0.0001	1,578.44	1,526.65	51.79	<0.0001
Site	2,071.39	2,069.36	2.03	0.15	2,095.61	2,094.52	1.09	0.28	2,007.11	2,005.26	1.85	0.17
Site type	1,578.33	1,390.76	187.57	<0.0001	2,117.23	2,050.41	66.82	<0.0001	2,064.39	2,002.86	61.53	<0.0001
Red signal time	1,607.82	1,606.58	1.24	0.26	1,509.11	1,500.09	9.02	0.00	1,553.40	1,545.29	8.11	0.00
Green signal time	2,194.35	2,066.93	127.42	<0.0001	1,693.72	1,692.23	1.49	0.21	1,509.17	1,507.02	2.15	0.14
Crossing length	1,588.46	1,490.85	97.61	<0.0001	2,134.53	1,907.14	227.39	<0.0001	1,864.35	1,781.98	82.37	<0.0001
Crossing width	1,524.16	1,521.89	2.27	0.13	2,022.49	2,020.7	1.79	0.18	1,802.47	1,800.87	1.60	0.19
TSCTs	2,074.25	1,771.58	302.67	<0.0001	1,517.60	1,502.84	14.76	0.00	1,564.34	1,234.62	329.72	<0.0001

who arrived during the LGS/YS phases maintain the average riding speed (less than 20 km/h), most of them might be unable to complete the crossing before the RS onset, which would lead to their exposure to conflicts with the passing cars (right-turn/left-turn/straight-pass vehicles) during the RS phase. Another incomplete crossing is defined as a crossing behavior in which the e-bikers start the crossing during the RS phase but cannot complete it before the GS onset. Approximately 61% of the e-bikers who arrived at the RS phase chose to cross, which is categorized as the most serious RLR behavior. Nearly 57% of these crossing e-bikers could not complete the crossing before the GS onset.

Table 7: Association of the predicted probabilities and the observed responses.

	GR near-violations	RR violations	RG violations
Percent concordant	85.7	86.3	83.9
Somers' D	0.701	0.745	0.698
Gamma	0.744	0.762	0.726
c	0.842	0.857	0.813

3.1.3. Violating Crossing. Based on the findings discussed above, e-bikers' crossing behaviors can be classified into four types: nonviolations, GR near-violations, RR violations, and RG violations (Figure 3). Nonviolations refer to the crossing behaviors in which e-bikers start to cross within the GS phases and complete it during the GS/YS phases. The Chinese Road Traffic Safety Law stipulates that vehicles (motor and nonmotor vehicles) which have crossed the stop line when the yellow light is on can continue the crossing; otherwise, they are prohibited from crossing. Thus, the e-bikers who start crossing during the YS phase are categorized as violators. In light of the stipulation, although the e-bikers who initiate the crossing within the GS phase and complete it during the RS phase are not categorized as violators, they would be exposed to the same level of danger as the e-bikers who start the crossing during the YS phase. Hence, the crossing behaviors, in which e-bikers start to cross within the GS/YS phase and complete it during the RS phase, are defined as GR near-violations. Additionally, the crossing behaviors in which e-bikers start to cross within the RS phase and complete it within the RS phase are classified as RR violations, while those that complete the crossing during the GS phase are denoted as RG violations. Since the e-bikers who started the crossing within the GS/YS phase and completed it by the GS/YS phases of the next cycle were extremely rare in our observations, this violation type is unconsidered. RR and RG violations are categorized as undisputed violations in compliance with the Chinese Road Traffic Safety Law, while GR near-violations are regarded as a special type of violations in this study.

The total number of violations among the observational subjects was 1,450. The descriptive statistics analysis of the violations at the study sites is presented in Table 5. The proportions of the GR near-violations, RR violations, and RG violations were 32%, 29%, and 39%, respectively. These findings revealed that the proportions of RG violations and GR near-violations were higher than that of RR violations; RG violations were the most prevalent of all types of violations. A plausible reason for the most prevalent RG violations is that most of passing cars were cleared at the end of the RS phase, and the e-bikers who arrived during the RS phase chose to cross during the last seconds to the GS onset for they could not endure a longer waiting time. For the second-prevalent GR near-violations, it could be due to that the light traffic volume (only right-turn vehicles) during the GS/YS phases led to e-bikers' weaker safety awareness and risk-ignorance of conflicting with passing cars from different directions in case of incomplete crossing before the RS phase. Furthermore, as shown in Figure 5, the proportions of RG violations and GR near-violations at Sites 3, 4, 5, and 7 with TSCTs were significantly more than those at Sites 1, 2, 6, and 8 without TSCTs, inferring that TSCTs installation might be associated with e-bikers' RLR behavior. Accordingly, our study considered TSCTs as a possible influencing factor. The violators corresponding to the three violation types are named GR near-violators, RR violators, and RG violators.

The time distributions before the GS onset when RG/RR violators started to cross were plotted at a 1 s interval, with a range from 0 to 15 s (Figure 6). We observed that most of the RG/RR violators started to cross within 0–3 s before the GS onset. This could be due to the installation of the 2-3 s All-Red clearance phase (which was used to clear all passing cars inside the intersection) in the traffic signals. Within the All-Red clearance phase, some e-bikers intended to cross through the traversable space-time gaps under light traffic volume. In the period earlier than 2-3 s before the GS onset, the number of RG/RR violations considerably declined. Moreover, we also found that only RG violations were in the interval from 0 to 5 s, indicating that the e-bikers who chose to cross during the last 5 s to the GS onset were unable to complete their crossing before the GS onset.

3.2. Effects of Independent Variables on RLR Behavior. As shown in Table 1, the independent variables were calibrated to compare the different impacts on the three violation types and explore the common influence on e-bikers' red-light infringement regardless of their violation types.

3.2.1. Different Violation Types. Based on the obtained data using the binary logistic model in SPSS, further analysis was conducted to determine the effects of the independent variables on the probability of e-bikers' RLR behavior. Previous studies have investigated the probability/rates of violation behaviors only for pedestrians who arrived and crossed during the red signal phase regardless of the differences in the violation types [9, 42–44]. The aforementioned three violation types were regarded as the subjects of the subsequent analysis. The 1,507 e-bikers who arrived at the GS/YS phases were included in the analysis of the GR near- violations, and 1,619 e-bikers who arrived at the RS phases were included in the analysis of the RR and RG violations.

Univariate analysis (variable added separately) was applied to choose the possible variables to be integrated into the binary logistic models for the three violation types. The analysis results of the deviances and the likelihood ratio test p-values are displayed in Table 6. The deviances $\Delta C = C_1 - C_2$ represent the error associated with the model when only an intercept is entered into the model for the case of C_1 (without variable) and when the independent variable is entered into the model for the case of C_2 (with variable). The higher the value of ΔC is, the stronger the significance of the variable in the model is. Finally, the variables entered into the model for the GR near-violations were gender, estimated age, leading violators, passing cars, site type, green signal time, crossing length, and TSCTs. The variables entered into the models for the RR and RG violations were the following: gender, estimated age,

Table 8: Results of the final logistic regression models for three violation types.

Variables	GR near-violations			RR violations			RG violations		
	B	S.E.	Pr > χ^2	B	S.E.	Pr > χ^2	B	S.E.	Pr > χ^2
Gender									
Male vs. female	0.277	0.212	0.0042	0.224	0.182	0.0059	0.328	0.062	0.0037
Estimated age									
Young vs. elderly	0.331	0.083	0.0005	0.180	0.133	0.0036	0.303	0.261	0.0004
Middle-aged vs. elderly	0.382	0.171	0.0003	0.212	0.079	0.0003	0.346	0.047	0.0052
Waiting position									
In designated area vs. in nondesignated area	–	–	–	−0.226	0.072	<0.0001	−0.102	0.162	<0.0001
Waiting time	–	–	–	0.141	0.161	<0.0001	0.105	0.111	0.0043
Leading violators	0.072	0.233	0.0005	0.058	0.094	0.0031	0.084	0.032	<0.0001
Passing cars	−0.094	0.551	0.0073	−0.122	0.042	<0.0001	−0.078	0.319	0.0087
Site type									
T-intersection vs. X-intersection	0.274	0.092	<0.0001	0.111	0.620	0.6102	0.164	0.574	0.4531
Red signal time	–	–	–	0.130	0.355	0.3327	0.080	0.412	0.9165
Green signal time	−0.056	0.256	0.0002	–	–	–	–	–	–
Crossing length	−0.097	0.320	0.0056	−0.135	0.122	<0.0001	−0.065	0.061	0.0002
TSCTs									
Installing TSCTs vs. uninstalling TSCTs	0.313	0.162	<0.0001	0.060	0.526	0.7524	0.502	0.177	<0.0001
Intercept	3.892	1.328	0.0146	4.060	1.643	0.0223	3.310	2.011	0.0175

waiting position, waiting time, leading violators, passing cars, site type, red signal time, crossing length, and TSCTs.

The selected independent variables were added to the binary logistic models for the three violation types. The goodness-of-fit for these three models was estimated through the Hosmer–Lemeshow test. In essence, the Hosmer–Lemeshow test is a chi-square goodness of fit test for grouped data [45]. The test results showed that the three models had a relatively good fit for the obtained data as the chi-square (χ^2) statistics values were smaller than the critical value of the chi-square distribution (with a p-value for $Pr > \chi^2$ not less than 0.05). As shown in Table 7, the percentages of the concordant observations were close to 100, and the values of Somers' D, Gamma, and c were all close to 1, indicating that these three models provided adequate goodness-of-fit. The results of the logistic models for the three violation types are presented in Table 8.

A positive parameter estimate for a continuous variable suggests that the probability of RLR behavior increases with the rise in the value of the variable. For the categorical variable, it suggests that the maintenance at that particular level increases the probability of RLR behavior compared to the reference level. Based on the estimated results, we found that most of the independent variables in the final models were statistically significant at the 0.01 level, revealing that these variables contributed significantly to the likelihood of e-bikers' RLR behavior.

As shown in Table 8, for GR near-violations, installing TSCTs had 1.368 ($e^{0.313}$) times probability of RLR behavior than uninstalling TSCTs, revealing that the GSCTs installation would increase the proportion of the GR near-violations. This

Table 9: Results of univariate analysis for all violations.

Variable	−2log likelihood			Pr > χ^2
	C_1	C_2	ΔC	
Gender	2,067.56	2,020.64	46.92	<0.0001
Estimated age	1,695.37	1,687.21	8.16	0.00
Waiting position	1,605.32	1,590.20	15.12	0.00
Waiting time	2,169.72	1,994.08	175.64	<0.0001
Leading violators	2,067.24	1,820.87	246.37	<0.0001
Passing cars	1,569.80	1,258.04	311.76	<0.0001
Site	1,511.16	1,510.03	1.13	0.28
Site type	2,031.79	2,021.66	10.13	0.00
Red signal time	1,649.90	1,647.37	2.53	0.11
Green signal time	1,564.78	1,563.19	1.59	0.20
Crossing length	2,092.82	1,817.47	275.35	<0.0001
Crossing width	1,647.93	1,645.62	2.31	0.13
TSCTs	2,123.67	2,109.75	13.92	0.00

result is contrary to our expectations, because the e-bikers who know the real-time left to RS onset are more likely to accelerate their crossing using the e-bike's high-speed and accelerating performance. The next crucial variable was estimated age, which had the most pronounced positive effect on the GR near-violations than on the other violation types. Specifically, the likelihood that young and middle-aged e-bikers would decide to cross during the last few seconds were 1.392 ($e^{0.331}$)

Table 10: Logistic regression model for all violations.

Variable	B	S.E.	$\Pr > \chi^2$
Gender			
Male vs. female	0.292	0.153	0.0003
Estimated age			
Young vs. elderly	0.241	0.415	0.0036
Middle-aged vs. elderly	0.325	0.076	0.0049
Waiting position			
In designated area vs. in nondesignated area	−0.183	0.133	0.0028
Waiting time	0.072	0.228	0.0002
Leading violators	0.081	0.052	<0.0001
Passing cars	−0.106	0.194	<0.0001
Site type			
T-intersection vs. X-intersection	0.113	0.523	0.5428
Crossing length	−0.082	0.097	<0.0001
TSCTs			
Installing TSCTs vs. uninstalling TSCTs	0.203	0.421	0.3262
Intercept	4.136	1.670	0.0288

and 1.465 ($e^{0.382}$) times than those of the elderly e-bikers. We also found that the green signal time influenced only the GR near-violations. To be specific, one unit increase in the green signal time decreased the likelihood of e-bikers' RLR behavior by 5.4%. Moreover, the site type was also a crucial contributor for GR near-violations, whereas it exerted no significant effect on the other types. The odds of e-bikers' RLR behavior at T-intersections was 1.315 ($e^{0.274}$) times than those at X-intersections. This result was due to the absence of conflicts of the e-bike flow 2 at T-intersections with passing cars during the whole traffic signal cycle (Figure 1). Thus, these e-bikers had a higher tendency to violate a red light. In addition to the above variables, gender, leading violators, passing cars, and crossing length also had significant effects on GR near-violations.

The findings for the RR violations showed that the waiting time influenced more considerably the RR violations than the RG violations ($e^{0.141}$ vs. $e^{0.105}$). The increase by one unit of waiting time augmented the likelihood of e-bikers' RLR behavior by 15.1%. The passing cars had the highest negative impact on the RR violations as compared to the influence of the other types ($e^{-0.122}$ vs. $e^{-0.094}$ vs. $e^{-0.078}$). Specifically, the rise in the number of passing cars by one unit decreased the probability of e-bikers' RLR behavior by 11.5%, indicating that e-bikers were less willing to undertake the risk of the crossing during the RS phase as the number of passing cars rose. The next crucial variable was the waiting position, which had a more significant negative impact on the RR violations than on the RG violations ($e^{-0.226}$ vs. $e^{-0.102}$). We found that the e-bikers waiting in the designated area were 0.798 less likely to commit red-light infringement than those waiting in the nondesignated area. The crossing length exerted the strongest effect on the RR violations than on the other types ($e^{-0.135}$ vs. $e^{-0.097}$ vs. $e^{-0.065}$). The elevation of the crossing length by one unit led to a decline in the probability of e-bikers' RLR behavior by 12.6%. Of the remaining variables, gender, estimated age, and leading violators were also significant variables, while the site type, red time, and TSCTs were insignificant. Interestingly, TSCTs had no significant effect on RR violations as compared with the other violation types. That is, the RR violations could not decide whether to cross or not in the remaining real-time of RSCTs.

TSCTs were the most significant contributor to the red-light infringement by the RG violations than to that by the other violation types. Due to the presence of RSCTs and the 2–3 s All-Red clearance phase, the e-bikers would be 1.652 ($e^{0.502}$) more likely to start crossing before the GS onset at the signalized intersections with RSCTs than those without RSCTs. The leading violators had the greatest influence on the RG violations of all violation types ($e^{0.084}$ vs. $e^{0.072}$ vs. $e^{0.058}$). The increase by one unit in the leading violators would augment the likelihood of red-light infringement during the few seconds left to the GS onset by 8.8%. Gender had the strongest effect on the RG violations as compared to that on the other violation types ($e^{0.328}$ vs. $e^{0.277}$ vs. $e^{0.224}$). Male e-bikers who arrived within the last few seconds of the RS phase were 1.388 more likely to violate a red light than female e-bikers. In addition to the above variables, the estimated age, waiting position, waiting time, passing cars, and crossing length were significant variables, while the site type, and red time were insignificant. It should note that passing cars had a lower effect on the RG violations than on the RR violations. The main reason was that the average number of passing cars was relatively lower when the RG violations began to cross against a red light within 0–3 s left to the GS onset.

Based on the analysis results above, we can conclude that the impact of the independent variables on the three violation types was different. However, there were still some commonalities. In the next part, the common impact of independent variables on e-bikers' red-light infringement, regardless of their violation types are discussed.

3.2.2. Red-Light Infringement. Three violation types were included for univariate analysis and binary logistic regression (Tables 9 and 10) to establish the common influence of the independent variables on the e-bikers' red-light infringement and compare our results with previous studies.

The site was excluded from the univariable analysis, while the site type remained, inferring that these two variables were inter-related as functions of each other, and the site type had a relatively stronger influence. The red signal and green signal times were also removed. This outcome could be due to the significant correlation between the red/green signal time and the waiting time, while the waiting time had a stronger effect on the RLR behavior than the red/green signal time. Additionally, the univariable analysis results rejected the crossing width. The possible reason is that the crossing width would widen as e-bike flow expands (which is not subject to the width of the nonmotorized lane) when e-bikers enter the intersection from the approaching lanes. The remaining variables were integrated into the binary logistic model for further estimate.

The results identified gender as a significant variable in influencing e-bikers' RLR behavior. More specifically, male e-bikers had 1.339 ($e^{0.292}$) times the probability of RLR behavior than female e-bikers. In other words, male e-bikers were apt to suffer a higher risk than female e-bikers to obtain the benefits of violating a red light (e.g., saving time or reaching the opposite side expediently). Our results are in good agreement with those of Yang et al.'s [9]. The findings of a few investigations on cyclists' violating behavior showed that female cyclists were more likely to act in accordance with the traffic regulation [12–16]. Furthermore, using the social-psychological approach, Yang et al. [10] found that male e-bikers recognized the RLR behavior much easier compared to female e-bikers, which also supported the gender difference in red-light infringement.

The findings of this study revealed that age was a significant variable. Specifically, the young and middle-aged e-bikers had 1.273 ($e^{0.241}$) and 1.384 ($e^{0.325}$) times odds of RLR behavior compared to the elderly e-bikers. In previous studies, the effect of age on e-bikers' RLR behavior was still indefinite. Zhang and Wu [22] established that young cyclists and e-bikers that were younger than 30 years old had a stronger intention to commit RLR behavior. However, Yang et al. [23] discovered that young (<30) and middle-aged (30–50) e-bikers were more likely to violate a red light than elderly e-bikers, but the age was an insignificant variable. This discrepancy may be due to certain errors in the estimation of the e-bikers' age by video recording or other observational methods.

The waiting position was identified as a significant variable on the final logistic regression model. Specifically, e-bikers waiting in the designated area had 0.833 ($e^{-0.183}$) times the likelihood of RLR behavior than those waiting in the nondesignated area. To some extent, e-bikers' waiting position partially represented their risk-perception. The e-bikers waiting in the designated area had higher safety awareness and could perceive the high risk of e-biker-car crashes in the nondesignated area. Some studies indicated that risk-perception was insignificant for predicting pedestrians' or e-bikers' violating behaviors using the theory of planned behavior [10, 50]. However, they also underlined that although risk-perception was not a significant predictor, it did not necessarily mean that risk-perception had no impact on violating behaviors. Our findings indirectly verified that risk-perception had a strong influence on e-bikers' RLR behavior. The result was in line with a previous study on pedestrians' crossing behavior, in which Koh et al. [42] uncovered that pedestrians standing in the designated waiting area were less likely to violate than those standing in the nondesignated waiting area.

Waiting time significantly contributed to e-bikers' decision to violate a red light. The likelihood of RLR behavior increased with the prolongation of the waiting time. Specifically, an increase by one unit in the waiting time augmented the likelihood of RLR behavior by 7.5%. This result was consistent with the findings of previous studies on cyclists and e-bikers [23, 46, 47]. In the related studies on pedestrians' red-light infringement, the findings also indicated that the longer the waiting time was, the higher the odds of red-light infringement would be [42, 43, 48].

The effect of leading violators was evident from the analysis, given that the number of other violators in front of e-bikers who started to cross had a significantly positive effect on e-bikers' tendency to violate a red-light. Specifically, the increase in the number of leading violators by one unit resulted in the rise in the likelihood of e-bikers' RLR behavior by 8.4%, showing that e-bikers' RLR behavior was easily influenced by the crossing behavior of the surrounding e-bikers. This phenomenon was caused by a mentality pattern called conformity tendency. The result could be supported by the previous studies which revealed the significant effect of the conformity tendency on pedestrians' violating crossing behavior by the application of social-psychological methods [49, 50].

As expected, passing cars substantially contributed to e-bikers' RLR behavior. The odds of e-bikers' red-light infringement declined with the increase in the number of passing cars. This result was consistent with Yang et al.'s study [23]. They found that a decrease in the motor vehicle volume would increase the violation hazard of cyclists and e-bikers in a hazard-based duration model. In a study on pedestrians' crossing behavior, Zhou et al. [51] obtained similar results, that is, the number of the incoming cars influenced pedestrians' RLR behavior significantly at the signalized intersections. The main reason for this phenomenon was that the traversable space-time gap under the light traffic volume was larger than that under the heavy traffic volume, and e-bikers were able to cross through the gap under the light traffic volume more easily and safely. The likelihood of e-bikers' RLR behavior decreased by 10.1% with the increase by one unit in the number of passing cars.

The results confirmed that the site type was an insignificant variable in the model for the whole violations, which is supported by Koh et al. [42] who simultaneously considered that Site-type 1 (intersection type), Site-type 2 (number of crossing lanes), and the crossing length were the factors influencing pedestrian's crossing behavior at signalized intersections. Their results showed that Site-type 2 and the crossing length were the most significant factors, while Site type-1 was insignificant. These findings could be due to adding crossing length in our study, which exerted a stronger effect than the site type on the RLR behavior.

We found that the likelihood that e-bikers would violate a red light decreased with the increase in the crossing length. Specifically, the increase in the crossing length by one unit would diminish the odds of RLR behavior by 7.9%. This result is consistent with the findings of Koh et al. [42], who reported that the odds of pedestrian's red-light infringement decreased with the increase in the crossing length.

The signalized intersections with TSCTs had 1.225 times the probability of RLR behavior than those without TSCTs, whereas the results showed that the effect of TSCTs installation was not significant. However, from the above analysis of violation types, TSCTs installation had a significant effect on GR near-violations and RG violations. Moreover, RG violations were more sensitive to TSCTs installation compared to GR near-violations. Accordingly, it was more meaningful to understand the impact of TSCTs on e-bikers' RLR behavior based on the violation types. Previous studies have also supported this analytical approach. For example, Lipovac et al. [35] revealed that TSCTs had no statistically significant effect on the number of violations during the red light for pedestrians regardless of location and vehicle volume, while there was a statistically significant difference during the first and last four seconds of the red light, at the crossing located in the city center with a heavy traffic volume. The results obtained by Fu and Zou [36] indicated that the RSCTs installation caused more children to choose a violating and running behavior during the RS phase, and the GSCTs installation had a significant effect by helping children to complete their crossing within the GS phase. Thus, the above results might have ignored the influence of TSCTs on pedestrians' violating behavior if the violation types or the signal phases had not been taken into account. Our findings depicted the effect of TSCTs on e-bikers' RLR behavior during the different traffic signal phases, which could provide suggestions for whether installing the TSCTs or not in the different signal phases at signalized intersections.

4. Limitations and Future Research

In this study, since the video recording could not provide complete coverage of the whole intersection, the left-turn e-bikers were excluded. Future studies are required to record a full coverage video information and code the left-turn e-bikers with advanced technologies (e.g., "Mega Eyes" of China Telecom) to investigate their crossing behavior and violations, and compare them with those of straight-pass e-bikers. In addition, the trip purposes of e-bikers during the morning peak, the evening peak and the nonpeak period are different, which would potentially influence the red-light running behavior. Thus, additional studies are needed to discuss the crossing behavior and violations of e-bikers during the morning peak and the nonpeak period in future works. Furthermore, the influence of unobserved factors such as trip purpose and psychological perspective on e-bikers' red-light infringement was not taken into account in this study. E-bikers' actual motivations for individual RLR behavior remain unclear. To address these problematic areas of our research, we consider using corresponding interviews and questionnaires as an effective method in future studies.

5. Conclusion

This paper investigated the e-bikers' crossing and violations, associated influencing factors, and their differences among the three violation types at signalized intersections using an observational study. Eight signalized intersections with different traffic conditions and characteristics were selected as the observational sites for this work. A total number of 3,126 e-bikers crossing the intersections were observed.

The late, incomplete, and violating crossing behaviors were discussed. It was observed that for late-entry e-bikers who arrived during the LGS/YS phases, some of them also chose to cross even during the YS phase. The analysis results revealed that the crossing length and site type were possibly associated with e-bikers' crossing behavior. Among the e-bikers who possibly could not complete the crossing before the RS onset, those who began to cross during the SGS phase generally could complete the crossing before the RS onset, whereas those who started to cross during the LGS/YS phases were likely unable to complete it. We classified the violations into three types: GR near-violations, RR violations, and RG violations. Our findings showed that the proportions of the RG violations and GR near-violations were higher than that of the RR violations, among which the RG violations were the most prevalent type. Moreover, the proportions of the RG violations and GR near-violations at the study sites with TSCTs were considerably more than those at the rest sites without TSCTs, inferring that TSCTs installation might influence e-bikers' RLR behavior. In addition, most RG violators intended to cross during the interval 0–3 s before the GS onset due to the presence of a 2-3 s All-Red clearance phase.

We used a binary logistic regression model to further elucidate the effect of the independent variables on e-bikers' red-light infringement. The findings indicated that the estimated age had the most pronounced positive effect on the GR near-violations as compared to its influence on the other violation types. Moreover, the green signal time and site type were the most significant contributors to the GR near-violations, whereas they exerted no significant effects on the other types. The waiting time, waiting position, passing cars, and crossing length most considerably contributed to the RR violations than to the other violation types. However, the effects of TSCTs, leading violators, and gender on RG violations were the most significant among the three violation types. Subsequently, in this study, we took into account a census of all three types of violations to summarize the common influence of the independent variables on e-bikers' red-light infringement. Our findings revealed that the gender, estimated age, waiting position, waiting time, leading violators, passing cars, and crossing length were the most significant variables, whereas the site, site type, red signal time, green signal time, crossing width, and TSCTs were insignificant. Nonetheless, the site type, green signal time, and TSCTs still had important impacts on the three violation types. In other words, it was more meaningful to investigate the effect of these independent variables on e-bikers' RLR behavior considering the specific violation types. Thus, the authors of previous studies [23, 42–44] might have ignored the effect of some crucial variables on riders/pedestrians' violations regardless of the differences in the violation types.

The findings of this study provided a better understanding of e-bikers' crossing behavior and violations at signalized intersections. Therefore, they could support the development and implementation of countermeasures to reduce e-bikers' red-light infringement and facilitate the design of proper signalized intersections for e-bikers by transport agencies, especially in countries with a high population of e-bikers.

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.

Authors' Contributions

The authors confirm contribution to the paper as follows: study conception and design: T. Tang, H. Wang, X. Zhou; data collection: J. Ma, H. Wang; analysis and interpretation of results: T. Tang, H. Wang, J. Ma; draft manuscript preparation: T. Tang, X. Zhou. All authors reviewed the results and approved the final version of the manuscript.

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